Mortality Risk Valuation in Policy Assessment

A Global Meta-Analysis of Value of Statistical Life Studies

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A GLOBAL META-ANALYSIS OF VALUE OF STATISTICAL LIFE STUDIES

OECD
BETTER POLICIES FOR BETTER LIVES

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Preface

Whether it's managing pandemics, reducing death from stroke and heart disease, enacting seat belt laws or regulating workplace safety – government policies are part of the essential fabric for preserving public health and well-being. At the same time, policymakers face challenges in formulating such foundational policies as they weigh the environmental and health benefits against their costs.

The "Value of Statistical Life" (VSL) is a concept that has for decades helped policymakers to assess the costs and benefits of any policy that involves changes in mortality risk, such as air pollution regulations. This concept considers trade-offs that individuals make between risk and income, and their willingness to pay for a small decrease in the probability of mortality. Data like this make it possible to estimate the economic benefits resulting from new or existing policies that reduce exposure to health risks. These benefits can then be considered against the costs of implementing the policies.

In 2012, the OECD produced a seminal report that included the largest VSL meta-analysis study ever conducted. Significant advances have been made since the publication of this report and the evidence base on valuation of mortality effects has grown substantially. Despite this evolution, no globally consistent valuation updates have been developed. As a result, practitioners have grappled with applying earlier estimates in the face of fragmented research, evolving circumstances and a global pandemic.

Mortality Risk Valuation in Policy Assessment: A Global Meta-Analysis of Value of Statistical Life Studies provides the first comprehensive global review of the VSL since the 2012 OECD report. It synthesises over 50 years of evidence to provide easy-to-use estimates for six country groupings, while at the same time providing guidance for their transferability across countries and over time. Results indicate that, even when adjusted for inflation, the new values are higher for most global regions. This reflects evolving preferences among individuals, newer and more geographically diverse data, updated meta-analysis methods and overall economic growth. These VSL estimates can help policymakers better understand the benefits of public investments that affect mortality risk across sectors, both within and between similar countries.

It is my hope that these updated estimates will be widely used to set or revise policies, not just for the environment, but also in the transport, energy, food safety and health sectors. If they are used as a starting point, the OECD is well-positioned to help practitioners leverage the report's values in practice.

Jo Tyndall

Director, OECD Environment Directorate

Foreword

Policymakers regularly face the challenge of making decisions that affect people's risk of death. For example, setting stricter vehicle fuel efficiency standards may lead to higher costs for consumers and businesses but at the same time save lives through improved air quality in urban areas, thus creating a trade-off between economic costs and the value of saving lives. Too often, these economic trade-offs are not assessed in a systematic manner using a consistent methodology. This report aims to equip policy makers with the valuation methodologies and economic valuations necessary to assess economic benefits of avoided fatalities, also known as the "Value of a Statistical Life" (VSL).

The VSL represents the value a given population places on avoiding the death of an unidentified individual, such as reducing the number of deaths from air pollution. In 2012, the OECD published *Mortality Risk Valuation in Environment, Health and Transport Policies,* which provided a comprehensive assessment of VSL based on meta-analysis and also offered recommendations for how VSL estimates could be used in policy analysis and how they may be transferred among countries and over time.

While OECD's 2012 report has become a standard reference for many cost-benefit practitioners, scientific methods have progressed, new data have become available and an update is therefore timely. In the last decade alone, the number of completed VSL studies globally has nearly doubled while during this period there have also not been any new comprehensive global reviews or meta-analyses published of comparable scope and aim to OECD's 2012 work. This updated report entitled *Mortality Risk Valuation in Policy Assessment: A Global Meta-Analysis of Value of Statistical Life Studies* fills this gap and provides a comprehensive update based on the latest methodological developments and data.

The value of statistical life estimates presented in this report are expected to be widely applicable in cost-benefit analyses and other assessments of policies and projects, covering any area where there is a need to monetise mortality risk effects and compare them against the costs of such initiatives. The estimates can also be used to assess indirect positive or negative mortality impacts of other polices.

Considering the heterogeneity of the meta data supporting this report, there are advantages to adopting simple, general guidelines that are applicable to most cost-benefit analyses and other assessments involving mortality risks. Thus, the recommended easy-to-use, transparent and consistent base VSL values that are presented in this report will contribute to an improved and common understanding of the marginal benefits (or costs) of public policies that affect mortality risks across sectors, at least within and between similar countries.

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Preliminary results of the analysis have been presented by the authors at three conferences: Workshop on mortality and morbidity risk valuation: Advances and remaining challenges (25-26 January 2024 in Paris) organised by Daniel Herrera-Araujo, the Society for Cost-Benefit Analysis (19-20 September 2024 in Warsaw), and at the annual conference of the European Association of Environmental and Resource Economists (16 June 2025 in Bergen). Comments from participants are gratefully acknowledged, Finally, the work benefitted from synergies with the EU Horizon projects: "Methodologies for assessing the real costs to health of environmental stressors (MARCHES) (grant no. 101095430)" and "Valuation of environmental stressors (VALESOR) (grant no. 101095611)".

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Abbreviations and acronyms

AUD	Australian Dollars
CAD	Canadian Dollars
CBA	Cost-Benefit Analysis
CE	Choice Experiments
CM	Consumer Market
CPI	Consumer Price Index
CWD	Compensating Wage Differentials
CV	Contingent Valuation
DALY	Disability-Adjusted Life Year
GDP	Gross Domestic Product
HW	Hedonic Wage
NZD	New Zealand dollars
PPP	Purchasing Power Parity
PV	Present Value
QALY	Quality-Adjusted Life Years
RP	Revealed Preferences
SE	Standard Error
SP	Stated Preferences
USD	United States dollars – all values shown in constant PPP adjusted 2022 dollars unless otherwise noted
USEPA	United States Environmental Protection Agency
VOLY	Value of a Statistical Life Year
VSL	Value of a Statistical Life
WTA	Willingness to Accept
WTP	Willingness to Pay

Executive summary

The idea of associating human life with a monetary value is intuitively challenging and can seem insensitive or harsh. However, policymakers regularly face decisions that impact people's risk of death. For example, setting stricter vehicle fuel efficiency standards may lead to higher costs for consumers and businesses but at the same time save lives through improved air quality in urban areas, thus creating a trade-off between economic costs and the value of saving lives.

The economic benefits of prevented fatalities can be expressed in terms of a "Value of Statistical Life" (VSL), which represents the value a given population places on avoiding the death of an unidentified individual, such as reducing the number of deaths from air pollution. Importantly, even if a change in mortality risk is not explicitly valued in monetary terms, it is implicitly valued through policy decisions with economic implications. However, such implicit values can vary considerably from case to case. While people may object to explicit valuations on ethical grounds, the use of implicit values is pervasive, even if these values are not always observable. Explicit values derived from carefully conducted valuation techniques improve the information available to decision makers by providing a consistent and transparent metric that can be applied across policy areas.

One important tool to promote consistency in policy assessments is cost-benefit analysis (CBA). CBA compares the total expected costs of a given policy against its total expected benefits, to determine net benefits for society. As policy decisions that impact human life are a major concern, the economic valuation of human health effects, including VSL, is therefore a cornerstone of CBA.

VSL estimates can be derived from surveys where individuals are asked about their willingness to pay for small improvements in mortality risk (stated preference methodologies) or from observing trade-offs that individuals make between income or wealth and the risk of dying (revealed preference methodologies), such as taking a higher-risk job in exchange for a higher salary. Given that VSL often constitutes a sizeable share of the total economic benefits of many public policies, it is important to use the best available estimates.

This report presents an update to the OECD's 2012 VSL report, which included the largest VSL meta-analysis (based on primary stated preference VSL studies published between 1970-2008) and quickly became an important international reference. In contrast, this report includes a meta-analysis of more than 4 000 individual estimates from 277 studies across 49 countries between 1970-2023, from which about 2 400 VSL estimates between 2009-2023 were used for the base VSL estimates. The current report is once again the largest VSL meta-analysis ever attempted and the first to develop VSL estimates based on both revealed and stated preference methodologies. While most of the primary VSL studies in the database are from Europe and North America, it also includes numerous studies from Latin America, Africa, Australia and Asia.

The report provides base VSL estimates (mean and median values, and confidence bands) for six country groups: OECD Member Countries, European Union, United States, Low-and middle-income countries, High-income countries and a Global estimate. The estimated mean base VSLs range from about USD 1 million in low- and middle-income countries to between USD 7.1 million and USD 8.5 million for OECD and high-income countries. Due to using newer data based on more recent methodological improvements, more comprehensive geographical coverage and the inclusion of both revealed and stated preference methods, the results presented in this report are not directly comparable to those in the OECD's 2012 report.

The base VSL estimates should be considered as a starting point for policy analyses that involve mortality risk and should be adjusted to the specific country and policy context whenever possible. Perhaps the most important determinant of the VSL is income, measured as household income or as GDP per capita. These findings stem from both the meta-analysis of valuation studies from all country groups, as well as from an analysis of the relevant scientific literature on the drivers of VSL.

This report provides the following recommendations for the use and adjustment of base VSL estimates:

- **Use base VSL estimates from the smallest relevant country grouping to derive country-level estimates.** Base VSL estimates can be used to compute country-level estimates for those that do not already have sufficient VSL evidence or guidelines. It is recommended to scale the base VSL estimates from the relevant country group to an individual country by using the ratio of GDP per capita between the target country and the country group of the base VSL estimate. Since countries may belong to more than one group, it is recommended that policymakers use the VSL estimates from the smallest grouping to which a country belongs as a starting point and further adjust VSL estimates to account for specific national and study contexts whenever possible (for example impacted population subsets or job sectors).
- **Use country-specific VSL estimates for evaluation of national policies.** For policies with multi-country impacts, it is recommended to also use national VSL estimates for each respective country affected. However, in some situations it may also be justifiable to apply a common VSL estimate across multiple jurisdictions to ensure that similar mortality effects receive similar consideration in all impacted jurisdictions (for example within the European Union).
- **Consider and value morbidity effects in addition to mortality.** In most situations where mortality risk is impacted, there are also impacts on morbidity (pain and suffering). Morbidity impacts should be considered and valued separately from mortality costs, both for morbidity prior to premature death as well as for non-fatal health outcomes.
- **It is not recommended to adjust VSL estimates for the type of mortality risk or the age of the population.** Except for cancer, this report suggests that the type of mortality risk does not significantly impact VSL estimates. Cancer, when included in primary valuation studies, led to significantly higher VSL estimates compared to studies where it was not included. However, cancer is a complex disease that can take many forms and be associated with differing symptoms, durations and outcomes, the details of which are not possible to capture in the meta-data used for this report. Therefore, even if cancer could in principle be a valid basis for adjusting VSL estimates, the data underlying this report does not offer sufficient evidence to recommend a specific approach for adjusting the VSL for cancer risk. Similarly, it is widely recognised that the age of the studied population could have a significant impact on the VSL estimate. However, adjusting for age is controversial as it implies that public policy and cost-benefit analysis outcomes could differ solely based on differences in the age of the populations studied and it is not common practice to make such adjustments.
- **Conduct uncertainty and sensitivity analyses** using alternative income elasticities of VSL when transferring benefits between countries and/or regions, as well as when adjusting VSL estimates over time. As shown in the ranges presented in this report, considerable uncertainty surrounds the VSL estimates. It is therefore recommended to conduct sensitivity analyses using alternative (but plausible) assumptions to test the robustness of any CBA that uses VSL.

The results presented in this report are expected to be widely applicable to policy analysis in which there is a need to assess the economic benefits of policies that impact mortality risks.

1 Introduction

Evaluating public policies in areas like the environment and health often requires a cost-benefit analysis that considers economic values of changes in mortality, morbidity, and well-being. This chapter provides an overview of mortality risk valuation methods used in regulatory bodies. The chapter notably discusses and builds on the previous OECD report from 2012, which provided guidelines on mortality risk valuation as well as estimates of the Value of Statistical Life (VSL) for various country groups. The chapter identifies the objectives and contribution of the report, which include updating the estimates and guidelines provided in the 2012 study based on the latest data and meta-analytical methods.

1.1. Valuation of mortality risk is important for policy appraisal and prioritisation

Public policies in domains such as the environmental, transport, energy, food safety and health have impacts on human health and safety. When conducting a cost-benefit analysis (CBA) of such policies, it is important to consider the economic value of changes in mortality risk, morbidity risk and well-being resulting from these policy interventions, or the lack thereof. When changes are valued in economic terms, they can be compared with other monetised benefits or costs arising from a policy or its alternatives. Assessing changes in monetary terms also provides a consistent metric that can be applied across different policy alternatives and therefore facilitates a better understanding of policy trade-offs for decision makers. This report focuses on providing a comprehensive update on the economic valuation of mortality risks.

The economic value of health improvements resulting from a policy often outweighs estimates of its environmental or other benefits. For example, in a review of 115 major federal regulations in the United States, 70% of the total benefits were directly attributable to the monetary value of reducing mortality risks, mainly through improvements in air quality (US Office of Management and Budget (OMB), 2014[1]). Mortality effects also dominate estimates of the costs of climate change, such as the social cost of carbon, where mortality effects are estimated to 50-80% of the total social costs of carbon (USEPA, 2023[2]). Another example is policy measures employed to combat the COVID-19 pandemic, which indicate very high economic values associated with improved health outcomes during the pandemic, particularly among the elderly and vulnerable groups (Hammitt, 2020[3]; Viscusi, 2020[4]).

To value changes in mortality risk resulting from different policy interventions, the concept of value of statistical life (VSL) is often used. VSL is an aggregated value of the willingness to pay (WTP) among individuals for a small reduction in the probability of a fatality or premature death[1]. It is called a *statistical* life because it is not the life of any particular person but an aggregation of the values that individuals place on small changes in the risk of premature death. Technically, VSL is an individual's marginal rate of substitution between money (measured as a change in income, wealth or costs) and mortality risk in a specified time period (Hammitt, Liu and Liu, 2022[5]). The term VSL has over the years often been misunderstood, to the point where some instead prefer using the term "value of a prevented fatality" (e.g. United Kingdom and Canada) or "value of reduced mortality risk" (Simon et al., 2019[6]; Ginbo, Adamowicz and Lloyd-Smith, 2023[7]). VSL is also just one of many alternative metrics to capture the value of changes in mortality risk. Other common metrics include the value-of-life-year (VOLY) which seeks to capture the impact of mortality risk on the length of life, and quality-adjusted-life year (QALY) which seeks to take into account both mortality and morbidity effects by accounting for life-years lost due to premature death as well as the quality of life for life-years with less than perfect health. These concepts are discussed further in Chapter 2.

There are two primary methodological approaches for deriving an individual's WTP for avoiding risk or accepting compensation in exchange for a higher risk. Methods based on surveys for capturing an individual's WTP for a hypothetical reduction in mortality risk are known as Stated Preference (SP) approaches. Alternatively, the WTP can be calculated from observations from real market behaviour, such as choosing riskier jobs in exchange for a higher wage or purchasing safety equipment such as helmets. These are referred to as Revealed Preference (RP) approaches. An overview of definitions and methodologies for estimating VSL are available in Chapter 2.

In CBA of policies or programmes that impact human health, effects are often quantified in terms of the number of fatalities or premature deaths that could be avoided with the proposed policy or programme, relative to a scenario without the proposed policy. There may also be public interventions with negative health impacts (such as higher speed limits on roads) that need to be balanced against other benefits, such as time savings. To derive a monetary estimate of the total value of the mortality effects resulting from a policy change, the VSL can be multiplied by the estimated number of avoided fatalities the policy is expected to achieve.

1.2. Current regulatory practices for valuing mortality risks

Regulatory practises regarding the estimation of VSL and its use in CBA vary widely among countries, and even between agencies within countries. This section provides a brief background and overview of practices for the valuation of mortality effects in OECD countries.

Historically, the United States has relied mainly on RP methods whereas Europe has relied mainly on SP methods for estimating VSL. However, the United States government agencies have progressively applied evidence from both national RP and SP studies when recommending VSL values (Robinson and Hammitt, 2016[8]; US Department of Health and Human Services, 2016[9]; US Department of Transportation, 2021[10]; USEPA, 2011[11]; USEPA, 2024[12])[2].

In the Nordic countries, Norway and Denmark conducted primary national SP surveys in 2012 and 2016 respectively to establish VSL estimates for use in CBAs by governmental agencies in the respective countries (Danish Ministry of Finance, 2019[13]; Norwegian Agency for Public and Financial Management, 2023[14]). The Norwegian ministry of Finance has also issued updated VSL estimates for future years based on the expected growth in GDP per capita (implicitly assuming an income elasticity of VSL of 1; cf. Section 5.2 of Chapter 5). Sweden has an official VSL value, but only in their CBA guidelines for transport projects, and it is based on using benefit transfer from previous SP surveys in other countries (Swedish Transport Administration, 2018[15]).

Within the European Union (EU), VSL estimates are used in economic assessments of external cost from transport and in CBAs of new projects and policies, especially for air pollution from transport and industry (see European Commission DG MOVE (2019[16]) and European Environment Agency (2021[17]), respectively). The VSL for the EU area in these regulatory analyses is based on reviews of RP studies and SP surveys in the United States and Europe that were performed within the EU Research project series ExternE - External Costs of Energy (ExternE, 2005[18]).

In the United Kingdom, the 2022 public CBA Guidelines also known as the Green Book (UK HM Treasury, 2022[19]) does not list a VSL estimate (referred to as the “value of a prevented fatality”). Instead only a quality-adjusted life year (QALY) value is included[3]. However, the Department of Transport still has an official VSL value in their guidance for transport appraisals (UK Department of Transport, 2013[20]).

The Treasury Board of Canada provides guidelines for cost benefit analysis for regulatory proposals in Canada. As of 2024, the guideline required users to apply updated results from a study published in 2009 that was based on literature prior to 2004, corresponding to CAD_{2020} 8 million[4], while also recognising the existence of more recent literature from a range of sources (Treasury Board of Canada Secretariat, 2023[21]). Ginbo, Adamowicz and Lloyd-Smith (2023[7]) performed a meta-analysis to update the Canadian VSL, which resulted in a weighted mean VSL estimate of CAD_{2020} 13 million[5] (with upper and lower values from two alternative valuation methods of CAD_{2020} 10 million and 16.5 million, respectively). This revised estimate is 60% higher than the value recommended for use in cost-benefit analysis by the Treasury Board of Canada as of 2024. According to the authors, the differences can mainly be attributed to risk preferences that change over time and advancements in empirical methods, the combination of which they argue would justify an update of the recommended values for use in cost benefit analysis. In general, the official VSL estimates in the United States and Canada are higher than those in European countries and used by the European Commission, even when adjusted for income differences.

For Australia, Ananthapavan et al. (2021[22]) perform a systematic literature review of Australian primary studies and international review papers reporting VSL estimates published from 2007 to January 2019 to update their national base VSL. Of the 18 studies in the review, two are primary Australian studies with a weighted mean VSL of AUD_{2017} 7.0 million. The median VSL in international review studies is AUD 7.3 million.[6] The authors recommended a general base VSL of AUD 7.0 million for people of all ages and across all risk contexts, which was 63% higher than the value used by the Australian government at that time (AUD 4.3 million).[7]

The New Zealand Transport Agency launched their CBA manual in 2024 (New Zealand Transport Agency (NZTA), 2024[23]) providing an updated VSL estimate based on a review of valuation studies from other countries, and a derived Value of a Statistical Life Year (VOLY) value used for air pollution impacts. This update increased the base VSL from NZD 5 million in 2022 to NZD 12.5 million in 2023, which made the VSL used to assess transport projects much higher than the official VSL estimates used by New Zealand public agencies in other sectors (New Zealand Institute of Economic Research (NZIER), 2023[24]).[8] This example highlights the importance of coordinating updates (and guidance) regarding VSL across agencies in order to support consistent and transparent assessments of public policy.

1.3. Previous OECD work on mortality risk valuation and recent developments

More than ten years have passed since OECD's landmark report on VSL (OECD, 2012[25]). This report offered the first global overview of VSL based on a comprehensive meta database of about 900 VSL estimates from around 90 SP studies published between 1970 and 2008. It also offered considerations and recommendations for policy makers. Since the publication of OECD's report in 2012, the number of VSL studies globally has increased dramatically and now includes many countries for which no studies were available in the 1970-2008 data. It is therefore timely to update the base VSL estimates and ranges reflecting this new information.

There have also been several methodological developments regarding the estimation, transfer and use of VSL estimates which may warrant an update of OECD's 2012 report. First, there has been an intense debate regarding what values to use to evaluate the health and lockdown policies introduced in the wake of the COVID-19 pandemic, especially the relationship between VSL and age and possible adjustments made on this basis (Colmer, 2020[26]; Hammitt, 2020[3]; Robinson, Sullivan and Shogren, 2021[27]; Viscusi, 2020[4]). It has also been recognised that events like the COVID-19 pandemic may influence the stated WTP elicited by primary valuation studies that coincide with such events (Mourato and Shreedhar, 2021[28]). Second, the academic literature on mortality risk valuation has highlighted new challenges. For instance, the transfer of VSL estimates from high-income countries to low-income countries is considered difficult in practice (Hoffmann, Krupnick and Qin, 2017[29]; Milligan et al., 2014[30]; Robinson, Hammitt and O'Keeffe, 2019[31]; Viscusi and Masterman, 2017[32]). Third, it is important to consider the inclusion of RP studies to better reflect the spectrum of available evidence on VSL. Finally, there is a need for guidance on how to derive VSL estimates applicable to individual countries that do not have recent domestic studies on which to rely.

Since the publication of OECD (2012[25]), no new comprehensive global reviews or meta-analyses of comparable scope and aim have been carried out. Some more limited reviews of the literature include, for example, Bahamonde-Birke et al. (2015[33]) (road safety); Cropper et al. (2024[34]) (selected studies from the United States, with a focus on the US EPA); Cropper, Hammitt and Robinson (2011[35]) and Kniesner and Viscusi (2019[36]) (generic VSL); Robinson, Hammitt and O'Keefee (2019[31]) and Robinson and Hammitt (2015[37]; 2016[8]) (general reviews with a focus on policy implications); Keller et al. (2021[38]) (global review of VSL, until mid-2019) and Ananthapavan et al. (2021[22]) (Australia). These studies demonstrate a heterogenous and diverse VSL literature in terms of the coverage of risk causes and contexts, methodologies and VSL estimates. The literature also does not provide a clear consensus on *how* VSL estimates should be summarised and applied in CBA. However, the large and growing body of literature and useful applications point to the importance of the VSL concept in policy evaluation and the value of providing updated and more precise VSL estimates for policy evaluation.

While several meta-analyses have been conducted since OECD's 2012 report (2012[25]), they are generally of limited scope. Most studies cover individual countries, such as US EPA (2016[39]) and Newbold et al. (2024[40]) (United States)[9], Ginbo et al. (2023[7]) (Canada) and Wang et al. (2024[41]) (People's Republic of China, hereafter 'China'). The aim of these studies is typically to derive VSL recommendations for national policy evaluation. Since OECD (2012[25]), there has been a heightened emphasis in policy and research circles on risks related to the environment and health and the need to tackle new policy contexts such as pandemics and extreme events (e.g. natural disasters related to climate change). These developments make mortality risk valuation even more important for efficient resource allocation globally (Robinson et al., 2019[42]).

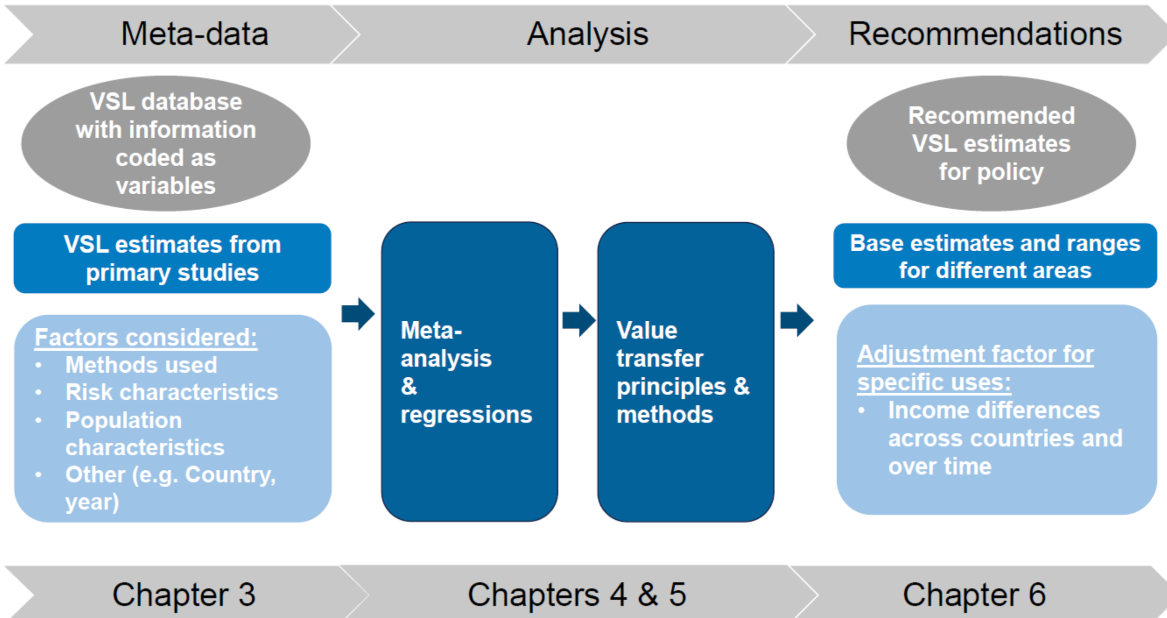
1.4. Objectives and contribution of this report

The objective of this report is to review and update the empirical evidence on VSL, utilising all available VSL studies globally that have been published in English to provide updated VSL estimates and guidance for value transfer across countries and regions.

The current analysis reflects important improvements to the work performed in 2012. First, the empirical evidence on which the analysis is based has been updated and expanded. The data used for the meta-analysis includes primary valuation studies from 1970 to 2023, covering the majority of the academic and grey literature on VSL that has been published in English during this time. Second, the current analysis represents the first comprehensive, global study of VSL estimates that integrates RP and SP methods using state-of-the art statistical meta-analysis methods to derive central tendencies in mortality risk valuation and assess the drivers of variation in VSL estimates. The inclusion of different VSL elicitation methods also allowed for a novel statistical model specification where the effect of the choice of elicitation method can be evaluated. Finally, the report provides recommended base VSL estimates for use in policy analysis, as well as guidance on how to adjust base VSL estimates to policy contexts of interest.

The meta-analysis is comprised of three main components, shown in Figure 1.1. In a first step, it proceeds with a search of the global scientific literature on VSL using systematic review procedures. VSL estimates, along with key meta data from the identified primary valuation studies, were compiled into a comprehensive database and coded for use in the meta-analysis. In a second step, the analysis reports descriptive statistics derives measures of central tendency (mean) of VSL estimates and uses meta-regression methods to examine the extent to which various factors explain observed variation in VSL estimates. Extensive robustness and sensitivity analysis are conducted as part of the meta-regression analysis. A third step consists in deriving a recommended set of base VSL estimates and ranges for groups of countries, as well as procedures for using and adjusting these values in policy analyses in different contexts.

Figure 1.1. The three steps of the study



It should be noted that the preferred method for assessing the economic value of mortality risk reductions is to conduct a primary valuation study, tailored to the specific policy in question within the relevant country (or group countries) where the policy will have an impact. Multiple studies are often needed given that each study will have advantages and limitations. However, in many instances, this may be too time-consuming, cost-prohibitive, or not strictly necessary for conducting a meaningful CBA (Robinson and Hammitt, 2015[37]). The VSL estimates recommended in this report are intended for use in situations where conducting primary valuation studies is not possible or financially feasible for the purposes of the assessment of policy costs and benefits.

The methodological approach used to derive these recommended base VSL estimates consists of a combination of systematic review and meta-analysis methods. Meta-analysis is a body of statistical methods that are used to review and evaluate existing empirical research (Harrer et al., 2021[43]; Schütt, 2021[44]; Stanley and Doucouliagos, 2015[45]; Stanley et al., 2013[46]; Stanley, 2001[47]). A systematic review is a scholarly synthesis of evidence on a topic, typically a structured literature review undertaken according to a fixed plan, system or method. Systematic reviews are often conducted in connection with more formal statistical meta-analysis of results.

The current analysis also uses the newly compiled database and updated VSL estimates to assess the appropriateness of various benefit and value transfer principles. This includes determining how to adjust mean VSL estimates across countries and what additional factors, such as income and demographic differences, may be considered as the basis for further adjustments.

As this report shows, there remains a lack of clear consensus in the academic literature on the preferred approaches surrounding several aspects of developing VSL recommendations based on meta-analytical results. While numerous meta-analyses exist (Ginbo, Adamowicz and Lloyd-Smith, 2023[7]; USEPA, 2016[39]), several research questions on how to apply VSL estimates in policy appraisals remain unsettled, such as how to adjust for income differences between countries and over time (Robinson, Hammitt and O'Keeffe, 2019[31]; Robinson and Hammitt, 2011[48]; SAB, 2017[49])[10]. To address outstanding uncertainties and ensure that the methodological decisions involved in each of the steps in Figure 1.1 are scientifically well-justified, the current analysis refers to the relevant academic literature where possible and has benefitted from input from a scientific advisory group with strong expertise in VSL-related issues and meta-analytic approaches.

The VSL estimates developed in this report are expected to be widely applicable in CBA, notably all instances where the economic value of incremental changes in mortality risk resulting from a project or policy must be monetised and compared against the costs or benefits of such interventions. It should also be noted that most situations involving impacts to mortality risk also involve impacts on morbidity (pain and suffering) that should be taken into account. While the valuation of morbidity effects is beyond the scope of this report, the OECD has published a number of studies providing valuations of potential reductions in non-fatal health effects such as asthma and chronic kidney disease (Appéré et al., 2023[50]; Dockins et al., 2023[51]).

1.5. Outline

The remainder of the report is organised into five chapters as follows:

Chapter 2 provides an overview of the concept of VSL for readers who may be unfamiliar with VSL and VSL elicitation methodologies. It briefly explains the theory and methods underlying the valuation of mortality risks and derived VSL, provides examples of primary valuation studies of both RP and SP, and describes benefit or value transfer (BT) methods based on secondary sources of VSL information.

Chapter 3 describes the sources of VSL meta-data and how they were compiled for this report. This includes a systematic review of new SP and RP studies completed between 2009 and 2023, as well as the SP studies used in the previous OECD report, which spanned 1970 to 2008. The chapter also provides information on RP studies dated before 2009. For all of these data sources, descriptive statistics and VSL estimates are provided for subsets of the meta data to gain a better understanding of the characteristics of the meta database before they are statistically evaluated via meta-analysis methods.

Chapter 4 discusses meta-analytic methods and options, as well as the approach selected for deriving mean VSL estimates from the distribution of VSL estimates in the meta data. It also describes how variables were coded to create the meta database and other issues for data analysis, including the treatment of outlier observations. This chapter also presents preliminary and unweighted VSL estimates for different groups of countries as well sensitivity analyses covering key areas of uncertainty. The estimates reported in Chapter 4 are purely statistical results that are not recommended for use in policy analysis without further adjustments.

Chapter 5 examines the relationship between VSL and income, or per GDP per capita, a measure referred to as the income elasticity of VSL, which is used in the benefit transfer of VSL estimates between countries. A meta-regression analysis estimates this elasticity and evaluates other factors that contribute to variations in VSL. Evidence from the literature on these and other factors, such as income, age and natural disasters is also reviewed in order to inform the discussion on potential policy adjustments to the preliminary and unweighted VSL estimates reported in Chapter 4.

Chapter 6 reports recommended base VSL estimates and ranges for country groups and discusses how these values should be applied when transferring VSL estimates over time and between countries. It also discusses whether the base estimates should be adjusted by other factors. In addition to the values reported in this chapter, further data and tools are expected to become available on the OECD website following the publication of this report.

Finally, the **technical annexes** (Annex A to Annex H) document the meta-data compilation procedures, meta-data and variable descriptions, full literature lists, and sensitivity analyses and robustness checks performed as part of this meta-analysis.

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Notes

[1] It could also be calculated based on individuals' willingness to accept compensation for a marginally higher risk. Cf. e.g. Boardman et al. (2018[54]) on the relationship between WTP and willingness to accept and its relevance for CBA.

[2] The US Department of Health and Human Services guidance also includes Quality-adjusted life year (QALY) estimates, and, in its annual updates, value of statistical life year (VSLY) estimates (U.S. Department of Health and Human Services, 2025[56]).

[3] According to Chilton et al. (2020[53]), Annex 1: "The approach outlined in Franklin (2015), based on data taken from Carthy et al. (1999), generates a Value of Life Year of around £60,000 and provides the basis for current Her Majesty's (HM) Treasury Green Book advice on appraisal of government projects that generate life expectancy gains." The UK DEFRA, however, use a Value of a Statistical Life Year (VOLY) valued derived directly in a UK SP study (Chilton et al., 2004[52]) in assessments of their own regulations.

[4] Corresponding to USD_{2020} 6.7 million (based on OECD PPP exchange rates).

[5] Corresponding to USD_{2020} 10.8 million (based on OECD PPP exchange rates).

[6] These values correspond to a weighted mean and median VSL of approximately USD_{2017} 5.4 million and USD_{2017} 5.6 million, respectively.

[7] This corresponds to a VSL of approximately USD_{2017} 3.3 million.

[8] These values correspond to an increase in base VSL from approximately USD_{2022} 3 million to USD_{2022} 7.5 million.

[9] In addition, the study by Banzhaf (2022[55]) conducts a "meta-analysis of meta-analyses" of meta-analysis studies from the United States.

[10] One such issue is which value of income elasticity of VSL should be used to transfer VSL estimates across countries with different income levels and to transfer VSL estimates in the same countries over time (Robinson and Hammitt, 2011[48]). This can be both because there is uncertainty in the measurement of income in surveys and because there is limited panel data on the development of income in the same population over time and the relation with VSL (SAB, 2017[49]). This issue is discussed further in Chapter 5.

2 Theory and methods of mortality risk valuation

There are many metrics for mortality risk and the economic benefits of reducing mortality risk can be estimated in different ways. This chapter provides a theoretical overview of the Value of Statistical Life (VSL), a key concept in cost-benefit analysis derived from the willingness-to-pay (WTP) approach. It discusses existing methods to elicit VSL estimates, in particular Stated Preferences (SP) and Revealed Preferences (RP) methods. The chapter also presents alternatives concepts to VSL, such as the Value of a Statistical Year (VOLY) and health-adjusted life years. Finally, the chapter presents approaches to transferring VSL estimates across policy contexts that differ by year and location.

2.1. The value of statistical life concept

The Value of Statistical Life (VSL) remains a key concept in cost-benefit analysis. Individuals constantly make decisions that embody trade-offs between costs and benefits. For example, a home buyer may observe a trade-off between neighbourhood environmental amenities and the price of a house. In the same vein, regulatory authorities may juxtapose the health benefits of shutting down a pollution-intensive plant against the social cost of higher unemployment in a small town. In this example, economic theory suggests that shutting down the plant would result in a welfare improvement only if the economic benefit of health improvements resulting from the closure exceeds the social cost of unemployment. Consequently, when a policy change involves changes in mortality risk, it can be useful to provide an economic value of such changes that can be compared against other costs and benefits of the proposed policy change.

VSL is commonly computed through the willingness to pay (WTP) approach. There is significant evidence showing that individuals exhibit a positive WTP to reduce their personal mortality risk[1] (Kniesner et al., 2012[1]). Formally, the WTP can be defined as the maximum amount that can be subtracted from an individual's income or wealth in exchange for a given improvement in mortality risk without leaving the individual worse off. Such a valuation may also be treated as the willingness to accept (WTA) a higher mortality risk in exchange for compensation, such as accepting a more hazardous job in exchange for a higher salary. VSL can thus be defined as the rate at which individuals are willing to trade off wealth or income for a reduction in their risk of dying. It is important to note that VSL is based on the value of marginal variations in mortality risk, rather than the value of risk attached to a specific death. This chapter discusses in detail the VSL concept, the methods by which it is estimated, and provides examples of these concepts. This chapter also discusses alternative metrics to VSL and how VSL can be applied to policy analysis where primary studies are not available through the use of benefit transfer methodologies.

Two primary approaches exist for eliciting an individual's WTP for changes in mortality risk, namely Stated Preference (SP) and Revealed Preference (RP) methods. SP methods rely on surveys, asking respondents to state their preferences for specific changes in mortality risks in a hypothetical scenario or situation. Such surveys may ask them directly for their WTP for a given but hypothetical mortality risk reduction or ask them to choose between mortality risk reduction scenarios with different costs attached to them. In contrast, RP methods observe actual behaviour relative to risk in labour and consumer markets, with a focus on observing trade-offs between mortality risk and income and between willingness to WTP for a product and its expected impact on an individual's risk of dying.

To derive a VSL estimate for a population, the average WTP of a population can be estimated through a survey for a given marginal improvement of a specific mortality risk, ΔR. The WTP for this risk change can then be aggregated until ΔR reaches 1, which corresponds to the value of a statistical life. Formally, VSL can therefore be defined as:

$$VSL = \frac{WTP|_{\Delta R}}{\Delta R} \qquad \text{Equation 2.1}$$

To illustrate, consider a risk scenario for a population where the average WTP for a fatality risk reduction of 1 in 100 000 (or 0.00001) is USD 50. The VSL can then be calculated as USD 50 ÷ 0.00001 = USD 5 million. The VSL can equivalently be thought of as the average individual WTP for a given marginal fatality risk reduction aggregated over a population until the fatality risk reaches 1, in this case 100 000 individuals, i.e. USD 50 per individual × 100 000 = USD 5 million.

2.2. Stated preference (SP) methods

Stated Preference (SP) studies explicitly ask individuals how much they would be willing to pay (or willing to accept in compensation) for a small reduction (increase) in mortality risk. The two main SP methods are the Contingent Valuation (CV) method and Discrete Choice Experiments (CE). The main difference between these two approaches is that CV methods explicitly ask respondents for their WTP for either a private good that reduces their mortality risk or for a public programme that reduces population-wide mortality risk. CV approaches cover different elicitation methods such as open-ended maximum WTP questions, single-bounded dichotomous choices, double bounded dichotomous choices, or payment cards listing amounts to choose from. Under the CE approach, respondents are asked to make a series of choices between risks with different characteristics (including different probabilities) and monetary costs. The design of SP methods should follow best practise guidelines, such as those laid out in Johnston et al. (2017[2]).

SP have three main advantages. First, they are able to elicit WTP from broad segments of the population. Second, the size of mortality risk changes are explicitly stated, unlike RP studies where the mortality risk may be less clear to the individuals making choices on trade-offs. Third, SP analyses can value the causes of death that are specific to certain types of risks (e.g. environmental hazards). However, the main limitation of SP methods is that the stated choices are hypothetical insofar as the amounts respondents indicate they are willing to pay may differ from what they may actually be willing to pay in reality.[2]

2.2.1. Contingent valuation methods

In Contingent Valuation (CV) surveys, a mortality risk reduction policy scenario is carefully constructed and presented to focus groups and survey respondents. The policy setting in these scenarios can be generic or refer to a specific intervention that reduces the respondents' probability of dying prematurely (e.g. traffic safety measures, air pollution policies or new health treatments). There are different ways of illustrating the mortality risk reduction, ranging from simply conveying the odds (e.g. 1 in 10 000 is the reduction in the probability of dying prematurely) to using grid cell diagrams or placing the mortality risk reduction in a geographical context. For example, respondents could be told to imagine that they live in a city of 10 000 inhabitants, and that a regulatory measure would reduce the number of premature deaths per year by one person. They are then asked for the maximum amount they would be willing to pay to achieve this (through an open-ended question or by showing them a payment card with different amounts from which they can choose the highest amount they would pay with certainty). In a dichotomous choice CV, respondents may be asked whether they would vote for or against a policy with an assigned cost, aimed at reducing their individual risk of dying prematurely by 1 in 10 000. Different sub-samples of the population are asked to pay different amounts. WTP estimates are subsequently derived from the percentage of respondents supporting the policy at different costs. Box 2.1 provides an example of a CV survey for deriving VSL.

Box 2.1. Contingent valuation for health effects in Kuwait

Alolayan et al. (2017[3]) uses CV methods to estimate VSL for Kuwaiti citizens. The valuation scenarios were related to cancer and heart attacks, and respondents were presented with a mortality risk reduction of 1 in 10 000 and 3 in 10 000, respectively. Consistency tests were performed which required that an individual reported strictly positive WTPs for mortality-risk reductions and that the responses to dichotomous choice CV questions for alternative risk reductions were consistent with the theoretical requirement that WTP should be less than, but close to proportional to the change in risk reduction. The authors estimated the VSLs to between USD 18 and 32 million, which is 2 to 3 times larger than values used in the United States. This finding was attributed mainly to the difference in net income levels between the United States and Kuwait. The authors suggested that the valuation results could be applicable to analysis of policy interventions in other countries in the region with similar income levels and societal contexts.

Source: Alolayan et al. (2017[3])

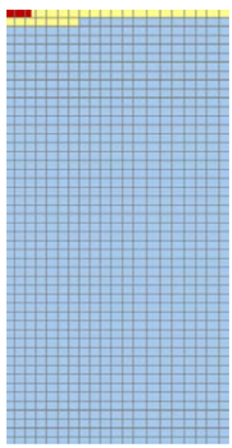
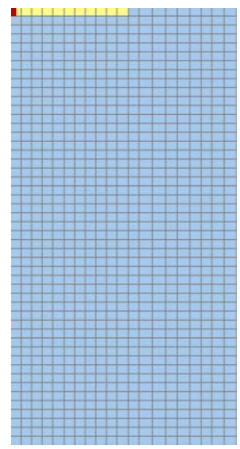
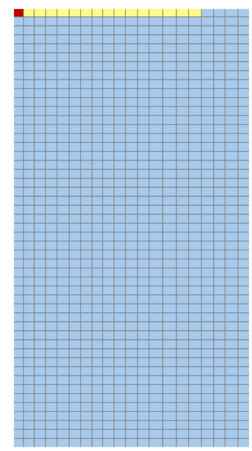
2.2.2. Discrete choice experiment methods

Discrete Choice Experiments (CE) are an indirect SP method that aims to derive an individual's valuation of the characteristics that define a given reduction in mortality risk. In addition to the mortality risk reduction itself, these characteristics may include the latency period, type of risk, the cause of death and the time in life (now or later) at which the risk impact would be expected. In practice, respondents are shown choice cards with a reference alternative (often including the status quo as a zero cost option) alongside one or more policy alternatives with different characteristics, including their cost. Respondents are then asked to choose their preferred alternative from a series of choice cards in which the values for each attribute, including the costs, vary across alternatives. Using data from these repeated choices, WTP for the different attributes and mortality risk reduction can be derived. Box 2.2 provides an example of a CE survey and the choice cards used.

Box 2.2. Discrete choice experiment for mortality and morbidity valuation in China

Huang, Andersson and Zhang (2018[4]) conducted a discrete choice experiment (CE) in Beijing, China to estimate the VSL and the value of a statistical illness[1] to be used for policy analysis in China. Figure 2.1 is an example of a choice card used to elicit individuals' WTP for mortality and morbidity risk reductions. The levels of the attributes, in addition to the cost attribute, for Programs A and B varied across choice cards, and respondents were asked to answer several of these choice cards. The analysis also examined how different payment regimes influenced WTP and whether WTP was age-dependent. VSL and the value of a statistical illness estimates were robust across different econometric model specifications and aligned with previous Chinese studies. There was no evidence of any VSL-age relationship, and the payment scheme had no significant effect on VSL (but had some effects on value of a statistical illness).

Figure 2.1. Discrete choice experiment choice card example

	Current situation	Program A	Program B
Number of times per year with symptoms similar to a cold	5	2	3
In 10 years, the probability of getting sick from respiratory or cardiovascular diseases caused by air pollution for yourself	2 500 / 100 000	1 000 / 100 000	1 500 / 100 000
In 10 years, the probability of dying from respiratory or cardiovascular diseases caused by air pollution for yourself	250 / 100 000	50 / 100 000	100 / 100 000
Yellow: probability of getting respiratory or cardiovascular diseases by air pollution **Red:** probability of dying from respiratory or cardiovascular diseases by air pollution **Blue:** probability of no health effect from air pollution			
Cost (RMB/month)	0	50	20
Your vote	□	□	□

Note: Table translated from Chinese by Huang, Andersson and Zhang (2018[4]); Figures adapted from Huang, Andersson and Zhang (2018[4]).
1. The value of a statistical illness (or a statistical case of a particular illness) is a morbidity equivalent of the VSL. Analogous to Equation 2.1, the value of a statistical illness can be defined as the WTP to reduce the probability of contracting a specific illness divided by the change in probability of contracting the illness resulting from the policy intervention.
Source: Huang, Andersson and Zhang (2018[4])

2.3. Revealed preference methods

Two main RP methods are used to derive VSL, namely the hedonic wage (HW) method, which analyses individuals' choice of jobs with different mortality risk, and the consumer market (CM) approach, which analyses individuals' consumption of consumer products that can reduce their mortality risk (also known as the averting cost approach). Both approaches are based on an analysis of individuals' *actual* behaviour in the labour and consumer product markets. in this way, the choices individuals make *reveal* their preferences for reducing their mortality risk.

2.3.1. Hedonic wage methods

The HW method (or wage-risk method) studies workers' actual behaviour in the labour market. All else equal, it is expected that an individual engaged in a job with an above-average mortality risk would require a higher wage to compensate for this risk. Hence, the value that they attach to the risk can be estimated by observing the wage premiums associated with higher risk jobs. While attractive in that it offers insights into actual behaviours, the HW method has some limitations that should be considered. First, it provides estimates of VSL only for working age population segments. Second, HW studies value mainly *current* risk of accidental death, whereas environmental hazards, (e.g. asbestos or PCBs), are likely to cause death (via cancer or chronic respiratory illness) only after a latency period. Third, HW analyses may not be able to distinguish between actual and perceived risks, as well as other factors that shape wage variation. Box 2.3 provides an example of a representative HW study.

Box 2.3. Using hedonic wage methodologies to estimate risk-based wage differentials in Australia

Hedonic wage (HW) regressions have served as the main econometric tool to estimate the size and significance of compensating wage differentials (CWDs) payments for work-associated disamenities. Studies that find evidence of CWDs can compute value of statistical life (VSL) and value of statistical injury estimates as they can be directly inferred from HW regressions. This HW study looked at whether for Australian workers using data from the Household, Income and Labour Dynamics in Australia Survey, and risk data from Safe Work Australia. The following model was estimated to determine the existence of CWDs for job risk:

$$\boldsymbol{w_{it}} = \boldsymbol{\beta_1 Risk_{it}} + \boldsymbol{\beta_2 Risk^2{}_{it}} + \boldsymbol{\beta_3 (Risk_{it} * U_{it})} + \boldsymbol{\beta_4 (Risk^2{}_{it} * U_{it})} + \boldsymbol{X'_{it} \beta_5} + \boldsymbol{\alpha_i} + \boldsymbol{\mu_{it}}$$

where $\boldsymbol{w_{it}}$ is the log of the respondent's hourly wage. $\boldsymbol{Risk_{it}}$ is the job fatality or injury risk, which varies by the worker's industry (industry risk), occupation (occupation risk) or industry-occupation (composite risk), depending on the model under consideration. Interaction terms between risk, risk squared, and the dummy variable for worker union membership, $\boldsymbol{Uit}$, are included to capture union influence in the size of CWDs for workplace risk. $\boldsymbol{X_{it}}$ is a vector of worker and workplace characteristics that includes work experience, work experience squared, occupation tenure, job tenure, six dummies for workplace size, a dummy for public sector, two dummies for employment contract type, a dummy for worker union status, four dummies for education, a dummy for marital status, two dummies for country of birth, two dummies for dependent children, eight dummies for waves, and twelve dummies for location. The location dummy controls are useful in capturing any differences in worker compensation benefits between states and territories. The wave dummies, which control for time effects, are expected to alleviate the impact of Safe Work Australia's exclusion of commuter deaths from the fatality reports from 2012 onwards. The unobservable individual-specific heterogeneity, represented by $\boldsymbol{\alpha_i}$, is treated as a part of the random error (pooled estimation) or individual-specific intercepts (fixed-effects estimation). The term $\boldsymbol{\mu_{it}}$ is the idiosyncratic error term.

The study found evidence of CWDs for the risk of workplace fatalities that are smaller in magnitude compared to the estimates previously reported in the 1990s for Australia. Using panel data and a risk variable that varies by both the worker's industry and occupation of employment, Australian workers facing the mean level of fatality risk were found to receive a CWD of between 0.13% and 0.44% for a unit increase in risk, depending on the model specification. These estimates correspond to a VSL of AUD 9.7 million and AUD 34.9 million.[1]

1. These correspond to USD_{2020} 6.9 million and USD_{2020} 24 million, respectively.
Source: Reynolds, Nahm and MacMillan (2022[5]).

2.3.2. Consumer market methods

Another RP approach to valuing mortality and morbidity risk is the consumer market (CM) approach, also known as the averting cost or self-protection approach. This method observes and analyses the expenditures that people make to reduce the probability or severity of an adverse outcome. Practical examples range from purchasing safer cars, safety helmets and fire alarms, to buying a residence in a safer and cleaner part of a city. The underlying assumption is that a rational consumer will buy these averting goods until the individual's marginal improvement in risk is equal to the price. One advantage of this RP method is that it is also based on actual behaviour. Moreover, it can cover a much larger part of the population than HW approaches since it is not tied to labour markets. Box 2.4 provides an example of a CM study to illustrate the approach.

Box 2.4. Valuing mortality risk through the housing markets

Bishop et al. (2024[6]) conduct a consumer market study to provide evidence on the rate at which spatial variation in all-cause mortality risk is capitalised into US housing prices. Using a hedonic framework, the study determined an annual implicit cost of a 0.1 percentage-point reduction in mortality risk among older Americans and found this cost to be less than USD 3 453 for a 67-year-old and diminishes with age to less than USD 629 for an 87-year-old. These estimates, while similar to estimates from the market for health care, are far below comparable estimates from markets for labour and automobiles, suggesting that the housing market could provide a lower cost alternative for reducing mortality risk. This conclusion was found to be robust to a wide range of econometric model specifications, including accounting for associated expenditures on property taxes and the physical and financial costs of moving.

Source: Bishop et al. (2024[6])

2.4. Alternatives to VSL

While this report focuses on VSL, alternative metrics to measure and compare health effects exist, including those that combine mortality and morbidity effects into a joint metric. This chapter briefly explains the most common alternative metrics.

2.4.1. The value of a statistical life year (VOLY)

The nature and time horizon of risk to life and health can differ. For example, some risks pose an immediate danger to life (e.g. road accidents) while others have lifetime impacts (e.g. air pollution). Furthermore, the implications of some risks may be uncertain or occur in the future (e.g. climate change). Consequently, it may sometimes be more appropriate to value some risks insofar as they impact the *length* of a life. To this end, a standard adaptation of the VSL concept is the value of a statistical life-year (VOLY or VSLY) which was first introduced by Moore and Viscusi (1988[7]). For simplicity it is often assumed that a VOLY is constant over an individual's remaining lifetime, i.e. that each remaining life-year is valued equally. With this approach, the relationship between VSL and VOLY can be described as follows:

$$VSL = \sum_{t}^{T} VOLY \cdot (1+\delta)^{-t} \quad \text{Equation 2.2}$$

In this equation, t represents time in years and T is the number of expected remaining life years, counting from the current average age of the population that is being studied ($t = 0$). The social discount rate is denoted δ and is applied to discount future life year. VOLY can be estimated directly through stated preference (SP) methods as well as from VSL estimates by applying a discount rate and using population demographic data. Studies that elicit VOLY directly exist but are relatively few (Chilton et al., 2004[8]; Desaigues et al., 2011[9]). VOLY studies were not included in the meta-data for this report since converting them to VSLs would require additional assumptions (see also Chilton et al. (2020[10]), for a review of approaches to estimate VOLY).

It is important to highlight that VOLY estimates can produce conflicting recommendations relative to the VSL, particularly if the policy disproportionately affects the very young or the very old. For example, using a constant VOLY for all age groups implies that saving young lives offers greater benefits than saving older lives due to their higher expected number of remaining life years. Even if older people were to value each remaining life year more than young adults (which both theory and empirical studies indicate, e.g. (Hammitt, 2023[11]; Robinson, Sullivan and Shogren, 2021[12]), it may still result in a higher valuation of younger lives due to the differences in expected remaining life years. Consequently, there may be differences in estimated policy benefits when using life years saved multiplied by a (constant) VOLY versus using the number of avoided premature deaths together with the VSL. Hammitt (2023[11]) concludes that the common practice of valuing a transient or persistent risk reduction using a constant VSL, VOLY or Value of a Quality Adjusted Life Year (QALY) yields large differences in aggregated benefits which depend on the age at which the risk reduction begins, its duration, evolution, and whether the future lives, life years, or quality-adjusted life years are discounted.

2.4.2. Health-adjusted life years: The case of QALY and DALY

In addition to the VSL and VOLY, other metrics seek to capture the *combined* effects of mortality and morbidity. One example where such approaches could be useful is in estimating the benefits of a policy aimed at reducing the occurrence of a disease that leads to *both* pain and suffering and premature death. The most common metrics in this context are Quality-Adjusted Life-Years (QALYs) and Disability-Adjusted Life-Years (DALYs). For a QALY, a life-year in perfect health is represented by a value of 1. The life-year can then be adjusted downwards to account for disability and loss of quality of life at different ages in a population, including full life-years lost due to premature death. To use QALYs for policy analysis, the sum of QALYs for different policy alternatives can be compared, where a larger number of QALYs would normally be preferred for a given cost. DALYs also vary from 0 to 1, but for an individual over his/her lifetime. In contrast to QALYs, DALYs measure the life-years lost due to disability and premature death and can be defined as the sum of life-years lost to premature death and life-years lost due to disability and/or pain and suffering. A weighting factor is usually applied to a year lived with disabilities to signify its severity relative to a life-year lost. DALYs can be summed over affected populations by policy alternatives and are often used in cost-effectiveness analysis, where for a given cost, the policy with the lowest DALY score is generally preferred. QALYs and DALYs can be converted to monetary terms but are more often used without monetisation for comparing the relative impacts of policies (UNEP, 2013[13]; IHME, 2024[14]).

2.5. Benefit transfer methods

There are many situations where it may not be feasible to conduct a primary valuation VSL study to estimate the economic value of mortality effects for a new policy, for example due to time or budget constraints. Therefore, many CBAs rely on transferring values from existing VSL studies to different study contexts within a country, transferring values from one country to another, as well as transferring VSL estimates over time. Considering the long practice of using benefit transfer methods, the guidance and best practices in this area are relatively well established (Johnston et al., 2021[15]). In this section, two main groups of benefit transfer approaches are discussed, namely unit value transfer approaches and benefit function approaches.[3]

2.5.1. Unit value transfer approaches

Simple (naïve) unit value transfer

The simple (naïve) unit value transfer approach is the most basic benefit transfer technique, in which benefit estimates are directly transferred from a study context to the policy context. This approach infers that the monetary value of a mortality risk reduction is the same in the study context as that of the policy context. This is a strong assumption which may not always be true. Two main drivers of potential differences in VSL across these contexts can be observed. First, affected individuals in the policy context might be different from those in the study contexts, for example in terms of their income, education, age, religion, ethnicity or other socio-economic characteristics that inform mortality risk valuations. Second, even if individuals' preferences for mortality risk reductions in the policy and study contexts were similar, the mortality risk characteristics (e.g. degree of suffering, dread, latency, voluntariness, etc.) and the magnitude of the risk change considered across these contexts may differ. Robinson et al. (2021[12]) discuss evidence related to several of these issues, including the magnitude of risk changes necessary to affect VSL estimates.

Unit value transfer with income adjustments

The simple unit value transfer approach should not be used for transferring values between areas with different income levels and costs of living. Instead, a unit transfer with income adjustments may be more appropriate. It has been shown in many studies that income is one of the key drivers of VSL differences between regions and countries (see Chapter 5 for a discussion). A common approach for an income-adjusted unit transfer is shown in Equation 2.3:

$$VSL_p = VSL_s \left(\frac{Y_p}{Y_s}\right)^{\beta} \qquad \text{Equation 2.3}$$

where VSL_p is the desired VSL to apply in the policy context, VSL_s is the original VSL estimate from the study context, Y_s and Y_p are the income levels in the study and policy context, respectively, and β is the income elasticity of VSL with respect to WTP for reducing the mortality risk.

Mortality risk reductions are considered to be a "normal" good with a positive income elasticity and many studies have attempted to estimate this elasticity, which is not necessarily constant. Note that, if the income elasticity β is equal to 1, then Equation 2.1 can be simplified to multiplying VSL at the study site by the ratio of income at the policy site to income at the study site. Chapter 5 provides details on estimations of the income elasticity of VSL based on the meta-data collected for this report.

Household income levels are not always available as a basis for income-based benefit transfers, as is indeed the case for the current report. When there is lack of data on the income, an alternative is to use Gross Domestic Product (GDP) per capita as an approximation for income in international benefit transfers[4]. An added complication in international benefit transfers is that applying official exchange rates to convert VSL estimates to the currency of the policy context may not reflect the true purchasing power of currencies given that official exchange rates reflect political and macroeconomic risk factors. It is therefore common practice to use Purchasing Power Parity (PPP) adjusted exchange rate for such conversions. Nevertheless, even if PPP-adjusted GDP figures and exchange rates can be used to adjust for differences in income and cost-of-living in different countries, other important differences may remain, such as differences in individual preferences, baseline levels of risks, magnitude of risk changes, risk contexts, or cultural and institutional differences between countries.

Unit value transfer for separate age groups

It is also common to adjust VSL values for age. However, translating age-adjusted analysis into practical policy has proven challenging for two main reasons. First, while there are theoretical grounds for employing age-differentiated VSLs in cost-benefit analysis (Hammitt, 2023[11]; Viscusi and Aldy, 2007[16]), the evidence on the relationship between age and VSL is at best mixed[5]. Second, the use of age-differentiated VSLs in policy analysis is in general unpopular, despite the recognition in policy circles that health benefits may accrue disproportionately across age groups. Notably, the ethical debates surrounding age-related adjustments are known to trigger social and political backlash[6]. Consequently, apart from using them for sensitivity analyses, applying age adjustments of any kind to central VSL estimates is not a common policy practice and is also not recommended in this report (see the discussion in Chapter 5).

2.5.2. Benefit function approaches

Benefit transfer function

Considering the challenges discussed above, it is unsurprising that transferring a more nuanced *benefit function* is theoretically more appealing than simply transferring unit values, as functions can account for more information in the transfer. Note that the benefit function could come from one study or from several studies combined (in e.g. a meta-analysis benefit function). Equation 2.4 shows a simple benefit function, which can be used for transferring benefits from a single primary valuation study:

$$WTP_{ij} = b_0 + b_1\boldsymbol{G}_j + b_2\boldsymbol{H}_i + e$$

Equation 2.4

Where WTP_{ij} is the willingness to pay of household i for mortality risk reduction j. $\boldsymbol{G}_j$ contains a set of mortality risk reduction characteristics (including the size of the mortality risk reduction), $\boldsymbol{H}_i$ is a set of characteristics pertaining to household i (e.g. household size or composition). Finally, b_0, b_1, and b_2 are parameters and e is the random error term.

To implement the approach above, the analyst could obtain estimates of the constant b_0 and the slope parameters b_1 and b_2 from existing studies in the literature. The second stage proceeds with data collection at the policy site covering the two sets of independent variables $\boldsymbol{G}$ and $\boldsymbol{H}$, which are then inserted into the equation to calculate the WTP in the policy context of interest. VSL is then computed by dividing the WTP by the mortality risk reduction.

Meta-analytic benefit transfer

A challenge in applying the benefit function approach is that the data needed for the independent variables in the benefit function are not necessarily available in published papers or in publicly available documentation, as there are no standard reporting requirements for VSL studies. Furthermore, the same type of data upon which the original benefit function was built is also necessary for applying the function to the context where the benefits are to be transferred. In practice, this information is often not available. Therefore, rather than simply transferring the benefit function from a single primary valuation study, results from several mortality risk valuation studies can be combined in a meta-analysis to estimate a common benefit function.

The meta-analysis approach has often been used to synthesise research findings, improve the quality of literature reviews of valuation studies and derive VSL unit values. Using this approach, several original studies are analysed as a group, with results from each survey treated as a single observation in a regression analysis. If multiple estimates from each survey are used, various meta-regression specifications can be used to account for such ‘panel effects’. Furthermore, it is possible to evaluate the influence of a wider range of characteristics of the mortality risk, the features of the samples used in each analysis (including characteristics of the affected population, such as age and income) and the modelling assumptions employed.

However, as noted above, the detailed characteristics of the mortality risk change and the underlying population are often unreported in primary studies. This is especially the case for studies published in academic journals given that their focus is often on methodological tests of valuation methods rather than on reporting monetary estimates. Hence, such studies may lack the type of data required for a meta-regression analysis, leading to challenges in obtaining such data.

Nevertheless, the resulting meta-regression functions explaining variations in VSL can be combined with collected data on the independent variables that describe the policy context to construct an adjusted VSL estimate. The regression from a meta-analysis looks similar to the benefit transfer function in Equation 2.4 above, but a set of variables capturing the differences across valuation methods must be added. The importance of accounting for heterogeneity in valuation methods cannot be overemphasised, as meta-analyses typically find that differences in valuation methodologies explain a significant part of the variation in mean WTP (or direct VSL) estimates across sampled studies. Chapter 4 provides a detailed discussion of the meta-analytic approach used in this report.

The valuation of mortality risks among individuals, and hence the derived VSL from RP and SP studies, can depend on a number of factors pertaining to the risk considered in the valuation, such as the cause of death (respiratory illness, cancer, road traffic accident), the beneficiary of the risk reduction (adults or children)[7] and the mode of provision for the risk reduction (public programme vs. private good). Additional factors relate to when the risk reduction sets in (i.e. latency vs. immediate), whether people have some degree of perceived control and whether there is perceived dread. Beyond these factors, demographic characteristics such as health status, gender, religion, country and income could also influence how individuals value the risk change. Chapter 5 explores the role of key mortality risk factors in the meta-analysis by including selected factors as explanatory variables in the meta-regression and conducting a literature review of related existing evidence in order to consider the resulting implications for potential adjustments to base VSL estimates.

2.5.3. Adjusting the VSL over time

Often, CBAs need to consider mortality effects that are expected to occur over time and therefore need to estimate the VSL for the future benefits of a policy, which means that the VSL for a future date must first be estimated from today's values based on growth in real income over time, and then be discounted to the present value of those future benefits using a social discount rate. The present value of a statistical life saved at a future point in time can therefore be written as a modification of Equation 2.4 above:

$$VSL_t|_{t0} = VSL_{t0}\left(\frac{Y_t}{Y_{t0}}\right)^{\beta}(1+\delta)^{-(t-t0)}$$ **Equation 2.5**

Where t is the time of the future VSL, $t0$ is the present time to which the future VSL is discounted, VSL_{t0} is the VSL at time $t0$, Y_t is the real income at time t, Y_{t0} is the real income at $t0$ and δ is the social discount rate. The role of the income elasticity β is discussed further in Section 5.2 of Chapter 5.

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Notes

[1] As well as fatalities among their broader population, indicating altruism (Long, 2022[23]; Robinson and Hammitt, 2011[21]).

[2] Note that both RP and SP studies assume that the individual making the choices that trade off risks for costs/income has a complete understanding of the risks and that their valuation of these risks is stable over time.

[3] Smith, Van Houtven and Pattanayak (2002[19]) suggest a less frequently used preference calibration transfer method. This method assumes a specific form for preferences and uses available benefit information to identify and calibrate preference parameters to match the existing benefit estimates.

[4] For a discussion of the differences between GDP per capita and the income measures used in most VSL studies, see for example Robinson et al. (2019[20]).

[5] Empirical evidence indicates that the age-VSL relationship may take different forms or shapes (e.g. inverted U-shape) (Aldy Seamus J Smyth et al., 2014[26]; O'Brien, 2018[22]; Viscusi and Aldy, 2003[17]).

[6] For example, the 2003 cost-benefit analysis by the US EPA (USEPA, 2003[18]) which applied a 37% social discount to the VSL of individuals over 70 years old, was heavily criticized, leading the US Congress to prohibit the use of age adjustments in the cost-benefit analyses conducted by Federal agencies (O'Brien, 2018[22]). More recently, similar ethical debates have arisen regarding the COVID-19 pandemic (Carrieri, Peccatori and Boniolo, 2020[25]; Ehni and Wahl, 2023[24]).

[7] More generally this pertains to whether the beneficiary of the risk reductions is a private (adult) individual or someone in addition to or instead of that individual (sometimes termed "public" risk), which may introduce complications regarding how to deal with altruistic preferences.

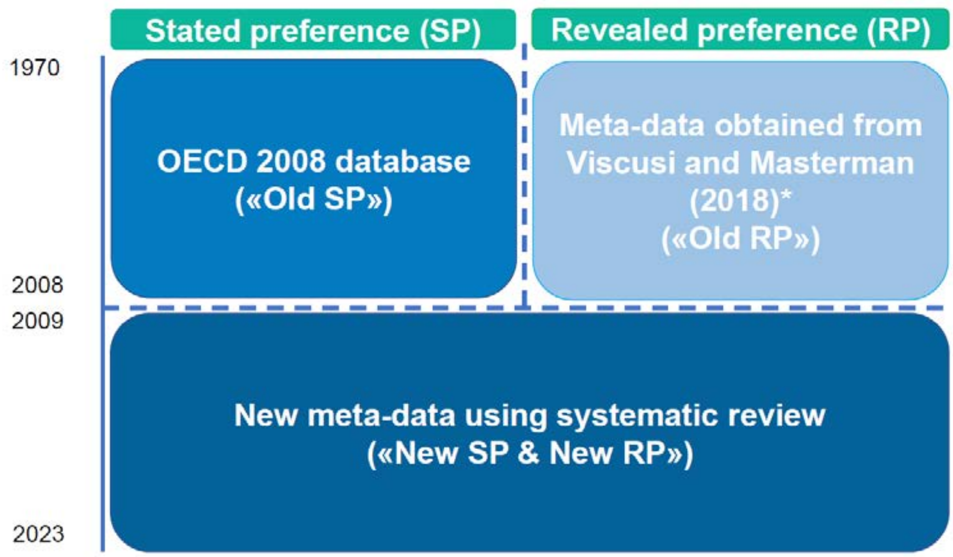
3 Sources and characteristics of meta-data on VSL

The updated meta database covers more than 50 years of VSL studies and more than 4 000 VSL estimates. This chapter provides an overview of how studies were selected for the meta-analysis and how VSL estimates from these studies were adjusted for comparability. The chapter reviews stated preference (SP) and revealed preference (RP) studies published between 1973 and 2009 and included in the previous OECD's 2012 study on mortality risk valuation from 2012. It then describes the new studies included in the meta-analysis of this report, i.e. studies published between 2009 and 2023, as well as additional RP studies published before 2009. The chapter provides descriptive statistics of these studies, such as study count and their methodological and geographical distribution.

3.1. Sources and meta-data preparation procedures

This chapter describes the meta-data used for the analysis, which is derived from three sources (Figure 3.1). The analysis makes use of data from the 2012 meta-analysis of value of statistical life (VSL) estimates (OECD, 2012[1]), as well as new meta-data that significantly expands the empirical basis for this report.

Figure 3.1. The three sources of meta-data used in this report



Note: * This RP dataset is the underlying data used in Viscusi and Masterman (2018[2]) and was made available to the authors by Kip Viscusi and Clayton Masterman. Although the dataset covers publications through 2016, the RP dataset used here only includes studies from this dataset published before 2009 since the 2009-2023 data collected covers both RP and SP using the systematic approach summarized in Figure 3.2.

3.1.1. OECD stated preference database (1970 –2008)

The meta-data source referred to in Figure 3.1 as the "OECD 2008 database" is the original database compiled for the OECD (2012[1]) report, which has also been analysed in many publications, including Lindhjem et al. (2011[3]), Robinson et al. (2019[4]) and Masterman and Viscusi (2018[2]). The construction of the database is described in OECD (2012[1]) and was intended to provide a comprehensive global coverage of all SP studies published in English, including literature not published in peer-reviewed outlets.

The OECD 2008 database contains about 850 VSL estimates from SP studies published between 1970 and the end of 2008 across 38 countries (Lindhjem et al., 2011[3]). A large range of study-related variables were extracted and coded from these SP studies. VSL estimates were either collected directly from studies or (for a smaller share[1]) calculated using reported willingness to pay (WTP) estimates for corresponding changes in mortality risks. To ensure the estimates were comparable over time and across countries, estimates expressed in local currencies were adjusted to 2005 price levels using the consumer price index and converted to 2005 USD using purchasing power-adjusted exchange rates (PPPs)[2]. This dataset is referred to as "Old SP" throughout the current report.

3.1.2. Revealed preference data (pre-2009)

The data referred to as "Old RP" in Figure 3.1 consists of 953 VSL estimates reported across 68 primary valuation studies (Masterman and Viscusi, 2018[2]).[3] The full list of papers comprising this dataset is provided in the supplementary materials to Masterman and Viscusi (2018[2]). Of this sample, 518 VSL estimates are from the United States. As with the "Old SP" database, the search for studies included in the "Old RP" dataset did not follow systematic review procedures. The construction of the database involved identifying all labour market VSL estimates from previous meta-analyses and supplementing these by searching the economics database EconLit for papers mentioning "VSL" or "Value of a Statistical Life", as well as searching the references in these studies for additional papers.[4] The underlying dataset was made available for the current analysis by the authors (Viscusi and Masterman), and only studies from before 2009 are used for this analysis.[5] This dataset is referred to as "Old RP" throughout the current report.

3.1.3. New meta-data using a systematic review procedure (2009 – 2024)

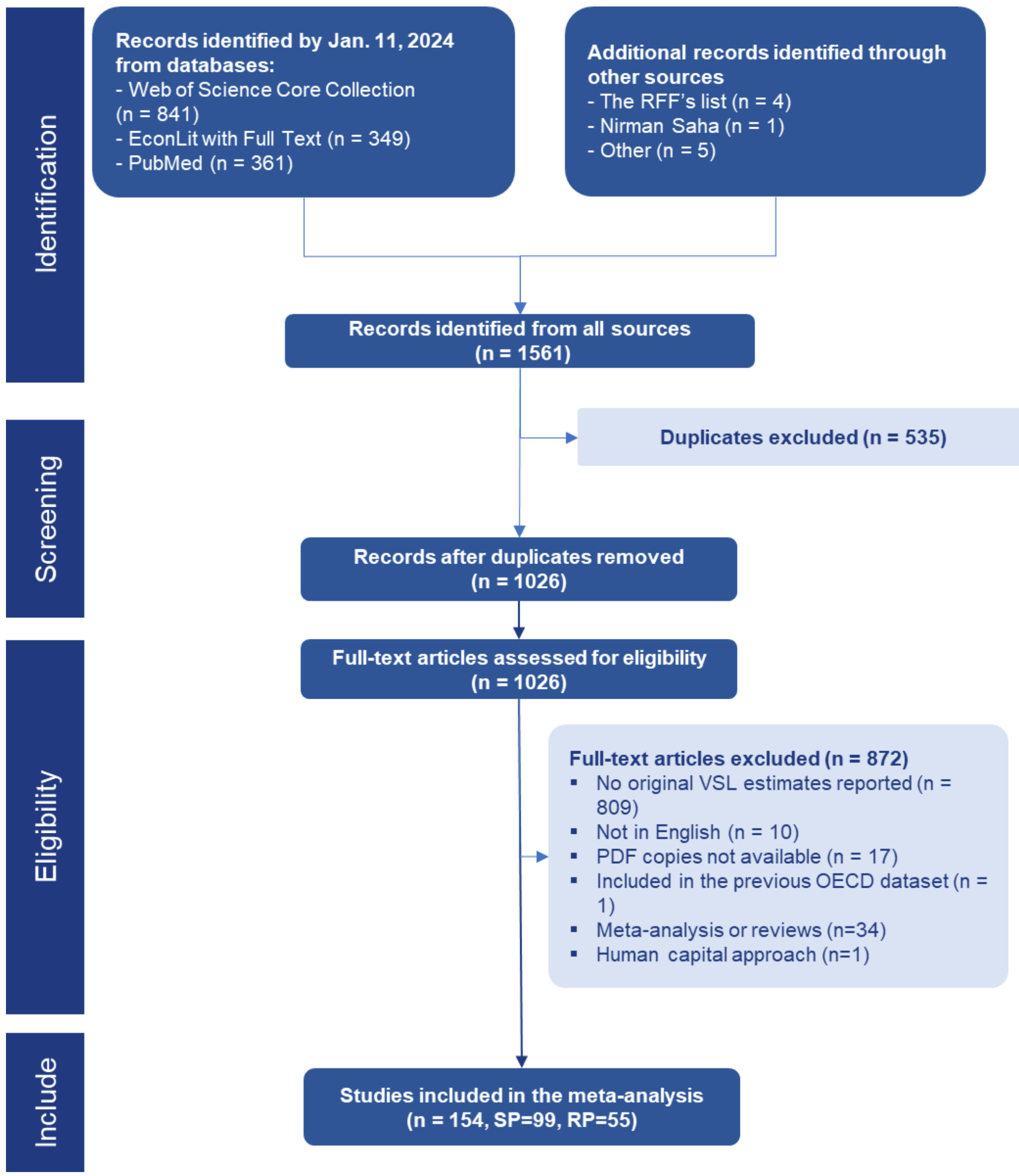
The new meta-data collected for the current analysis was compiled through a search for VSL estimates published between January 2009 and January 2024[6]. Primary valuation studies were identified using systematic review procedures (Moher et al., 2009[5]; Page et al., 2021[6]) and from works cited by other recent literature on the subject (Jacobsen, Boyers and Avenell, 2020[7]; Mazzei et al., 2020[8]). This collection approach, based on the PRISMA 2020 guidelines, constitutes the best practice in current research synthesis and meta-analysis methodologies (Page et al., 2021[6]). The transparency of the search methodology is designed to enable reproducibility and to avoid any potential influence (direct or indirect) that researchers may have on the search procedure and results of the data collection effort.[7]

The aim of the latest review was to identify global SP and RP studies published in English,[8] that report VSL estimates based on primary data. VSL estimates of interest are for the adult population, implying that VSL is a measure of how adults value mortality risks for themselves rather than for others, including children and family members. The search methodology employed was pre-registered at the Center for Open Science (see Annex A for details). The search process underwent trial periods to assess the extent to which the search terms and included databases capture the studies that have been collected by other sources (e.g. recent reviews such as (Keller et al., 2021[9])) and to evaluate the functionality of the internal screening procedure, in terms of the relevance of the returned studies and reported VSL estimate(s). Screening of the articles gathered by the search was performed manually, e.g. by reading abstracts to assess their relevance.

Following the screening process, the collected literature was reviewed by the project's advisory group, which revealed several missing studies that should have been identified (and/or not screened out) in the search. Consequentially, search terms were updated, additional database sources were added, internal screening procedures were refined, and the search methodology was finalised in January 2024. The full list of studies included in the collected meta-data is provided in Annex H. The RP and SP studies published after 2008 that were identified through this search will subsequently be referred to as "New RP" and "New SP", respectively, or collectively as the "New" data.

Figure 3.2 depicts the various steps comprising the PRISMA2020 methodology to construct the meta-data database, including identification, screening, eligibility and final study selection. The first step of the process (Identification) consisted of a search of scientific databases for VSL studies, which returned a total of 1 561 records. The next step (Screening) eliminated duplicate records, yielding 1 026 studies. In a subsequent step (Eligibility), the abstracts and full text of all records were manually checked against several eligibility criteria (cf. box in Figure 3.2 related to Full-text articles excluded), which resulted in the removal of 870 records. This search process identified a final number of 156 eligible records, of which 100 SP studies and 56 were RP studies.

Figure 3.2. PRISMA chart of the systematic review process for new stated preference and revealed preference data



Source: Produced by the authors.

The next step in the review and meta-analysis process was to extract information from the included primary valuation studies and code these as quantitative variables (e.g. dummies, categorical or continuous variables) in order to be able to provide descriptive information about the characteristics of the body of studies collected (Section 3.2), analyse factors that can explain variation in VSL estimates (Chapter 4) and better understand the relationship between VSL estimates and various factors that could potentially be used to adjust base VSL estimates for use in different policy contexts (Chapter 5). The variable of interest in this analysis is the estimate of VSL, i.e. the so-called "effect size" in the meta-analysis. To ensure the coherence of the analysis, the coding procedure for New SP was based in part on the way in which variables were coded in the Old SP database. The coding procedure for New RP data was inspired by and cross-checked against the Old RP database provided by Masterman and Viscusi (2018[2]). The coded variables are defined and discussed in Section 4.3 of Chapter 4, and descriptive statistics of all coded variables are provided in Annex C.

While a number of variables related to the quality of the primary valuation studies are coded at this stage, the overall quality of the studies included in the meta-data is not assessed until a later stage (cf. Section 4.3.3 of Chapter 4). Note that it is appropriate to determine whether to exclude or assign lower weights to studies considered to be of lower quality before undertaking an analysis of the data.

3.1.4. Conversion of VSL for comparability between data sources

The current analysis extracts VSL estimates reported anywhere in the full texts of the identified studies.[9] There is considerable variation in how VSL estimates are reported. For example, studies generally report estimates in different currencies and for different years and only a small minority uses consumer price index (CPI) adjustments. To render VSL estimates comparable within and between data sources, all VSL estimates are converted to 2022 USD by using domestic CPIs[10] and purchasing power parity (PPP) rates from 2022 (the latest year where data was widely available at the time of analysis). The conversion formula for the currency/country i in year t is:

$$VSL_{2022\ USD} = VSL_{t,\,i} \times \frac{CPI_{2022,i}}{CPI_{t,\,i}} \times \frac{PPP_{2022\ USD}}{PPP_{2022,i}} \qquad \text{Equation 3.1}$$

The information used for the conversion was sourced from official OECD statistics.[11] This conversion generally followed the same procedure as in OECD (2012[1]) which remains relevant in the current literature. US EPA (2016[10]) used estimates of income elasticity of VSL and GDP per capita to adjust VSL estimates over time (as increasing income can be assumed to affect VSL estimates) when compiling meta-data for analysis. However, this procedure was later advised against by the US EPA Scientific Advisory Board (SAB) (SAB/USEPA, 2017[11]).[12,13] The details of the conversion procedure (including exceptional cases where it was not straightforward) is provided in Annex B. Unless otherwise noted, the notation USD is used throughout the report to denote constant 2022 US Dollars, calculated using the formula in Equation 3.1.

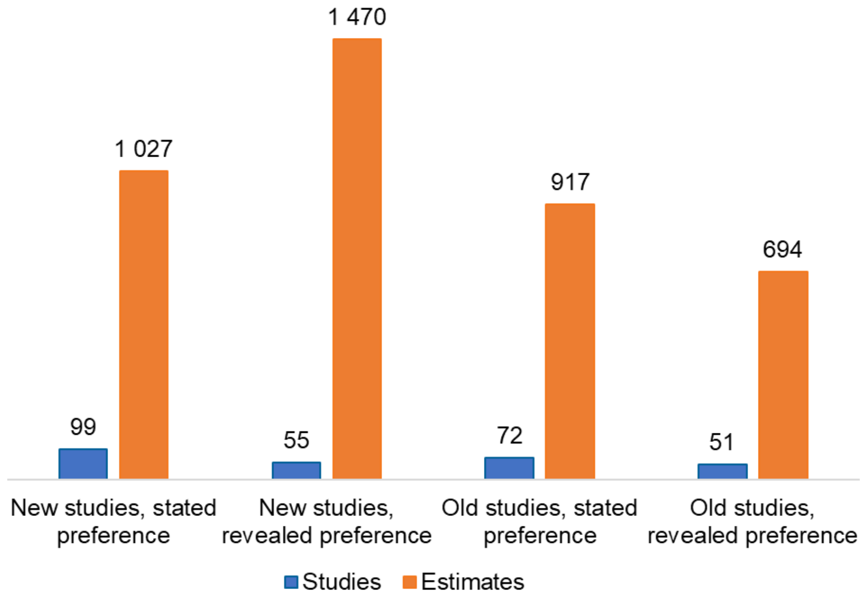
3.2. Characteristics of VSL studies

This chapter provides descriptive information about the meta-data sources. The purpose is to provide an overview of the data used in the statistical analysis carried out in Chapter 4, which will serve as the basis of the recommendations for use of VSL estimates in Chapter 6.

3.2.1. Number of studies and estimates

Figure 3.3 shows the total number of studies identified by the search procedure in each of the four databases. More SP studies (99) were identified in the period from 2009 until 2024 as compared to the previous database covering the earliest SP applications until the end of 2008 (72). For RP, only slightly more studies (4) were identified in the period after 2009 compared with older studies. On average, more estimates are provided per study for RP studies (27) than for SP studies (10).

Figure 3.3. Number of primary valuation studies and VSL estimates from the new and old meta-data, by valuation method



Note: *Old* refers to primary valuation studies published before 2009, and *New* refers to primary valuation studies published since 2009.

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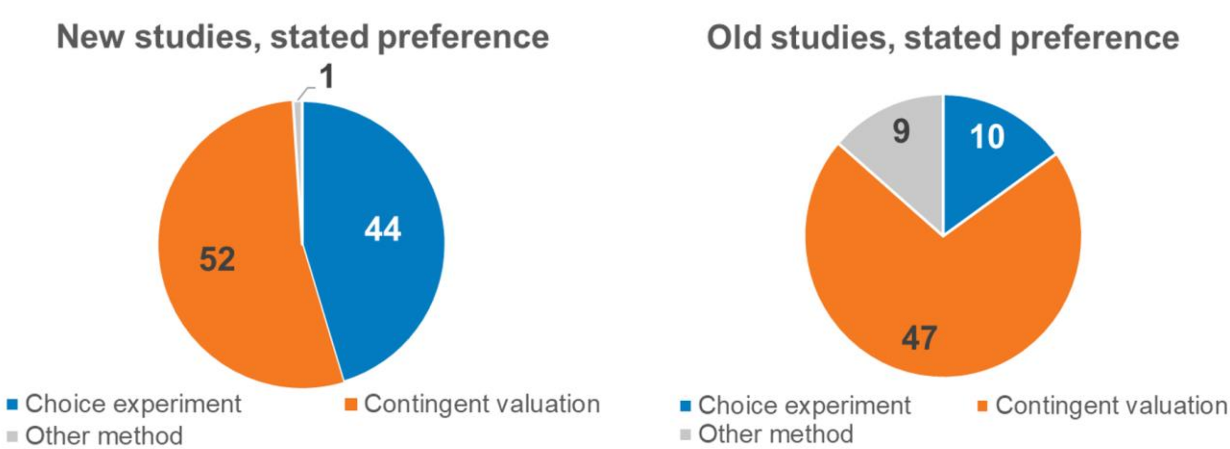
Figure 3.4 and Figure 3.5 further divide primary valuation studies across databases into different types of SP and RP valuation methods. Comparing the valuation methods used by studies in the old and new SP databases, Figure 3.4shows that the use of choice experiments (CEs) has gained popularity over time relative to contingent valuation (CV). In the new SP data, the method mix is approximately equally split between the two methods. For the RP data, the Old RP dataset includes only studies using hedonic wage (HW) methods, whereas the New RP dataset also includes consumer market (CM) studies. In the New RP dataset, 9 out of 55 RP studies use CM methods.

Figure 3.4. Number of studies using different stated preference (SP) methods



Note: *Old* refers to studies published before 2009, and *New* refers to studies published since 2009.

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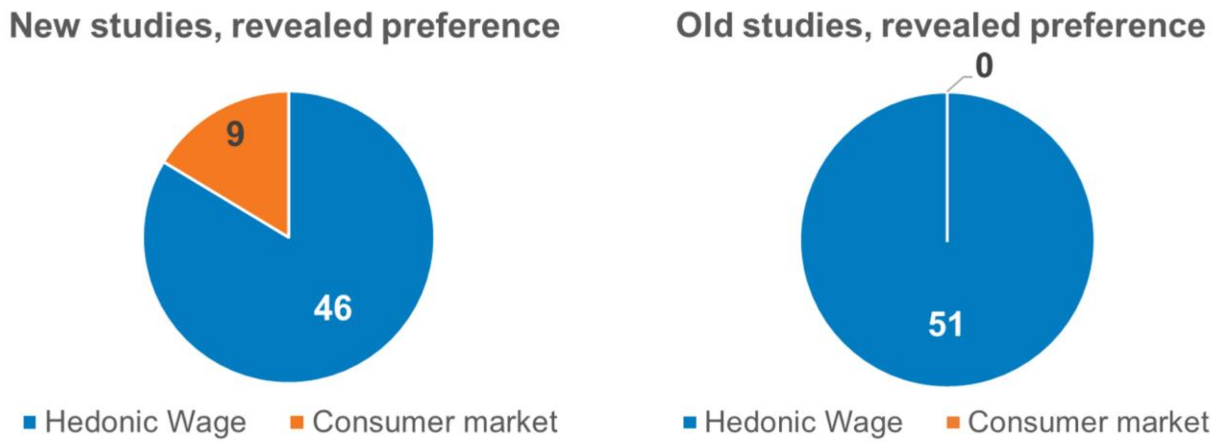
Figure 3.5. Number of studies using different revealed preference (RP) methods



Note: *Old* refers to studies published before 2009, and *New* refers to studies published from 2009.

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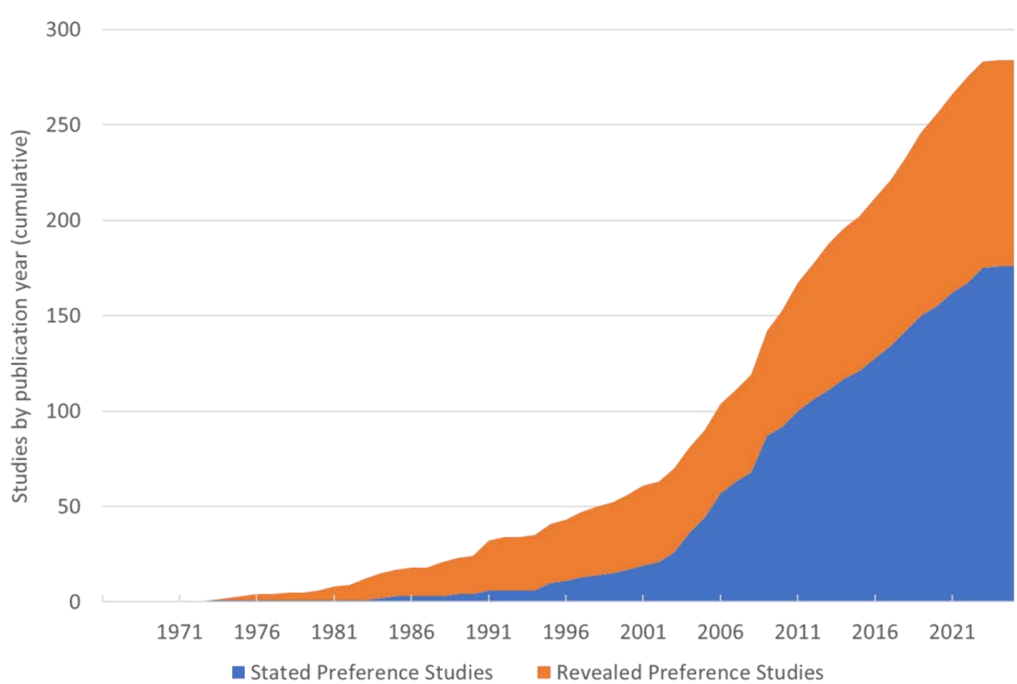
3.2.2. Growth in mortality risk valuation studies over time

Figure 3.6 shows the total number of SP and RP valuation studies reporting VSL estimates by year, indicating substantial growth in the number of studies over time. While RP studies tended to outnumber SP studies in the years before 2000, there has been significant growth in SP studies since then, leading to SP studies outnumbering RP studies by the end of 2023. Note that a lag of several years can exist between the underlying RP and SP data and the publication of VSL estimates. This is due in part to the use of HW data, which reflect long time series and also due to the time needed for analysis before VSL estimates are published.

Figure 3.6. Cumulative number of mortality risk valuation studies by method



StatLink https://stat.link/usvnl9

3.2.3. Geographical distribution of SP and RP studies

Figure 3.7 and Figure 3.8 show the geographical distribution of primary valuation studies using SP and RP methods, respectively. While both methods are used primarily in countries with relatively higher income levels, more recent studies tend to include a broader spectrum of countries and income levels, including in Latin America, Africa and Asia. Traditionally, RP methods have been used more frequently in North America, especially in the United States, compared to Europe and the rest of the world. Further, RP methods have a narrower geographical distribution then SP methods. SP methods are generally considered easier to implement given that conducting population surveys is relatively straightforward, while RP methods, especially hedonic wage studies, require large datasets on wage and risk factors for different sectors, which are typically not easily available or available at all in lower-income countries.

Figure 3.7. Geographical distribution of all stated preference studies, 1970-2024

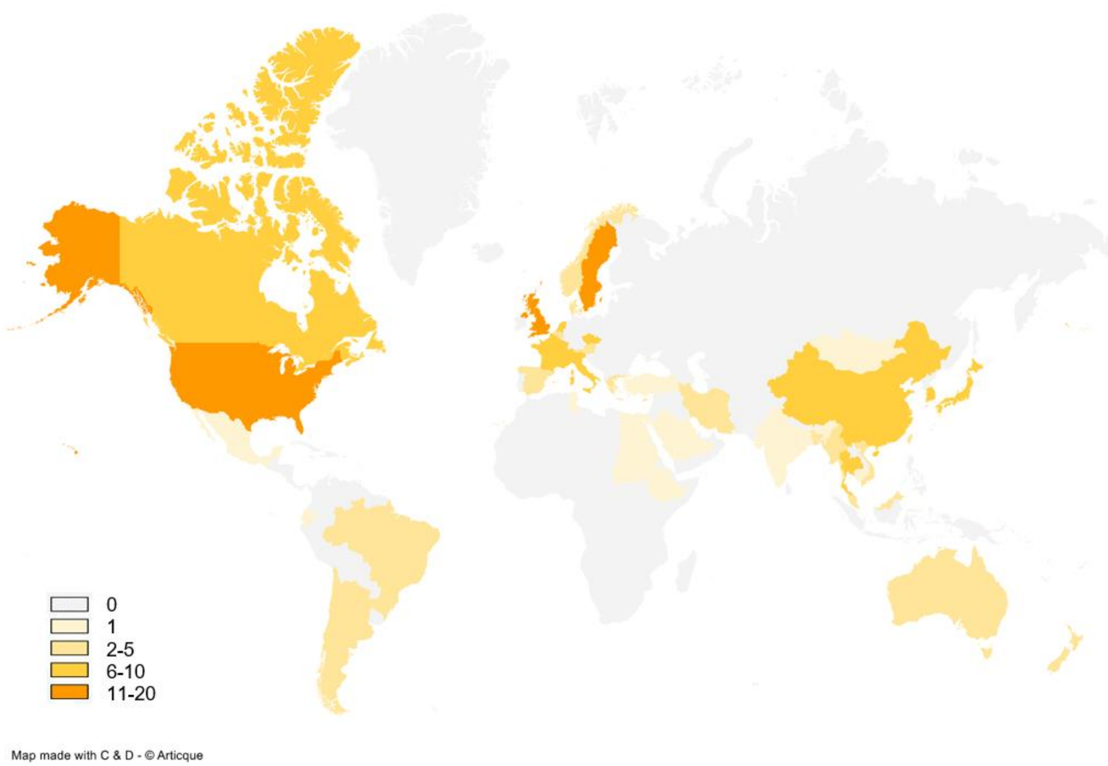


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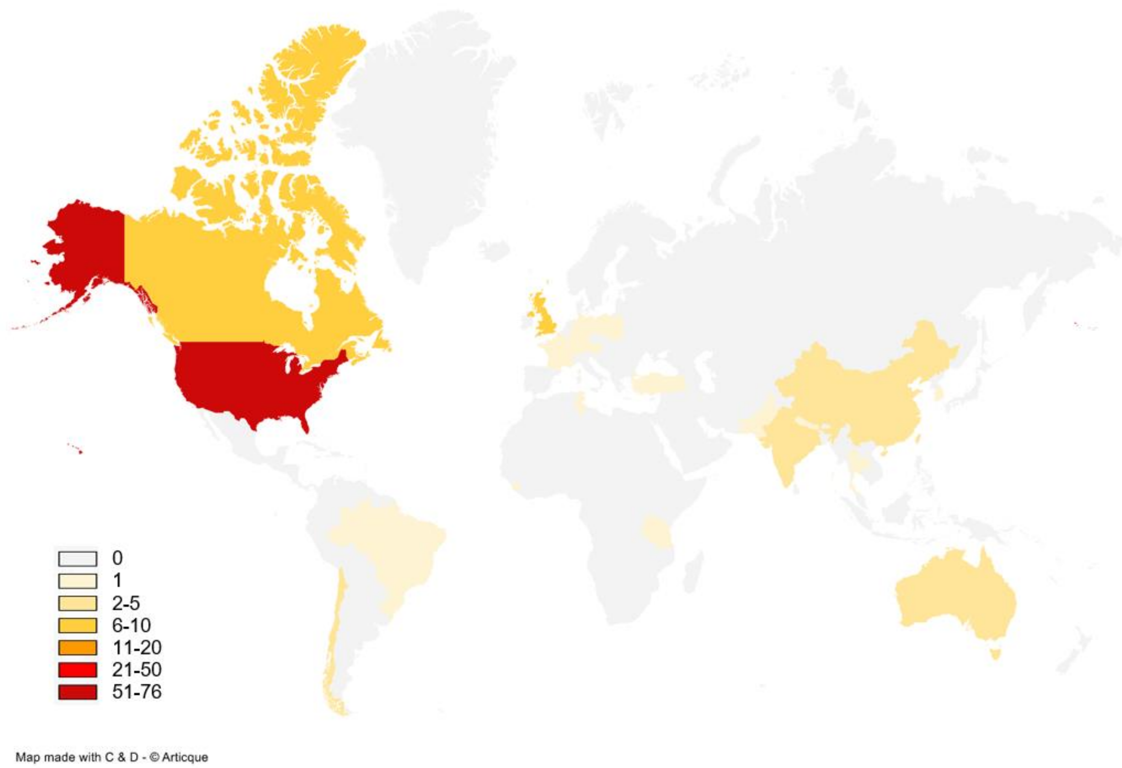
Figure 3.8. Geographical distribution of all revealed preference studies, 1970-2024



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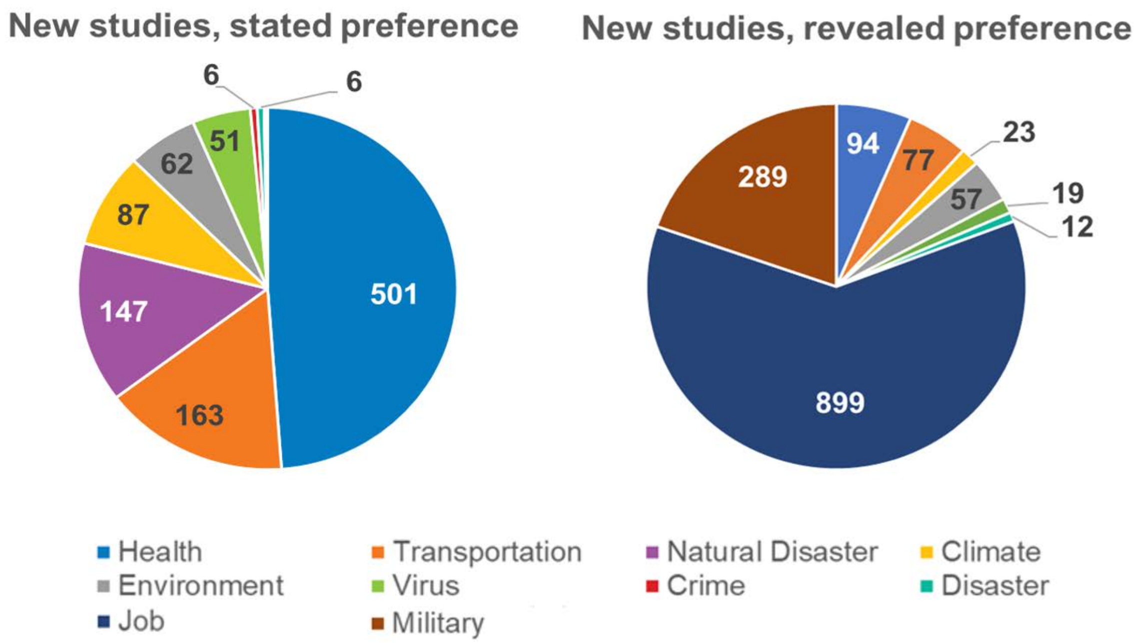
3.2.4. Characteristics of risks valued

Figure 3.9 provides an overview of the sources of risks underlying the VSL estimates reported in the New SP and New RP data. Non-contagious health-related risks are the largest single type of data source for the basis of SP estimates (501 estimates). These risks include fatality causes such as cancer, heart disease and stroke. The second largest source of risks include transport-related risks (163), followed by natural disasters (147) which include fatalities from events such as avalanches, floods and earthquakes. Climate-related risks (87), which include extreme weather, sea level change and the depletion of fisheries, and heat stroke also constitute a significant portion of risk estimates, as well as environmental risks (62) such as air and water pollution and contagious disease-related health risks ("virus" in Figure 3.1) (51)[14]. Several risk categories have very few estimates, including those related to e.g. crime, man-made (i.e. not natural) disasters and suicide. For the New SP, the mean (median) annualised risk change levels valued in the primary studies is 0.0015 (0.00015) for CV and 0.001 (0.0001) for CE.[15] Regarding the sources of risk that serve as the basis for RP VSL estimates, many are job-related risks, the specific causes of which can be multiple and difficult to isolate (899 estimates). Health-related risks (94), transportation-related risks (77), and environment-related risks (57) are the next most common types of risk treated in studies in the New RP dataset. Several VSL estimates pertain to risk changes regarding contagious diseases (19), climate change (23) and natural disasters (12). For HW especially, it is not straightforward to estimate the risk levels associated with the reported VSL estimates.

Figure 3.9. Number of VSL estimates attributed to various risk sources

New studies, stated preference and revealed preference



Note: The "health" category refers to non-viral diseases (e.g. heart disease). "Environment" refers to environmental hazards other than climate events and natural disasters (e.g. air pollution). "Disaster" category refers to man-made disasters (e.g. nuclear accident). In the New SP dataset, a number of missing values that have been assigned to the "Health" category based on the coding procedure for risk types used in the Old SP dataset.

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The New SP and New RP datasets are also coded to distinguish between acute (traumatic) and chronic (illness-related) causes of mortality risks. 38% of VSL estimates are related to acute risks, 14% to chronic risks, and 48% relate to mixed risks, which are considered to be risks that are a mix of chronic and acute risks (as can be the case in many RP studies) or risks that are not clearly specified or easy to determine. Acute risks could for example include traffic accidents, while chronic risks are typically related to illnesses or conditions that last for a period of time before death, such as cancer.

3.3. Summary statistics of VSL estimates in the meta-data

This chapter reports summary statistics of the VSL estimates included in the meta-analysis. Depending on how the VSL estimates from each study is treated the results of the meta-analysis could potentially be different. The mean of VSL at the "estimate level" is calculated as the mean of all individual VSL estimates reported in all studies, with each estimate given equal weight. In contrast the mean of VSL at the "study level" reflects the mean VSL estimate calculated using a single estimate from each study. Each study-level estimate is calculated as the mean of all of the estimates reported in the study. Mean VSL at the "estimate level" implicitly gives more weight to the results of studies that report many estimates.

3.3.1. Estimate level VSLs in the dataset

Table 3.1 reports the basic descriptive statistics of VSL estimates for the four different datasets, including mean, standard deviation (SD) and number of studies (N). Following common statistical procedures, extreme outliers (or "far-outs") are excluded from the values reported in the table.[16] Outliers are defined based on the interquartile range and are further discussed in the context of the meta-analysis of the VSL data in Chapter 4.

For all data combined regardless of the valuation method, i.e. a total of 3 986 individual VSL estimates from 280 studies, the overall mean VSL estimate at the estimate level is USD 7.8 million (Table 3.1) .For the respective datasets New SP, New RP, Old SP and Old RP, the mean of VSL estimates at the estimate level are USD 7.3, 6.5, 6.8 and 12.9 million. Hence, the differences among the first three datasets are relatively small. Standard deviations of the mean of VSL estimates at the estimate level across the three meta-data sources are also similar.

Considering SP and RP data separately, and merging the Old SP and New SP datasets together, as well as the Old RP and New RP datasets together, yields mean VSL estimates of USD 7.1 and 8.4 million at the estimate level for SP studies and RP studies, respectively. Hence, the difference between the two methods, considering all publication dates, is not very large. For the new data only, the mean VSL estimate is USD 6.8 million at the estimate level. Note that these values reflect overall descriptive statistics and that a more robust comparison would account for other differences in the data that can explain variation in VSL estimates, such as income levels. The impact of such differences on VSL estimates will be examined in the meta-analysis conducted in Chapter 4, which controls for a number of such factors.

Excluding far-outs appears to have a substantial influence on the estimate-level mean VSLs. Including these values would result in an increase in the estimates to USD 60, 8.6, 12.9 and 15 .3 million for the New SP, New RP, Old SP and Old RP meta-data, respectively. Descriptive statistics of the various datasets, with and without outlier values, are provided in Annex C.

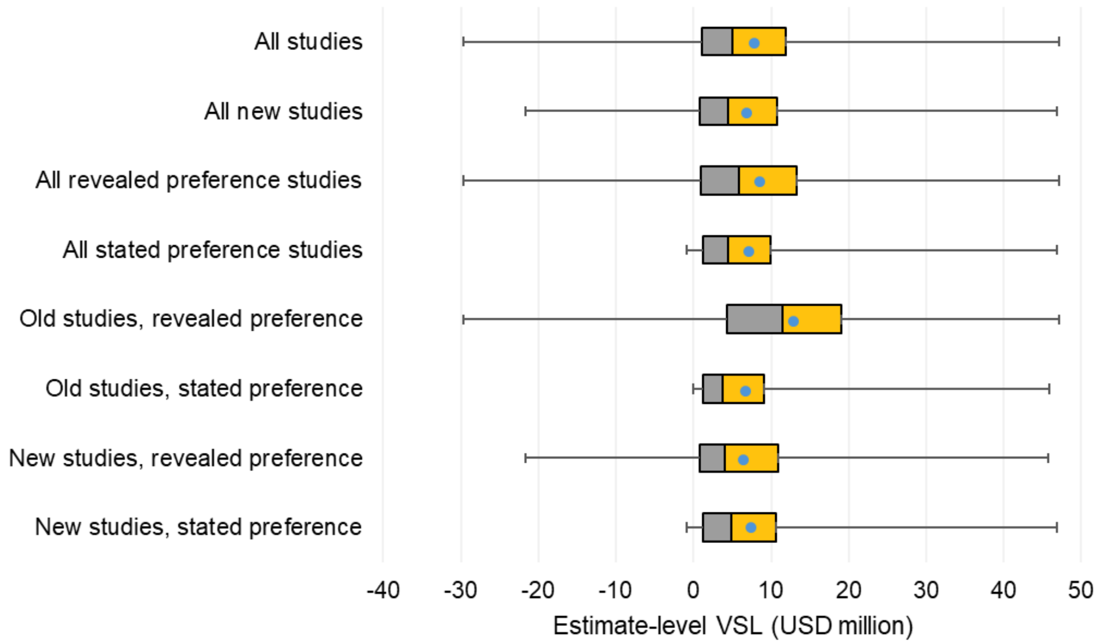
Table 3.1. Meta-data estimate-level VSLs by dataset

Datasets	Number of VSL estimates	Mean	St. Dev	Median	Number of studies	Percent far-out
				USD_{2022} Million		
New studies, Stated preference [2009-2023]	1 030	7.3	7.8	4.9	99	1.4%
New studies, Revealed preference [2009-2023]	1 436	6.5	7.8	4.0	55	2.3%
Old studies, Stated preference [1970-2008]	861	6.8	8.0	3.8	71	6.1%
Old studies, Revealed preference [1970-2008]	653	12.9	11.9	11.4	51	5.9%
Subtotal SP	1 874	7.1	7.9	4.4	170	3.6%
Subtotal RP	2 089	8.4	9.8	5.8	106	3.5%
Subtotal *New*	2 449	6.8	7.9	4.4	154	1.9%
All	3 963	7.8	9.0	5.0	276	3.5%

Note: *SP* refers to "Stated Preference", and *RP* refers to "Revealed preference". *Old* refers to studies published before 2009, and *New* refers to studies published in 2009 and later. This table presents summary statistics of all individuals VSL estimates collected across studies. The results exclude outliers ("far-outs"), which are defined as VSL $\notin [Q25 - 3(Q75 - Q25), Q75 + 3(Q75 - Q25)]$. Estimates are inflation-adjusted to 2022 from the year a VSL estimate is reported according to the procedure described in Section 3.1.4.

Figure 3.10 reports the quartiles, median, minimum and maximum values of estimate-level VSLs. The left-hand side of the figure displays estimates for the four datasets, while the right-hand side of the figure displays estimates for various merged groups of meta-data. Median and mean estimate-level VSL estimates are relatively similar across the New SP, Old SP and New RP datasets. The width of the distributions (reflecting the interval between the 25% and 75% quartiles) is reflected in the width of the boxes. The horizontal lines ("whiskers") reflect minimum and maximum values. Note that although some VSL estimates, especially for HW studies, may be reported as negative in the statistical analyses in primary valuation studies, they are nevertheless included here in order to reduce potential publication bias[17]. Mean estimate-level VSL estimates for New SP and RP together ("All New") are very similar to the full dataset ("All merged").

Figure 3.10. Box plot of estimate-level VSL estimates by dataset excluding far-outs



Note: Outliers ("far-outs") are excluded, defined as VSL $\notin [Q25 - 3(Q75 - Q25), Q75 + 3(Q75 - Q25)]$. Blue dots reflect mean VSL estimates, the midlines of boxes reflect median VSL estimates, the upper boundary of the boxes reflect the 75% quartile of VSL estimates, the lower boundary of the boxes reflect the 25% quartile of VSL estimates, and the horizontal lines ("whiskers") reflect the minimum and maximum VSL estimates, respectively.

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Annex C provides additional detailed information, including a display of the cumulative distribution functions of VSL estimates in the four datasets and for those obtained using RP and SP methods, respectively.

3.3.2. Study level VSLs in the dataset

Mean study-level VSL estimates are calculated as USD 5.3, 8.1, 6.4 and 11.3 million for the New SP, New RP, Old SP and Old RP datasets, respectively (Table 3.2). Mean study-level VSL estimates are lower than mean estimate-level VSL estimates, particularly in the New SP dataset. Smaller differences are observed between the mean estimates of VSL at the study and estimate levels for RP, SP and All new data combined. The overall mean VSL estimate at the study level combining all meta-data sources is relatively unchanged, at USD 7.2 million (compared to USD 7.8 million at the estimate level in Table 3.1.

One reason for the difference between study-level and estimate-level results is that high VSL estimates are likely to be generated as part of the robustness checks and sensitivity analyses that may be carried out in primary valuation studies. Moreover, such high estimates are more likely to be reported by studies that report many estimates, including from robustness checks and sensitivity analyses, whereas studies that produce fewer estimates are less likely to include very high estimates. Therefore "close-to-the-average" estimates from studies reporting fewer estimates may be underweighted when viewing VSL estimates at the estimate-level. This underweighting is reduced in the calculation of mean VSL estimates at the study level.

Excluding extreme values (far-outs) also has a substantial influence on the mean VSLs at the study level. For example, for the new SP data, the mean study-level VSL estimate increases from USD 5.3 million to USD 25.9 million when the extreme values are included. Descriptive statistics of the various datasets, with and without outlier values, are provided in Annex C.

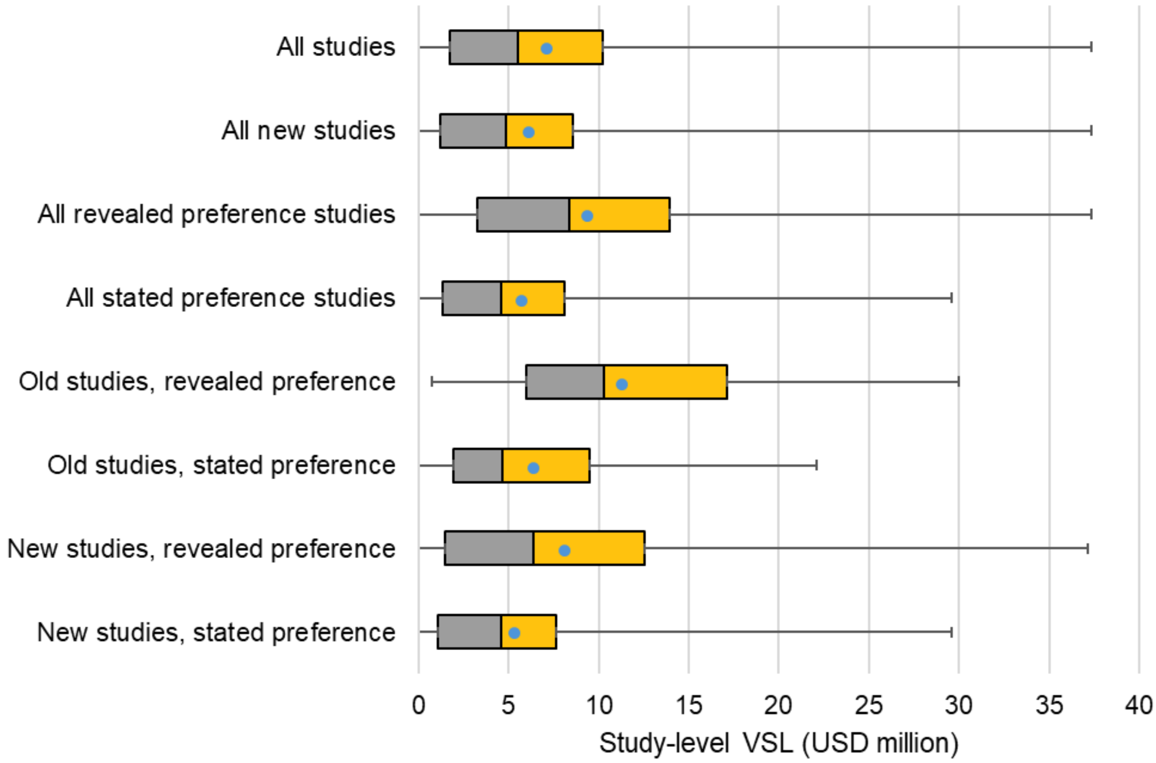
Table 3.2. Meta-data study-level VSL estimates by dataset

Datasets	Number of Studies	Mean	Standard deviation	Median	Percent far-outs
				USD2022 Million	
New SP[2009-2023]	99	5.3	5.6	4.6	1.4%
New RP[2009-2023]	55	8.1	7.1	6.6	2.9%
Old SP[1970-2008]	71	6.4	5.9	4.6	5.1%
Old RP[1970-2008]	51	11.3	6.9	10.3	4.7%
Subtotal SP	170	5.8	5.7	4.6	2.9%
Subtotal RP	106	9.6	7.1	8.6	3.8%
Subtotal *New*	154	6.3	6.3	5.0	1.9%
All	276	7.2	6.6	5.6	3.3%

Note: *SP* refers to "Stated Preference", and *RP* refers to "Revealed preference". *Old* refers to studies published before 2009, and *New* refers to studies published from 2009. Study Level = Weighted by the inverse of the number of estimates from each study. Outliers ("far-outs") are excluded, defined as VSL $\notin [Q25 - 3(Q75 - Q25), Q75 + 3(Q75 - Q25)]$. Far-outs has a slightly different interpretation at the study level compared to Table 3.1. Here, e.g. 3.3 % are removed due to far-out estimates, implying that all estimates from those studies are removed. of VSL estimates are inflation-adjusted to 2022 from the year a VSL estimate is reported according to the procedure described in Section 3.1.4 of Chapter 3.

Figure 3.11 reports the quartiles, mean, median and minimum and maximum estimates of study-level VSL estimates.

Figure 3.11. Box plot of study-level VSL estimates by dataset, excluding far-outs



Note: Outliers ("far-outs") are excluded, defined as VSL $\notin [Q25 - 3(Q75 - Q25), Q75 + 3(Q75 - Q25)]$. Blue dots reflect mean VSL estimates, the midlines of boxes reflect median VSL estimates, the upper boundary of the boxes reflect the 75% quartile of VSL estimates, the lower boundary of the boxes reflect the 25% quartile of VSL estimates, and the horizontal lines ("whiskers") reflect the minimum and maximum VSL estimates, respectively.

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Notes

[1] This share was ca. 7.7 per cent (78 estimates).

[2] An international dollar would buy a comparable amount of goods and services in the cited country that a U.S. dollar would buy in the United States. This term is often used in conjunction with Purchasing Power Parity (PPP) data (World Bank, 2024[24]). In what follows, the abbreviation "USD" is used to refer to this measure of international US dollars.

[3] The database contains estimates from each study included in Bellavance et al. (2009[12]), Viscusi (2015[13]), Viscusi and Aldy (2003[14]) and Viscusi and Masterman (2017[15]). The full list of papers from which they draw VSL estimates can be found in the Supplementary materials to Masterman and Viscusi (2018[2]).

[4] Based on personal communication with Masterman and Viscusi. One additional paper was identified and included due to co-authorship (Gentry and Viscusi, 2016[16]).

[5] Data from 2009 to 2016 in the dataset from Masterman and Viscusi (2018[2]) is used to crosscheck the quality of RP data in corresponding years collected for the current analysis (e.g. with respect to variable coding procedures).

[6] This included academic journals and other research outlets, the majority of which were subject to some type of peer review. 71% of the VSL estimates in the coded dataset were published in journals (cf.

Annex C). Of the remaining 29%, 20% were classified as "unpublished", 3% as conference proceedings, 6% as theses and less than 1% as book sections.

[7] The search methodology for the current analysis has not made use of artificial intelligence tools. Although artificial intelligence may have potential for contributing to search methodologies (Fabiano et al., 2024[17]), the use of AI tools is still relatively immature in this field as of 2024.

[8] This is the conventional approach in the systematic reviews and meta-analysis papers known to the authors, including OECD (2012[1]). To investigate potential limitations or valuation biases introduced by only using English-language studies, prominent researchers based in non-English speaking countries were consulted. For several countries (e.g. Poland, China, Germany, Spain, France, Nordic countries) it was confirmed that most reasonable-quality studies are published in English language journals. For some countries such as Japan and France (and some Latin American countries), where publication in the national language has historically been more common, some additional studies were identified. However, among the contacted researchers, none expressed concerns that ignoring a relatively small number of non-English VSL studies would lead to a systematic bias in the VSL estimates presented in this study.

[9] In contrast to the database used for OECD (2012[1]), the current analysis does not include VSL estimates derived from other available measures (e.g. WTP for a specified change in mortality risk). This choice was made to avoid any calculation errors and/or misunderstandings related to the intentions of original study authors and to make the data collection procedure as transparent and replicable as possible. As noted above, the proportion of such estimates was relatively small in the Old SP database.

[10] Note that this practice assumes that the way people value mortality risks over time follows the same pattern as their WTP for the basket of consumer goods the CPI is based on. This constitutes standard practice in the meta-analysis literature. Since there is no "CPI for mortality risk reductions" and making other assumptions is difficult to justify.

[11] CPI and PPP values are retrieved from OECD (2025[18]) and OECD (2025[19]), respectively, and are available from the OECD Data Explorer: https://www.oecd.org/en/data/datasets/oecd-DE.html.

[12] The US EPA SAB states that it is not appropriate to conduct this transformation as part of constructing the input data for meta-analysis due to the fact that it makes strong assumptions about income elasticity of VSL over time. However, the SAB considers that it may be appropriate when making recommendations for the use of VSL estimates in specific applications (i.e. benefit transfer). The SAB also noted that VSL estimates from RP hedonic wage studies are derived from Marshallian willingness to accept a marginal increase in mortality risk (i.e. holding income constant), while VSL estimates from SP studies are derived from Hicksian WTP for a marginal reduction in mortality risk (i.e. holding utility constant). As has been shown in the literature, willingness to accept is often found to be larger than WTP (Tunçel and Hammitt, 2014[20]). The advisory board offers no specific solution to this issue, and for the purposes of this analysis no attempt is made to correct for this potential disparity, as this would not align with the existing meta-analysis literature.

[13] Banzhaf (2022[21]) uses different assumptions about income adjustment of VSL, including assuming an income elasticity of VSL of zero for sensitivity analysis, stating that: "Some analysts may prefer this more conservative approach, especially given the uncertainty about the role of permanent income versus current income, cross-sectional variation in income and time series variation, and the measurement of income" (p 194-195).

14 The following definitions were used risk causes: Disaster-related risk: man-made disasters; Climate-related risk: extreme weather, sea level change and depletion of fisheries, heat stroke; Virus: COVID-19, dengue fever, rabies.

15 Note that CE studies by design provide many risk change levels. For these studies risk change levels were averaged over the ranges used in CE designs. For RP studies it is often not possible or meaningful to derive risk measures from primary valuation studies. As discussed in e.g. Ginbo et al. (2023[22]), many RP studies do not report the risk differential between alternative and risky jobs, so that it is impossible to identify the exact level of risk change valued in RP studies.

16 Following the definition of Tukey's fences, far-outs are considered to be values that falling outside of an interval delimited by a lower value equal to the 25th percentile minus three times the difference between the 25th and the 75th percentile, and an upper value equal to the 75th percentile plus this amount (Tukey, 1977[23]). Formally VSL $\notin \{Q25 - 3(Q75 - Q25), Q75 + 3(Q75 - Q25)\}$. Note that it has not been assessed whether and how individual studies have addressed potential extreme values in their primary SP or RP data.

17 Approximately 2.5% of VSL estimates in the full dataset are equal to or less than zero.

4 Meta-analysis method and preliminary unadjusted VSL estimates

This chapter presents the meta-analytical methodology used to derive preliminary unadjusted value of statistical life (PUVSL) estimates, which are intermediary values to the value of statistical life (VSL) estimates, and provides details on how the data was prepared and screened. The chapter highlights best-practices in meta-analyses and explains the concept of the random-effect model used in this report. The chapter presents the PUVSL estimates obtained for the OECD, the EU, the United States, high-income countries, low- and middle- income countries and at the global level. The chapter also presents results from sensitivity analyses of the PUVSL estimates.

4.1. Main approach to the analysis of VSL meta-data for policy use

In many cases, it may not be possible to perform primary valuation studies to estimate the economic benefits or costs of mortality effects associated with a policy under consideration. A common practice is therefore to use existing value of statistical life (VSL) estimates in cost-benefit analyses (CBA). This chapter presents the methodological approach for estimating VSLs from existing primary studies. The preliminary VSL estimates presented in this chapter are not recommended for use without further adjustments, which are discussed in Chapters 5 and 6. This chapter also discusses data quality considerations and presents sensitivity analyses of the preliminary estimates presented.

This report considers four different options for deriving updated VSL estimates from existing VSL primary studies. The first option is a form of unit or benefit function transfer () in which primary VSL estimates from a subset of studies are compared, matched and then adjusted to the extent possible, to the relevant policy context. USEPA (2016[1]) observes that a key advantage of this option is its potential to enhance the precision of the transfer if suitable studies matching the policy context are available. Conversely, this approach carries a risk that analytical accuracy could be reduced when the availability of such studies or primary estimates is limited. Moreover, this approach is not feasible for new policy contexts for which primary valuation estimates are not available. Finally, this approach requires some degree of analytical judgement, potentially complicating the ultimate transparency and objectivity of the approach.

The second approach proceeds by establishing one or more base VSL estimates, and then reviews available evidence from the literature to identify appropriate adjustments factors (e.g. differences in risk and population characteristics, or child vs. adult mortality risk). Under this approach, the “evidence speaks” without a need to impose restrictive assumptions, such as introducing estimation covariates that would require assumptions about the functional relationship between VSL and risk characteristics. Despite its flexibility in terms of assumptions, this approach relies on supplementary evidence from a broader literature on the relationship between VSL and other factors in the primary valuation data. Considering that the meta-data collected from primary valuation data are often not detailed enough to allow for robust estimations, this approach may also be challenging to implement in practice.

The third approach is the standard meta-regression approach in which meta-functions are estimated and used directly in the benefit transfer (Johnston et al., 2021[2]; Johnston et al., 2017[3]) (cf. discussion in Section 2.5 of Chapter 2 and examples in Lindhjem and Navrud (2015[4])). In this approach, values for relevant covariates specific to the policy context such as type of risk, age, and income are inserted into the meta-function. Values for certain methodological characteristics[1] are also identified and the meta-regression function is then used to calculate the relevant VSL estimate for the policy context of interest. While this third approach is the most general of the three options, it also requires significant effort to collect and code information on a wide range of descriptors from each study, which can be challenging as this information is not always readily available for all studies. Additionally, it requires that meta-data are extensive enough to identify functional relationships between VSL and a range of variables (Boyle and Wooldridge, 2018[5]). This can be difficult to achieve in practice, especially in the case of global meta-data where heterogeneity in methods and other factors can be high. Finally, relevant data from the policy context of interest (e.g. information on risk and population characteristics) must also be available in order to carry out benefit transfers using this approach.

Given the high level of heterogeneity in the study characteristics and policy of global meta-data of VSL estimates, most of the approaches used to carry out benefit transfer across countries in the academic literature pertain to situations where the data is less heterogenous (e.g. national datasets such as in Johnston et al. (2017[3])), and so have less relevance to more heterogeneous international contexts as a basis for practical policy guidance. A suitable alternative to the comprehensive meta-analytic approach is therefore a simpler reduced form meta-function containing only the most critical variables such as income, country/region, cause of mortality and valuation methods (Lindhjem and Navrud, 2015[4]). This approach can, however, be sensitive to the choice of functional form and the models' ability to explain the variations in the data (Johnston et al., 2021[2]). A simpler and more transparent approach that uses unit transfers based on the baseline distribution of VSL estimates can also produce reliable results (Johnston et al., 2021[2]; Lindhjem and Navrud, 2015[4]; Robinson et al., 2019[6]).

Another common approach is to combine the second and third approaches described above. This approach proceeds by establishing one or more base VSL estimates along with a range of estimates for "default" case(s). It then uses meta-regression analysis, literature review and expert assessment to identify the adjustment factors that are appropriate to apply to the base VSL estimates. This approach was used in OECD (2012[7]), wherein the central tendencies (mean and median) of the distribution of VSL estimates was estimated from the meta-data. The study then carried out (i) a meta-regression analysis to estimate the income elasticity of VSL to use in benefit transfer between countries and (ii) a general review of the evidence underpinning other potential adjustments. In its most recent review of VSL literature from the United States, the US EPA (2016[1]) similarly opted for a combination of the second and third approaches discussed above.[2]

The approach taken in the present report is similar to that of OECD (2012[7]) and US EPA (2016[1]). In particular, it first estimates preliminary and unweighted mean VSL (PUVSL) estimates and ranges (Section 4.5). Second, it considers potential adjustments to the base VSL estimates for specific policy use cases based on meta-regression analysis (Sections 5.2 and 5.3 of Chapter 5), as well as a review of other available empirical evidence (Section 5.4 of Chapter 5).

4.2. Choice of meta-data for updating the VSL analysis

A number of choices regarding data and methodology must be made in deriving new base VSL estimates and potential adjustment factors. This chapter discusses the choice of the scope of studies included in the meta-analysis.[3] A critical question is how well current evidence reflects individuals' trade-offs between mortality risk reduction and income or wealth, and whether this provides a reliable basis for assessing such trade-offs in the future. This is difficult to evaluate, as a number of factors can change over time that can make older studies less reliable for future projections. For example, structural economic changes, including to industries and demographics, may alter how individuals make trade-offs between income and mortality risk reductions (cf. discussion in Chapter 5 on the income elasticity of VSL).

In many policy applications, individual preferences are often assumed to be constant (e.g. regarding ranking products or making trade-offs between savings and consumption). This implies that changes in willingness to pay (WTP) and therefore in VSL estimates over time are primarily functions of income and other factors that shape individuals' utility and the trade-offs they make between income or wealth and reductions in mortality risk (St-Amour, 2024[8]). While this assumption may hold over short time periods, it may be more difficult to justify over longer horizons. Further, such temporal dynamics require highly specific data in order to be captured empirically (e.g. longitudinal panel studies of the same individuals) (Hammitt, Liu and Liu, 2022[9]; Ørbeck et al., 2024[10]; SAB/USEPA, 2017[11]).[4] In addition, if assuming that the quality of VSL estimates improves over time as scientific methodologies improve, using a set of newer studies can be considered to provide higher quality estimates than older studies.

A number of studies have explored the temporal stability of preferences and WTP for various types of non-market goods, especially for environmental goods. Some evidence indicates that preferences are reasonably stable across short periods of a few years (Ørbeck et al., 2024[10]).[5] For example, in identical consumer market (CV) surveys of cancer risks carried out in 2014 and 2019, Alberini and Ščasný (2021[12]) found that VSL increased by 41% over this time period. The authors attribute this increase to an increase in income and a lower dread of cancer among participants in 2019. Hammitt et al. (2019[13]) found that VSL increased by a factor of 25 over a 11-year period for a repeated CV survey conducted in China. The authors observed that this increase could be explained by income growth, although their implied income elasticity of 3 falls in the upper range of parameters when compared to other studies (cf. discussion in Section 5.4 of Chapter 5).

Overall, however, the evidence on the stability of preferences for mortality risks and VSL over time is limited (Alberini and Ščasný, 2021[12]; Hammitt et al., 2019[13]; Hammitt, Liu and Liu, 2022[9]), and the issue of when empirical evidence becomes irrelevant remains unsettled, in particular for VSL estimates. Consequently, systematic review procedures follow no standard rules on this issue, suggesting that the time period covered by meta-data should depend on the policy issue of interest. A common practice in the literature is to limit systematic reviews to a consideration of more recent studies, such as those published in the last 10 to 20 years (e.g. (Keller et al., 2021[14]), which performed a systematic review of VSL estimates based on evidence from 2009 to 2019). Generally speaking, justification for the choice of time period covered in systematic reviews and meta-analyses is seldom provided. Further, no established guidelines exist regarding the weighting of evidence from older studies in meta-analyses. It seems reasonable to include as much of the existing empirical evidence as possible, even if some of such evidence may be outdated or perceived as less informative, and especially when the available pool of studies to draw from is limited. Including all studies regardless of their age has been the approach favoured by the US EPA (2016[1]) as well as in other single country reviews (Ananthapavan et al., 2021[15]; Ginbo, Adamowicz and Lloyd-Smith, 2023[16]).[6] When following such an approach, however, it is unclear how any challenges related to older evidence (e.g. relative weighting) should be addressed.

As highlighted in Chapter 3, while there are four meta-data sources available for this analysis, only the newer datasets (new stated preference (New SP) studies and new revealed preference (New RP) studies), covering publications in the period 2009 – 2024 are used to derive VSL estimates.[7] In light of the above discussion, this choice is motivated by four reasons.

The first reason for limiting the meta-analysis to more recent studies is that the recommendations presented in this report are expected to be used to value the effects of policies pertaining to mortality risks in future years. To this end, more recent studies are likely to better reflect the current preferences of individuals and circumstances under which (real or hypothetical) choices underpinning VSL estimates are made. Second, assuming that SP and RP methodologies, and the scientific quality of valuation analyses more generally, have improved over time, VSL estimates from more recent studies can be considered more reliable than those from older studies. Third, considering uncertainty in the literature regarding how the income elasticity of VSL may change over time, limiting the data to more recent SP and RP studies reduces the possible impact of such uncertainty. As the descriptive data in Section 3.3 of Chapter 3 indicates, the choice between using all available studies versus only the new SP and RP datasets is unlikely to significantly impact base VSL estimates. Fourth, unlike the older data sources, the new SP and RP studies were compiled using a pre-registered set of transparent systematic review procedures following current best practice (cf. description in Section 3.1.3 of Chapter 3 and Annex A). These methods substantially alleviate the potential for selection bias arising from data collection procedures. Moreover, the use of such methods facilitates replication efforts, enabling the analysis to be repeated for subsequent updates of the meta-data and lending methodological consistency over time. An analysis of the sensitivity of estimated mean VSL estimates to the choice of data source is nevertheless provided in Section 4.7.

4.3. Data preparation and screening

4.3.1. Conversions and outlier exclusion

Apart from using CPI and PPP to adjust for inflation and normalise the VSL estimates obtained from different studies to 2022 USD, no other adjustments are applied to the VSL estimates in the data preparation for analysis (cf. Section 3.1.4 of Chapter 3). This approach eliminates the risk of making assumptions that may not be theoretically well-founded or difficult to document based on information from the available primary valuation studies.

There is no consensus in the meta-analysis literature on VSL regarding the superiority of certain pre-screening procedures for addressing challenges such as the discounting of mortality risks that occur at different times. In practice, it is difficult to extract highly specific information from a substantial portion of primary valuation studies, and it may be undesirable to exclude certain studies from the meta dataset because they lack this information[8]. Moreover, each VSL estimate was elicited under certain circumstances and contexts that are unique to that estimate. Such circumstances can only be partially extracted or quantitatively coded in the analysis. As discussed in Section 3.3 of Chapter 3, the only VSL estimates that are excluded from the current analysis are outliers that are defined via statistical procedures as implausibly high or low (far-outs). This screening procedure is common practice in the scientific literature and results on the impact of removing far-out observations are provided in Annex E.

4.3.2. Coding of variables

As explained in Chapter 3, information contained in primary valuation studies in the New RP and SP datasets was screened and extracted to code a set of basic variables for analysis. Table 4.1 describes these variables. As extensively discussed in OECD (2012[7]), it is impossible to capture information on all of the factors that may explain variations in VSL estimates across studies. This is due to the fact that some studies do not report the information needed to code all factors or because certain explanatory factors are unique to particular valuation methods or application contexts (e.g. specific experimental variations in SP survey instruments). The variation in study types and comprehensiveness of reporting across studies results in significant proportions of missing values for some coded variables. For example, in SP surveys, respondents can be presented with scenarios that can vary along a range of dimensions, including types and sizes of risks, , risk acuteness, different interventions that can be taken to reduce risks, the types and period of payments that can be made to reduce risks, etc.

It is also relevant to note that, when merging SP and RP datasets, there are SP- and RP- specific variables that cannot be meaningfully analysed with merged VSL data. Following the literature and previous meta-analysis studies (OECD, 2012[7]; Ginbo, Adamowicz and Lloyd-Smith, 2023[16]; Lindhjem et al., 2011[17]; Masterman and Viscusi, 2018[18])[9], however, several variables specific to the SP and RP datasets were nevertheless coded in order to enable for method-specific analyses. The definitions of coded variables in Table 4.1 are grouped into categories: *Risk type*, *risk acuteness*, *Elicitation methods*, *Sample data characteristics*, and *Methodological characteristics*. Variables under the latter category are SP- and RP-specific, and some of which may be treated as proxies for study quality (see discussion in Section 4.3.3). In addition to the variables shown in the table, other variables in the database were coded to identify individual countries and country groups (i.e. the OECD, EU, Low- and middle-income countries and High-income countries[10]). Summary statistics of all coded variables are provided in Table A C.5 of Annex C.

Table 4.1. Description of coded variables in the meta dataset

Variable Name	Description
WB income category	World Bank income category (Hamadeh, Van Rompaey and Metreau, 2023[19])
GDP per capita (USD thousand)	Country's GDP per capita in the year of VSL estimate, adjusted to thousands of 2022 USD
Journal	1 if published in a peer-reviewed journal, 0 otherwise
Risk types	
Climate	1 if climate-related risk, 0 otherwise
Crime	1 if crime-related risk, 0 otherwise
Disaster	1 if disaster-related, 0 otherwise
Environment	1 if environment-related risk, 0 otherwise
Health	1 if health-related risk, 0 otherwise

Variable Name	Description
Job	1 if job-related risk, 0 otherwise
Military	1 if military-related risk, 0 otherwise
Natural Disaster	1 if natural disaster-related risk, 0 otherwise
Not Specified	1 if no cause/type of risk specified, 0 otherwise
Suicide	1 if suicide-related risk, 0 otherwise
Transportation	1 if transportation-related risk, 0 otherwise
Virus	1 if virus-related risk, 0 otherwise
Cancer	1 if cancer is mentioned in the study/survey, 0 otherwise
Risk acuteness	
Acute	1 if risk occurs in the immediate term, 0 otherwise
Chronic	1 if risk occurs in the long term, 0 otherwise
Mixed/job-related	1 if risk occurs over an undetermined time frame or is job-related, 0 otherwise
Elicitation methods	
CM	For RP studies: 1 if consumer market (hedonic price), 0 otherwise
HW	For RP studies: 1 if hedonic wage, 0 otherwise
CV	For SP studies: 1 if contingent valuation, 0 otherwise
CE	For SP studies: 1 if choice experiment, 0 otherwise
Other SP method	For SP studies: 1 if other SP methods, 0 otherwise
Sample data characteristics	
Avg sample income (USD thousand)	Average annual income in the sample, as reported, adjusted to thousands of 2022 USD
Household income	1 if average sample income is household income, 0 if individual income
Nationwide	1 if the target population is nationwide, 0 otherwise
General population	1 if the target population covers the general adult population, 0 if the target population is specific groups
Representative	For SP studies: 1 if random or probabilistic sampling is used, 0 otherwise For RP studies: 1 if all sample of a specific group is used, 0 otherwise
Sample income	1 if any income information (e.g. mean, range) of the sample is reported, 0 otherwise
Sample age	1 if any age information (e.g. mean, range) is reported, 0 otherwise
Sample average age	Average age of the sample, as reported
Sample gender	The proportion of male individuals in the sample
Only male	1 if the sample is limited to male individuals (i.e. Sample gender = 1), 0 otherwise
Only female	1 if the sample is limited to female individuals (i.e. Sample gender = 0), 0 otherwise
Methodological characteristics	
SP representative	1 if the SP study uses random or probabilistic sampling (same as *Representative*), 0 otherwise
SP study including baseline risk	1 if the survey clearly defined the baseline risk, 0 otherwise
SP study focusing on scope sensitivity	1 if the study reports a scope test (including external and internal), 0 if otherwise
SP study including visual aids	1 if the study uses visual aids, 0 otherwise.
SP with risk change	Annualised risk change used in the SP survey
RP study using Census of Fatal Occupational Injuries (CFOI) data	1 if CFOI data is used, 0 otherwise
RP study using IV estimate	1 if the VSL is estimated using an IV estimator for fatality rate, 0 otherwise
RP study controlling for non-fatal injury risks	1 if the regression controlled for non-fatal injury risk, 0 otherwise
RP with full sample	1 if the full sample of employed individuals is used, 0 if particular groups of workers are used
Hedonic wage RP study	1 if the dependent variable in the HW regression is wage rather than natural logarithm of wage, 0 otherwise
Quality score (SP)	1 if: SP study including baseline risk = 1 and SP study focusing on scope sensitivity = 1 and SP study including visual aids = 1, 0 otherwise
Quality score (RP)	1 if: RP study using CFOI data = 1 and RP study using IV estimate = 1 and RP study controlling for non-fatal injury risk = 1, 0 otherwise

Note: Risk types are defined as the following: Disaster-related risk: nuclear accident, house fire; Natural disaster-related risk: avalanche, flood, earthquake; Climate-related risk: extreme weather, sea level change and depletion of fisheries, heat stroke; Virus: COVID-19, dengue fever, rabies.

4.3.3. Quality considerations

Valuation studies vary in their methodological rigor and the robustness of their estimates. Moreover, as with other methods of scientific inquiry, valuation methods improve over time. A key methodological question for meta-analyses is whether estimates from less rigorous studies, i.e. "invalid" estimates, should be excluded from analyses on the basis of which VSL recommendations are made. "Invalid" estimates can be understood as estimates that are systematically biased from the true underlying VSL estimates (Bishop and Boyle, 2019[20]). The concept of validity is different from reliability, as the latter is related to uncertainty (i.e. the variance) in the estimates around the true values[11]. In principle, excluding VSL estimates considered to be invalid may be sensible since (highly) biased estimates do not accurately reflect individuals' true trade-offs between risk and income.

Varying practices exist in the literature regarding screening for the quality of primary valuation studies. OECD (2012[7]) carries out a quality screening based on the size and representativeness of the samples and whether information about risk changes was provided. Other criteria are used in the broader health literature (e.g. Keller et al. (2021[14])[12]) but may not be easily applied when assessing the validity of VSL estimates. Additional criteria that were considered (for SP in particular) are whether WTP is higher for larger risk reductions (i.e. whether VSL estimates pass a scope test), whether certain estimates have been identified as "best estimates", and whether the surveys are well-tested and of high quality (Lindhjem et al., 2011[17]). US EPA (2016[1]), for example, applies relatively strict eligibility and quality criteria for the inclusion of primary valuation studies based on earlier VSL guidance (USEPA, 2011[21])[13]. This procedure was critiqued by US EPA SAB (2017, p. 18[22]), stating that: "…it may not be possible to determine that a study or estimate is valid, but it may be possible to decide that there is insufficient evidence to support a conclusion of invalidity and the data are therefore worthy of inclusion in the analyses. In such cases the burden of proof should be on rejecting studies. If the weight of evidence points toward validity, the study should be included."[14] They propose a list of quality criteria, while recognising the difficulty of operationalising it, and highlight that more work is needed in the future[15]. Ultimately the US EPA SAB (2017[11]) argues that, until more objective and transparent criteria become available, it is preferable to include estimates rather than to exclude them, for transparency and other reasons.

It is difficult to determine a set of transparent and generally acceptable criteria for assessing study quality that are stable over time. This is due in part to the continuing evolution of scientific methodologies, as well as the fact that scientific opinions regarding these criteria can vary at any one point in time. What may be considered to be highly valuable by an analyst in one context may not be deemed appropriate by a different analyst in another context. Moreover, various considerations may drive an analyst's preferred quality criteria, ranging from minimum requirements to desirable requirements. Additionally, the effects of quality screening on VSL estimates may vary substantially across studies/contexts, and could be difficult to assess systematically. Finally, some factors that are considered important for research quality in the context of peer-reviewed journal publications (e.g. advanced econometrics) may be considered less relevant for producing valid VSL estimates in contexts where more practical considerations (e.g. sampling, SP survey design, testing and data quality)[16] carry more weight than academic sophistication. Existing guidelines remain unsettled on several important methodological issues, especially for SP methods (see for example (Johnston et al., 2017[23])). While some issues also remain unsettled for RP methods, several best practices are nevertheless well-established in this area (Evans and Taylor, 2020[24]).

Based on the considerations above, this report adopts a conservative approach, erring on the side of including rather than excluding studies based on quality criteria that are difficult to define[17]. Consequently, to the extent possible, information on several quality indicators for both RP and SP studies are recorded in the database. For SP studies, examples include whether probabilistic sampling and visual aids to display risks are used. For hedonic wage RP studies, examples include an indicator of the quality of underlying risk data[18], of the use of instrumental variables (IV) and of controlling for non-fatal injuries (Viscusi, 2019[25]) (cf. Table 4.1). Another quality variable indicates whether studies have been published in peer-reviewed journals[19]. Using the information provided by these variables, sensitivity analyses to assess the importance of study quality on the results are provided in Section 4.7 and Annex E. Basing the recommendations in this report on an inclusive dataset allows practitioners to make their own choices with respect to controlling for such quality criteria.

Further, to integrate measures of statistical error associated with VSL estimates in the analysis, standard errors are extracted, included and estimated (or imputed if missing) (cf. Section 4.4 and Annex D), allowing for some control of uncertainty in the estimation of VSL estimates. As a result, VSL estimates from studies with small samples that are associated with relatively higher uncertainty have a lower weight in the meta-analysis relative to more reliable estimates. The use of Bayesian imputation for the standard errors in this study represents a methodological advancement relative to previous VSL literature (McElreath, 2018[26]).

4.3.4. Publication bias

A final point related to data quality concerns so-called publication selection bias. This can occur when authors selectively report their research results and also if journals systematically avoid publishing certain results. If this process systematically prevents the publishing of certain results, it may bias the body of evidence in the literature over time. In other words where publication selection bias is present, published studies are no longer a representative sample of the available evidence. This problem is likely to be more serious in other types of economic research where it is often necessary to document statistically significant relationships in order to publish an analysis (Askarov et al., 2023[27]). However, such bias has also been investigated by a few explorative studies in the VSL literature (Doucouliagos, Stanley and Giles, 2012[28]; Masterman and Viscusi, 2020[29]). Current evidence of publication bias in the VSL literature is still relatively limited and the methods to detect such bias are not necessarily fully appropriate. The general method of detecting publication bias is based on statistical methods that derive so-called “funnel plots”. Both the methods used to derive these plots and interpretation of their results, have limitations, some of which are discussed here as examples: First, a critical assumption for analyses of publication bias is the independence between VSL estimates and standard error (SE) estimates. An implication of this assumption is that imputed SE estimates cannot be used in analyses of publication bias because they are derived from a relationship between the SE and mean VSL estimates (implying that imputed SEs and mean VSL estimates are correlated).[20] Second, funnel plots are unable to provide insights regarding the causes of suspected bias. Doucouliagos et al. , for example, find that the mean VSL estimate from the hedonic wage literature is 70-80% lower when accounting for publication bias. Masterman and Viscusi report a similar magnitude of publication bias, resulting in a reduction of the mean VSL estimate from SP studies by 90%. Third, it should be noted that the bias-findings are also sensitive to the assumptions made about the underlying true distribution of the VSL estimates and how the primary VSL study was structured. For example, it is common in the stated preference literature to use statistical methods and tests that ensure that respondents exhibit a positive willingness to pay to reduce risk, which then by design eliminates the negative willingness to pay that can sometimes be observed in revealed preference studies. As discussed above, existing research suggests that the impact of publication selection bias could potentially be large. However, further investigation is needed, regarding both the validity and use of these methods to detect bias and the potential reasons why large biases may exist. To the authors’ knowledge, no existing guidance regarding CBA and the valuation of mortality risks recommends adjusting base VSL estimates for publication bias, and therefore no adjustments were made in this report.

Several steps have nevertheless been taken in the present report to reduce potential publication bias. First, studies were identified based on a keyword search with a wide topical scope that covered economics, health, as well as interdisciplinary publication outlets. Second, the VSL meta-data includes publication types beyond traditional journal papers, such as working papers, conference proceedings, academic theses and other studies that were not published in journals. Third, the full range of VSL estimates have been included in the analysis, including a small share of negative VSL estimates, which are statistically possible outcomes of analyses of primary valuation data. In addition, Annex E provides an estimate of the impact on the preliminary unweighted VSL estimates of limiting the sample to peer-reviewed journals, and Chapter 5 also includes the marginal effect of peer reviewed journals and of using two study quality scores.

4.4. Meta-analysis methodology for estimating mean VSL

4.4.1. Best practice meta-analysis methods

Drawing on best practice guidelines provided by US EPA (2006[30]), Nelson and Kennedy (2009[31]) and Nelson (2015[32]), the meta-analysis in this report uses a multilevel random effects model (Harrer et al., 2021[33]; Sera et al., 2019[34]). This approach normally considers three key characteristics of the meta-data: sample heterogeneity, heterogeneity in the variance of VSL estimates (so-called heteroskedasticity), and correlation within and between primary studies (Nelson and Kennedy, 2009[31]). In this report a fourth level is added that considers heterogeneity resulting from the choice of elicitation approach. This is further discussed below and described formally in Box 4.1.

Primary valuation studies use different samples and methods to estimate VSL estimates, which generates heterogeneity in VSL estimates in the meta-data. Previous meta-analyses use either a meta-regression approach, which accounts for variation through the inclusion of regressors (Viscusi, 2019[25]) or a random effects approach, which accounts for variation by including random intercepts (Kochi, Hubbell and Kramer, 2006[35]). In this study, both approaches are used: a random effects model (Section 4.4.2 and Box 4.1) and a meta-regression, also controlling for random effects (Chapter 5).

Due to heterogeneity in the characteristics of primary valuation studies, VSL estimates generally have heteroskedastic variances. Meta-analyses require variance (i.e. standard error) estimates from primary studies in order to calculate weighted averages and to correct for heteroskedasticity. Nelson and Kennedy (2009[31]) therefore strongly recommend researchers to collect primary data on variances[21]. However, many recent meta-analyses of VSL estimates are mixed in that some studies collect, calculate or impute these estimates from primary studies (Lindhjem et al., 2011[17]; Viscusi, 2019[25]), while others approximate variances using sample sizes instead (Ginbo, Adamowicz and Lloyd-Smith, 2023[16]).

In this report standard errors of VSL estimates are collected from the primary valuation studies. When standard errors are not reported, they are recovered from other available information, such as confidence intervals. In the absence of both, standard errors are imputed using a Bayesian imputation method (McElreath, 2018[26])[22]. With this information, the random effects model considers each estimate's sampling error as a random draw from a normal distribution, taking into account each estimate's variance from the primary study. This standard error information, together with higher-level random effects, are used to calculate mean VSL estimates (Harrer et al., 2021[33]; Sera et al., 2019[34]) and to correct for heteroskedasticity.

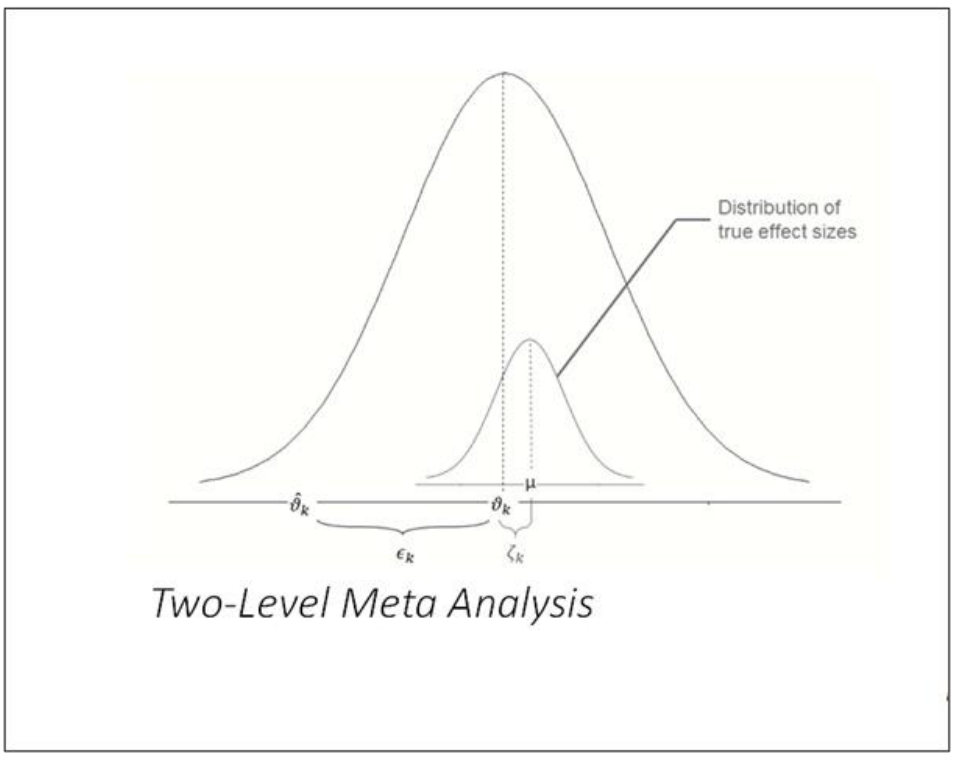
Multilevel random effects models also address the independence assumption of estimates within and between studies. Since most primary valuation studies of VSL report multiple estimates, the independence assumption between estimates from the same study can easily be violated. Although Nelson and Kennedy (2009[31]) call attention to this problem of non-independence, most previous meta-analyses of VSL have taken this into account only to a limited extent.[23]

In addition to accounting for random effects at the estimate level, multilevel random effects models can also account for random effects at the study level (level three) in order to address non-independence. This enables the model to capture heterogeneity in VSL estimates between studies by allowing a random effect to vary across studies. The use of three-level random effects models is common practice in the meta-analysis literature in subjects such as medicine and natural sciences (Brown et al., 2024[36]; Harrer et al., 2021[33]; Sera et al., 2019[34]).

4.4.2. The random effects model concept

The most basic random effects model, also called the two-level random effects model, introduces an additional variance component (in addition to the "usual" sample variance) that accounts for the fact that VSL estimates do not come from a single population. Instead, each VSL estimate is assumed to be an independent draw from a "universe" of populations (Harrer et al., 2021[33]). This two-level random effects model is illustrated in Figure 4.1. The true VSL value (or "effect size" in the figure) θ_k of study k differs from the observed VSL value $\hat{\theta}_k$ by a sampling error ϵ_k. However, the true VSL value θ_k of study k is only a point within a distribution of true VSL values of mean μ. The difference (or error) between the true VSL value θ_k of study k and the mean μ of the distribution of true VSL values is ς_k. In this example, the observed VSL value $\hat{\theta}_k$ of study k deviates from the mean of the distribution of true VSL values μ by two sources of error (ϵ_k and ς_k).

Figure 4.1. Intuition behind the random effects model (two levels)



Source: Harrer et al. (2021[33])Results from the four-level random effects model are reported in Table 4.2.

4.5. Estimated preliminary and unweighted mean VSL (PUVSL) by country group using a multilevel random effects model

As described above, the random effects meta-analysis model accounts for the fact that the VSL estimates collected from many studies have more potential sources of variation than those drawn from a single homogeneous population. Unlike the fixed-effects[24] meta-analysis approach, the random effects model assumes that individual VSL estimates deviate from the true VSL value not only due to pure sampling error, but also due to other sources of variation. After testing a number of alternative econometric specifications of random effects models, a four-level model was selected as the basis for the reported results. This model accounts for four sources of heterogeneity in the data, namely sampling variations within estimates of a study, heterogeneity between estimates in a study, heterogeneity among VSL studies, and heterogeneity resulting from the choice of VSL elicitation method. The use of a fourth level that accounts for VSL elicitation methods is a methodological improvement that has not previously been used in the VSL literature to the authors knowledge. The detailed specification of the random effects model is provided in Box 4.1.

Alternative specifications to the final model and related discussions are also available in Annex E. Table 4.1and Figure 4.1 report mean preliminary unweighted VSL (PUVSL) estimates and 95% confidence intervals (CI) for studies conducted in the following country groups:

- All countries
- OECD
- EU
- United States
- World Bank income categories country groups[25]:
    - High-income countries
    - Low- and middle-income countries

Box 4.1. Econometric specification of the multilevel random effects model

To formalise the multilevel random effects model, let an observed VSL estimate $\boldsymbol{i}$ from a study $\boldsymbol{s}$ that uses an elicitation method[1] $\boldsymbol{m}$ be defined as $\widehat{\boldsymbol{\theta}_{msi}}$. For example, the selected dataset that includes newer SP and RP studies has 2 469 VSL estimates ($\boldsymbol{i = 1, \dots 2\,469}$) produced by 156 studies ($\boldsymbol{s = 1, \dots, 156}$). The first-level random effects model accounts for sampling variations within estimates in a study by assuming that an observed individual VSL estimate, $\widehat{\boldsymbol{\theta}_{msi}}$, can be decomposed into the estimate's true VSL estimate $\boldsymbol{\theta_{msi}}$ and a pure sampling error $\boldsymbol{\varepsilon_{msi}}$ (i.e. $\widehat{\boldsymbol{\theta}_{msi}} = \boldsymbol{\theta_{msi} + \varepsilon_{msi}}$). The sampling error is assumed to follow a standard normal distribution with an observed standard error estimate $\widehat{\boldsymbol{\sigma}_{msi}}$: $\boldsymbol{\varepsilon_{msi} \sim N(0, \widehat{\sigma_{msi}}^2)}$.

The second-level random effects model captures heterogeneity between VSL estimates within studies. The true individual VSL estimate $\boldsymbol{\theta_{msi}}$ is now modelled as follows: $\boldsymbol{\theta_{msi} = \theta_{ms} + u_{msi}^{L2}}$, with $\boldsymbol{u_{msi}^{L2} \sim N\left(0, \tau_{L2}^2\right)}$ where $\boldsymbol{u_{msi}^{L2}}$ is a random intercept at the estimate level and $\boldsymbol{\tau_{L2}^2}$ will be estimated in the model. $\boldsymbol{\theta_{ms}}$ is the true study-level VSL estimate.

Three-level random effects model captures heterogeneity in VSL estimates between studies within elicitation methods. The true study-level VSL estimate can now be decomposed as follows: $\boldsymbol{\theta_{ms} = \theta_m + u_{ms}^{L3}}$, $\boldsymbol{u_{ms}^{L3} \sim N\left(0, \tau_{L3}^2\right)}$, where $\boldsymbol{u_{ms}^{L3}}$ is a random intercept at the study level. The three-level model ends here, and the true VSL estimate from the level three model is $\boldsymbol{\theta_m}$, which will be reported under three-level models.

The four-level random effects model goes one step further by capturing also the heterogeneity in VSL estimates between elicitation methods (i.e. CE, CV, HW and CM). With this added component, the true elicitation-method-level VSL estimate can be decomposed as follows: $\boldsymbol{\theta_m = \theta + u_m^{L4}}$, $\boldsymbol{u_m^{L4} \sim N\left(0, \tau_{L4}^2\right)}$. $\boldsymbol{u_m^{L4}}$ is a random intercept at the level of the elicitation method. The true population VSL estimate $\boldsymbol{\theta}$ is reported as the results of the four-level model.

Heterogeneity in variance parameters $\boldsymbol{\tau_L}$ are higher the greater the heterogeneity within each level $\boldsymbol{L}$. For example, if the estimate of $\boldsymbol{\tau_{L4}^2}$ is not statistically significantly different from zero, the data suggests that the three-level model is preferable to, or not distinguishable from, the four-level model[2].

In summary, an observed individual VSL estimate using the population VSL estimate (which is the estimand[3]) can be written as follows:

$$\widehat{\theta_{msi}} = \theta + u_m^{L4} + u_{ms}^{L3} + u_{msi}^{L2} + \varepsilon_{msi},$$
$$u_m^{L4} \sim N(0, \tau_{L4}^2),$$
$$u_{ms}^{L3} \sim N(0, \tau_{L3}^2),$$
$$u_{msi}^{L2} \sim N(0, \tau_{L2}^2),$$
$$\varepsilon_{msi} \sim N(0, \widehat{\sigma_{jk}}^2).^4$$

Equation 4.1

1. I.e. Choice experiment (CE), contingent valuation (CV), hedonic wage (HW) or consumer market (CM).
2. A likelihood-ratio test is used to determine whether a four-level model is statistically different from a three-level model.
3. An estimand is a quantity that is to be estimated in a statistical analysis.
4. Note that although Shapiro-Francia tests reject strict normality distribution of residuals of levels 1-3 (not 4), the residuals are distributed almost symmetrically around zero (these results are not reported for brevity). It should also be noted that normality of the residuals is not essential in linear estimators and has little impact on the point estimates (Rubio-Aparicio et al., 2018[37]; Schmidt and Finan, 2018[38]; Wooldridge, 2014[39]). Log transformation worsens the model fit for the four-level random effects model.

The results presented in Table 4.2 and Figure 4.2 exclude so-called far-out observations of VSL estimates. Figure A E.5 in Annex E presents results from a sensitivity analysis of the estimated PUVSLs for all countries to the inclusion of far-outs. The results suggest that including far-outs increases the PUVSL by approximately 5%. Hence, the effect of extreme values in the simple (non-parametric) means at the estimate level shown in Section 3.3 of Chapter 3 are accounted for and almost fully removed in the four-level random effects model.

It should be noted that the mean PUVSL estimates reported in Table 4.2 are not recommended values for policy use. Further adjustments, detailed in Chapters 5 and 6, are necessary when applying them in specific policy settings. As can be seen in Table 4.2, estimated mean PUVSL vary between ca. USD 0.9 million for the low- and middle-income country group to USD 7.6 million for the EU. There is little variation within the groups of relatively richer countries, with mean PUVSL estimates ranging from USD 7.1 million for the OECD to USD 7.6 million for the EU.[26]

Table 4.2. Mean Preliminary Unweighted VSL (PUVSL) estimates by country group

New SP and RP data, USD million

Countries	Mean PUVSL estimate	95% CI (Lower bound)	95% CI (Upper bound)	Number of studies	Number of estimates
All countries	5.5	3.7	7.2	156	2 449
OECD	7.1	5.4	8.8	108	1 928
EU	7.6	6.4	8.9	36	467
United States	7.2	5.4	8.9	38	1 042
High income countries	7.1	5.7	8.6	113	2 016
Low- and middle-income countries[2]	0.9	0.3	1.5	43	433

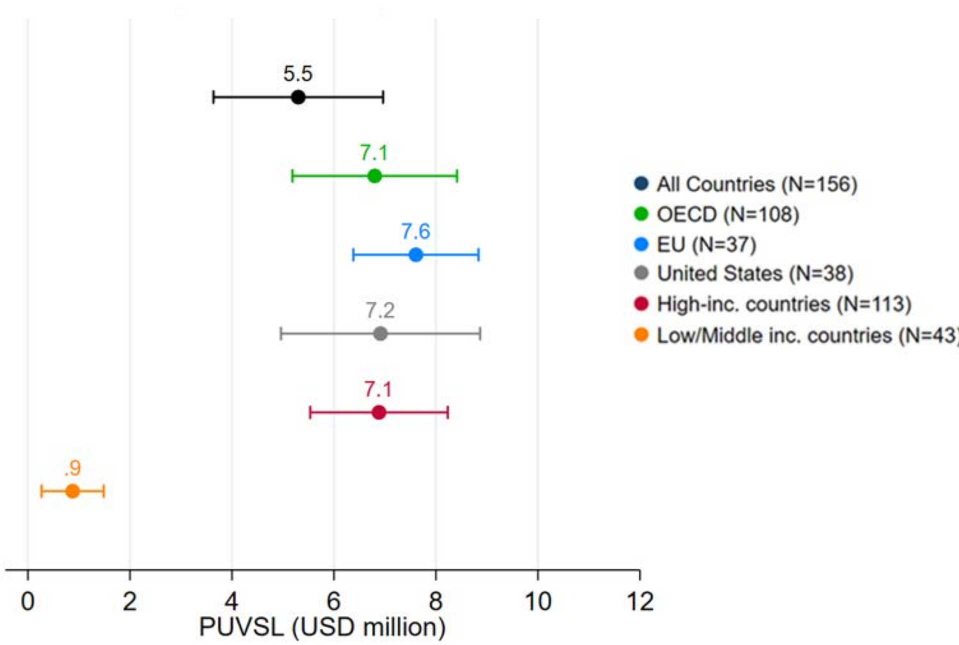
Note: The mean VSL estimate (population parameter $\widehat{\theta_{msi}}$ from Equation 4.1) and 95% confidence intervals were estimated using the statistical software package STATA. The STATA code for reproducing these results is available upon request.

All Countries refer to the unweighted mean of all countries for which VSL studies were included. OECD reflects its 38 member countries as of 2025. EU refers to the 27 members of the European Union in 2025. The three World Bank income country categories are defined as: Low income (Gross National Income (GNI) per capita < USD 1 145), Lower-middle income (GNI per capita = USD 1 146 – 4 515) and Upper-middle income (GNI per capita = USD 4 516 – 14 005). Low-, lower-middle and upper-middle income categories are merged to form the category "Low- and middle-income countries" in order to have a sufficient number of studies to estimate the mean VSL with reasonable levels of uncertainty. "High-income countries" reflects countries with GNI per capita > USD 14 005).

Note that the relative over-representation of high-income countries in the sample increases the mean for the *All countries* group to USD 5.5 million. For example, the Gross National Income (GNI) per capita for the middle- and low-income group ranges between USD 4 466 to 13 845, while the average GNI per capita in the EU is around USD 59 000 (OECD, 2025[40]). As is shown in Chapter 5, income differences are a key driver of the differences in the PUVSL for the low- and middle-income group of countries and that for the EU and other high-income country groups, and also one of the key reasons why the PUVSLs need to be adjusted to be representative of each respective country group.

The confidence intervals around the means are relatively narrow due to a relatively high number of estimates for all groups, as is evident in Figure 4.2. Note that since these estimated mean PUVSL estimates take into account the four-levels of random effects, i.e. sources of heterogeneity in VSL estimates,[27] the estimates derived through this statistical meta-analysis procedure are not directly comparable to the descriptive estimate-level and study-level means presented in Section 3.3 of Chapter 3.

Figure 4.2. Preliminary unweighted VSL estimates (PUVSL) by country group



Note: Based on four-level random effects model estimates. 47 far-out estimates excluded. All Countries refer to the unweighted mean of all countries for which VSL studies were included. OECD reflects its 38 member countries as of 2025. EU refers to the 27 members of the European Union in 2025. The three World Bank income country categories are defined as: Low income (Gross National Income (GNI) per capita < USD 1 145), Lower-middle income (GNI per capita = USD 1 146 – 4 515) and Upper-middle income (GNI per capita = USD 4 516 – 14 005). Low-, lower-middle and upper-middle income categories are merged to form the category "Low- and middle-income countries" in order to have a sufficient number of studies to estimate the mean VSL with reasonable levels of uncertainty. "High-income countries" reflects countries with GNI per capita > USD 14 005).

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As noted above, the estimated mean PUVSL values in Table 4.2 are a starting point for calculating recommended base VSL values. In order to arrive at a recommended estimate that can be used in policy analysis, additional adjustments need to be considered, such as adjustments for income, risk type and other evidence in the literature. Potential adjustments are considered in Chapter 5.

4.6. Sensitivity of preliminary unweighted VSL estimates to valuation methods and datasets

This section presents and discusses the sensitivity of PUVSL estimates to the choice of valuation methods and datasets. This is first done “partially”, i.e. considering only comparing each factor in isolation. Chapter 5 reports the results of a meta-regression analysis controlling for income and other factors, as well as results of sensitivity analyses regarding the choice of SP or RP methods and datasets.

4.6.1. Choice of SP and RP methods and data sources

Figure 4.3 depicts the sensitivity of the mean PUVSL estimate for the *All countries* group (USD 5.5 million) to the choice of valuation method (SP or RP) and dataset (Old or New). The top line shows the main model estimate of mean USD 5.5 million and a confidence interval of USD 3.6 to 6.9 million.

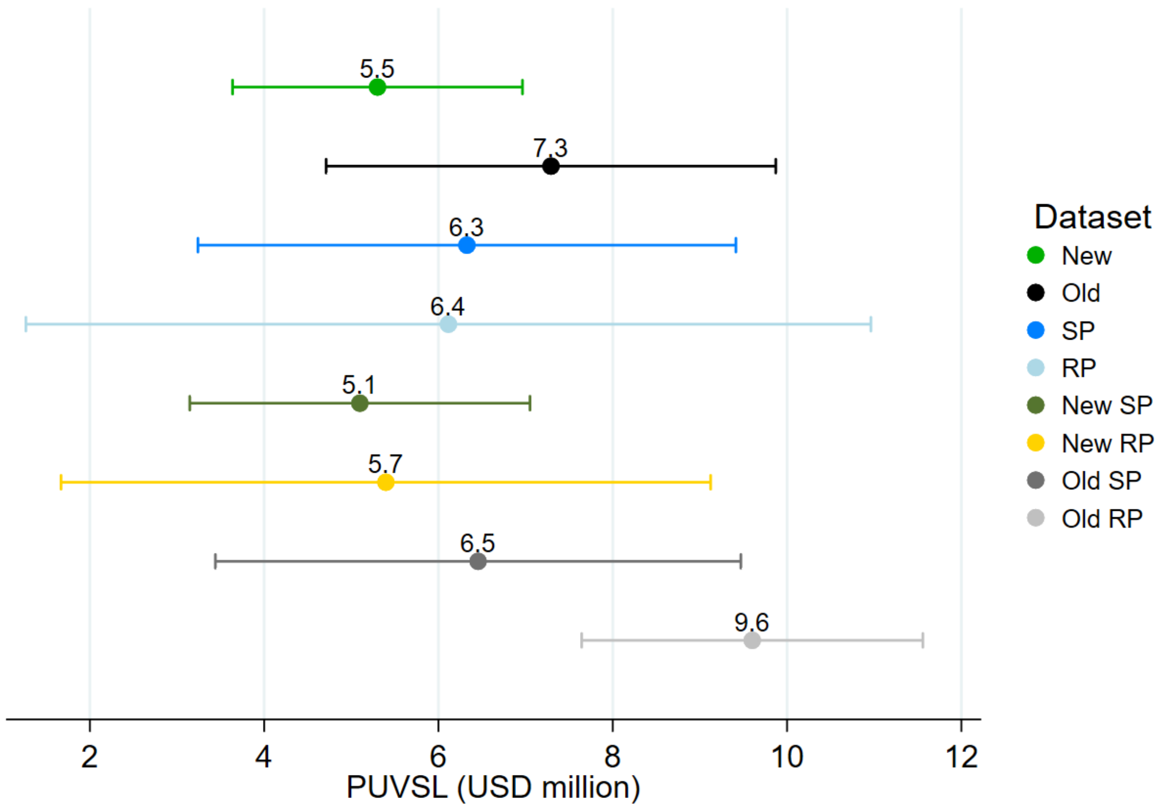
The mean PUVSL is USD 5.1 million for the new SP data and USD 5.7 million for the new RP data. The similarity of these estimates suggests that the two main types of valuation methods exhibit a large degree of convergent validity. However, this is not the case when comparing the Old SP and RP data, where the Old RP data yields significantly higher PUVSL estimates than the Old SP data. When comparing SP and RP data (both old and new data), the PUVSL estimates are USD 6.3 million for SP data and USD 6.4 million for RP data. A further analysis of differences, including the types of RP and SP methods is discussed in Section below.

Other studies such as US EPA (2016[1]), which is limited to studies from the United States only, find that RP estimates tend to be systematically higher than SP estimates. An older meta-analysis study, Kochi et al. (2006[35]), also find that RP estimates are significantly higher than SP estimates. Note that both of these studies only include hedonic wage studies (not consumer market studies) as RP studies. In contrast to these findings, Ginbo et al. (2023[16]) find that SP methods yield VSL estimates roughly twice as high as RP methods among VSL studies in Canada. While these studies document evidence of differences in VSL estimates across valuation methods, the reasons for these differences remain unclear.

Note also that the new dataset (New SP and New RP datasets) yields a PUVSL estimate of USD 5.5 million, compared to USD 7.3 million for the old dataset. An important reason for the decrease in VSL estimates for the new dataset compared to the old is the inclusion of CM studies in the new dataset, which tends to yield systematically lower values. Another important reason is that the use of both SP and RP methods have spread to other parts of the world with lower income levels (cf. Section 3.2.3 of Chapter 3) and hence lower VSL estimates. There may also be an element of increasing methodological prudence due to dissemination and use of best practice guidance for non-market valuation studies over time and to new regions producing more conservative VSL estimates. The PUVSL estimate of the merged datasets (old and new) is close to the middle value at USD 6.2 million (see Figure A E.3 in Annex E). Further details on PUVSL estimates calculated on the basis of different datasets are provided in Annex E.

Figure 4.3. Sensitivity of PUVSL estimates to elicitation methods and dataset

All countries



Note: The figure displays mean PUVSL estimates and 95% confidence intervals using a four-level random effects model for the *All countries* group. *SP* refers to "Stated Preference" and *RP* refers to "Revealed preference". *Old* refers to studies published before 2009, and *New* refers to studies published from 2009.

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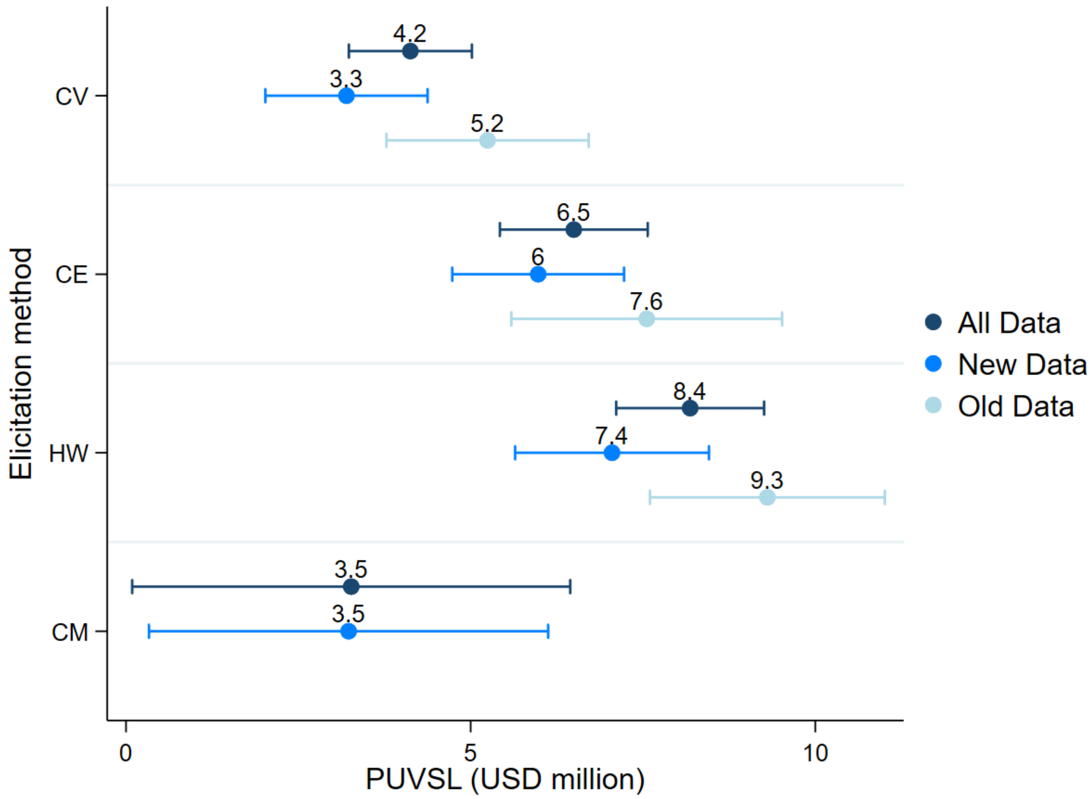
4.6.2. Elicitation methods (CE, CV, HW, CM)

This section investigates the sensitivity of PUVSLs to the specific types of RP and SP methods, i.e. contingent valuation (CV), choice experiments (CE), hedonic wage (HW) and consumer market (CM) methods. Exploring the sensitivity of PUVSL estimates to elicitation methods contributes to understanding the differences in VSL estimates between SP and RP observed in Section 4.6.1. Figure 4.4 depicts mean PUVSL estimates and 95% confidence intervals across these four methods for the old and new meta-data.

The top three lines reflect results from CV for all, new and old meta-data, focusing only on the overall mean (for the *All countries* group)[28]. These results indicate that CV, CE, HW, and CM yield PUVSL estimates of USD 4.2, 6.5, 8.4 and 3.5 million, respectively. The RP method produces quite heterogenous estimates, containing both the highest and lowest estimates. As noted in Chapter 3, this effect is in part due to that CM studies (a type of RP method) tend to give systematically lower estimates than HW studies (unknown for which reasons), and the Old RP database did not include any CM studies. Additionally, relatively few VSL estimates come from CM studies overall, yielding a wide confidence interval for estimates produced using this method. CE and HW, in contrast, yield relatively similar estimates. CV methods tend to yield lower VSL estimates than CE and HW methods, but higher than CM methods. Taken together, these results demonstrate that the type of SP- or RP-specific elicitation method used can have a larger effect on PUVSL estimates than the choice of SP or RP methods more generally.

Figure 4.4. Sensitivity of PUVSL to CV, CE, HW and CM methods

All countries



Note: The figure displays mean PUVSL estimates and 95% confidence intervals using a three-level random effects model for the *All countries* group. *SP* refers to "Stated Preference" and *RP* refers to "Revealed preference". *Old* refers to studies published before 2009, and *New* refers to studies published from 2009

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4.7. Sensitivity of PUVSL to quality and screening factors

This section briefly discusses several other factors that could potentially be used to screen the dataset before estimating PUVSL using the random effects meta-analysis model described in Section 4.4.2. Such factors could include the scope of the population covered in the primary valuation study or aspects related to the scientific quality of the study. As discussed in Section 4.3, making assessments about the quality of primary valuation studies and deciding to exclude studies on the basis of such assessments requires careful consideration and justification.

Table 4.3 reports the effects of screening factors on the PUVSL estimate for the *All countries* group as reported in Table 4.2. For this analysis, the dummy variables defined in Section 4.3.2 are used to screen the dataset before the estimation. Note that this analysis is partial in that it assesses the effect of each of these factors individually without controlling for other factors. Results in Table 4.3 are reported in the following order:

- Screening for population coverage:
    - Nationwide: Whether or not the target population is nationwide.

- General population: Whether the target population covers the general adult population or specific groups.
- Aspects of study quality:
  - Random sampling: For SP studies, whether random or probabilistic sampling is used; for RP studies, whether an entire sample of a specific group is used.[29]
    - No standard errors of VSL estimates are reported.
    - SP-specific: Whether the survey clearly defines the baseline level of risk.
  - SP-specific: Whether the study reports a scope test (including external and internal)[30].
    - SP-specific: Whether a visual aid to explain risk is used.
    - RP-specific: Whether risk data is based on the Census of Fatal Occupational Injuries (CFOI).
    - RP-specific: Whether VSL is estimated using an instrumental variable (IV) estimator for fatality rate.
    - RP-specific: Whether the regression controls for non-fatal injury risk.

Figure A E.6 through Figure A E.15 of Annex E report PUVSL estimates resulting from screening the dataset according to the factors above. It is important to note that while this analysis indicates differences in PUVSL estimates based on these screenings, it does not provide insights regarding the causes or significance of the differences. Instead, the exercise is mainly intended for illustration purposes to demonstrate the potential consequences of analyst choices regarding whether and how to screen datasets of VSL estimates based on certain criteria.

Table 4.3 shows, for example, that limiting the data only to studies that are nationwide or cover the general population increases the mean PUVSL estimate from USD 5.5 million for the *All countries* group to USD 6.8 and 6.3 million, respectively. Using quality controls also appears to impact mean PUVSL estimates.

Table 4.3. Summary of PUVSL estimates when screening data based on target group and quality measures

All countries, USD million

Variable	PUVSL (pooled data)	Yes (=1)	No (=0)
Population and target group variables:			
Nationwide	5.4	6.8	3.7
General population	5.4	6.3	4.6
Quality dimensions of studies:			
Random sampling (representative sample)	5.4	5.0	6.6
No standard errors of VSL estimates reported	5.4	5.1	6.0
SP-specific: Whether the survey clearly defines the baseline risk	4.8	5.9	3.9
SP-specific: Whether the study reports a scope test (including external and internal)	4.8	6.0	3.7
SP-specific: Whether the survey uses a visual aid to explain risk	4.8	5.8	3.9
RP-specific: Whether risk data is based on the Census of Fatal Occupational Injuries (CFOI)	6.8	5.3	9.9
RP-specific: Whether VSL is estimated using an instrumental variable (IV) estimator for fatality rate	6.8	7.0	6.8
RP-specific: Whether the regression controls for non-fatal injury risk	6.8	7.6	6.1

Note: The mean baseline VSL for SP and RP, respectively, are different from USD 5.5 million because they are derived based on data from only one of the two methods. "Yes" means the dummy of the variable of interest is equal to one, and the exercise is performed only on data that e.g. are nationwide. "No" means that studies with the characteristic of interest, e.g. nationwide, are not included in the exercise (the dummy is set to zero). These values are based on a three-level meta-analysis model, as opposed to values presented in and, which are based on a four-level meta-analysis model. This is because incorporating the quality dimension leads to insufficient variation in elicitation methods, making the four-level model not possible to perform (see Table A C.5. in Annex A, which provides descriptive statistics of estimates per elicitation methods and methodological characteristics).

Table A E.1 in Annex E also presents the results of a sensitivity analysis to investigate the impact of including only mean PUVSL estimates from studies published in journals. Although journal publication is relevant for assessing quality, as discussed in Section 4.3.3, it is not recommended to be used as criterion in isolation. The impact of this screening on PUVSL estimates is observable for most country groups. For the group of *All countries*, the PUVSL estimate increases by USD 300 000 from USD 5.5 to 5.9 million. Estimates for most other country groups also increase somewhat (except for the low- and middle-income country groups), with the largest increase observed for the United States.

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Notes

[1] Typically, these values are set at "best practice" or sample means, or alternatively at values to, for example, balance the evidence used from SP and RP approaches (Johnston et al., 2021[63]; USEPA, 2016[6]).

[2] It is worth noting that the US EPA study did not conduct a standard meta-regression analysis, and the US EPA Scientific Advisory Board (SAB) (2017[11]) did not object to this general approach.

[3] Additional tests and sensitivity analyses that informed the choice of approach are provided in Annex E.

[4] As noted in Section 3.1.4 of Chapter 3, it may not be appropriate to adjust older VSL estimates by income using strong assumptions about income elasticity and then convert to a common year for analysis.

[5] A previous version of this paper is available as a working paper: Ørbeck et al. (2022[41]). This study provides a review of the most important literature on the temporal stability of preferences.

[6] Ginbo et al. (2023[16]) included all Canadian studies from 1989-2018, while Anthapavan et al. (2021[15]) include Australian studies from 2007 to 2019, where the first primary valuation study of VSL in Australia was conducted in 2017.

[7] As described in Chapter 3, there is a lag between the years of the data for analysis and the publication year of VSL estimates. As a result, VSL estimates reported in studies published between 2009 and 2024 may be based on older data. Note that such time lags also apply to the old SP and RP data.

[8] USEPA (2016[1]), for example, states that they "only include estimates for immediate risk reductions or those that begin within one year (under the assumption that this is "nearly" immediate)". However, the time frame for risk reductions is not always clear in studies estimating VSL.

[9] The meta-data used in OECD (2012[7]) (i.e. the Old SP dataset) included coded variables such as public vs. private risk, willingness to pay vs. willingness to accept compensation, household vs. individual WTP and types of payment vehicles. Based on the experience of gathering and using these data, many of these variables were not coded in the newer data (New SP and New RP datasets). Given that only a fraction of the studies provided the information needed to code these variables, doing so was expected to limit the number of primary valuation studies that could be used in the analysis.

[10] World Bank income categories are used to define the country classification by income level (Hamadeh, Van Rompaey and Metreau, 2023[19]).

[11] This difference is illustrated well by Bishop and Boyle (2019[42]) with a dart board where validity reflects the extent to which the arrows are clustered evenly around the centre or around some other point, and reliability reflects how distant the arrows are from the centre.

[12] Keller et al. (2021[14]) assessed the quality of studies included in the review based on a modification of the Consolidated Health Economic Evaluation Reporting Standards (CHEERS) checklist (Husereau et al., 2013[43]).

[13] See Table 1 in USEPA (2016[1]).

[14] Note that while the recency of studies can also be considered to be related to their quality (e.g. as discussed in Section 4.2), US EPA SAB (2017[22]) does not articulate a clear position regarding whether or not to exclude older studies for quality reasons. In this regard, they do not discuss the impact of potential changes in preferences and circumstances over time on the validity of VSL estimates from older studies (for other reasons than quality per se). USEPA SAB (2017, p. 39[22]) recommends "to explore whether older or newer studies have a strong influence on the VSL estimate [...] the EPA should consider conducting a sensitivity analysis." (USEPA SAB, 2017, p. 39[22]). This report provides results from sensitivity analyses based on the old, new and merged meta-data in Annex E.

[15] The list contains 10 items pertaining to SP studies:

1. Was the survey pretested using focus groups, one-on-one interviews, or field pretests?
2. Was the survey applied to a random sample of a clearly specified population?
3. Did the survey clearly define the baseline risk?
4. Did the survey clearly explain the change in risk to be valued?
5. Was the valuation scenario consequential (mandatory payment and valuation response with a non-zero probability of influencing provision of the item being valued)?
6. Was the stated preference question a binary choice framed as a referendum or product purchase?
7. Were robustness checks conducted of the statistical analyses that led to the value estimate?
8. Were construct validity tests conducted?
9. Was the sample of respondents investigated for comparability to the population sampled?
10. Has the study been subject to peer review?

[16] This means for example that using "journal publication" or some rank of journals (such as in (Newman and Noy, 2023[44])) may be a bit simplistic as a screening criterion for quality.

[17] Note that this choice is not contradictory to the screening out of statistically implausible VSL estimates (far-outs), as described in Section 4.3.1, which is based on objective and relatively standard statistical criteria.

[18] And specifically whether it is based on data from the Census of Fatal Occupational Injuries (CFOI) which is a record of fatal work injuries produced by the Bureau of Labour Statistics in the United States.

[19] As noted in Section 3.1.3 of Chapter 3 around 70% of the primary valuation studies in the new meta dataset have been published in journals. It is nevertheless difficult to use this criterion alone to judge study quality and suitability, notably because peer review processes for journals compared to e.g. working papers, book chapters, conference proceedings, these and other study types are difficult to compare.

[20] In explorative analysis of publication bias in the VSL estimates of the new SP and RP data (where estimates with imputed SE have been removed due to the noted endogeneity problem), no clear indication of small-study effects was found (i.e. when results from small sample studies are systematically different than for large sample studies), nor evidence of selective reporting. However, more specific investigations, beyond the scope of this report, are required on the methods of bias detection and the explanation of likely sources in published primary VSL estimates, if such bias indeed exists.

[21] Nelson and Kennedy (2009, p. 350[31]): "Given the wide range of outcomes in primary estimates, it is recommended that future researchers place a high priority on collecting primary data on variances and sample sizes."

[22] Information on the calculation methods used in this analysis are provided in Table A D.1 in Annex D. A comparison between observed and imputed standard errors is illustrated in Figure A D.1 in Annex D.

[23] This is typically done by either including only estimate-level random effects, which is equivalent to a two-level random effects model (Kochi, Hubbell and Kramer, 2006[35]) or though weighted-least-squares estimation using the inverse of the variance as weights (Viscusi, 2019[25]).

[24] The fixed-effect model assumes that each observed estimate can be decomposed into a true population estimate and a pure sampling error (Borenstein et al., 2010[45]). In other words, it assumes that all estimates reported by various studies share the estimate from a single homogeneous population and that variation in observations is solely due to sampling errors. This is equivalent to a weighted-least-squares meta-regression using only the intercept as a regressor (Nelson and Kennedy, 2009[31]).

[25] The three World Bank income country categories are defined as: Low income (Gross National Income (GNI) per capita < USD 1 145), Lower-middle income (GNI per capita = USD 1 146 – 4 515) and Upper-middle income (GNI per capita = USD 4 516 – 14 005). Low-, lower-middle and upper-middle income categories are merged to form the category “Low- and middle-income countries” in order to have a sufficient number of studies to estimate the mean VSL with reasonable levels of uncertainty. “High-income countries” reflects countries with GNI per capita > USD 14 005) (Hamadeh, Van Rompaey and Metreau, 2023[46]).

[26] The higher mean VSL in the EU compared to the US, despite lower GDP per capita in the EU, can be partially explained by CV studies from the United States reporting systematically lower mean VSL estimates compared to those from the EU (USD 6.5 million vs. USD 8.2 million) (for unknown reasons), as well as by the fact that the only CM studies that were included in the meta-analysis, which produce systematically lower VSL estimates than other methods, were conducted in the United States. This effect is only partly counteracted by CE and HW studies from the United States, which produce relatively higher VSL estimates than EU studies. Note that US estimates are also characterised by wider confidence intervals, suggesting that studies from the United States are more heterogenous, at least in terms of elicitation methods.

[27] A sensitivity analysis of mean VSL estimates is provided in Figure A E.2 and Figure A E.3 in Annex E.

[28] Further disaggregating the results into individual country groups would significantly reduce the sample size in some cases.

[29] This increases the chance of obtaining a representative sample.

[30] The result of the scope tests per se are not coded, only whether scope test results is reported or not.

5 Potential VSL adjustment factors

It is important to understand the drivers of VSL levels in order to be able to better adjust the values to reflect the relevant policy problem and geographic location. This chapter considers potential factors that could be used to adjust value of statistical life (VSL) estimates for application in specific contexts. It uses the updated meta-data to examine the relationship between income and VSL and assess its use as an adjustment factor. It also presents the results of meta-regression analyses to assess the evidence for adjusting VSL estimates based on the quality of primary valuation studies and risk type. Finally it also reports the results of several sensitivity analyses and reviews evidence from the literature regarding the impact of these and other factors on VSL estimates.

5.1. Introduction

A number of socio-demographic and study-related factors can impact VSL estimates. This chapter considers potential factors that could be used to adjust VSL estimates for application in specific contexts. Section 5.2 uses the updated meta-data to examine the relationship between income and VSL, i.e. the income elasticity of VSL, and assess its use as an adjustment factor. Section 5.3 presents the results of meta-regression analyses to assess the evidence for adjusting VSL estimates based on the quality of primary valuation studies and risk type. Section 5.3 also presents sensitivity analyses of several aspects of the data. Finally, Section 5.4 reviews evidence from the literature regarding the impact of these and other factors on VSL estimates.

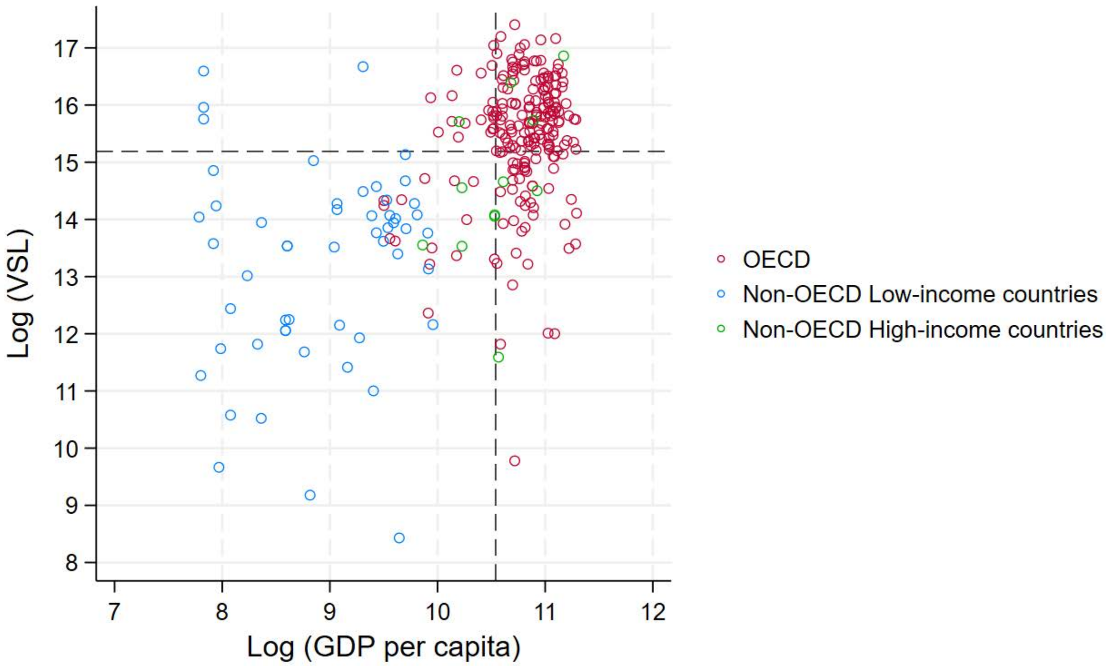
5.2. Relationship between VSL and income

As discussed in Chapter 2, willingness to pay (WTP) for mortality risk reductions is expected to increase with the income of the affected adult population. This means that VSL estimates can also be expected to increase with income, a relationship that is typically measured by what's known as the income elasticity of VSL. This elasticity expresses the statistically derived percentage increase in VSL associated with a one percent increase in income. As noted in Chapter 2, the income elasticity of VSL is important for two reasons. First, in order to accurately assess the costs and benefits of policies that have impacts across populations (typically across countries), mortality risk values must be adjusted to reflect differences in income levels across countries. Second, for policies with long-lasting effects, it is necessary to estimate how the value of mortality risk reductions increase over time as income increases. Note that there is generally a lack of information from primary valuation studies about the mean household or individual income of the sample from which VSL estimates are derived. An alternative source of income data can be found in official statistics of gross adjusted disposable income (OECD, 2023[1]). However, these data are often not available in all years for all countries. Hence, GDP per capita or Gross National Income (GNI) per capita is often used as a proxy for income[1]. GDP per capita is also a commonly used measure for undertaking benefit transfer analyses across policy contexts.

5.2.1. Main estimation models

Several characteristics of the meta-data present challenges for estimating the relationship between VSL estimates and GDP per capita. For example, limited variation in income levels exists among high-income countries as compared to low-income countries (cf. Figure 5.1). At the same time, most VSL estimates are from high- or middle-income countries and may also vary for reasons other than differences in GDP. Many countries in the dataset are also characterised by no or very few combinations of VSL estimates and GDP per capita for any given year. This analysis utilises the full dataset spanning 1970 to 2023 to assess variation in income and VSL estimates over time and across countries, as both dimensions are relevant for estimating a statistical relationship between income and VSL.

Figure 5.1. Relationship of log(GDP) to log(VSL) in OECD and non-OECD countries



Note: Points reflect study-level average VSL estimates after removing far-outs. GDP per capita and VSL are expressed in 2022 USD using the same conversion procedure as for primary VSL estimates, cf. Annex B.

Table 5.1 reports the results of five meta-regression models using the same approach as described in Section 4.4 of Chapter 4, but introducing additional explanatory regressors into the multilevel model to estimate the true population estimate of VSL θ as follows (see Box 4.1 in Chapter 4 for a definition of components):

$$\widehat{\theta_{msi}} = \mathbf{x}_{msi}\boldsymbol{\beta} + u_m^{L4} + u_{ms}^{L3} + u_{msi}^{L2} + \varepsilon_{msi},$$
$$u_m^{L4} \sim N(0, \tau_{L4}^2),$$
$$u_{ms}^{L3} \sim N(0, \tau_{L3}^2),$$
$$u_{msi}^{L2} \sim N(0, \tau_{L2}^2),$$
$$\varepsilon_{mis} \sim N(0, \widehat{\sigma_{jk}}^2) \; .$$

Equation 5.1

The dependent variable in Equation 5.1 is the logarithm of VSL and the covariate $\mathbf{x}_{msi}$ is a vector of explanatory variables. All models include the logarithm of GDP per capita as an explanatory variable within this vector. Since the model is log-log, the estimated coefficients of GDP per capita in Table 5.1 can be interpreted as the income elasticity of VSL. Models 3-5 include additional controls such as types of SP and RP methods and years since data collection. Models 4 and 5 control for fixed effects at the country and year levels, respectively. The estimate of income elasticity of VSL in Model 4 is estimated using within-country variation in VSL estimates and income levels, and therefore on the basis of variation in these factors over time within each country. In Model 5, on the other hand, the estimate of the income elasticity of VSL is estimated using within-year variation across countries.

Models 1 and 2 yield similar estimates of the income elasticity of VSL of around 1.1, both of which are statistically significant. Model 3 controls for types of SP and RP methods and years since data collection and yields a statistically significant estimate of the income elasticity of VSL of approximately 1.

Model 5 yields a slightly higher, statistically significant estimate of 1.1, and Model 4 yields a higher estimate of 1.4, although this value is not statistically significant. These results suggest that the income elasticity of VSL over time may be higher than the income elasticity of VSL across countries, although this finding does not appear robust and is difficult to detect in the full dataset 1970-2023 dataset used here.

Table 5.1. Estimated income elasticity of VSL across models

Dependent variable = log(VSL), sample of all meta-data

Explanatory variables	Model 1	Model 2	Model 3	Model 4	Model 5
	Four-level	Three-level	Three-level	Three-level	Three-level
	Only GDP	Only GDP	Controls	Country FE	Year FE
Log income (log(GDP) per capita)	1.109***	1.109***	1.016***	1.622	1.139***
	[0.668,1.550]	[0.668,1.550]	[0.539,1.494]	[-1.542,4.787]	[0.533,1.746]
Elicitation method					
Hedonic wage method (base)					
Contingent valuation method			-0.373	-0.479	-0.33
			[-1.455,0.709]	[-1.893,0.935]	[-1.757,1.096]
Choice experiment			0.317	0.092	-0.215
			[-0.991,1.625]	[-1.872,2.056]	[-1.884,1.454]
Consumer market valuation method			-0.968	-1.569	-1.385
			[-2.632,0.696]	[-3.523,0.384]	[-3.633,0.863]
Other SP method			0.744	0.154	0.122
			[-1.568,3.056]	[-3.040,3.348]	[-2.552,2.797]
Years since data collection			0.046**	0.05	
			[0.001,0.090]	[-0.021,0.121]	
Constant	3.084	3.083	3.338	-3.681	1.966
	[-1.504,7.672]	[-1.506,7.672]	[-1.963,8.639]	[-39.606,32.244]	[-5.487,9.420]
Country fixed effects	No	No	No	Yes	No
Year fixed effects	No	No	No	No	Yes
N Studies	276	276	276	276	276
N Estimates	3870	3870	3870	3870	3870
N Countries	49	49	49	49	49
N Years	51	51	51	51	51
Only 1 GDP by Country	18	18	18	18	18
Only 1 GDP by Year	14	14	14	14	14

Note: The table displays coefficients as well as their confidence intervals (in brackets). Stars indicate statistical significance at the 10% level (*); at the 5% level (**); and at the 1% level (***). 93 negative VSL estimates are not included due to log transformation (as taking the log of negative numbers is not possible). Model 4: Elasticity estimates are identified by within-country variation of (49-18) countries, as information from 18 countries is not used. Model 5: Elasticity estimates are identified by within-year variation of (51-14) years, as information from 14 years is not used. FE stands for fixed effects. Log (GDP) is log (GDP per capita). Details regarding variable definitions are provided in Table 4.1 of Chapter 4.

5.2.2. Alternative models and robustness checks

A number of alternative estimations and robustness checks regarding the estimation of the income elasticity of VSL are included in Annex E. A summary of the most important results is provided below:

- **New SP and RP:** Basing the estimations shown in Table 5.1 on only the new RP and SP data leads to slightly higher estimates of the income elasticity of VSL, ranging from 1.12 to 1.25, all of which are statistically significant. The exception is Model 4 (reflecting within-country variation over time), which yields an insignificant elasticity estimate of 3.5 (Table A F.1 in Annex F).
- **Old SP and RP:** Basing the estimations shown in Table 5.1 on only the old RP and SP data yields similar estimates of the income elasticity of VSL as using the entire dataset, ranging from 0.98 to 1.14, all of which are statistically significant, except for Model 4 (reflecting within-country variation over time), which yields an insignificant elasticity estimate of 1.58 (Table A F.2 in Annex F).
- **Comparing SP and RP**: When estimating the models using SP and RP data separately, the SP data yields a systematically higher income elasticity of VSL (1.33 to 1.45, all statistically significant) than RP (0.71 to 1.35, all statistically significant). Model 4 yields insignificant estimates of 0.16 and 3.1 for SP and RP, respectively (Table A F.3 and Table A F.4 in Annex F).
- **Elasticity by country and income groups:** Splitting the data by the country groups defined in Section 4.5 of Chapter 4 and running one regression model for each group separately generates large variations in income elasticity estimates, although most are statistically insignificant, and the lower sample sizes in these models reduce their statistical power. For the high-income group, the estimates vary from -0.6 to 1.5, indicating a lower elasticity within this group than when considering the whole sample. Estimates of the income elasticity of VSL among low- and middle-income country groups are significant and range from 1.16 to 2.14. These results suggest that the income elasticity of VSL for lower income countries may be higher than it is for higher income countries (Table A F.5 in Annex F).
- **Alternative econometric specifications:** Alternative model specifications, such as the inclusion of interaction effects between GDP and higher than average income (Table A F.6 in Annex F) and specifications to control for study-level effects (Table A F.7 in Annex F) were also examined, yielding relatively robust results across specifications.

From the results presented here and in Annex F, estimates of the income elasticity of VSL for the full dataset range between 0.5 to 1.5, with most estimates at or slightly greater than 1. Estimates of the income elasticity of VSL are more likely to be identified by cross-country variations (by including fixed effects as proxies for year-specific unobservable variables) and less likely to be identified by within-country variation. This is because only a subset of estimates in the meta-data can be used to estimate models reflecting within-country variation over multiple years. As a result, the estimates of income elasticity of VSL based on models reflecting variation within countries over time, such as Model 4, exploit only 40 percent of the meta-data, which come largely from a few countries in which many studies were carried out. For this reason, estimates of the income elasticity of VSL from these models should be considered less globally representative than estimates from models based on variation across countries.

Given the large variation in the estimates of income elasticity of VSL across countries as estimated in models by country and income group and the lack of sufficient variation in VSL estimates within countries over time, it is challenging to identify suitable and robust elasticity estimates that could be used for specific elasticity estimates by country group (such as those defined in Section 4.5 of Chapter 4) or that can be applied over time. This issue is discussed further with respect to other evidence from the literature in Section 5.4.2 and with respect to recommendations for the use of the income elasticity of VSL in policy assessments in Chapter 6.

5.3. Other meta-regression results

5.3.1. Quality of primary valuation studies

This section presents the results of meta-regressions that assess the extent to which a number of additional factors impact VSL estimates. The results below are based on the three-level random effects meta-regression model used to estimate the relationship between income and VSL estimates (Equation 5.1) but employ a linear dependent variable VSL (rather than log) in order to retain negative VSL estimates in the analysis. Table 5.2 reports the results of six models with different sets of covariates, estimated using the pooled new SP and RP data.

As can be seen in Table 5.2, the coefficient of income (GDP per capita) is statistically significant and positive in all five models in which it is included[2]. Estimates from both Contingent Valuation (CV) and Consumer Markets (CM) methods yield significantly lower VSL estimates compared to Hedonic Wage (HW) methods (the base category) for all models. Estimates based on Discrete Choice Experiments(CE) methods are not statistically different from those based on HW methods. The coefficient for years since data collection is statistically significant in all four models. This indicates a trend of declining VSL estimates over time, even when controlling for GDP and valuation methods[3].

Whether the study is published in a peer-reviewed journal is statistically significant and positive in Models 3-5, and whether the target population is nationwide is statistically significant and positive only in Model 6. Other statistically significant variables include the Quality Score variables 2 and 3. Quality Scores are intended to serve as a rough measure of the scientific quality of the underlying primary valuation studies (cf. Sections 4.3.3 and 4.6 of Chapter 4). The Quality Scores for SP and RP are defined as:

$$Quality\ Score\ SP = SP_{Base\ risk} + SP_{Scope\ sensitivity} + SP_{Visual\ Aids} \quad if\ SP = 1$$

$$Quality\ Score\ RP = RP_{CFOI} + RP_{IV\ estimate} + RP_{Injury\ risk} \quad if\ RP = 1$$

Where the right-hand side elements are dummy variables representing the presence or absence of various quality characteristics in SP and RP studies. $SP_{Base\ risk}$, $SP_{Scope\ sensitivity}$, and $SP_{Visual\ Aids}$ reflect whether the survey clearly defines the baseline risk, reports a scope test and uses visual aids to explain risk, respectively. RP_{CFOI}, $RP_{IV\ estimate}$ and $RP_{Injury\ risk}$ indicate whether VSL estimates were estimated using an instrumental variable for fatality rate, whether the estimating regression controls for non-fatal risk of injury and whether the study relied on the Census of Fatal Occupational Injuries (CFOI) as a source for risk data. Further discussion of quality aspects is provided in Section 4.7 of Chapter 4.

The coefficients of Quality Scores taking values 2 and 3 are positive and statistically significant in Models 5 and 6. This indicates that studies with these quality characteristics tend to yield higher VSL estimates, although the reasons for this result are unclear. Whether studies target the general population ("General Population"), use random sampling strategies ("Representative") or whether standard errors (SE) are reported ("No Reported Standard Errors") do not have a statistically significant effect on VSL estimates across models, nor do the gender variables ("Only Male", "Only Female"), which reflect whether the study surveyed only male or female respondents, respectively. Excluding GDP per Capita in Model 6 does not significantly change the above results, except that the variable "Nationwide" now becomes positive and statistically significant.

Table 5.2. Three-level random effects meta-regression models to assess quality indicators

Dependent variable = VSL (USD million), New RP and SP data pooled

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
GDP per capita (thousand USD)	0.116***	0.119***	0.124***	0.124***	0.122***	
	[0.089,0.143]	[0.092,0.147]	[0.094,0.154]	[0.094,0.154]	[0.092,0.152]	
Elicitation method						
Hedonic wage method (base)						
Contingent valuation method	-2.454***	-2.501***	-1.818*	-1.831*	-2.147*	-1.998
	[-4.081,-0.827]	[-4.126,-0.876]	[-3.972,0.337]	[-3.993,0.330]	[-4.397,0.103]	[-4.581,0.585]
Choice experiment	-0.635	-0.688	0.266	0.254	-0.105	0.661
	[-2.307,1.036]	[-2.358,0.981]	[-1.956,2.488]	[-1.975,2.483]	[-2.414,2.205]	[-1.976,3.299]
Consumer market valuation method	-2.451*	-2.135	-1.08	-1.086	-0.688	-1.486
	[-5.276,0.374]	[-4.980,0.711]	[-4.096,1.935]	[-4.104,1.933]	[-3.728,2.352]	[-5.040,2.068]
Other SP method	8.542***	8.407***	-5.995	-6.002	-5.03	-4.814
	[4.018,13.066]	[3.884,12.930]	[-14.214,2.224]	[-14.222,2.218]	[-13.305,3.246]	[-14.380,4.752]
Years since data collection	0.156***	0.153***	0.142***	0.142***	0.127**	0.102*
	[0.062,0.250]	[0.059,0.247]	[0.042,0.242]	[0.042,0.242]	[0.026,0.228]	[-0.011,0.215]
Journal		1.564	2.385**	2.376**	2.512**	0.836
		[-0.366,3.494]	[0.333,4.437]	[0.323,4.428]	[0.449,4.575]	[-1.529,3.200]
No reported standard errors			-0.339	-0.343	-0.241	-0.595
			[-1.450,0.771]	[-1.455,0.769]	[-1.357,0.874]	[-1.804,0.615]
Only male				-0.08	-0.075	-0.101
				[-0.720,0.560]	[-0.715,0.565]	[-0.754,0.552]
Only female				-0.234	-0.24	-0.265
				[-1.023,0.554]	[-1.028,0.548]	[-1.067,0.536]
Nationwide			0.433	0.43	0.308	2.477***
			[-1.182,2.048]	[-1.187,2.046]	[-1.312,1.928]	[0.729,4.226]
General population			1.610**	1.586**	1.508**	1.391
			[0.131,3.090]	[0.099,3.074]	[0.007,3.009]	[-0.332,3.113]
Representative			-1.089	-1.096	-1.242	-1.826*
			[-2.820,0.643]	[-2.829,0.636]	[-2.990,0.505]	[-3.854,0.201]
Quality score						
Quality score 0 (Base)						
Quality score 1					0.935*	1.135*
					[-0.148,2.018]	[-0.004,2.275]
Quality score 2					1.252*	1.506**
					[-0.117,2.621]	[0.042,2.970]
Quality score 3					2.223*	2.938**
					[-0.183,4.629]	[0.178,5.697]
Constant	-0.622	-2.055	-3.523**	-3.467**	-3.915**	2.252
	[-2.967,1.723]	[-4.989,0.878]	[-6.970,-0.077]	[-6.934,-0.001]	[-7.427,-0.403]	[-1.385,5.888]
N	2449	2449	2234	2234	2234	2234
AIC	14615.14	14606.84	13203.8	13197.97	13179.11	13241.03
BIC	14667.37	14664.87	13283.77	13289.36	13287.63	13343.84
AICc	14615.21	14606.93	13203.99	13198.22	13179.45	13241.34
CAIC	14676.37	14674.87	13297.77	13305.36	13306.63	13361.84

Note: This table presents regression results from Models 1-6. For each variable, the table displays its regression coefficients and corresponding confidence intervals in brackets. Stars indicate statistical significance at 10% (*); at 5% (**); at 1% (***) levels. Details regarding variable definitions are provided in Table 4.1 of Chapter 4.

5.3.2. Types of risk evaluated

Table 5.3 reports the results of six additional models estimated using the new SP and RP data that include covariates reflecting different risk types studied (Models 1-2 and 5-6), as well as information on whether the studied risks were acute (traumatic death) or chronic (a period of e.g. illness before death) (Models 3-4). Results indicate that statistically significant risk types are cancer (significant and positive across all models), military risk (significant and negative in Models 1 and 2), acute risk (significant and positive in Model 3) and mixed risk (significant and positive in Models 3 and 4). The other risk types (e.g. climate, virus, transportation-risks) are not significant in any model. The impact of traumatic/acute risk is not robust and only statistically significant at the 10% level in Model 3. GDP per capita continues to be statistically significant and positive across all models.

Table 5.3. Three-level random effects meta-regression models to assess risk types

Dependent variable = VSL (USD million), New RP and SP dataset pooled

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
GDP per capita (thousand USD)	0.119***	0.123***	0.112***	0.105***	0.111***	0.102***
	[0.091,0.147]	[0.091,0.155]	[0.080,0.144]	[0.067,0.143]	[0.078,0.145]	[0.061,0.143]
Elicitation method						
Hedonic wage method (base)						
Contingent valuation method	-1.841	-1.766	-0.26	-0.88	-1.005	-1.632
	[-5.366,1.685]	[-5.750,2.219]	[-2.857,2.338]	[-4.074,2.314]	[-4.590,2.580]	[-5.988,2.724]
Choice experiment	0.078	0.303	1.386	1.142	0.404	0.141
	[-3.465,3.622]	[-3.690,4.295]	[-1.280,4.052]	[-2.020,4.305]	[-3.251,4.060]	[-4.112,4.394]
Consumer market valuation method	-1.785	-0.778	-0.122	0.164	-1.284	-1.208
	[-5.846,2.275]	[-5.218,3.663]	[-3.379,3.135]	[-3.517,3.846]	[-5.267,2.699]	[-5.858,3.442]
Other SP method	9.211***	-4.542				
	[3.724,14.698]	[-13.620,4.535]				
Years since data collection	0.127**	0.100*	0.150***	0.148**	0.121**	0.125*
	[0.029,0.224]	[-0.006,0.206]	[0.047,0.253]	[0.025,0.271]	[0.009,0.233]	[-0.009,0.258]
Journal	1.3	2.181*	1.639*	1.893*	1.523	1.923
	[-0.897,3.496]	[-0.147,4.509]	[-0.195,3.473]	[-0.254,4.039]	[-0.672,3.718]	[-0.550,4.395]
Risk type						
Job (base)						
Climate	-1.557	-1.849			-0.542	-0.475
	[-6.083,2.969]	[-6.874,3.177]			[-6.678,5.595]	[-7.227,6.276]
Crime	-3.671	-2.837			-1.668	-2.171
	[-11.226,3.883]	[-17.046,11.373]			[-16.199,12.863]	[-17.059,12.716]
Disaster	2.048	1.323			-1.29	-1.9
	[-4.528,8.625]	[-5.434,8.080]			[-9.806,7.227]	[-11.093,7.294]
Environment	-2.167	-2.325			-4.278	-5.359
	[-5.874,1.540]	[-6.152,1.501]			[-11.580,3.023]	[-13.198,2.480]
Health	-0.44	-0.311			-3.304	-2.614
	[-3.855,2.976]	[-3.866,3.244]			[-10.220,3.612]	[-9.974,4.747]
Military	-5.898**	-4.964*			-4.057	-4.148
	[-11.521,-0.276]	[-10.800,0.872]			[-10.667,2.553]	[-11.567,3.271]
Natural disaster	-0.54	-0.149			0.704	1.732
	[-5.138,4.058]	[-4.996,4.699]			[-5.634,7.042]	[-5.182,8.647]
Not Specified	-1.783	-1.323			-3.699	-1.732
	[-11.306,7.739]	[-11.136,8.490]			[-14.647,7.249]	[-13.292,9.829]
Suicide	-1.191	-1.548			-0.067	-0.723

	[-13.888,11.507]	[-14.228,11.131]			[-13.313,13.179]	[-14.311,12.864]
Transportation	-1.603	-1.068			0.205	0.245
	[-4.835,1.629]	[-4.406,2.271]			[-5.344,5.754]	[-5.827,6.317]
Virus	-2.646	-1.975			-5.382	-5.35
	[-7.811,2.518]	[-7.325,3.375]			[-13.652,2.889]	[-14.352,3.652]
Cancer			2.058**	1.881**	1.872**	1.602*
			[0.478,3.638]	[0.195,3.567]	[0.118,3.626]	[-0.218,3.421]
Risk acuteness						
Chronic (base)						
Acute			1.41	1.273	-2.398	-3.312
			[-0.558,3.378]	[-0.927,3.474]	[-7.595,2.800]	[-9.165,2.542]
Mixed			3.689**	2.688*	-0.775	-2.494
			[0.815,6.563]	[-0.457,5.834]	[-7.131,5.580]	[-9.324,4.336]
No reported standard errors		-0.402		-0.12		-0.42
		[-1.564,0.761]		[-1.455,1.215]		[-1.835,0.995]
Only male		-0.074		0.304		0.319
		[-0.715,0.566]		[-0.377,0.984]		[-0.365,1.002]
Only female		-0.24		0.208		0.205
		[-1.028,0.548]		[-0.713,1.129]		[-0.718,1.127]
Nationwide		0.245		0.539		0.749
		[-1.455,1.945]		[-1.360,2.438]		[-1.352,2.849]
General population		1.224		1.17		0.964
		[-0.378,2.826]		[-0.484,2.825]		[-0.861,2.789]
Representative		-0.977		-0.12		0.069
		[-2.797,0.844]		[-2.070,1.830]		[-2.026,2.163]
Quality score						
Quality score 0 (base)						
Quality score 1		0.914		1.043*		1.111*
		[-0.184,2.011]		[-0.086,2.173]		[-0.045,2.266]
Quality score 2		1.159		1.414*		1.362*
		[-0.242,2.561]		[-0.122,2.949]		[-0.238,2.962]
Quality score 3		1.74		0.329		-1.015
		[-0.879,4.358]		[-2.678,3.336]		[-4.512,2.483]
Constant	-0.985	-2.606	-5.108***	-6.023***	0.082	-0.136
	[-4.203,2.233]	[-6.521,1.308]	[-8.990,-1.226]	[-10.597,-1.449]	[-6.895,7.059]	[-7.961,7.689]
N	2448	2234	1750	1646	1750	1646
AIC	14536.4	13121.26	10621.55	9827.206	10568.08	9773.589
BIC	14658.26	13292.61	10687.16	9940.734	10693.83	9946.584
AICc	14536.78	13122.11	10621.73	9827.775	10568.72	9774.898
CAIC	14679.26	13322.61	10699.16	9961.734	10716.83	9978.584

Note: This table presents regression results from Models 1-6. For each variable, the table displays its regression coefficients and corresponding confidence intervals in brackets. Stars indicate statistical significance at 10% (*); at 5% (**); at 1% (***) levels. Risk types covered include Cancer; Climate: extreme weather events, sea level rise, depletion of fisheries, heat stroke; Disaster: human-caused disaster (e.g. nuclear accident); Environment: environmental hazards other than climate events and natural disasters (e.g. air pollution); Health: disease other than cancer (e.g. heart failure, stroke); Mixed: a combination of any of the above risks; Natural Disaster: avalanches, earthquakes and floods; Transportation: transport-related fatalities; Virus: contagious diseases such as COVID-19, dengue fever or rabies. Details regarding variable definitions are provided in Table 4.1 of Chapter 4.

5.3.3. Sensitivity analyses

Annex F provides the results of several sensitivity analyses, including results from using all RP and SP data, using each specific dataset separately (New RP and New SP), and accounting for impacts of mortality risk types.

The results in Table A F.8 in Annex F indicate that carrying out the same regression as in Table 5.2, but using all RP and SP data (rather than new RP and SP data only), yields results that are similar to those reported in Table 5.2 in terms of statistical significance, although coefficient values differ somewhat. When SP data is assessed separately (Table A F.9 in Annex F), a number of other variables are statistically significant in addition to GDP per capita (which is significant in all models). In addition, CE methods generally yield higher VSL estimates than CV methods (statistically significant in three out of four models), as do journal publications (statistically significant in two out of four models). Random sampling, as measured by the "Representative" variable, is statistically significant and positive in one out of the two models in which it is included. The annualised risk change is statistically significant and strongly negative where it is included in Models 3 and 4. Although theory suggests that VSL estimates should be independent of this risk change (Lindhjem et al., 2011[2]), this result is typical for SP studies. Similar results are also reported in a meta-regression analysis of Canadian studies (Ginbo, Adamowicz and Lloyd-Smith, 2023[3]). The only risk type variable that is statistically significant, positive and robust across all four models is cancer risk (Models 1-2, 5-6 in Table A F.10 in Annex F). The variable for acute risk is also statistically significant and positive, but only in two out of four models in which it is included (Models 1-2 in Table A F.10 in Annex F)

A separate analysis of RP data (Table A F.11 in Annex F) indicates that GDP per capita is statistically significant and positive in all models. The only other variable that is statistically significant and robust across models (though negative) is "RP with Full Sample". This indicates that VSL estimates are lower when estimated based on a representative sample of employed individuals compared to sample of individuals employed in specific sectors or job types. For the analysis of RP data including risk categories (Table A F.12 in Annex F), the risk types "disaster", "health", "environment", "acute" and "mixed" are all significant and negative in at least two models. The reasons for these results are unclear and the results are also not robust across models.

Taken together, the meta-regression results presented above do not provide sufficiently robust results for any variables beyond income (GDP per capita) that would justify their use in adjusting base VSL estimates. One potential exception could be cancer risk. However, adjusting VSL estimates for this type of risk is difficult to operationalise based on the relatively limited information available in the meta-data (e.g. whether cancer was mentioned in the study or what type of cancer was mentioned).

5.4. Evidence from the literature on the relationship between VSL and various factors

This section provides an updated review of comparable meta-analyses, review papers and primary valuation studies on how factors such as age, adult vs. child mortality, pandemics and other large-scale events impact VSL estimates. The purpose of this review is to better understand the state of the current evidence on several important factors that could potentially be used to adjust base VSL estimates for application in specific policy contexts.[4] This is particularly relevant considering the data limitations of the current analysis (e.g. few studies consistently report information about all of these factors) and the heterogenous nature of the meta dataset that prevents a full investigation of such factors using the meta-regressions presented in Sections 5.2 and 5.3.

It is important to note that even if certain variables have been found to have statistically significant and robust impacts on VSL estimates in one or more studies or countries, these results do not necessarily indicate that such factors should be systematically used to adjust base VSL estimates. Determining which adjustment factors to use will also depend on other concerns, such as whether information about the factors is available for the policy context or country in which VSL estimates will be applied, whether trade-offs exist between equity and ethical concerns, and whether the simplicity and transparency of the guidance is considered important. These considerations are discussed further in Chapter 6.

5.4.1. Results from other meta-analyses, reviews and primary valuation studies

Several notable quantitative reviews using meta-analysis methods have been carried out since 2012. Some studies cover individual countries, including USEPA (2016[4]) and Newbold et al. (Newbold et al., 2024[5])[5] (in the United States), Ginbo et al. (2023[3]) (in Canada) and Wang et al. (Wang et al., 2024[6]) (in China). The aim of these studies is typically to derive VSL recommendations for policy evaluation within a given country, and some also investigate methodological issues (e.g. which factors help to explain variation in VSL estimates).

USEPA (2016[4]) conducts a meta-analysis study in the United States to derive updated VSL estimates for use in assessing the mortality impacts of environmental policies. The study uses various screening criteria for SP and RP studies, and different statistical (parametric and non-parametric) methods to derive mean VSL estimates. A number of procedures used were later criticised by a scientific advisory board reviewing the study (SAB/USEPA, 2017[7]). Noting this caveat, the study recommends a VSL estimate for the general adult population in the United States of USD_{2013} 10.3 million[6]. USEPA (2016[4]) does not recommend any adjustments for risk characteristics or other factors (except for increasing income over time). The authors, "leave the task of estimating adjustment factors to account for the influence of risk and individual characteristics on VSL estimates, possibly through inclusion of additional control variables in the meta-regression model, for future work" (USEPA, 2016, p. 9[4]). Cropper, Joiner and Krupnick (2024[8]) review the recent HW, CM and SP literature of relevance in the United States and conclude that recent evidence is "sufficiently rich to permit a revision of EPA's baseline estimate".

Banzhaf (2022[9]) conducts a meta-analysis of previous meta-analysis studies from the United States to derive a VSL estimate for policy use. The baseline statistical model yields a central VSL estimate of USD_{2019} 8 million from the included meta-analysis studies, with a 90% confidence interval of 2.4 to 14.0 million. This is somewhat lower than USEPA (2016[4]), taking into account that their estimate is in USD_{2013}.

Ginbo et al. (2023[3]) provide an updated measure of VSL (specifically the value of reduced mortality risk, VRMR) in Canada. The analysis is based on 18 primary studies published between 1989 and 2018, yielding 158 VSL estimates. The authors select nine studies for inclusion in the meta-analysis that were considered to have samples representative of the country's population[7]. The authors use a weighted least squares approach with clustered errors and panel data regression procedures. The analysis yields a mean VSL estimate of CAD_{2020} 13 million (ca. USD_{2020} 9.5 million), while the lower and higher values from two alternative valuation methods are about CAD 10 million and CAD 16.5 million, respectively[8]. This updated mean VSL estimate is 60% higher than VSL recommended by Canadian as of 2024, which according to the authors, can mainly be attributed to risk preferences that change over time and advancements in empirical methods. Further, the authors find that the levels of baseline risk and risk reduction are among the main determinants of VSL estimates. Considerable variation exists in mean VSL estimates, e.g. depending on the type of data source used. As noted in Chapter 4, Ginbo et al. (2023[3]) find that SP studies yield VSL estimates that are about two times higher than those from RP studies.

Wang et al. (2024[6]) conduct a meta-analysis of 19 primary SP surveys of the Chinese population between 1998 and 2019. For government programs in China, they recommend VSL estimates of CNY_{2020} 5.18 million, 11.64 million and 1.68 million (equivalent to USD_{2020} 1.24 million, 2.8 million and 0.4 million) for environmental, health and transport related mortality risks, respectively. Income, as well as the type and magnitude of risk reduction, are the most important factors influencing VSL estimates. Unlike research conducted in developed countries, they find no evidence of publication bias.

In addition to the meta-analysis studies above, several other reviews of the VSL literature are worth mentioning, notably the global systematic review by Keller et al. (2021[10]) of 120 global VSL studies (both SP and RP) published between 2009 and 2019. The authors do not use statistical meta-analysis methods to derive central tendencies and conclude that: "Estimates for VSL varied substantially by context (sector, developed/developing country, socio-economic status, etc), with the median of midpoint purchasing power parity-adjusted estimates of USD_{2019} 5.7 million, 6.8 million, 8.7 million, and 5.3 million for health, labour market and transportation safety sectors, respectively" (Keller et al., 2021, p. 1521[10]). These estimates are roughly comparable to the raw mean and median VSL estimates at the estimate and study levels reported in Section 3.3 of Chapter 3. From these findings, the authors further conclude that the large variation observed in the reported VSL estimates depends mainly on the context rather than the method used (although this is difficult to verify without further statistical analysis, e.g. meta-regression analysis).

As noted in Chapter 1, other reviews of the VSL literature with more limited scope include Bahamonde-Birke et al. (2015[11]) focusing on road accidents, Cropper et al. (2024[8]) on US EPA-relevant studies in the United States, Kniesner and Viscusi (2019[12]) on generic VSLs, Robinson and Hammitt (2015[13]; 2016[14]) who carry out reviews with a focus on policy implications, and Ananthapavan et al. (2021[15]) who undertake a systematic review for Australia. These studies demonstrate a heterogenous and diverse literature in terms of risk causes, contexts, methods and VSL estimates. This report draws on these studies further in the following sections, especially when considering recommended VSL estimates for policy use.

5.4.2. Income

A number of studies investigate the income elasticity of VSL within and/or across countries. Masterman and Viscusi (2018[16]) estimate income elasticities of VSL of around 0.94 to 1.05 based on global SP studies. They also find evidence that elasticities may decrease with income, suggesting an elasticity of around 1 for lower-income countries and 0.55 for higher-income countries. Lindhjem et al. (2011[2]) analyse almost identical data to the new SP data used in the current analysis and find elasticities of between 0.7 and 0.9, with significantly lower elasticities for quality-screened models that use similar SP surveys.

Based on a global dataset of HW studies, Viscusi and Masterman (2017[17]) estimate an elasticity of VSL of between 0.5 and 0.7 for the United States, and just above 1 for other countries. They also find evidence that much of the observed disparity in elasticities across countries is attributable to income differences, as elasticity estimates are higher for lower-income populations.

Based on HW data, Kniesner et al. (2010[18]) also find higher income elasticity of VSL values for lower-income deciles (ranging from around 2.2 in the lowest income decile to 1.2 in the highest), except within the United States. In their discussion, Robinson, Hammitt and O'Keeffe (2019, p. 24[19]) note that while studies published before 2010 found elasticities ranging from as low as 0.1 to 2.0, more recent reviews have found elasticities closer to 1.0, and they recommend using elasticities around 0.8 for extrapolating transfers between high-income countries and between 1.0 and 1.2 for lower-income countries.

There are a number of challenges in measuring the income elasticity of VSL, especially over time, as such an analysis is ideally informed by a representative longitudinal panel of individuals whose willingness to pay for mortality risk reductions is measured over time, data that is not available. USEPA (2017[7]) discusses some of the challenges of estimating elasticities, especially over time, including the use of longitudinal vs cross-sectional data and the challenge of accurately measuring income in surveys. Another important consideration is that even if GDP per capita grows (often a proxy for income across countries), individual incomes may not change in the same way. This is the case, for example, when an increase in mean income is accompanied by an increase in income inequality.

According to Hammitt et al. (2022[20]) only two studies have estimated VSL for a population over time, and both found that VSL estimates increased more rapidly than income over time, suggesting an income elasticity of VSL larger than 1. Costa and Kahn (2004[21]) used HW data from 1940-1980 and GDP as proxy for income to estimate an implied income elasticity of 1.5 to 2.0. Hammitt et al. (2022[20]) notes that estimating the income elasticity of VSL is vulnerable to the endogeneity problem associated with an individual worker's VSL because it reflects their choice of job risk and wage, which is determined by optimising over the set of available jobs she is qualified for.

In SP studies that were performed in China in 2005 and repeated in 2016, Hammitt et al. (2019[22]) find an implied income elasticity of 3. The elasticity is implied insofar as it assumes that the preference (utility) function is stable over time. For example, if individuals become more concerned about safety over time (unrelated to income), this may exaggerate the importance of income growth when accounting for why VSL has increased over time. Hammitt et al. (2022[20]) use HW data from Chinese Taipei from 1982-1997 to estimate income elasticities of 2 to 5, assuming that all of the observed differences in VSL estimates compared to income are attributable to income growth. Controlling for the endogeneity of the data as noted above instead yields much lower elasticity estimates of between 0.65 and 0.91.

Alberini and Ščasný (2021[23]), investigate increases in VSL and income over time by comparing two identical CV surveys carried out five years apart in the Czech Republic, estimating an income elasticity of VSL of ca. 0.77.

In summary, the cross-country results presented in Section 5.2 are similar to those found in other studies, with income elasticities of VSL ranging from 0.5 to 1.5, and the majority of estimates around 1. While there are some indications that the income elasticity of VSL may be higher for lower-income countries (and lower for higher-income countries), including in the meta-data of the present report, it is methodologically challenging to discern changes in elasticity estimates within countries over time. As is shown in the sensitivity analysis in Annex F, elasticity estimates within country groups lack robustness and depend on estimation approaches.

5.4.3. Age (of adults)

As noted in OECD (2012[24]) a significant controversy erupted in the United States over the so-called "senior discount", i.e. the practice of downward adjustment of VSL estimates for older individuals. Because environmental policies often reduce risks more for the very young or the very old, the use of differentiated VSL estimates with respect to age arose first in this sector. The US EPA employed a lower VSL for older individuals in sensitivity analyses conducted for air pollution rules prior to 2004, including the Clear Skies Initiative, where benefits to senior citizens constituted the majority of the policy benefits (Robinson, 2007[25]). Aldy and Viscusi (2007[26]) point out that whether VSL should vary by age is not a matter of equity or political expediency, but should rather be grounded in how individuals' WTP for risk reductions vary with age. As people age, their life expectancy shortens, but their economic resources vary (and often increase) as well, giving rise to a theoretical indeterminacy in the age-VSL relationship (see also Viscusi, 2009[95]). Discussions about this issue have arisen again recently in many countries that have considered the costs and benefits of COVID-19 policies (see below).

While there is some empirical evidence that VSL declines at older ages, this relationship is uncertain and possibly follows an inverted U-shape (Hammitt, 2007[27]; Krupnick, 2007[28]; Viscusi and Aldy, 2007[26]). More recent studies and reviews have confirmed many of the previous findings. For example Brey and Pinto-Prades (2017[29]) find that different econometric approaches to the analysis of their SP data produce similar results, namely, an inverted-U relationship between VSL and age. Utilising RP data from car purchase decisions in the United States, O'Brien (2018[30]), also find a significant inverted U-shaped relationship between age and VSL, ranging from USD_{2009} 1.9 to 19.2 million. Aldy (2019[31]) also find an inverted U-shape with age in a US context.

Other evidence, however, does not support this relationship. Herrera-Arujo and Rochaix (2020[32]), for example, find a negative relationship between age and VSL when analysing combined data on wage-differentials and detailed data on workers' medical histories. Mitani, Liu and Lindhjem[108] (in preparation) find only a weak U-shaped relationship in a SP survey related to pandemic risk in Japan. The authors speculate that the high accumulation of wealth among the elderly in Japan may increase WTP (and thus VSL estimates) and/or the life expectancy of adults, making it difficult to capture a (potential) negative impact of age on VSL estimates for this population.

While adjusting VSL estimates for age may be perceived to be problematic for equity reasons, the evidence on this relationship is also still not fully clear in the literature (cf. also (Kniesner and Viscusi, 2019[12])). Even if the relationship between VSL and age is characterised by an inverted U-shape in some contexts, it is difficult to determine how an age adjustment could be executed in practice. As limited age information is available in the new RP and SP data used for this analysis, this issue has not been investigated in the current meta-analysis[9]. OECD (2012[24]) carried out a basic analysis of the old SP meta-data and found no clear relationship between age and VSL, although for a subset of the data indications of such a relationship were found insofar as VSL estimates increased with age to about 40-50 years and then declined.

5.4.4. Adults vs. children

As noted in OECD (2012[24]), VSL estimates appear to be higher for children, with evidence from the United States and Europe indicating that such estimates can be twice as high as that of adults (OECD, 2010[33]; USEPA, 2003[34]). More generally, in cases where a policy intervention particularly affects children, either because of the nature of the policy (e.g. pesticides in school grounds) or because children are particularly vulnerable to a specific hazard (e.g. lead in drinking water), child-specific VSL estimates are likely to be useful in ensuring that resources and policy efforts are allocated efficiently. Based on these arguments OECD (2012[24]) recommended that, for policies that target reducing risks for children or that reduce these risks indirectly, the VSL estimates used for children should be 1.5 to 2.0 times higher than those used for adults.

A more recent review by Keller et al. (2021[10]) found that VSL estimates for children were up to 4.66 times higher when parents were asked to value mortality risks for their children compared to themselves. Keller et al. (2021[10]) are unable to explain the factors behind the premium. Even though some recent evidence exists for “child premiums”, a number of studies consider the evidence for such an adjustment to be too limited to draw clear conclusions. While finding evidence of premiums, reviews by Raich et al. (2018[35]) and Robinson et al. (2019[36]), also note that more research is needed to accurately estimate a potential adjustment factor for VSL estimates for children. Kniesner and Viscusi (2024[37]) review the evidence regarding adjustments for VSL estimates (including age adjustments) and conclude that there are many reasons why it may be difficult to make such adjustments. These include both potential methodological limitations in the primary valuation studies and the “implausibility” of using this reasoning in practical policy analysis, e.g. applying a percent drop in VSL at 18 (the age of legal majority in the United States) compared to age 17, in the context of the US Consumer Product Safety Commission and the US EPA.

VSL estimates for children were screened out of the meta-data used for this report (cf. Chapter 3). Because the evidence remains limited and uncertainties are likely to be even larger when considering potential adjustment factors across countries, as well as extrapolating to countries beyond those where relevant evidence exists, the approach taken in this report is to use the same base VSL estimates for all age groups.

5.4.5. Pandemics and other large-scale events

An important issue that has become increasingly relevant is mortality risk valuation in the context of COVID-19 and other extreme events that could occur in the future (e.g. pandemic, natural disaster or climate change-induced) where risks are non-marginal and disproportionately affect specific groups or areas (Hammitt, 2020[38]; Viscusi, 2020[39]; Viscusi, 2021[40]). For example, there has been an intense debate over which VSL estimate to use to evaluate the health and lockdown policies introduced in the wake of the COVID-19 pandemic (Hammitt, 2020[38]). In addition, events like the COVID-19 pandemic may influence estimates obtained from SP studies conducted during these periods (Mourato and Shreedhar, 2021[41]), or may result in persistent changes to risk preferences that should be considered when valuing mortality risks in the future (Hanaoka, Shigeoka and Watanabe, 2018[42]). When investigating the possible impact of COVID-19 on VSL estimates in the meta-regression analysis in Section 5.3, the models did not detect any such effects, neither as a cause of risk nor as differences evident in the estimates produced by studies conducted during the pandemic (cf. Table 5.3).

Regarding which VSL estimate to use to value mortality risk reductions from COVID-19 policies, the main debate has centred around how to deal with the fact that most of these risk reductions accrue in older people (Hammitt, 2020[38]; Robinson, Sullivan and Shogren, 2021[43]), as the decision of whether or not to adjust VSL estimates for older individuals is consequential for the results of any CBA of COVID-19 policies. As noted in section above, VSL estimates may follow an inverted U-shaped relationship with age (Brey and Pinto-Prades, 2017[29]). However, even if this result is empirically supported, it could be considered unethical to value the lives of older people less than those of younger people. It should also be noted that COVID-19 policies have other direct and indirect effects on different population groups and their mortality risks from other causes, e.g. due to increased social isolation and mental health problems. Generally, the same set of principles should be considered and applied when deciding how to value all mortality risk changes from COVID-19.

Viscusi (2020[39]) estimates, for example, that the global mortality cost of COVID-19 (by July 2020) was around USD 3.5 trillion, but the estimate is substantially reduced if the shorter life expectancy and the lower income of COVID-19 victims relative to the general population are taken into account. The authors acknowledge the fundamental equity concerns of such methodological choices. Robinson et al. (2021[43]) investigate the impact of using three different approaches to adjusting VSL estimates for age, namely i) an invariant population-average VSL, ii) a constant value per statistical life-year (VSLY) and iii) a VSL that follows an inverse-U pattern, peaking in middle age. The authors find that when applied to the U.S. age distribution of COVID-19 deaths, these approaches result in average VSL estimates of USD 10.63 million, 4.47 million and 8.31 million, respectively, and that the choice of which of these VSL estimates are used affect the resulting policy conclusions regarding social distancing measures.

Hammitt (2020[38]) estimates the mortality costs of COVID-19 in the United States alone at USD 1 trillion using a constant (age independent) VSL estimate of USD 10 million. The author argues that the total mortality costs of the pandemic may be too high for two main reasons, namely that i) COVID-19 impacted the elderly the most and ii) the mortality risks of COVID-19 are non-marginal, yielding a smaller rate of substitution of wealth for risk reduction. On the other hand, other researchers argue that non-marginality should yield higher mortality costs due to the willingness to accept vs. willingness to pay disparity observed when mortality risk reductions are non-marginal (Colmer, 2020[44]). Taken together, this suggests that further consideration is warranted, especially considering concerns raised in the literature regarding non-marginal risks (Adler, 2020[45]). A related issue, recently considered in more general non-market valuation of health and environmental benefits, may be that the mortality (and morbidity) costs of a pandemic of this scale will yield non-marginal impacts, requiring considerations of general equilibrium effects in the valuation of mortality risks (and other non-market impacts) (Carbone and Smith, 2008[46]; Carbone and Smith, 2013[47]). It should be noted that the concept of VSL, as presented and discussed in this report is limited to the valuation of marginal changes to mortality risk only, and does not include morbidity risk.

In addition to the issues of age and non-marginal risk changes, several studies observe the importance of other factors when considering how to value mortality risk reductions from COVID-19 policies. Examples include the health status of those affected, the size of the risk change (as noted above), the extent to which the risk is dreaded, uncertain, ambiguous and catastrophic, as well as the extent to which it is involuntarily incurred and outside of one's control (Colmer, 2020[44]; Hammitt, 2020[38]; Robinson, Sullivan and Shogren, 2021[43]). While many of these factors could be considered likely to increase VSL estimates, Robinson et al. (2021[43]) note that their potential interactions and impact on VSL remain uncertain due to a lack of empirical evidence.

In many ways, the challenges of providing general guidance on how changes in mortality risks should be valued are the same as discussed in OECD (2012[24]) and only amplified in the face of the COVID-19 pandemic. As noted by Colmer (2020, p. 57[44]): "Almost all benefit-cost analyses apply VSL estimates to new populations. As such, it is important that VSL estimates are chosen carefully, and that the assumptions that give VSL estimates a meaningful interpretation are plausible, when applied to new contexts. These considerations are of particular importance in the context of COVID-19".

As noted in Section 5.3.2, the results of the current meta-analysis do not indicate any effect of pandemic-related risks on VSL estimates or differences in VSL estimates for studies that were conducted during the pandemic. It is, however, possible that pandemic-specific factors could influence VSL estimates for the reasons discussed above. When studies use CE methods, for example, it is easier to investigate characteristics associated with pandemics and their trade-offs with costs. Studies using SP methods to estimate VSL during the less serious, but comparable SARS pandemic[10], for example, found significantly higher VSL estimates than normal. This effect was thought to be attributed to "the high degree of concern about SARS at the time the data were collected" (Liu et al., 2005, p. 83[48]). COVID-19, and similar pandemics in the future, could be expected to generate a larger effect than SARS. Even so, given the lack of sufficient evidence from the literature, as well as other reasons (e.g. the difficulty of operationalising guidance on adjusting for pandemic- or natural disaster-related risks), the approach taken in this report is not to assume specific adjustments to base VSL estimates due to these factors.

5.4.6. Other factors

The health valuation literature is large, especially in high-income countries and a number of additional factors have been found to affect VSL estimates (cf. Chapter 2). These factors include (but are not limited to): cancer and dread of death (or risk perceptions more generally), the health status of those affected and their baseline risk (Herrera-Araujo and Rochaix, 2020[32]), the size of the risk, the timing of risk (latency), its immediate (traumatic) vs. chronic (illness) nature, individuals' degree of control over the risk (Robinson et al., 2010[49]), and altruism and private and public risks (Andersson, Levivier and Lindberg, 2019[50]; Chanel, Luchini and Shogren, 2021[51]). OECD (2012[24]) reviews many of these factors, as do the reviews and meta-analyses referenced above. As noted above, the evidence regarding the relationship between VSL and many of these factors appear to be heterogeneous and context specific. Furthermore, even if clear evidence of robust effects for any of these factors did exist, it would nevertheless be difficult to operationalise workable and transparent guidance on how to make relevant adjustments within and across countries and populations.

Some of the factors above have been analysed at a basic level in the meta-regression analysis in Section 5.3. One of these factors is cancer, as the meta-regression models indicate a positive and statistically significant "cancer premium" for studies in which cancer is mentioned. This finding aligns with other studies, such as Olofsson et al. (2019[52]) and Viscusi, Huber and Bell (2014[53]). However, given the large range of types, degrees of seriousness and treatments for cancers, it is difficult to defend a universal "cancer premium" across all cancer types in the context of general VSL guidance intended to apply across countries and policy types. The available information about cancer types in the primary studies included in the current analysis is moreover insufficient to provide a sufficient basis for such guidance. Other risk characteristics, e.g. traumatic vs chronic death and different risk types and causes, are not significant and robust in the meta-regression results presented in Section 5.3.

In conclusion, the meta-regression analysis and review of the literature above indicate that income (GDP per capita) is the only factor whose impacts are found to be statistically significant and robust across models and heterogenous global datasets. As such, the approach taken in this report is to adjust VSL estimates on the basis of income alone.

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Notes

[1] The difference between these two measures is marginal in practice (World Bank, 2025[54]; World Bank, 2025[55]).

[2] Note that this coefficient cannot be interpreted as elasticity because the income and VSL values are not log transformed.

[3] The covariate “Years since data collection” takes the value zero at 2022 and increases sequentially to reflect data collected in prior years.

[4] Certain factors, such as age and income, would be good candidates for their own systematic reviews, which is outside of the scope of this review.

[5] Newbold et al. (2024[5]) focuses on methodological issues to a greater extent, investigating a two-stage random effects meta-analysis model and alternative specifications, and does not provide VSL estimates per se. This analysis is referred to in Section 4.4 of Chapter 4 regarding meta-analysis approaches.

[6] This estimate is not directly comparable with the base value estimated for the United States in Section 4.5 of Chapter 4. One reason is the use of income adjustment of VSL estimates before deriving central tendency. Another is that the body of studies is much smaller and older.

[7] It is unclear whether other screening criteria (e.g. for outliers) are applied to studies for inclusion in the analysis.

[8] One reason for these relatively high values is likely to be that the authors adjust VSL estimates to 2020 proportionally with growth in real income (i.e. assuming an income elasticity of VSL of 1).

[9] While mean age of the main survey sample of some studies is reported in some cases, such information is typically not reported for subsamples used for sensitivity analyses from which VSL estimates are also derived.

[10] An outbreak of the severe acute respiratory syndrome (SARS) viral respiratory disease occurred between 2002 and 2004.

6 Recommended VSL estimates for policy analysis

This chapter presents recommended base VSL estimates and ranges for different country groups based on adjustments discussed in Chapter 5 and the econometric model discussed in Chapter 4. Base estimates are provided for the United States, the OECD, the European Union (EU), high-, low- and middle-income countries and at the global level. This chapter also provides guidelines for adjusting the base VSL estimates across countries and over time and discusses how to handle remaining uncertainty in the estimated values when applying them in specific policy settings. Finally, the chapter also provides considerations for future work and applications of the base VSL estimates.

6.1. Introduction

This chapter presents recommended value of statistical life (VSL) base estimates and ranges for use in policy assessments, programmes or projects involving changes in mortality risks. These VSL estimates reflect the existing empirical evidence regarding the trade-offs that individuals make between changes in mortality risks and changes in their income or wealth. The recommended VSL estimates are based on the mean preliminary unweighted VSL (PUVSL) estimates from the meta-analysis results reported in Section 4.5 of Chapter 4. Base estimates are provided for the United States, the OECD, the European Union (EU), as well as for high-, low- and middle-income countries[1]. This chapter also provides guidelines for adjusting the base VSL estimates across countries and over time and discusses how to handle remaining uncertainty in the estimated values when applying them in specific policy settings. Finally, considerations for future work and applications of the base VSL estimates are provided.

6.2. Recommended base values for policy analysis

The primary valuation studies and VSL estimates from the countries included in the meta-data for the current analysis are not necessarily representative of all the countries included in the country groups presented below. In fact, some countries are not represented with studies in the meta-data sample, an issue that is particularly pronounced when considering a global VSL estimate. In addition, the income levels (GDP per capita) under which each VSL estimate was derived were not harmonised before estimating average preliminary VSLs. As a result, the PUVSL estimates presented in earlier chapters must be adjusted for by differences between the income levels of the sample for each country group and the actual income levels for each country group.

The recommended VSL estimates may additionally need to be adjusted when evaluating changes in mortality risk of a specific policy in a specific country. There may also be specific rules or regulations in individual countries that necessitate modifications to the values and approaches presented in this report. The results reported in this chapter should therefore be viewed as a starting point for valuations that involve VSL.

To adjust the PUVSL estimates presented in Chapter 4 to reflect differences in income between the meta-data sample and the current income level of the country or country group, an income elasticity of 1 is recommended, based on results from the meta-regression analysis and literature review in Chapter 5. A population-weighted measure of GDP per capita for a country group *i* can then be calculated from the PUVSL estimates of Chapter 4 as:[2]

$$\text{Base VSL}_i = \text{PUVSL}_{Sample(i)} * \frac{\text{GDP}/Capita_{Population(i)}}{\text{GDP}/Capita_{Sample(i)}} \qquad \textbf{Equation 6.1}$$

Table 6.1 presents the recommended base VSL estimates and ranges for each group of countries based on the PUSVL estimates in Table 4.2 of Chapter 4 and the income information in Annex G.[3] Variation in the ranges reflect the size of the samples, but also the variation of VSL estimates within the respective country group samples. The estimated base VSLs are similar for high-income groups assessed, ranging from USD 7.1 million for OECD member countries to USD 8.5 million for the United States and USD 8.4 million for the EU. Note that Table 6.1, in addition to the mean base VSL, also presents a calculated median VSL. This value is calculated from the mean base VSL utilising OECD data on household income for 2022 (OECD, 2025). It is intended to provide an estimate of the VSL for a median income household, a measure that may be desirable for policy purposes. Across OECD countries, the median disposable household income is generally 10-20% below the mean household disposable income.

For each country group shown in Table 6.1, the base VSL estimate represents a population-weighted income adjustment that reflects population differences among countries and groups of countries rather than weighting every country equally. Practically, this means that the GDP per capita of more populous countries count more in the calculation of the weighted average base VSL for a group of countries. One area where this has a particularly pronounced effect is for the base VSL estimate for the world (Global) which is reduced from the preliminary unweighted meta-analysis results of USD 5.5 million, to USD 2.7 million, reflecting the lower global population-weighted GDP per capita compared to the sample GDP per capita in the meta-analysis.

Table 6.1. Population-weighted base VSL estimates and ranges

USD million

Country Group[1]	**Base VSL** (Mean)	**Base VSL** (Calculated Median[2])	**Range**[3] (95% Confidence Interval)
Global	2.7	2.2	1.9 – 3.6
OECD	7.1	6.1	5.4 – 8.8
EU	8.4	7.4	7.0 – 9.8
United States	8.5	6.8	6.4 – 10.5
High-income countries	7.9	6.8	6.4 – 9.6
Low- and middle-income countries	1.1	0.9	0.4 – 1.9

1. “Global” reflects a re-weighting of the full sample VSL estimate with the population-weighted mean GDP per capita across all countries. OECD reflects its 38 member countries as of 2025. EU refers to the 27 members of the European Union in 2025. The three World Bank income country categories are defined as: Low income (Gross National Income (GNI) per capita < USD 1 145), Lower-middle income (GNI per capita = USD 1 146 – 4 515) and Upper-middle income (GNI per capita = USD 4 516 – 14 005). Low-, lower-middle and upper-middle income categories are merged to form the category “Low- and middle-income countries” in order to have a sufficient number of studies to estimate the mean VSL with reasonable levels of uncertainty. “High-income countries” reflects countries with GNI per capita > USD 14 005). The GDP per capita values for the population and samples of the different country groups used for adjusting mean PUVSL estimates reported in Section 4.5 of Chapter 4 are available in Annex G.
2. The calculated median VSL is calculated based on the ratio between median and mean income in OECD countries based on OECD’s household income data for 2022, in which the median disposable income as a percentage of the mean was 88% for the European Union, 86% for OECD (also applied for High-income countries due to lack of specific data), and 80% for the United States (also applied for Global and Low- and middle-income countries due to a lack of specific data for these country groups).
3. Ranges are based on the 95% confidence intervals of the PUVSLs reported in Section 4.5 of Chapter 4.

In some circumstances it may be appropriate to use base VSL estimates that are adjusted by a country-weighted measure of GDP per capita instead of a population-weighted measure, which provides equal weight to each country in a given country group. Table 6.2 provides base VSL estimates that are adjusted using country-weighted GDP per capita. These estimates are relatively similar to those calculated on the basis of population-weighted GDP per capita in Table 6.1 for high-income country groups, ranging from USD 7.7 million for OECD Member Countries to USD 8.7 million for the EU. A comparison of the country- and population-weighted VSLs shown in Figure 6.1 indicates a larger discrepancy for the global country group than for other groups.

Table 6.2. Country-weighted base VSL estimates and ranges

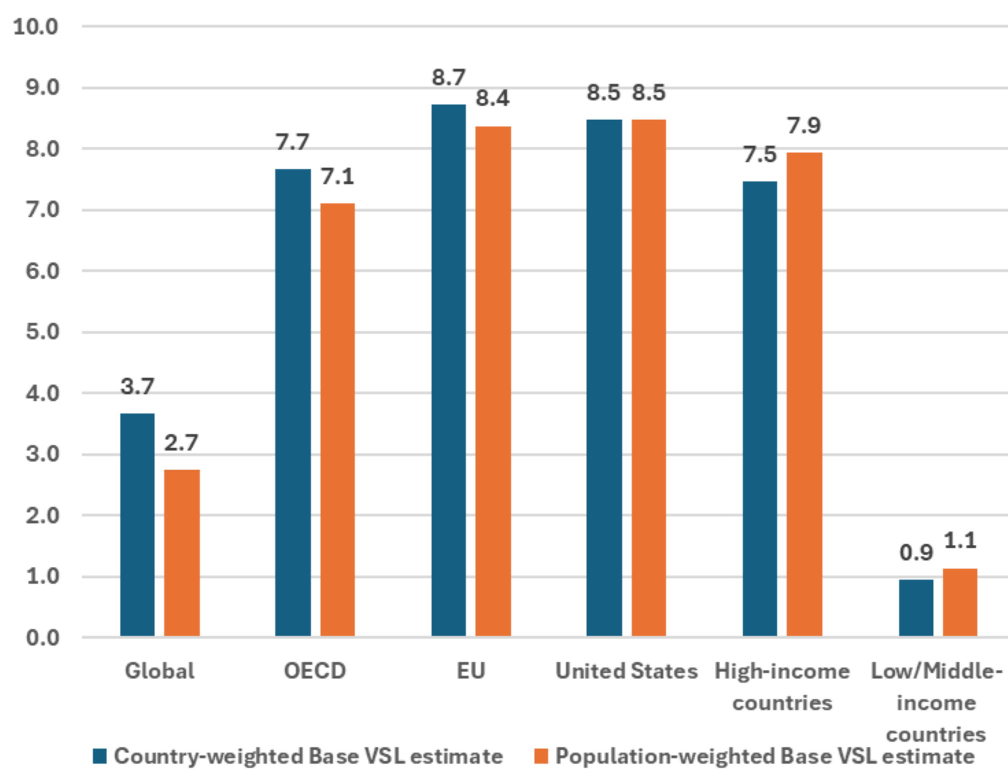
USD million

Country Group[1]	Base VSL (Mean)	Base VSL (Calculated Median[2])	Range[3] (95% Confidence Interval)
Global	3.7	3.0	2.5 – 4.8
OECD	7.7	6.6	5.8 – 9.5
EU	8.7	7.7	7.3 – 10.2
United States[5]	8.5	6.8	6.4 – 10.5
High income countries	7.5	6.5	6.0 – 9.0
Low- and middle-income countries[3]	0.9	0.7	0.3 – 1.6

1. "Global" reflects a re-weighting of the full sample VSL estimate with the country-weighted mean GDP per capita across all countries. OECD reflects its 38 member countries as of 2025. EU refers to the 27 members of the European Union in 2025. The three World Bank income country categories are defined as: Low income (Gross National Income (GNI) per capita < USD 1 145), Lower-middle income (GNI per capita = USD 1 146 – 4 515) and Upper-middle income (GNI per capita = USD 4 516 – 14 005). Low-, lower-middle and upper-middle income categories are merged to form the category "Low- and middle-income countries" in order to have a sufficient number of studies to estimate the mean VSL with reasonable levels of uncertainty. "High-income countries" reflects countries with GNI per capita > USD 14 005). The GDP per capita values for the population and samples of the different country groups used for adjusting mean PUVSL estimates reported in Section 4.5 of Chapter 4 are available in Annex G.
2. The calculated median VSL is calculated based on the ratio between median and mean income in OECD countries based on OECD's household income data for 2022, in which the median disposable income as a percentage of the mean was 88% for the European Union, 86% for OECD (also applied for High-income countries due to lack of specific data), and 80% for the United States (also applied for Global and Low- and middle-income countries due to a lack of specific data for these country groups).
3. Ranges are based on the 95% confidence intervals of the PUVSLs reported in Section 4.5 of Chapter 4.

Figure 6.1. Base VSL estimates (mean) and ranges by country group

USD million



Note: For details on the definition of each country group, see notes to Table 6.1.

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Note that in calculating the recommended base VSL estimates, no adjustment was made for factors other than income, as discussed in detail in Chapter 5. The VSL estimates are also based on SP and RP studies over the 2009-2023 period and are not randomly distributed across countries or regions. No adjustments were made for methods or for other factors that could potentially be "over- or under-represented" compared to an ideal "randomly drawn" evidence base[4]. This is, however, the nature of working with meta data. For example, it may be the case that certain countries have focused more on certain mortality risks in their VSL studies (e.g. air pollution) than other countries. As shown in this report, the choice of valuation approach (SP or RP) does not significantly influence the results, but the choice of types of individual SP and RP methods (HW, CM, CE and CV) and how these are distributed over time and across countries could potentially play a role in explaining differences in observed VSL estimates between countries and regions (cf Section 3.3 of Chapter 3 and Section 4.6 of Chapter 4) . Other aspects that are not captured in the meta-analysis and data likely also contribute to the observed differences, such as between the EU and the United States, despite the GDP per capita being significantly higher in the United States.

Box 6.1. Differences between OECD 2012 study and the current analysis

The base VSL estimates presented in this report differ from those reported in OECD (2012[1]) study in several ways and the results are therefore not directly comparable. The base recommendations in OECD (2012[1]) were USD_{2005} 3 million for OECD Member Countries (ranging from 1.5 to 4.5 million) and USD_{2005} 3.6 million for the EU (ranging from 1.8 to 5.4 million). Adjusted for inflation and real income growth over the 2005-2022 period, this translates to USD_{2022} 4.6 and 5.1 million for OECD Member Countries and the EU, respectively, as compared with USD_{2022} 7.1 and 8.4 million in the current analysis (Table 6.1). Several factors may explain the remaining difference in estimates:

- Difference in the meta-data used. In addition to encompassing far more primary VSL valuation studies than the 2012 report, several measures were taken in the current report to enhance the quality of the meta-data used for the analysis. First, the meta-data are subject to a more systematic review and screening procedure (see Section 3.1.3 of Chapter 3). Second, unlike the 2012 report, which includes only SP data, the current report includes both RP and SP data. Third, considering that the quality of scientific research improves over time, the current analysis focuses on the use of the new SP and RP data (2009-2023). As a result, the VSL estimates provided by the current analysis are based on an entirely different dataset than that used in 2012. Fourth, the analysis of the raw data is characterised by a more systematic approach for eliminating extreme outliers in the current analysis relative to that in 2012.
- Differences in the weighting procedure used for primary VSL estimates. In this report, the mean VSL estimates derived from primary valuation studies are treated as "observations", i.e. random draws, from a true but unknown underlying distribution of VSL estimates. To account for potential differences in the uncertainty of VSL estimates from different primary valuation studies, each VSL observation is weighted by its standard error. It is best practice in the meta-analysis literature to extract or estimate standard errors from primary studies when possible. This procedure serves to give VSL estimates with greater statistical certainty more weight than those with relatively less certainty in the calculation of mean VSL estimates.
- Improved empirical model. Following the weighting approach outlined above, the random effects model presented in Section 4.4.2 of Chapter 4 and the subsequent meta-regressions carried out in Chapter 5 provide a more accurate estimate of true underlying mean VSL estimates by accounting for i) sampling errors in individual VSL estimates, ii) differences in VSL estimates within studies, iii) differences in VSL estimates across studies and iv) differences in VSL estimates across elicitation methods.

- Differences in the measure of central tendency used for recommended VSL estimates. OECD (2012[1]) calculates the central moments of mean and median directly from the mean VSL estimates reported in primary valuation studies, and recommends a median value for use in policy analysis in order to account for possible skewness in the distribution of VSL estimates caused by high-value outliers. In contrast, the current analysis bases its policy recommendations on mean estimates of VSL, as estimated via a random effects model (cf. Section 4.4.2 of Chapter 4) that takes into account variation in primary VSL estimates at several levels, and eliminates extreme outliers in VSL estimates, as noted above. A calculated median value is offered as an estimate of the VSL for the median household based on OECD data on the difference between median and mean disposable household income.

6.3. Principles for use of base VSL estimates in policy assessments

6.3.1. National and international assessments

The base VSL estimates provided in Table 6.1 and Table 6.2 represent a starting point for the valuation of mortality effects. Adjustments may be appropriate to account for the type of policy or programme considered, as well as for the countries/populations involved. One key issue is whether to use a single VSL estimate to assess the mortality effects within a group of countries, or if different VSL estimates should be used across countries or populations, for example due to differences in income levels (GDP per capita).

The most common approach for valuing mortality impacts in international cost benefit analyses (CBA), as recommended in the research and policy guidance literature, is to apply *differentiated* VSL estimates to value policy-related impacts in different countries (Robinson et al., 2019[2]; USEPA, 2024[3]). This approach is motivated by the fact that GDP per capita is strongly correlated with willingness to pay for risk reductions[5]. The use of differentiated VSL estimates is the default approach recommended in this report.

The base VSL estimates for a given country *j*, which is a part of country group i (Equation 6.1), can be derived by scaling the base VSL estimate of the relevant country group by the ratio of the GDP per capita (2022 USD) of country *j* and that of the country group *i* following Equation 6.2.[6] As discussed in Chapter 5, an income elasticity of 1 is recommended based on the results of the current meta-analysis and a review of relevant literature.

$$\text{Base VSL}_j = \text{PUVSL}_{Sample(i)} * \frac{\text{GDP}/Capita_{Population(j)}}{\text{GDP}/Capita_{Sample(i)}} \quad \textbf{Equation 6.2}$$

Scaling the base VSL estimate as described above applies to both national and international studies[7]. There may be situations in which using differentiated VSL estimates in an international multi-country context may not be desirable, such as for policies that affect a more formally associated group of countries (e.g. the EU) and in the assessment of common policies based on shared analytical frameworks. In such situations, where each country typically has one vote, it could be considered more appropriate to use a single VSL estimate to assess impacts across countries within the country group. In the case of the EU, this could be the country-weighted base VSL estimate for the EU reported in Table 6.2. The implication of using a country-weighted base VSL estimate is that estimates from the more populous countries within the group are weighted equally as those with small populations. Another example of where a single VSL estimate could be considered is in the assessment of the benefits of the mortality risk reductions stemming from a policy that affects multiple countries, such as air pollution or climate change-related policies, e.g. Bressler (2021[4]) and Broome (2012[5])[8]. However, the most common approach to valuing the mortality impacts of climate change in integrated assessment models and in other climate impact studies (e.g. those using estimates of the social cost of carbon) remains the use of VSL estimates that are differentiated by country using the mean GDP per capita of each country (Carleton et al., 2022[6]; Rennert et al., 2022[7]; USEPA, 2024[3]; World Bank, 2024[8]).[9] Many of these studies use a VSL estimate from the United States as a basis for differentiation (Rennert et al., 2022[7]; World Bank, 2024[8]). It is recommended that estimates presented in this report be used in future studies as a basis for differentiation instead, as they reflect the best available global evidence. It is further recommended that the VSL estimate for the smallest country group to which a country belongs (e.g. for Portugal, the EU instead of the high-income country group) is used as a basis for calculating country-specific VSL estimates based on income differences following Equation 6.2.

6.3.2. Use of VSL estimates over time and other adjustments

In forward-looking CBAs of policy initiatives, benefits and costs accrue into the future. When using VSL estimates to assess such impacts, it is recommended that practitioners adjust the base VSL estimates to account for how they evolve over time. In a first step, this involves adjusting for inflation as well as for real annual growth in GDP per capita (applying an income elasticity of 1) as measured from 2022 to the year(s) for which the VSL is sought. Hence, if real GDP is expected to grow by 2% annually, the VSL estimate should also be expected to increase by 2% annually. In a second step, the monetised mortality benefits (or costs) should be discounted back to the year in which the CBA is being carried out in order to calculate the net present value of future costs and benefits, following best practice or standard guidance on the choice of discount rate from national or international CBA guidelines.

As supported by the meta-regression analysis (Section 5.3 of Chapter 5) and a review of the literature (Section 5.4 of Chapter 5), it is not recommended to adjust the base VSL estimates presented above for factors such as age, gender and the type of mortality risk considered. This applies to VSL estimates for country groups as well as for individual countries. As discussed in Section 5.4.6 of Chapter 5, although cancer was found in to have a significant effect on the VSL estimates in the meta-regression analysis, a “cancer premium” is difficult to operationalise due to the large variation of cancer types and relevant contexts. Other factors, such as placing a higher value on mortality risk impacts for children, or differentiating VSL estimates by age more generally, is also not recommended due to a lack of sufficiently robust evidence to justify such systematic treatment.

Note that there are private and public costs that are additional to the mortality valuation, such as the costs of treatments and hospitalisation that should be added to the VSL when estimating the total social value of preventing a fatality. Analysts should also be aware of the risk of double-counting of morbidity and mortality effects when aggregating health-related impacts in a given CBA.

While this report provides recommended base VSL estimates for use in policy assessment, there may be compelling reasons for making adjustments to the base VSL estimates beyond what is presented here to reflect specific policy and country contexts. Specific rules or regulations in individual countries may also necessitate adjustments that differ from what is presented here. Furthermore, to the extent there are primary studies available in a country, it may be preferrable to use these on their own as basis for a recommended domestic VSL estimate rather than to use the transfer procedures outlined here that draw on a larger evidence base from the group to which the country belongs. The two approaches could also be combined, e.g. for sensitivity analysis. Pros and cons of both approaches will need to be considered in the specific country situation (see also discussion in the next subsection).

6.3.3. Uncertainty and sensitivity analyses

The main underlying uncertainty of the base VSL estimates is reflected in the ranges around the mean estimates reported in Table 6.1 and Table 6.2, based on the meta-analysis confidence intervals. These ranges should be considered when adjusting base VSL estimates to specific policy or country contexts. In addition, it is good practice in CBA to investigate the sensitivity of CBA results to key assumptions, especially if the stakes are high or the estimated costs and benefits of a policy are of similar magnitude.

While it is clear that GDP per capita is strongly correlated with VSL, the measure remains a relatively crude measure of income, and the income elasticity of VSL can have a relatively large effect on VSL estimates across countries following Equation 6.2 above. The uncertainty involved in extrapolating VSL estimates across countries based on GDP per capita is particularly large for countries with very low and very high GDP per capita levels.

Furthermore, uncertainty remains regarding most appropriate values to use for the income elasticity of VSL, with studies indicating that the value could be higher for lower-income countries and lower for higher-income countries. It is therefore recommended to perform sensitivity analyses using an income elasticity of VSL value of 0.5 when extrapolating to individual countries within the high-income country group (e.g. from base VSL estimates for OECD Member Countries or the EU) and a value 1.5 when extrapolating to countries within the low- and middle-income country group[10]. This implies that the adjustment of the VSL estimates will be relatively lower for high-income countries compared to using the recommended default elasticity of 1. For transferring VSL estimates to countries in the low- and middle-income categories, using a higher elasticity would imply a larger adjustment of the VSL estimate, relative to using a default elasticity value of 1. Note that this implies that countries in the high-income country group will use VSL estimates closer to the mean of the group, while the opposite will be the case for countries in lower-income country groups.

Conducting sensitivity analysis using income elasticity estimates of 0.5 and 1.5 can also contribute to determining the extent to which VSL estimates for individual countries can be considered plausible. For example, for a country such as Luxembourg, which is characterised by a high GDP per capita relative to other countries, the calculated VSL estimate would be USD 19.2 million using the default assumption of an income elasticity of VSL of 1. Although this may be considered a relatively high number, there is little guidance in the literature to assess what should be considered high or low bounds on VSL estimates (or WTP more generally). Assessing the mean WTP as indicated by the VSL estimate as a share of GDP per capita or other income measures (e.g. median disposable income or household expenditures), could be a way to “ground truth” VSL estimates for individual countries. If WTP is unrealistically high (or low) compared to a reasonable measure of income or other expenditures, the VSL estimate may be considered implausible[11]. Considering the uncertainty of the estimates and the lack of firm guidance in the literature, however, it is difficult to formulate more detailed guidance on this issue.

Assuming an income elasticity of VSL of 0.5, for example, would reduce the VSL estimate for Luxembourg to a relatively more modest USD 12.1 million. In contrast, for a country such as Tanzania with a relatively low GDP per capita relative to other countries, the derived VSL estimate would be about USD 240 000 when assuming an income elasticity of VSL of 1, compared to ca. USD 127 000 when assuming an elasticity of 1.5. Again, assessing WTP against GDP per capita and other income measures could provide some perspective regarding the plausibility of the calculated VSL estimates for individual countries.

Less is known about the income elasticity of VSL over time than across countries and populations. It has become relatively standard to use an income elasticity of 1 to adjust VSL with projected growth in real GDP per capita for forward-looking analysis of policy proposals, and this is the approach taken in this report. The current analysis did not adjust VSL estimates taken from primary valuation studies for differences in income when compiling the meta-data for the meta-analysis. Instead, an adjustment for income is made after the meta-analysis to account for the difference between the GDP per capita in 2022 of the relevant country group and the income level reflected in the meta-data sample (see Equation 6.1). This approach follows USEPA SAB (2017, p. 5[9]), which argues that adjusting for income on the input-side of the meta-analysis “goes beyond any meta-analytic practices in the literature” and is a type of adjustment more appropriate as part of benefit transfer procedures when adjusting VSL into the future for CBA purposes. However, two examples of meta-analysis studies have used such adjustments recently (Banzhaf, 2022[10]; Ginbo, Adamowicz and Lloyd-Smith, 2023[11]). Hence, this issue appears to have yet to be fully resolved.[12]

In addition to the assumptions regarding the income elasticity of VSL, a number of other factors could be explored in sensitivity analyses of CBAs. For example, if analysts prefer to use specific quality criteria, which are coded in the dataset (see Chapter 4), they may wish to screen the data for distinct country groups before calculating new mean VSL estimates using the meta-analysis procedure outlined in Chapter 4. Sections 4.6 and 4.7 of Chapter 4, as well as Annex E provide VSL estimates calculated using various screening procedures. Since peer-reviewed journal publications may be of particular interest to some analysts, the mean VSL estimates for the meta-data screened on this basis are provided for illustrative purposes in Table A E.1 in Annex E.

6.4. Potential next steps using the results from this report

The VSL estimates derived in this report have many potential applications for assessing the benefits (costs) of policies involving reductions (increases) in mortality risks. Such applications can be found in the environment, transport, energy, food safety and health sectors. Geographically, the VSL estimates presented here are applicable at the local, national, as well as international and global levels. Local applications could include the assessment of health benefits from reducing air pollution in cities or reducing water pollution in certain lakes or rivers. National applications could involve valuing mortality effects from changing vehicle fuel standards, tailpipe emissions or water quality. International applications could include the assessment of common EU policies to increase food safety or to reduce cross-border pollution. At the global level, such estimates could be used to update current estimates of the social cost of greenhouse gases.

In addition to the more standard CBA of projects, programmes, or policies, the VSL estimates reported here could also be used in studies that estimate health costs of inaction or the total mortality costs of certain problems (e.g. traffic planning assessments or for certain diseases). Such assessments can, moreover, be forward- or backward-looking. Analyses of the effects of previously implemented policies can be highly informative, such as the ex-post analysis of the Clean Air Act in the United States. The VSL estimates presented here can also be applied to the valuation of environmental and health impacts in corporate green metrics as part of the social costs of emissions from various sources impacting a company’s products and supply chains.

For all such analyses, morbidity impacts should be valued separately and added to the mortality costs, both for morbidity prior to premature death and for non-fatal health outcomes resulting from the policy under evaluation. The updated evidence provided here on how people across countries value mortality risks constitutes an important basis for better-informed and more efficient policy decisions in the future.[13]

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Notes

[1] Based on country categories defined by the World Bank.

[2] Since the meta-analysis model takes account of the varying number of VSL estimates from individual studies, the mean GDP per capita at the study level for each country group is used to calculate the sample mean GDP per capita.

[3] Since estimated mean VSL from Table 4.2 of Chapter 4 is multiplied by a constant reflecting the difference in GDP per capita between the sample and the population, the confidence intervals for the values in Table 6.1 are also derived multiplying the confidence intervals in Table 4.2 by the same constant.

[4] Other than the uncertainty of estimates (standard errors) and that there are more estimates from some studies. These factors are accounted for in the meta-analysis.

[5] While other income measures can be used, such as Gross National Income (GNI), the impact of doing so is marginal in practice (World Bank, 2025[12]).

[6] Note that this is equivalent to directly multiplying mean VSL for group *i* from the meta-analysis in Chapter 4 and in Equation 6.1 by the ratio of GDP per capita for country *j* to GDP per capita in the sample of country group *i*.

[7] Note that a discontinuity will exist at the boundary between high-income and low- or middle-income countries. For a hypothetical country with a GDP per capita of USD 13 485, the VSL estimate would be USD_{2022} 1.7 million if the country is considered to be in the high-income country group and USD_{2022} 1.1 million if considered to be in the low- or middle-income country group. In such cases, a smoothing procedure, e.g. based on interpolation (i.e. the average between 1.7 and 1.1 million = 1.4 million) could be employed.

[8] Bressler (2021[4]) references Broome (2012[5]) when discussing ethical arguments in supplementary material.

[9] There is an ongoing discussion in research and policy circles regarding whether so-called equity weighting should be used in national and international policy assessments. Equity weighting refers to the practice of weighting the benefits or costs for disadvantaged groups (e.g. lower-income groups) more heavily in a single measure that combines both welfare (efficiency) and distributional equity. There appears to be no agreement regarding the rationale or usefulness of this approach, as well as how it should be implemented in practice. As a result, equity weighting is not considered here. More discussion on this matter is provided in in e.g. Viscusi (2024[13]), Prest et al. (2024[14]), Sunstein (2023[15]) and Acland and

Greenberg (2023[16]), as well as other papers from the 2023 Symposium on Equity Issues in Cost-Benefit Analysis published in the Journal of Benefit-Cost Analysis.

[10] 1.5 is recommended by e.g. Robinson et al. (2019[17]) when transferring VSL estimates to lower-income countries.

[11] This approach is described in e.g. Robinson et al. (2019[2]).

[12] In a "meta-analysis of meta-analyses" Banzhaf (2022[10]) finds that not adjusting the data in this way in preparation for the meta-analysis (i.e. by assuming an income elasticity of VSL of zero between the year of the primary valuation study and the year of the meta-analysis, the same approach as is taken in this report), reduced the mean VSL estimate found in the study from USD_{2019} 8 million to 7.1 million (about 11%), relative to making such adjustments and assuming an income elasticity of VSL of 1. For interested analysts, it is possible to investigate the sensitivity of VSL estimates when making such income adjustments back in time, using the dataset accompanying this report.

[13] Based on the findings of this meta-analysis, the OECD aims to publish a simple online tool to enable practitioners to develop differentiated VSL estimates to assess the costs and benefits of policies with mortality implications across nations, which will include options for analysts to validate any assumptions they may wish to make.

Annex A. Systematic review procedure

Description

The objective of the review is to collect all existing studies that provide a primary estimate of the value of statistical life (VSL). Under this criterion, both stated preference (SP) and revealed preference (RP) studies that are published in English and that report original VSL estimates based on primary data anywhere in the full text are considered. The systematic review follows the PRISMA 2020 guideline (Page et al., 2021[1]).

Identification

The databases used to build the meta database include the Web of Science, Econlit, and PubMed for full-text publications of all document types written in English published between January 1, 2009, and December 31, 2023.

The search terms used to identify publications include “VSL,” “VoSL,” “value of statistical life,” “value of a statistical life,” “willingness to pay for mortality risk reduction,” “value of prevented fatality,” “VPF,” “value of risk reduction,” “value of reduced mortality risk,” “VRMR,” “value of a mortality risk reduction” and “value of a life year.” The exact combination of query terms is shown below:

- WoS & Econlit
  - "VoSL" OR "value* of statistical li*" OR "value* of a statistical li*" OR "willingness to pay for mortality risk reduction*" OR "value* of a prevented fatality "OR "value* of prevented fatalit*" OR "value* of risk reduction*" OR "value* of reduced mortality risk*" OR "VRMR" OR "value of a life year" OR "value of a mortality risk reduction" OR "value* of mortality risk reduction*" OR "value* per statistical life" OR (("VSL" OR "VPF" OR "statistical li*") AND ("WTP" OR "willingness to pay" OR "WTA" OR "willingness to accept" OR "human capital" OR "stated preference" OR "revealed preference" OR "CVM" OR "hedonic" OR "CE" OR "contingent valuation" OR "choice experiment*" OR "wage differential*"))
- PubMed
  - "VoSL" OR "value of statistical li*" OR "value of a statistical li*" OR "value of risk reduction*" OR "VRMR" OR "value of a life year" OR "value of mortality risk reduction*" OR "value* per statistical life" OR (("VSL" OR "VPF" OR "statistical li*") AND ("WTP" OR "willingness to pay" OR "WTA" OR "willingness to accept" OR "human capital" OR "stated preference" OR "revealed preference" OR "CVM" OR "hedonic" OR "CE" OR "contingent valuation" OR "choice experiment*" OR "wage differential*"))

In a first step, all studies reporting VSL estimates regardless of their method were identified. In a second step, these studies were screened in order to only keep SP and RP studies that report original VSL estimates. Next, the reference lists of all selected studies were cross-checked with previous meta-analyses and review articles to identify additional relevant studies. Finally, selected group of economists with extensive experience in VSL studies reviewed the resulting list of VSL studies for potential missing work which resulted in several added studies.

Selection

To be eligible for inclusion in the meta-analysis, a publication had to be an original research study written in English using an SP or an RP method to elicit VSL estimates. This selection criterion excluded any article that did not include primary VSL estimates, that was not written in English, and any articles that used previously reported values to estimate the VSL, such as the value transfer method or meta-regression analysis. After removing these, the authors screened the full text of the remaining studies.

Hypothesis

Collected studies reveal global variation in observed VSL estimates regarding countries, time, methodology, and scope characteristics. The original study's quality, value elicitation method, sample and population characteristics and risk types are considered.

References

Page, M. et al. (2021), "PRISMA 2020 explanation and elaboration: Updated guidance and exemplars for reporting systematic reviews", *The BMJ*, Vol. 372, https://doi.org/10.1136/BMJ.N160. [1]

Annex B. USD$_{2022}$ conversion procedure for VSL and GDP

Conversion procedure for VSL (aligned with the OECD 2012 Study):

All VSL estimates included in the meta database were converted to 2022 USD, using inflation data and PPP currency exchange rates data from the OECD National Accounts statistics. If VSL estimates from a non-U.S. country were expressed (only) in USD instead of the relevant national currency, estimates are first converted back to the national currency, using the exchange rates indicated in the article, and then adjusted for inflation and converted back to 2022 USD as described above. The conversion formula for the currency/country i in year t is:

$$VSL_{2022,Int\$} = VSL_{t,\,i} \times \frac{CPI_{2022,i}}{CPI_{t,\,i}} \times \frac{PPP_{2022,Int\$}}{PPP_{2022,i}} \qquad \text{Equation A B.1}$$

About 30 non-US studies reported their VSL estimates in USD, and four non-EUR country studies reported their VSL estimates in EUR. For these studies, estimates are first converted back to the national currency, using the exchange rates indicated in the article, and then adjusted for inflation and converted back to 2022 USD as described above. For three studies that reported single VSL estimates from four countries, the average CPI of four countries for adjusting inflation is used.

Procedure for GDP

The conversion process of GDP per capita – used as a proxy for income in the country in which a VSL study has been conducted – follows the same formula as for VSL. First, the nominal GDP of the country - in national currency and from the same year of the VSL study - is divided by the population of the country in that same year to calculate a GDP per capita figure for the country. Then, this GDP per capita figure is adjusted to 2022 price level using national CPI and then converted to international dollars using PPP exchange rates. Note that whether Gross National Income (GNI) or GDP is used as a proxy measure is not important as these two measures follow each other very closely[1].

Note

[1] GNI measures the total income earned by residents of a country, including income earned abroad, while GDP instead counts only income generated from goods and services produced domestically. These two measures follow each other very closely (see, for example, GNI per capita vs. GDP per capita, 2022).

Annex C. Descriptive statistics of VSL and coded variables

The four tables below provide full descriptive statistics for the VSL estimates reported in Section 3.3 of Chapter 3 on the estimate and study levels, including (Table A C.1 and Table A C.3) and excluding far-outs (Table A C.2 and Table A C.4).

Descriptive statistics of VSL estimates at the estimate level

Table A C.1. Summary statistics for VSL estimates at the estimate level

VSL estimates in USD million, including far-outs

Datasets	N Estimates	Mean	SD	Q25	Q50	Q75	Min	Max	N Studies
New SP	1027	60.8	1627.9	1.3	5.1	10.9	-0.9	52162	99
New RP	1470	8.6	19.6	0.8	4.2	11.2	-89.6	378	55
Old SP	917	12.9	31.3	1.3	4.2	11.0	0.0	307.2	72
Old RP	694	15.3	21.9	4.5	12.0	21.0	-83.0	173	51
Subtotal SP	1944	38.2	1183.3	1.3	4.7	11.0	-0.9	52162	171
Subtotal RP	2164	10.8	20.6	1.1	6.3	14.1	-89.6	378	106
Subtotal *New*	2497	30.1	1044.1	0.9	4.6	11.2	-89.6	52162	154
All	4108	23.8	814.2	1.2	5.3	12.7	-89.6	52162	277

Note: New SP and New RP studies refer to Stated Preferences and Revealed Preferences studies published in the period 2008-2023. Old SP and Old RP studies refer to Stated Preferences and Revealed preferences studies published in the period 1970-2008.

Table A C.2. Summary statistics for VSL estimates at the estimate level

VSL estimates in USD million, far-outs excluded

Datasets	N Estimates	Mean	SD	Q25	Q50	Q75	Min	Max	N Studies	% Far-outs
New SP	1013	7.3	7.8	1.2	4.9	10.6	-0.9	46.9	99	1.4%
New RP	1436	6.5	7.9	0.8	4.0	10.9	-21.7	45.8	55	2.3%
Old SP	861	6.8	8.0	1.2	3.8	9.0	0.0	45.9	71	6.1%
Old RP	653	12.9	11.9	4.2	11.4	19.0	-29.6	47.2	51	5.9%
Subtotal SP	1874	7.1	7.9	1.2	4.4	9.9	-0.9	46.9	170	3.6%
Subtotal RP	2089	8.5	9.8	1.0	5.8	13.3	-29.6	47.2	106	3.5%
Subtotal New	2449	6.9	7.9	0.9	4.4	10.8	-21.7	46.9	154	1.9%
ALL	3963	7.8	9.0	1.1	5.0	12.0	-29.6	47.2	276	3.5%

Note: New SP and New RP studies refer to Stated Preferences and Revealed Preferences studies published in the period 2009-2023. Old SP and Old RP studies refer to Stated Preferences and Revealed preferences studies published in the period 1970-2008.

Descriptive statistics of VSL estimates at the study level

Table A C.3. Summary statistics for VSL estimates at the study level

VSL estimates in USD million, including far-outs

Datasets	N Studies	Mean	SD	Q25	Q50	Q75	Min	Max
New SP	99	26.1	177.5	1.0	4.6	7.8	0.0	1751
New RP	55	11.1	16.2	1.7	6.6	13.8	0.1	109
Old SP	72	11.6	24.5	2.0	4.6	9.6	0.0	163
Old RP	51	12.1	13.7	5.1	10.3	17.1	-32.6	68
Subtotal SP	171	20.0	135.9	1.3	4.6	8.4	0.0	1751
Subtotal RP	106	11.6	15.0	3.2	8.6	15.7	-32.6	109
Subtotal *New*	154	20.8	142.5	1.3	5.1	9.2	0.0	1751
ALL	277	16.8	107.1	1.7	5.7	11.0	-32.6	1751

Note: New SP and New RP studies refer to Stated Preferences and Revealed Preferences studies published in the period 2009-2023. Old SP and Old RP studies refer to Stated Preferences and Revealed preferences studies published in the period 1970-2008.

Table A C.4. Summary statistics for VSL estimates at the study level

VSL estimates in USD million, far-outs excluded

Datasets	N Estimates	Mean	SD	Q25	Q50	Q75	Min	Max	% Far-outs
New SP	99	5.3	5.6	1.0	4.6	7.7	0.00	29.6	0.0%
New RP	55	8.1	7.1	1.7	6.6	12.8	0.05	37.4	0.0%
Old SP	71	6.4	5.9	1.9	4.6	9.5	0.02	22.1	1.4%
Old RP	51	11.3	6.9	6.0	10.3	17.1	0.73	30.0	0.0%
Subtotal SP	170	5.8	5.7	1.3	4.6	8.1	0.00	29.6	0.6%
Subtotal RP	106	9.6	7.1	3.7	8.6	14.0	0.05	37.4	0.0%
Subtotal *New*	154	6.3	6.3	1.3	5.0	8.7	0.00	37.4	0.0%
ALL	276	7.2	6.6	1.8	5.7	10.4	0.00	37.4	0.4%

Note: New SP and New RP studies refer to Stated Preferences and Revealed Preferences studies published in the period 2009-2023. Old SP and Old RP studies refer to Stated Preferences and Revealed preferences studies published in the period 1970-2008.

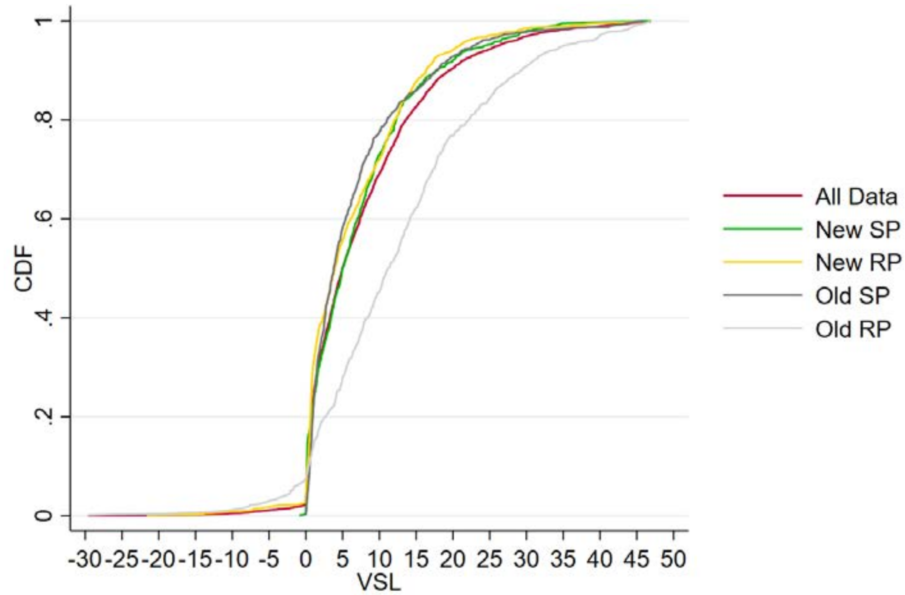
Cumulative distribution functions (CDF) of VSL estimates

A CDF is defined as the probability (Y-axis) that a random variable X, in this case a VSL estimate, will take a value less than or equal to x (X-axis).

Figure A C.1 and Figure A C.2 show the cumulative distribution functions for the four datasets and specific RP and SP methods, respectively. As can be seen from Figure A C.1, the distributions of Old SP, New SP and New RP follow each other relatively closely, while the cumulative distribution function (CDF) of the Old RP data has a more right-skewed distribution. Figure A C.2 shows that CM studies and CM and HW have relatively different distributions, while the CDFs of the SP methods (CE and CV) are located between the two RP methods.

Figure A C.1. Cumulative distribution function (CDF) of VSL estimates per dataset

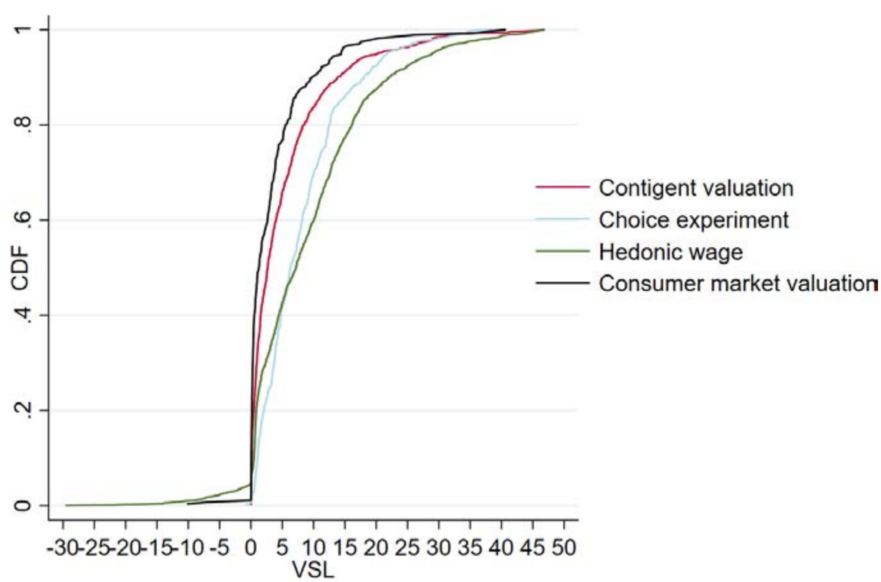
VSL estimates in USD million, far-outs excluded



Note: New SP and New RP studies refer to Stated Preferences and Revealed Preferences studies published in the period 2009-2023. Old SP and Old RP studies refer to Stated Preferences and Revealed preferences studies published in the period 1970-2008.

Figure A C.2. Cumulative distribution function (CDF) for VSL estimates per specific methods

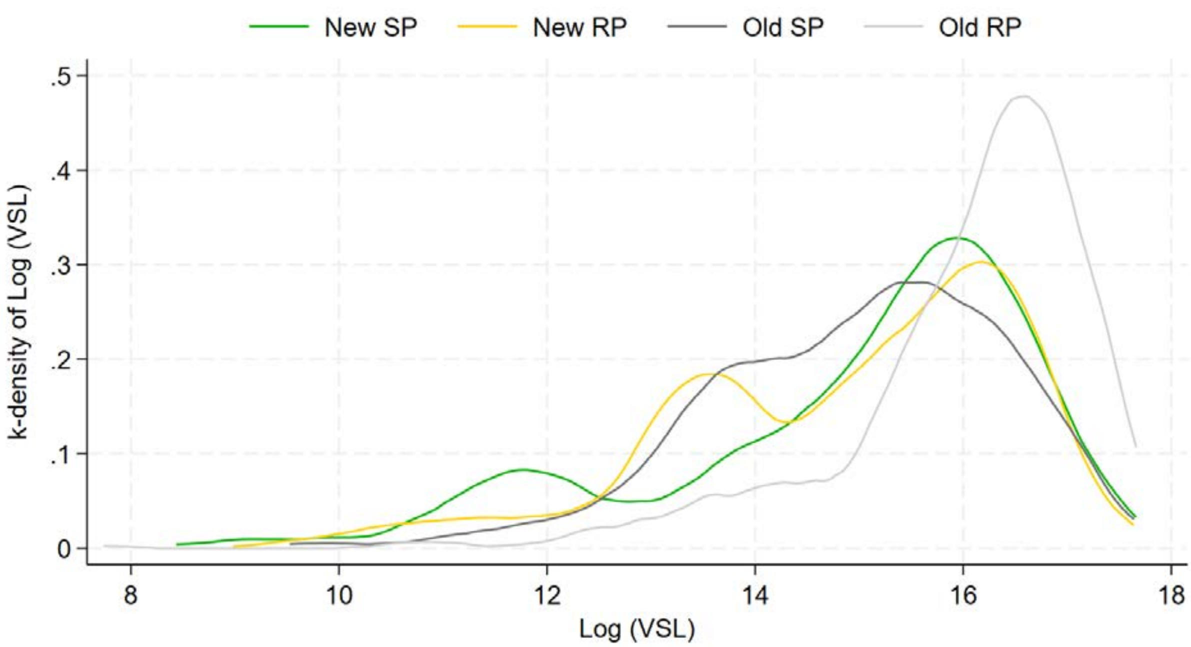
VSL estimates in USD million, far-outs excluded



Log-distribution of VSL for the different datasets

Figure A C.3 shows the statistical distributions for the natural logarithm of VSL estimates for the four datasets. It shows that the Old RP data follows a distribution that is somewhat different compared to the other three datasets.

Figure A C.3. Statistical distribution of log(VSL), by data source



Note: Study Level = Weighted by the inverse of the number of estimates from each study. Outliers ("far-outs") are excluded, defined as $\notin [Q25 - 3(Q75 - Q25), Q75 + 3(Q75 - Q25)]$. VSL estimates are expressed in 2022 USD. New SP and New RP studies refer to Stated Preferences and Revealed Preferences studies published in the period 2009-2023. Old SP and Old RP studies refer to Stated Preferences and Revealed preferences studies published in the period 1970-2008.

Descriptive statistics of coded variables

Table A presents the mean and number of estimates (N) for coded variables for the four datasets. These variables are divided into six categories:

- Article information and estimates
- Country characteristics
- Risk types by cause (including cancer if mentioned in the study, and acute, chronic or mixed risk)
- Elicitation methods (how data is derived, specific SP or RP method)
- Sample data characteristics
- Methodological characteristics (some of which may be related to quality of the study)

Table A C.5. Coded variables, mean and number of observations (N) for the four datasets

	All data		New RP and SP		New SP		New RP		Old SP		Old RP	
	Mean	N	Mean	N	Mean	N	Mean	N	Mean	N	Mean	N
Article information and estimates												
Journal	0.69	4108	0.71	2 517	0.74	1027	0.69	1470	0.40	917	1.00	694
Publication Year	2010	4108	2016	2 517	2015	1027	2017	1470	2004	917	1998	694
Year of VSL estimate	2004	4108	2009	2 517	2010	1027	2009	1470	2000	917	1989	694
VSL estimates (2022 USD million)	23.76	4108	30.1	2 517	60.81	1027	8.55	1470	12.91	917	15.30	694
Standard errors of VSL estimates (2022 USD million)	14.62	4108	17.14	2 517	31.15	1027	7.32	1470	8.02	917	14.25	694
Country characteristics												
G7	0.61	4108	0.61	2 517	0.40	1027	0.75	1470	0.36	917	0.93	694
EU	0.19	4108	0.19	2 517	0.41	1027	0.04	1470	0.30	917	0.01	694
EEA	0.20	4108	0.2	2 517	0.43	1027	0.04	1470	0.33	917	0.01	694
OECD	0.81	4108	0.79	2 517	0.77	1027	0.81	1470	0.72	917	0.97	694
USA	0.40	4108	0.43	2 517	0.13	1027	0.64	1470	0.07	917	0.75	694
WB (High-income countries)	0.83	4108	0.83	2 517	0.76	1027	0.87	1470	0.73	917	0.97	694
WB (Upper-middle income countries)	0.05	4108	0.05	2 517	0.08	1027	0.04	1470	0.07	917	0.01	694
WB (Low-middle income countries)	0.09	4108	0.08	2 517	0.16	1027	0.04	1470	0.18	917	0.00	694
WB (Low-income countries)	0.03	4108	0.03	2 517	0.00	1027	0.05	1470	0.02	917	0.01	694
GDP per capita (thousands of 2022 USD)	47.0	4108	50.62	2 517	46.56	1027	53.46	1470	36.67	917	47.60	694
Risk types based on causes												
Climate	0.03	3413	0.04	2 516	0.08	1026	0.02	1470	0.00	917	.	.
Crime	0.00	3413	0	2 516	0.01	1026	0.00	1470	0.00	917	.	.
Disaster	0.01	3413	0.01	2 516	0.01	1026	0.01	1470	0.00	917	.	.
Environment	0.08	3413	0.05	2 516	0.06	1026	0.04	1470	0.17	917	.	.
Health	0.31	3413	0.24	2 516	0.49	1026	0.06	1470	0.49	917	.	.
Job	0.26	3413	0.36	2 516	0.00	1026	0.61	1470	0.00	917	.	.
Military	0.08	3413	0.12	2 516	0.00	1026	0.20	1470	0.00	917	.	.
Natural Disaster	0.04	3413	0.06	2 516	0.14	1026	0.00	1470	0.00	917	.	.
Not Specified	0.00	3413	0	2 516	0.00	1026	0.00	1470	0.00	917	.	.
Suicide	0.00	3413	0	2 516	0.00	1026	0.00	1470	0.00	917	.	.
Transportation	0.16	3413	0.1	2 516	0.16	1026	0.05	1470	0.35	917	.	.
Virus	0.02	3413	0.03	2 516	0.05	1026	0.01	1470	0.00	917	.	.
Cancer (if addressed in the paper)												
Cancer	0.22	3326	0.26	2 429	0.47	1003	0.11	1406	0.12	917	.	.
Risk acuteness												
Acute	0.39	1874	0.39	1 894	0.66	498	0.29	1376	.	.	.	.
Chronic	0.13	1874	0.13	1 894	0.32	498	0.07	1376	.	.	.	.
Mixed/job-related	0.47	1874	0.47	1 894	0.00	498	0.64	1376	.	.	.	.

Elicitation methods												
Consumer Market valuation method	0.07	4108	0.11	2 517	0.00	1027	0.19	1470	0.00	917	0.00	694
Hedonic Wage method	0.46	4108	0.48	2 517	0.00	1027	0.81	1470	0.00	917	1.00	694
Contingent Valuation method	0.27	4108	0.2	2 517	0.49	1027	0.00	1470	0.67	917	0.00	694
Choice Experiment	0.15	4108	0.2	2 517	0.48	1027	0.00	1470	0.13	917	0.00	694
Other SP method	0.05	4108	0.01	2 517	0.02	1027	0.00	1470	0.20	917	0.00	694
Sample data characteristics												
Average sample income (USD thousand)	44.3	2676	45.37	1 457	53.3	563	40.3	879	35.5	540	49.0	694
Disposable household income	0.31	2660	0.34	1 441	0.71	492	0.15	934	0.60	540	0.00	694
Nationwide	0.63	3297	0.71	2 400	0.4	910	0.90	1470	0.41	917	.	.
General Population	0.66	3264	0.56	2 367	0.86	877	0.39	1470	0.92	917	.	.
Representative sample	0.57	3199	0.58	2 302	0.74	812	0.50	1470	0.55	917	.	.
Sample Average Age	41.6	2325	39.53	2 372	44.6	548	37.1	1165	47.4	612	.	.
Only male	0.20	4108	0.19	2 372	0.00	1027	0.32	1470	0.01	917	0.47	694
Only female	0.06	4108	0.06	1 728	0.04	1027	0.08	1470	0.03	917	0.09	694
Methodological characteristics												
% of SP studies with representative sample	0.64	1729		829	0.74	812	.	.	0.55	917	.	.
% of SP studies including baseline risk of respondents	0.65	1919		1 019	0.67	1002	.	.	0.62	917	.	.
% of SP studies focusing on scope sensitivity	0.66	1925		1 025	0.61	1008	.	.	0.72	917	.	.
% of SP studies using visual aids	0.71	1943		1 043	0.65	1026	.	.	0.78	917	.	.
% of RP studies using Census of fatal occupational injuries (CFOI) data	0.48	2164		801	.	.	0.49	1470	.	.	0.46	694
% of RP studies using IV estimates	0.14	2123		1 473	.	.	0.16	1429	.	.	0.10	694
% of RP studies controlling for non-fatal injury risks	0.35	2164		1 432	.	.	0.29	1470	.	.	0.47	694
% of Hedonic wage RP studies	0.10	2164		1 473	.	.	0.10	1470	.	.	0.12	694

Note: New SP and New RP studies refer to Stated Preferences and Revealed Preferences studies published in the period 2009-2023. Old SP and Old RP studies refer to Stated Preferences and Revealed preferences studies published in the period 1970-2008.

Annex D. Procedure for imputation of standard errors of VSL estimates

Table A D.1 displays estimates of standard errors (SE) of the reported VSL estimates required to use the meta-analysis approach presented in Chapter 4. As can be seen from Table A D.1, only a fraction of the studies reports these. If not reported, the standard error can be estimated based on information about reported confidence intervals (CI)[1]. If this information is also not available, it is also possible to impute this information, for example based on information about sample size and relationship with standard errors reported by the other studies. There are a number of options for imputation in the literature (Viscusi, 2019[1]). In this study a Bayesian imputation method is used to recover missing SE error estimates.

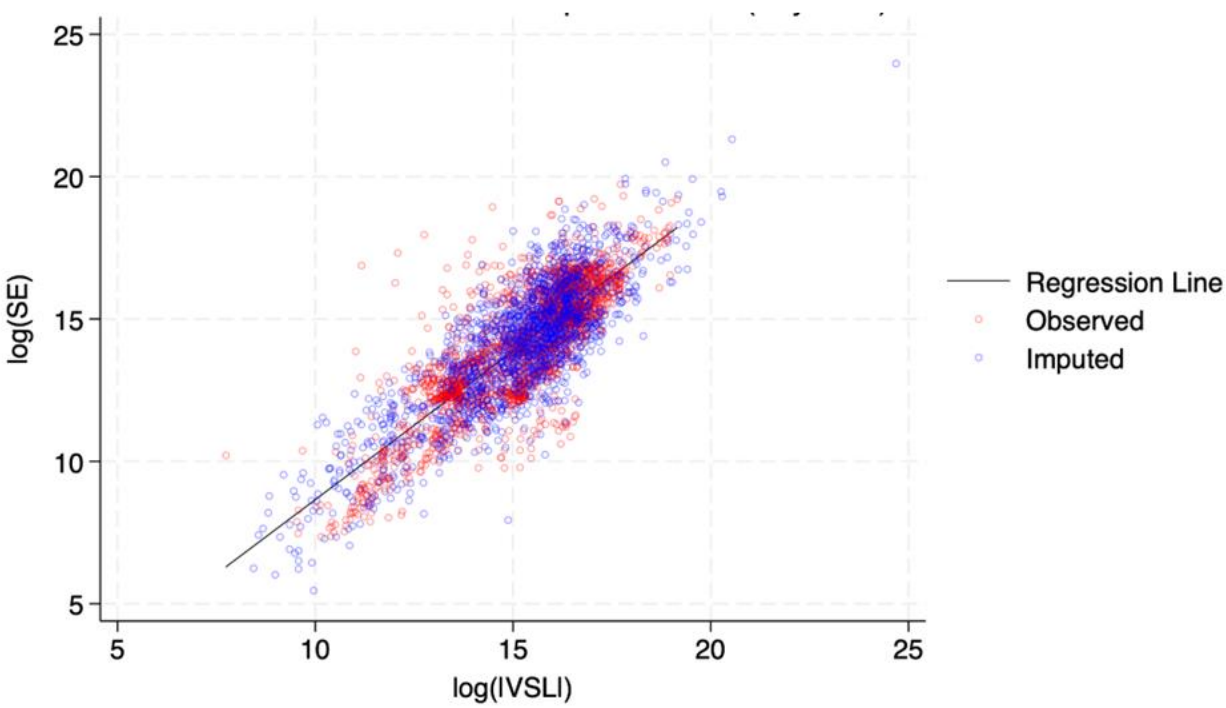
Following the Bayesian imputation method and based on the cumulative distribution function (CDF) of the VSL estimates, the standard errors (SEs) of VSL estimates are assumed to be randomly missing. Therefore, observed information is used to impute the missing SEs. Information on the observed 2 474 SEs is used to impute the missing 1 634 SEs by fitting Bayesian models (McElreath, 2018[2]). The estimation for each model is based on four parallel Markov chains sampled by the No-U-Turn Sampler (NUTS), and each chain has 2 000 draws with 2 000 iterations to tune. A simple Bayesian linear regression model is used where the mean of the $log(SE)$ is assumed to be a linear function of the only regressor $log(|VSL|)$. Figure A D.1 shows that this method yields imputed SE values that closely follow the observed values and is therefore considered a valid approach.

Table A D.1. Standard errors (SE) or confidence intervals (CI) reported in the different datasets

	New SP	New RP	Old SP	Old RP	Total
SE or CI reported	541	960	411	562	2474
SE reported	367	208	411	562	1548
CI reported	174	752	0	0	926
SE Imputed	486	510	506	132	1634
Total	1027	1470	917	694	4108
% SE Imputed	47.3%	34.7%	55.2%	19.0%	40.0%

Note: All data, including far-outs. New SP and New RP studies refer to Stated Preferences and Revealed Preferences studies published in the period 2009-2023. Old SP and Old RP studies refer to Stated Preferences and Revealed preferences studies published in the period 1970-2008.

Figure A D.1. Observed vs. imputed standard errors (SE) using Bayesian imputation method



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McElreath, R. (2018), "Statistical rethinking: A bayesian course with examples in R and stan", *Statistical Rethinking: A Bayesian Course with Examples in R and Stan*, pp. 1-469, https://doi.org/10.1201/9781315372495/STATISTICAL-RETHINKING-RICHARD-MCELREATH/ACCESSIBILITY-INFORMATION. [2]

Viscusi, W. (2019), "Risk guideposts for a safer society: Introduction and overview", *Journal of Risk and Uncertainty*, Vol. 58/2-3, pp. 101-119, https://doi.org/10.1007/S11166-019-09307-3/TABLES/3. [1]

Note

[1] Calculations based on reported CI: $SE = \frac{CI_{0.95U} - CI_{0.95L}}{3.91992796080108}$, where U is Upper bound and L is Lower bound.

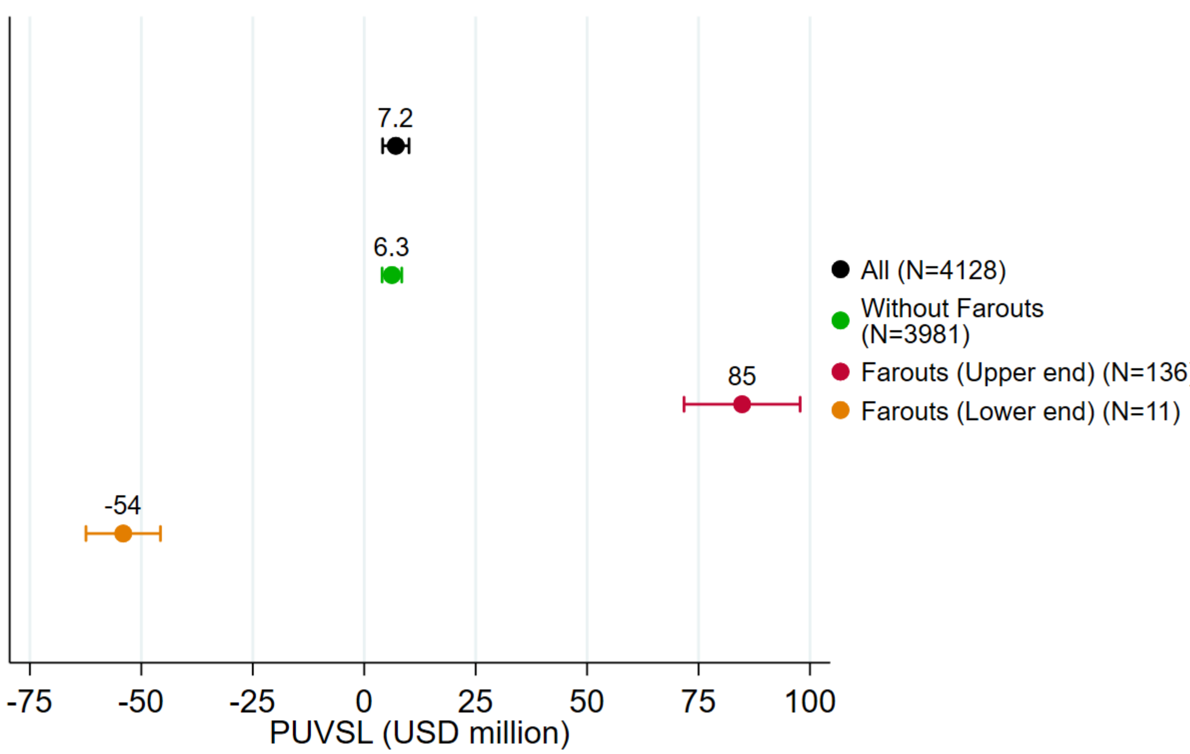
Annex E. Additional sensitivity analysis and robustness checks for meta-analysis

Description and test of far-outs (outliers)

As discussed in Section 3.3 of Chapter 3 and 4.3.2 of Chapter 4 a standard outlier exclusion procedure from statistics is chosen to avoid the influence of implausibly high or low VSL estimates. In the general meta-analysis literature, it is often justified to remove an observation that is defined as an outlier in the sense that the upper bound of the 95% confidence interval of the estimate is lower than the lower bound of the pooled mean 95% confidence interval (i.e., extremely small estimates) or the lower bound of the 95% confidence interval is higher than the upper bound of the pooled mean 95% confidence interval (i.e., extremely large estimates) (Viechtbauer and Cheung, 2010[1]).

Figure A E.1 shows the 95% intervals of the meta-analysis estimates using (1) all pooled estimates (N=4 128), (2) the main estimates after removing far-outs (N=3 981), (3) the upper far-out estimates (N=136) based on Tukey's fences, and (4) the lower far-out estimates (N=11). These results indicate that the removal of far-out observations is very conservative and well justified by common practice (Viechtbauer and Cheung, 2010[1]). In fact, the lower bound of the upper far-out is much higher than the upper bound of the pooled estimates ("All") and the upper bound of the lower far-out is much lower than the lower bound of the pooled estimates ("All") (cf. Section 4.3.1 of Chapter 4).

Figure A E.1. Mean and confidence bands of far-outs (outliers) compared to all data



Note: "Far-outs (Upper end)" (Lower end) are far-out estimates removed from the main analysis ("Without Far-outs") because they exceed/are inferior to the far-out upper (lower) threshold.

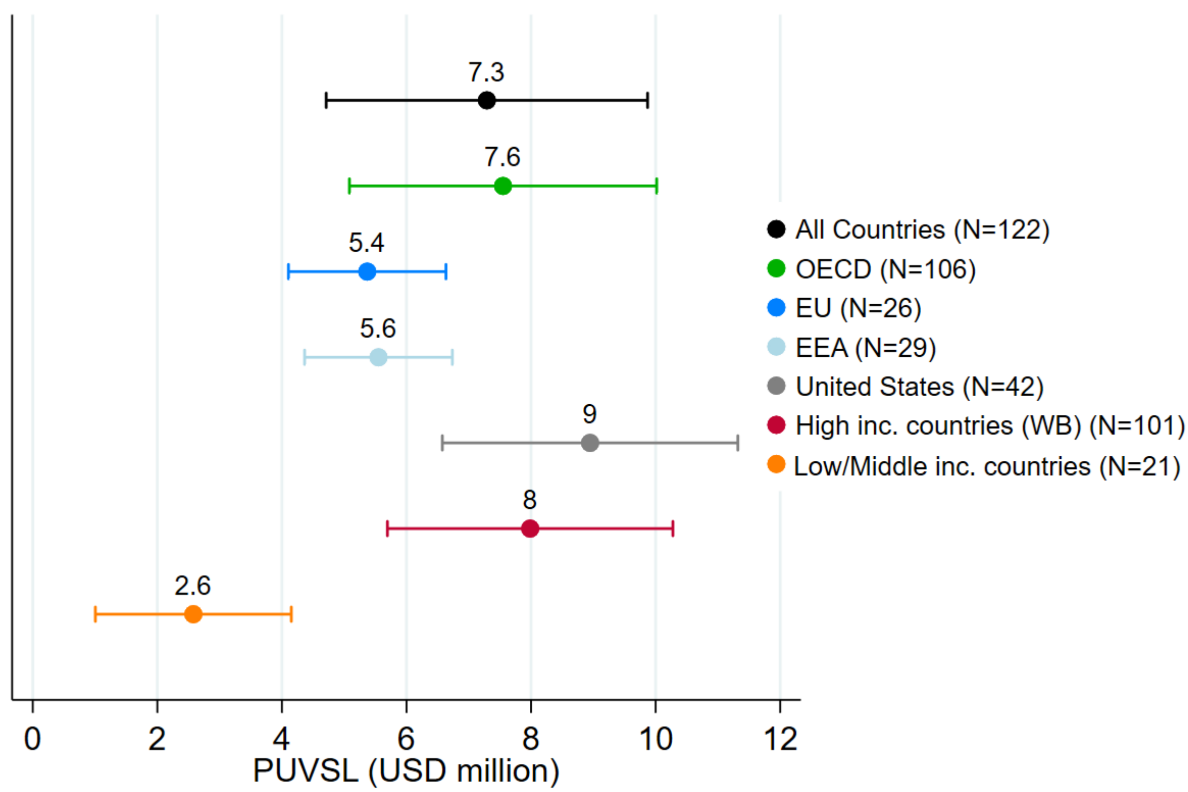
Sensitivity analysis of estimated mean VSL to main datasets

Figure A E.2 shows the PUVSL estimates and 95% confidence intervals from the Old SP and RP databases only. Compared to the corresponding estimates for New SP and RP data (Figure 4.2 and Table 4.2 of Chapter 4), some mean estimates are higher and some are lower. For example, *All countries*, *OECD* and *United States* PUVSLs increased from USD 5.5 to 7.3, 7.1 to 7.6 and 7.2 to 9 million, respectively. For *EU* and *EEA*, PUVSLs decreased from USD 7.6 to 5.4 and 7.4 to 5.6 million, respectively. For the lower- and middle-income group, the older dataset gives much higher PUVSL, (USD 2.6 million compared to USD 0.9 million).

Note that the number of estimates of each country group is lower for all groups making confidence intervals somewhat wider for the older data compared to the new.

Figure A E.2. Estimated PUVSL for country groups based on "old" data

Old meta-data

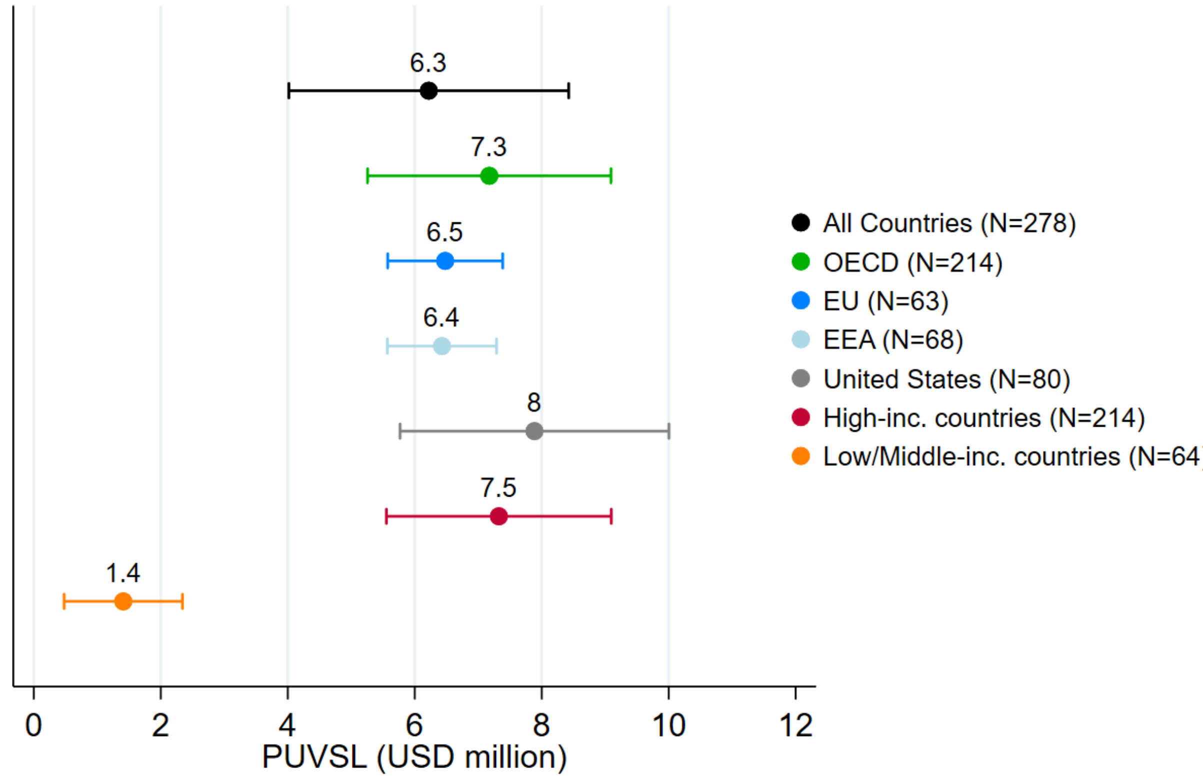


Note: Estimates based on four-level random effects meta-analysis. 99 far-out estimates excluded. Old meta-data refers to studies published in the period 1970-2008.

Figure A E.3 shows the estimated mean VSL and 95% confidence intervals based on the merged data (all four datasets). In this case, the mean VSL estimates are not substantially different when merging the old dataset with the new; some country group estimates are somewhat higher, and some are lower. The increase in total number of estimates narrows the confidence intervals slightly.

Figure A E.3. Estimated PUVSL by country group based on "all" data

All data



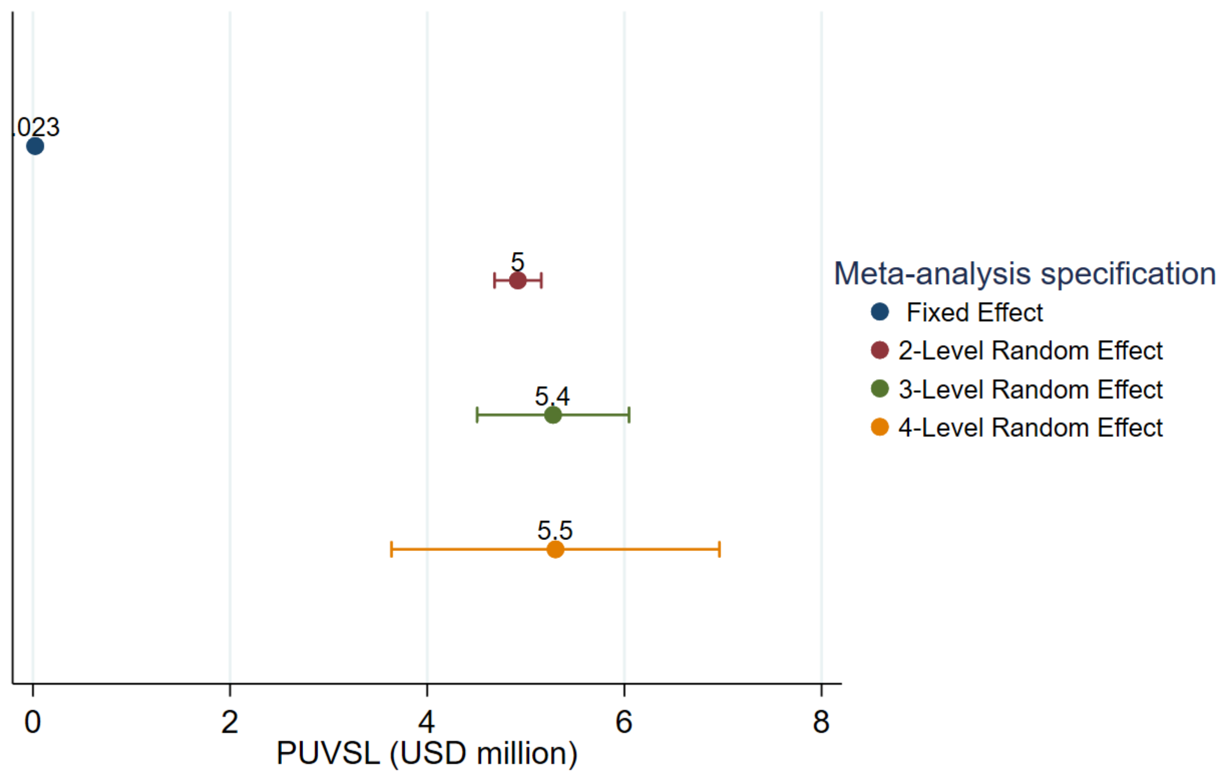
Note: Estimates based on four-level random effects meta-analysis.

Sensitivity of mean VSL to econometric specifications

Figure A E.4 below shows sensitivity of mean VSL for all countries (i.e. all new SP and RP data) to three alternative econometric meta-analysis specifications: Fixed effect meta-analysis, two-levels random effects meta-analysis and three-levels random effects meta-analysis specification. The four-level random effects approach is the one used to estimate mean VSL in the main model (Table 4.2 of Chapter 4). Results show that the three- and four-level random effects models yield identical mean VSL estimates of USD 5.4 and 5.5 million, while the two-level model yields a mean VSL estimate of USD 4.9 million.

Figure A E.4. Sensitivity of mean VSL to alternative econometric meta-analysis specifications

New meta-data



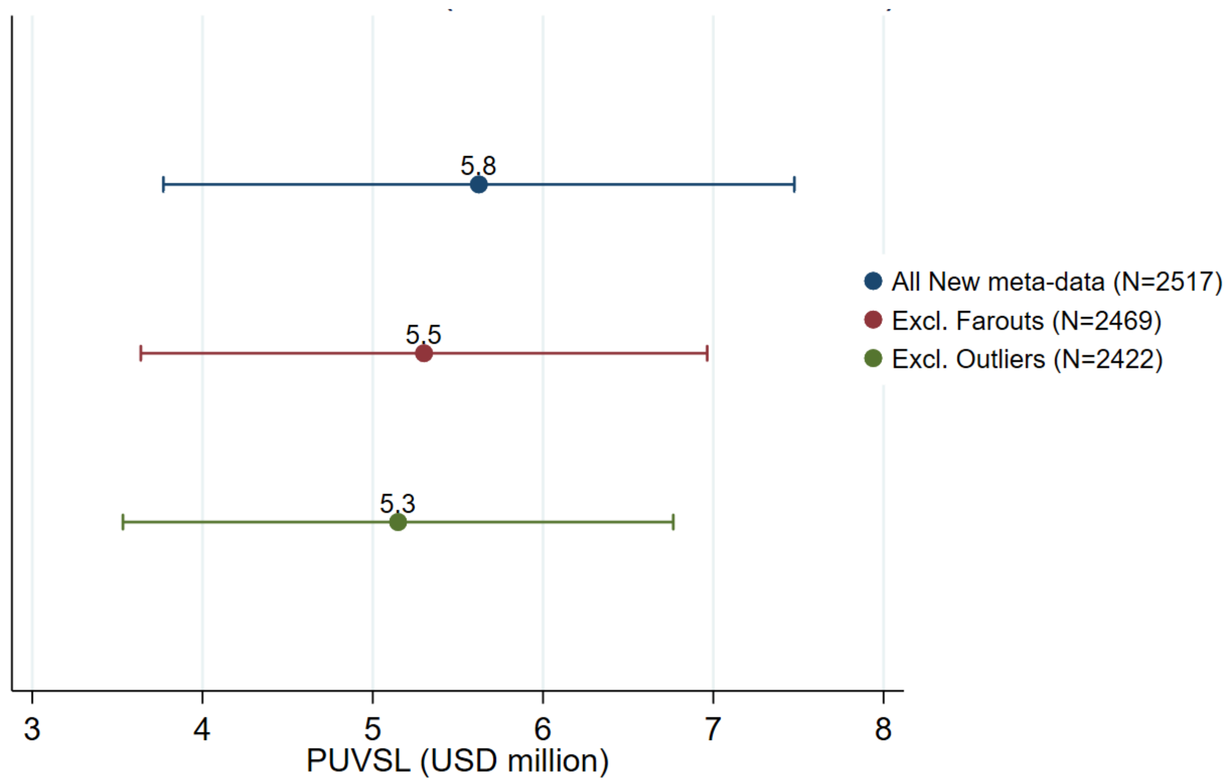
Note: Sensitivity test (alternative specification). New meta-data refers to studies published in the period 2009-2023.

Sensitivity of mean VSL to exclusion of outliers and far-outs

The main analysis in Chapter 4 has excluded so-called far-outs, i.e. outliers or extreme values. Figure A E.5 below shows the sensitivity of the estimated mean VSL for all countries of USD 5.5 million from Table 4.2 of Chapter 4. This estimate is shown by the dot and the CI by the middle line in the figure, where far-outs have been excluded. Above this line is the mean VSL estimate if all reported VSL data is included (i.e. not excluding far-outs or outliers). In this case, the mean VSL estimate increases by USD 300 000 to USD 5.8 million. If instead a stricter exclusion criterion is used, i.e. considering more of the distribution as outliers, the mean VSL estimate decreases from USD 5.5 million to USD 5.3 million instead (bottom dot and CI). Hence, overall, the mean VSL is not very sensitive to either of these criteria.

Figure A E.5. Sensitivity of estimated mean VSL to exclusion of outliers and far-outs

New meta-data



Note: Sensitivity test (Far-outs). Far-outs/Outliers are defined as outside the range of $[p25 - k(p75 - p25), p75 + k(p75 - p25)]$ where k=3 for far-outs and k=1.5 for outliers. New meta-data refers to studies published in the period 2009-2023.

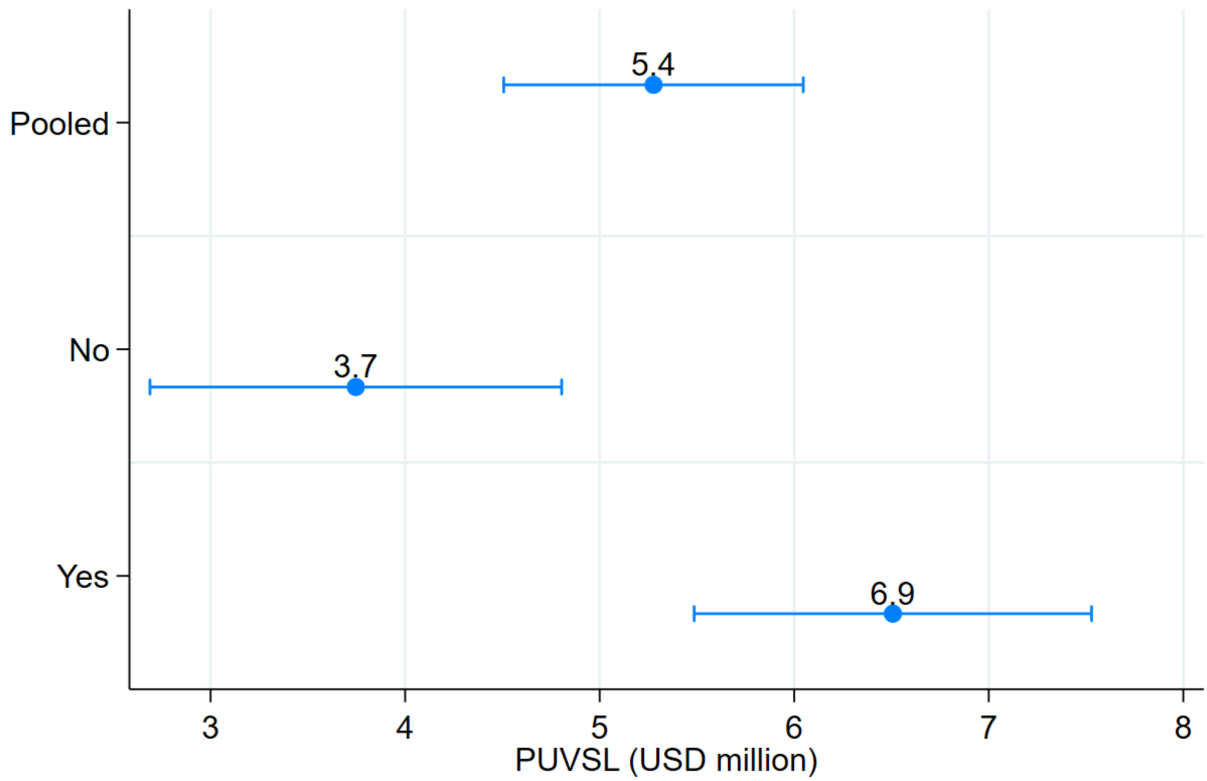
Sensitivity analysis of estimated mean VSL to quality and other screening factors

Studies that are nationwide

In some contexts, it may be relevant to limit the data to studies that have a nationwide coverage, rather than specific geographical areas of a country (especially if there are potentially important differences between areas that are difficult to control for). Figure A E.6 provides VSL estimates by group of studies, i.e. whether the VSL estimates come from a nationwide study or not. The “pooled” estimate is the USD 5.5 million for all countries, as shown in Table 4.2 of Chapter 4. Limiting the scope to nationwide studies increases this estimate to USD 6.9 million. On the other hand, the VSL estimate for studies which are not nationwide is USD 3.7 million. It is difficult to assess the reasons for such a difference without more detailed analysis and information about each primary study.

Figure A E.6. Sensitivity of mean VSL if study is nationwide

New meta-data



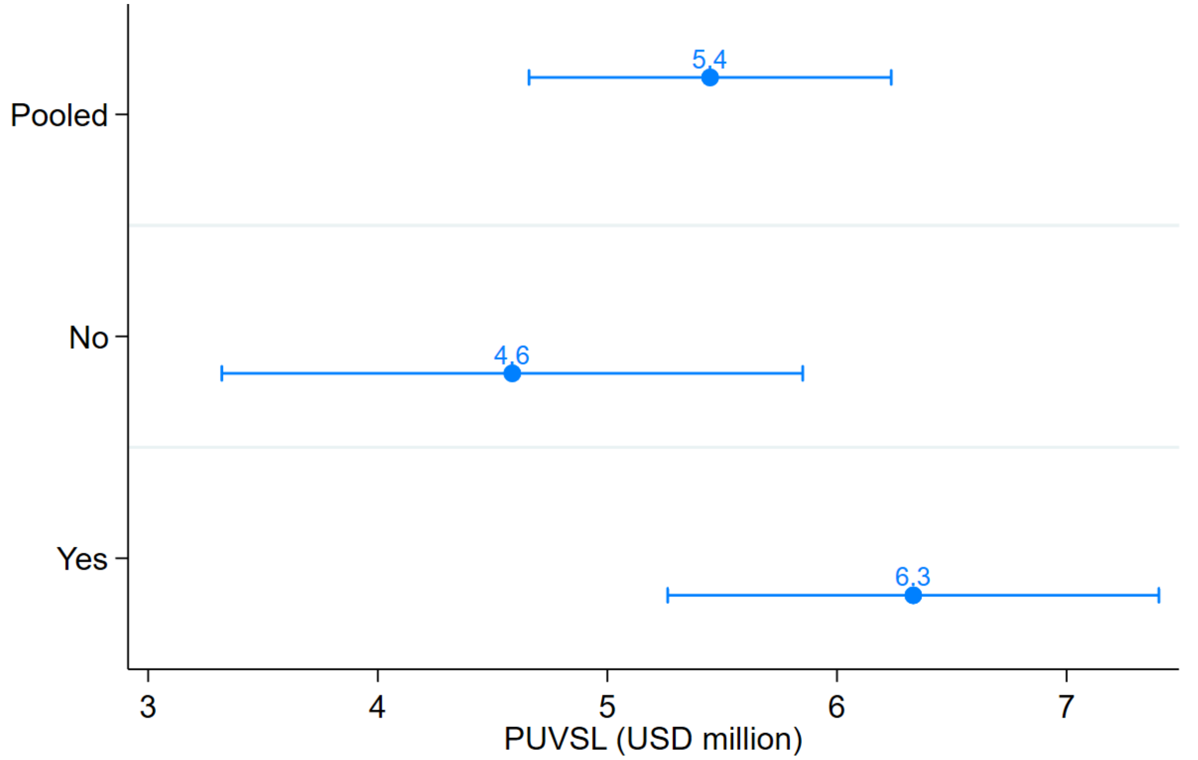
Note: Sensitivity test (Nationwide). A three-level random effects meta-analysis model is used. New meta-data refers to studies published in the period 2009-2023.

Studies of the general population

Some VSL studies target the general population, while others target specific groups. In the same way as for the nationwide approach, it may in some contexts be desirable to limit the underlying sample of VSL estimates to studies that cover the general population. Figure A E.7 shows that the difference in the mean VSL estimates between the general population and specific groups is around USD 2.8 million, as opposed to a mean VSL estimate of USD 5.3 million when pooled (Table 4.2 of Chapter 4). Similar to the results comparing national versus sub-national studies, the studies that focus on the general population tend to have been performed in economies with a higher per capita income which contributes to such studies showing a higher VSL estimate.

Figure A E.7. Sensitivity of mean VSL if study is of the general population

New meta-data



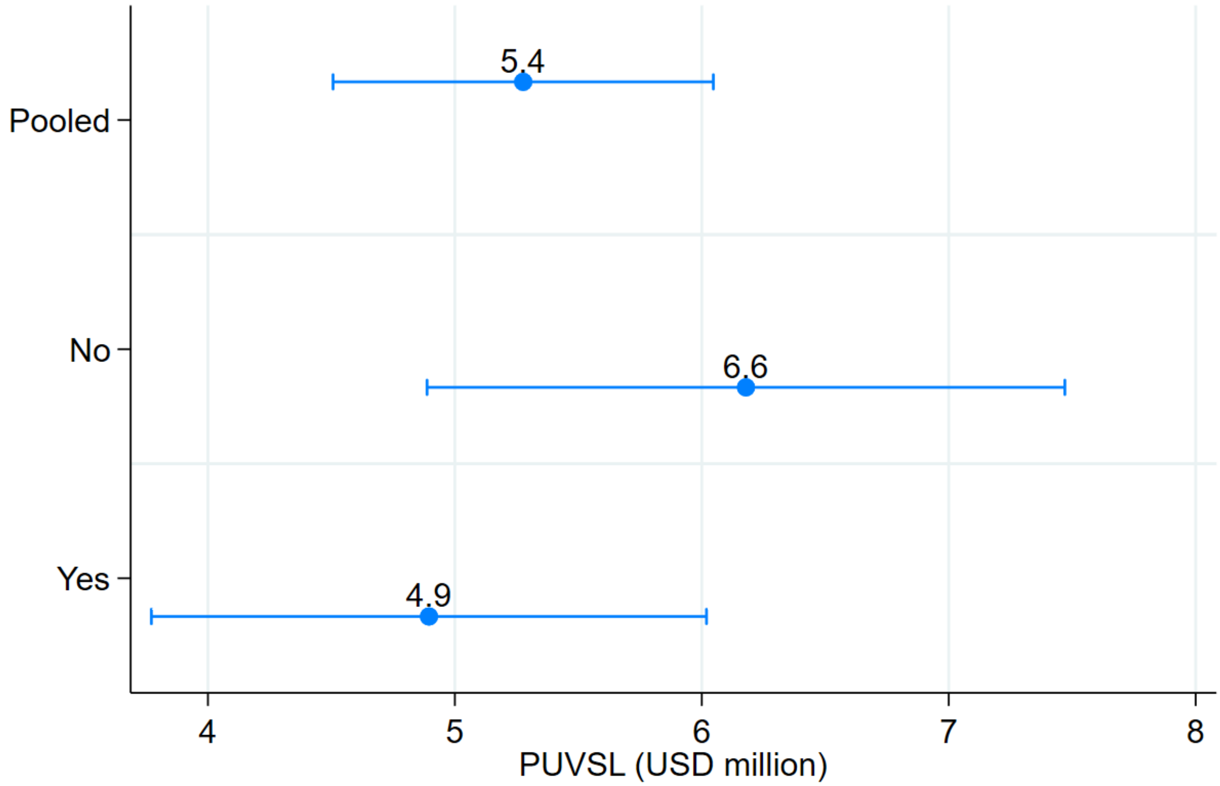
Note: Sensitivity test (General Population). A three-level random effects meta-analysis model is used. New meta-data refers to studies published in the period 2009-2023.

Representative samples

It is often hard to judge how representative the samples are that VSL estimates are based upon. In addition, few studies provide sufficient information to be able to adjust for any non-representativeness. Representativity is affected by sampling strategy, which ideally should be random and based on a sampling frame that represents the population. However, in practice, non-response bias and sample selection effects can play a role, even if the sampling was randomised. Despite such potential risks, the use of random sampling can be seen as a proxy for the quality of a study. Comparing studies that have use such a sampling strategy with those that do not yield some differences, as shown in Figure A E.8. The results suggest that non-random sampling strategies yield generally higher VSL estimates. The reasons for this are not clear, but could be affected by income, which is slightly higher for the studies in the non-random sample group. Limiting the data to only representative estimates lowers the main mean VSL estimate for *All countries* from USD 5.4 million to USD 4.9 million.

Figure A E.8. Sensitivity of mean VSL if representative sample

New meta-data



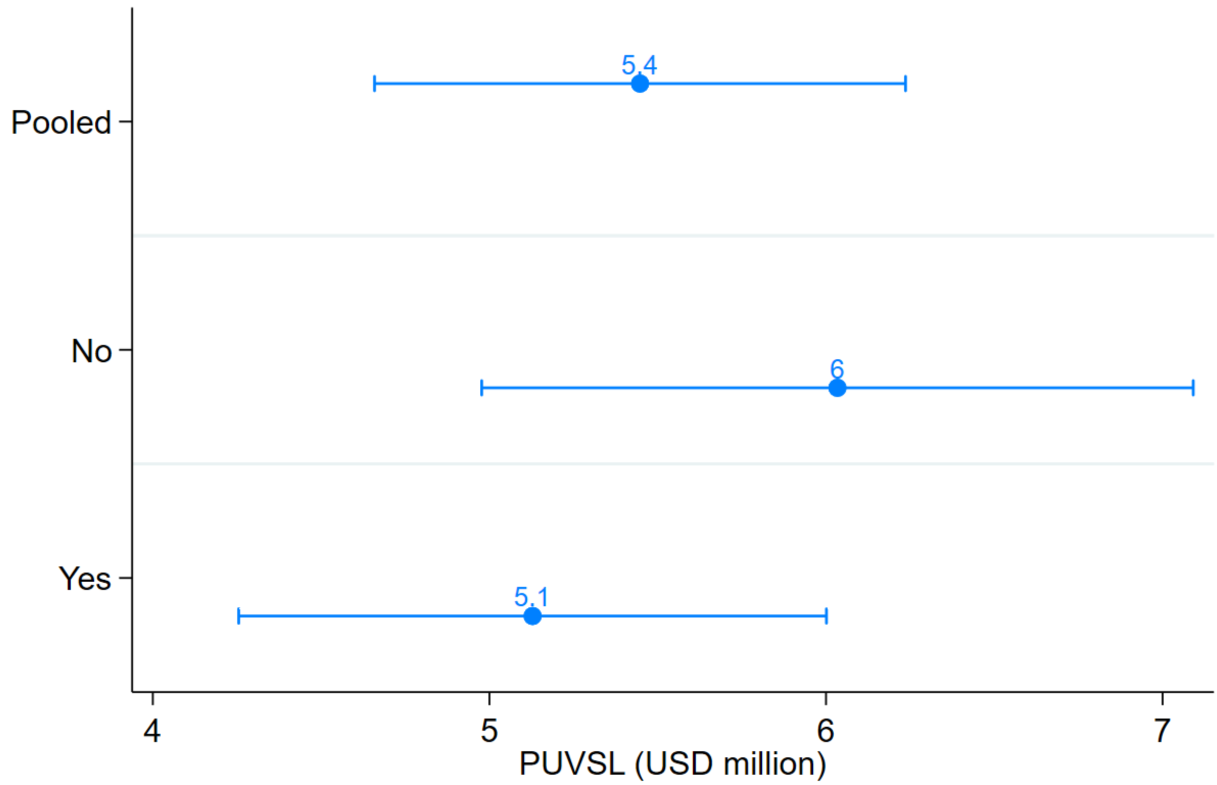
Note: Sensitivity test (Representativeness). A three-level random effects meta-analysis model is used. New meta-data refers to studies published in the period 2009-2023.

No standard errors reported

It is generally considered good practice to report standard errors (SE) of any statistical metric in a scientific study, including for mean VSL estimates. Even so, many studies do not report this (cf. Table A D.1 in Annex D). This could be a rough indicator of lack of quality (though some of the studies report confidence intervals, but not standard errors). Figure A E.9 below compares VSL estimates between studies that report standard errors and those that do not, suggesting that studies that include standard errors show a lower overall VSL estimate.

Figure A E.9. Sensitivity of mean VSL if study does not report standard error of VSL estimate

New meta-data



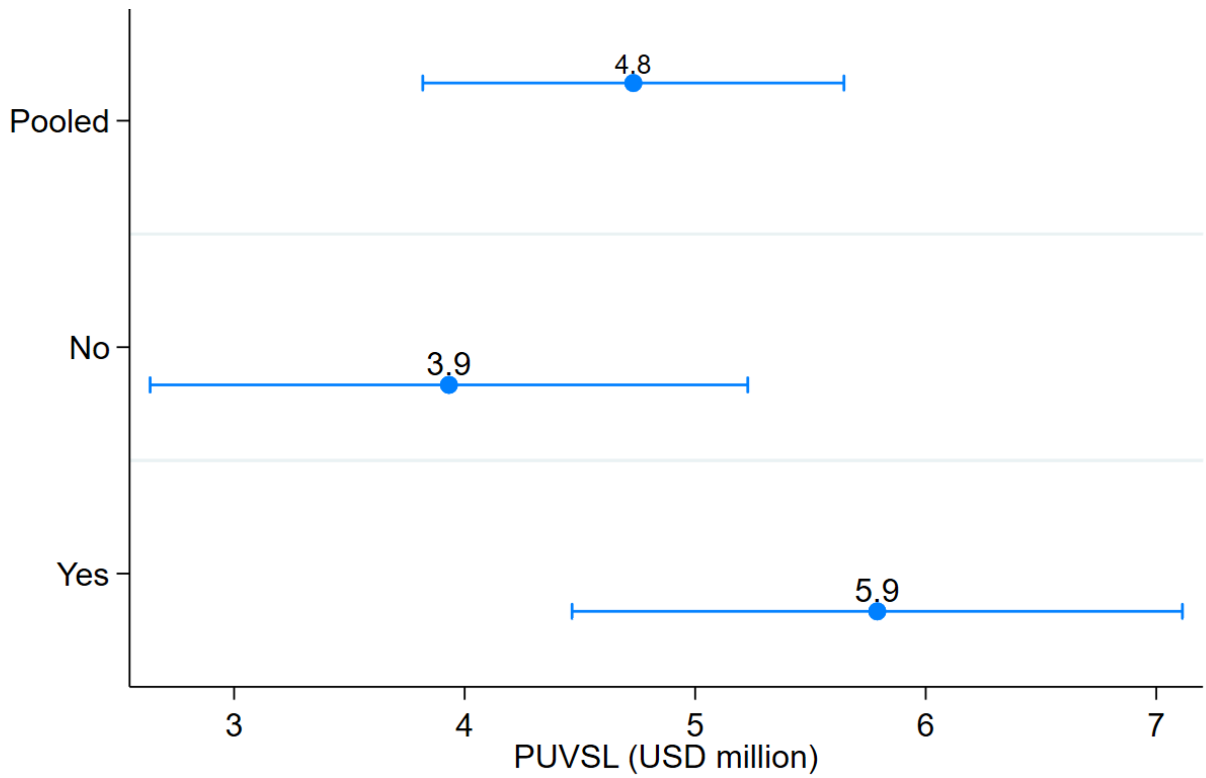
Note: Sensitivity test (No reported standard errors). A three-level random effects meta-analysis model is used. New meta-data refers to studies published in the period 2009-2023.

Baseline risks clearly defined in SP

In theory, the baseline risk should affect VSL. If the baseline risk is not clearly defined in the primary SP survey, it could suggest a lower quality of the SP study. Figure A E.10 suggests that the articulation of base risk impacts the VSL: When baseline risk is clearly specified, mean VSL is estimated to USD 5.9 million, and USD 3.9 million when it is not. The pooled estimate is USD 4.8 million (which is different from the USD 5.5 million in Table 4.2 of Chapter 4 for all countries, because results are derived from SP data only). Note that in this case income is actually higher for those studies where baseline risk is not clearly explained (not shown in Figure A E.10).

Figure A E.10. Sensitivity of mean VSL to the definition of baseline risk

New meta-data



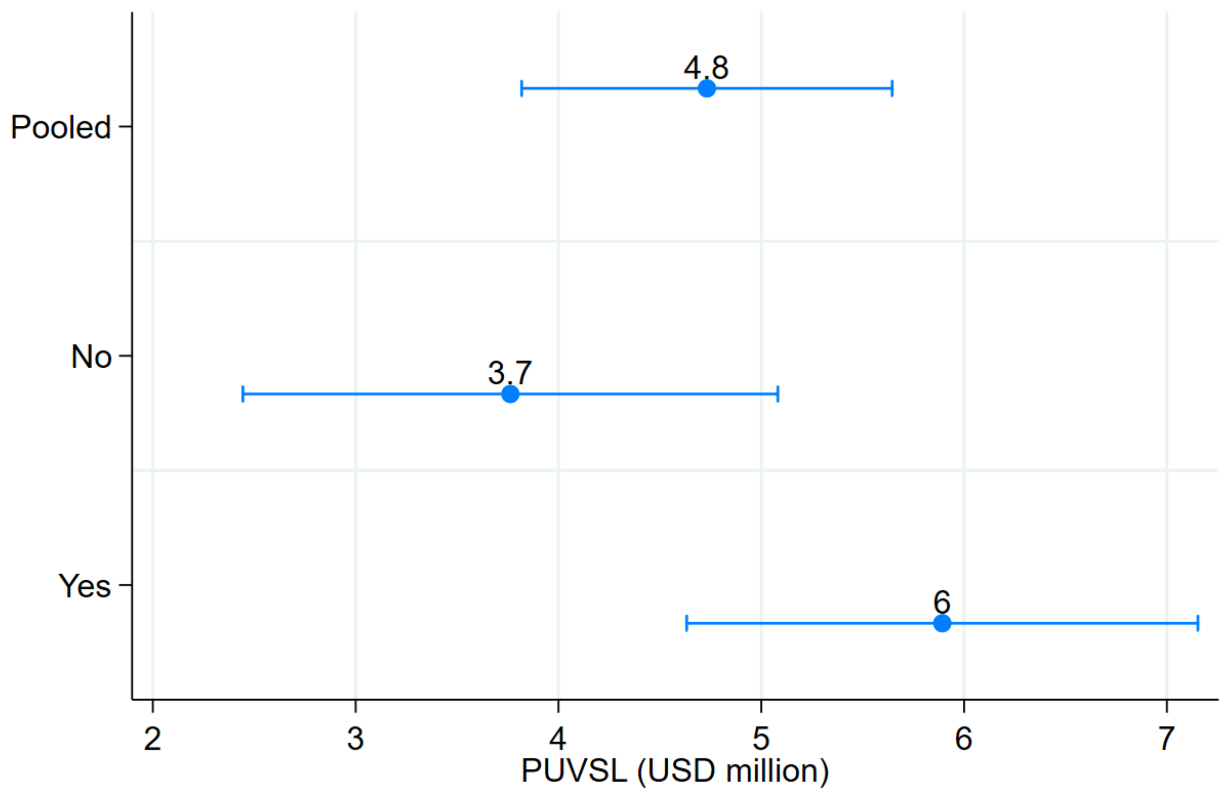
Note: Sensitivity test (SP study including Baseline Risk). A three-level random effects meta-analysis model is used. New meta-data refers to studies published in the period 2009-2023.

Scope sensitivity test included in SP

Scope sensitivity – the phenomenon that people generally should be willing to pay more for a large mortality risk reduction than a small one – has been important for assessing validity of SP studies since the National Oceanic and Atmospheric Administration panel on the CV method delivered its report (Arrow, 1993[2]). In recent years, the emphasis on scope sensitivity has moved somewhat from consideration of validity to the degree of economic significance of such results (Dugstad et al., 2021[3]; Kipperberg et al., n.d.[4]). One reason is that studies have shown that scope sensitivity could be relatively low, but still be in line with economic theory (Amiran and Hagen, 2010[5]). The meta-data for the current study includes a variable on whether a scope test was reported in the primary SP study. Figure A E.11 shows that studies with scope tests have a mean VSL estimate that is about USD 2 million higher than those do not include a scope test.

Figure A E.11. Sensitivity of mean VSL if study includes a scope test

New meta-data



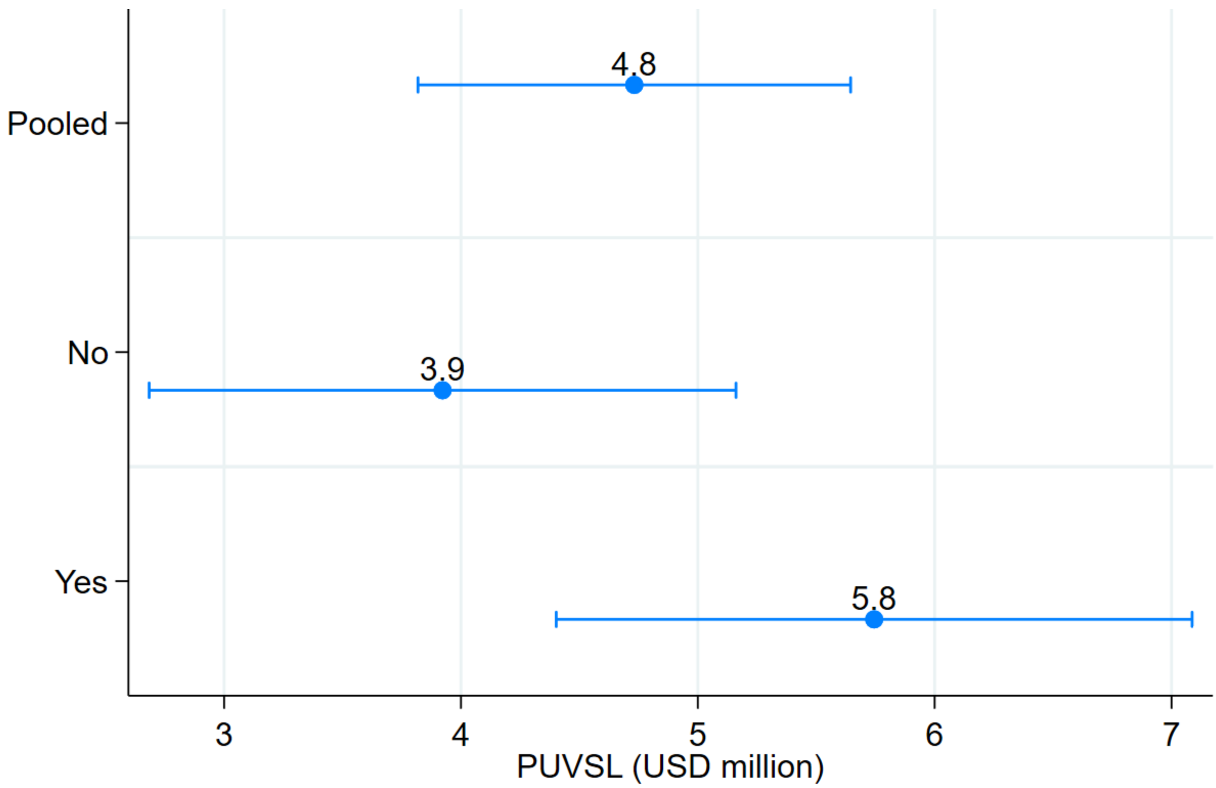
Note: Sensitivity test (SP study focusing on Scope Sensitivity). A three-level random effects meta-analysis model is used. New meta-data refers to studies published in the period 2009-2023.

Visual aid used to display risk for SP

In the old SP database, there was a variable indicating whether or not a SP study had used visual display or other proper explanation of the risk reduction (e.g. a risk ladder, grid or similar). At the time (and still) this was seen as best practice. This coding procedure was extended into the new SP database. Figure A E.12 shows that studies that do not have such explanation yield lower VSL estimates. This is contrary to the results in Lindhjem et al. (2011[6]) who find that such studies yield higher VSL estimates for the old SP database. There is some degree of subjectivity of the coding of this variable, so results here should be interpreted accordingly.

Figure A E.12. Sensitivity of mean VSL if SP survey explained risk change using visual aid

New meta-data



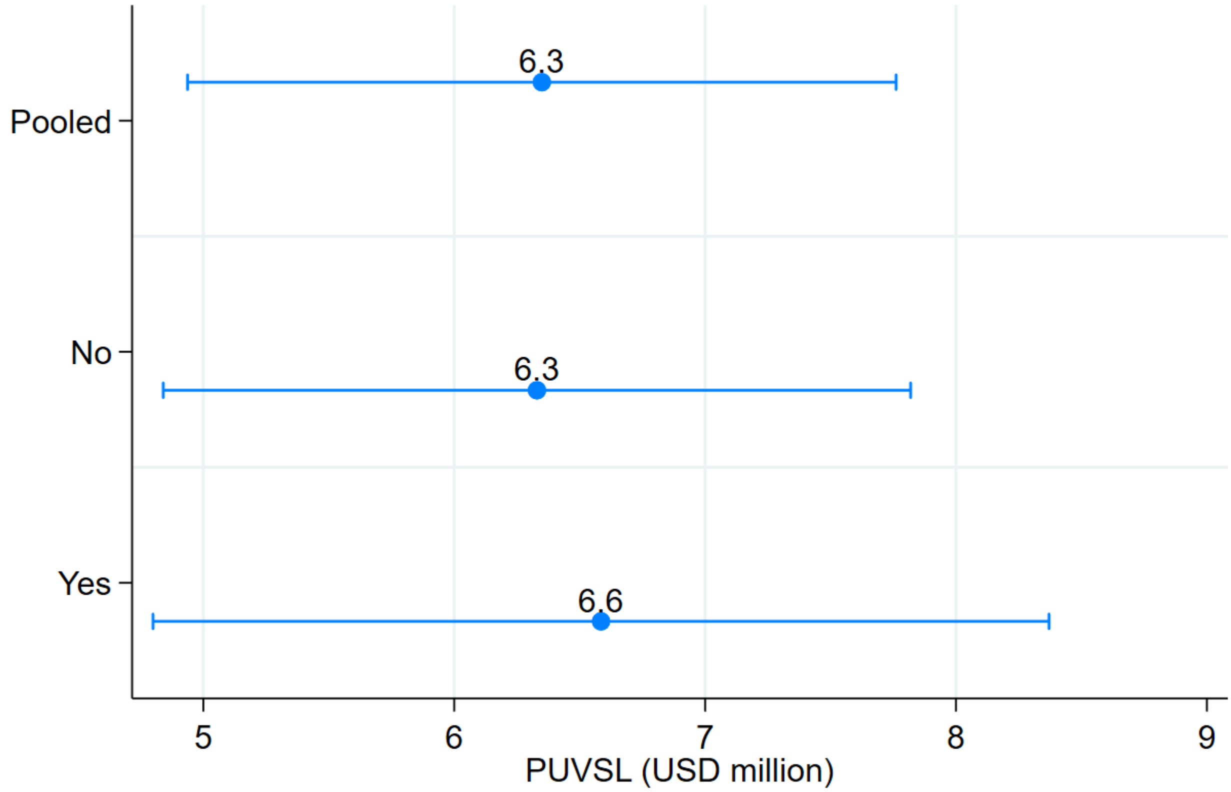
Note: Sensitivity test (SP study including Visual Aids). A three-level random effects meta-analysis model is used. New meta-data refers to studies published in the period 2009-2023.

Instrument variable regression for RP

The use of instrument variables is common in hedonic wage risk studies (cf. Section 4.3 of Chapter 4). Figure A E.13 shows that the use of instrument variables in the estimation of the VSL in RP studies has a relatively minor effect on the mean VSL estimate (a difference of about USD 300 000).

Figure A E.13. Sensitivity of mean VSL if the RP study used instrument variable regression

New meta-data



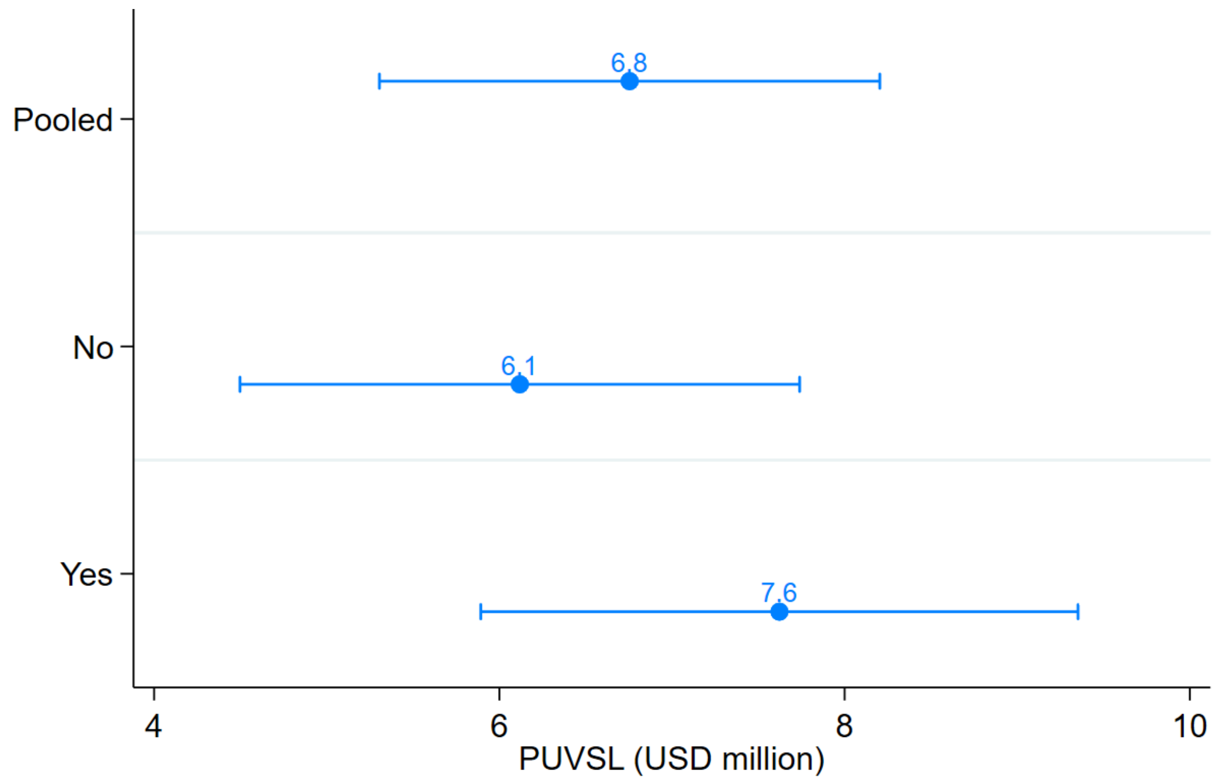
Note: Sensitivity test (RP study using IV Estimate). A three-level random effects meta-analysis model is used. New meta-data refers to studies published in the period 2009-2023.

Non-fatal injury risk included in RP

Another factor that is considered important in high-quality hedonic wage studies is to control for non-fatal injury risk in the regressions. When controlling for such risks, the mean VSL estimate is USD 7.6 million compared to USD 6.1 million when not controlling for this risk (Figure A E.14).

Figure A E.14. Sensitivity of mean VSL to control for non-fatal injury risks

New meta-data



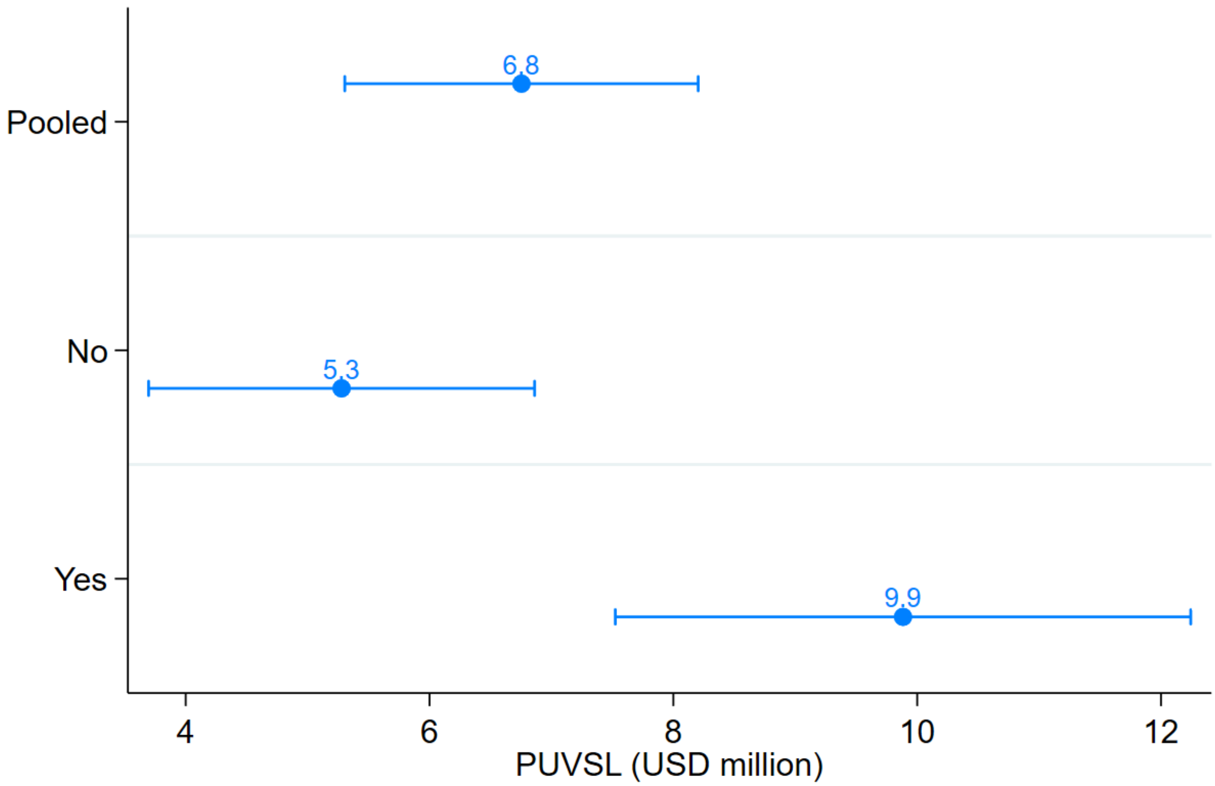
Note: Sensitivity test (RP study controlling for Non-Fatal Injury Risks). A three-level random effects meta-analysis model is used. New meta-data refers to studies published in the period 2009-2023.

Census of fatal occupational injuries (CFOI) data in RP

Whether the highest quality risk data is used in hedonic wage risk studies is often considered important for quality. For example, in the case of the United States, the highest quality risk data is generally considered to come from the Census of Fatal Occupational Injuries (CFOI). When such data is used, it has a substantial impact on the VSL estimates, as can be seen from Figure A E.15 (with the caveat that income also appears higher in that sample – not shown).

Figure A E.15. Sensitivity of mean VSL to the use of CFOI data

New meta-data



Note: Sensitivity 3 Study using CFOI data (Quality controls). A three-level random effects meta-analysis is used. New meta-data refers to studies published in the period 2009-2023.

Mean VSL estimates from studies published in journals

Table A E.1 shows PUVSL results where the underlying primary studies are limited to those published in peer reviewed journals (compare to Table 4.2 of Chapter 4). The results suggest that for the full sample ("all countries") the PUVSL increases from 5.5 to 5.9 million when limiting the sample to peer reviewed journal-published studies. Estimates for OECD and High-income countries also increase slightly, while estimates for EEA decline. The largest change is observed for the United States's estimate, which increases from USD 7.2 to 8.7 million, though the reasons for this substantial increase remain unclear.

Table A E.1. Estimated mean PUVSL estimates for (groups of) countries, limited to studies published in journals

USD million, New meta-data

Countries	Mean VSL	Confidence interval (lower bound)	Confidence interval (upper bound)	Number of studies	Number of estimates
All countries	5.9	4.1	7.7	137	1720
OECD	7.5	5.6	9.4	93	1270
EU	7.1	6.0	8.2	34	342
EEA	6.8	5.7	8.0	36	363
United States	8.7	7.2	10.3	30	605
High income countries	7.6	5.9	9.3	98	1358
Low/Middle-income countries	1.0	0.3	1.7	39	362

Note: New meta-data refers to studies published in the period 2009-2023.

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Annex F. Additional results from meta-regression analysis

Income elasticity of VSL

Table A F.1. Estimated income elasticity of VSL

Regression results. New meta-data. Dependent variable = log (VSL).

	Model 1	Model 2	Model 3	Model 4	Model 5
	Four-level	Three-level	Three-level	Three-level	Three-level
Control variables	Only GDP	Only GDP	Additional controls	Additional controls + Country FE	Additional controls + Year FE
log(GDP)	1.142***	1.142***	1.118***	3.508	1.255***
	[0.587,1.698]	[0.587,1.698]	[0.533,1.703]	[-0.958,7.974]	[0.410,2.101]
Hedonic wage (base)					
Contingent valuation method			-0.468	-0.447	-0.101
			[-1.886,0.951]	[-2.384,1.489]	[-2.129,1.927]
Choice experiment method			0.45	-0.029	-0.153
			[-1.023,1.922]	[-2.683,2.625]	[-2.173,1.868]
Consumer market valuation method			-0.803	-1.521	-1.236
			[-2.506,0.899]	[-3.603,0.560]	[-3.689,1.217]
Other SP method			0.427	0.809	-0.454
			[-6.651,7.504]	[-16.615,18.234]	[-7.989,7.082]
Years since data collection			0.083**	0.148**	
			[0.003,0.162]	[0.017,0.278]	
Constant	2.485	2.484	1.705	-25.906	0.536
	[-3.320,8.289]	[-3.321,8.290]	[-4.934,8.344]	[-76.538,24.726]	[-9.763,10.834]
Country fixed effects	No	No	No	Yes	No
Year fixed effects	No	No	No	No	Yes
N Studies	154	154	154	154	154
N Estimates	2405	2405	2405	2405	2405
N Countries	46	46	46	46	46
N Years	30	30	30	30	30

Note: The table displays regression coefficients as well as their confidence intervals (in brackets). Stars indicate statistical significance at 10% (*); at 5% (**); at 1% (***). FE stands for fixed effects. New meta-data refers to studies published in the period 2009-2023. Details regarding variable definitions are provided Table 4.1 of Chapter 4.

Table A F.2. Estimated income elasticity of VSL

Regression results. Old meta-data. Dependent variable = log(VSL).

	Model 1	Model 2	Model 3	Model 4	Model 5
Random model	Four-level	Three-level	Three-level	Three-level	Three-level
Control variables	Only GDP	Only GDP	Additional controls	Additional controls + Country FE	Additional controls + Year FE
log (GDP)	1.139***	1.139***	0.978**	1.578	0.995*
	[0.371,1.907]	[0.371,1.907]	[0.107,1.849]	[-5.953,9.109]	[-0.082,2.073]
Hedonic wage (base)					
Contingent valuation method			-1.142	-1.321	-0.865
			[-3.169,0.886]	[-4.167,1.524]	[-3.648,1.918]
Choice experiment			-1.093	-1.1	-0.361
			[-4.099,1.914]	[-5.166,2.965]	[-4.110,3.388]
Other SP method			-0.216	-0.875	-0.236
			[-3.072,2.640]	[-4.879,3.129]	[-3.652,3.180]
Years since data collection			-0.032	-0.034	
			[-0.129,0.065]	[-0.206,0.137]	
Constant	3.305	3.305	6.446	-0.036	4.236
	[-4.624,11.233]	[-4.624,11.233]	[-3.270,16.162]	[-86.269,86.196]	[-8.858,17.329]
Country fixed effects	No	No	No	Yes	No
Year fixed effects	No	No	No	No	Yes
N Studies	122	122	122	122	122
N Estimates	1465	1465	1465	1465	1465
N Countries	26	26	26	26	26
N Years	36	36	36	36	36

Note: The table displays regression coefficients as well as their confidence intervals (in brackets). Stars indicate statistical significance at 10% (*); at 5% (**); at 1% (***). FE stands for fixed effects. Remaining acronyms are listed in the Acronyms tab and in Table 4.1 of Chapter 4. Note that CM is not included in the table, as it is not part of Old RP studies. Old meta-data refers to studies published in the period 1970-2008. Details regarding variable definitions are provided in Table 4.1 of Chapter 4.

Table A F.3. Estimated income elasticity of VSL

Regression results. Stated preference data only. Dependent variable = log(VSL).

	Model 1	Model 2	Model 3	Model 4	Model 5
Random model	Four-level	Three-level	Three-level	Three-level	Three-level
Control variables	Only GDP	Only GDP	Additional controls	Additional controls + Country FE	Additional controls + Year FE
log(GDP)	1.452***	1.452***	1.372***	0.157	1.332***
	[0.870,2.034]	[0.870,2.034]	[0.728,2.017]	[-3.923,4.237]	[0.446,2.219]
Hedonic wage (base)					
Contingent valuation method			-0.819	-0.728	-0.115
			[-3.225,1.586]	[-4.068,2.612]	[-3.239,3.010]

Choice experiment			-0.457	-0.056	-0.029
			[-2.997,2.083]	[-3.554,3.442]	[-3.405,3.347]
Consumer market valuation method					
Other SP method					
Years since data collection			0.044	-0.005	
			[-0.045,0.133]	[-0.138,0.128]	
Constant	-0.396	-0.396	0.306	13.775	1.048
	[-6.331,5.540]	[-6.331,5.540]	[-7.077,7.689]	[-33.120,60.671]	[-9.598,11.694]
Country fixed effects	No	No	No	Yes	No
Year fixed effects	No	No	No	No	Yes
N Studies	170	170	170	170	170
N Estimates	1871	1871	1871	1871	1871
N Countries	43	43	43	43	43
N Years	37	37	37	37	37
Only 1 GDP by Country	16	16	16	16	16
Only 1 GDP by Year	11	11	11	11	11

Note: The table displays regression coefficients as well as their confidence intervals (in brackets). Stars indicate statistical significance at 10% (*); at 5% (**); at 1% (***). FE stands for fixed effects. Details regarding variable definitions are provided in Table 4.1 of Chapter 4.

Table A F.4. Estimated income elasticity of VSL

Regression results. Revealed preference data only. Dependent variable = log(VSL).

	Model 1	Model 2	Model 3	Model 4	Model 5
Random model	Four-level	Three-level	Three-level	Three-level	Three-level
Control variables	Only GDP	Only GDP	Additional controls	Additional controls + Country FE	Additional controls + Year FE
log(GDP)	0.59	0.714*	0.573	3.131	1.353**
	[-0.135,1.316]	[-0.008,1.437]	[-0.145,1.291]	[-6.595,12.856]	[0.143,2.563]
Hedonic wage (base)					
Contingent valuation method					
Choice experiment					
Consumer market valuation method			-1.239	-1.478	-0.266
			[-2.951,0.474]	[-3.567,0.612]	[-3.611,3.079]
Other SP method					
			0.039	0.082	

Years since data collection			[-0.012,0.091]	[-0.060,0.224]	
Constant	8.258**	7.347*	8.201**	-20.937	-2.71
	[0.523,15.993]	[-0.306,15.000]	[0.245,16.157]	[-130.809,88.934]	[-18.042,12.623]
Country fixed effects	No	No	No	Yes	No
Year fixed effects	No	No	No	No	Yes
N Studies	106	106	106	106	106
N Estimates	1999	1999	1999	1999	1999
N Countries	23	23	23	23	23
N Years	44	44	44	44	44
Only 1 GDP by Country	14	14	14	14	14
Only 1 GDP by Year	24	24	24	24	24

Note: The table displays regression coefficients as well as their confidence intervals (in brackets). Stars indicate statistical significance at 10% (*); at 5% (**); at 1% (***). FE stands for fixed effects. Details regarding variable definitions are provided in Table 4.1 of Chapter 4.

Table A F.5. Estimates of income elasticity for different country groups

Estimates of income elasticity of VSL, three-level meta-regression with split samples

	OECD	EU	EEA	USA	High Income	Low- and middle-income
Model 1	-0.172	1.767	1.336	-3.318	-0.599	1.156*
Only GDP	[-1.655,1.311]	[-3.180,6.714]	[-3.305,5.976]	[-8.076,1.439]	[-2.228,1.030]	[-0.192,2.505]
Model 2	0.503	1.716	1.261	13.452	0.146	1.981**
Additional controls	[-1.173,2.178]	[-4.078,7.510]	[-4.290,6.811]	[-14.282,41.187]	[-1.833,2.124]	[0.156,3.807]
Model 3	1.372	-2.951	-3.858	13.452	1.42	4.314
Additional controls + Country Fixed effects	[-5.738,8.482]	[-24.776,18.874]	[-20.817,13.101]	[-14.282,41.187]	[-5.918,8.758]	[-3.468,12.096]
Model 4	1.025	2.31	1.375	2.031	0.62	2.137*
Additional controls + Year Fixed effects	[-1.362,3.412]	[-5.597,10.216]	[-5.685,8.435]	[-86.788,90.850]	[-3.226,4.465]	[-0.327,4.602]
N Studies	212	62	67	80	212	64
N Estimates	3088	750	792	1515	3192	678

Note: The table displays income elasticities as well as their confidence intervals (in brackets). Stars indicate statistical significance at 10% (*); at 5% (**); at 1% (***). Income elasticities were estimated for subsets of the data for those groups only). Model specifications are the same as in Table 5.1 of Chapter 5. Only the coefficient of log (GDP) is reported here. Note that none of the elasticity estimates is statistically significant except those for Low- or middle-income countries. The comparison between High income countries and Low- and Middle-income countries suggests that elasticity can be higher for Low- and middle-income countries compared to High income countries, but they are not precisely estimated.

Table A F.6. Alternative specifications to estimate income elasticity

Study-level Random Effects (RE), Generalized Least Squares (GLS)

	RE GLS	RE GLS	RE GLS	RE GLS
Control variables	Only GDP	Additional controls	Additional controls + Country FE	Additional controls + Year FE

log (GDP)	1.196***	1.146***	2.033***	1.232***
	[0.894,1.499]	[0.854,1.439]	[0.986,3.080]	[1.014,1.451]
Hedonic wage (base)				
Contingent valuation method		-0.659***	-0.648***	-0.513***
		[-1.033,-0.286]	[-1.080,-0.216]	[-0.881,-0.146]
Choice experiment		-0.385*	-0.316	-0.196
		[-0.790,0.019]	[-0.772,0.141]	[-0.577,0.185]
Consumer market valuation method		-0.498	-0.796	-0.252
		[-1.575,0.579]	[-2.072,0.480]	[-1.273,0.769]
Other SP method		-0.732	-0.765	-0.683
		[-1.826,0.363]	[-1.890,0.361]	[-1.746,0.379]
Years since data collection		0.013	0.028**	
		[-0.004,0.029]	[0.004,0.051]	
Constant	2.579	3.202**	-7.057	2.059
	[-0.643,5.801]	[0.133,6.271]	[-19.010,4.895]	[-0.440,4.557]
Country fixed effects	No	No	Yes	No
Year fixed effects	No	No	No	Yes

Note: The table displays coefficients as well as their confidence intervals (in brackets). Stars indicate statistical significance at 10% (*); at 5% (**); at 1% (***). FE stands for fixed effects. Details regarding variable definitions are provided Table 4.1 of Chapter 4.

Table A F.7. Alternative models to estimate income elasticity

One observation (mean) from each study. OLS method.

Control variables	Only GDP	Additional Controls	Additional Controls + Country FE	Additional Controls + Year FE
log (GDP)	1.063***	1.005***	0.523**	1.150***
	[0.804,1.321]	[0.756,1.254]	[0.097,0.948]	[0.917,1.382]
Hedonic wage (base)		-0.627***	-0.574**	-0.537**
		[-0.995,-0.260]	[-1.091,-0.058]	[-0.955,-0.119]
Contingent valuation method		-0.442**	-0.511*	-0.343
		[-0.864,-0.020]	[-1.070,0.047]	[-0.832,0.147]
Choice experiment				
Consumer market valuation method		-0.444	-0.918	-0.204
		[-1.487,0.600]	[-2.341,0.505]	[-1.339,0.932]
Other SP method		0.201	-0.199	-0.088
		[-0.592,0.995]	[-1.146,0.748]	[-1.018,0.842]
Years since data collection		0.020**	0.004	
		[0.004,0.035]	[-0.015,0.022]	
Constant	3.953***	4.490***	10.030***	3.111**
	[1.197,6.709]	[1.763,7.217]	[5.152,14.909]	[0.458,5.764]
Country fixed effects	No	No	Yes	No

Year fixed effects	No	No	No	Yes
N Observations	276	268	264	268

Note: The table displays coefficients as well as their confidence intervals (in brackets). Stars indicate statistical significance at 10% (*); at 5% (**); at 1% (***). FE stands for fixed effects. Details regarding variable definitions are provided Table 4.1 of Chapter 4.

Meta-regressions

Table A F.8-Table A F.12 report the following additional meta-regression results:

Table A F.8: Base estimation results for all data (i.e. same as Table 5.2 of Chapter 5 except all RP and SP data are used). Results here are similar to Table 5.1 of Chapter 5 in terms of significance, although coefficient values have changed somewhat.

Table A F.9: Estimation results only for new SP data.

Table A F.10: Estimation results only for new SP data with risk type variables

Table A F.11: Estimation results only for new RP data.

Table A F.12: Estimation results only for new RP data with risk type variables

Table A F.8. Estimation results for all stated preference and revealed preference data

New and old datasets combined

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
GDP per capita (USD thousand)	0.115***	0.117***	0.117***	0.117***	0.115***	
	[0.089,0.142]	[0.090,0.144]	[0.090,0.144]	[0.090,0.144]	[0.088,0.141]	
Hedonic wage (base)						
Contingent valuation method	-2.799***	-2.636***	-2.636***	-2.649***	-2.815***	-3.691***
	[-4.208,-1.390]	[-4.091,-1.181]	[-4.091,-1.180]	[-4.119,-1.178]	[-4.331,-1.300]	[-5.313,-2.069]
Choice experiment	-0.948	-0.809	-0.808	-0.818	-0.922	-1.158
	[-2.508,0.612]	[-2.399,0.781]	[-2.399,0.783]	[-2.422,0.785]	[-2.553,0.709]	[-2.908,0.593]
Consumer market valuation method	-3.104*	-2.885*	-2.897*	-2.893*	-2.563	-3.571*
	[-6.423,0.216]	[-6.242,0.472]	[-6.265,0.471]	[-6.263,0.478]	[-5.923,0.797]	[-7.232,0.089]
Other SP method	-0.865	-0.626	-0.623	-0.637	-0.596	-1.345
	[-2.939,1.209]	[-2.767,1.515]	[-2.767,1.520]	[-2.791,1.517]	[-2.788,1.596]	[-3.651,0.961]
Years since data collection	0.083***	0.085***	0.084***	0.084***	0.088***	0.065**
	[0.030,0.137]	[0.031,0.139]	[0.030,0.139]	[0.030,0.139]	[0.034,0.142]	[0.007,0.123]
Journal		0.689	0.688	0.691	0.789	-0.079
		[-0.825,2.203]	[-0.827,2.203]	[-0.825,2.206]	[-0.722,2.300]	[-1.710,1.552]
No reported standard errors			-0.035	-0.034	0.057	-0.18
			[-0.764,0.694]	[-0.764,0.695]	[-0.681,0.796]	[-0.939,0.578]
Only male				-0.037	-0.013	-0.074
				[-0.665,0.591]	[-0.642,0.615]	[-0.712,0.563]
Only female				-0.29	-0.284	-0.307

				[-1.045,0.465]	[-1.039,0.471]	[-1.071,0.456]
Quality score 0 (base)						
Quality score 1					0.51	0.731
					[-0.361,1.382]	[-0.165,1.628]
Quality score 2					1.119**	1.384**
					[0.075,2.164]	[0.306,2.463]
Quality score 3					0.698	0.494
					[-0.882,2.279]	[-1.168,2.157]
Constant	0.941	0.184	0.218	0.232	-0.346	6.161***
	[-1.265,3.146]	[-2.579,2.946]	[-2.634,3.069]	[-2.629,3.092]	[-3.262,2.570]	[3.471,8.851]
N	3963	3963	3963	3963	3963	3963
AIC	24374.1	24367.41	24362.77	24355.37	24337.37	24408.96
BIC	24430.66	24430.26	24431.9	24437.07	24437.92	24503.23
AICc	24374.15	24367.47	24362.83	24355.46	24337.5	24409.08
CAIC	24439.66	24440.26	24442.9	24450.07	24453.92	24518.23

Note: The table displays coefficients as well as their confidence intervals (in brackets). Stars indicate statistical significance at 10% (*); at 5% (**); at 1% (***). Details regarding variable definitions are provided Table 4.1 of Chapter 4.

Table A F.9. Estimation results for new stated preference data

Three-Level random effects meta-regression. Dependent Variable = VSL (USD million)

	Model 1	Model 2	Model 3	Model 4
GDP per capita (USD thousand)	0.130***	0.154***	0.139***	0.143***
	[0.097,0.163]	[0.112,0.195]	[0.101,0.178]	[0.099,0.187]
Contingent valuation method (base)				
Choice experiment	1.405**	1.771***	0.801	1.087
	[0.113,2.698]	[0.432,3.110]	[-0.635,2.237]	[-0.307,2.482]
Other SP method	16.023***		15.761***	
	[10.670,21.376]		[10.053,21.468]	
Years since data collection	0.096	0.058	0.09	0.033
	[-0.023,0.215]	[-0.079,0.196]	[-0.045,0.226]	[-0.117,0.182]
Journal	1.011	2.972**	1.48	2.36
	[-1.300,3.321]	[0.001,5.942]	[-0.980,3.939]	[-0.501,5.220]
No reported standard errors	-0.446	-0.752	-0.143	-0.559
	[-1.716,0.825]	[-2.118,0.615]	[-1.582,1.295]	[-2.097,0.978]
Only male	0.803	0.607	-0.055	-0.113
	[-2.400,4.006]	[-2.431,3.644]	[-4.351,4.241]	[-3.854,3.628]
Only female	-0.585	-0.269	-0.285	-0.325
	[-3.296,2.127]	[-3.094,2.557]	[-4.103,3.532]	[-3.751,3.101]
	0.422	0.255	0.318	-0.361

SP study including baseline risk of respondents	[-1.215,2.058]	[-1.792,2.301]	[-1.607,2.242]	[-2.572,1.851]
Scope sensitivity	1.333	1.327	0.803	0.861
	[-0.289,2.955]	[-0.553,3.208]	[-1.001,2.607]	[-0.999,2.720]
Visual aids	1.329	1.760*	1.365	1.627
	[-0.270,2.927]	[-0.165,3.685]	[-0.454,3.185]	[-0.384,3.638]
Nationwide		0.194		0.485
		[-1.761,2.148]		[-1.541,2.511]
General population		0.893		0.505
		[-1.136,2.922]		[-1.537,2.547]
Representative		-2.147*		-0.35
		[-4.504,0.210]		[-2.863,2.163]
Risk change			-13.442***	-13.236***
			[-23.507,-3.377]	[-22.256,-4.215]
Constant	-4.533**	-6.070***	-5.087**	-5.436**
	[-8.036,-1.029]	[-10.386,-1.755]	[-9.007,-1.167]	[-9.681,-1.191]
N	969	775	751	652
AIC	5695.871	4431.535	4463.817	3740.245
BIC	5764.138	4505.981	4533.138	3816.406
AICc	5696.311	4432.253	4464.47	3741.21
CAIC	5778.138	4521.981	4548.138	3833.406

Note: The table displays coefficients as well as their confidence intervals (in brackets). Stars indicate statistical significance at 10% (*); at 5% (**); at 1% (***). Details regarding variable definitions are provided Table 4.1 of Chapter 4.

Table A F.10. Estimation results for New stated preference data, with all risk categories

Three-level random effects meta-regression. Dependent Variable = VSL (USD million)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
GDP per capita (USD thousand)	0.088***	0.081***	0.127***	0.157***	0.089***	0.079***
	[0.049,0.127]	[0.039,0.124]	[0.092,0.162]	[0.113,0.201]	[0.045,0.132]	[0.030,0.129]
Contingent valuation method (base)						
Choice experiment	1.401*	1.708**	1.494**	1.786**	1.207	1.931*
	[-0.268,3.070]	[0.099,3.317]	[0.139,2.849]	[0.399,3.174]	[-0.717,3.131]	[-0.047,3.910]
Other SP method			15.958***			
			[10.598,21.318]			
Years since data collection	0.064	0.032	0.07	0.016	0.043	0.012
	[-0.071,0.200]	[-0.136,0.200]	[-0.057,0.198]	[-0.129,0.161]	[-0.111,0.198]	[-0.185,0.208]
Journal	0.104	0.102	0.913	2.68	-0.209	0.114
	[-1.727,1.935]	[-2.242,2.445]	[-1.688,3.515]	[-0.525,5.886]	[-2.424,2.006]	[-2.693,2.920]
No reported standard errors	-0.717	-0.546	-0.362	-0.735	-0.755	-0.578
	[-2.280,0.846]	[-1.974,0.883]	[-1.688,0.964]	[-2.147,0.678]	[-2.430,0.920]	[-2.115,0.960]

Only male	-0.373	0.131	1.036	0.871	-0.276	0.071
	[-4.361,3.614]	[-2.717,2.979]	[-2.201,4.273]	[-2.173,3.915]	[-4.419,3.866]	[-2.848,2.989]
Only female	-1.321	-0.264	-0.415	-0.058	-1.269	-0.397
	[-4.807,2.164]	[-2.907,2.379]	[-3.200,2.371]	[-2.918,2.802]	[-4.999,2.460]	[-3.178,2.384]
SP study including baseline risk	-0.673	-1.088	-0.088	-0.31	-1.153	-1.25
	[-2.420,1.074]	[-2.971,0.794]	[-2.015,1.839]	[-2.601,1.981]	[-3.366,1.060]	[-3.586,1.087]
SP study focusing on scope sensitivity	1.23	0.79	1.503*	1.312	1.813	1.026
	[-0.836,3.295]	[-1.311,2.890]	[-0.212,3.217]	[-0.699,3.322]	[-0.459,4.085]	[-1.531,3.582]
SP study including visual aids	1.398	1.616	1.571*	1.709	1.514	1.284
	[-0.317,3.114]	[-0.331,3.562]	[-0.217,3.360]	[-0.406,3.824]	[-0.495,3.522]	[-0.973,3.542]
Nationwide		0.774		-0.002		0.768
		[-1.193,2.741]		[-2.038,2.034]		[-1.425,2.962]
General population		1.428*		0.945		1.366
		[-0.249,3.105]		[-1.220,3.110]		[-0.761,3.494]
Representative		1.061		-2.558**		0.995
		[-1.103,3.225]		[-5.072,-0.043]		[-1.484,3.473]
Risk acuteness (base = mixed)						
Acute	2.621***	2.468***			1.547	2.352
	[0.822,4.420]	[0.696,4.239]			[-3.350,6.444]	[-2.632,7.335]
Risk type (base = transportation)						
Cancer	2.018**	2.286***			1.864*	2.205**
	[0.233,3.803]	[0.602,3.970]			[-0.269,3.997]	[0.303,4.107]
Climate			1.108	-0.631	0.2	-0.65
			[-4.177,6.394]	[-8.483,7.222]	[-4.228,4.627]	[-6.928,5.628]
Crime			-1.419	-0.886	-2.723	-2.848
			[-7.677,4.839]	[-14.567,12.796]	[-15.668,10.223]	[-15.480,9.785]
Disaster			4.582	4.887	4.214	3.229
			[-3.444,12.608]	[-3.283,13.056]	[-3.969,12.398]	[-4.492,10.951]
Environment			-1.114	-0.791	-0.377	0.29
			[-3.276,1.048]	[-2.957,1.374]	[-5.488,4.734]	[-4.967,5.547]
Health			0.432	0.984	-1.543	0.137
			[-1.065,1.929]	[-0.513,2.480]	[-6.134,3.048]	[-4.448,4.721]
Natural disaster			-0.476	-0.003	-0.162	0.93
			[-3.707,2.755]	[-3.493,3.487]	[-2.910,2.587]	[-1.946,3.806]
Not specified			-2.533	-0.258	-1.539	1.488
			[-11.155,6.089]	[-9.077,8.562]	[-10.282,7.204]	[-6.826,9.802]
Suicide			-0.781	-1.089	-1.418	-1.186
			[-12.972,11.410]	[-13.282,11.104]	[-13.198,10.362]	[-12.688,10.316]
Virus			-3.384	-4.408*	-2.253	-0.412
			[-7.870,1.102]	[-9.265,0.448]	[-8.442,3.936]	[-7.096,6.272]

Constant	-3.145*	-4.760**	-3.969**	-4.918**	-1.611	-4.549
	[-6.680,0.391]	[-8.761,-0.759]	[-7.876,-0.063]	[-9.607,-0.230]	[-7.665,4.442]	[-11.492,2.394]
N	471	368	969	775	471	368
AIC	2777.057	2015.107	5653.14	4388.489	2742.149	1984.239
BIC	2839.38	2085.452	5765.294	4504.81	2841.865	2089.757
AICc	2778.112	2017.066	5654.308	4390.225	2744.839	1988.686
CAIC	2854.38	2103.452	5788.294	4529.81	2865.865	2116.757

Note: The table displays coefficients as well as their confidence intervals (in brackets). Stars indicate statistical significance at 10% (*); at 5% (**); at 1% (***). Details regarding variable definitions are provided Table 4.1 of Chapter 4.

Table A F.11. Estimation results for New RP data

Three-level random effects meta-regression. Dependent variable = VSL (USD million)

	Model 1	Model 2	Model 3	Model 4
GDP per capita (USD thousand)	0.094***	0.109***	0.102***	0.112***
	[0.029,0.160]	[0.031,0.188]	[0.032,0.172]	[0.029,0.195]
Hedonic wage (base)				
Consumer market valuation method	-1.588	-0.557	-1.014	-0.073
	[-5.468,2.292]	[-4.963,3.849]	[-5.172,3.145]	[-4.786,4.640]
Years since data collection	0.181*	0.256**	0.159	0.225*
	[-0.029,0.391]	[0.026,0.487]	[-0.062,0.380]	[-0.018,0.468]
Journal	2.782	2.398	3.370*	3.091
	[-0.711,6.274]	[-1.280,6.077]	[-0.524,7.265]	[-1.003,7.184]
No reported standard errors	-0.354	-0.836	1.372	0.859
	[-2.666,1.958]	[-3.242,1.570]	[-1.792,4.536]	[-2.556,4.275]
Only male	-0.193	-0.111	-0.737*	-0.655
	[-0.847,0.462]	[-0.770,0.547]	[-1.584,0.109]	[-1.512,0.201]
Only female	-0.282	-0.237	-0.846*	-0.789
	[-1.097,0.532]	[-1.051,0.577]	[-1.824,0.133]	[-1.771,0.194]
RP study using IV estimate	0.346	0.436	0.166	0.258
	[-0.857,1.549]	[-0.773,1.644]	[-1.055,1.387]	[-0.970,1.487]
RP study controlling for non-fatal injury risks	1.353*	1.390*	1.292*	1.343*
	[-0.166,2.871]	[-0.168,2.948]	[-0.244,2.828]	[-0.234,2.921]
RP study using Census of Fatal Occupational Injuries (CFOI) data	1.16	0.152	1.141	0.326
	[-2.383,4.702]	[-3.794,4.097]	[-2.720,5.002]	[-3.891,4.542]
Nationwide		0.395		0.553
		[-3.265,4.055]		[-3.357,4.463]
General population		2.966**		2.473
		[0.098,5.833]		[-0.522,5.468]
Representative		-0.516		-0.521
		[-4.347,3.316]		[-4.476,3.435]
Hedonic wage RP study			1.39	1.259

			[-0.704,3.484]	[-0.850,3.368]
RP study with full sample			-0.740**	-0.710**
			[-1.436,-0.044]	[-1.411,-0.009]
Constant	-3.142	-5.811	-4.294	-6.61
	[-8.864,2.580]	[-13.150,1.528]	[-10.468,1.881]	[-14.598,1.377]
N	1403	1403	1387	1387
AIC	8305.46	8283.366	8201.279	8180.928
BIC	8373.663	8367.308	8279.803	8275.156
AICc	8305.722	8283.758	8201.629	8181.428
CAIC	8386.663	8383.308	8294.803	8293.156

Note: The table displays coefficients as well as their confidence intervals (in brackets). Stars indicate statistical significance at 10% (*); at 5% (**); at 1% (***). Details regarding variable definitions are provided Table 4.1 of Chapter 4.

Table A F.12. Estimation results for only new RP data, with all risk categories

Three-level random effects meta-regression. Dependent Variable = VSL (USD million).

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
GDP per capita (USD thousands)	0.107**	0.115**	0.123***	0.131***	0.136***	0.156***
	[0.019,0.195]	[0.011,0.218]	[0.038,0.208]	[0.034,0.228]	[0.045,0.227]	[0.040,0.272]
Hedonic wage (base)						
Consumer market valuation method	-3.283	-2.392	-0.626	1.425	-0.756	-1.025
	[-9.394,2.828]	[-9.529,4.746]	[-7.615,6.363]	[-6.726,9.575]	[-7.271,5.758]	[-9.082,7.031]
Years since data collection	0.146	0.219	0.19	0.267**	0.099	0.125
	[-0.089,0.382]	[-0.055,0.493]	[-0.038,0.418]	[0.016,0.518]	[-0.128,0.325]	[-0.133,0.382]
Journal	3.076	2.562	2.106	2.691	3.638	3.172
	[-1.436,7.587]	[-2.362,7.485]	[-2.761,6.973]	[-2.453,7.834]	[-2.053,9.329]	[-3.153,9.497]
No reported standard errors	-0.576	-0.911	-0.81	-0.904	-0.576	-0.866
	[-3.118,1.966]	[-3.586,1.763]	[-3.337,1.717]	[-3.506,1.698]	[-3.092,1.940]	[-3.488,1.756]
Only male	0.248	0.309	-0.192	-0.115	0.292	0.304
	[-0.470,0.966]	[-0.415,1.033]	[-0.847,0.464]	[-0.775,0.546]	[-0.425,1.009]	[-0.420,1.028]
Only female	0.229	0.248	-0.271	-0.229	0.236	0.242
	[-0.758,1.215]	[-0.736,1.233]	[-1.087,0.544]	[-1.045,0.586]	[-0.752,1.223]	[-0.745,1.228]
RP study using IV estimate	0.332	0.392	0.383	0.435	0.465	0.5
	[-0.909,1.573]	[-0.855,1.638]	[-0.834,1.601]	[-0.788,1.658]	[-0.779,1.709]	[-0.750,1.749]
RP studies controlling for non-fatal injury risks	1.575*	1.670**	1.378*	1.499*	1.358*	1.523*
	[-0.024,3.174]	[0.009,3.331]	[-0.190,2.946]	[-0.106,3.104]	[-0.241,2.957]	[-0.134,3.181]
RP studies using Census of Fatal Occupational Injuries (CFOI) data	0.018	-0.679	0.388	-0.524	-0.619	-0.892
	[-4.167,4.203]	[-5.422,4.064]	[-3.877,4.653]	[-5.170,4.123]	[-5.122,3.885]	[-5.776,3.992]
Nationwide		0.896		1.464		-1.511
		[-3.799,5.591]		[-3.128,6.056]		[-7.206,4.183]
General population		2.358		2.667		1.158

		[-1.109,5.825]		[-0.676,6.010]		[-2.215,4.532]
Representative		-0.033		-0.156		0.876
		[-4.655,4.588]		[-4.494,4.182]		[-3.610,5.363]
Risk acuteness (base = chronic)						
Acute	-6.653	-5.501			-28.953***	-29.702***
	[-15.244,1.938]	[-14.894,3.891]			[-43.355,-14.550]	[-46.577,-12.828]
Mixed	-4.999	-4.762			-21.280***	-21.043***
	[-13.714,3.717]	[-14.125,4.602]			[-34.366,-8.195]	[-34.747,-7.339]
Risk type (base = job)						
Cancer	-0.143	-0.364			-0.355	-0.46
	[-3.983,3.698]	[-4.312,3.583]			[-4.070,3.360]	[-4.277,3.357]
Climate			-1.439	1.391	6.384	6.07
			[-10.563,7.686]	[-8.920,11.703]	[-4.128,16.895]	[-5.283,17.422]
Disaster			1.2	-0.773	-20.718**	-21.472**
			[-10.547,12.947]	[-14.533,12.987]	[-36.960,-4.476]	[-39.658,-3.285]
Environment			-4.664	-5.636	-26.338***	-25.819***
			[-16.038,6.709]	[-17.728,6.456]	[-42.263,-10.414]	[-42.673,-8.965]
Health			-4.627	-5.168		
			[-14.414,5.161]	[-15.560,5.224]		
Military			-5.274	-2.8	2.152	2.988
			[-14.051,3.504]	[-12.711,7.111]	[-8.217,12.522]	[-9.118,15.093]
Transportation			-0.792	-0.589	6.554	7.686
			[-4.597,3.012]	[-4.431,3.254]	[-1.341,14.449]	[-2.587,17.960]
Virus			2.113	1.202		
			[-9.340,13.566]	[-11.786,14.189]		
Constant	2.299	-0.666	-3.16	-7.663*	18.001**	17.559**
	[-9.983,14.580]	[-14.913,13.581]	[-10.087,3.767]	[-16.695,1.368]	[2.795,33.208]	[0.007,35.111]
N	1247	1247	1403	1403	1247	1247
AIC	7502.899	7484.09	8261.932	8241.534	7462.971	7446.175
BIC	7584.955	7581.531	8366.859	8362.201	7570.67	7569.259
AICc	7503.342	7484.709	8262.539	8242.335	7463.725	7447.157
CAIC	7600.955	7600.531	8386.859	8385.201	7591.67	7593.259

Note: The table displays coefficients as well as their confidence intervals (in brackets). Stars indicate statistical significance at 10% (*); at 5% (**); at 1% (***). Details regarding variable definitions are provided Table 4.1 of Chapter 4.

Annex G. Recommended VSL estimates: Descriptive statistics

Descriptive statistics

Table A G.1 provides the GDP per capita values for the meta sample (study level) and the population used to convert mean PUVSL estimates from Section 4.5 of Chapter 4 to base values for the different country groups in Table 6.1 and Table 6.2 of Chapter 6. The sample values for the sample limited to journal publications are also included. These would be needed to estimate base VSL estimates based on these data only.

Table A G.1. GDP per capita (USD thousand, nominal) in population and meta-analysis sample (New SP and RP) of countries within groups

	Population values		Sample values (study level)		Sample values (estimate level)	
Country group	**GDP/capita (PW)**	**GDP/capita (CW)**	**GDP/capita (all public.)**	**GDP/capita (journals)**	**GDP/capita (all public.)**	**GDP/capita (journals)**
All countries	21 623	28 914	43603	42157	50442	45746
OECD	56 224	60 622	56213	54816	60118	56330
EU	58 043	60 490	52703	51584	57345	52903
EEA	58 852	63 137	54125	53192	58310	54458
United States	77 178	77 178	65534	65407	67706	64929
High-income countries	62 989	59 194	56324	55020	59246	55281
Low- and middle-income countries	13 576	11 207	10766	10824	9450	9978

Note: PW = VSL adjusted by population-weighted GDP per capita. CW = VSL adjusted by country-weighted GDP per capita. GDP per capita data of OECD countries is computed using OECD data on GDP (OECD, 2024[1]) and population (OECD, 2024[2]). GDP per capita data comes from the World bank (World Bank, 2024[3]) for non-OECD countries. GDP and population data come from the World Economic Outlook database (IMF, 2024[4]) for Chinese Taipei. GDP per capita data for all countries are expressed in PPP.

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Annex H. List of studies 2009-2024

Date of list: 4. December 2023.

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Mortality Risk Valuation in Policy Assessment

A Global Meta-Analysis of Value of Statistical Life Studies

Policymakers are often faced with decisions affecting human health and mortality risk. For example, new vehicle fuel efficiency standards may lead to higher costs for consumers but could also save lives by improving air quality in urban areas, thus creating a trade-off between economic costs and the value of reducing mortality risk. Yet, too often, these economic trade-offs are not assessed in a systematic manner using a consistent methodology.

This report aims to equip policymakers with the methodologies and economic valuations to quantify economic benefits of avoided fatalities, also known as the "Value of a Statistical Life" (VSL). The findings are based on a meta-analysis of 277 studies and more than 4 000 VSL estimates covering six country groups with guidance on how to apply the values across countries and over time. The VSL estimates presented in this report are intended to support cost-benefit analyses and other policy assessments, covering any area where monetising and comparing mortality risk effects against the costs of such initiatives could inform decision making.

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