Value of a statistical life in road safety: A benefit-transfer function with risk-analysis guidance based on developing country data

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Abstract
We model a value of statistical life (VSL) transfer function for application to road-safety engineering in developing countries through an income-disaggregated meta-analysis of scope-sensitive stated preference VSL data. The income-disaggregated meta-analysis treats developing country and high-income country data separately. Previous transfer functions are based on aggregated datasets that are composed largely of data from high-income countries. Recent evidence, particularly with respect to the income elasticity of VSL, suggests that the aggregate approach is deficient because it does not account for a possible change in income elasticity across income levels. Our dataset (a minor update of the OECD database published in 2012) includes 123 scope-sensitive VSL estimates from developing countries and 185 scope-sensitive estimates from high-income countries. The transfer function for developing countries gives $VSL = 1.3732E-4 \cdot (\text{GDP per capita})^{2.478}$, with $VSL$ and $\text{GDP per capita}$ expressed in 2005 international dollars (an international dollar being a notional currency with the same purchasing power as the U.S. dollar). The function can be applied for low- and middle-income countries with GDPs per capita above $1268$ (with a data gap for very low-income countries), whereas it is not useful above a GDP per capita of about $20,000$. The corresponding function built using high-income country data is $VSL = 8.2474E+3 \cdot (\text{GDP per capita})^{.6932}$; it is valid for high-income countries but over-estimates VSL for low- and middle-income countries. The research finds two principal significant differences between the transfer functions modeled using developing-country and high-income-country data, supporting the disaggregated approach. The first of these differences relates to between-country VSL income elasticity, which is 2.478 for the developing country function and .693 for the high-income function; the difference is significant at $p<0.001$. This difference was recently postulated but not analyzed by other researchers. The second difference is that the traffic-risk context affects VSL negatively in developing countries and positively in high-income countries. The research quantifies uncertainty in the transfer function using parameters of the non-absolute distribution of relative transfer errors. The low- and middle-income function is unbiased, with a median relative transfer error of -.05 (95% CI: -.15 to .03), a 25th percentile error of -.22 (95% CI: -.29 to -.19), and a 75th percentile error of .20 (95% CI: .14 to .30). The quantified uncertainty characteristics support evidence-based approaches to sensitivity analysis and probabilistic risk analysis of economic performance measures for road-safety investments.

Key words: value of statistical life; mortality risk valuation; road safety; transport economics; developing countries; risk analysis; benefit transfer

Highlights
• We model the first developing country-based VSL transfer function via meta-analysis
• We use the new comprehensive stated preference dataset from the OECD (2012)
• VSL income elasticity: 2.478 (developing); .693 (high income); different at $p<.001$
• We expand existing techniques to quantify uncertainty in transfer functions
• Results support evidence-based risk analysis of economic performance forecasts

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1. Introduction

Analyses of investments to prevent road fatalities often use the net present value (NPV), the internal rate of return (IRR) or the social benefit-cost ratio as a prospective transport performance measure. These performance measures require estimates of both the value of a statistical life (VSL) and the value of a statistical injury (VSI). A robust and conservative engineering economic analysis using these performance measures also requires estimates of uncertainty in VSL and VSI. Many developing countries do not have appropriate VSL estimates and need to adapt existing estimates from elsewhere using transfer functions in a process called benefit-transfer. The currently available benefit-transfer functions are based on meta-analyses of datasets composed primarily of high-income country data, which may not be appropriate for application in developing countries.

The objectives of this research are to (1) develop a new VSL transfer function for application to transport safety in developing countries that is based on VSL estimates from developing countries, (2) determine whether this function differs significantly from functions that are based on VSL estimates from developed countries and (3) quantify the uncertainty associated with this new transfer function for practical application to the risk analysis of performance measures.

The study accomplishes these objectives by performing a new meta-analysis on a database of VSL estimates that has been made available as an accompaniment to the publication *Mortality Risk Valuation in Environment, Health and Transport Policies* (OECD 2012). Meta-analysis, which is widely used in road safety and other fields of research, is “a quantified synthesis of the results of several studies” (Elvik, Høye, et al. 2009, 20). The research also expands on the existing techniques for transfer error analysis and interpretation to validate the transfer function and enable its application in a stochastic framework.

The work is a subset of a project at the World Bank to develop a flagship report entitled *Comprehensive Assessment of Transport Policies and Projects* that will provide ex ante evaluation instruments to allow engineers to incorporate wider, multi-sectoral benefits of transport as well as environmental and safety costs into decision-making supports.

2. Existing Knowledge, Practices, and Needs

This section is organized into four subsections. Section 2.1 presents the general need for VSL estimates as inputs to the social benefit-cost analysis of road safety investments. Section 2.2 provides an overview of the methods used to create original VSL estimates along with their strengths and weaknesses. Section 2.3 describes the process of transferring VSL estimates to policy contexts in which no appropriate original VSL estimate exists and the current practice for assessing the uncertainty related to these transfers. Finally, Section 2.4 describes the state of existing practice for obtaining VSL estimates in developing countries and the emergence of opportunities to improve the state of this practice.

2.1 The transport safety problem and the need for VSL estimates in benefit-cost analysis

The need for this research is fundamentally predicated on the transport safety problem in developing countries, which has the dimensions of a global disease. While transport risks to individual users may appear low, the cumulative impact of these risks places a high burden on society. Nordfjærn et al. (2012) describe the problem as “increasing towards endemic proportions in developing countries” (p.1862). Worldwide, there are approximately 1.3 million road transport fatalities per year—or approximately 3500 per day (WHO 2012). Analysts expect these rates to increase, and developing countries bear a high share of the burden (World Bank and WHO 2004). Because of the magnitude of the problem and in recognition of health-related millennium development goals, the World Bank focuses on...
safety as the first of three themes in its transport business strategy for 2008 to 2012, entitled Safe, Clean, and Affordable Transport for Development (World Bank 2008).

Many engineering countermeasures—in the form of policies or projects—are available to reduce the risk of transport fatalities and injuries. Elvik et al. (2009) review the expected effectiveness levels of various countermeasures, as do several other handbooks and toolkits. With the resulting estimated changes to physical indicators in hand (i.e., reductions in fatalities or serious injuries), governments turn to social benefit-cost analysis (BCA) to develop performance measures that evaluate transport safety spending vis-à-vis other potential public spending from the perspective of overall welfare. An in-depth guide to project evaluation using social BCA is provided by Dasgupta, Sen and Marglin (1972). Market prices often provide suitable information about public preferences for use in BCA, but in many cases, they do not. In these cases, social BCA requires the use of shadow prices, which are notional prices for the physical costs and benefits used by the government to reflect public preferences for evaluation purposes (Dasgupta, Sen and Marglin 1972). When social BCA addresses transport safety, shadow prices are required for the benefits of reduced transport risks because no market directly deals in these benefits. Most work to develop shadow prices for road safety produces a VSL or a VSI. The costs of property damage only (PDO) collisions are more amenable to evaluation at market prices because there are functioning markets that deal in the repair or replacement of damaged property (namely, vehicles). Furthermore, although the PDO costs are significant, they are small compared with the costs of injuries and fatalities. It is important to note that the VSL values do not reflect the moral value of a person’s life. An appropriate VSL value is one that supports social BCA by reflecting the preferences of individual members of the public related to their individual marginal rates of substitution between risk and income. Although social BCA is a widely used tool to evaluate road safety investments according to public preferences, it is not the only approach. Other approaches to evaluate road safety investments include cost-effectiveness analysis, vision zero (see support in (Rosencrantz, Edvarsson and Hansson 2007) and criticism in (Elvik 1999)), multi-criteria analysis (e.g., an impact tableau (Manheim 1979)), and citizen’s juries (see arguments in favor by (Hauer 2011)). Although some researchers prefer and argue for these other approaches, this paper develops a new VSL benefit transfer function for application to road safety BCA in developing countries—though alternative approaches to BCA exist—under the assumption that the conventional practice of social BCA will continue for some time and that social BCA is useful for evaluation purposes.

2.2 Methods to estimate VSL and their strengths and weaknesses

The methods used to estimate the value of a statistical life fall into two categories: the human capital (HC) method and the willingness to pay (WTP) method. The HC method uses lost productivity calculations, and analysts have almost completely abandoned this method because it fails to account for intangible dimensions, such as suffering and grief. They instead favor the WTP method, which implicitly includes these dimensions and is based on consumer preferences, which form the basis of BCA under the new welfare economics paradigm. The WTP method is further classified into two categories: the stated preference (SP) and revealed preference (RP) methods.

The stated preference (SP) method uses surveys that are designed to elicit from participants a statement about the quantity of money that they would be willing to spend to achieve a small reduction in mortality risk. These surveys are based on an assumption that individuals can state their real preferences regarding a marginal rate of substitution between wealth and a specific type of mortality risk reduction when asked hypothetical questions about these preferences. If a person states a willingness to pay $10,000 towards a policy that will reduce their risk of dying from 1.5% to .5%, the value of a statistical life is calculated as the willingness to pay divided by the risk reduction, or $10,000 divided by 1%, giving $1 million. If there were 100 identical people, the expected number of deaths reduced by implementing the policy for the entire group is 1 (reduced from 1.5 to .5), and as a group, the total willingness to pay to save that one statistical life is $1 million (100 people times $10,000).

The revealed preference (RP) method observes behavior in a proxy market to measure the actual willingness to pay for small reductions in mortality risk; the method then calculates the VSL in the same
way that the SP method uses. The RP method requires a market for behavior observation. The RP method uses two markets: (1) the labor market and (2) the market for risk-reducing consumer goods (OECD 2012) (Hauer 2011) (Kochi, Hubbell and Kramer 2006) (Viscusi and Aldy 2003) (Miller 2000). The labor market method attempts to identify the wage premium associated with risk in jobs. The risk-reducing consumer goods market method attempts to identify the WTP for risk reduction by combining prices for protective goods—such as smoke alarms or safer cars—with estimates of the corresponding risk reductions offered by these goods. This WTP reflects a lower-bound WTP for the buyers of the good and an upper-bound WTP for the non-buyers of the good. Within RP methods, the wage-risk market is used more frequently than the risk-reducing consumer goods market.

Among developed countries, the United States has traditionally relied on RP methods using the labor market for VSL estimates, whereas European countries, Canada, and Australia tend to use the SP approach (OECD 2012). Overall, there is a growing emphasis on SP methods (OECD 2012), and the use of RP methods has slowed significantly since 1990 (Miller 2000).

Table 1 summarizes the literature on the strengths and weaknesses of the SP and RP methods for obtaining VSL estimates for use in engineering economics. The main strengths of the SP method are its ability to match survey questions to the policy risk context and achieve broad representation through survey design and control. The main strength of the RP method is its basis on actual behavior.

Table 1: Strengths and weaknesses of the stated and revealed preference methods

<table>
<thead>
<tr>
<th>Stated Preference</th>
<th>Weaknesses</th>
<th>Revealed Preference</th>
<th>Weaknesses</th>
</tr>
</thead>
<tbody>
<tr>
<td>Strengths</td>
<td></td>
<td>Strengths</td>
<td></td>
</tr>
<tr>
<td>-Flexibility to control for many variables including risk context&lt;sup&gt;a&lt;/sup&gt;</td>
<td>-Based on hypothetical behaviour&lt;sup&gt;a,b&lt;/sup&gt;</td>
<td>-Based on actual behaviour&lt;sup&gt;a,c&lt;/sup&gt;</td>
<td>-Context-insensitive, but risk valuation is context-sensitive&lt;sup&gt;a,d,e,f&lt;/sup&gt;</td>
</tr>
<tr>
<td>-Can elicit preferences for non-observable attributes&lt;sup&gt;g&lt;/sup&gt;</td>
<td>-Lack of systematic responses to very small risk changes&lt;sup&gt;a,f,h&lt;/sup&gt;</td>
<td>-Some research finds consensus that wage is responsive to risk&lt;sup&gt;i&lt;/sup&gt;</td>
<td>-Some research finds that the wage-risk relationship is spurious&lt;sup&gt;c,j&lt;/sup&gt;</td>
</tr>
<tr>
<td>-Can be representative of population if well designed&lt;sup&gt;f&lt;/sup&gt;</td>
<td></td>
<td></td>
<td>-Difficult to account for non-risk determinants of wage variation&lt;sup&gt;a,b,f,k&lt;/sup&gt;</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>-Panel data only gives cross-individual rates of substitution&lt;sup&gt;d&lt;/sup&gt;</td>
</tr>
<tr>
<td></td>
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<td></td>
<td>-High transaction costs means that workers not at wage-risk equilibrium&lt;sup&gt;h&lt;/sup&gt;</td>
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<tr>
<td></td>
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<td></td>
<td>-Wage-earners are not representative of the population&lt;sup&gt;i&lt;/sup&gt;</td>
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<tr>
<td></td>
<td></td>
<td></td>
<td>-Estimates are distorted by the gap between real and perceived risks&lt;sup&gt;a,b,h&lt;/sup&gt;</td>
</tr>
</tbody>
</table>

Notes: <sup>a</sup> (Hauer 2011); <sup>b</sup> (Kochi, Hubbell and Kramer 2006); <sup>c</sup> (Cnaan and Kang 2011), <sup>d</sup> (Grüne-Yanoff 2009); <sup>e</sup> (Mrozek and Taylor 2002) <sup>f</sup> (OECD 2012) <sup>g</sup> (Goldberg and Roosen 2007); <sup>h</sup> (McConnel 2006); <sup>i</sup> (Ruser and Butler 2009); <sup>j</sup> (Miller 2000); <sup>k</sup> (Viscusi and Aldy 2003).

Table 1 indicates that one of the weaknesses of RP wage-risk market studies is the lack of equilibrium in the employment market because of the high transaction costs associated with changing jobs, which results in an upward bias in RP-based VSL estimates. For a given risk difference between two jobs, the wage premium required to switch jobs is thus higher than the actual risk premium because of the transaction costs. Because this method bases VSL on the ratio of the wage premium to the risk difference,
the transaction cost effectively upwardly biases the VSL estimate. Another factor that can introduce an upward bias in the RP wage-risk methods is a tendency of regression modelers to remove workplace injury risk from the regression models to avoid any associated multicollinearity issues, with the result that the calculated wage premium for mortality risk is actually the premium for mortality and injury risk together (Miller 2000). This theoretical upward bias is also demonstrated empirically: Kochi et al. (2006) compare distributions of VSL estimates based on SP and RP methods and find that RP estimates are higher and more dispersed than SP estimates.

The main weakness of the SP method, stemming from its hypothetical basis, is that SP surveys sometimes fail to elicit systematic responses to very small risk changes. People have difficulty comprehending small numbers and small risk changes (Hauer 2011), and they may sometimes respond with the same WTP for risk changes that differ significantly.

Although both methods have weaknesses, there are opportunities to address these weaknesses by applying the methods within a careful design. For example, in SP surveys, the use of visual aids to help participants understand risk changes greatly reduces the variability in the resulting VSL estimates (OECD 2012). In RP wage-risk studies, the use of multivariate regression modelling can be employed to isolate risk factors from other determinants of wages.

This paper uses VSL estimates developed using SP methods to model transfer functions, principally due to the methods’ inability to investigate risk context. There is some degree of uncertainty in all VSL estimates, and this should be quantified and accounted for to support robust economic assessments to the greatest extent possible.

2.3 Transferring VSL estimates between policy contexts: needs, methods, and uncertainty

Many countries do not have SP-based VSL (Dahdah and McMahon 2008) (Miller 2000). When a social BCA is required to support engineering economic analysis in a policy context without an appropriate VSL estimate, analysts use benefit-transfer to obtain an estimate for the policy context based on estimates that have been derived elsewhere. The OECD (2012) gives details on five methods to conduct benefit-transfer. In order of the amount of information incorporated into the transfer process, these methods are: (1) simple (naive) unit value transfer; (2) unit value transfer with income adjustments; (3) unit value transfer for separate age groups; (4) benefit function transfer from a single study; and (5) benefit function transfer by meta-analysis. This paper uses benefit function transfer by meta-analysis, which incorporates the greatest amount of information in the transfer process.

The quality of a benefit transfer function and the uncertainty associated with using it are measured using a process called transfer error analysis. The OECD (2012) describes this process as follows, drawing on Navrud and Ready (2007), Kristofersson and Navrud (2005), and Kristofersson and Navrud (2007). For one application of a transfer function where the result of the transfer function, \( VSL_{TF} \), can be compared with a benchmark value, \( VSL_B \), the transfer error is commonly defined as

\[
TE = 100\% \times \frac{|VSL_{TF} - VSL_B|}{VSL_B}.
\]

After many comparisons are made and a set of \( TE \) values is generated, previous studies have summarized transfer error performance using the mean or median \( TE \) values. The OECD (2012) tests the transfer function results using the actual estimates in the database as benchmark values. This allows as many tests of the transfer function as there are estimates in the database.

Previous studies (e.g., OECD 2012) summarize benefit transfer performance using the mean or median absolute transfer error. A summary of benefit transfer performance using the mean of absolute transfer errors has some limitations—namely, that this measure (1) is actually a description of the dispersion of non-absolute errors, (2) does not account for bias or asymmetry in the data, and (3) is highly sensitive to outliers. Some past studies have suggested ways to expand the approach to transfer error analysis. For example, Lindhjem and Navrud (2008) note the influence of \( TE \) outliers in the discussion of their Figure 3, prompting a focus on the 40th, 50th, and 70th percentiles of the absolute \( TE \) distribution. Rosenberger and Loomis (2000) show both absolute and non-absolute values of percent errors in their
Table 5; the ranges of values that they obtain for the absolute errors show a clear asymmetry around zero of the error data, which in turn suggests that the use of absolute errors leads to some information loss.

2.4 VSL and VSI in developing countries

All of the transfer functions used to estimate VSL for a developing country rely on evidence or assumptions about the between-country income elasticity of VSL. This elasticity is a ratio of the percentage difference in VSL between two countries to the percentage difference in incomes between two countries. Between-country income elasticity may differ from within-country income elasticity; consequently, generalizations from one to the other can be misleading. This paper focuses on between-country income elasticity rather than within-country income elasticity because the former is the elasticity that is relevant to transfer functions.

In early work on VSL transfer to developing countries, Miller (2000) develops a set of preliminary VSL transfer functions, but they are based on a regression of estimates from 13 primarily high income countries. Miller (2000) proposes that the functions could provide reasonable estimates for developing countries but notes an urgent need for more research to investigate the ability of these functions to predict VSL for lower-income countries that are beyond the range of the source data for the functions. The functions, built using a database composed largely of high-income country VSL estimates, indicate an income elasticity for VSL between .85 and 1.0.

Viscusi and Aldy (2003) provide a meta-analysis based on 60 estimates from wage-risk studies. The study uses a database composed largely of high-income country estimates, although four of the studies in the meta-analysis are based on developing countries. They find an income elasticity of VSL in the range of .5 to .6. They note that the regression results for the income elasticity of VSL are sensitive to the choice of studies included in the meta-analysis. This paper systematically includes and excludes studies from the meta-analysis based on income level, offering insight regarding whether the sensitivity of a model’s income elasticity to the included studies noted by Viscusi and Aldy (2003) is related in part to the income levels of the countries on which the studies are based.

Dahdah and McMahon (2008) develop an engineering rule-of-thumb approach for estimating VSL in developing countries using a regression of official VSL figures from 12 developed countries and 10 developing countries. Of the 10 developing country estimates, two are based on the WTP method, whereas eight are based on the HC method. The rule of thumb suggests a VSL value of 70 times GDP per capita with upper and lower values for sensitivity analysis of 60 and 80 times GDP per capita, respectively. An initial log-log model specification for their data yields an income elasticity of 1.125, so they opt for a simpler linear model specification because the elasticity is so close to 1.0. This rule of thumb transfer function has been widely used in developing countries by the International Road Assessment Programme (iRAP) and by international financial institutions, such as the World Bank. Dahdah and McMahon (2008) also develop a rule of thumb for the value of a serious injury at 25% of VSL for developing countries, which is based on the VSI / VSL ratios in developed countries adjusted upwards to account for higher collision severity in developing countries. As described below, new data now exist to update the work of Dahdah and McMahon (2008) for VSL values. A primary reason for the update is that the rule of thumb was built using only 2 WTP-based values from developing countries, and the new dataset contains 123 WTP-based values from developing countries.

Hammit and Robinson (2011) raise the question of whether the income elasticity of VSL changes with income level, postulating that it makes sense for elasticity to be greater than 1.0 at low income levels and less than 1.0 at higher income levels. They review longitudinal within-country wage-risk studies, a limited sample of between-country VSL comparisons, and two within-country cross-sectional wage-risk studies employing quantile regression, finding increasing evidence that the income elasticity of VSL is greater than 1.0 at lower income levels. Hammit and Robinson (2011) indicate that a substantial degree of uncertainty exists in the VSL estimates for developing countries obtained using transfers of high-income estimates, and they suggest that more research on VSL for low-income countries is required to improve transfer functions. The elasticity evidence presented by Hammit and Robinson (2011) is based on a small sample of mostly wage-risk data. Additionally, both Bhattacharya et al. (2006) for India and Mahmud
(2008) for Bangladesh find SP-based VSL values that are lower than the values that would be obtained using a high-income based transfer function with an elasticity of 1.0 or nearly 1.0. These VSL values located below a linear VSL-income plot suggest convexity of the relationship (elasticity above 1.0) in the low-income range. Extensive information on SP-based VSL estimates from developing countries that became available after publication of Hammit and Robinson (2011) provides an opportunity to systematically test their elasticity findings.

The OECD (2012) provides a rich database of VSL estimates from SP surveys in transport, health, and environmental risk contexts, including 221 estimates from developing countries. A few other developing country estimates have been published since then. The evidence presented by Hammit and Robinson (2011) for a possible income elasticity greater than 1.0 in developing countries suggests a research need to re-examine the transfer functions developed by Miller (2000) (with elasticity below 1.0) and the rule-of-thumb transfer function of Dahdah and McMahon (2008) (with elasticity = 1.0). The database provided in (OECD 2012), along with a few additional studies published since then, presents a new opportunity to address this research need by a meta-analysis of VSL estimates from developing countries. To the authors’ knowledge, this paper is the first to develop a VSL transfer function for application to transport safety engineering in developing countries that is based on VSL estimates from developing countries alone.

3. Methodology
This section describes the methodology for the research in three subsections organized according to the objectives of the research. Overall, the methodology follows the approach used by the OECD (2012), with some departures. Section 3.1 describes the methodology and data sources for developing the transfer functions through meta-analytic regression models disaggregated by income level. Section 3.2 describes the methodology used to test for significant differences between the transfer functions obtained for different income groups. Section 3.3 describes the methodology for quantifying the uncertainty associated with the transfer functions.

3.1. Data sources and methodology for the development of the transfer function
To obtain a developing-country VSL transfer function, the method follows five steps: (1) selecting the original database of VSL estimates; (2) disaggregating the database by income level; (3) applying quality screening to the disaggregated database of estimates; (4) establishing the characteristics of the quality-screened subset relevant to meta-analysis; and (5) selecting an appropriate model specification and a regression approach. This section outlines the methods used in each of these five steps.

3.1.1. Selection of the original database of VSL estimates
The original database for this meta-analysis is a comprehensive set of 862 VSL estimates from around the world. The OECD (2012) has compiled 856 of these estimates, which are available at www.oecd.org/env/policies/vsl, and we add six estimates that were published between the compilation of the OECD database and December 2013. The additional estimates are from Mongolia (Hoffman, et al. 2012), South Korea (Lee, et al. 2011), the United States (Viscusi, Huber and Bell 2013), and Sweden (Svensson 2009). In addition to updating the OECD database with six estimates from new studies, we add a field to the database that gives the country GDP per capita from the year of the survey expressed in 2005 international dollars. The database consists only of VSL estimates based on stated preference studies. Some researchers prefer revealed preference estimates. However, the use of stated preference studies allows for the investigation of risk-context effects and the inclusion of population-representative samples (see the background discussion in Section 2.2).
3.1.2. Disaggregation of the original database of VSL estimates by income levels

Disaggregating the regression by income levels indicates whether the influence of the explanatory variables (including income) changes significantly with income level. This research represents the first income-disaggregated meta-analysis of VSL estimates in the literature. This methodology requires a threshold for income disaggregation. The World Bank provides a widely used threshold, which is updated annually, for grouping countries according to GNI per capita. The country income groups are as follows: low income, lower middle income, upper middle income, and high income. Countries in the first three groups are commonly called developing countries, though the use of the term “developing country” does not imply that all countries in these groups are developing or that all countries in the high-income group have finished developing. We disaggregate the original database according to the 2005 threshold between high-income and upper-middle-income countries, which is a GNI per capita of $10,725 USD, using currency conversion with the Atlas method.

3.1.3. Application of quality screening to the disaggregated database of VSL estimates

A prerequisite for a suitable transfer function is that the original studies meet an acceptable level of quality and rigor. In this study, we require that original estimates meet four criteria: (1) the survey is from a country-representative sample; (2) the survey sample size is at least 200, and the subsample from which the estimate is derived is at least 100; (3) the original study reports the size of the risk change valued to obtain the VSL estimates; and (4) the estimates have passed an external or internal scope-sensitivity test. This quality-screening approach follows one of the screening levels used in the OECD (2012) meta-analysis. From our database of 862 estimates, 308 pass the quality screening (i.e., 123 from developing countries and 185 from high income countries). Although we adopt the quality screening criteria of the OECD, we differ in one small way when applying these criteria: the OECD rejected all estimates from a study in India (Bhattacharya, Alberini and Cropper 2006) because the sample of respondents was not considered representative of the country in terms of income and education. However, in reviewing this study, we found that five of the estimates were derived from a large and representative sample, whereas the remaining 13 were from non-representative sub-samples. These five estimates also met the other three quality criteria, and we retained them for our meta-analysis.

Figure 1 shows the estimates that pass and those that fail the screening process plotted against GDP per capita. The Figure shows that the screening process excludes some estimates that are obvious outliers. For example, the group of exclusions includes very high estimates at just under $10,000 GDP per capita from a study in Brazil that failed screening because the study focuses on high-income vehicle owners rather than a country-representative population. This does not mean that the Brazil study is a bad study; it simply does not suit the purposes of this research. Variability in the data at any given income level occurs partly a result of variation in other explanatory variables in addition to income (e.g., risk context). Because of this, a best-fit line in Figure 1 does not necessarily represent the relationship between income and VSL in the transport risk context. Multiple linear regression accounts for the effects of these other explanatory variables.

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We originally followed one of the less strict quality screening criteria from the OECD (2012) that did not require the fourth criteria of scope sensitivity. Many studies do not report scope sensitivity. We thank the reviewers for noting the importance of using only scope-sensitive estimates, which is emphasized in (Viscusi, Huber and Bell 2013). Scope sensitivity refers to the sensitivity of WTP answers to the size of the risk change offered in a contingent valuation survey. It can be evaluated at the individual level by offering the same person multiple risk changes (internal scope sensitivity) or at the cross-group level by offering a different risk change to multiple independent groups (external scope sensitivity) (OECD 2012). An example of the failure of a scope sensitivity test would be if the same individual expressed the same WTP for risk changes of different magnitudes. This undermines the premise of VSL calculations (VSL = WTP/(risk change)) and suggests participant difficulty in understanding low risks.
3.1.4 Establishment of the characteristics of the quality-screened subset relevant to meta-analysis

Table 2 shows that the 123 developing country VSL estimates that pass the quality screening came from six surveys in five developing countries, with between 1 and 86 estimates per survey.

<table>
<thead>
<tr>
<th>Survey ID</th>
<th>Survey year</th>
<th>Country</th>
<th>Publication</th>
<th>Mean VSL ($\times 10^5$)</th>
<th>Std. Dev ($\times 10^5$)</th>
<th>N</th>
<th>Scope-sensitive?</th>
</tr>
</thead>
<tbody>
<tr>
<td>8</td>
<td>2003</td>
<td>Thailand</td>
<td>(Vassanadumrondgee and Matsuoka 2005)</td>
<td>1,555,256</td>
<td>225,888</td>
<td>4</td>
<td>Yes</td>
</tr>
<tr>
<td>34</td>
<td>2005</td>
<td>India</td>
<td>(Bhattacharya, Alberini and Cropper 2006)</td>
<td>41,805</td>
<td>10,387</td>
<td>5</td>
<td>Yes</td>
</tr>
<tr>
<td>36</td>
<td>2005</td>
<td>China</td>
<td>(Krupnick, et al. 2006)</td>
<td>378,458</td>
<td>189,787</td>
<td>86</td>
<td>Yes</td>
</tr>
<tr>
<td>37</td>
<td>2005</td>
<td>China</td>
<td>(Krupnick, et al. 2006)</td>
<td>213,545</td>
<td>60,789</td>
<td>24</td>
<td>Yes</td>
</tr>
<tr>
<td>38</td>
<td>2003</td>
<td>Bangladesh</td>
<td>(Mahmud 2008)</td>
<td>3,138</td>
<td>707</td>
<td>4</td>
<td>Yes</td>
</tr>
<tr>
<td>-</td>
<td>2010</td>
<td>Mongolia</td>
<td>(Hoffman, et al. 2012)</td>
<td>378,275</td>
<td>-</td>
<td>1</td>
<td>Yes</td>
</tr>
</tbody>
</table>

Total | 152 |

Notes: aCorresponds to an identifier in the OECD dataset at www.oecd.org/env/policies/vsl. bAll are classified as low- and middle-income (developing) countries according to the 2005 World Bank thresholds for 2005 GNI per capita. cThe mean of the included value of statistical life (VSL) estimates from each survey, in 2005 international dollars. dThe number of the included VSL estimates from each survey, used as a weight in the regression to account for each survey equally. eThe study reported passing either an internal or external scope-sensitivity test.

The five developing countries represented include countries from the low-, lower-middle-, and upper-middle-income country groups. The survey years of the estimates range from 2003 to 2010, and the mean survey VSL values range from $3138 to $1.5 million. The fact that the quality screened subset contains...
multiple estimates per survey requires a weighting approach to avoid bias, and Section 3.1.5 further
discusses this aspect of the method.

3.1.5. Selection of appropriate model specification and regression approach

The regression model specification follows (OECD 2012), which in turn is based on standard
practice in the meta-analytic literature. The model is

\[ \ln v_{sl} = \beta_0 + \beta_1 \ln gdpcap + \sum_{k} \beta_k X(k) + \epsilon, \]

where \( v_{sl} \) is the value of statistical life, \( gdpcap \) is the PPP-adjusted GDP per capita, \( X(k) \) is a vector of \( k \) mostly binary explanatory variables describing risk context and study method, and the various \( \beta \)s
represent the model coefficients. In this model specification, the coefficient for \( \ln gdpcap \) has the natural
interpretation as the between-country income elasticity of VSL.

The model includes explanatory variables based on two revisions to those included in the fourth
scope-sensitive screening model used by the OECD (OECD 2012). Table 3 shows the resulting variables
in the model for this research, after the following two revisions to the OECD model.

1. First, the model includes the target \( \ln v_{sl} \) and the variable \( \ln gdpcap \) in 2005 international dollars using
standard purchasing power parity exchange rates, whereas the OECD (2012) model uses purchasing
power parity (PPP) exchange rates that are adjusted for actual individual consumption (AIC). AIC-
adjusted values are helpful in that they reflect the individual consumption situation better than does
GDP per capita because they include non-GDP sources of consumption (e.g., foreign aid) and because
they do not include the portion of GDP per capita directed away from consumption. Despite these
advantages, AIC-adjusted values are available at intermittent time intervals and only for select
countries through the International Comparison Program of the World Bank, whereas the more
common values using standard PPP exchange rates are available for more countries and are provided
on a more regular basis. The latter were selected to facilitate practical application of the transfer
function.

2. Second, the model removes the following explanatory variables that are constant for the developing
country data set: \( public \) (a binary risk-context variable that is set to 1 if the survey concerned
personal valuation of public risk changes as opposed to valuation of private risk changes) and
\( noexplan \) (a methodological variable that is set to 1 if the survey included no risk explanation tools
such as a 1000-square grid to help the respondents understand risks). All of the surveys in the
developing country dataset valued private rather than public risk changes, and all of the surveys used
risk explanation tools.

The regression approach must account for the fact that, in many cases, several VSL estimates in the
database are derived from the same survey. The regression used is a weighted least-squares regression
with the weights equal to the inverse of the number of estimates in a given survey to give equal weighting
to each survey rather than to each estimate, following several previous studies (OECD 2012) (H.
reduce the bias resulting from multiple estimates derived from one study that are potentially non-
independent. Nelson and Kennedy (2009) provide a discussion on non-independence resulting from
multiple estimates per study included in a meta-analysis. They find that almost 80 percent (110 of 140) of
the reviewed meta-analyses used multiple estimates per study, creating a potential non-independence
problem. One third of the meta-analyses (40 of 140) also implement no controls to address this potential
dependency. They discuss several options to address this potential dependence. As a best option, if
sufficient data are available, they recommend using only one estimate per primary study to avoid
dependency problems altogether. This option is not ideal for this meta-analysis because it would result in
an unacceptably low sample size. This option is also not ideal because, in several cases, the explanatory
variables under investigation vary within a group of estimates in a primary study, and drawing only one
estimate per primary study would reduce the ability to investigate the impact of these explanatory
variables. A second option that they identify is the use of a multilevel or panel regression approach. This
option is also not ideal, because some of the primary study surveys, which define the panels, have only
one estimate, and could not be included in a panel approach, resulting in unacceptable information loss
given the size of the data set. A third option that they identify is to apply a weighting procedure that
recognizes equal contributions from each primary survey. We apply this option, which is the most
suitable given our dataset and the independent variables (particularly income and risk context) that we are
interested in investigating. All regression analyses use R (R Core Team 2013) with the robust linear
modeling tools of the MASS package (Venebles and Ripley 2002). The analysis uses robust modelling
with MM estimates. Robust modelling is a group of techniques that are used to reduce the influence of
unusual observations on regression results; the use of MM-estimates is a specific technique within robust
modelling that offers the combined advantages of high efficiency and a high breakdown point (Yohai
1987).

<table>
<thead>
<tr>
<th>Variable</th>
<th>Type</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>lnvsl</td>
<td>target, continuous</td>
<td>natural log of VSL in 2005 international dollars</td>
</tr>
<tr>
<td>lngdpcap</td>
<td>explanatory, continuous</td>
<td>natural log of GDP per capita in 2005 international dollars</td>
</tr>
<tr>
<td>lnchrisk</td>
<td>explanatory, continuous</td>
<td>natural log of the size of the risk change valued in a survey</td>
</tr>
<tr>
<td>turnbull</td>
<td>explanatory (methodological), binary</td>
<td>1 if the estimate is based on a turnbull lower bound estimator, 0 otherwise</td>
</tr>
<tr>
<td>env</td>
<td>explanatory (risk context), binary</td>
<td>1 if the estimate is based on a valuation of environmental risks, 0 otherwise</td>
</tr>
<tr>
<td>traffic</td>
<td>explanatory (risk context), binary</td>
<td>1 if the estimate is based on a valuation of transport related risks, 0 otherwise</td>
</tr>
<tr>
<td>household</td>
<td>explanatory (risk context), binary</td>
<td>1 if the estimate is based on a valuation of risks to a person’s entire household, 0 otherwise</td>
</tr>
<tr>
<td>cancer</td>
<td>explanatory (risk context), binary</td>
<td>1 if the estimate is based on a valuation of cancer risks, 0 otherwise</td>
</tr>
<tr>
<td>latent$^a$</td>
<td>explanatory (risk context), binary</td>
<td>1 if the estimate is based on a valuation of risks with a long gap between risk exposure and consequence, 0 otherwise, 0 for all traffic risks</td>
</tr>
</tbody>
</table>

$^a$This variable is relevant in health and environment contexts where, e.g., exposure to a carcinogenic substance can lead to a cancer death 20 years later; it is not relevant to transport risks and should be set to 0 in the transport policy context (personal communication with Ståle Navrud, Nils-Axel Braathen, and Henrik Lindhjem, authors of the OECD report, August 9, 2012).

3.2. Methodology to test for significant differences between transfer functions

To test for differences between transfer functions (such as different elasticity) under a null hypothesis of zero difference for each coefficient, this research uses the methodology proposed by Paternoster et al. (1998). This method calculates a z-score for a difference in coefficients as follows:

$$z = \frac{\beta_1 - \beta_2}{SE_{\beta_1}^2 + SE_{\beta_2}^2}$$

where $\beta_1$ and $\beta_2$ are the coefficients for the same variable from the two groups being tested for a difference and $SE_{\beta_1}$ and $SE_{\beta_2}$ are the standard errors of these coefficients. The two-tailed p-value corresponding to this z-score can be used to evaluate the statistical significance of observed differences by indicating the likelihood that the observed difference in coefficients occurred by chance alone.

3.3. Methodology to quantify and apply transfer function uncertainty information

To quantify transfer function uncertainty, this paper compares records in the database to the corresponding transfer function predictions, generally following the OECD (2012) method described in Section 2.3, but with some adaptations designed to offer additional insight. The first adaptation is to not
use absolute values of the transfer errors because the distribution of errors is asymmetric around zero and because taking absolute values removes information about the differences between the function over-estimates and the function under-estimates. The second adaptation is to present a set of reference percentiles of the distribution of transfer errors instead of only the mean or median absolute error value. Although the mean or median absolute error value is a good summary statistic for the dispersion of the error distribution, a set of reference percentiles of the non-absolute error distribution gives an analyst more information to apply in a sensitivity or risk analysis. Some of the limitations with mean absolute transfer error that motivate this approach are set out in Section 2.3. A final adaptation is the use of the term “relative transfer error” (RTE) to emphasize that we are dealing with normalized errors (although past studies dealing with TE also have used normalized values). The adapted formula for RTE corresponding with the TE formula in Section 2.3 is

\[\text{RTE} = \frac{(VSL_{TF} - VSL_{B})}{VSL_B},\]

with the terms as described in Section 2.3. Using this adaptation, when the RTE distribution is analyzed, the central tendency measures no longer indicate the magnitude of a typical RTE—instead, they indicate the size and direction of any overall bias in the transfer function. The median RTE is used for this purpose because of its insensitivity to large outliers. Reference percentiles of the non-absolute RTE distribution indicate reliability of the transfer function. For example, the 25th percentile RTE gives the magnitude of a typical underestimate, and the 75th percentile RTE gives the magnitude of a typical overestimate, and half of all RTEs lie between these two values. This also allows asymmetry in the RTE distribution to be reflected in the summary statistics, and it provides statistics with natural interpretations for practical application. This paper uses the percentile bootstrap method described by Mooney and Duval (1993) to estimate confidence intervals for the reference percentiles of the error distribution using the boot package in R (Canty and Ripley 2013) (Davison and Hinkley 1997).

To apply transfer function uncertainty information in a policy context, the result given by the transfer function can be adjusted correspondingly with a given \((x)\)th percentile of the relative transfer error distribution \((RTE_x)\). This procedure, based on the definition of RTE, is relatively straightforward. The adjustment equation is

\[VSL_{TFadj} = (1 + RTE_x)^{-1} \times VSL_{TF},\]

where \((1+RTE_x)^{-1}\) represents an adjustment factor linked to the \(x)\th percentile of the RTE distribution, \(VSL_{TFadj}\) represents an adjusted transfer function result for sensitivity or risk analysis, and the other terms are as described earlier. There are two common types of uncertainty analyses in the engineering economic assessment portion of transport project appraisals in World Bank projects: sensitivity analysis (see, e.g., the assessment for a road safety project in Argentina (World Bank 2010a)), and probabilistic risk analysis (see, e.g., the assessment for a highway project in Ningxia, China (World Bank 2010b)). Sensitivity analysis checks the change in the output values corresponding to a few discrete changes in individual input values, generally using a typical or expected high and low input value. This paper proposes using the 25th and 75th percentile RTE values to develop adjustments to the VSL transfer function results corresponding with the typical high and low values for sensitivity analysis. Probabilistic risk analysis often uses a Monte Carlo simulation that randomly varies all input values according to a triangular probability distribution to generate a simulated probability distribution for the output value. This process is described in the documentation for the Roads Economic Decision Model (Archondo-Callao 2004). This process requires practical maximum and minimum values for the input parameters to define the triangle distributions. For the process to be realistic, the maximum and minimum values should result in a triangle distribution that reasonably approximates the actual distribution for the input parameter. In the case of a parameter distribution with long, flat tails, the use of actual maximums and minimums is not practical because doing so would result in a triangle distribution that over-estimates the likelihood of more extreme parameter values. Practical maximum and minimum values for generating the triangle distributions may be selected on the basis of achieving a reasonable match between the triangle distribution and the actual distribution.
4. Results

4.1. Transfer function regression results

Table 4 shows the summary results for three transfer functions based on the weighted robust least-squares regression. Each function gives $\ln vsl$ as the sum of each coefficient, $\beta$, times the corresponding variable value for that coefficient. For example, the all-income function gives $\ln vsl = (4.387+(.551)*lngdpcap + (-.534)*lnchrisk + \ldots + (-.382)*\text{latent})$. The $r^2$ values in the Table show that the models have reasonably strong explanatory power. However, higher $r^2$ values are expected in a robust regression because they indicate the amount of variability explained in the weight-transformed dataset; they should thus not be relied on as the sole criterion for a goodness-of-fit assessment (Willett and Singer 1988). Instead, model performance is more thoroughly assessed in Section 4.2 with the relative transfer error distributions.

Table 4: Transfer function regression results for the high-, low- and-middle-, and all-income functions, with significant differences between the coefficients of the different functions.

<table>
<thead>
<tr>
<th></th>
<th>All-income model</th>
<th>High-income model</th>
<th>Low- and middle-income model</th>
<th>High-low coefficient comparison</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>$n = 410, r^2 = .88$</td>
<td>$n = 258, r^2 = .78$</td>
<td>$n = 152, r^2 = .77$</td>
<td></td>
</tr>
<tr>
<td>(Intercept)</td>
<td>4.387</td>
<td>3.383</td>
<td>-12.941</td>
<td>16.324</td>
</tr>
<tr>
<td></td>
<td>0.183</td>
<td>1.425</td>
<td>0.383</td>
<td>0.000</td>
</tr>
<tr>
<td>$p$</td>
<td>&lt;.001</td>
<td>&lt;.009</td>
<td>&lt;.001</td>
<td></td>
</tr>
<tr>
<td>lngdpcap</td>
<td>0.551</td>
<td>0.693</td>
<td>2.478</td>
<td>-1.785</td>
</tr>
<tr>
<td>$SE$</td>
<td>0.020</td>
<td>0.138</td>
<td>0.073</td>
<td>0.000</td>
</tr>
<tr>
<td>$p$</td>
<td>&lt;.001</td>
<td>&lt;.001</td>
<td>&lt;.001</td>
<td></td>
</tr>
<tr>
<td>lnchrisk</td>
<td>-0.534</td>
<td>-0.481</td>
<td>-0.698</td>
<td>0.217</td>
</tr>
<tr>
<td>$SE$</td>
<td>0.011</td>
<td>0.018</td>
<td>0.043</td>
<td>0.000</td>
</tr>
<tr>
<td>$p$</td>
<td>&lt;.001</td>
<td>&lt;.001</td>
<td>&lt;.001</td>
<td></td>
</tr>
<tr>
<td>turnbull</td>
<td>-0.557</td>
<td>-0.598</td>
<td>-0.598</td>
<td></td>
</tr>
<tr>
<td>$SE$</td>
<td>0.077</td>
<td>0.055</td>
<td>0.055</td>
<td></td>
</tr>
<tr>
<td>$p$</td>
<td>&lt;.001</td>
<td>&lt;.001</td>
<td>&lt;.001</td>
<td></td>
</tr>
<tr>
<td>env</td>
<td>-0.805</td>
<td>-0.645</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>$SE$</td>
<td>0.059</td>
<td>0.102</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>$p$</td>
<td>&lt;.001</td>
<td>&lt;.001</td>
<td>&lt;.001</td>
<td></td>
</tr>
<tr>
<td>household</td>
<td>-1.419</td>
<td>-1.225</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>$SE$</td>
<td>0.054</td>
<td>0.094</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>$p$</td>
<td>&lt;.001</td>
<td>&lt;.001</td>
<td>&lt;.001</td>
<td></td>
</tr>
<tr>
<td>traffic</td>
<td>0.723</td>
<td>0.823</td>
<td>-2.377</td>
<td>3.200</td>
</tr>
<tr>
<td>$SE$</td>
<td>0.055</td>
<td>0.091</td>
<td>0.128</td>
<td>0.000</td>
</tr>
<tr>
<td>$p$</td>
<td>&lt;.001</td>
<td>&lt;.001</td>
<td>&lt;.001</td>
<td></td>
</tr>
<tr>
<td>cancer</td>
<td>0.390</td>
<td>0.470</td>
<td>-1.552</td>
<td>2.022</td>
</tr>
<tr>
<td>$SE$</td>
<td>0.049</td>
<td>0.080</td>
<td>0.132</td>
<td>0.000</td>
</tr>
<tr>
<td>$p$</td>
<td>&lt;.001</td>
<td>&lt;.001</td>
<td>&lt;.001</td>
<td></td>
</tr>
<tr>
<td>latent</td>
<td>-0.382</td>
<td>-0.496</td>
<td>-0.147</td>
<td>-0.350</td>
</tr>
<tr>
<td>$SE$</td>
<td>0.049</td>
<td>0.090</td>
<td>0.059</td>
<td>0.007</td>
</tr>
<tr>
<td>$p$</td>
<td>&lt;.001</td>
<td>&lt;.001</td>
<td>&lt;.001</td>
<td></td>
</tr>
</tbody>
</table>

Notes: Functions predict $\ln vsl$. Variables defined in Table 4. $\beta$ denotes coefficients. The income threshold is 2005 PPP-adjusted GDP per capita of $14,000.

The Table shows that the coefficients in the all-income and high-income models are fairly similar but that some significant differences exist between the coefficients for the high-income model and the low- and middle-income model. Although the between-country income elasticity (the $lngdpcap$ coefficient) for the high-income function is .693, the Table indicates a between-country income elasticity of VSL of 2.478 for the low- and middle-income country model. This is consistent with the finding of Hammit and Robinson (2011), who provide theoretical reasoning behind this finding and discuss increasing evidence in support of elasticity greater than 1 among low-income countries; it is also consistent with previous studies (Mahmud 2008) (Bhattacharya, Alberini and Cropper 2006), which note that the VSL values obtained in Bangladesh and India are lower than what would be obtained under transfer from developing countries with elasticities of 1. The difference in between-country income elasticities is significant at a $p$-value of less than .001.

A second difference between the high-income model and the low- and middle-income model is the coefficient for the traffic-risk context parameter. If the coefficient for this parameter is positive, the WTP for traffic-related VSL is, in general, higher than the WTP for VSL in other risk contexts—people value saving a life on the road more than saving a life elsewhere. If it is negative, the opposite is true. The coefficient is significant in both models: it is positive in the high-income model (.823) and negative in the low-income model (-2.377), and the difference in the coefficient between models is significant at $p < .000$. The income threshold for this parameter is 2005 PPP-adjusted GDP per capita of $14,000$. The WTP for traffic-related VSL of 3.383 in the high-income model is consistent with previous studies (Mahmud 2008) (Bhattacharya, Alberini and Cropper 2006), which note that the VSL values obtained in Bangladesh and India are lower than what would be obtained under transfer from developing countries with elasticities of 1. The difference in between-country income elasticities is significant at a $p$-value of less than .001.
This difference may be related to cultural factors, such as fatalistic attitudes towards traffic risks, which are explored by Nordfjærn et al. (2012).

A possible reason for the differences found in the low- and middle-income country model is that baseline risks and competing risks may affect VSL beyond the explanatory variables considered. Andersson and Treich (2011) present a theoretical argument for relationships between VSL and baseline risks and between VSL and competing risks, but they also note that the empirical evidence in support of these relationships is mixed. The nature of the dataset limited the ability of this meta-analysis to investigate these possible reasons in detail. For example, half of the studies in the low- and middle-income country dataset do not report baseline risk, and little information is available on competing risks.

The significantly different coefficients in the models indicate that it is more appropriate to use transfer functions based on developing country data for application in developing countries than to use transfer functions based on all- or high-income country data. Section 4.3 further illustrates this point for the road-safety context.

4.2. Transfer function errors and the uncertainty analysis

Figure 2 and Table 5 show the results of a transfer error analysis on the models by presenting the frequency distributions of relative transfer error (RTE). RTE, described in Section 3.3, compares the estimates in the database to what the transfer function would predict for that estimate.

Figure 2 shows that the low- and middle-income country function has the narrowest RTE distribution; however, for all functions, the majority of relative transfer errors lie within +/-50%. The Figure also shows asymmetry in the RTE distributions for the high-income and all-income functions, but not in the low- and middle-income function. Table 5 shows the reference percentiles of the RTE distributions along with the confidence intervals for these percentiles obtained by bootstrap resampling.
Table 5: Percentiles of the relative transfer error distribution with bootstrapped 95% confidence intervals for low- and middle-income, high-income, and all-income transfer functions.

<table>
<thead>
<tr>
<th>Percentile</th>
<th>RTE.LMI</th>
<th>RTE.HI</th>
<th>RTE.AI</th>
</tr>
</thead>
<tbody>
<tr>
<td>0%</td>
<td>-0.745 (-0.745, -0.593)</td>
<td>-0.985 (-0.985, -0.798)</td>
<td>-0.994 (-0.994, -0.836)</td>
</tr>
<tr>
<td>5%</td>
<td>-0.533 (-0.624, -0.43)</td>
<td>-0.68 (-0.754, -0.562)</td>
<td>-0.675 (-0.772, -0.483)</td>
</tr>
<tr>
<td>10%</td>
<td>-0.434 (-0.498, -0.309)</td>
<td>-0.527 (-0.667, -0.413)</td>
<td>-0.458 (-0.532, -0.405)</td>
</tr>
<tr>
<td>15%</td>
<td>-0.333 (-0.442, -0.253)</td>
<td>-0.41 (-0.525, -0.322)</td>
<td>-0.37 (-0.438, -0.315)</td>
</tr>
<tr>
<td>20%</td>
<td>-0.268 (-0.371, -0.201)</td>
<td>-0.333 (-0.413, -0.203)</td>
<td>-0.308 (-0.363, -0.23)</td>
</tr>
<tr>
<td>25%</td>
<td>-0.223 (-0.29, -0.185)</td>
<td>-0.218 (-0.358, -0.132)</td>
<td>-0.229 (-0.299, -0.177)</td>
</tr>
<tr>
<td>30%</td>
<td>-0.191 (-0.253, -0.169)</td>
<td>-0.139 (-0.234, -0.078)</td>
<td>-0.174 (-0.229, -0.126)</td>
</tr>
<tr>
<td>35%</td>
<td>-0.181 (-0.212, -0.13)</td>
<td>-0.094 (-0.172, 0.006)</td>
<td>-0.127 (-0.179, -0.069)</td>
</tr>
<tr>
<td>40%</td>
<td>-0.156 (-0.188, -0.06)</td>
<td>-0.019 (-0.119, 0.064)</td>
<td>-0.071 (-0.129, -0.023)</td>
</tr>
<tr>
<td>45%</td>
<td>-0.128 (-0.176, -0.01)</td>
<td>0.028 (-0.066, 0.116)</td>
<td>-0.034 (-0.075, 0.039)</td>
</tr>
<tr>
<td>50%</td>
<td>-0.047 (-0.149, 0.032)</td>
<td>0.086 (0.01, 0.211)</td>
<td>0.03 (-0.036, 0.118)</td>
</tr>
<tr>
<td>55%</td>
<td>-0.005 (-0.125, 0.097)</td>
<td>0.198 (0.068, 0.276)</td>
<td>0.111 (0.026, 0.145)</td>
</tr>
<tr>
<td>60%</td>
<td>0.042 (-0.043, 0.145)</td>
<td>0.227 (0.121, 0.324)</td>
<td>0.134 (0.09, 0.212)</td>
</tr>
<tr>
<td>65%</td>
<td>0.114 (0.006, 0.181)</td>
<td>0.315 (0.213, 0.397)</td>
<td>0.206 (0.131, 0.275)</td>
</tr>
<tr>
<td>70%</td>
<td>0.161 (0.065, 0.229)</td>
<td>0.373 (0.284, 0.501)</td>
<td>0.274 (0.202, 0.365)</td>
</tr>
<tr>
<td>75%</td>
<td>0.202 (0.136, 0.295)</td>
<td>0.478 (0.333, 0.621)</td>
<td>0.368 (0.267, 0.483)</td>
</tr>
<tr>
<td>80%</td>
<td>0.258 (0.179, 0.332)</td>
<td>0.598 (0.445, 0.726)</td>
<td>0.49 (0.373, 0.603)</td>
</tr>
<tr>
<td>85%</td>
<td>0.308 (0.237, 0.409)</td>
<td>0.712 (0.568, 0.852)</td>
<td>0.664 (0.518, 0.789)</td>
</tr>
<tr>
<td>90%</td>
<td>0.4 (0.302, 0.493)</td>
<td>0.861 (0.707, 2.444)</td>
<td>0.86 (0.723, 2.276)</td>
</tr>
<tr>
<td>95%</td>
<td>0.543 (0.404, 0.682)</td>
<td>3.29 (1.072, 5.098)</td>
<td>4.027 (1.758, 13.528)</td>
</tr>
<tr>
<td>100%</td>
<td>0.749 (0.645, 0.749)</td>
<td>12.506 (5.888, 12.506)</td>
<td>67.74 (22.773, 67.74)</td>
</tr>
</tbody>
</table>

Notes: RTE = relative transfer error; LMI = low- and middle-income; HI = high-income; AI = all-income. Confidence intervals by percentile bootstrap method with B = 2000 resamples.

Based on Figure 2 and Table 5, the following points indicate the transfer error analysis results concerning (1) transfer function bias, (2) likely high and low values for sensitivity analysis, and (3) practical maximum and minimum values for probabilistic risk analysis using triangle distributions.

1) Bias: Table 5 shows that there is no statistically significant bias in the low-income and all-income transfer functions and a small but a statistically significant bias in the high-income transfer function, based on the 95% CI for the median RTE.

2) Likely low and high values for sensitivity analysis: The first and third quartiles of the error distributions provide a range of likely errors when using the transfer function: half of all relative transfer errors are between these values. With the methodology explained in Section 3.3 and the first and third quartile RTE values from Table 5, adjustment factors ((1 + RTE)_i) can be estimated to apply to the transfer function results and obtain high and low values for sensitivity analysis. The low adjustment factors are .83, .68, and .73, and the high adjustment factors are 1.29, 1.28, and 1.30 for the low- and middle-, high-, and all-income transfer functions, respectively.

3) Practical minimum and maximum values for probabilistic risk analysis using triangle distributions: Some forms of probabilistic risk analysis, as described in Section 3.3, require practical maximum and minimum values to generate a triangular distribution for an input parameter that roughly approximates the actual distribution. The high-income and all-income RTE distributions are positively skewed and have longer tails; the 5th and 85th percentiles of these provide values that can be used to create a reasonable triangle distribution. The low- and middle-income RTE distribution is not seriously skewed, and its 5th and 95th percentiles can be used to create a reasonable triangle distribution. Based on Table 5, the adjustment factors ((1 + RTE)_i) to obtain practical minimums for risk analysis are .65, .58, and .60, and the adjustment factors to obtain practical maximums for risk analysis are 2.14, 3.12, and 3.07 for the low- and middle-, high-, and all-income transfer functions, respectively.
4.3. Results applied to the transport safety policy context

This section presents the transfer function results for the transport safety policy context. Adapting the function for this context involves setting the binary risk context and methodological variables appropriately (\(turnbull = 0; \ env = 0; \ traffic = 1; \ household = 0; \ cancer = 0; \ latent = 0\)), setting the risk change variable, and taking the antilog of the model defined by the coefficients in Table 5. Setting the risk change variable involves some ambiguity. There are two options for setting the risk change variable:

- **Option 1:** Set the risk change variable to a constant value for policy purposes. This gives a consistent VSL across road-safety projects in a given country. In this option, there is ambiguity as to what constant value should be used, beyond the fact that the value should be some proportion of the baseline risk for the group represented by the transfer function.

- **Option 2:** Set the risk change variable on a project-by-project basis according to the estimated risk change offered by the project. This would give different VSL values for different projects in a country.

For the presentation and discussion of our results, we follow Option 1. Within Option 1, we set the risk change values in each transfer function to be half of the baseline risk for the respective income group using 2011 baseline risk data from the World Health Organization (World Health Organization 2014). The 2011 baseline health risks for road mortality in all-income, high-income, and low- and-middle-income countries were 18.2, 9.0, and 19.9 per 100,000, respectively; we set the risk change values in the transfer functions at 9.1, 4.5, and 10.0 per 100,000, respectively. In an application context, a practitioner could follow Option 1 with these risk change values or Option 1 with different risk change values (e.g., a quarter of the baseline risks); alternatively, a practitioner could follow Option 2. This ambiguity in application could have been removed by not including risk change in the model, but this would have been at the expense of achieving less clarity with respect to the coefficients for other variables of interest.

With the variables set for the transport policy context, VSL becomes a function of GDP per capita. The low- and middle-income transfer function is

\[
VSL_{TF,LMI} = 1.3732 \times 10^{-4} \times gdp\text{cap}^{2.478},
\]

the high-income transfer function is

\[
VSL_{TF,HI} = 8.2474 \times 10^{3} \times gdp\text{cap}^{6.932},
\]

and the all-income transfer function is

\[
VSL_{TF,\text{AI}} = 2.3834 \times 10^{4} \times gdp\text{cap}^{5.508}.
\]

The functions are modelled for GDP per capita and VSL values expressed in 2005 international dollars, whereas a typical assessment of economic performance measures will likely require results in either US dollars or national currency values at current prices. Because the functions are non-linear with respect to income, function application using the wrong currency units can yield errors; correct function application requires attention to currency conversions and price deflators.\(^4\)

Figure 3 shows that the transfer functions with VSL vary by GDP per capita for the transport-policy context, illustrating the impact of modeling transfer functions for the developing-country context.

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\(^4\) The transfer function calculates \(VSL_{i,n,\text{ID,2005}}\) (country \(i\) in year \(n\) in international dollars at 2005 prices) using \(GDP\_CAP_{i,n,\text{ID,2005}}\), which is calculated as \(GDP\_CAP_{i,n,\text{NC,CP}} \times (PPP_{i,n})^{-1} \times (GDP\_\text{DEF}_\text{US,2005} / GDP\_\text{DEF}_\text{US,n})\), where \(NC\) denotes national currency, \(CP\) denotes current prices, \(PPP\) denotes the implied purchasing power parity exchange rate, and \(GDP\_\text{DEF}\) denotes the GDP deflator (to reflect changes in the price levels connected to the international dollar, which is linked to the purchasing power of the US dollar). After obtaining \(VSL_{i,n,\text{ID,2005}}\) from the transfer function, \(VSL_{i,n,\text{NC,CP}}\) (the VSL for country \(i\) in year \(n\) in national currency at current prices) may be obtained by reversing the above conversion. All of the parameters required for this conversion are available in the International Monetary Fund’s *World Economic Outlook Database* (IMF 2012).
based on developing country data. The function modeled using high-income data provides transferred VSL values in the low- and middle-income range that are significantly higher than the functions modeled using low- and middle-income country data. The same is true for the function modeled using an aggregate of all-income data. The low- and middle-income country function crosses the all-income country function at just below $20,000 GDP per capita and crosses the high-income function at just above $20,000 GDP per capita; this figure of $20,000 GDP per capita is near the upper limit of usefulness for the low- and middle-income function. The lower limit of usefulness for the low- and middle-income function is approximately $1268 GDP per capita; there are no VSL estimates in the database below this value. Twenty-two countries, most of which are located in Sub-Saharan Africa, have estimates of the 2012 GDP per capita below this value, and at these very low values, policy makers may consider alternatives to WTP-based VSL values in the road-safety context.

The iRAP rule of thumb is a rough transfer function used by the International Road Assessment Programme and the World Bank that estimates VSL by applying a factor of 70 to GDP per capita (Dahdah and McMahon 2008). Figure 3 shows that below a GDP per capita of about $7,000, the iRAP rule of thumb gives slightly higher values than does the new low- and middle-income transfer function, whereas above $7,000 GDP per capita, the new low- and middle-income transfer function gives significantly higher values than does the iRAP rule of thumb.

Figure 3 also shows what can be interpreted as a changing economic-good nature of transport safety-risk reductions across income levels. In the lower-income range, with a between-country income elasticity of 2.478, WTP-based VSL increases more than proportionally with income; the function is convex. Among high-income countries, with a between-country income elasticity of .6932, WTP-based VSL increases less than proportionally with income; the function is concave.

Figure 3: VSL by GDP per capita for the transport-policy context according to new income-disaggregated benefit-transfer functions. Note: 70GDP reference indicates the iRAP rule of thumb for calculating VSL = 70 * (GDP per capita). Section 2.4 explains this rule of thumb (Dahdah and McMahon 2008). In this graph, the risk-change variable in each function is set to half of the baseline road-mortality risk for the countries in the income group represented by the function.
4.4. Results for other contexts

Whereas the main objectives of this research relate to road safety, the results can also be applied to environmental, health, and cancer risk contexts by using the coefficients from Table 5 and specifying appropriate values for the risk-context variables. Furthermore, the high-income function in Table 5 can be applied to various risk contexts in developed countries, either in the absence of appropriate local VSL estimates or as an overall appropriateness check on the reasonableness of local estimates.

5. Conclusions

This paper presents the development of a new value of a statistical life (VSL) transfer function for application to transport-safety engineering in developing countries that is based on VSL estimates from developing countries. The transfer function estimates the value of statistical life as

\[ VSL_{TF,LM0} = 1.3732 \times 10^{-4} \times gdpcap^{2.478} \]

where \( VSL_{TF,LM0} \) represents the value of statistical life given by the transfer function for low- and middle-income countries and \( gdpcap \) represents gross domestic product (GDP) per capita expressed in 2005 international dollars. The function is applicable for countries with GDPs per capita between $1268 and $20,000, expressed in 2005 international dollars. Below this income range, policy makers may wish to apply alternative methods to the valuation and evaluation of transport-risk reductions. This transfer function is significantly different from a transfer function modeled on data from high-income countries, supporting this new approach, which develops transfer functions that are disaggregated by income level. In particular, the between-country income elasticity of 2.478 in developing countries, compared with that of .6932 in developed countries, is significantly different, at \( p < 0.001 \). This finding provides confirmation of initial evidence found by Hammit and Robinson (2011).

This paper also analyzes the uncertainty associated with the new transfer function using adaptations to the transfer error analysis techniques in (OECD 2012) and other previous literature. This analysis shows that there is no statistically significant bias in the new transfer function. Furthermore, the transfer error analysis develops adjustments to the transfer function results to support the use of VSL values in robust economic assessments during the project appraisal process.

Taken together, these results can support the prospective performance measurement of projects impacting road safety in developing countries in a way that is practical, accounts for input uncertainty, and is amenable to application in a comprehensive assessment framework.

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8. References


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