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Working Party on National Environmental Policies

THE VALUE OF STATISTICAL LIFE: A META-ANALYSIS

This document cancels and replaces the version placed on OLIS on 3 December 2010 so as to include the EU disclaimer in the foreword on page two of the report.

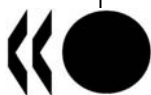
This paper was prepared by Vincent Biauxque, Ecole Nationale de la Statistique et de l'Administration Economique, Paris.

The paper presents a number of meta-analyses of the value of a statistical life in stated preferences surveys, and is an input to a technical report and a user's guide for policy makers on the use of VSL values in policy assessments that is being prepared.

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FOREWORD

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The paper presents a number of meta-analyses of the value of a statistical life in stated preferences surveys, and is an input to a technical report and a user's guide for policy makers on the use of VSL values in policy assessments that is being prepared.

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THE VALUE OF STATISTICAL LIFE: A META-ANALYSIS

Introduction

1. The value of statistical life (VSL) is still a highly contentious subject in economic research. In the minds of many, “You can’t put a price on life!” However, observations of individual and group behaviour paint quite a different picture. When purchasing an automobile, for example, a driver will seek a trade-off between expensive safety features and the price of the car. Likewise, government authorities may weigh the impact that closing a dangerous factory (because of environmental or health concerns) would have on the job supply. Since societies must contend with a large number of risks (traffic, environment, health, etc.), regulators must intervene as effectively as possible to reduce these risks. As a rule, the utility associated with reducing a risk must compensate for the disutility associated with the cost of reducing that risk. And in performing this type of “cost-benefit” analysis a monetary value for human life can prove invaluable. Many studies have attempted to address this issue, but the values obtained exhibit a high degree of variability (the figures placed on this value in this document apparently range from \$2 660 to \$20 000 000!¹). The purpose of this study is therefore to gain the best understanding possible of these variations in order to provide insight for policy makers. A meta-analysis was therefore carried out by Nils Axel Braathen at the OECD, who collected all the published values for statistical life calculated by contingent valuation methods. In all, 1 095 values from 92 different studies were collected.

2. After an initial analysis of this main sample (Braathen, Lindhjem and Navrud, 2009), the authors whose estimates had been included in the meta-analysis were asked to give their opinion on the inclusion of their estimates in the meta-analysis. This document is therefore the second stage in the process initiated by the OECD process to examine variations in the value of statistical life and provide the best guidance possible for public decision-makers.

3. The first section of this study presents the classical economic theories that can be used to calculate the value of statistical life, with particular emphasis on the model of individual willingness to pay (developed by Drèze in 1962) which has become the standard in this field. This step will allow us, firstly, to gain a thorough understanding of the contingent valuation methods used to estimate these values and secondly to obtain a number of avenues for econometric modelling.

4. The second section presents some contingent valuation models for the VSL referenced in the articles selected for the meta-analysis. This examination will allow us to gain a better understanding of the variations observed in the different estimated values. In fact, many authors derived several VSLs from a single published dataset using different methodologies.

5. The third section describes how we constructed the database, as well as the procedures by which we culled a considerable number of observations from the initial sample. This section includes descriptive statistics for what we call our “final sample”. In particular, we observe the extent of the variability in estimates of the value of statistical life.

¹ In 2005 dollars, adjusted using the purchasing power parity (PPP) exchange rate method.

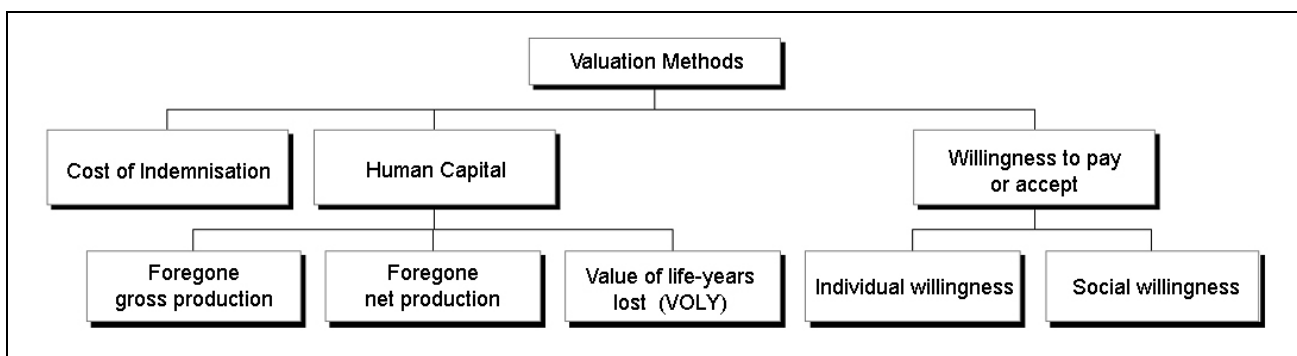
6. Lastly, in the fourth section the study focuses on the variations in the value of statistical life. Specifically, we find that these variations are highly correlated with the wealth of a country, as measured by per capita GDP (adjusted using purchasing power parity), but also with the degree of risk reduction proposed during the contingent valuation.

1. Theories concerning the value of statistical life

1.1 The different valuation methods

7. We can divide the methods used to determine the value of statistical life into three broad categories. These different approaches are summarised in Figure 1.

Figure 1 - Methods for determining the value of statistical life



Source: Boiteux and Baumstark (2001).

8. The first category of methods used for these calculations draws on the compensation paid to accident victims by insurance companies and accounts for the fact that these benefits only cover insured losses. The second group, referred to as human capital, estimates the prejudice caused to society by the death or injury of an individual. The third category, willingness to pay, will be discussed in depth in the next section. For the purposes of the OECD meta-analysis, this last method was chosen as the common denominator for estimated and published values of statistical life. In fact, without a doubt this approach has received the most attention in recent years, its strength lies in the fact that it best reflects the true aspirations of individuals – which is vital for any cost-benefit analysis undertaken by a government decision-maker.

1.2 The individual willingness to pay method

9. This method, which has become the standard for calculating the value of statistical life, was first formulated by Dréze (1962) and then popularized by Jones Lee (1976), Schelling (1968), Mishan (1971), and Weinstein *et al.* (1980). This model postulates that, at a given period in time, each individual possesses an expected utility function of the type

$$E(w, r) = (1 - r)u_a(w) + ru_d(w),$$

where r designates the risk of death during the period, w wealth, $u_a(\cdot)$ the utility function if the individual survives the period, and $u_d(\cdot)$ utility if he or she dies during the period (typically, this latter utility is associated with legacies). Thus, each individual's willingness to pay (WTP), allowing him or her to maintain the same expected utility when the risk shifts from r to $r' \leq r$, is defined as the solution to the equation

$$E(w - WTP, r') = E(w, r).$$

10. In keeping with the classical approach, we shall also make some additional assumptions on the utility functions

$$u_a > u_d; u'_a > u'_d \geq 0; u''_a \leq 0 \text{ and } u''_d \leq 0.$$

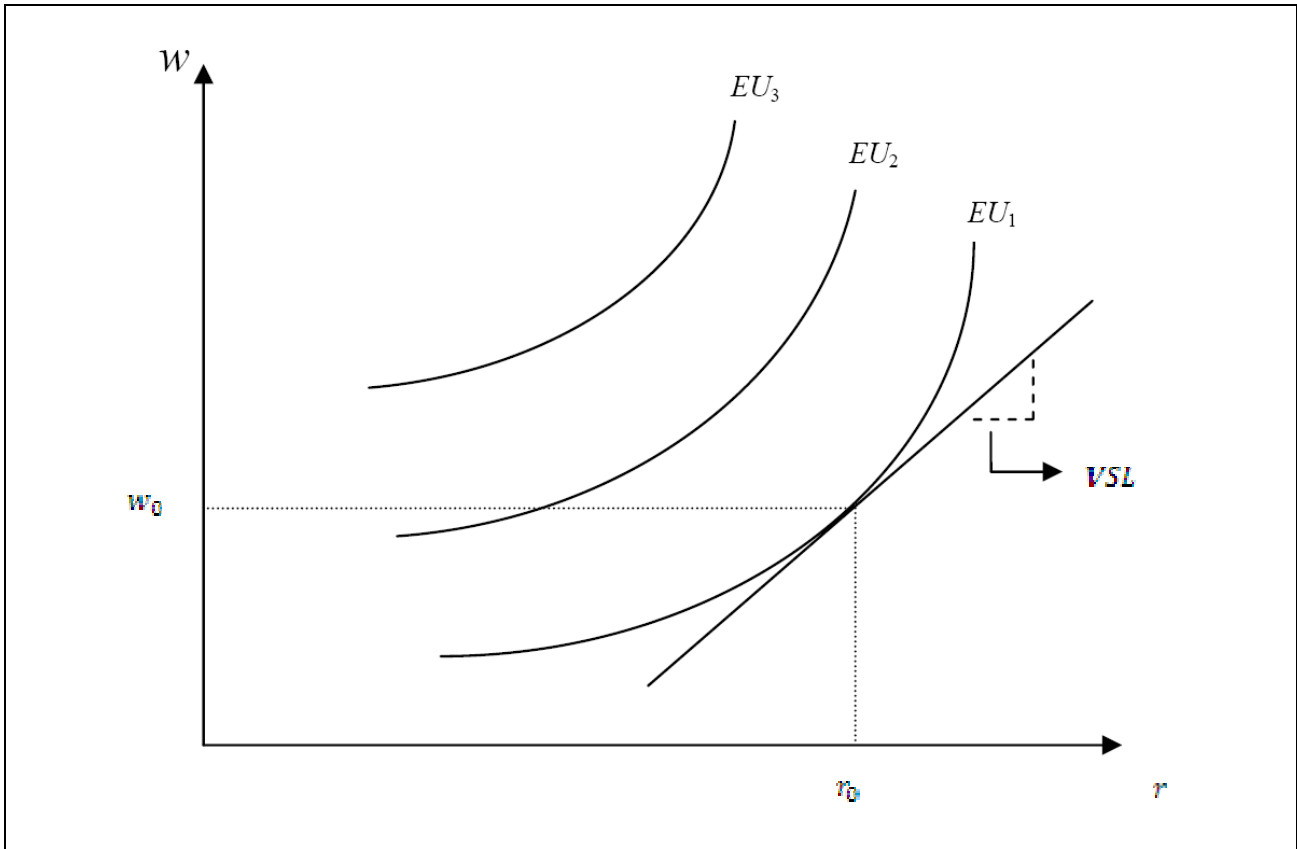
11. Let us assume that the members of a population are willing to pay an average of five dollars each to reduce a given risk level from 3/100 000 to 2/100 000; if everyone in that population contributes five dollars, then, on average, one life will be saved per group of 100 000 people at a cost of \$500 000 to each such group.

12. This is the principle underlying this economic theory of the value of statistical life. We thus generally define this value as the marginal rate of substitution between wealth and the risk of dying

$$VSL = \left. \frac{dw}{dr} \right|_{EU=k} = \frac{u_a(w) - u_d(w)}{(1-r)u'_a(w) + ru'_d(w)}.$$

13. It can be seen that, given our assumptions, this value is positive and depends on the individual utility functions u_a , u_d and u'_d , but also on existing wealth and risk levels. A graphical interpretation of this value is given in Figure 2.

Figure 2 - Value of statistical life



14. Pursuing this theoretical approach, it would now be interesting to see how the VSL varies with wealth and mortality risk. Intuitively, we would expect it to be an increasing function of wealth (since willingness to pay clearly is) and also an increasing function of mortality risk. In fact, an individual confronting a very high underlying mortality risk might also demonstrate a very high willingness to pay, because particular weight might attach to any reduction in this risk.

15. In order to examine the impact of wealth or the underlying risk on the VSL, we can calculate partial derivatives of the equation for VSL

$$\frac{dVSL}{dr} = \frac{[u_a(w) - u_d(w)][u'_a(w) - u'_d(w)]}{[(1-r)u'_a(w) + ru'_d(w)]^2}$$

and

$$\frac{dVSL}{dw} = \frac{E'(w)[u'_a(w) - u'_d(w)] - E''(w)[u_a(w) - u_d(w)]}{E'(w)^2}$$

16. Letting $E'(w) = \frac{d}{dw} [(1-r)u_a(w) + ru_d(w)]$ and $E''(w) = \frac{d^2}{dw^2} [(1-r)u_a(w) + ru_d(w)]$, we observe that the first partial derivative is positive because of the assumptions we made. The sign of the second expression is less obvious, but it can be shown that it, too, is positive. Thus, our intuition is corroborated, and the value of statistical life moves in the same direction as wealth and the underlying risk level.

17. To illustrate, we specify the following functional forms for utility. Let utility be nil in the event of death, and $u_a(w) = w^{1-\gamma}/(1-\gamma)$, where $\gamma \in [0,1[$, if the individual survives the period. Then the VSL is given by

$$VSL = \frac{w}{r(1-\gamma)}$$

for constant underlying risk r . We find that the VSL is an increasing function of w and a decreasing function of r . This relationship can be rewritten as

$$\log(VSL) = Cte + \log(w) - \log(r).$$

2. Estimating willingness to pay

18. As we saw above, the value of statistical life can be calculated from individual willingness to pay. In practical terms, if individuals are willing to pay \$100 for a 1/1000 reduction in the underlying risk of death, the value of human life works out to \$100 000.

$$VSL = \frac{WTP}{\Delta r} = \frac{100}{1/1000} = \$100\ 000$$

19. However, we need to start by evaluating individual willingness to pay.

2.1 Turnbull's non-parametric estimator

20. Willingness to pay for a reduction in mortality risk is generally estimated from surveys in which the envisaged scenario is explained to each individual (nature, consequences, etc.). In the "classical" contingent valuation approach (as opposed to so-called *choice modelling* or *contingent ranking* approaches, which we will discuss below), each person is asked to assign a value to his or her willingness to pay when confronted with the scenario in question. This can take the form of a single open-ended question ("How much would you be willing to pay for this project?") or a series of one or more closed-ended questions ("Would you be willing to pay at least x dollars for this project?").

21. In the case of a single closed-ended question, the Turnbull estimator yields a lower bound for individuals' willingness to pay. Consider a sample of T persons who are randomly offered one of M different amounts, denoted t_j (these amounts are ordered: $t_1 < t_2 < \dots < t_M$). Each individual i 's willingness to pay is represented by WTP_i , a random variable distributed according to the F distribution, we have

$$P(WTP_i < t_j) = F(t_j) = F_j.$$

22. Letting T_j be the number of people to whom t_j is proposed, and N_j the number who refuse to pay at least t_j , a natural estimator for F_j is

$$\hat{F}_j = \frac{N_j}{T_j},$$

which proves to be a maximum likelihood estimator as well. In practice, however, there is no assurance that this will be an increasing function. The Turnbull procedure consists of imposing a monotonicity condition on this estimator:

- Compute \hat{F}_j for each $j = 1 \dots M$,
- Starting with $j = 1$, compare \hat{F}_j to \hat{F}_{j+1} ,
- If $\hat{F}_j < \hat{F}_{j+1}$, set $\hat{F}_j^* = \hat{F}_j$,
- If we obtain a sequence $\hat{F}_j > \hat{F}_{j+1} > \dots > \hat{F}_{j+s}$, replace \hat{F}_j with $\hat{F}_j = \frac{N_j + \dots + N_{j+s}}{T_j + \dots + T_{j+s}}$,
- Set $\hat{F}_{M+1} = 1$.

23. This yields a consistent estimator for F . However, it only provides a *lower bound for the willingness to pay*. This is obtained with the equation

$$\hat{E}_{w,f}(WTP) = \sum_{j=1}^M t_j (\hat{F}_{j+1}^* - \hat{F}_j^*).$$

24. The central lesson of this section is that the Turnbull estimator is very appealing because it allows us to determine willingness to pay without requiring any assumptions on parameters. On the other hand, this estimator can be considered very conservative, in the sense that it only yields an estimate of the lower bound.

25. Applications of this method can be found in references [20] and [26].

2.2 Stochastic utility models

26. As in the previous model, the surveyed individuals confront two situations: the status quo and the contingent situation involving a reduction in the underlying risk. The key concept is that individuals answering the question will choose the option that maximizes their utility. Formally, for each individual i , we postulate the existence of two indirect utility functions of the type

$$u_{i\epsilon}(w_i, x_i, \epsilon_{i\epsilon}) = w_i \beta + x_i' \alpha_\epsilon + \epsilon_{i\epsilon}$$

where $\epsilon = 0$ designates the status quo, $\epsilon = 1$ the contingent situation, w_i the individual's wealth, x_i a vector of individual characteristics (sex, age, etc.), and $\epsilon_{i\epsilon}$ an error term (or unobserved characteristics). If we let Y_i represent the dichotomous response to the question "Do you agree to the contingent situation at an estimated cost of t_i dollars to you?" we have

$$P(Y_i = 1) = P[u_{i1}(w_i - t_i, x_i, \epsilon_{i1}) \geq u_{i0}(w_i, x_i, \epsilon_{i0})]$$

which can be written

$$P(Y_i = 1) = P[x_i'(\alpha_1 - \alpha_0) - t_i \beta + (\epsilon_{i1} - \epsilon_{i0}) \geq 0].$$

27. Assuming that the distribution of the independent and identically distributed variables $(\epsilon_{i1} - \epsilon_{i0})$ is logistic, we can estimate this model's parameters $(\alpha_1 - \alpha_0)$ and β .

28. Since the willingness to pay of individuals is defined as the amount that will leave them indifferent between the status quo and the proposed project, the quantity WTP_i is defined as

$$u_{i0}(w_i, x_i, \varepsilon_{i0}) = u_{i1}(w_i - WTP_i, x_i, \varepsilon_{i1}),$$

yielding the relation

$$WTP_i = \frac{1}{\beta} [x_i'(\alpha_1 - \alpha_0) + (\varepsilon_{i1} - \varepsilon_{i0})].$$

29. Thus, we can estimate average WTP in the sample with the equation

$$E(WTP) = \frac{1}{\beta} [\bar{x}'(\alpha_1 - \alpha_0)].$$

30. Note that, in this model, the assumptions are fairly limiting. We first assumed that the functional form of the indirect utility function is linear, and also that the marginal utility of wealth is not dependent on state. These assumptions are reasonable if the change proposed for the contingent situation is small.

31. Applications of this method can be found in reference [31].

2.3 *A few words on some other methods*

32. The use of stochastic utility models can be extended to other types of questionnaires. This is particularly the case if the survey participants are offered a menu of choices. Depending on the form of the questionnaire, two different techniques are available. When respondents are asked to choose a *single* alternative that will yield the highest level of well-being, we talk of *choice modelling*, and when we ask them to *rank* options in order of preference, we talk of *contingent ranking*. Both cases involve estimating polytomous logit models. In such cases the degree to which the proposed risk is reduced differs between the proposals, making it possible to directly calculate the value of statistical life from the parameters of the model. An application of this method can be found in reference [31].

33. If the sample contains a significant number of individuals who assign no value to the proposed programme, we may be dealing with so-called “free riders”. These are liable to bias the estimates. Several methods can then be used to process these observations. These methods largely depend on the form of the questionnaire. If the questionnaire contains a single closed-ended question we can use the spike model, which introduces a discontinuity at zero into the previously selected distribution of the willingness to pay and then estimates it using maximum likelihood. In the presence of open-ended questions like “How much are you willing to pay for this programme?” we can use censored data models (such as the Tobit model) to account for zero values. For applications of these methods, see articles [20] and [25].

34. Many contingent evaluation questionnaires use two-stage closed-ended questions to increase the statistical power of the measurement. Each individual i is offered an initial amount t_i , if he or she agrees to pay this amount, another value $t_i' > t_i$ is proposed, otherwise, a value $t_i'' < t_i, t_i'' < t_i$ is proposed. In this way we obtain a narrower interval for the willingness to pay. Stepwise regression procedures allow us to calculate the average willingness to pay in the sample. This method is undoubtedly the one most commonly used because it is simple to apply and considered to represent sound valuation practice given the specific form of the questionnaire. An application can be found in reference [2].

35. With regard to the sample studied here, Table 1 presents a breakdown of the methods used for our meta-analysis. Note that we only have information on the estimation method used for 82% of the observations in our initial sample –namely 893 observations out of 1 095.

3. Description of the database

3.1 Construction of the database

36. Since this is a meta-analysis, all the information used in this study was either collected from published papers or provided directly by their authors. Our aim was to cover all studies which applied contingent valuation methods to mortal risk in the areas of environment, health, and traffic and which produced one or more values of statistical life or the information needed to calculate that value. As far as possible, we also collected any information that could help us understand the disparities. This analysis therefore includes results published in academic journals, books, publications of government ministries or bodies, but also discussion papers, working documents, and doctoral theses.

37. As mentioned previously, most papers on this subject provide not one, but several, values of statistical life. These estimates are calculated from sub-samples differentiated on the basis of age, income, or sex, or reflecting different estimation techniques, assumptions regarding the distribution of willingness to pay, or values of the proposed risk reduction, etc. We collected a number of variables for these differences, such as the estimation method and characteristics of the questionnaire.

38. Ancillary information was also incorporated into the database when it did not feature in the study. For example, per capita GDP at the time and place of the survey, which plays a key explanatory role in the value of statistical life, was obtained from OECD databases.

39. All of these data were tabulated into an “initial sample”. Following a preliminary analysis of this database (cf. Braathen, Lindhjem and Navrud, 2009), the authors whose estimates were included in the initial database were asked for their opinion on retaining their results for the final analysis. Specifically, the question was:

“It would be excellent if you could indicate if you think that a given VSL estimate ought to be included in our analysis. We would like you to distinguish between four ‘options’: “Only”, “Yes”, “Perhaps” and “No”. Please use “Only” to indicate *the* preferred estimate from a given survey (if any), “Yes” to indicate that the estimate is one among several estimates that ought to be included, “Perhaps” to indicate that you are in doubt and “No” if you think that a given estimate definitively should not be included in the meta-analysis.”

40. This process yielded opinions from the authors regarding 627 out of a total of 1 095 observations, or slightly under 60%. We decided to remove from the initial sample those estimates for which the authors had answered “No”.

41. We also removed from the initial sample estimates from studies that did not meet the following criteria:

- The value of statistical life calculated from an average (some published this value based on a calculated median, others only used a single year, etc.): 158 observations removed.
- Sample size used for the estimation greater than 100: 144 observations removed.
- Initial sample size greater than 200: 12 observations removed.
- Value of statistical life calculated on the basis of willingness to pay (some of the VSL in the initial sample were based on willingness to accept): 12 observations removed.

- Sample representative of the population (for instance, some of the VSL estimates in the sample were for scientists living near a nuclear power plant): 204 observations removed.
- Access to risk reduction proposed during the contingent valuation: 144 observations removed.

42. Note that, once these observations had been taken out of the “initial sample”, only 33 of the remaining observations had received a negative recommendation from the authors (out of the 627 opinions received from the authors, 220 were negative). Also, with the approval of the authors, we decided to eliminate 22 observations for which we received the opinion “Perhaps”.

43. In all, application of these criteria resulted in 729 observations, or approximately two thirds of the database, being removed from the “initial sample”. In consequence, the “final sample” includes 366 observations on the value of statistical life distributed across 34 study groups (categories named “surveyid”). Each category comprised VSL estimates calculated using the same group of individuals.

3.2 Descriptive Statistics

44. Braathen, Lindhjem and Navrud (2009) provides descriptive statistics on the “initial sample”.

45. In order to render values comparable across locations and time, they are expressed in 2005 dollars, adjusted using the purchasing power parity exchange rate based on actual individual consumption. Table 1 contains a summary of the VSL dataset in the “final sample”. Table 2 provides the same information, but disaggregated by three broad risk categories: environmental risks, health risks, and risks related to road traffic.

46. These two tables provide a preliminary glimpse into the variability of estimates of the value of statistical life: The average is more than twice the median in our sample! We observe that this disparity is particularly striking in the case of health risks.

Table 1 – Summary of the estimates of the value of statistical life
Levels in 2005 dollars

	Final sample	Final sample excluding VSL distribution tails (2.5% – 97.5%)
Average VSL (standard deviation)	2 968 048 (197 101)	2 656 273 (157 509)
Average VSL, weighted by the reciprocal of the number of observations in each “surveyid” (standard deviation)	3 135 447 (264 911)	3 235 125 (243 653)
Median VSL	1 406 306	1 406 306
Min value of the VSL	4 450	59 031
Max value of the VSL	22 100 000	14 500 000
Number of observations	366	348

Table 2 – Summary of the estimates of the value of statistical life by risk category
Levels in 2005 dollars

	Environment	Health	Traffic
Mean VSL (standard deviation)	2 455 982 (242 267)	2 574 140 (245 292)	4 884 853 (491 192)
Median VSL	2 395 349	875 060	3 946 727
Min value of the VSL	24 427	4 450	267 615
Max value of the VSL	7 641 706	22 100 000	17 500 000
Number of observations	51	250	65

47. Table 3 presents a description of the studies included in the final sample. It should be noted that VSL estimates are particularly low in developing countries such as China, Thailand, and Bangladesh, thus lending some credence to the economic theory predicting that this value varied in the same direction as wealth. However, a nation's wealth is not the sole explanation for the variations we observe. In fact, VSL estimates for the United States vary between \$200 000 and \$9 400 000.

4. Analysis of variability in the value of statistical life

4.1 Factors that affect the value of statistical life

48. As we saw in Section 1.2, the *level of wealth* theoretically varies in the same direction as VSL. This is also more or less borne out by the descriptive statistics of our database. Empirically, this relationship has been extensively documented in many studies, such as those by de Blaeij *et al.* (2003), Liu *et al.* (1997), Miller (2000), Mrozek and Taylor (2002), and Viscusi and Aldy (2003), with an elasticity generally between zero and one. For the purposes of our study, two measurements of wealth are available: per capita GDP and the average disposable income of the households canvassed. However, while household disposable income is more precise and better reflects the individual situations of survey participants, it is only available for half of the observations. For this reason, we use per capita GDP as a proxy for individual wealth, especially since we observe a correlation of 0.92 between the logarithms of per capita GDP and average disposable household income.

49. *The underlying risk level* also theoretically varies in the same direction as VSL. In this case, however, the empirical evidence is ambiguous: the papers by de Blaeij *et al.* (2003) and Persson *et al.* (2001) suggest that they move in the same direction, but Andersson (2007) and Viscusi and Aldy (2003) find the opposite to be true. In our data, we opted to eliminate this variable from the regressions because the information was unavailable for 25% of our final sample, whereas we seem to detect a non-monotonic relationship between this variable and the log of VSL, as Figure 3 indicates.

Figure 3 – VSL vs. Underlying risk

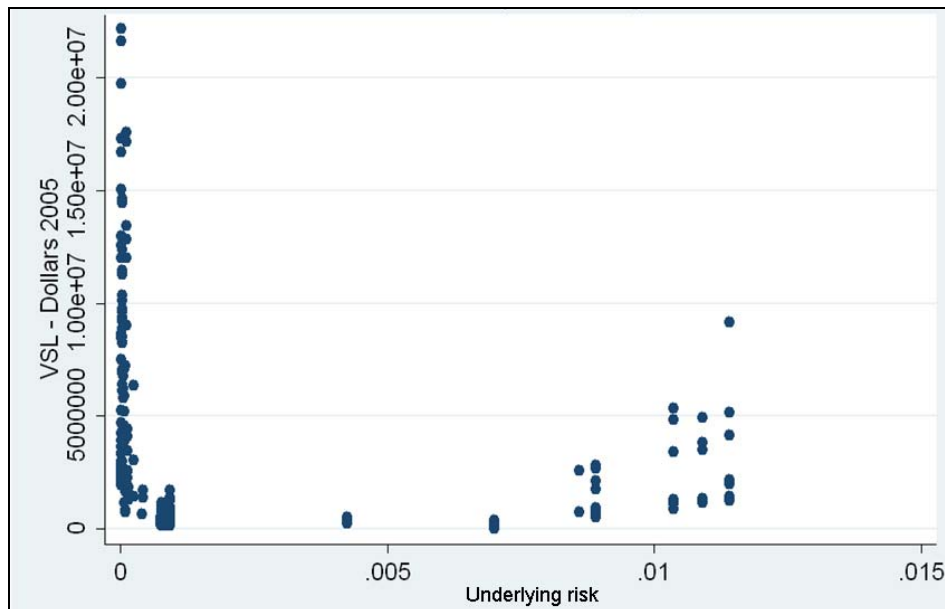


Table 3 – Descriptive statistics for the studies included in the meta-analysis

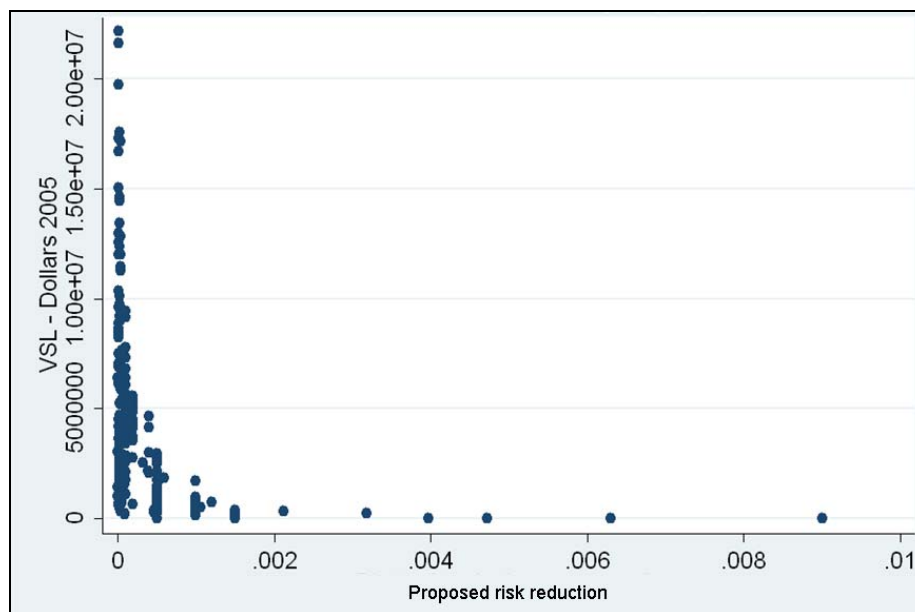
Paper	Biblio. Ref.	No. Obs.	Publication year	Country	Mean VSL (in 2005 dollars)	Range (*10 ⁶ 2005 dollars)	Per capita VSL/GDP ratio
ADB	[6]	4	2005	Malaysia	1 194 228	0.7 – 1.7	104
Alberini & Chiabai	[1]	7	2006	Italy	2 701 947	1 – 5.6	97
Alberini & Kahn	[8]	12	2006	United States	1 266 037	0.2 – 6.4	30
Alberini et al.	[3]	11	2006	Czech Republic	2 965 895	0.7 – 5.4	146
Alberini et al.	[2]	2	2004	United States	1 421 025	1.1 – 1.7	34
Alberini et al.	[4]	3	2007	Italy	3 598 485	1.4 – 6.3	130
Alberini et al.	[5]	2	2006	Canada - United States	1 036 062	0.8 – 1.2	27
Buzby, Ready & Skees	[7]	2	1995	United States	6 521 801	5.4 – 7.6	156
Chestnut et al.	[9]	12	2009	Canada - United States	5 142 629	2.5 – 9.4	134
Desaigues et al.	[12] [31]	20	2004-2007	France	2 943 355	0.9 – 9.1	99
Ghani & Faudzi	[14]	8	2003	Malaysia	1 269 214	0.7 – 1.9	111
Gibson et al.	[15]	1	2007	Thailand	659 955	##	96
Giergiczny	[16]	3	2006	Poland	795 082	0.2 – 1.7	59
Guo, Haab & Hammitt	[17]	1	2006	China	24 427	##	6
Hakes & Viscusi	[19]	2	2004	United States	6 247 816	6.1 – 6.4	150
Hammitt & Zhou	[20]	12	2006	China	115 515	0.02 – 0.4	28
Itaoka et al.	[21]	19	2007	Japan	1 280 220	0.5 – 2.8	42
Johannesson, Johannsson & Löfgren	[22]	14	1997	Sweden	4 509 711	2.8 – 5.5	141
Johannesson, Johannsson & O'Conor	[23]	4	1996	Sweden	4 652 973	2 – 7.1	145
Jones-Lee, Hammerton & Philips	[24]	4	1985	United Kingdom	5 226 967	3.9 – 7.2	166
Krupnick et al.	[25]	8	2002	Canada	1 758 343	1.1 – 3.6	50
Krupnick et al.	[26]	110	2006	China	562 225	0.1 – 1.7	137
Leiter & Pruckner	[27]	24	2008-2009	Austria	3 021 948	1.9 – 5.2	89
Leiter & Pruckner	[28]	4	2008	Austria	2 445 736	2.1 – 2.8	72
Liu et al.	[29]	24	2005	Chinese Taipei	12 300 000	5.8 – 22.1	472
Mahmud	[30]	4	2006	Bangladesh	5 248	0.04 – 0.07	4
Leung et al.	[18]	8	2009	New Zealand	2 870 491	1.8 – 4.4	117
Persson et al.	[32]	7	2001	Sweden	3 107 326	1.6 – 4.2	97
Rheinberger	[33]	2	2009	Switzerland	4 362 827	4.2 – 4.5	123
Schwab Christe & Soguel	[34]	4	1995	France	1 094 639	0.3 – 2.2	37
Schwab Christe & Soguel	[34]	6	1995	Denmark	13 600 000	9 – 17.5	404
Svensson	[35]	14	2009	Sweden	7 693 884	3 – 9.6	240
Tsuge, Kishimoto & Takeuchi	[36]	1	2005	Japan	2 695 444	##	89
Vassanadumrondgee & Matsuoka	[37]	4	2005	Thailand	1 555 256	1.3 – 1.8	226
duVair & Loomis	[13]	3	1993	United States	352 962	0.2 – 0.5	8

50. According to the descriptive statistics (cf. Table 2), the category of risk also appears to play an important role, with traffic-related risks appearing to receive greater weight than those associated with health or the environment. However, as we shall see in the next section, this result needs to be placed in context since these variables are highly correlated with variables of the type: Public-Private, or Individual-Collective, risk. Since this issue has been largely ignored in the literature, little empirical evidence has been brought to bear on the matter.

51. The *degree of risk reduction* proposed in the contingent valuation should not, theoretically, have an impact on the VSL. However, theory and reality do not always coincide, and VSL is calculated as the ratio of willingness to pay to risk reduction. Also, when values of willingness to pay are similar, this ratio becomes extremely sensitive to the denominator, which is generally very small. Thus, we expect the VSL to move in the opposite direction to the change in risk proposed in the contingent valuation. *A priori*, this corresponds to what we observe in Figure 4.

52. It should be noted that a highly negative correlation exists between this variable and per capita GDP (correlation coefficient of -0.49 in our data). This may be attributable to the fact that the underlying risk level is lower in wealthy countries than in developing countries, so that the marginal cost of risk reduction is higher. This observation is important for the regressions we will perform, because omitting this variable would bias the results – in particular the elasticity with respect to wealth.

Figure 4 – Log (VSL) vs. Proposed risk reduction

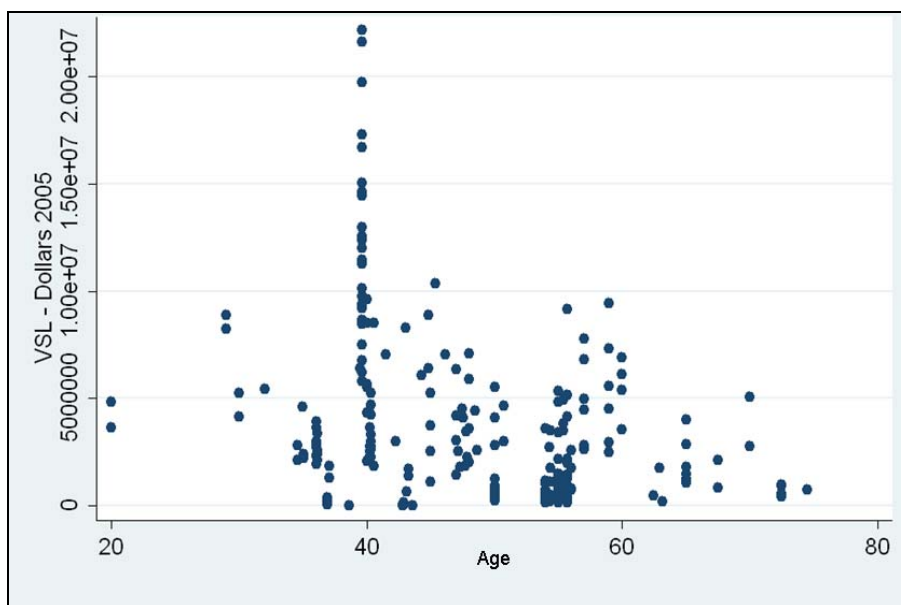


53. *Altruism* in willingness to pay is also frequently regarded as a contributing factor to disparities in the values of statistical life. Again, the empirical results presented in the literature are quite ambiguous. In this document, the examination of altruism will be broken down into two parts: a variable capturing differentiated public-private effects (typically, willingness to pay for an overall improvement in road safety is compared to the sale of airbags in cars), and another variable capturing differentiated individual-household effects (in all the studies in this meta-analysis the willingness to pay is either individual or at the level of the household, divided by the number of individuals it contains).

54. *Age* is a variable of interest for studying variability in VSL. Most studies find either an empirical relationship with an inverted U-shape or a certain degree of independence (cf. Alberini *et al.* (2004, 2006); Andersson (2007); Hammitt and Liu (2004); Johannesson *et al.* (1999); Jones-Lee *et al.* (1985); Viscose

and Ady (2007); and Krupinica (2007)). Once again, we omit this variable from our regressions because the information is only available for 75% of our sample; the initial descriptive statistics (and even the regressions) suggest that there is little correlation with the VSL, even if we seem to detect an approximately inverse-U-shaped curve (cf. Figure 5).

Figure 5 – Log(VSL) vs. Age



4.2 Regressions

55. In this section we shall conduct a “decorrelated” regression analysis of the VSL variability. Owing to numerous problems with missing values for some variables and the scarcity of observations, the number of covariates was kept to a minimum. In particular, the “income” and “age” variables were not included in the regressions: if both were included, our sample would shrink to 183 observations and a definite bias would be introduced into our estimates.

56. Our econometric model thus takes the form

$$\log(VSL)_{si} = \beta_0 + \beta_1 \log(GDP)_{si} + \beta_2 \log(RCh)_{si} + \sum_k \beta_k X_{si}(k) + \varepsilon_{si},$$

where $\log(GDP)_{si}$ designates the logarithm of per capita GDP for observation i in study group s , $\log(RCh)_{si}$ the logarithm of the level of risk reduction proposed in the contingent valuation, and X_{si} a vector of dichotomous explanatory variables. This model is estimated using ordinary least squares. However, since the number of observations varies widely across groups s (ranging from 1 to 86), the ordinary least squares are weighted by the reciprocal of the number of observations in each group so as to weight each group equally. Moreover, the “cluster” option is used for estimating standard errors in order to account for the correlation between different observations in the same group.

57. We use a log-log model, since this provides the best fit for our data and has the additional advantage that the estimated coefficients have a natural interpretation as elasticities.

58. In Table 4, we present the results of these estimations for different groups of dichotomous variables X . The “Environment” and “Traffic” variables refer to the risk category; the “Public” and “Household” variables were explained in the previous section; the “Cancer” variable equals one if the

survey questionnaire specifically referred to a cancer risk; the dichotomous “Latent” variable equals one if the reduction in risk envisaged during the contingent valuation only takes effect after a certain lag (deferred risk reduction). The “No explanation” variable refers to the contingent valuation questionnaire: it equals one when the proposed risk reduction is not accompanied by an in-depth explanation. Indeed, it is well known that survey participants have difficulty fully appreciating decreases in mortality risk, especially when rates are very low. To alleviate these problems, some survey questionnaires provide explanatory grids to help respondents visualise the numbers at issue, and thus better understand their willingness to pay. The “Turnbull” variable, for its part, equals one if the VSL estimator was calculated using the Turnbull method, which yields a lower bound on willingness to pay (cf. Section 2.1). Also, in model V, the reference category is associated with a health risk that is private, individual, immediate, and that has no explicit link with cancer – and the estimation of which reflects what might be called “good practice” (explaining risk levels to survey participants carefully and giving an average value, rather than a lower bound, for willingness to pay).

59. We observe in Table 4 that all the estimated coefficients have the expected signs. We also see that the values of R^2 for these regressions are remarkably high, between 0.719 [for only two explanatory variables, $\log(GDP)$ and $\log(RCh)$] and 0.855 for model V, indicating that the chosen models do a fairly good job of explaining the data of this meta-analysis.

60. The elasticity of the value of statistical life with respect to wealth is significant and approximately equal to one, which is entirely consistent with earlier studies (cf. Section 4.1). The elasticity with respect to risk reduction is also significant, and has the expected sign, but its interpretation is more subtle. In fact, this variable was added to the regression to check the elasticity of wealth, but it proved to be a key variable for explaining variations in VSL in its own right. In addition, the significantly negative coefficient of the dichotomous “Public” variable is noteworthy – capturing a certain degree of individualism in willingness to pay and, by extension, in the valuation of human life. We also observe the impact of questionnaire design over the “No_explanation” variable: when the reduction in risk is poorly explained, people tend to overstate their willingness to pay.

61. In summary, our analysis appears to suggest that the value of statistical life primarily depends on individual wealth, but also – and this is problematic – on technical considerations with regard to how this value is calculated. In any theoretical scenario, the value of the risk reduction proposed during the contingent valuation should be independent of VSL. But this is not what we observe. It even appears that in rich countries great value is attributed to life, in part because average willingness to pay is high (reflecting high levels of individual wealth), but also because there is limited scope for reducing risk, mechanically yielding a large ratio.

62. We have replicated, in an appendix, the regressions on the same econometric models as above, but with the addition of a second-degree polynomial form for the underlying risk. In fact, since the underlying risk is negatively correlated with per capita GDP, these variables should theoretically have been included in the model. However, including them eliminates 25% of the observations in our sample and nearly half the study groups. In consequence, the observed variability in the coefficients may be primarily attributable to a sampling bias.

Table 4 – Results of the regressions

	Model I	Model II	Model III	Model IV	Model V
log(GDP)	1.022*** (0.206)	1.029*** (0.166)	1.075*** (0.150)	1.066*** (0.154)	0.963*** (0.202)
log(RCh)	-0.445*** (0.0942)	-0.576*** (0.0951)	-0.552*** (0.0846)	-0.580*** (0.0612)	-0.555*** (0.0666)
Environment		-1.395*** (0.365)	-0.634** (0.308)	-0.596** (0.280)	-0.483* (0.250)
Traffic		-0.635** (0.283)	-0.317 (0.296)	-0.463* (0.247)	-0.522** (0.201)
Public			-0.949*** (0.255)	-0.958*** (0.260)	-0.862*** (0.242)
Household			-0.0405 (0.279)	0.0574 (0.219)	-0.0484 (0.222)
Cancer				-0.0980 (0.235)	0.00997 (0.231)
Latent				-0.491 (0.430)	-0.415 (0.432)
No_explanation					0.626*** (0.208)
Turnbull					-0.370 (0.574)
Constant	0.0433 (2.098)	-0.726 (1.727)	-0.978 (1.575)	-1.050 (1.672)	0.0632 (2.317)
No. observations	366	366	366	366	366
No. observations Cluster	34	34	34	34	34
R-squared	0.719	0.798	0.832	0.839	0.855

Robust standard errors in parentheses

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

63. In the following section, we use more specific meta-analysis techniques to test the robustness of our principal results.

4.3 Specific meta-regression techniques for analysing variability in the VSL

64. The key notion underlying this section is to use the available information regarding variability in the estimates of the value of statistical life and to assign greater weight to those that are more accurate.

4.3.1 Description of a method

65. Let us consider n studies that measure a parameter of interest y (in our case, this is the logarithm of the VSL). However, as we were able to establish above, a certain number of covariates may have an incidence on the “true” parameter values y_1, \dots, y_n . Thus, we have a standard regression of the form

$$y_i = x_i' \beta + \epsilon_i$$

where x_i designates a vector of covariates from study i and ϵ_i is an error term that we denote the “inter-study heterogeneity term”. We shall assume that the ϵ_i are independent and identically distributed

$N(0, \tau^2)$. While we do not exactly observe the “true” values y_1, \dots, y_n , we do have estimates, $\hat{y}_1, \dots, \hat{y}_n$. Thus, for each i we can write

$$\hat{y}_i = y_i + \delta_i$$

where δ_i is an “inter-study heterogeneity term”. We shall now assume that the δ_i is independent and identically distributed $N(0, v_i)$. Note that, generally, we have estimates for the values v_1, \dots, v_n . Therefore, we are dealing with a model of the type

$$\hat{y}_i = x_i' \beta + \delta_i + \epsilon_i$$

where the parameters β and τ^2 are to be estimated.

66. There are many methods which can be used to estimate β and τ^2 , including empirical Bayesian techniques (cf. duMouchel-Harris and DerSimonian-Kacker). However, these techniques are all extremely demanding computationally and would make the running the simulations in the next section very long. We shall therefore use a simpler method involving the method of moments to estimate the “inter-study” variance term. Formally, we begin by estimating an ordinary least squares regression weighted by the reciprocals of the estimated variances v_1, \dots, v_n . This yields an initial estimate for β that can be written

$$\hat{\beta}_1 = (X'V^{-1}X)^{-1}X'V^{-1}\hat{Y}$$

where $X^i = (x_1, \dots, x_n)$, $\hat{Y} = (\hat{y}_1, \dots, \hat{y}_n)$, and $V = \text{diag}(v_1, \dots, v_n)$. $X' = (x_1, \dots, x_n)$,

67. Thus, the average of the residual sum of squares, $RSS = \sum_{i=1}^n (\hat{y}_i - x_i' \hat{\beta}_1) / v_i$, is

$$E(RSS) = (n - m) + \tau^2 \{ \text{Tr}(V^{-1}) - \text{Tr}[V^{-1}X(X'V^{-1}X)^{-1}X'V^{-1}] \}$$

where m is the number of covariates (including the constant). This yields a natural estimator for τ^2 by the method of moments:

$$\hat{\tau}^2 = \max \left\{ \frac{RSS - (n - m)}{\text{Tr}(V^{-1}) - \text{Tr}[V^{-1}X(X'V^{-1}X)^{-1}X'V^{-1}]}, 0 \right\}.$$

68. We now use this information to obtain a second estimate of β .

$$\hat{\beta}_2 = (X'\hat{V}^{-1}X)^{-1}X'\hat{V}^{-1}\hat{Y},$$

with $\hat{V} = \text{diag}(v_1 + \hat{\tau}^2, \dots, v_n + \hat{\tau}^2)$.

4.3.2 Adapting the method to the data

69. The method presented above only works for independent observations on y_1, \dots, y_n . Consequently, it cannot be directly applied to our data. The approach we propose below therefore involves taking a random sample consisting of a single observation from each study group and

then performing a meta-regression on this “small sample”. We will repeat this process 1000 times so as to obtain an empirical distribution of the parameters to be estimated.

70. However, there is a problem with our “final sample” – we are no longer dealing with the same sample, since we do not have all the required information about the estimated variances. This information is only available for 254 observations from 21 study groups. Table 5 presents the descriptive statistics for the new sample. In particular, it can be seen that we no longer have observations on the value of statistical life for Malaysia or the Czech Republic.

71. Since this sample contains 21 study groups, each “small sample” will include 21 observations only. For this reason, only two regressors were chosen: the logarithm of per capita GDP and the logarithm of the risk reduction proposed in the contingent valuation. The logarithm of the value of statistical life remains our dependent variable. At each iteration of the process described above we obtain an estimate of the model’s coefficients. In Figure 6, we see the empirical distributions of the estimates of the model’s coefficients (elasticity of wealth and of risk reduction).

$$\log(VSL)_i = \beta_0 + \beta_1 \log(PIB)_i + \beta_2 \log(RCh)_i + \delta_i + \varepsilon_i.$$

Figure 6 – Empirical distributions of the coefficients of the regressions, by methods specific to meta-analysis and simulation

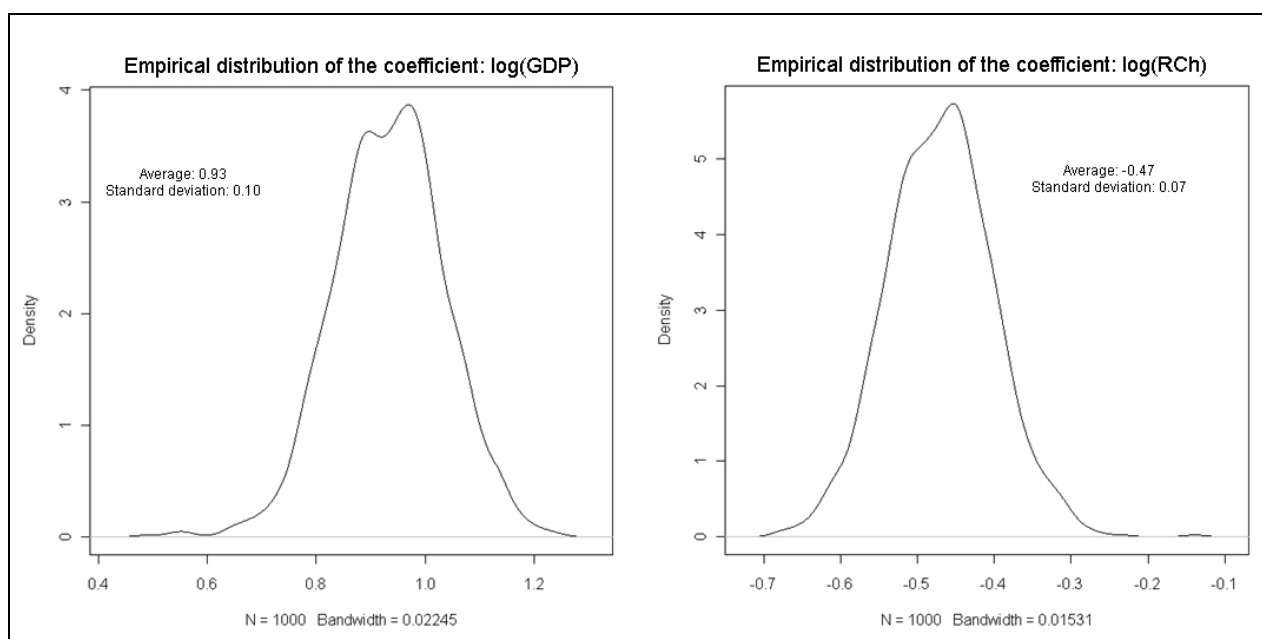


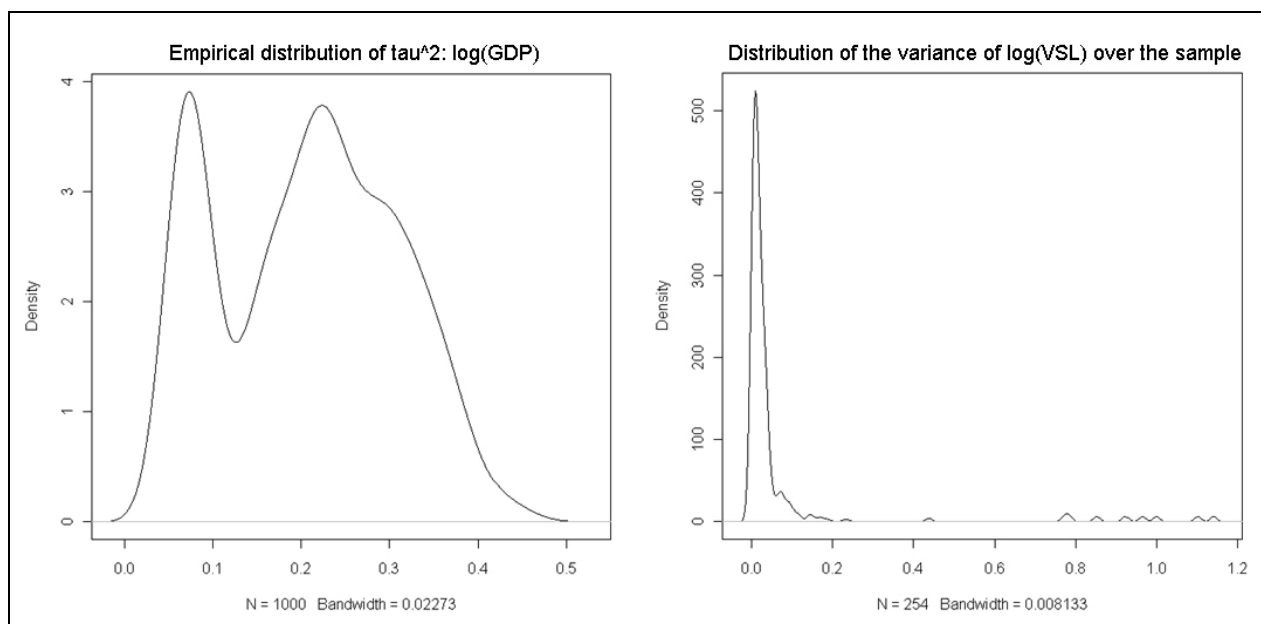
Table 5 -- Descriptive statistics; sample with standard deviations

Paper	Biblio. Ref.	No. Obs.	Publication year	Country	Average VSL	Range	Per capita VSL/GDP ratio
Alberini <i>et al.</i>	[2]	2	2004	United States	1,421,025	1.1 – 1.7	34
Alberini <i>et al.</i>	[4]	3	2007	Italy	3,598,485	1.4 – 6.3	130
Alberini <i>et al.</i>	[5]	2	2006	Canada - United States	1,036,062	0.8 – 1.2	27
Chestnut <i>et al.</i>	[9]	12	2009	Canada - United States	5,142,629	2.5 – 9.4	134
Desaigues <i>et al.</i>	[12] [31]	6	2004-2007	Denmark	2,651,682	1.1 – 4.9	79
Gibson <i>et al.</i>	[15]	1	2007	Thailand	659,955	##	96
Giergiczny	[16]	3	2006	Poland	795,082	0.2 – 1.7	59
Hakes & Viscusi	[19]	2	2004	United States	6,247,816	6.1 – 6.4	150
Hammit & Zhou	[20]	12	2006	China	115,515	0.02 – 0.4	28
Itaoka <i>et al.</i>	[21]	19	2007	Japan	1,280,220	0.5 – 2.8	42
Johannesson, Johansson & O'Connor	[23]	4	1996	Sweden	4,652,973	2 – 7.1	145
Jones-Lee, Hammerton & Philips	[24]	4	1985	United Kingdom	5,226,967	3.9 – 7.2	166
Krupnick <i>et al.</i>	[25]	8	2002	Canada	1,758,343	1.1 – 3.6	50
Krupnick <i>et al.</i>	[26]	110	2006	China	562,225	0.1 – 1.7	137
Leiter & Pruckner	[27]	24	2008-2009	Austria	3,021,948	1.9 – 5.2	89
Leiter & Pruckner	[28]	4	2008	Austria	2,445,736	2.1 – 2.8	72
Mahmud	[30]	4	2006	Bangladesh	5,248	0.04 – 0.07	4
Leung <i>et al.</i>	[18]	8	2009	New Zealand	2,870,491	1.8 – 4.4	117
Rheinberger	[33]	2	2009	Switzerland	4,362,827	4.2 – 4.5	123
Schwab Christe & Soguel	[34]	6	1995	Denmark	13,600,000	9 – 17.5	404
Svensson	[35]	14	2009	Sweden	7,693,884	3 – 9.6	240
Vassanadumrondgee & Matsuoka	[37]	4	2005	Thailand	1,555,256	1.3 – 1.8	226

72. It can be seen that the empirical distributions of the calculated coefficients are fully consistent with the results obtained in the regressions in Section 4.2. This corroborates our finding that the elasticity of the value of statistical life with respect to wealth is approximately 0.95, with a 95% confidence interval between 0.73 and 1.13 for this last method.

73. To assess whether the inter-study heterogeneity term plays an important role in the results obtained from the methods described above, we can also give the empirical distribution of τ^2 obtained from the 1000 iterations previously performed. This distribution is then compared with that of the variance of $\log(VSL)$ from our sample of 254 observations, again weighting them with the reciprocal of the number of observations in each study group. These distributions can be seen in Figure 7. We observe that inter-study heterogeneity appears to play an important role in the weighting, because the empirical probability that the factor τ^2 is greater than 0.1 exceeds 0.75, while the distribution of the logarithm of the value of statistical life is largely concentrated between 0 and 0.1. This indicates that the various components of heterogeneity (heterogeneity from the estimates of the VSL in study i and heterogeneity from inter-study differences) are essentially attributable to inter-study heterogeneity.

Figure 7 – Empirical distribution of inter-study heterogeneity and the distribution of the variance of $\log(VSL)$ over our sample



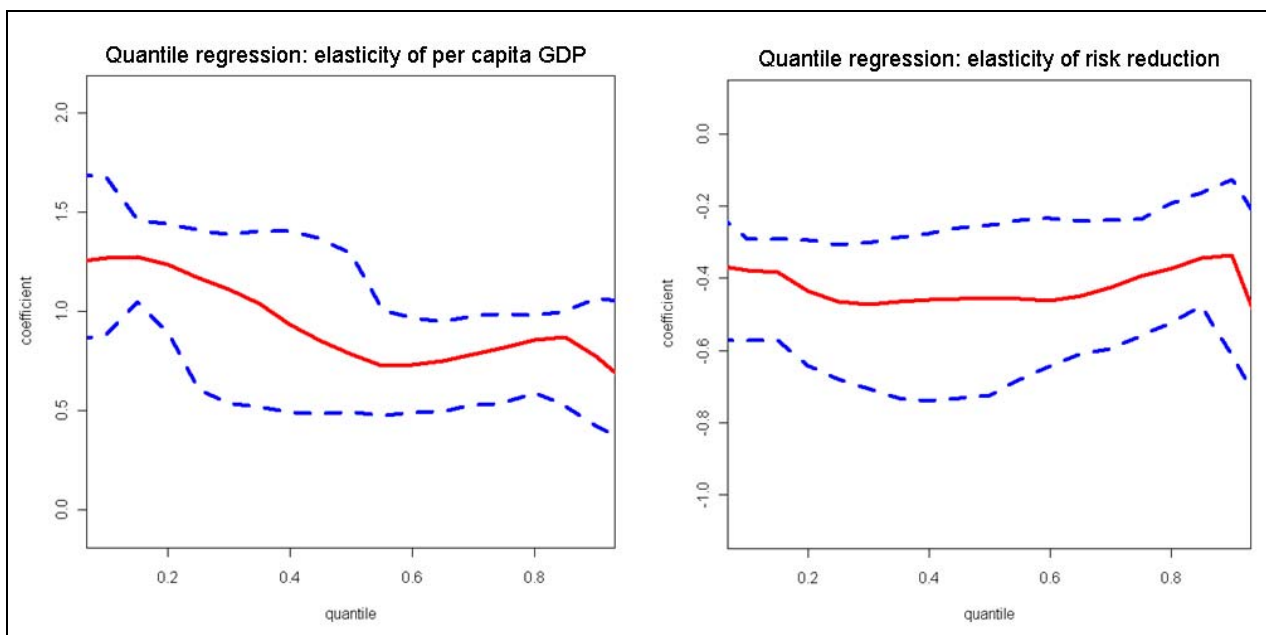
4.3.3 Quantile regressions

74. In order to probe a little deeper into the data than we did with the results of our mean regressions, we here use quantile regressions to assess whether the calculated elasticities differ by quantile. To this end, we again use simulation techniques that involve drawing a random sample of a single observation from each study group (in order to obtain independent observations). This time, each sub-model assumes is expressed as follows

$$\log(VSL)_i = \beta_0(q) + \beta_1(q)\log(PIB)_i + \beta_2(q)\log(RCh)_i + \varepsilon_i(q).$$

where q is a quantile between zero and one and $\epsilon_i(q)$ is an error term such that its q -quantile equals zero. As in the previous section, we weight the observations to assign greater weight to more accurate observations, but also include an inter-study heterogeneity term. However, the techniques described above for estimating the term τ^2 were not designed for quantile regressions. We are therefore using these estimates on a purely experimental basis. For each quantile and each sub-sample, we estimate this parameter using the method of moments discussed in section 4.3.1 (estimation based on regression on a mean!) and we perform a quantile regression using the weights $w_i = 1/(v_i + \tau^2)$. In practical terms, for each quantile q , 1000 sub-samples are randomly selected according to the protocol explained above, and we calculate the empirical distribution of the coefficients $\beta_1(q)$ and $\beta_2(q)$. Figure 8 depicts the median and the 2.5% and 97.5% quantiles of the two empirical distributions as a function of quantile q . The two solid lines represent the median and the dashed lines represent the 2.5% and 97.5% quantiles.

Figure 8 – Quantile regressions



75. We first observe that the results obtained by this technique are consistent with the coefficients estimated above; namely, we find that the elasticity of VSL with respect to wealth is approximately 1, and its elasticity with respect to risk reduction is approximately -0.4 . However, we now see that the elasticity associated with risk reduction is fairly constant across quantiles, while that of per capita GDP appears to decrease with the quantile. In other words, the explanatory power of wealth for the value of statistical life appears greater for low values of VSL. One should therefore be prudent when using the elasticity of wealth. In countries considered to be rich, differences in terms of wealth or disposable income seem to play a muted role in explaining variations in the value of statistical life. In developing countries, on the other hand, these variations seem more straightforward.

4.3.4 Non-parametric regression

76. In order to view these effects differently, we shall now use non-parametric regression techniques. Here, the objective is to estimate the influences that the logarithm of per capita wealth and the logarithm of risk reduction exert on the logarithm of the value of human life, while making the fewest possible prior assumptions as to the form of the model. Once again, the complexity and heterogeneity of our data preclude direct application of standard methods. In particular, the problem of dependency between

observations arises once again. Therefore, as in the two previous sections, simulation methods will be used. The following operation will be repeated 1 000 times:

- Select a single observation for each group of studies.
- Perform a non-parametric penalised cubic-spline regression on this small sample (the smoothing parameter will be chosen by cross validation).
- Use this model to obtain a sequence of the form $[E(\log(VSL) | \log(PIB) = x_k)]_k$, $[x_k]_k$ being a size 100 sequence equispaced between seven and 11 (values related to our data).

77. Thus, for each value of x_k , we obtain 1 000 different values of $E(\log(VSL) | \log(PIB) = x_k)$; we will then select the 2.5%, 50% and 97.5% quantiles in order to construct a 95% confidence interval for $E(\log(VSL) | \log(PIB) = x_k)$.

78. Figure 10 shows the results of these simulations on the samples of 366 and 254 observations, the constructions of which were described in detail above. As on the quantile regression graphs, the solid line refers to the median value of the non-parametric regression, whereas the dotted lines refer to the lower and upper boundaries of this type of regression.

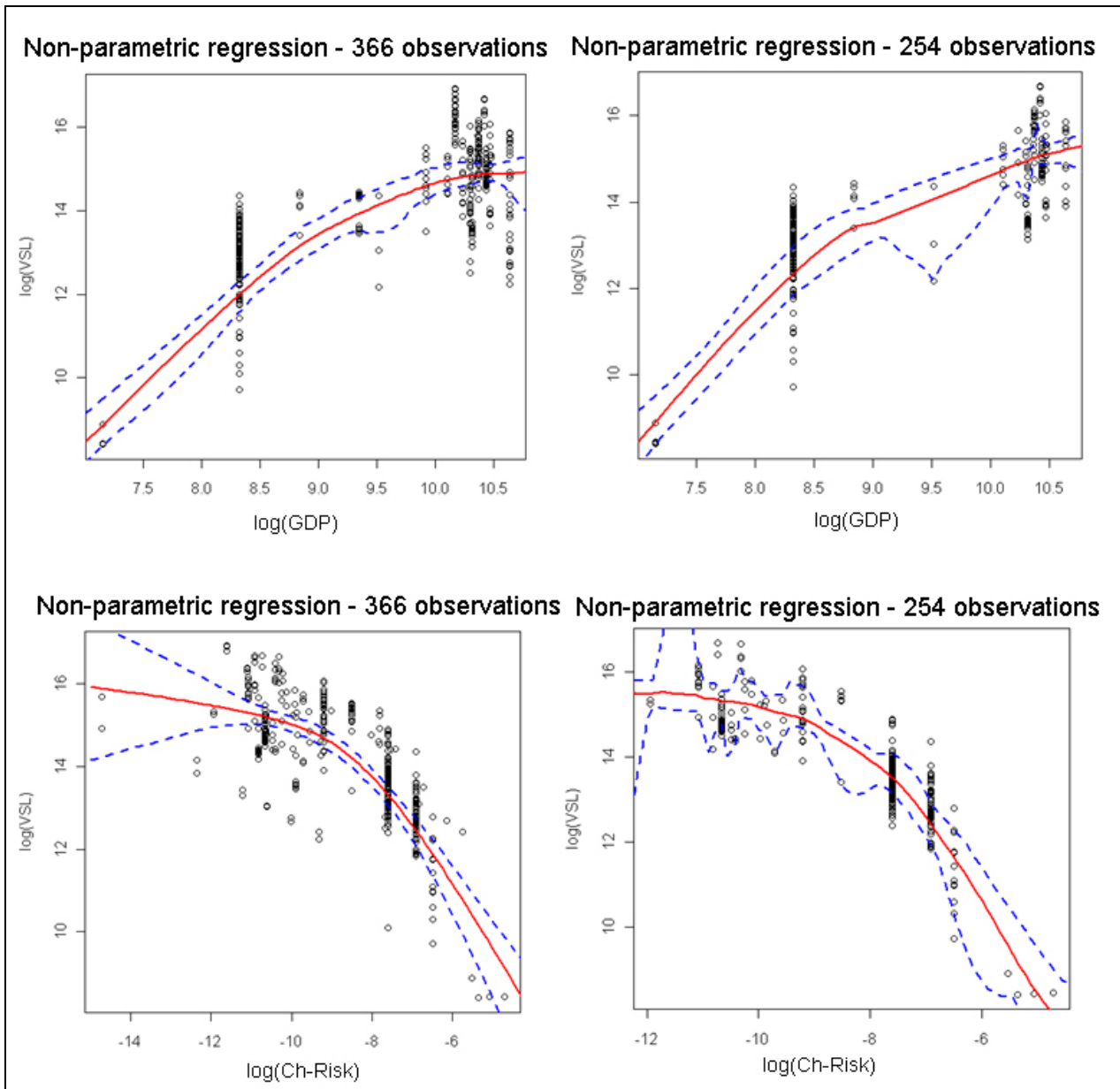
79. The effects that had been noted when using quantile regressions in respect of the influence of the logarithm of per capita GDP can in fact been seen on the graphs; *i.e.*, the influence of wealth on the statistical value of human life seems less substantial in countries that are already rich. It is also found that the influence of risk reduction is also greater when this risk reduction is fairly substantial. These findings are fully consistent with what we have explained in this document, inasmuch as we had already noted that when per capita GDP is high the proposed risk reduction is generally rather low (negative correlation between per capita GDP and the proposed risk reduction).

5. Conclusions

80. This survey of published results from studies of the value of statistical life based on contingent valuation, undertaken under the aegis of the OECD, had a three-fold purpose. Firstly, we set out to put some order into the values held to reflect individual preferences in the area of risk and willingness to pay. Secondly, we analysed the differences observed which were genuinely significant. It should be recalled that in the sample of 366 observations that we used, the value of statistical life ranged from \$4 450 (a Bangladeshi study from 2006) to \$22 100 000 (a Taiwanese study from 2005). Lastly, our final objective was to formulate recommendations for interested countries, in particular OECD Member countries.

81. The sorting and grouping phase was undoubtedly the most complicated and most debatable in that there were a number of shortcomings in the procedure used to select observations, even though this procedure was largely a matter of common sense. For example, it would have been possible to adopt other approaches, such as disregarding the opinions of authors or including values of statistical life based on willingness to accept. However, the compromise we struck here appears to corroborate the theoretical and empirical results found in the relevant literature. Furthermore, many other tests were conducted which failed to identify any particular sensitivity to the key choices we made (especially with regard to acting on the choices of authors).

Figure 10 – Non-parametric regression by simulation techniques



82. The wide range of calculated values of statistical life creates a quandary for governments that need to select a value to address a particular issue. Choosing a value that fails to reflect the willingness to pay of individuals can lead to poor decisions. Studying the variability of VSL provides an insight into some of the differences observed. In this paper we demonstrate that the two factors with the greatest influence on the value of statistical life are national wealth (measured using per capita GDP) and the magnitude of risk reduction proposed during the contingent valuation. The VSL varies proportionally with per capita GDP and inversely with risk reduction. We also show that, in comparison to traffic-related and environmental risks, health risks have a significant positive impact on the value of statistical life, which was not apparent strictly on the basis of the descriptive statistics. Our data also reveal that individuals tend to place a lower value on programmes associated with public or collective goods than on private goods. Also, we observe that certain methodological factors related to the valuation questionnaires and estimation

methods appear to play a role in the variability of VSL: when survey participants are not provided with a thorough explanation of the reduction in risk, their willingness to pay is significantly greater.

83. All these considerations may enable decision-makers to identify a value of statistical life that is uniquely tailored to the programme they are considering. However, for the following reasons this type of adjustment is far from simple. First, there is a need for a reference value – which does not necessarily exist! Subsequently, even if this value is set on the basis of certain criteria, the adjustment remains delicate because the coefficients estimated in this study are not robust. Indeed, the econometric models used require assumptions such as equal impacts of environmental risk across all countries. Of course, the ideal would be to directly measure the value of statistical life by conducting a survey targeting the affected population. But of course such surveys are both costly and time consuming.

BIBLIOGRAPHY

- Andersson, H. (2007), “Willingness to Pay for Road Safety and Estimates of the Risk of Death: Evidence from a Swedish Contingent Valuation Study”. *Accident Analysis and Prevention* 39(4), 853-865.
- Andersson, Henrik & Treich, Nicolas, (2008), “The Value of statistical life”, Working Papers 2008:1, Swedish National Road & Transport Research Institute (VTI).
- Bellavance, Francois & Dionne, Georges & Lebeau, Martin (2009), “The value of statistical life: A meta-analysis with a mixed effects regression model.” *Journal of Health Economics*, vol. 28(2), pages 444-464, March.
- Boiteux Marcel , Baumstark Luc (2001), « Transports : choix des investissements et coûts des nuisances », *La Documentation Française*.
- Braathen, N. A., H. Lindhjem and S. Navrud (2008-2010) “Valuing lives saved through environmental, transport and health policies: A Meta-analysis of stated preference studies”. OECD, Paris. Available at [www.oecd.org/officialdocuments/displaydocumentpdf?cote=env/epoc/wpnep\(2008\)10/final](http://www.oecd.org/officialdocuments/displaydocumentpdf?cote=env/epoc/wpnep(2008)10/final).
- Crooker, J.R., and Herriges, J.A. (2004), “Parametric and semi-non-parametric estimation of willingness-to-pay in the dichotomous choice contingent valuation framework.” *Environmental and Resource Economics*, 27: 451-480.
- A. De Blaeij, R.J.G.M. Florax, P. Rietveld and E. Verhoef, (2003) “The value of statistical life in road safety: a meta-analysis”, *Accident Analysis and Prevention* 35 (2003), pp. 973–986.
- DerSimonian R, Kacker R. (2007) , “Random-effects model for meta-analysis of clinical trials: an update.” *Contemporary Clinical Trials* 2007; 28:105–114.
- Drèze, Jacques (1962). “L’utilité sociale d’une vie humaine,” *Revue française de recherche opérationnelle*, vol. 1, p. 93-118.
- DuMouchel William H., Harris Jeffrey E. (1983), “Bayes methods for combining the results of cancer studies in human and other species.” *Journal of the American Statistical Association*, Volume 78, number 382
- Gourieroux Christian, « Aspects statistiques de la méthode d’évaluation contingente », *Économie publique*, Numéros, 01-1998/1
- Hammit, James K. (2009), “Methodological Review of WTP and QALY Frameworks for Valuing Environmental Health Risks to Children.” Paper prepared for the OECD Project on the “Valuation of Environment-Related Health Impacts, with a Particular Focus on Children” (VERHI).
- Hammitt, J. K. and J.-T. Liu (2004), “Effect of Disease Type and Latency on the Value of Mortality Risk”. *Journal of Risk and Uncertainty* 28(1), 73-95.

- Jones-Lee, Michael W. (1976). *The Value of statistical life: An Economic Analysis*, Chicago: University Press.
- Kochi, I., B. Hubbel and R. Kramer (2006), “An empirical Bayes approach to combining and comparing estimates of the value of statistical life for environmental policy analysis”,
- Mishan, Ezra J. (1971), “Evaluation of Life and Limb: A Theoretical Approach,” *Journal of Political Economy*, vol. 79, p. 687-705.
- Miller, T. R. (2000), “Variations between Countries in Values of a statistical life.” *Journal of Transport Economics and Policy*, 34, 169-188.
- Mrozek, J. R. and L. O. Taylor (2002), “What Determines the Value of Life? A Meta-Analysis”, *Journal of Policy Analysis and Management*, 22(1), pp. 253–270.
- Nelson, J. P. and P. E. Kennedy (2009), “The Use (and Abuse) of Meta-Analysis in Environmental and Natural Resource Economics: An Assessment”, *Environmental and Resource Economics*.
- Persson, U., A. Norinder, K. Hjalte, and K. Gralén (2001), “The Value of statistical life in Transport: Findings from a new Contingent Valuation Study in Sweden”, *Journal of Risk and Uncertainty* 23(2), 121-134.
- Schelling, Thomas C. (1968). “The Life you Save May be your Own,” in *Problems in Public Expenditure Analysis*, S. Chase, ed., Washington, Brookings Institution, p. 127-162.
- Terra Sebastien (2005), « Guide de bonnes pratiques pour la mise en œuvre de la méthode des prix hédoniques », Document de travail, MEDD, D4E, mars 2005
- US EPA (2006), Report of the EPA Work Group on VSL Meta-Analysis, Report NCEE-0494, National Center for Environmental Economics, EPA.
- Viscusi, W. K. and J. E. Aldy (2003), “The Value of statistical life – A Critical Review of Market Estimates throughout the World”, *Journal of Risk and Uncertainty*, 27 (1); pp. 5-76.
- Viscusi, W. Kip, *The Value of Life* (2003), “Estimates with Risks by Occupation and Industry” (May 2003). *Harvard Law and Economics Discussion Paper* No. 422
- Weinstein, Milton C., Donald S. SHEPARD, and Joseph S. PLISKIN (1980). “The Economic Value of Changing Mortality Probabilities: A Decision-Theoretic Approach,” *The Quarterly Journal of Economics*, vol. 94, p. 373-396.

STUDIES INCLUDED IN THE META-ANALYSIS

- [1] Alberini, Anna and Aline Chiabai (2007), “Urban Environmental Health and Sensitive Populations: How Much are Italians Willing to Pay to Reduce Their Risks”, *Regional Science and Urban Economics*, 37, pp. 239-258. DOI:10.1016/j.regsciurbeco.2006.08.008.
- [2] Alberini, Anna, Maureen Cropper, Alan Krupnick and Nathalie B. Simon (2004), “Does the value of statistical life vary with age and health status? Evidence from the US and Canada”, *Journal of Environmental Economics and Management*, 48, pp. 769-792. DOI:10.1016/j.jeem.2003.10.005.
- [3] Alberini, Anna, Milan Scasny, Marketa Braun Kohlov, and Jan Melichar (2006), “The Value of statistical life in the Czech Republic: Evidence from a Contingent Valuation Study”, in B. Menne and K. L. Ebi (Eds.) (2006), *Climate Change and Adaptation Strategies for Human Health*. Springer-Verlag New York, LLC.
- [4] Alberini, Anna, Stefania Tonin, Margherita Turvani and Aline Chiabai (2007), “Paying for Permanence: Public Preferences for Contaminated Site Cleanup”, *The Journal of Risk and Uncertainty*, 34, pp. 155-178. DOI: 10.1007/s11166-007-9007-8.
- [5] Anna Alberini & Maureen Cropper & Alan Krupnick & Nathalie Simon (2006), “Willingness to pay for mortality risk reduction: does latency matter?” , *The Journal of Risk and Uncertainty*, Springer, vol. 32(3), pages 231-245, May
- [6] Asian Development Bank (2005), “The Cost of Road Traffic Accidents in Malaysia”, *Accident Costing Report AC 5: Malaysia*, Asian Development Bank
- [7] Buzby, Jean C., Richard C. Ready and Jerry R. Skees (1995), “Contingent Valuation in Food Policy Analysis: A Case Study of a Pesticide-Residue Risk Reduction”, *Journal of Agricultural and Applied Economics*, 27 (2), December, 1995: pp. 613-625.
- [8] Carson, Richard T. and Robert Cameron Mitchell (2006), “Public preferences toward environmental risks: The case of trihalomethanes”, in Anna Alberini and James R. Kahn (Eds.) (2006), *Handbook on Contingent Valuation*, Edward Elgar.
- [9] Chestnut, Lauraine G., Robert D. Rowe, and William S. Breffle (2004), “Economic Valuation of Mortality Risk Reduction: Stated Preferences Approach in Canada.” Report prepared for Paul DeCivita, Economic Analysis and Evaluation Division, Healthy Environments and Consumer Safety Branch, Health Canada, Ottawa, Ontario.
- [10] de Blaeij, Adriana Tanneke (2003), “Value of statistical life in Road Safety: Stated Preference Methodologies and Empirical Estimates for the Netherlands.” Doctoral dissertation, Department of Spatial Economics, Vrije Universiteit, Amsterdam, No. 308 of the Tinbergen Institute Research Series.
- [11] Desaigues, Brigitte and Ari Rabl (1995), “Reference Values for Human Life: An Econometric Analysis of a Contingent Valuation in France”, in Nathalie G. Schwab Christe and Nils C. Soguel (Eds.) (1995), *Contingent Valuation, Transport Safety and the Value of Life*, Kluwer Academic Publishers, Boston / Dordrecht / London.
- [12] Desaigues, Brigitte, Ari Rabl, Dominique Ami, Boun My Kene, Serge Masson, Marie-Anne Salomon and Laure Santoni (2007), “Monetary value of Life Expectancy Gain due to Reduced Air Pollution - Lessons from a Contingent Valuation in France”, *Revue d'économie politique*, 117 (5) septembre-octobre 2007, Numéro spécial en Hommage à Brigitte Desaigues.

- [13] duVair, Pierre and John Loomis (1993), “Household's Valuation of Alternative Levels of Hazardous Waste Risk Reductions: an Application of the Referendum Format Contingent Valuation Method”, *Journal of Environmental Management*, 39, pp. 143-155.
- [14] Ghani M.N. and M.Y. Faudzi. 2003. “Value of Life of Malaysian Motorists: Estimates from a Nationwide Survey”. *Journal of the Eastern Asia Society for Transportation Studies*, Vol.5, October 2003.
- [15] Gibson, John, Sandra Barns, Michael Cameron, Steven Lim, Frank Scrimgeour and John Tressler (2007), “The Value of statistical life and the Economics of Landmine Clearance in Developing Countries”, *World Development*, Vol. 35, No. 3, pp. 512-531. DOI:10.1016/j.worlddev.2006.05.003.
- [16] Giergiczny, Marek (2008), “Value of statistical life – the Case of Poland”, *Environmental and Resource Economics*, 41:pp. 209-221. DOI: 10.1007/s10640-007-9188-2.
- [17] Guo, Xiaoqi, Timothy C. Haab and James K. Hammitt (2006), “Contingent Valuation and the Economic Value of Air-Pollution-Related Health Risks in China”, Paper prepared for the 3rd World Congress of Environmental and Resource Economics, Kyoto, Japan, 3-7 July 2006.
- [18] Guria, Jagadish, Wayne Jones, Michael Jones-Lee, Mike Keall, Joanne Leung and Graham Loomes (2003), “The New Zealand Values of a statistical life and of the Prevention of Injuries”. Unpublished, draft study prepared for the Land Transport Safety Authority in New Zealand.
- [19] Hakes, Jahn K. and W. Kip Viscusi (2004), “The Rationality of Automobile Seatbelt Usage: The Value of statistical life and Fatality Risk Beliefs”. Discussion Paper No. 475, Harvard Law School John M. Olin Center for Law, Economics and Business Discussion Paper Series.
- [20] Hammitt, James K. and Ying Zhou (2006), “The Economic Value of Air-Pollution-Related Health Risks in China: A Contingent Valuation Study”, *Environmental and Resource Economics*, 33: pp. 399–423. DOI : 10.1007/s10640-005-3606-0.
- [21] Itaoka, Kenshi, Alan Krupnick, Makoto Akai, Anna Alberini, Maureen Cropper and Nathalie Simon (2007), “Age, health, and the willingness to pay for mortality risk reductions: a contingent valuation survey of Shizuoka, Japan, residents”, *Environmental Economics and Policy Studies*, 8: pp. 211-237. DOI : 10.1007/s10018-007-0127-9.
- [22] Johannesson, Magnus, Per-Olov Johansson and Karl-Gustaf Löfgren (1997), “On the Value of Changes in Life Expectancy: Blips Versus Parametric Changes”, *The Journal of Risk and Uncertainty*, 15:pp. 221-239.
- [23] Johannesson, Magnus, Per-Olov Johansson and Richard M. O'Connor (1996), “The Value of Private Safety Versus the Value of Public Safety”, *The Journal of Risk and Uncertainty*, 13:pp. 263-275.
- [24] Jones-Lee, M. W., M. Hammerton and P. R. Philips (1985), “The Value of Safety: Results of a National Sample Survey”, *The Economic Journal*, Vol. 95, No. 377. (Mar. 1985), pp. 49-72.
- [25] Krupnick, Alan, Anna Alberini, Maureen Cropper, Nathalie Simon, Bernie O'Brien, Ron Goeree and Martin Heintzelman (2002), “Age, Health and the Willingness to Pay for Mortality Risk Reductions: A Contingent Valuation Survey of Ontario Residents”, *Journal of Risk and Uncertainty*, 24 (2), pp. 161-186.
- [26] Krupnick, Alan, Sandra Hoffmann, Bjørn Larsen, Xizhe Peng, Ran Tao, Chen Yan and Michael McWilliams (2006), “The Willingness to Pay for Mortality Risk Reductions in Shanghai and Chongqing, China”. Report to the World Bank, Jostein Nygard, Team Leader, ECM Project, June 5, 2006.
- [27] Leiter, Andrea M. and Gerald J. Pruckner (2006), “Dying in an Avalanche: Current Risks and Valuation”. Discussion paper, Center for Natural Hazard Management, May 2006.

- [28] Leiter, Andrea M. and Gerald J. Pruckner (2008), “Proportionality of Willingness to Pay to Small Risk Changes: The Impact of Attitudinal Factors in Scope Tests”, *Environmental and Resource Economics*, DOI: 10.1007/s10640-008-9214-z.
- [29] Liu, Jin-Tan, James K. Hammitt, Jung-Der Wang and Meng-Wen Tsou (2005), “Valuation of the risk of SARS in Taiwan”, *Health Economics*, 14: pp. 83-91. DOI:10.1002/hec.911.
- [30] Mahmud, Minhaj (2006), “Contingent Valuation of Mortality Risk Reduction in Developing Countries: A Mission Impossible?”, *Keele Economics Research Papers*, 2006/01.
- [31] NewExt (2004), *New Elements for the Assessment of External Costs from Energy Technologies, Final Report to the European Commission, DG Research, Technological Development and Demonstration (RTD); IER, Germany; ARMINES / ENSMP, France; PSI, Switzerland; Université de Paris I, France; University of Bath, United Kingdom; VITO, Belgium.*
- [32] Persson, Ulf, Anna Norinder, Krister Hjalte and Katarina Gralén (2001), “The Value of statistical life in Transport: Findings from a New Contingent Valuation Study in Sweden”, *The Journal of Risk and Uncertainty*, 23:2; pp. 121-134.
- [33] Christoph M. Rheinberger (2009), “Paying for Safety: Preferences for Mortality Risk Reductions on Alpine Roads” (September 17, 2009). *Fondazione Eni Enrico Mattei Working Papers*. Working Paper 338.
- [34] Schwab Christe N. & Soguel N. (eds)(1995), “Contingent Valuation, Transport Safety and the Value of Life” (eds), *Kluwer Academic Publishers, Boston.*
- [35] Svensson, Mikael (2007), “Precautionary Behavior and Willingness to Pay for a Mortality Risk Reduction: Searching for the Expected Relationship” *Working Papers 2007:3*, Örebro University, Swedish Business School, revised 18 Feb 2008.
- [36] Tsuge, Takahiro, Atsuo Kishimoto and Kenji Takeuchi (2005), “A Choice Experiment Approach to the Valuation of Mortality”, *The Journal of Risk and Uncertainty*, 31:1; pp. 73-95.
- [37] Vassanadumrongdee, Sujitra and Shunji Matsuoka (2005), “Risk Perceptions and Value of statistical life for Air Pollution and Traffic Accidents: Evidence from Bangkok, Thailand”, *The Journal of Risk and Uncertainty*, 30:3; pp. 261-287.

APPENDIX

Regressions including a second-degree polynomial for the underlying level of risk

VARIABLES	Model I	Model II	Model III	Model IV	Model V
log(GDP)	0.607*** (0.103)	0.744*** (0.156)	0.798*** (0.160)	0.823*** (0.202)	0.646*** (0.155)
BL-Risk	-0.468*** (0.0935)	-0.263* (0.129)	-0.247* (0.136)	-0.256 (0.150)	-0.378*** (0.121)
BL-Risk^2	0.0433*** (0.00772)	0.0210* (0.0118)	0.0185 (0.0122)	0.0189 (0.0131)	0.0324*** (0.00998)
log(RCh)	-0.392*** (0.0845)	-0.494*** (0.0839)	-0.475*** (0.0885)	-0.437*** (0.125)	-0.323*** (0.1000)
Environment		-0.828** (0.297)	-0.586* (0.325)	-0.794 (0.495)	-0.380 (0.302)
Traffic		-0.420 (0.302)	-0.348 (0.300)	-0.353 (0.306)	-0.269 (0.211)
Public			-0.235 (0.271)	-0.137 (0.274)	-0.160 (0.202)
Household			-0.201 (0.215)	-0.259 (0.235)	-0.258 (0.196)
Cancer				0.392 (0.478)	0.349 (0.358)
Latent				-0.234 (0.233)	-0.142 (0.222)
No_explanation					0.698** (0.251)
Turnbull					-0.588 (0.345)
Constant	5.067*** (1.259)	3.055** (1.438)	2.742* (1.344)	2.888* (1.389)	5.457*** (1.223)
Observations	272	272	272	272	272
No. Clusters	18	18	18	18	18
R-squared	0.818	0.847	0.855	0.858	0.887

Robust standard errors in parentheses

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

Comparison of the results in Table 5 with this final sample.

VARIABLES	Model I	Model II	Model III	Model IV	Model V
log(GDP)	0.570*** (0.150)	0.691*** (0.147)	0.725*** (0.148)	0.731*** (0.161)	0.615*** (0.150)
BL-Risk					
BL-Risk^2					
log(RCh)	-0.579*** (0.0777)	-0.633*** (0.0589)	-0.617*** (0.0600)	-0.601*** (0.0800)	-0.526*** (0.0732)
Environment		-0.898*** (0.218)	-0.641** (0.283)	-0.751* (0.394)	-0.525** (0.245)
Traffic		-0.419 (0.264)	-0.328 (0.278)	-0.332 (0.281)	-0.328 (0.221)
Public			-0.230 (0.286)	-0.173 (0.316)	-0.198 (0.248)
Household			-0.155 (0.203)	-0.183 (0.221)	-0.216 (0.193)
Cancer				0.210 (0.389)	0.235 (0.318)
Latent				-0.158 (0.282)	-0.0610 (0.300)
No_explanation					0.618** (0.256)
Turnbull					-0.556 (0.404)
Constant	3.472** (1.581)	2.121 (1.564)	1.948 (1.619)	2.049 (1.745)	3.714* (1.765)
Observations	272	272	272	272	272
No. Clusters	18	18	18	18	18
R-squared	0.785	0.833	0.839	0.840	0.866

Robust standard errors in parentheses

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