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The value of a statistical life: A meta-analysis with a mixed effects regression model

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A B S T R A C T

The value of a statistical life (VSL) is a very controversial topic, but one which is essential to the optimization of governmental decisions. We see a great variability in the values obtained from different studies. The source of this variability needs to be understood, in order to offer public decision-makers better guidance in choosing a value and to set clearer guidelines for future research on the topic. This article presents a meta-analysis based on 39 observations obtained from 37 studies (from nine different countries) which all use a hedonic wage method to calculate the VSL. Our meta-analysis is innovative in that it is the first to use the mixed effects regression model [Raudenbush, S.W., 1994. Random effects models. In: Cooper, H., Hedges, L.V. (Eds.), The Handbook of Research Synthesis. Russel Sage Foundation, New York] to analyze studies on the value of a statistical life. We conclude that the variability found in the values studied stems in large part from differences in methodologies.

1. Introduction

More than ever before, our society must face numerous risks, notably in spheres such as health, the environment, natural disasters, transportation, as well as occupational safety. Cost–benefit analysis is a very popular project-evaluation tool for reducing these social risks. What the government has to do from a national perspective is to set up projects or regulations whose benefits will outweigh the costs of their implementation. It is usually quite easy to determine costs. But how is one to evaluate the benefits linked to protecting a human life?

Individuals are everyday making decisions that reflect the value they put on their health, life, and limb, whether when at the wheel of their car, smoking a cigarette, or working at a dangerous job. Risk evaluation is in some sort a matter of

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individual preference. Each individual, to some degree, chooses his optimal level of exposure to risk and the corresponding value of his life. The number of studies conducted on this topic since the 1970s is quite impressive. Many values of human life have been estimated with the help of several different methods. The wide variability of the results obtained makes it hard for governments to choose a value. In effect, the VSLs observed range from $0.5 million up to $50 million (US$ 2000).

The principal objective of this article is to help in understanding the source of this great variability in results. We thus wish to find out just how sensitive the values obtained empirically are to the population under study (average income, level of initial risk, race, sex, etc.). We shall also look to see whether the results obtained are influenced by differences in the methodologies of the studies. To attain these objectives we shall use meta-analysis, a statistical tool of growing popularity in the financial and economic literature.

The methodology selected for our meta-analysis is based on the mixed effects regression model (Raudenbush, 1994) which accounts for heterogeneity in different value estimations. We are the first to use this approach to analyze studies on the value of a statistical life and this is which distinguishes our research from other meta-analyses.

The next section presents the willingness-to-pay (WTP) approach. This section serves to clarify the concepts to be used in the meta-analysis. This approach is based on an individual's willingness to pay to reduce the risk of death. It is worth mentioning that we are here speaking of a completely anonymous member of society. To avoid any confusion, we use the term "value of a statistical life" (VSL). We shall at no time touch on any of the sentimental and ethical aspects that such an issue might engender. It is also imperative to understand that the value-of-statistical-life concept is not based on the value of the risk of "certain" death, but rather on the value of a variation in the risk of death (Viscusi, 2005).

Section 3 presents the meta-analysis tool. It offers a survey of some of the meta-analyses associated with the VSL to be found in the literature. It also discusses the different methodological issues associated with the estimation of a VSL. In the fourth section, we go on to give a descriptive analysis of the studies selected. The fifth section deals with the results of the meta-analysis, which are presented and analyzed in full. In conclusion, we summarize the main results and we discuss some potential extensions and implications for public decision-makers.

2. Theoretical model

Based on the willingness-to-pay (WTP) concept, the standard model for evaluating the VSL was formulated by Drèze (1962). It was subsequently popularized mainly by Schelling (1968), Mishan (1971), Jones-Lee (1976), and Weinstein et al. (1980).

The model stipulates that each individual is endowed with an initial wealth w and is subject to only two possible states of nature in relation to his existence, either to be alive (a) or to be dead (d). The probabilities associated with these states are respectively $(1-p)$ and p. The individual's well-being is represented by his expected utility:

$$EU(w) = (1-p)U_a(w) + pU_d(w), \tag{1}$$

where $U_a(w)$ and $U_d(w)$ represent, respectively, his state-dependent von Neumann–Morgenstern utility functions during his existence as well as at his death.

Intuitively, one may suppose that the individual will prefer life to death and that the utility drawn from his wealth will therefore be greater in state a than in state d. Thus we have the following inequality:

$$U_a(w) > U_d(w) \quad \forall w. \tag{2}$$

Wealth is the same in both states of nature, since it is supposed that the individual has access to an insurance market providing coverage for all financial and material losses (Dionne and Lanoie, 2004). The literature often proposes that the marginal utility drawn from wealth is greater in the state of survival than in the state of death:

$$U'_a(w) \geq U'_d(w) > 0 \quad \forall w. \tag{3}$$

This hypothesis comes from the intuition that the individual must necessarily profit more from increasing his wealth while he is alive rather than when he is deceased. It also implies that the optimal insurance plan does not cover all pain and suffering (Cook and Graham, 1977; Dionne, 1982). The individual has aversion to risk in both states of nature. This means that his marginal utility is strictly decreasing in both states:

$$U''_a(w), U''_d(w) < 0 \quad \forall w. \tag{4}$$

As mentioned above, willingness-to-pay corresponds to the amount a person is ready to pay to reduce his exposure to risk. In this model, it is a matter of asking what amount x of his initial wealth w the individual would be ready to pay to see his probability of death p reduced to p^*, while keeping his expected utility constant. So we need only find the value of x that satisfies this equality:

$$EU(w) = (1-p)U_a(w) + pU_d(w) = (1-p^*)U_a(w-x) + p^*U_d(w-x). \tag{5}$$

To find the WTP, we take the total differentiation of the above equation with respect to w and p, under the hypothesis that (5) remains constant. With this we obtain:

$$\mathrm{WTP} = \frac{\mathrm{d}w}{\mathrm{d}p} = \frac{U_a(w) - U_d(w)}{(1-p)U_a'(w) + pU_d'(w)}, \tag{6}$$

where the marginal WTP corresponds to the marginal substitution rate between wealth and the initial probability of death. The term in the numerator on the right hand side of (6) represents the difference (in terms of utility) between life and death. The denominator represents the marginal expected utility of wealth. With this marginal amount (WTP) that the individual is willing to pay to avoid a small variation in risk (dp), we can determine the corresponding VSL: $(\mathrm{d}w/\mathrm{d}p)/\Delta p$, Δp being the non-marginal variation of initial probability.

Using the hypothesis in (2), we can verify that the individual may ask for positive remuneration before accepting an increase in his risk. To determine the variation of WTP in function of risk exposure, we must derive the willingness-to-pay in relation to p in order to see how it reacts to a variation in exposure to the initial risk:

$$\frac{\mathrm{dWTP}}{\mathrm{d}p} = \frac{\mathrm{d}^2 w}{\mathrm{d}p^2} = -\frac{(U_a(w) - U_d(w))(U_d'(w) - U_a'(w))}{[pU_d'(w) + (1-p)U_a'(w)]^2}. \tag{7}$$

The result is ambiguous and depends on the hypothesis in (3). If we accept (3) and affirm that the marginal utility of wealth is greater in the state of survival, we can then say that Eq. (7) is positive. The individual's willingness-to-pay (WTP) thus increases with his initial level of risk. One economic interpretation of this result is that individuals previously exposed to higher risks (firefighters, miners, etc.) should generally be more reluctant to increase their risk than others with the same level of variation, since they do not have full coverage for pain and suffering. However, this result is not unanimously accepted among authors writing on the subject. Using a questionnaire, Smith and Desvousges (1987) obtain conflicting results where the WTP is higher for lower risks. Breyer and Felder (2005) focus their analysis precisely on the relation between the initial risk of death and individuals' willingness-to-pay in various circumstances. They try to determine whether the intuitive reasoning that the individual profits more from increasing his health when he is alive holds the road. They come to two broad conclusions. The first is that an egoist with an aversion to risk will always see his WTP increase with the risk of death. The authors then affirm that the result may be just the opposite for an altruist and that the WTP sometimes decreases with the initial risk. A sufficient condition for this would consist in the loss of a significant portion of potential wealth at the death of the individual (as human capital). A negative relation in (7) can also be explained by greater marginal utility when dead than when alive. This possibility may be due to the fact that heirs are taken into account. Cook and Graham (1977) use this difference between marginal utilities to show that optimal insurance would be greater than full monetary loss and would include compensation for pain and suffering. This over-insurance result must, however, contain an upper bound in the presence of moral hazard (Dionne, 1982). This argument involving inheritance utility is akin to what Breyer and Felder (2005) have to say about altruism. For the interpretation of the empirical results, it will be important to remember that assumption (3) affects the optimal insurance compensation for risk and the sign of (7).

It is also worth analyzing the way WTP varies in relation to w, in order to find the effect of initial wealth on WTP. Intuitively, one might expect that a richer person would be willing to pay more than a poorer one. After a few calculations we find:

$$\frac{\mathrm{dWTP}}{\mathrm{d}w} = \frac{\mathrm{d}^2 w}{\mathrm{d}p\mathrm{d}w} = \frac{EU'(w)(U_a'(w) - U_d'(w)) - EU''(w)(U_a(w) - U_d(w))}{[EU'(w)]^2}. \tag{8}$$

We can verify that Eq. (8) is usually positive. Willingness-to-pay increases with the initial level of the individual's wealth. This result does not truly constitute a problem, since it is unanimously accepted in the literature and can be obtained whatever the opinion about (3). This is risk aversion that matters here. The result does however raise a question about equity. As Michaud (2001) points out, projects involving the prosperous are likely to seem preferable to those meant for people with less money. One of our objectives is to analyze empirically the predictions in (7) and (8).

3. Meta-analysis

3.1. *Meta-analysis of the value of a statistical life*

A few meta-analyses have recently attempted to synthesize information drawn from studies estimating the value of a statistical life. These meta-analyses differ in the composition of their samples, in the regression models they use, as well as in the explanatory variables of their specifications. In this section, we shall make a brief survey of these meta-analyses.

Liu et al. (1997) were probably among the first researchers to do a meta-analysis of studies estimating the value of a statistical life. They studied 17 VSLs for which average income and average probabilities of death were available. These observations were selected from Viscusi's Table 2 (1993) which, for the most part, contains American studies. The authors use a simple ordinary least squares (OLS) regression containing only two explanatory variables (income and risk). The natural logarithm of the values of a statistical life is used as the dependent variable. They obtain a positive but non-significant coefficient for the income variable and a negative and significant coefficient for the risk variable. The income-elasticity obtained by the regression shows a value of 0.53, but it is not statistically significant.

Table 1
Summary and results of meta-analyses.

	Risk		Income		Income elasticity
	Sign	Signif.	Sign	Signif.	
Liu et al. (1997)	–	YES	+	NO	0.53
Miller (2000)	n.a.	n.a.	+	YES	0.85–1.00
Bowland and Beghin (2001)	+	YES	+	YES	1.7–2.3
Mrozek and Taylor (2002)	+	YES	+	YES	0.46–0.49
Viscusi and Aldy (2003)	–	YES	+	YES	0.46–0.60
De Blaeij et al. (2003)	+	YES	+	YES	0.5

Miller (2000) analyses a sample composed of 68 studies from 13 different countries. Unlike Liu et al. (1997) who consider only studies favoring the wage-risk method, Miller also includes studies on the consumer market and the contingent-evaluation method to measure willingness-to-pay. He incorporates binary variables into his regressions to account for the method applied in the studies. Another special feature of Miller's study is that, instead of personal income, it uses the gross domestic product (GDP) and the gross national product (GNP) *per capita* as explanatory variables. The coefficients associated with income (whether GDP or GNP) are positive and significant in all specifications. The income-elasticity remains relatively stable from one model to the next and oscillates between 0.85 and 1.00. It is surprising to note that no risk variable is present in the different specifications.

Bowland and Beghin (2001) do a meta-analysis based on the 33 studies in Viscusi (1993) and Desvousges et al. (1995). These studies all come from industrialized countries and consider either the wage-risk method or the contingent evaluation method. The authors' goal being to utilize their results to estimate the value of a statistical life in Chili, they link each study to the demographic characteristics of the country where it was conducted. Concerned about the non-normality of the residuals, the authors employed the Huber-type (1964) method of robust regressions. This method assigns a lower weight to less credible data. Bowland and Beghin obtain a significant income-elasticity ranging between 1.7 and 2.3 for several specifications. The parameters estimated for the probability of death are mainly positive and significant. The results obtained with the ordinary least squares (OLS) method are very similar. We note that the authors incorporate none of the studies' methodological characteristics among their explanatory variables. These characteristics can explain the variability in the values of a statistical life estimated.

Mrozek and Taylor (2002) construct a sample of 33 studies (American and others) using the hedonic wage method. These authors include all the specifications available in the studies. A total of 203 observations are considered. As already mentioned, this procedure may possibly produce a distortion, since many observations lose their independence. To guard against giving more weight to studies with a large number of different specifications, a $1/N$ weight is assigned to each observation, where N corresponds to the number of values of a statistical life drawn from the study in question. The estimation is thus obtained by weighted least squares rather than by OLS. All the models presented by the authors indicate a positive and significant relation between average risk and the value of a statistical life. From their complete model, Mrozek and Taylor (2002) obtain a significant income elasticity of 0.49. A reduced form of the model excluding three of the explanatory variables generates a significant income elasticity of 0.46.

Viscusi and Aldy (2003) make a meta-analysis based on a sample composed of about 50 studies from 10 different countries. As in the Mrozek and Taylor (2002) sample, only the studies employing the wage-risk method are selected. The estimation is made with Huber's (1964) robust regressions as well as ordinary least squares. The results obtained remain quite stable from one specification to the next. The parameters associated with the average risk variable are all negative and significant. The income elasticity is positive and significant for all the specifications. It ranges between 0.49 and 0.60 for the specifications with OLS and oscillates between 0.46 and 0.48 for results obtained by robust regressions.

De Blaeij et al. (2003) do a meta-analysis based on studies measuring the value of a statistical life in a road safety context. They construct a sample composed of 95 values of a statistical life from 30 different studies. As with Mrozek and Taylor (2002), they consider several VSLs from the same study. The aim of their article is to explain the origin of the variations observed in the VSL estimations. The authors are particularly interested in comparing the effect produced by the revealed-preference as opposed to the contingent-evaluation approach. The authors form several groups with common characteristics and then compare them. The results show wide variations between groups as well as within these groups. The authors next do a meta-multivariate analysis in order to increase the robustness of their results. In some specifications, a weight reflecting the reliability of the estimation is assigned to the dependent variable (VSL). Instead of obtaining the VSL variance for each of the studies, they use the size of their samples as weights. They obtain a significant income elasticity of 1.67, where income is expressed in GDP *per capita*. The authors attribute this high result to the presence of multicolinearity with the time-trend variable which measures time. Without this effect, the income elasticity falls to 0.50. The only significant results for the risk variable are to be found in the models which include only studies with the contingent-evaluation approach. The parameters estimated in these models are positive. Finally, the results of the meta-regression allow the authors to conclude that the revealed-preference approach produces significantly lower VSLs than does the contingent-evaluation approach.

Table 1 presents a summary of the results from the different meta-analyses performed.[1] We can affirm that there is definitively a positive relation between incomes and estimations of the value of a statistical life. We also observe that, except for the Bowland and Beghin study (2001), the income elasticity obtained by these different meta-analyses is always equal to or lower than 1. However, we can reach no conclusion as to the relation between average risk and the value of a statistical life. In some cases, the authors obtain positive and significant coefficients but in other cases negative and significant ones. This relation seems ambiguous, as predicted by the theory.

3.2. Methodological approach

As already mentioned, wide variations in values of a statistical life are observed. These variations complicate the work of public decision-makers who must choose a value to insert in their cost–benefit calculations. In order for them to make a more enlightened choice, it is of primary importance that they understand the origin of this variability in results. To grasp the sources of this variability, we shall perform a meta-analysis with a different methodology. By employing a mixed effects regression model (Raudenbush, 1994), we want to distinguish our contribution from all the other meta-analyses performed so far and to test the robustness of their results.

Suppose that each study uses a perfectly identical methodology and that their samples are all the same size and constructed randomly from the same population. The VSLs obtained will not be identical because the samples studied are most likely different. However, this variation in the results is entirely due to the variance in sampling (Raudenbush, 1994). It can also be called a variance in estimation, since the variations in the samples will have an impact on the VSL estimations. But several methodological differences are observable across the studies. These differences likely explain, in part, the variations in the VSL estimations. And even if each author used exactly the same methodology, several other non-observable and uncontrollable factors could influence the results. The mixed effects regression model takes this heterogeneity into account, hypothesizing that the estimation variance is not the only source of the variations observed.

Therefore, the value of a statistical life VSL_j in each of the m studies selected is modeled with the following mixed effects regression model:

$$\text{VSL}_j = \beta_0 + \sum_{k=1}^{p} \beta_k X_{jk} + u_j + e_j, \tag{9}$$

where β_0 is the constant; X_{jk} is the characteristic k of study j which is used to estimate VSL_j; $\beta_1, \ldots, \beta_p$ are the coefficients of the regression which capture the fixed effects of the study characteristics on VSL; u_j is a random effect term associated with study j which takes into account the non-observed effects that influence VSL_j. Each random effect is independent, with a mean of zero and a variance of σ_u^2; $e_j, j = 1 \ldots m$, are the estimation errors; they are independent, of null mean and of variance equal to $\sigma^2_{VSL_j}$.

In a fixed effects model, the random effect is simply withdrawn from Eq. (9). The fixed effects model thus supposes that the characteristics of the studies fully explain the variations in VSLs between these studies. The mixed effects regression model accounts for the existence of the heterogeneity caused by non-observed characteristics which cannot be considered in the model but which explain in part the variations in the VSLs. This model's special feature is that it has two elements in the error term: the random effect and the estimation error. The variance of VSL_j ($\sigma^{2*}_{\text{VSL}_j}$), as conditioned by the characteristics of X_{jk}, is equal to

$$\sigma^{2*}_{\text{VSL}_j} = \text{Var}(u_j + e_j) = \sigma_u^2 + \sigma^2_{\text{VSL}_j}. \tag{10}$$

As Raudenbush (1994) maintains, it would not be appropriate to use an OLS regression to estimate Eq. (9), since this method retains homoskedasticity as its hypothesis—meaning that the errors in the regression model would have the same variance. Our model is instead based on a hetereoskedasticity hypothesis. The residual variance in our model ($\sigma^{2*}_{\text{VSL}_j}$) is not constant, since $\sigma^2_{\text{VSL}_j}$ differs from one study to the next. We must therefore use the weighted least squares method where the optimal weights (weight_j^*) are the inverse of the variances obtained in each of the studies:

$$\text{weight}_j^* = \frac{1}{\sigma^{2*}_{\text{VSL}_j}} = \frac{1}{\sigma_u^2 + \sigma^2_{\text{VSL}_j}}. \tag{11}$$

If σ_u^2 is null, then the fixed-effects model will not be rejected and the optimal weights will be $1/\sigma^2_{\text{VSL}_j}$. The calculation of $\sigma^2_{\text{VSL}_j}$ is rather straightforward and requires only certain data contained in the studies. As we see in Eq. (11), calculating the optimal weights for the mixed effects regression model requires an additional term—the variance of the random effect (σ_u^2). This effect is not given in the studies and must thus be estimated.

[1] The six meta-analyses just presented are, to our knowledge, the only ones published in a scientific journal. For other unpublished meta-analyses, the reader can consult Desvousges et al. (1995), Day (1999), and Dionne and Michaud (2002).

Our meta-analysis is concerned with the hedonic wage method. The corresponding econometric specification for a given study *j* estimating VSL with this method is the following:

$$\ln(w_i) = X_i\beta + p_i\phi + u_i, \tag{12}$$

where w_i is the wage of individual *i*, X_i is a vector of explanatory variables comprising the characteristics of this individual, p_i represents his probability of death, β and ϕ are the parameters to be estimated, and $u_i \sim N(0, \sigma^2)$. Index *j* is omitted in (12) to simplify notation.

By using a linear regression with ordinary least squares or other methods to estimate the parameters of Eq. (12), we obtain $\hat{\phi}$, which is the average wage premium for a marginal increase in the probability of death. Based on Eq. (12), we can obtain the average WTP of the sample by multiplying $\hat{\phi}$ by the average income. The WTP must be adjusted so that it is expressed in annual dollars. Finally, to calculate the value of a statistical life, the WTP must be divided by the non-marginal variation in the probability of death. In the regression analysis, this variation in the probability of death corresponds to a unit of the variable p_i.[2] We can then express the estimate of the value of a statistical life of the population *j* studied as follows:

$$\mathrm{VSL}_j = \frac{\hat{\phi}_j\ (\text{sample average of annual income})_j}{(\text{unit of probability of death})_j}, \tag{13}$$

where the numerator corresponds to the WTP in annual dollars, the denominator to the non-marginal variation in the probability of death, and $\hat{\phi}_j = \partial \ln(w_i)/\partial p_i$. We must mention that the studies we analyze are limited to the data from workers having accepted the risk. They may thus contain a sample bias (Ashenfelter, 2006). Moreover, the values obtained may be very sensitive to the econometric specifications used. Our objective is to identify the methodological differences which render VSL evaluations most sensitive.

We can use Eq. (13) to calculate the value of a statistical life for each study retained. When the specification contains interaction of some variables with the risk of death, the value of a statistical life is calculated with the average of each variable. For example, a specification may contain a squared risk variable as well as a risk variable interacting with age:

$$\ln(w_i) = X_i\beta + p_i\phi_1 + p_i^2\phi_2 + p_i\,\mathrm{age}_i\phi_3 + u_i. \tag{14}$$

The corresponding VSL calculation for this study will take this form:

$$(\hat{\phi}_{1j} + 2p_j\hat{\phi}_{2j} + \mathrm{age}_j\,\hat{\phi}_{3j})\frac{(\text{sample average of annual income})_j}{(\text{unit of probability of death})_j},$$

where $p_j = (1/n_j)\sum_{i=1}^{n_j} p_i$ and $\mathrm{age}_j = (1/n_j)\sum_{i=1}^{n_j} \mathrm{age}_i$ are, respectively, the average probability of death and the average age of the n_j individuals in study *j*.

Since most of the studies come from the United States, we employed the US$ 2000 as the common monetary unit. This makes it possible to minimize the number of conversions required. The first step consists in converting the values into American currency. For non-American studies, we have used purchasing power parity (PPP) as the exchange factor.[3] As Summers and Heston (1991) point out, when comparing incomes from several countries, it is more appropriate to take the PPP into account, rather than just making a conversion based on the exchange rate. Goods and services usually cost less in poor countries as compared to rich ones and using the exchange rate as the conversion factor will not allow comparison of the intrinsic value of salaries. The second step consists in applying the consumer price index (CPI)[4] to adjust VSL and average income values to US$ 2000.

In Eq. (11) the value-of-a-statistical-life variance ($\sigma^2_{\mathrm{VSL}_j}$) is needed for each study to construct the weights. We calculate this variance from the standard deviation associated with coefficient $\hat{\phi}_j$. This statistic is often included in regression analyses to measure the accuracy of estimations. The standard error (SE) of the value of a statistical life on a given study *j* is calculated in this manner:

$$\mathrm{SE}(\mathrm{VSL}_j) = \frac{\mathrm{SE}(\hat{\phi}_j)(\text{sample average of annual income})_j}{(\text{unit of probability of death})_j}. \tag{15}$$

The sample average of annual income and the unit of probability of death in Eq. (15) correspond exactly to the same variables in Eq. (13). If there are one or more terms of interaction between the probability of death and other explanatory variables, the calculation of the standard error will then require covariance terms. For example, take the case of a single interaction term in the wage equation:

$$\ln(w_i) = X_i\beta + p_i\phi_1 + (p_i \times \mathrm{age}_i)\phi_2 + u_i. \tag{16}$$

[2] In the majority of studies, the variable measuring the probability of death is expressed in deaths per 10,000 workers. In these cases, the unit of the variable p_j is 1/10,000.

[3] These values are drawn from PennWorld Table 6.0 (http://pwt.econ.upenn.edu).

[4] This index can be obtained from the Council of Economic Advisers (2005).

We obtain the expression of the value of a statistical life for the study:

$$\mathrm{VSL}_j = \frac{(\hat{\phi}_{1j} + \mathrm{age}_j \hat{\phi}_{2j})(\text{sample average of annual income})_j}{(\text{unit of probability of death})_j}. \quad (17)$$

The standard error of the value of a statistical life is thus obtained as follows:

$$\mathrm{SE}(\mathrm{VSL}_j) = \frac{\left[\sqrt{\mathrm{SE}^2(\hat{\phi}_{1j}) + (\mathrm{age}_j)^2\,\mathrm{SE}^2(\hat{\phi}_{2j}) + 2\,\mathrm{age}_j \operatorname{cov}(\hat{\phi}_{1j}, \hat{\phi}_{2j})}\right](\text{sample average of annual income})_j}{(\text{unit of probability of death})_j}. \quad (18)$$

However, the covariances needed to calculate the standard errors are not usually published by the authors. This prevents us from calculating with Eq. (18) the standard deviations for VSLs drawn from articles using terms of interaction. We shall evaluate them with an indirect procedure for a sensitivity analysis (see Section 5.3).

3.3. Methodological choices

In each of the studies estimating the value of a statistical life, the authors are obliged to make methodological choices, whether in constructing the sample or in doing the technical analysis. These different choices may certainly influence the results obtained and probably explain the wide variability in the values of a statistical life published. In this section we shall touch on a few of these choices and predict their direct or indirect impact on the value of a statistical life.

3.3.1. Choice of samples

One of the main explanations of the variations in values of a statistical life arises from the differences in the characteristics of the samples used. Here are a few of the characteristics which may have a strong impact. We know that wealth and probability of death can have an impact on individuals' WTP and thus on the value of a statistical life. As theory indicated, studies using samples of more wealthy individuals should obtain higher estimations of the value of a statistical life. As to samples of persons more at risk, the results expected are ambiguous.

As a rule, women are rarely to be found in dangerous occupations. Even within the same occupational field, the riskiest tasks were traditionally assigned to men (Leigh, 1987). It is thus not surprising to note that most deaths, whether classified by industry or by occupation, are those of men. Some authors exclude women from their sample, others include them but incorporate a binary variable (man or woman) in their regressions.[5]

Many authors have studied the effect of unionization on workers' WTP. Several conclude that union membership is associated with a higher WTP. The main reason explaining this higher wage premium among unionized workers is their access to more accurate information concerning their safety. What is more, unions can be good mechanisms for letting corporate directors know about workers' safety concerns and for negotiating better salaries. However, certain authors (Marin and Psacharopoulos, 1982; Meng, 1989; Sandy and Elliott, 1996) obtain higher WTPs for non-unionized workers and lower ones for workers who are union members.[6] In most studies, the authors account for this effect by simply introducing a binary variable without interaction.

Racial differences may also influence the values of a statistical life obtained in the studies. Viscusi (2003) obtains considerably lower values of a statistical life among black as compared to white workers. Viscusi proposes two reasons which may explain this result. First, one observes that black workers are, in general, employed in more dangerous jobs than white workers. It is possible that the preferences for risk differ among races. Second, there may be fewer work opportunities for blacks. Several studies still illustrate the presence of racial discrimination on the job market, as is apparent in the wage differences between whites and blacks doing the same job.[7]

Certain authors pay special attention to workers' occupation, particularly to the impact of including blue and white collar workers in the same sample. Since blue collars are victims of four to five times more accidents (Root and Sebastian, 1981), some authors exclude them from their studies. For this same reason, others will instead exclude white collar workers. These choices will have an impact on the value of a statistical life as well as on the meaningfulness of the results.

3.3.2. Choice of the risk variable

The variable measuring workers' risk of death is one of the most important in the hedonic wage method. The ideal risk measurement would be the one perceived by workers. However, the majority of researchers use risk measurements produced by organizations which count the number of deaths by industry or occupation.[8]

The Bureau of Labor Statistics (BLS), a section of the U.S. Department of Labor, is the source used by most American researchers. From the 1960s to the early 1990s, the BLS obtained its data from an annual survey distributed to hundreds of

[5] Leigh (1987) obtains only a slight difference in the value of a statistical life when he excludes women from his sample.
[6] For a more complete review of studies analyzing the impact of unionization, see Sandy et al. (2001) as well as Viscusi and Aldy (2003).
[7] According to Dionne and Lanoie (2004), workers' mobility is essential to the wage-risk analysis.
[8] Researchers usually average probabilities of death over a few years. This prevents the distortions caused by a catastrophe which might occur in a specific year in a specific industry.

thousands of firms in several industries. These data were then compiled with the two- or three-digit Standard Industrial Classification (SIC) code—thus in a rather aggregated fashion. This method of obtaining and compiling data left some researchers concerned about the possibility of measurement errors (Moore and Viscusi, 1988a). As already specified, it is important to obtain a disaggregated measurement of risk. Assigning the same probability of death to every worker in the same industry may cause measurement errors, for none of these workers holds the same job and faces the same risk.

The National Institute of Occupational Safety and Health (NIOSH) has been allowing researchers to utilize their occupational data since 1980. The NIOSH obtains its information from the death certificates issued after workplace accidents. According to Moore and Viscusi (1988a), this method is more suitable, since it is based on a census rather than a survey. The authors also compare the statistics from the two organizations. They observe that the probabilities of death with NIOSH data are approximately the double of those constructed with BLS data. Since 1992, the BLS has also been relying on a census called the Census of Fatal Occupational Injuries (CFOI) to gather its data. Comparing the probabilities of death over the period running from 1992 to 1995, the differences between the two bodies are smaller; we note that it is now the BSL's turn to post higher probabilities of death.[9]

Some studies also consider actuarial data[10] drawn from a study published in 1967 by the Society of Actuaries (SOA). One very important characteristic of this study is that it measures the number of deaths that exceed a certain expected value.[11] Its measurement of risk is thus not identical to that of the BLS and the NIOSH. A second important characteristic of this source is its particular interest in the riskiest jobs. Consequently, samples of studies with this source show average probabilities of death which are much higher compared to others. Non-American studies usually draw their data from government sources. Canadian studies, for example, often use data collected by Statistics Canada and the Ministry of Revenue. Each province allows access to their data on work accidents. These comparisons between different organizations allow us to grasp the significance and impact of choosing the source of the risk variable. The data can vary widely depending on the organization chosen and will probably generate widely different values of a statistical life.

3.3.3. Choice of models and control variables

Most of the studies use the ordinary least squares method (OLS) to estimate Eq. (12). These models often treat the risk variable as an exogenous one. Simple OLS estimates may bias the results associated with endogenous risk (Kniesner et al., 2007). As a rule, higher values of a statistical life are observed in studies with endogenous risk (Garen, 1988; Siebert and Wei, 1994; Sandy and Elliott, 1996; Shanmugam, 2001; Gunderson and Hyatt, 2001).

Researchers must also choose the other independent variables to be inserted in their models. These choices are rather subjective, but they will certainly influence the results. Some authors use not only a linear form of the risk variable but also the squared form. This makes it possible to take the non-linear relation between wage and risk into account. The risk variable can also be used in interaction with certain characteristics of workers (race, age, sex, unionization, region, etc.). These interactions allow segmentation of the job market (Day, 1999). For example, it may happen that individuals from two different regions will not receive the same pay for the same risk or that individuals in a given age bracket will be more accepting of certain risks.

In principle, workers should demand a higher wage not only for the risk of death but also for the risk of injury. However, including the injury variable in models does raise a number of questions. First, omitting this variable can put a positive bias on the coefficient linked to the risk of death. Though, as Viscusi and Aldy (2003) point out, the risk of death is closely correlated with the risk of injury. So, owing to colinearity, the use of both variables in the same specification may produce very large standard errors. But Arabsheibani and Marin (2000) maintain that including or excluding the injury variable has no significant effect on the coefficient for the risk-of-death variable.

In the literature, many researchers seem to forget the existence of work-accident compensation. As discussed in Section 2, the presence of insurance compensation may affect the link between WTP and p. Arnould and Nichols (1983) argue that recipients of compensation usually demand lower salaries for increased risk of death. Empirical evidence has shown that the existence of compensation implies big reductions in wage levels (Fortin and Lanoie, 2000). These authors claim that studies omitting this variable must necessarily obtain biased results.

4. Choice of studies

Most of the studies have been drawn from literature reviews in the works of Viscusi (1993), Michaud (2001), and Viscusi and Aldy (2003). Other articles have been retrieved by key-word searches with the search engines Proquest, ScienceDirect, JSTOR, EconLit and SSRN and by systematically looking at the references of the articles identified. By retaining only the studies that use the hedonic wage method to calculate the value of a statistical life, we come up with a total of 49 articles.

We excluded the Lott and Manning (2000) study, since their work focuses solely on the risks of death from cancer contracted in the workplace. Next, to get a more homogeneous sample, we withdrew the studies whose estimation was not obtained with a regression similar to Eq. (12). The studies by Melinek (1974) and Needleman (1980) were thus eliminated.

[9] We must mention that serious criticisms have been aimed at the official statistics on occupational risks in the U.S. (see, for example, Leigh et al., 1997).

[10] See Thaler and Rosen (1975), Brown (1980), Arnould and Nichols (1983) as well as Gegax et al. (1991).

[11] This expected value is computed in terms of the age structure within each occupation, and with survival tables.

Table 2
Average value of a statistical life according to country of origin.

	Number	Average	Median	Standard deviation
United States	16	6,273,000	4,648,493	5,045,182
Canada	7	9,160,083	4,041,961	10,392,347
United Kingdom	3	16,995,764	14,181,264	12,592,129
Australia	2	11,173,881	11,173,881	9,625,769
South Korea	1	1,552,525	1,552,525	–
India	1	16,070,278	16,070,278	–
Japan	1	12,812,755	12,812,755	–
Taiwan	1	1,198,975	1,198,975	–
Total	32	8,420,568	4,955,810	7,890,597

We also wanted each VSL estimate to be carried out on different samples. Of the remaining 46 articles, 3 had to be withdrawn because their samples had already been used in other studies. The three articles in question are those of Moore and Viscusi (1990a), Sandy et al. (2001), and Kniesner and Viscusi (2005).[12]

Since the value of a statistical life obtained based on each study constitutes the dependent variable of our meta-analysis, all the studies for which we could not calculate this value ourselves with Eq. (13) were removed. Among these studies are to be found those of Moore and Viscusi (1988b, 1989, 1990b), of Herzog and Schlottmann (1990), as well as that of Dorman and Hagstrom (1998). Finally, the Leigh study (1987) was not selected, since the author fails to publish the average probability of death in his sample. This variable is one of the most important in our meta-analysis.

The final sample is thus made up of 37 studies. In most cases, they contain several regressions and thus several estimations of the value of a statistical life. As we do not want more than one estimation from the same sample, only one value of a statistical life is chosen from studies that use only one sample. To select the most suitable specification, we set selection criteria. First, to compute the standard error of the estimated VSL with Eq. (15), we chose specifications containing no terms of interaction between the probability of death and other explanatory variables. A second criterion is based on the homogeneity of the specifications across studies. Thus the specification selected must coincide as closely as possible with the specifications and models of the other studies included in the meta-analysis. For example, in Kniesner and Leeth (1991), we had the choice between specifications which took account injuries and others which did not. Since most articles include an injury variable which is encouraged by most authors in the literature, we chose a specification that incorporates it. A third criterion relates to the sample used. In articles with overlapping samples, our choice was influenced by the size and the characteristics of the samples; larger samples with characteristics most similar to the other studies were preferred. In a few studies, the goodness-of-fit of the regression model and the statistical significance of the results also influenced the choice, but were never the only criteria used. Sometimes the author's opinion was the selection criterion. Indeed, certain authors, like Smith (1974), point out the best specification in their article. Finally, the opinion of other authors helped in our selection. For example, the Viscusi and Aldy (2003) article helped us decide which specification to select in the Leigh (1995) article.

Several estimations can be drawn from the same study, provided that they were calculated based on different and independent samples. We are aware that adding these estimations may have an impact on the independence of our observations, since they were produced in the framework of the same article and thus from the same analytical viewpoint. This decision concerns only one article (Kniesner and Leeth, 1991), for a total of three observations. So we have a potential of 39 observations for our meta-analysis. The characteristics of these 39 selected observations are presented in Appendix 1 along with two examples to illustrate the corresponding calculation of the VSL. Note that we were unable to compute the standard error of VSL for seven of these observations (Appendix 1, italicized rows in table) due to their interaction with the risk of death in the specification. Therefore, we did not use these observations in the main analyses presented in the next section. We reintroduce these seven observations in Section 5.3, for a sensitivity analysis.

5. Results

5.1. Descriptive analysis of the sample

The average value obtained for the VSLs from the 32 observations stands at \$8.4 M and the median at \$5 M (Table 2). Of these studies, 16 come from the United States and their average value is \$6.3 M. The average and median of values from the United Kingdom (\$17 M and \$14.2 M) are definitely higher. We shall take this aspect into account in our meta-analysis. In Table 3, we present a descriptive analysis of the most important methodological factors. Among other things, we note that: 94% of the studies use an observed risk measurement; 13% treat the risk of death as endogenous; 16% take into account compensation; and 9% have recourse to data from the Society of Actuaries (SOA).

[12] The studies that use the same samples are respectively those of Moore and Viscusi (1989), Sandy and Elliott (1996) and Viscusi (2004). The first article to have used the sample in question was retained.

Table 3
Descriptive statistics of the sample ($n = 32$).

Variables	Average
Average income (US$ 2000)	29,559
Average probability (10,000×)	2.05
White-workers only sample	13%
Men only sample	47%
Unionized only sample	13%
Sample without white collars	41%
Injuries taken into account	56%
Compensation taken into account	16%
Endogenous risk	13%
Observed risk	94%
SOA	9%

Standard deviation of income = 9576; standard deviation of probability = 2.32.

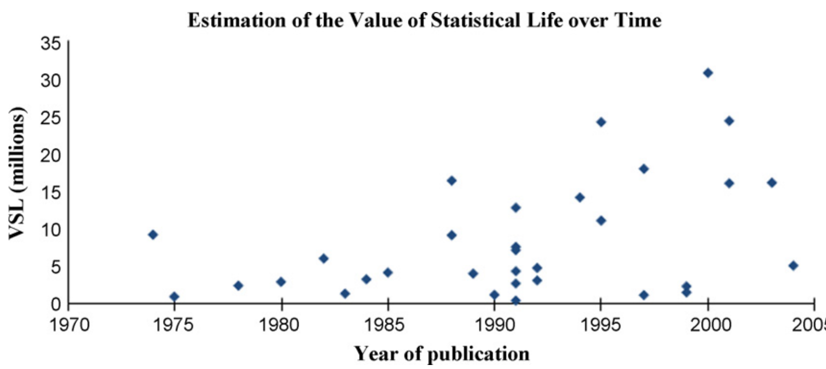

Fig. 1. Estimation of the value of statistical life over time.

After 30 years of research and publication on the topic, we might expect a certain convergence in the values obtained. When we examine Fig. 1, we note quite the contrary. The most recent studies seem to diverge instead. And it is also interesting to observe a positive relation between the values of a statistical life and the year of publication. Several hypotheses have been advanced to explain this result. First, as we mentioned earlier, using the probability of death as an endogenous variable usually produces higher values. This technique has only been applied since 1988. We can suppose that workers are better informed than before concerning the risks inherent in their jobs and that they are now demanding more adequate pay. Finally, it is possible that, given their longer life expectancy and potential period of retirement, workers are now simply assigning a higher value to their life.

In Fig. 2, we present the relation between the value of a statistical life and the probability of death. At first sight, this relation seems negative. When we analyze the figure more closely, we note that this relation is amplified by two extreme values for the probability of death. These values come from the studies by Thaler and Rosen (1975) and Gegax et al. (1991). These authors use data from the Society of Actuaries (SOA) to assign the risk of mortality in the workplace. We shall take this fact into account in our meta-analysis.

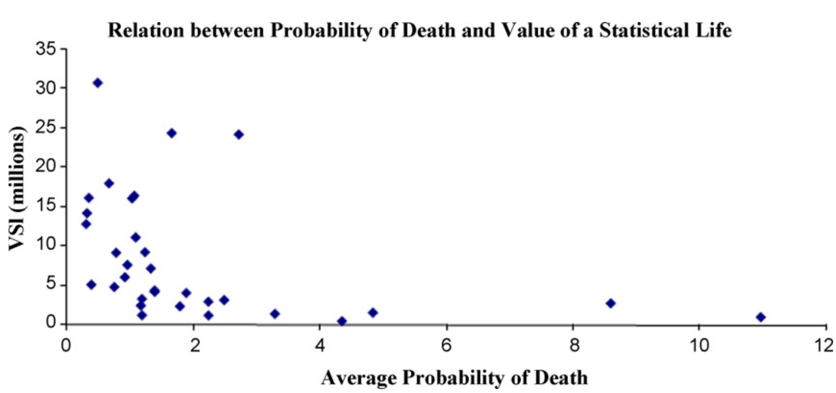

Fig. 2. Relation between probability of death and value of a statistical life.

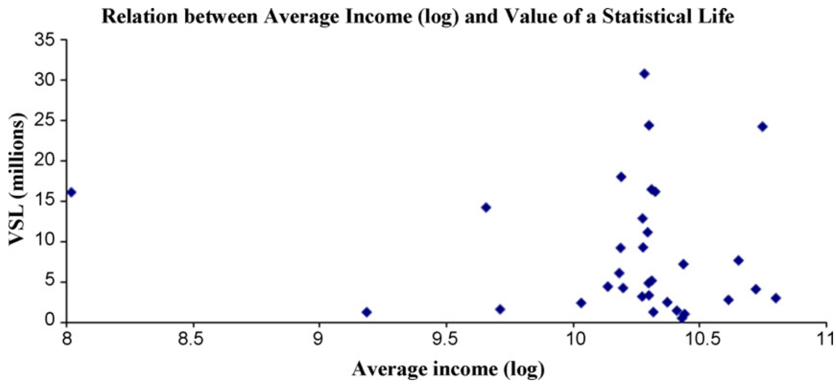

Fig. 3. Relation between average income (log) and value of a statistical life.

We expect a positive relation between average income and the value of a statistical life. However, this is not definitely confirmed by Fig. 3. The meta-analysis, with the natural logarithm of the average income in Eq. (9), will tell us more about this relation.

5.2. Results and discussion of the meta-analysis

In Table 4, we present the results of the meta-analysis. The statistic $\hat{\sigma}_u^2$ at the bottom of the table represents the variability left unexplained by the model. The weaker this value, the greater the amount of variability explained by the model. If we reject the hypothesis $\sigma_u^2 = 0$, then a portion of the variability observed remains unexplained. The hypothesis of a null random effect has been rejected for all the specifications.

The first specification in Table 4 includes only the constant. The estimation of the constant in this model is 5,863,609 and this value represents the weighted average of the value of a statistical life based on the 32 studies selected in the meta-analysis, as obtained with the weights in Eq. (11). This value is in line with those in Dionne and Lanoie (2004) and Kniesner et al. (2007). As for the other specifications, we note that, on average, the values of the statistical life in the studies increase with the years of publication.

We obtain a positive relation between the value of a statistical life and the logarithm of the sample's average income. It is thus confirmed that wealthier people have a higher willingness-to-pay. Given that we use a level-log model, we must divide the coefficient associated with the average income by the average value of a statistical life to obtain the income elasticity. We find that the income elasticity of the value of a statistical life ranges between 0.84 and 1.08. This result is similar to the one obtained by Miller (2000). It is high enough to point out the importance of having a representative sample when assigning a VSL to a certain population.

We can say that the studies with the risk of death as an endogenous variable do have high values of a statistical life. This confirms the results obtained by many authors (Garen, 1988; Siebert and Wei, 1994; Sandy and Elliott, 1996; Shanmugam, 2001; Gunderson and Hyatt, 2001). The studies that treat risk endogenously obtain, on average, VSLs between $12 and $13 M higher than those with other procedures—*ceteris paribus*. Accepting the hypothesis that the risk variable must be treated in this way, the studies with other procedures would end up underestimating the VSL considerably (see however the analysis of Kniesner et al., 2007). Studies incorporating a variable measuring compensation for work accidents obtain, on average, VSLs that are from $3.5 to $5 M lower than other studies, depending on the specification. It is thus verified that individuals who benefit from compensation usually demand lower risk premia. This result also falls in line with the theoretical discussion on the relationship between the average probability of death and the VSL. Higher insurance compensation is associated with a negative relationship.

Our results indicate that the VSL is higher for samples composed entirely of white workers. These results confirm those obtained by Viscusi (2003). It must be pointed out that this does not imply that a black person's life is worth less than that of a white person's. These results simply indicate that, for the same variation in the probability of death, the WTP of white workers is, in general, higher than that of black workers. Are these results caused by racial discrimination on the job market? We cannot answer this question here.

We have seen that there is no consensus regarding the effect of unionization on workers' willingness-to-pay. Our results do, however, seem to correspond to the findings of Marin and Psacharopoulos (1982), Meng (1989) as well as Sandy and Elliott (1996), pointing to a negative relation between unionization and the VSL. The parameters estimated are, however, not statistically significant. In fact, only two of the three specifications including this variable obtain significant coefficients and only at the level of 10%.

We have pointed out that the average for the values of a statistical life in the studies from the UK is very high compared to other countries. The meta-analysis does effectively suggest a positive and significant relation. This result does not necessarily mean that British workers assign greater value to life. It will take further investigation to find the reasons explaining these

Table 4
Results of the meta-analysis.

Variables	Specifications					
	0	1	2	3	4	5
Constant	5,863,609 (10.02)	−7.10E + 08 (3.29)	−7.81E + 08 (3.78)	−8.50E + 08 (4.02)	−9.84E + 08 (4.52)	−1.01E + 09 (4.44)
Year of publication	–	335,114 (3.22)	369,740 (3.71)	401,469 (3.94)	464,614 (4.44)	479,170 (4.36)
Average income (log)	–	4,896,217 (2.64)	5,079,834 (2.90)	5,602,916 (3.13)	6,348,381 (3.52)	5,886,691 (2.97)
Average probability of death	–	−656,039 (2.52)	−485,427 (1.93)	−336,340 (1.24)	−147,900 (0.53)	−318,792 (0.84)
Endogeneity of risk	–	12,144,598 (4.12)	12,769,291 (4.46)	13,191,741 (4.59)	12,917,337 (4.51)	12,740,607 (4.34)
Compensation	–	−3,581,246 (1.98)	−4,073,194 (2.38)	−4,697,596 (2.67)	−4,866,783 (2.78)	−4,836,143 (2.64)
White-workers sample	–	–	4,760,292 (2.47)	6,073,123 (2.86)	7,111,574 (3.30)	7,165,757 (3.21)
Union sample	–	–	–	−3,618,915 (1.48)	−4,603,245 (1.87)	−4,790,231 (1.86)
UK study	–	–	–	–	6,708,723 (2.40)	6,814,157 (2.35)
SOA	–	–	–	–	–	2,080,352 (0.70)
N	32	32	32	32	32	32
$\hat{\sigma}_u^2$	7.16E + 12	8.41E + 12	7.15E + 12	7.15E + 12	7.02E + 12	7.82E + 12
Prob. $\sigma_u^2 = 0$	0	0	0	0	0	0

Notes: (1) Dependent variable: VSL. (2) Absolute value of the *t*-statistic in parentheses.

Table 5
Results of the meta-analysis (without studies using SOA).

Variables	Specifications				
	0	1	2	3	4
Constant	6,519,243 (9.88)	−8.29E+08 (3.38)	−9.02E+08 (3.81)	−8.78E+08 (3.82)	−9.96E+08 (4.22)
Year of publication	–	397,154 (3.35)	432,049 (3.77)	419,944 (3.77)	475,149 (4.17)
Average income (log)	–	4,661,556 (2.23)	4,914,203 (2.47)	4,948,056 (2.56)	5,606,813 (2.88)
Average probability of death	–	−1,928,822 (3.29)	−1,590,198 (2.77)	−1,543,579 (2.79)	−1,239,987 (2.18)
Endogeneity of risk	–	11,129,173 (3.67)	11,746,697 (3.98)	12,260,997 (4.19)	12,120,680 (4.16)
Compensation	–	−3,928,681 (2.03)	−4,394,831 (2.39)	−4,567,507 (2.55)	−4,725,900 (2.66)
White-workers sample	–	–	3,901,022 (1.89)	4,979,976 (2.23)	5,996,964 (2.63)
Union sample	–	–	–	−3,445,325 (1.08)	−4,216,413 (1.32)
UK study	–	–	–	–	5,696,197 (1.99)
N	29	29	29	29	29
$\hat{\sigma}_u^2$	8.18E+12	9.29E+12	7.99E+12	7.31E+12	7.15E+12
Prob. $\sigma_u^2 = 0$	0	0	0	0	0

Notes: (1) Dependent variable: VSL. (2) Absolute value of *t*-statistic in parentheses.

differences between countries. Do British institutions use different procedures when collecting information on workers? Or is it rather British researchers who apply particular methodologies that push the VSL higher?

We have seen that the relation between the average probability of death and the value of a statistical life is in theory ambiguous. According to our results, this relation seems to be negative. For specifications 1 and 2, we obtain a coefficient that is significant at the 5% and 10% level respectively. However, for the next three specifications, we observe non-significant coefficients. Thus we cannot say with any certainty that the relation is negative. It might be that this drop in the variable's significance is due to a multicolinearity problem. By analyzing the correlation matrix in Appendix 2, we find a significant correlation coefficient between the probability of death and SOA, a variable which takes the value of 1 when the Society of Actuaries is the source of the probability of death and 0 otherwise.[13] This result is not very surprising. However, the SOA variable is present only in specification 5 and thus cannot explain the results obtained in specifications 3 and 4. Since the SOA is the only variable in the models which is significantly correlated with the probability of death, we do not believe that multicolinearity is the source of the weak levels of significance.

The SOA variable is also correlated significantly with the "year of publication" variable. This does not come as a surprise, since the Society of Actuaries is a source of data which was used mainly in the 1970s and the 1980s. We redid the analysis including the SOA variable in each of the specifications, but excluding the two variables correlated with SOA. This allowed us to check for the impact of this source on the values of statistical life estimated. The results of this exercise are presented in Appendix 3. We note that excluding the two variables has a strong impact on the SOA parameter estimated. It becomes negative and relatively significant.[14] We can conclude that the SOA source of data on risk does have an impact on the value of a statistical life estimated. We must thus make sure that the negative relation observed between the average probability of death and the VSL presented in Table 4 is not simply due to the fact that our sample includes studies using the SOA. We thus withdrew the observations with the SOA from our sample and then estimated the parameters again. The new results are presented in Table 5.

The coefficient associated with the probability of death remains negative and is more significant for each of the specifications than in Table 4. This leads us to conclude that the relation between the average probability of death and the VSL in the studies selected is effectively negative. The economic interpretation of this finding would stipulate that, in general, individuals already exposed to a greater risk of death are less reluctant to increase their risk than those who are not. Our results corroborate the theoretical works of Dionne (1982), Cook and Graham (1977), as well as those of Breyer and Felder (2005). Note that the resulting negative sign in (7) is compatible with a positive sign in (8) when risk aversion is sufficiently high.[15] As for the other parameters estimated and presented in Table 5, we observe no major difference between them and the results shown in Table 4. It can be pointed out that the income elasticity of the value of a statistical life drops slightly, now ranging between 0.72 and 0.86.

5.3. Sensitivity analyses

We tested the robustness of our results by excluding the extreme values from our sample. We used two methods to identify outlying observations. The first excludes all the observations with more than three standard deviations from the average. Only two studies are isolated: Shanmugam (2001) for a weak average income and Thaler and Rosen (1975) for a high average probability of death. The study of Shanmugam uses a sample of Indian workers. It is predictable that the average

[13] In our complete sample composed of 39 observations, we note that studies using the SOA report an average of 7.96 deaths per 10,000 workers, whereas the others obtain a 1.41 average. For our reduced sample of 32 observations, the averages are respectively 7.28 and 1.50.
[14] The parameter is significant at 5% for the first specification and at 10% for specifications 2 and 3. The parameter is not significant for specification 4.
[15] See Dachraoui et al. (2004) and Eeckhoudt and Hammitt (2004) for recent analyses of the relationship between risk aversion and willingness to pay.

income is low in that country. Thaler and Rosen use the Society of Actuaries as their source of the probability of death. We redid the analyses presented in Tables 4 and 5 without these two observations and found no significant difference with previous results. In fact, the coefficients associated with the probability of death are even more significant.

The median and the interquartile range were also used to identify outlying observations as follows: (observed value – median) divided by (interquartile range). If this computed value is higher than three or lower than minus three then it is considered an extreme value. This method excludes two additional observations: Liu et al. (1997) for a low average income and Gegax et al. (1991) for a high average probability of death. The study of Liu et al. uses a sample of workers in Taiwan. Gegax et al. use the SOA as source of the probability of death. We redid the analysis without the four observations with extreme values. Again we observed that coefficients of probability of death were more significant than those in Tables 4 and 5. However, the average income was not statistically significant in all the specifications. These results certainly raise the question of the inclusion of studies estimating VSL from developing countries along with those from other countries without controlling for this characteristic.

We also performed a residual analysis for each specification in Tables 4 and 5. We found that two VSLs are constantly outliers: Lanoie et al. (1995) and Arabsheibani and Marin (2000). These two articles have a very high VSL. We redid the analyses in Tables 4 and 5 excluding these two studies and we did not observe any significant change in the results.

We withdrew from the analyses seven observations for which the standard error could not be calculated. However, we do believe that these observations do contain information that is relevant to our analysis. We have thus attempted to estimate standard errors for the values of a statistical life obtained in these studies, so as to make use of this information. We first applied an ordinary least squares regression to the 32 observations for which we had previously calculated the standard error. The dependent variable of this OLS consists in an SE/VSL (standard error/value of a statistical life) relation. A single dependent variable – sample size – is introduced in this regression model. As a rule, the larger the sample size used, the more accurate the VSL estimation (weak SE/VSL relation).[16] We then applied the regression equation and the sample sizes of the seven studies selected to estimate the SE/VSL. Since we know the values of statistical life, we can easily determine the standard errors. Using the 39 observations, we repeated the same analysis as applied to Tables 4 and 5. The results are presented in Appendix 4. We discern no important changes other than an increased significance of the probability of death variable and a reduced significance of the union variable.

Several explanatory variables which do not appear in the tables of results have been tested in various specifications. Their exclusion from the tables stems in large part from the weak significance and instability of the results obtained. First, we wanted to measure the consequences of taking the risk of injury into account when estimating the VSL. The results obtained lead us to the same conclusion as that reached by Arabsheibani and Marin (2000): there is no impact. We also wanted to test for the author's influence on the VSL. We focused our attention on the most prolific of the authors in the field, W. Kip Viscusi. But we found no relation between our binary variable "Viscusi" and the VSL. A variable "impact factor" was also inserted to measure the impact of the quality of scientific journals in which each article was published. However, no relation was observed. Our different tests also allowed us to conclude that samples composed solely of white-collar workers have no influence on the VSL, and that observed probability of death (instead of perceived probability) does not seem to influence significantly the VSL. Finally, we obtain mixed results for the men only variable. In certain specifications, we can observe a positive and slightly significant relation (10% level) between having a sample composed only of men and the VSL. However, given the instability of the results from one specification to the next, we cannot conclude that such a relation really exists.

When our results are compared to those of previous meta-analyses (Table 1), we note that, as concerns the risk and income variables, they are somewhat similar to those reported in Liu et al. (1997), and in Viscusi and Aldy (2003). As for the income elasticity of the VSL, our results are similar to those obtained by Miller (2000).

6. Conclusion

In this article, we have presented willingness-to-pay as the most suitable method for measuring individual preferences in matters of risk. But we have also found that this method has its weaknesses. We now realize that the theoretical properties of the WTP are rather fragile. One interesting extension would be to have models that consider insurance compensation as a choice variable. Another extension would be to pay more attention to theoretical models other than the expected utility approach (such as ambiguity aversion, anticipated utility, or behavioral economics) and other than the hedonic wage method (such as search theory with imperfect competition or bargaining and matching theory).

Then, surveying the numerous studies having tried to estimate the VSL, we find wide discrepancies in the values obtained: this poses a problem for public decision-makers. Using a VSL which does not adequately reflect citizens' willingness-to-pay may cause public authorities to make wrong decisions. This meta-analysis was mainly motivated by the need to find the source of these discrepancies. Our meta-analysis distinguishes itself from others done on the same topic in its application of a mixed effects regression model (Raudenbush, 1994). This model's special feature is that it takes into account the heterogeneity in VSL estimations. The results allow us to conclude that the variability observed in the VSLs reported by different studies is, in part, owing to differences in methodologies.

[16] It is worth noting that the correlation between the variables "sample size" and "SE/VSL" is −0.325 and is significant at 10% (bilateral).

Several methodological factors have a strong impact on the VSLs estimated. For example, researchers who take the endogenous nature of the risk variable into account obtain higher VSLs. Results are also influenced by the form of econometric specifications used. When a variable measuring workers' compensation is included in the models, we obtain lower VSLs. The population under study is also important. Samples composed of wealthier economic agents generate higher VSLs. Samples composed of altruistic agents generate a negative relationship between VSL and accident probability. These agents may also be more compensated by insurance. Finally, we note that the VSL is significantly influenced by a study's country of origin, by year of publication, by race, and by the source of the risk variable. These results inform public decision-makers of the importance of using appropriate methodologies and representative samples or of adjusting the estimated values to the target population when making a decision.

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Appendix 1. Detailed description of studies selected

#	Authors	Year of publication	Country	Sample size	Average income[a]	Average probability of death[b]	Compensation	Endogeneity of risk	White workers sample	Union sample	SOA	Coefficient ϕ	Location in the article: Page	Table	Specification	Criteria[c]	VSL[a]	Standard error (VSL)[a]
1	Smith	1974	USA	3,183	29,029	1.25	0	0	1	0	0	0.636	743	A	2	5, 6	9,231,222	3,846,343
2	Thaler and Rosen	1975	USA	907	34,195	10.98	0	0	0	0	1	0.000286	293	4	2	1, 2, 6	977,980	594,995
3	Viscusi	1978	USA	496	31,953	1.182	0	0	0	0	0	0.00153	368	2	2	2, 5	2,444,383	1,405,920
4	Brown	1980	USA	470	49,019	2.25	0	0	0	0	1	0.06	128	2	2	2, 4	2,941,140	588,228
5	*Olson*	*1981*	*USA*	*5,993*	*33,509*	*0.9508*	*0*	*0*	*0*	*0*	*0*	*0.4245*	*175*	*1*	*1*	*2*	*12,374,191*	*4,978,545*[d]
6	Marin and Psacharopoulos	1982	UK	5,509	26,415	0.93	0	0	0	0	0	0.229	836	4	3	1	6,049,041	1,338,283
7	*Arnould and Nichols*	*1983*	*USA*	*1,832*	*34,195*	*10*	*1*	*0*	*0*	*0*	*1*	*0.355*	*338*	*1*	*2*	*5*	*1,351,335*	*570,002*[d]
8	*Dorsey and Walzer*	*1983*	*USA*	*1,697*	*21,636*	*0.5756*	*1*	*0*	*0*	*1*	*0*	*0.635*	*652*	*4*	*4*	*2*	*11,768,688*	*4,971,544*[d]
9	Low and McPheters	1983	USA	72	33,172	3.3	0	0	0	0	0	129.42	277	2	1	2, 5	1,391,218	1,008,129
10	Dillingham and Smith	1984	USA	879	29,707	1.2	0	0	1	1	0	0.2218	275	1	1	3	3,294,506	1,565,559
11	*Leigh and Folsom*	*1984*	*USA*	*1,529*	*35,694*	*1.42*	*0*	*0*	*1*	*0*	*0*	*0.3629*	*60*	*3*	*3*	*2, 3*	*10,067,308*	*4,260,731*[d]
12	Dillingham	1985	USA	514	26,825	1.4	0	0	0	0	0	0.3124	285	5	2	5	4,189,995	2,323,006
13	*Weiss et al.*	*1986*	*Austria*	*4,225*	*12,841*	*1.28*	*0*	*0*	*0*	*0*	*0*	*1.2894*	*15*	*2*	*2*	*1, 5*	*8,369,952*	*3,436,763*[d]
14	Garen	1988	USA	2,863	30,013	1.08	0	1	0	0	0	0.00547	14	3	2	1, 5	16,416,982	3,538,143
15	Moore and Viscusi (a)	1988	USA	1,349	26,559	0.7918	0	0	1	0	0	0.00345	485	5	2	1, 5	9,162,972	2,390,341
16	Meng	1989	Canada	718	45,313	1.9	0	0	0	0	0	0.0892	421	2	4	1	4,041,961	2,336,394
17	Meng and Smith	1990	Canada	777	30,236	1.2	0	0	0	0	0	0.04023	141	1	1	1	1,216,395	2,252,583
18	Berger and Gabriel	1991	USA	22,837	42,316	0.97	0	0	0	0	0	0.0018	315	2	1	3	7,616,966	1,336,310
19	Gegax et al.	1991	USA	228	40,664	8.6075	0	0	0	1	1	0.0168	594	3	5	3	2,732,627	1,379,418
20	Kniesner and Leeth (1)	1991	Japan	20	28,975	0.32	0	0	0	0	0	4.422	81	2	4	2	12,812,755	6,707,897
21	Kniesner and Leeth (2)	1991	Australia	44	25,260	1.4	1	0	0	0	0	1.729	81	2	7	1, 2	4,367,434	1,753,567
22	Kniesner and Leeth (3)	1991	USA	8,868	33,843	4.36	1	0	0	0	0	0.1365	84	3	11	2, 4	461,958	310,247
23	Leigh	1991	USA	1502	34,045	1.34	0	0	0	0	0	0.0021	386	1	6	3	7,149,454	2,175,732
24	Cousineau et al.	1992	Canada	32,713	29,658	0.764	0	0	0	0	0	0.00162	168	2	5	2, 3	4,804,628	464,664
25	Martinello and Meng	1992	Canada	4,352	28,925	2.5	0	0	0	0	0	0.1087	340	2	6	1, 2	3,144,141	949,892
26	Siebert and Wei	1994	UK	1,353	15,627	0.332	0	1	0	1	0	0.9075	70	3	1	3, 5	14,181,264	6,746,558
27	Lanoie et al.	1995	Canada	63	46,535	2.73	0	0	0	1	0	0.052	248	3	1	2, 4	24,198,149	7,657,642
28	Leigh	1995	USA	1,528	29,552	1.1016	0	0	0	0	0	0.00376	91	3	2	3, 6	11,111,731	2,084,361
29	*Sandy and Elliott*	*1996*	*UK*	*440*	*30,211*	*0.452*	*0*	*1*	*0*	*1*	*0*	*3797.31*	*299*	*3*	*2*	*2*	*53,626,554*	*22,969,379*[d]
30	Liu et al.	1997	Taiwan	18,987	9,748	2.252	0	0	0	0	0	0.0123	356	2	5	2, 3	1,198,975	106,623
31	Miller et al.	1997	Australia	18,850	26,638	0.68	0	0	0	0	0	0.675	367	2	3	2	17,980,328	1,369,408
32	Kim and Fishback	1999	South Korea	321	16,516	4.85	0	0	0	0	0	0.094	238	1	1	1	1,552,525	324,796
33	Meng and Smith	1999	Canada	1,503	22,743	1.8	1	0	0	0	0	0.1035	1,106	2	10	1, 2	2,353,931	609,827
34	Arabsheibani and Marin	2000	UK	3,608	29,176	0.5	0	0	0	0	0	1.0542	258	2	5	2, 3	30,756,987	6,179,825
35	Gunderson and Hyatt	2001	Canada	2,014	29,709	1.67	0	1	0	0	0	0.082	389	3	2	2	24,361,374	3,460,422

Appendix 1 (*Continued*)

#	Authors	Year of publication	Country	Sample size	Average income[a]	Average probability of death[b]	Compensation	Endogeneity of risk	White workers sample	Union sample	SOA	Coefficient ϕ	Location in the article			Criteria[c]	VSL[a]	Standard error (VSL)[a]
													Page	Table	Specification			
36	Shanmugam	2001	India	522	3,038	1.04407	0	1	0	0	0	0.0529	270	2	2	1, 2, 5	16,070,278	7,183,853
37	*Leeth and Ruser*	*2003*	*USA*	*45,001*	*24,860*	*0.9757*	*1*	*0*	*0*	*0*	*0*	*0.116*	*268*	*3*	*2*	*3*	*2,723,710*	*598,605*[d]
38	Viscusi	2003	USA	83,625	30,449	0.362	1	0	1	0	0	0.0053	29	5	1	3	16,137,876	1,522,441
39	Viscusi	2004	USA	99,033	30,041	0.402	1	0	0	0	0	0.0017	39	3	1	3	5,106,991	600,822

[a] In US$ 2000.

[b] Number of deaths per 10,000 workers.

[c] Criteria used to select the specification: (1) S.E. of VSL calculable; (2) specification and model similar to the other studies; (3) sample size and characteristics; (4) goodness of fit/statistical significance of results; (5) author's opinion; (6) other author's opinion.

[d] Study not included in the main analyses; the standard error was estimated by linear regression with the study sample size (see Section 5.3 for details) for sensitivity analyses.

Two examples to illustrate the calculation of the VSL using Eq. (13) for the meta-analysis.

- Dillingham (1985)

$$\mathrm{VSL} = \frac{\hat{\phi}(\text{average income})(\text{CPI (US) 2000}/\text{CPI (US) 1977})}{\text{unit of probability of death}},$$

$$\mathrm{VSL} = \frac{0.3124(9440(172.2/60.6))}{1/500} = 4,189,995.$$

- Leigh (1995)

$$\mathrm{VSL} = \frac{\hat{\phi}(\text{average income})(\text{CPI(US)2000}/\text{CPI(US)1981})}{\text{unit of probability of death}},$$

$$\mathrm{VSL} = \frac{0.00376(15,600(172.2/90.9))}{1/100,000} = 11,111,731.$$

Appendix 2. Pearson correlation matrix for independent variables (bilateral significance level in parentheses)

	Average income (log)	Average probability of death	Endogeneity	Compensation	White workers sample	Union sample	UK	SOA
Year of publication	−0.363 (0.041)*	−0.292 (0.105)	0.245 (0.176)	0.368 (0.038)*	−0.181 (0.321)	0.002 (0.993)	0.043 (0.816)	−0.372 (0.036)*
Average income (log)	1	0.157 (0.392)	−0.482 (0.005)**	0.033 (0.859)	0.048 (0.796)	0.091 (0.620)	−0.108 (0.555)	0.263 (0.146)
Average probability of death		1	−0.168 (0.359)	−0.072 (0.697)	−0.189 (0.299)	0.194 (0.287)	−0.205 (0.260)	0.737 (0.000)**
Endogeneity			1	−0.163 (0.374)	−0.143 (0.435)	0.143 (0.435)	0.203 (0.266)	−0.122 (0.507)
Compensation				1	0.098 (0.595)	−0.163 (0.374)	−0.138 (0.450)	−0.138 (0.450)
White workers sample					1	0.143 (0.435)	−0.122 (0.507)	−0.122 (0.507)
Union sample						1	0.203 (0.266)	0.203 (0.266)
UK							1	−0.103 (0.573)
SOA								1

* Correlation is statistically significant at the 5% level (bilateral).
** Correlation is statistically significant at the 1% level (bilateral).

Appendix 3. Results of the meta-analysis without variables significantly correlated with SOA

Variables	Specifications			
	1	2	3	4
Constant	−3.04E + 07 (1.55)	−2.87E + 07 (1.54)	−2.91E + 07 (1.56)	−3.03E + 07 (1.63)
Average income (log)	3,560,666 (1.86)	3,336,120 (1.83)	3,380,231 (1.86)	3,467,593 (1.90)
SOA	−5,247,906 (2.39)	−4,542,959 (2.17)	−3,928,476 (1.79)	−3,480,995 (1.57)
Endogeneity of risk	14,033,231 (4.67)	14,588,347 (4.98)	14,866,533 (5.06)	14,665,995 (4.98)
Compensation	−778,705 (0.46)	−949,291 (0.59)	−1,140,995 (0.71)	−840,395 (0.52)
White workers sample	–	4,238,228 (2.13)	4,948,844 (2.32)	5,335,718 (2.49)
Union sample	–	–	−2,328,582 (0.93)	−2,698,516 (1.07)
UK study	–	–	–	4,620,276 (1.62)
N	32	32	32	32
$\hat{\sigma}_u^2$	9.77E + 12	8.55E + 12	8.50E + 12	8.51E + 12

Notes: (1) Dependent variable: VSL. (2) absolute value of t-statistic in parentheses.

Appendix 4. Results of the meta-analysis (with standard errors estimated by an indirect procedure for seven studies)

Variables	Specifications							
	With studies using SOA				Without studies using SOA			
	1	2	3	4	5	6	7	8
Constant	−4.06E + 08 (2.16)	−4.67E + 08 (2.59)	−4.76E + 08 (2.62)	−5.53E + 08 (2.99)	−5.30E + 08 (2.44)	−5.86E + 08 (2.79)	−5.83E + 08 (2.76)	−6.41E + 08 (2.98)
Year of publication	189,187 (2.08)	219,560 (2.51)	223,701 (2.55)	260,520 (2.91)	254,040 (2.40)	281,671 (2.76)	280,236 (2.72)	307,788 (2.94)
Average income (log)	3,554,709 (2.13)	3,532,810 (2.23)	3,607,623 (2.27)	3,956,852 (2.49)	3,391,112 (1.80)	3,371,767 (1.88)	3,369,811 (1.89)	3,626,391 (2.03)
Average probability of death	−620,056 (2.86)	−470,189 (2.23)	−445,461 (2.04)	−343,874 (1.55)	−2,073,689 (3.72)	−1,809,023 (3.36)	−1,801,905 (3.40)	−1,629,751 (3.00)
Endogeneity of risk	12,936,013 (4.54)	13,472,562 (4.85)	13,576,268 (4.87)	13,204,929 (4.74)	11,622,614 (3.92)	12,125,413 (4.20)	12,172,100 (4.21)	11,936,488 (4.12)
Compensation	−2,201,799 (1.50)	−2,469,896 (1.79)	−2,572,852 (1.84)	−2,610,875 (1.88)	−3,524,430 (2.03)	−3,724,861 (2.26)	−3,715,599 (2.28)	−3,666,063 (2.25)
White workers sample	–	4,247,376 (2.41)	4,521,541 (2.43)	5,102,759 (2.73)	–	3,347,475 (1.78)	3,399,806 (1.72)	3,913,987 (1.95)
Union sample	–	–	−980,187 (0.47)	−1,409,395 (0.68)	–	–	−158,385 (0.06)	−430,322 (0.16)
UK study	–	–	–	5,148,482 (1.94)	–	–	–	4,033,856 (1.44)
N	39	39	39	39	35	35	35	35
$\hat{\sigma}_u^2$	7.63E + 12	6.54E + 12	6.57E + 12	6.45E + 12	8.82E + 12	7.59E + 12	7.35E + 12	7.32E + 12
Average value of a statistical life (US$ 2000)		5,718,516 (95% C.I.: 4,645,724; 6,791,308)				6,568,461 (95% C.I.: 5,315,621; 7,821,300)		

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