CIRPÉE
Centre interuniversitaire sur le risque, les politiques économiques et l'emploi

Cahier de recherche/Working Paper **06-46**

The Value of a Statistical Life: A Meta-Analysis with a Mixed Effects Regression Model

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Décembre/December 2006

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Financial support by CREF is acknowledged.

Abstract:
The value of a statistical life (VSL) is a very controversial topic, but one which is essential to the optimization of governmental decisions. Indeed, our society faces any number of risks (health, transportation, work, etc.) and, as resources are limited, their complete elimination is impossible. The role of governments is to act as effectively as possible in reducing these risks. To do so, one must first determine the value that society is willing to pay in order to save a human life. However, 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 40 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, 1994) to analyze studies on the value of a statistical life. The outcome of our meta-analysis allows us to conclude that the variability found in the results studied stems in large part from differences in methodologies.

Keywords: Value of a statistical life, meta-analysis, mixed effects regression model, hedonic wage method, risk

Résumé:
La valeur statistique d'une vie humaine (VSV) est un sujet de recherche très controversé, mais essentiel à l'optimisation des décisions gouvernementales. En effet, la société fait face à de nombreux risques (santé, transports, travail, etc.) et l'élimination complète de ceux-ci est impossible, les ressources étant limitées. Le rôle des gouvernements est d'intervenir le plus efficacement possible dans la réduction de ces risques. Pour ce faire, il est primordial de déterminer la valeur que la société est prête à payer pour la sauvegarde d'une vie humaine. On constate cependant une grande variabilité dans les valeurs obtenues des différentes études. Il est important de comprendre la provenance de cette variabilité, afin de mieux éclairer les décideurs publics quant au choix d'une valeur et de mieux orienter les futures recherches sur le sujet. Cet article effectue une méta-analyse basée sur 40 observations provenant de 37 études de neuf pays différents, qui estiment la VSV à l'aide de la méthode hédonique d'estimation des salaires. Notre méta-analyse innove car elle est la première à utiliser le modèle de régression à effets mixtes (Raudenbush, 1994) pour analyser les études sur la valeur de la vie. Les résultats de la méta-analyse nous permettent de conclure que la variabilité des résultats provient, en grande partie, de différences méthodologiques.

Mots Clés: Valeur statistique d'une vie, méta-analyse, modèle de régression à effets mixtes, méthode hédonique des salaires, risque

JEL Classification: D80, D13, D61, H43, H51, H53, I18, J38, J58

Introduction

More than ever before, our society must face numerous risks, notably in spheres such as health (SARS, HIV, avian flu, etc.), the environment (Bhopal), natural disaster (Katrina), transportation (road and air accidents), as well as occupational safety. It is useless to nourish the utopian thought that all these risks must be completely eliminated, for government actions are, of course, hemmed in by budgetary constraints. Public authorities must thus figure out the optimal budget for each project aimed at reducing risks.

Cost-benefit analysis is a very popular project-evaluation tool. 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 (Viscusi and Aldy, 2003). Risk is in some sort a matter of individual preference. Each individual, to some degree, chooses his or her optimal level of exposure to risk. The unconditional minimization of risk is no more desirable for a particular individual than it is for governments. It is by these kinds of market decisions—usually implying a trade-off between risk and a certain sum of money—that economists try to measure the amount society is ready to pay in order to save a human life.

The number of studies conducted on this topic since the 70s is quite impressive. Several values 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 used by the studies. We believe that our results will allow a better understanding of the whole issue surrounding the evaluation of a human life and will enable us to give public decision-makers better guidance in choosing a value in their cost-benefit analyses. To attain this objective we shall use meta-analysis, a statistical tool of growing popularity in the financial and economic literature.

The first section presents the willingness-to-pay (WTP) approach. This approach is based on an individual's willingness to pay to reduce the risk of death or on his willingness to accept a certain amount to see his life expectancy reduced. It is worth mentioning that we are here speaking of a completely anonymous member of society. To avoid any confusion, we shall 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 small variation in the risk of death (Viscusi, 2005). This section serves to clarify the concepts to be used in the meta-analysis. We next analyze how researchers go about measuring empirically the statistical value of a human life. We also survey the different methodological options open to researchers and their possible impact on estimations of the VSL.

Section 2 presents the meta-analysis tool. It also offers a survey of some of the meta-analyses associated with the VSL to be found in the literature. At the end of this section, the methodology selected for our meta-analysis is described in detail. This methodology is based on the mixed effects regression model (Raudenbush, 1994) which accounts for heterogeneity in its estimations of the VSL. We are the first to use this approach and it is this which distinguishes our research from other meta-analyses of the VSL.

In the third section, we go on to give a descriptive analysis of the sample selected. The fourth section deals with the results of the meta-analysis, which are presented and analyzed in full. Finally, we discuss what implications these results have for public decision-makers.

1 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 Jones-Lee (1976), Schelling (1968), Mishan (1971), and Weinstein et al. (1980).

The model stipulates that each individual is endowed with an initial sum of wealth w and is subject to only two possible states of nature in relation to her 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 her expected utility:

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

where $U_a(w)$ and $U_d(w)$ represent respectively her conditional von Neumann-Morgenstern utility functions during her existence as well as at her death.

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

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

This 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).[1]

The literature often proposes that the marginal utility drawn from wealth is greater in the state of survival than in the state of death:

$$U_a'(w) > U_d'(w) > 0, \quad \forall w. \tag{3}$$

[1] This hypothesis is not needed to derive the model but does simplify its presentation.

This hypothesis comes from, among others, Pratt and Zeckhauser (1996) who found their argument on a dead-anyway effect. According to them, the individual must necessarily profit more from increasing his wealth while he is alive rather than when he is deceased. The individual has aversion to risk in both states of nature. This means that his marginal utility is decreasing in both states.

$$U_a^{"}(w), U_d^{"}(w) \leq 0, \quad \forall w. \tag{4}$$

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 *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 need only 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:

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

being the marginal WTP corresponding to the marginal substitution rate between wealth and the initial probability of death. The term in the numerator on the right 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 that the individual is willing to pay to avoid a small variation in risk (*dp*), we can determine the corresponding VSL: (*dw/dp*)/Δ*p*.

Using the hypothesis in (2), we can verify that the individual will always ask for positive remuneration before accepting an increase in his risk. To determine the shape of the indifference curve in plane (*w,p*), we must first 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:

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

The result is ambiguous and depends on hypothesis (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 equation (7) is positive. The individual's willingness-to-pay (WTP) thus increases with his initial level of risk. The economic interpretation of this result shows that individuals previously exposed to a greater risk (firefighters, miners, etc.) should, in general, be more reluctant to increase their risk than others would be, with the same level of variation. 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, among other things, to determine whether the intuitive reasoning of Pratt and Zeckhauser (1996) holds the road. They come to two broad conclusions. The first is that, with a perfect insurance market, an egoist with an aversion to risk will always see his WTP increase with the risk of death. However, this is mainly due to an income effect rather than to Pratt and Zeckhauser's dead-anyway effect. 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 the fact that individuals have greater marginal utility when dead than when alive. In Dionne (1982) this possibility is explained by 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 compensation. Dionne (1982) shows that this over-insurance result cannot be viable in the presence of moral hazard. This argument involving inheritance utility is akin to what Breyer and Felder (2005) have to say about altruism.

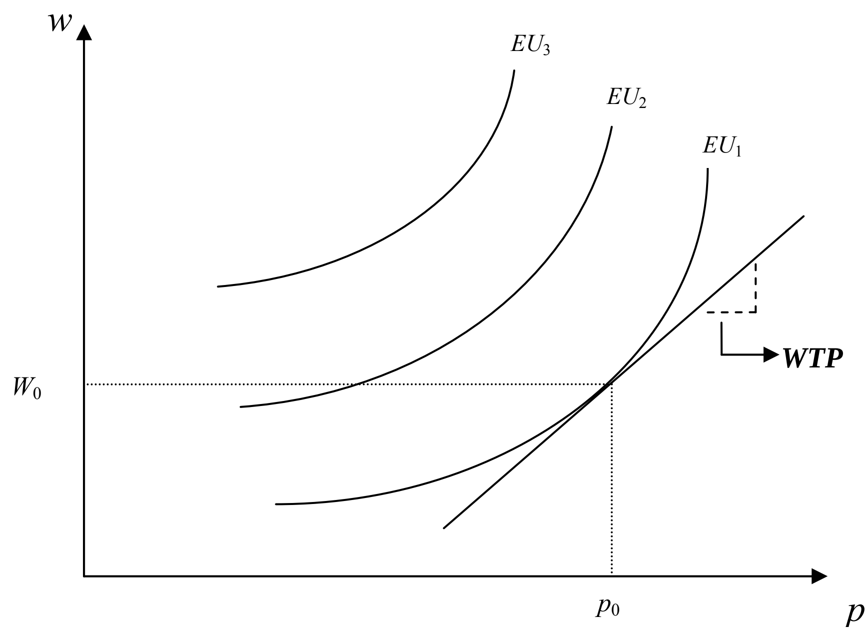
It is also worth analyzing the way WTP varies in relation to w, in order to find the effect of initial wealth on WTP. Intuitively one might expect that a richer person would be willing to pay more than a poorer one. After a few calculations we find:

$$\frac{dWTP}{dw}=\frac{d^2w}{dpdw}=\frac{EU^{'}(w)\left(U_a^{'}(w)-U_d^{'}(w)\right)-EU^{''}(w)\left(U_a(w)-U_d(w)\right)}{\left[EU^{'}(w)\right]^2}. \tag{8}$$

Once again, according to our hypotheses, we can verify that equation (8) is 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 (3). Here this is risk aversion that matters. It 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.

If we accept the hypothesis that the marginal utility of wealth is higher in life than in death, equations (7) and (8) are positive and we can draw the indifference curves between the individual's wealth and probability of death. As shown in Figure 1, the indifference curves are convex with positive slopes. The slope of the indifference curves corresponds to the marginal substitution rate between wealth and probability of death, indicating the individual's willingness-to-pay. Similarly, at the same given probability of death, the individual necessarily moves up to a higher level of expected utility when his wealth increases. Conversely, for a fixed level of wealth, an increase in the individual's probability of death will lower his expected utility.

Figure 1
Shape of Indifference Curves between Wealth and Probability of Death



1.1 More risk aversion and WTP

The literature frequently suggests that risk aversion may modify individuals' willingness-to-pay. It is often claimed that individuals with more aversion to risk are willing to pay more to reduce their probability of death (Eeckhoudt and Hammitt, 2001). This may create problems when the wage-risk method is used to determine the value of a statistical life. On the competitive job market, there is indeed a natural migration of more risk averse individuals towards less risky occupations and *vice versa.* Studies using a wage-risk method might thus underestimate the statistical life of individuals who decide not to take risky jobs and overestimate the statistical life of individuals whose jobs are more risky (Eeckhoudt and Hammit, 2004).

Dachraoui et al. (2004) attempt to explain how individuals' risk aversion influences their willingness-to-pay to reduce these risks. To do so they use the mixed risk aversion model which is often associated with increasing utility functions whose derivatives have alternate signs (Caballé and Pomansky, 1996). They show that if a certain individual A is more risk averse than another individual B, the former will be readier to pay to reduce his risk than B, but only if the probability of death is lower than ½. We can thus affirm that, in general, individuals' WTP does not necessarily increase with risk aversion. This rather surprising result is explained by the fact that a variation in willingness-to-pay implies a first-order effect on wealth and not merely a pure risk-variation effect.

1.2 Heterogeneity in risks

Each individual must face different degrees of risk, which at the same time has its influence on the benefits drawn from each intervention. Viscusi (2000) even describes three sources of heterogeneity in risks which should be taken into account when seeking more viable public safety decisions.

First, there is heterogeneity in exposures to risks; individuals face different degrees of risks depending on their job, their age, their sex, etc. Second, we may find heterogeneity in willingness to accept risk. For example, some people will avoid walking in parks at night for fear of being attacked, whereas others will not perceive this as a very big risk. Finally, there is heterogeneity in individual preferences for risky activities. Scuba diving, downhill skiing, motorcycling or even smoking all introduce greater risk, but their practitioners find satisfaction in these activities. And this satisfaction will vary from one person to the next.

These three different sources of heterogeneity in risks are evidently closely related. People with a passion for high-risk activities should be consistent in their choices. Smoking is probably the best illustration of this point. A study by Viscusi and Hersch (1998) shows that male smokers are 16% less likely to wear their safety belt than are men who do not smoke.

1.3 Concentration of risks

Pratt and Zeckkauser (1996) show that measurement of the aggregated WTP may be affected by the concentration or dispersal of risks within a given population. Suppose there are n individuals with an aggregated risk equal to P. Each of these individuals faces a risk of $p = P/n$ and has the possibility of a $r = R/n$ reduction in this risk. The authors try to find out how the aggregated

WTP to reduce *P* by an amount *R* is affected by the number of individuals exposed (*n*). Two effects can influence the result:

- With the dead-anyway effect, the more highly concentrated the risk, the higher the WTP.
- With the high-payment effect, conversely, the more highly concentrated the risk, the more ready to pay are those concerned, thus increasing the marginal utility of their wealth. This, in some sort, produces an income effect which, for a given gain in utility, will reduce the WTP of those concerned when the risk is more concentrated.

According to Pratt and Zeckhauser (1996), the aggregated WTP seems higher when the risk is concentrated. Since the majority of government interventions make only slight reductions in the probabilities of death, we can suppose that the dead-anyway effect should exert the strongest influence.

This section has given us a better understanding of all the complexity involved in obtaining an accurate measurement of a population's WTP, before making decisions on government projects. In the next section, we shall examine the empirical approach researchers use to measure the WTP of a population sample.

2 Empirical approach

To date, a very large number of empirical studies have been published concerning the value of a statistical life. We shall limit our analysis to the hedonic wage method, since this is where our meta-analysis will be focused.

2.1 Methodology

In his book titled *The Wealth of Nations*, Adam Smith stipulates that the wage of workers will vary depending on their working conditions. This affirmation in fact describes a market for risk. Vying in this market are workers and employers. The workers come to offer their labour in exchange for a wage and the employers to offer a wage for work done. The equilibrium wage resulting from the interaction between the two parties will indicate the amount to be paid for the job. By accepting the job, the worker also accepts its characteristics, including the risks they entail. The hedonic wage method tries to use this equilibrium point to evaluate the risk premium paid to workers.

Figure 2
Equilibrium on the Job Market

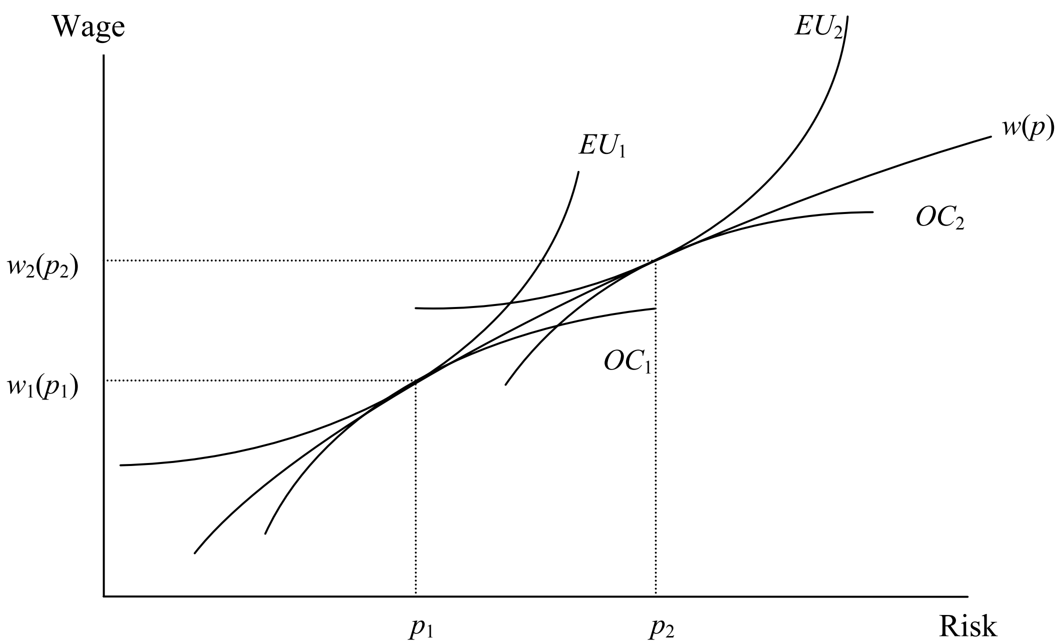


Figure 2 illustrates the situation for two workers and two employers. The indifference curves of the two workers are represented by EU_1 and EU_2. They correspond to equation (5). As for the isoprofit curves, they are represented by OC_1 and OC_2. The two points of tangency found in Figure 2 correspond to the WTP of the two workers. Thaler and Rosen (1975) were the first to use this methodology empirically. Their idea was to estimate a curve intercepting the equilibrium points, as $w(p)$ does in figure 2.

2.2 Econometric model and estimation of WTP

The general model for estimating willingness-to-pay takes the following form:

$$w_i = X_i\beta + p_i\phi \text{ , } i = 1,\dots,n \tag{9}$$

where w_i is the wage of individual i, X_i is a vector of explanatory variables comprising the characteristics of the individual, p_i represents his probability of death, and β and ϕ are associated with the parameters of the equation to be estimated by regression.

According to Mincer (1974), the wage of an individual is instead given by:

$$w_i = e^{(X_i\beta + p_i\phi)} \text{ .} \tag{10}$$

This is the reason why most researchers use the semi-logarithmic form of (9) instead,

$$\ln(w_i) = X_i\beta + p_i\phi \text{ .} \tag{11}$$

By deriving (11) with respect to p_i we obtain,

$$\frac{d\ln(w_i)}{dp_i} = \phi \text{ ,} \tag{12}$$

where ϕ represents the variation in the logarithm of the wage of individual i for a variation of a unit of p_i. In other words, we are looking at the wage premium individual i will ask before accepting a marginal variation in his risk. To obtain the willingness-to-pay (or to accept) what we need instead is $\frac{dw_i}{dp_i}$. From (12) we obtain:

$$\frac{d\ln(w_i)}{dp_i} = \frac{1}{w_i} \cdot \frac{dw_i}{dp_i} = \phi \tag{13}$$

$$WTP = \frac{dw_i}{dp_i} = w_i \cdot \phi . \tag{14}$$

The WTP of individual i is thus obtained by multiplying ϕ parameter by this individual's income. Depending on the dependent variable unit w_i, the WTP will be expressed in hourly, weekly, monthly or annual terms. It is important to take this into account when calculating the value of a statistical life.

The econometric specification is obtained by simply adding a random error term (u_i) to equation (11), reflecting the non-observable factors that influence the wage of i,

$$\ln(w_i) = X_i\beta + p_i\phi + u_i\,,\ i = 1,\ldots,n \tag{15}$$

where

$$u_i \sim N(0, \sigma^2). \tag{16}$$

By using a linear regression with ordinary least squares or other methods to estimate the parameters of equation (15), we obtain $\hat{\phi}$, which is the average wage premium for a marginal increase in the probability of death. Based on equation (15), 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 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 studied as follows:

[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_i is 1/10,000.

$$VSL = \frac{\hat{\phi} \cdot (sample\ average\ of\ \ annual\ income)}{(unit\ of\ \ probability\ of\ death)}, \quad (17)$$

where the numerator corresponds to the WTP in annual dollars and the denominator to the variation in the probability of death (Δp). 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. Moreover, the values obtained may be very sensitive to the econometric specifications used (Ashenfelter, 2006). Our objective is to identify the methodological differences which render VSL evaluations most sensitive.

2.3 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 briefly on a few of these choices and predict their direct or indirect impact on the value of a statistical life.

2.3.1 *Choices 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. It is clear that all the decisions a researcher makes which can influence the characteristics of his sample will also affect the value of a statistical life estimated. Here are a few of the characteristics which may have a strong impact.

As shown in the preceding section, both wage 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 value of a statistical life. As to samples of persons more at risk, the results expected are ambiguous. To date, no study seems to have been done to test these hypotheses directly.

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. A probability of death which would incorporate both men and women should thus more accurately reflect risk for men than for women. This is the reason why certain authors totally exclude women from their sample. Others include them but incorporate a binary variable (man or woman) in their regressions. It is thus possible that whether women are included in or excluded from the sample may have some impact on the coefficients estimated and thus on the VSL.[3]

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. Without this exact information, workers may underestimate their risk and therefore ask for a lower wage in return. 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.[4] Therefore, we do not find consensus on the true influence of unionization on WTP. To measure this impact, certain authors simply split their sample in two (unionized and non-unionized). Others introduce into their regressions a binary unionization variable which interacts with the risk variable. However, in most studies, the authors account for this effect by simply introducing a binary variable without interaction.

[3] Leigh (1987) obtains, however, only a slight difference in the value of a statistical life when he excludes women from his sample.

[4] For a more complete review of studies analyzing the impact of unionization, see Sandy et al. (2001) as well as Viscusi and Aldy (2003).

Racial differences may also influence the values of a statistical life obtained in the studies. Viscusi (2003) has actually devoted an entire article to this subject. He 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. It is worth noting that this racial discrimination may also reduce the mobility of black workers.[5]

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.

2.3.2 *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.[6]

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 thousands of firms in several industries. These data were then compiled using the two- or three-digit Standard Industrial Classification

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[5] According to Dionne and Lanoie (2004), this mobility is essential to the wage-risk analysis.
[6] 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.

(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.

Table 1
Average Probability of Death by Industry
(BLS: 1972-1982, NIOSH: 1980-1985)

Industries	**Number of deaths per 100,000 workers**	
	NIOSH	**BLS**
Mining	40.0	18.7
Construction	32.7	28.7
Manufacturing	4.4	1.5
Transportation, communication and utilities	20.2	10.7
Wholesale trade	2.2	2.7
Retail trade	3.2	2.0
Finance, insurance and real estate	2.3	4.0
Services	3.4	0.9

Source : Moore and Viscusi (1988a)

The National Institute of Occupational Safety and Health (NIOSH) has been allowing researchers to use their occupational data since 1980. The NIOSH obtains its information from the death certificates issued after workplace accidents. According to Viscusi and Moore (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 (Table 1). They observe that the probabilities of death using 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, we find noticeable changes (Table 2). First, the differences between the two bodies are smaller; next, we note that it is now the BSL's turn to post higher probabilities of death.

Table 2
Average Probability of Death by Industry (1992-1995)

Industries	Number of deaths per 100,000 workers	
	NIOSH	BLS
Agriculture, forestry, fishing	17.0	23.9
Mining	24.5	26.3
Construction	12.8	13.4
Manufacturing	3.6	3.8
Transportation, communication and utilities	10.4	10.6
Wholesale trade	3.5	5.4
Retail trade	2.8	3.6
Finance, insurance and real estate	1.1	1.5
Services	1.5	1.8

Source : Viscusi and Aldy (2003)

Some studies also use actuarial data[7] 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.[8] 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 using 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.

[7] See Thaler and Rosen (1973), Brown (1980), Arnould and Nichols (1983) as well as Gegax, Gerking and Schulze (1991).
[8] This expected value is computed in terms of the age structure within each occupation, and using survival tables.

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.

2.3.3 *Choice of models*

Most of the studies use the ordinary least squares method (OLS) to estimate equation (15). These models treat the risk variable as an exogenous one. This hypothesis means that using an OLS would bias the estimated coefficient associated with risk (ϕ). In order to treat the risk variable as endogenous to the model, simultaneous equations must be used. Garen (1988) was the first researcher to adapt this type of model for use in estimating a statistical life. As a rule, higher values of a statistical life are observed in studies using this method (Garen, 1988; Siebert and Wei, 1994; Sandy and Elliott, 1996; Shanmugam, 2001; Gunderson and Hyatt, 2001). Viscusi (1978a) insists that the income effect must be taken into account.

Researchers must also choose the 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 income 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 then 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. Arnould and Nichols (1983) argue that recipients of compensation usually demand lower salaries for increased risk of death. These authors also claim that studies omitting this variable must necessarily obtain biased results. However, we observe that very few American studies incorporate this variable. The main reason for this is probably the difficulty in obtaining data. Empirical evidence has also shown that the existence of compensation implies big reductions in wage levels (Fortin and Lanoie, 2000).

3 Meta-analysis

3.1 Introduction

The term meta-analysis was introduced by Gene V. Glass in 1976. It implies applying a statistical procedure to a set of studies in order to integrate and synthesize them and make full use of the information they contain (Wolf, 1986). Contrary to traditional literature reviews, meta-analyses provide a basis for an exhaustive scientific analysis of results drawn from different studies. Given the scope of data to be analyzed, Glass et al. (1981) maintain that it is essential to use a scientific approach to do a complete and rigorous analysis. Meta-analysis also makes it possible to sharpen the focus of future research (Hunter and Schmidt, 2004). It has not been very surprising to note the emergence of studies using this powerful tool over the past twenty years.

The methodology used in meta-analyses relies mainly on the construction and analysis of a statistical indicator common to each study; this indicator is called the “effect size”. Most meta-analyses compare either correlation coefficients, differences in averages or odds ratios. In our study, the “standardized” outcome is the value of a statistical life.

3.2 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 subsection, we shall make a brief survey of these meta-analyses.[9]

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 used 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. In their analysis, the same weight is assigned to each of the 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 is not statistically significant.

Miller (2000) uses a sample composed of 68 studies from 13 different countries. Unlike Liu et al. (1997) who use only studies favouring the wage-risk method, Miller also includes studies using 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 it uses the gross domestic product (GDP) and the gross national product (GNP) *per capita* as explanatory variables instead of personal income. Once again, the same weight is assigned to each of the studies. 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.

[9] For literature reviews on the subject, the reader can consult the works of Fisher et al. (1989), Miller (1990) and Viscusi (1993).

Bowland and Beghin (2001) do a meta-analysis based on the 33 studies used in Viscusi (1993) and Desvousges et al. (1995). These studies all come from industrialized countries and use either the wage-risk method or the contingent evaluation method. The authors' goal being to use 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 a Huber-type (1964, 1981) 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. As seen above, these characteristics can partially 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 used. As already mentioned, this procedure may possibly produce a distortion, since the observations lose their independence. To guard against giving more weight to studies using 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. Using 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 sample (2002), only the studies employing the wage-risk method are selected. The estimation is made using Huber's robust regressions (1981) 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 using 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 use several VSLs from the same study. The aim of their article is to explain the origin of the variations observed in the VSLs estimated by this type of study. The authors are particularly interested in comparing the effect produced by using the revealed-preference as opposed to the contingent-evaluation approach. They use a two-step methodology. They start of by performing a bivariate analysis with Q-Tests.[10] 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 (which would be more appropriate), they use the size of their samples as weights.[11] They obtain a significant income elasticity of 1.67, where incomes are 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 using 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-preferences approach produces significantly lower VSLs than does the contingent-evaluation approach.

[10] Q-Tests serve to detect heterogeneity in a subgroup.

[11] Since the size of the sample is usually inversely related to the variance, researchers often use it to replace or estimate the variance.

Table 3
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 to 1.00
Bowland and Beghin (2001)	+	YES	+	YES	1.7 to 2.3
Mrozek and Taylor (2002)	+	YES	+	YES	0.46 to 0.49
Viscusi and Aldy (2003)	-	YES	+	YES	0.46 to 0.60
de Blaeij et al. (2003)	+	YES	+	YES	0.5

In Table 3, we present a summary of the results from the different meta-analyses performed.[12] 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 the income elasticity obtained by these different meta-analyses is always equal to or lower than 1, except for the Bowland and Beghin study (2001). 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 thus seems ambiguous.

3.3 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 of studies estimating the value of a statistical life. By employing a mixed effects regression model (Raudenbush,

[12] The six meta-analyses just presented were chosen based on their popularity in the literature. They are also, to our knowledge, the only ones published in a scientific journal. For other meta-analyses, the reader can consult Desvousges et al. (1995); Day (1999); Dionne and Michaud (2002).

1994), we want to distinguish our contribution from all the other meta-analyses performed so far.

First, suppose that each study uses a perfectly identical methodology and that the samples used are all the same size and constructed randomly from the same population. The VSLs obtained will not be identical because the samples used are most likely different. However, we can state that 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. If we believe that the variability in the results obtained is strictly due to this estimation variance, then we should use a fixed-effects model. But several methodological differences are observable in 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 would 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.

We shall now present the mixed effects regression model in greater detail, describing each of the procedures to be followed. We must first estimate the value of a statistical life VSL_j in each of the m studies selected. This means estimating the "true" value of a statistical life θ_j. The relation between the two values can then be written as follows:

$$VSL_j = \theta_j + e_j, \qquad j = 1...m \tag{18}$$

where the estimation errors (e_j) are independent, of null mean and of variance equal to $\sigma^2_{VSL_j}$, corresponding to the sample's variability. We next construct a model to predict the true value of a statistical life:

$$\theta_j = \beta_0 + \sum_{k=1}^{p} \beta_k X_{jk} + u_j, \tag{19}$$

where

β_0 is the constant;

X_{jk} are the characteristics of study *j* which estimate VSL_j;

$\beta_1,...,\beta_p$ are the coefficients of the regression which capture the relation between θ_j s and the characteristics of the studies;

u_j is a random effect term associated with study *j* which takes into account the non-observed effects that influence θ_j. Each random effect is independent, with a mean of zero and a variance of σ_θ^2.

In a fixed effects model, the random effect is simply withdrawn from equation (19). This model thus supposes that the characteristics of the studies fully explain the variations in true VSLs between these studies. The mixed effects regression model, for its part, 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 true VSLs.

By substituting (19) in (18) we obtain the mixed effects regression model to be estimated:

$$VSL_j = \beta_0 + \sum_{k=1}^{p} \beta_k X_{jk} + u_j + e_j . \qquad (20)$$

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 $\left(\sigma_{VSL_j}^{2*}\right)$, as conditioned by the characteristics of X_{jk}, is found by:

$$\sigma_{VSL_j}^{2*} = Var(u_j + e_j) = \sigma_\theta^2 + \sigma_{VSL_j}^2 , \qquad (21)$$

where $\sigma_{VSL_j}^2$ is the variance in the *VSL* estimation in study *j* (*j* = 1,…,*m*).

As Raudenbush (1994) maintains, it would not be appropriate to use an OLS regression to estimate equation (20), since this sort of method takes 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 $\left(\sigma^{2*}_{VSLj}\right)$ is not constant, since $\sigma^2_{VSL_j}$ differs from one study to the next. We must therefore use the weighted least squares method where the optimal weights are the inverse of the variances obtained in each of the studies:

$$w_j^* = 1/\sigma^{2*}_{VSL_j} = 1/\left(\sigma^2_\theta + \sigma^2_{VSL_j}\right). \tag{22}$$

If σ^2_θ is null, then the fixed-effects model will be adequate and the optimal weights will be $1/\sigma^2_{VSL_j}$. The calculation of $\sigma^2_{VSL_j}$ is rather straightforward and requires only certain data contained in the studies, one being the standard deviation associated with coefficient $\hat{\phi}$. As we see in equation (22), calculating the optimal weights for the mixed effects regression model requires an additional term—the variance of the random effect $\left(\sigma^2_\theta\right)$. This effect is not given in the studies and must thus be estimated. We use the method of moments to estimate the parameters of equation (20).

4 Analysis of the sample

4.1 Choice of studies

Most of the studies have been drawn from literature reviews in the works of Viscusi (1993, 2003,) and Michaud (2001). Other articles have been retrieved by key-word searches with the search engines Proquest, ScienceDirect, JSTOR, EconLit and SSRN.[13] 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.

[13] The key words used are the following: "*value of a statistical life', "wage + risk", "wage + compensation", "risk + compensation", "life + risk", "wage premium + risk"*. The search period ran from January 2005 to August 2005.

First, we excluded the Lott and Manning study (2000), since their work focuses solely on the risks of death from cancer contracted in the workplace. Their VSL cannot be compared to the estimations of the other studies which use a much broader definition of risk of death. Next, to get a more homogeneous sample, we withdrew the studies whose estimation was not obtained with a regression similar to equation (11). The studies by Melinek (1974) and Needleman (1980) were not selected, as they are the only ones that do not use a regression. We also wanted that each VSL estimate 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), of Sandy et al. (2001), and of Kniesner and Viscusi (2005).[14]

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 were removed. Among these studies are to be found those of Moore and Viscusi (1988b, 1989, and 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 without contradiction 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 will be chosen from studies that use only one sample. 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. We do however believe that adding these estimations can help us discern more clearly the source of the variability in results, which is the primary objective of this work. This decision concerns

[14] The studies that use the same samples are respectively those of Moore and Viscusi (1989), Sandy and Elliott (1996) and Viscusi (2004). The articles were simply chosen chronologically by date of publication. The first article to have used the sample in question was retained.

only two articles (Leigh and Folsom, 1984; Kniesner and Leeth, 1991), for a total of five observations. So we use 40 observations.

4.2 Descriptive statistics

We use equation (17) to calculate the value of a statistical life for each of the 40 observations retained. When the specifications contain interaction variables, the value of a statistical life is calculated using the average of each of the variables. For example, the specification chosen contains a squared risk variable as well as a risk variable interacting with age:

$$\ln(w_j) = X_j\beta + p_j\phi_1 + p_j^2\phi_2 + p_j age_j\phi_3 + u_j, \qquad (24)$$

where $p_j = \frac{1}{n_j}\sum_{i=1}^{n_j} p_{ij}$ and $age_j = \frac{1}{n_j}\sum_{i=1}^{n_j} age_{ij}$ are respectively the average probability of death and average age of the n_j individuals in study j. Then the VSL calculation will take this form:

$$\left(\hat{\phi}_1 + 2p_j\hat{\phi}_2 + age_j\,\hat{\phi}_3\right)\cdot\left(sample\ \ average\ \ of\ \ annual\ \ income\ \right)_j \cdot 1/(unit\ \ of\ \ risk\ )_j\ .$$

Each of the values was first calculated using the original data from the studies. Since most of the studies come from the United States, we decided to use the $US 2000 as the common monetary unit. This makes it possible to minimize the number of conversions required and thus any possible calculation errors. 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.[15] As Summers and Heston (1991) point out, when comparing incomes from several countries, it is absolutely necessary 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 using the consumer

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

price index (CPI)[16] to adjust VSL and average income values to $US 2000. These 40 observations are presented in Appendix 1.

Table 4
Average Value of a Statistical Life according to Country of Origin

	Number	Average	Median	Standard deviation
United States	22	6,811,237	6,128,222	4,967,967
Canada	7	9,160,083	4,041,961	10,392,347
United Kingdom	4	26,153,462	22,469,126	21,003,845
Australia	2	11,173,881	11,173,881	9,625,769
Austria	1	8,369,952	8,369,952	-
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	40	9,523,347	6,599,247	10,183,847

The average value obtained for the VSLs from the 40 observations stands at $9.5 M and the median at $6.6 M (Table 4). Of these studies, 22 come from the United States and their average value is $6.8 M. The average and median of values from the United Kingdom ($26.2 M and $ 22.5 M) are definitely higher than the average. It could thus be interesting to take this aspect into account in our meta-analysis. This can be done by inserting the study's country of origin into our models as an explanatory variable.

In Table 5, we present a descriptive analysis of the most important methodological factors. Among other things, we note that 95% of the studies use an observed risk measurement, that

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

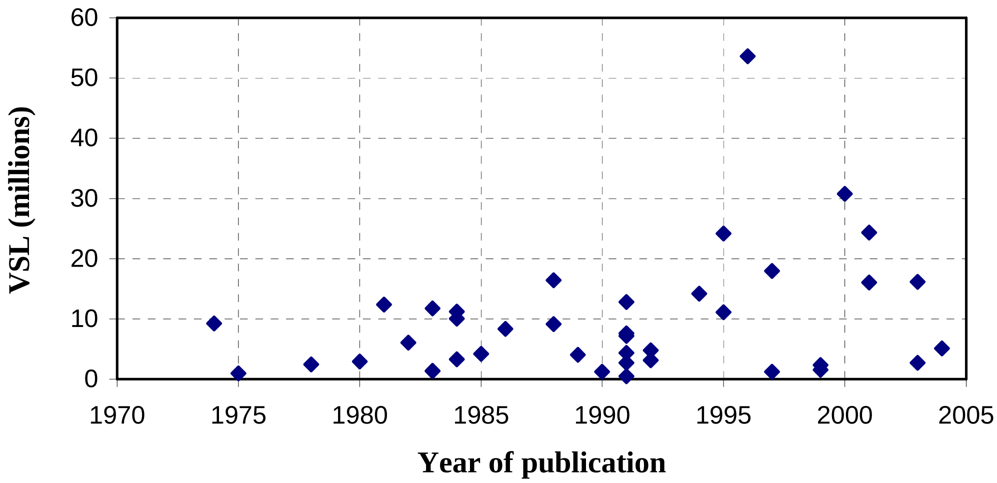
13% treat the risk of death as endogenous, and that 10% have recourse to data from the Society of Actuaries (SOA).

Table 5
Descriptive Statistics of the Sample (n = 40)

Variables	Average	Standard deviation	Minimum	Maximum
Average income ($US 2000)	29,395	9,248	3,038	49,019
Average probability (× 10,000)	2.06	2.47	0.32	10.98
White-workers only sample	15%	-	-	-
Men only sample	50%	-	-	-
Unionized only sample	15%	-	-	-
Sample without white collars	48%	-	-	-
Injuries taken into account	58%	-	-	-
Compensation taken into account	20%	-	-	-
Endogenous risk	13%	-	-	-
Observed risk	95%	-	-	-
SOA	10%	-	-	-

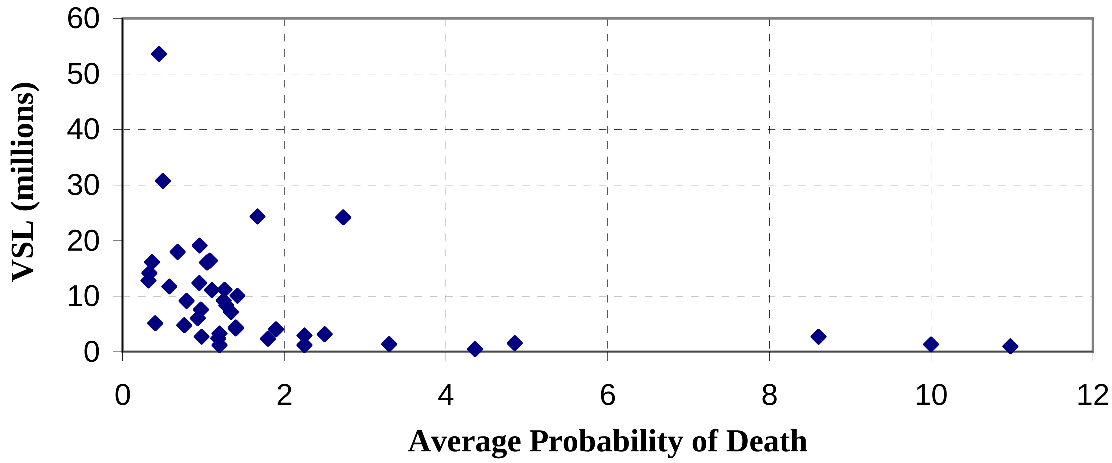
After 30 years of research and publication on the topic, we might expect a certain convergence in the values obtained. When we examine Figure 3, we note quite the contrary. The most recent studies seem to diverge instead. And it is also interesting to observe a positive relation between the values of 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 in use 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.

Figure 3
Estimations of the Value of a Statistical Life over Time



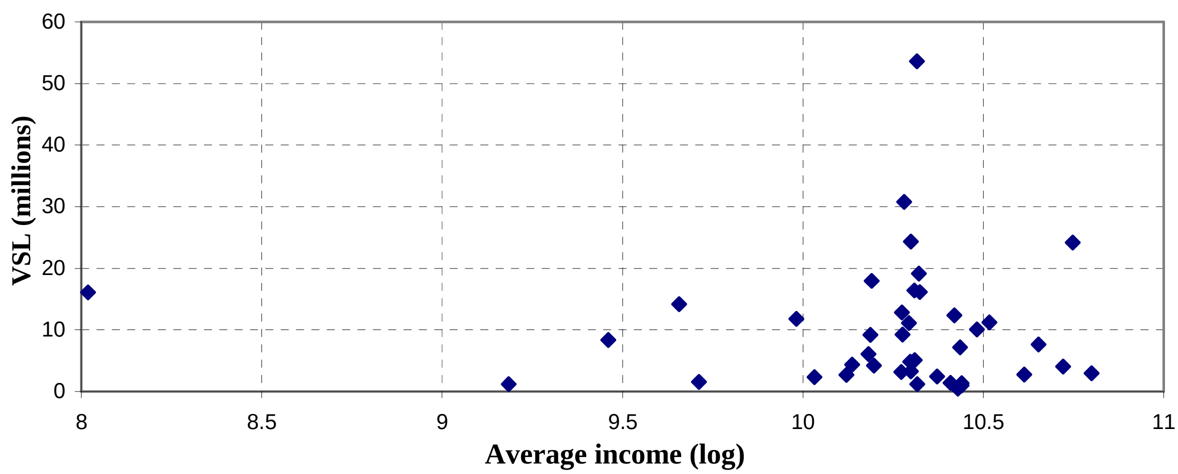
In Figure 4, we present the relation between the value of a statistical life and the probability of death. At first sight, this relation seems negative. When we analyze the figure more closely, we note that this relation is amplified by three extreme values for the probability of death. These values come from the studies by Thaler and Rosen (1975), Arnould and Nichols (1983) and Gegax et al. (1991). In all three cases, the authors use data from the Society of Actuaries (SOA) to assign the risk mortality in the workplace. We shall take these facts into account in our meta-analysis.

Figure 4
Relation between Probability of Death and Value of a Statistical Life



We expect a positive relation between average income and value of a statistical life. However, this is not definitely confirmed by Figure 5. The meta-analysis, using the natural logarithm of the average income in equation (20), may tell us more about this relation.

Figure 5
Relation between Average Income (log) and Value of a Statistical Life



The source of the studies selected is also an important factor to be considered. In fact, the process of selection and publication differs from one scientific journal to the next and may be a source of distortion. Among other things, it is possible that some journals will favour studies that obtain results that fall in line with trends in the literature. And, depending on the journal's line of thought, it may happen that only articles with very strong or very weak results will be selected.[17]

5 Results

5.1 Restriction on model

In equation (22) we saw that the value-of-a-statistical-life variance $\left(\sigma^2_{VSL_j}\right)$ is needed to construct optimal weights. We calculate this variance by using the standard deviation associated with coefficient $\hat{\phi}$. This statistic is often included in regression analyses to measure the accuracy of estimations. It corresponds to the square root of the variance. The standard error of the value of a statistical life is calculated in this manner:

$$SE(VSL_j) = \frac{SE(\hat{\phi}_j) \cdot (sample\ average\ of\ annual\ income)_j}{(unit\ of\ probability\ of\ death)_j}. \tag{25}$$

The sample average of annual income and the unit of probability of death in equation (25) correspond exactly to the same variables used in equation (17). 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:

$$\ln(w_{ij}) = X_{ij}\beta + p_{ij}\phi_{1j} + (p_{ij} \cdot age_{ij})\phi_{2j} + u_{ij}, \quad i = 1,...,n_j, \quad j = 1,...,m. \tag{26}$$

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

$$VSL_j = \frac{(\hat{\phi}_{1j} + age_j\,\hat{\phi}_{2j}) \cdot (sample\ average\ of\ annual\ income)_j}{(unit\ of\ probability\ of\ death)_j}. \tag{27}$$

[17] Remember that some authors may refrain from publishing their results so as not to damage their research record. For example, they may do so when the results obtained are not significant or when these results are the opposite of what was expected.

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

$$SE(VSL_j) = \frac{\left[\sqrt{\sigma_{1j}^2 + (age_j)^2 \sigma_{2j}^2 + 2\, age_j \operatorname{cov}(\hat{\phi}_{1j}, \hat{\phi}_{2j})}\right] \cdot (sample\ average\ of\ annual\ income)}{(unit\ of\ probability\ of\ death)_j} . \quad (28)$$

However, the covariances needed to calculate the standard errors are not usually published by the authors. This prevents us from calculating the standard deviations for VSLs drawn from articles using terms of interaction. Looking at Appendix 1, we note that eight observations are affected by this problem. For the moment, we withdraw these observations from our sample and use the 32 others to estimate the determinants of the variability of the values of a statistical life. We reintroduce the 8 observations at the end of Section 5.2, for sensitivity analysis.

5.2 Results and discussion of the meta-analysis

In Table 6, we present the results of the meta-analysis. It is important to explain two aspects of the table. First, the statistic $\hat{\sigma}_\theta^2$ at the bottom of the table represents the variability left unexplained by the model. The weaker this variable, the greater the amount of variability explained by the model. Before analyzing the parameters, it is worth mentioning that a test hypothesis was applied to each specification to find out if the random effect variance is null. If we do not reject hypothesis $\sigma_\theta^2 = 0$, then the statistically significant characteristics of the studies included in the specification of the model explain all the variability observed between the VSLs. If we reject hypothesis $\sigma_\theta^2 = 0$, then a portion of the variability observed remains unexplained. The hypothesis of a null random effect has been rejected for all the specifications (see Table 6).

The first specification in Table 6 includes only the constant. The estimation of the constant in this model is 5,863,609 (95% C.I.: 4,669,805; 7,057,414) 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 equation (22).

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. According to some authors, this result is to be explained by the use of new econometric tools such as the endogeneity of the probability of death. However, we cannot adopt this strategy, since the binary variable accounting for this endogeneity is present in each of the models. This variable does not seem to have any effect on the significance of the coefficient associated with the year of publication.

Table 6
Results of the Meta-analysis

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

Notes :
1. Dependent variable: VSL.
2. Absolute value of the Student statistic between parentheses.

We obtain a positive relation between the value of a statistical life and the logarithm of the sample's average income. It is thus true 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 for us to point out the importance of using a representative sample when assigning a value of a statistical life to a certain population.

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. This result is not very surprising. We have already mentioned that the studies using this source are characterized by a very high average probability of death. However, the SOA variable is found 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.[18]

We can say that the studies using the risk of death as an endogenous variable do have high values of a statistical life. This confirms the results obtained by Garen (1988), Siebert and Wei (1994), Sandy and Elliott (1996), Shanmugam (2001) as well as Gundersen and Hyatt (2001). Something else that must be pointed out is the strength and scope of the significance of the

[18] We are aware that a non-significant correlation coefficient, presented in Appendix 2, may hide a certain relation, especially when binary variables are involved. We shall however focus our attention solely on the strong correlations.

parameter estimated in each of the specifications. The studies that treat risk endogenously obtain, on average, values of a statistical life between \$12 and \$13 M higher than those using other procedures—*ceteris paribus*. Accepting the hypothesis that the risk variable must be treated in this way, the studies using other procedures would end up underestimating the VSL considerably. It is thus of primary importance for researchers to form a consensus as to the relevance of using this methodology.

Studies incorporating a variable measuring compensation for work accidents obtain, on average, values of a statistical life that are from \$3.5 to \$5 M lower than other studies, depending on their specification. It is thus true that individuals who benefit from compensation usually demand lower pay hikes when their risk of death increases.

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? It would be interesting to study this question more in depth. This is not, however, the objective of this article.

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 a nominal level of 10%. But then a hard and clear relation was never expected.

We used Table 4 to point 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 differences between countries. Do British institutions use different procedures when collecting information on workers? Or is it rather British researchers who use particular methodologies that push the VSL higher?[19]

Finally, in specification 5, we have included the binary SOA variable in order to account for the source of the risk variable. However, the use of this source does not seem to have any impact on the value of a statistical life. But the SOA variable is correlated significantly with two other independent variables (Appendix 2). First, we notice a negative correlation 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 70s and the 80s. Next, we find a positive correlation with the average probability of death. Once again, these results are not surprising, since we knew that using this source would generate much higher than average probabilities of death.[20]

In light of these observations, we do not think the SOA variable should be used in a model including the "average probability of death" variable or the "year of publication" variable. For this reason, we redid an 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.[21] We can conclude that using the SOA as a 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 value of a statistical life presented in Table 6 is not simply due to the fact that our sample includes studies using the SOA. We thus withdrew the observations

[19] Each study uses the hedonic wage method. But they have not all been conducted in the same work environment nor in the same analytical spirit. Each researcher has his own way of doing things and his own way of solving problems.

[20] In our complete sample composed of 40 observations, we note that studies using the SOA report an average probability of death of 7.96 deaths per 10,000 workers, whereas the others obtain a 1.40 probability. For our reduced sample of 32 observations, the probabilities are respectively 7.28 and 1.50.

using the SOA from our sample and then estimated the parameters again. Though this operation involved only three observations, a careful analysis of Figure 4 shows that, when such observations correspond to extreme values, it takes only a few to influence results. The new results are presented in Table 7.

The coefficient associated with the probability of death remains negative and is more significant for each of the specifications than in Table 6. This leads us to conclude that the relation between the average probability of death and the value of a statistical life 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.

We thus refute the intuition expressed by Pratt and Zeckhauser (1996), that use the dead-anyway effect to predict the opposite result. Our results corroborate the theoretical works of Dionne (1982) as well as those of Breyer and Felder (2005). Other investigations must however be made to re-examine the theoretical properties of WTP. It is, among other things, theoretically impossible to obtain both a negative sign in equation (7) and a positive one in equation (8). Yet this is what we do obtain empirically. This result can be explained by the fact that, when heirs are taken into account, the marginal utility of workers is higher in case of their death than that prevailing when they are alive. As for the other parameters estimated and presented in Table 7, we observe no major difference between them and the results shown in Table 6. 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.

[21] 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.

Table 7
Results of the Meta-analysis (without SOA)

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

Notes :
1. Dependent variable : VSL
2. Absolute Student statistic between parentheses.

We previously withdrew eight observations for which standard error could not be calculated. However, we 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 apply 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 used in this regression model. As a rule, the larger the sample size used, the more accurate the VSL estimation (weak SE/VSL relation).[22] Several researchers indeed use sample size to approximate the standard deviation, since it is an easily accessible variable. We then use the regression equation and the sample sizes of the eight studies selected to estimate the SE/VSL. Next, since we know the values of statistical life, we can easily determine the standard errors. Finally, using the 40 observations, we repeat the same analysis as applied to Tables 6 and 7. 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 sample" 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. However, no relation was observed. Our different tests also allowed us to conclude that using a sample composed solely of white-collar workers has no influence on the VSL. And using an observed probability of death does not seem to influence significantly the VSL. Finally, we obtain mixed results for

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

the “men only” variable. In certain specifications, we can observe a positive and slightly significant relation (10% level) between using 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 3), 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).

5.3 Implications for governments

Surveying the results obtained, we can conclude that it is of primary importance that the sample used for the VSL estimation should be representative of the population targeted by the government project. Indeed, we have seen that individuals’ willingness-to-pay varies with average income, average probability of death, and race. This also means that governments must adjust the VSLs calculated with WTPs from other countries before attempting to apply them in their own country. However, given the numerous influential factors involved, this “conversion” of the VSL is far from easy. The ideal would be to measure the VSL directly, based on a sample of the target population. But this would be quite costly.

Conclusion

For over 30 years now, economists have been trying to measure the value of a statistical life by various means. 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. First, we have come to realize that the theoretical properties of the WTP are rather fragile and apparently do not provide a very good empirical fit with those of the VSL. Then, surveying the numerous studies having tried to use the WTP to estimate the VSL, we find wide discrepancies in the values obtained: this poses a problem for governments. 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 use 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 methodology. The samples composed of wealthier economic agents that are less exposed to risk of death generate higher VSLs. These results inform public decision-makers of the importance of using representative samples or of adjusting the estimated values to the target populations when making a decision.

Several other methodological factors also have a strong impact on the VSLs estimated. For example, researchers who take the endogenous nature of the risk variable into account obtain considerably 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. Finally, we note that the VSL is significantly influenced by a study's country of origin, year of publication, and the source of its risk variable.

Appendix 1: Detailed Description of Studies Selected

#	Authors	Year of publication	Country	Sample size	Average income[1]	Average probability of death[2]	Compensation	Endogeneity of risk	White workers sample	Union sample	SOA	VSL[1]	Standard error (VSL)[1]
1	Smith	1974	USA	3,183	29,029	1.25	0	0	1	0	0	9,231,222	3,846,343
2	Thaler and Rosen	1975	USA	907	34,195	10.98	0	0	0	0	1	977,980	594,995
3	Viscusi (b)	1978	USA	496	31,953	1.182	0	0	0	0	0	2,444,383	1,405,920
4	Brown	1980	USA	470	49,019	2.25	0	0	0	0	1	2,941,140	588,228
5	Olson	1981	USA	5,993	33,509	0.9508	0	0	0	0	0	12,374,191	-
6	Marin and Psacharopoulos	1982	UK	5,509	26,415	0.93	0	0	0	0	0	6,049,041	1,338,283
7	Arnould and Nichols	1983	USA	1,832	34,195	10	1	0	0	0	1	1,351,335	-
8	Dorsey and Walzer	1983	USA	1,697	21,636	0.5756	1	0	0	1	0	11,768,688	-
9	Low and McPheters	1983	USA	72	33,172	3.3	0	0	0	0	0	1,391,218	1,008,129
10	Dillingham and Smith	1984	USA	879	29,707	1.2	0	0	1	1	0	3,294,506	1,565,559
11	Leigh and Folsom - 1	1984	USA	1,529	35,694	1.42	0	0	1	0	0	10,067,308	-
12	Leigh and Folsom - 2	1984	USA	361	36,946	1.26	0	0	1	0	0	11,193,983	-
13	Dillingham	1985	USA	514	26,825	1.4	0	0	0	0	0	4,189,995	2,323,006
14	Weiss et al.	1986	Austria	4,225	12,841	1.28	0	0	0	0	0	8,369,952	-
15	Garen	1988	USA	2,863	30,013	1.08	0	1	0	0	0	16,416,982	3,538,143
16	Moore and Viscusi (a)	1988	USA	1,349	26,559	0.7918	0	0	1	0	0	9,162,972	2,390,341
17	Meng	1989	Canada	718	45,313	1.9	0	0	0	0	0	4,041,961	2,336,394
18	Meng and Smith	1990	Canada	777	30,236	1.2	0	0	0	0	0	1,216,395	2,252,583
19	Berger and Gabriel	1991	USA	22,837	42,316	0.97	0	0	0	0	0	7,616,966	1,336,310
20	Gegax et al.	1991	USA	228	40,664	8.6075	0	0	0	1	1	2,732,627	1,379,418
21	Kniesner and Leeth - 1	1991	Japan	20	28,975	0.32	0	0	0	0	0	12,812,755	6,707,897

#	Authors	Year of publication	Country	Sample size	Average income[1]	Average probability of death[2]	Compensation	Endogeneity of risk	White workers sample	Union sample	SOA	VSL[1]	Standard error (VSL)[1]
22	Kniesner and Leeth - 2	1991	Australia	44	25,260	1.4	1	0	0	0	0	4,367,434	1,753,567
23	Kniesner and Leeth - 3	1991	USA	8,868	33,843	4.36	1	0	0	0	0	461,958	310,247
24	Leigh	1991	USA	1502	34,045	1.34	0	0	0	0	0	7,149,454	2,175,732
25	Cousineau et al.	1992	Canada	32,713	29,658	0.764	0	0	0	0	0	4,804,628	464,664
26	Martinello and Meng	1992	Canada	4,352	28,925	2.5	0	0	0	0	0	3,144,141	949,892
27	Siebert and Wei	1994	UK	1,353	15,627	0.332	0	1	0	1	0	14,181,264	6,746,558
28	Lanoie et al.	1995	Canada	63	46,535	2.73	0	0	0	1	0	24,198,149	7,657,642
29	Leigh	1995	USA	1,528	29,552	1.1016	0	0	0	0	0	11,111,731	2,084,361
30	Sandy and Elliott	1996	UK	440	30,211	0.452	0	1	0	1	0	53,626,554	-
31	Liu et al.	1997	Taiwan	18,987	9,748	2.252	0	0	0	0	0	1,198,975	106,623
32	Miller et al.	1997	Australia	18,850	26,638	0.68	0	0	0	0	0	17,980,328	1,369,408
33	Kim and Fishback	1999	South Korea	321	16,516	4.85	0	0	0	0	0	1,552,525	324,796
34	Meng and Smith	1999	Canada	1,503	22,743	1.8	1	0	0	0	0	2,353,931	609,827
35	Arabsheibani and Marin	2000	UK	3,608	29,176	0.5	0	0	0	0	0	30,756,987	6,179,825
36	Gunderson and Hyatt	2001	Canada	2,014	29,709	1.67	0	1	0	0	0	24,361,374	3,460,422
37	Shanmugam	2001	India	522	3,038	1.04407	0	1	0	0	0	16,070,278	7,183,853
38	Leeth and Ruser	2003	USA	45,001	24,860	0.9757	1	0	0	0	0	2,723,710	-
39	Viscusi	2003	USA	83,625	30,449	0.362	1	0	1	0	0	16,137,876	1,522,441
40	Viscusi	2004	USA	99,033	30,041	0.402	1	0	0	0	0	5,106,991	600,822

1. In $US 2000
2. Number of deaths per 10,000 workers.

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

* Correlation is significant at the 5% level (bilateral).
** Correlation is 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
$\hat{\sigma}_\theta^2$	9.77E+12	8.55E+12	8.50E+12	8.51E+12

Notes:
1. Dependent variable: VSL
2. Absolute Student statistic between parentheses.

Appendix 4: Results of the Meta-analysis (with Standard Errors Estimated for 8 Studies)

	Specifications							
	With SOA				Without SOA			
Variables	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Constant	-3.97E+08 (2.12)	-4.66E+08 (2.59)	-4.76E+08 (2.62)	-6.23E+08 (3.32)	-5.21E+08 (2.40)	-5.85E+08 (2.80)	-5.80E+08 (2.75)	-7.08E+08 (3.25)
Year of publication	184,754 (2.03)	219,159 (2.52)	223,620 (2.55)	291,584 (3.22)	248,762 (2.35)	280,942 (2.76)	278,546 (2.72)	337,123 (3.20)
Average income (log)	3,626,952 (2.18)	3,551,251 (2.25)	3,626,666 (2.29)	4,761,568 (2.93)	3,488,098 (1.86)	3,407,577 (1.91)	3,397,342 (1.92)	4,425,177 (2.42)
Average probability of death	-634,069 (2.93)	-469,696 (2.23)	-443,487 (2.04)	-287,572 (1.30)	-2,084,163 (3.74)	-1,800,054 (3.36)	-1,793,931 (3.40)	-1,491,716 (2.77)
Endogeneity of risk	12,902,625 (4.53)	13,479,523 (4.86)	13,588,788 (4.88)	13,410,361 (4.85)	11,595,421 (3.91)	12,140,100 (4.22)	12,207,269 (4.23)	12,148,468 (4.23)
Compensation	-2,232,200 (1.52)	-2,484,263 (1.80)	-2,589,727 (1.86)	-2,690,067 (1.96)	-3,562,007 (2.05)	-3,747,619 (2.29)	-3,731,196 (2.30)	-3,735,292 (2.33)
White workers sample	-	4,358,706 (2.56)	4,623,587 (2.59)	5,506,240 (3.07)	-	3,502,495 (1.93)	3,579,507 (1.90)	4,382,707 (2.30)
Union sample	-	-	-1,035,050 (0.50)	-1,621,242 (0.79)	-	-	-297,019 (0.11)	-501,825 (0.19)
UK Study	-	-	-	6,193,274 (2.59)	-	-	-	5,164,928 (2.05)
N	40	40	40	40	36	36	36	36
$\hat{\sigma}_{\theta}^{2}$	7.64E+12	6.50E+12	6.52E+12	6.27E+12	8.82E+12	7.51E+12	7.26E+12	7.03E+12
Average value of a statistical life ($US 2000)	5,774,145 (95% C.I.: 4,705,384; 6,842,904)				6,628,822 (95% C.I.: 5,382,802; 7,874,842)			

Bibliography

ARABSHEIBANI, G. Reza and Alan MARIN (2000). “Stability of Estimates of the Compensation for Danger,” *Journal of Risk and Uncertainty*, vol. 10, n° 3, p. 247-269.

ARNOULD, Richard J. and Len M. NICHOLS (1983). “Wage-Risk Premiums and Worker’s Compensation: A Refinement of Estimates of Compensating Wage Differentials,” *Journal of Political Economy*, vol. 91, p. 332-340.

ARTHUR, W. Brian (1981). “The Economics of Risks to Life,” *American Economic Review*, vol. 71, n° 1, p. 54-64.

ASHENFELTER, Orley (2006). “Measuring the Value of a Statistical Life: Problems and Prospects,” *The Economic Journal*, vol. 116, C-10-C23.

BERGER, Mark C. and Paul E. GABRIEL (1991). “Risk Aversion and the Earnings of U.S. Immigrants and Natives,” *Applied Economics*, vol. 23, p. 311-318.

BLINCOE, Lawrence J., Angela G. SEAY, Eduard ZALOSHNJA, Ted R. MILLER, Eduardo O. ROMANO, Stephen LUCHTER, and Rebecca S. SPICER (2002). “The Economic Impact of Motor Vehicle Crashes, 2000,” Washington D.C.: National Highway Traffic Safety Administration, DOT HS 809 446, 86 p.

BLOMQUIST, G. (1979). “Value of a statistical life Saving: Implications of Consumption Activity,” *Journal of Political Economy*, 87(3), 540-558.

BOWLAND, Bradley J. and John C. BEGHIN (2001). “Robust Estimates of Value of a Statistical Life for Developing Economies,” *Journal of Policy Modeling*, vol. 23, p. 385-396.

BREYER, Friedrich and Stefan FELDER (2005). “Mortality Risk and the Value of a Statistical Life: The Dead-Anyway Effect Revis(it)ed,” *The Geneva Risk and Insurance Review*, vol. 30, n° 1, p. 41-56.

BROWN, Charles (1980). “Equalizing Differences in the Labor Market,” *Quarterly Journal of Economics*, vol. 94, n° 1, p. 113-134.

CABALLÉ, Jordi and Alexey POMANSKY (1996). “Mixed Risk Aversion,” *Journal of Economic Theory*, vol. 71, p. 485-513.

CHESTNUT, L.G., D. MILLS and R.D. ROWE (1999). “Air Quality Valuation Model Version 3.0 (AQVM 3.0) Report 2: Methodology,” prepared for Environment Canada, *Health Canada by Status Consulting Inc*., Boulder, CO.

COOK, Phillip J. and GRAHAM, Daniel A. (1977). "The Demand for Insurance and Protection: The Case of Irreplaceable Commodities," Journal of Quantitative Economics, vol. 91, p. 143-156.

COUNCIL OF ECONOMIC ADVISERS (2005). "Economic Report of the President," Washington, DC: Government Printing Office.

COUSINEAU, Jean-Michel, Robert LACROIX and Anne-Marie GIRARD (1992). "Occupational Hazard and Wage Compensating Differentials," *The Review of Economics and Statistics*, p. 166-169.

DACHRAOUI, Kais, Georges DIONNE, Louis EECKHOUDT and Philippe GODFROID (2004). "Comparative Mixed Risk Aversion: Definition and Application to Self-Protection and Willingness to Pay," *Journal of Risk and Uncertainty*, vol. 29, n° 3, p. 261-276.

DARDIS, Rachel (1980). "The Value of a statistical life: New Evidence from the Marketplace," *American Economic Review*, vol. 70, n° 5, p. 1077-1082.

DAY, Brett (1999). "A Meta-analysis of Wage-risk Estimates of the Value of Statistical Life," *Centre for Social and Economic Research on the Global Environment*, University College London, mimeo.

De BLAEIJ, Arianne, Raymond J.G.M. FLORAX, Piet RIETVELD and Erik VERHOEF (2003). "The Value of Statistical Life in Road Safety: A Meta-Analysis," *Accident Analysis and Prevention*, vol. 35, p. 973-986.

DESVOUSGES, William H., F. Reed JOHNSON, H. Spencer BANZHAF, R.R. RUSSELL, Erin E. FRIES, K.J. DIETZ and S.C. HELMS (1995). "Assessing the Environmental Externality Costs for Electricity Generation," *Research Triangle Park*, NC: Triangle Economic Research.

DILLINGHAM, Alan E. (1985). "The Influence of Risk Variable Definition on Value-of-Life Estimates," *Economic Inquiry*, vol. 24, p. 227-294.

DILLINGHAM, Alan E. and Robert S. SMITH (1984). "Union Effects on the Valuation of Fatal Risk" in *Proceedings of the Industrial Relations Research Association 36th Annual Meeting*, San Francisco, December, p. 270-277.

DIONNE, Georges (1982). "Moral Hazard and State–Dependent Utility Function," *Journal of Risk and Insurance*, vol. 49, p. 405-422.

DIONNE, Georges and Paul LANOIE (2004). "Public Choice about the Value of a Statistical Life for Cost-Benefit Analyses: The Case of Road Safety," *Journal of Transport Economics and Policy*, vol. 38, n° 2, p. 247-274.

DIONNE, Georges and Pierre-Carl MICHAUD (2002). "Statistical Analysis of Value-of-Life Estimates Using Hedonic Wage Method," *Working paper*, HEC Montréal, n° 02-01.

DORMAN, Peter and Paul HAGSTROM (1998). "Wage Compensation for Dangerous Work Revisited," *Industrial and Labor Relations Review*, vol. 52, n° 1, p. 116-135.

DORSEY, Stuart and Norman WALZER (1983). "Workers Compensation, Job Hazards, and Wages," *Industrial and Labor Relations Review*, vol. 36, p. 642-654.

DREYFUS, Mark K. and W. Kip VISCUSI (1995). "Rates of Time Preference and Consumer Valuations of Automobile Safety and Fuel Efficiency," *Journal of Law and Economics*, vol. 38, n° 1, p. 79-105.

DRÈZE, Jacques (1962). "L'utilité sociale d'une vie humaine," *Revue française de recherche opérationnelle*, vol. 1, p. 93-118.

DRÈZE, Jacques (1992). "From the "Value of a statistical life" to the Economics and Ethics of Population: the Path is Purely Methodological," *Recherches Économiques de Louvain*, vol. 58, n° 2, p. 147-166.

EECKHOUDT, Louis and James K. HAMMITT (2001). "Risk Aversion and the Value of Mortality Risk," Center for Risk Analysis, Harvard University working paper.

EECKHOUDT, Louis and James K. HAMMITT (2004). "Does Risk Aversion Increase the Value of Mortality Risk?" *Journal of Environmental Economics and Management*, vol. 47, p. 13-29.

FISHER, Ann, Lauraine G. CHESTNUT and Daniel M. VIOLETTE (1989). "The Value of Reducing Risks of Death: A Note on New Evidence," *Journal of Policy Analysis and Management*, vol. 8, n° 1, p. 88-100.

FLORAX, Raymond J.G.M. (2001). "Methodological Pitfalls in Meta-Analysis: Publication Bias," VU Research Memorandum, n° 2001–28, Amsterdam.

FORTIN Bernard and Paul LANOIE (2000). "Effects of Workers' Compensation: A Survey", in *Handbook of Insurance*, Georges Dionne (Ed.), Kluwer Academic Publishers, Boston, p. 421-457.

GAREN, John (1988). "Compensating Wage Differentials and the Endogeneity of Job Riskiness," *Review of Economics and Statistics*, p. 9-16.

GEGAX, Douglas, Shelby GERKINGm and William SCHULZE (1991). "Perceived Risk and the Marginal Value of Safety," *The Review of Economics and Statistics*, p. 589-597.

GLASS, Gene V. (1976). “Primary, Secondary and Meta-analysis of Research,” *Educational Researcher*, vol. 5, p. 3-8.

GLASS, Gene V., B. MCGRAW, and M.L. SMITH (1981). *Meta-analysis in Social Research ,* Sage Publications: Beverly Hills, CA.

GUNDERSON, Morley and Douglas HYATT (2001). “Workplace Risks and Wages: Canadian Evidence from Alternative Models,” *Canadian Journal of Economics*, vol. 34, n° 2, p. 377-395.

HERZOG, Henry W. and Alan M. SCHLOTTMANN (1990). “Valuing Risk in the Workplace: Market Price, Willingness to Pay, and the Optimal Provision of Safety,” *Review of Economics and Statistics*, p. 463-470.

HUBER, Peter J. (1964). “Robust Estimation of a Location Parameter,” *Annals of Mathematical Statistics*, vol. 35, p. 73-101.

HUBER, Peter J. (1981). *Robust Statistics,* New York: John Wiley & Sons, Inc.

HUNTER, John E. and Frank L. SCHMIDT (2004). *Methods of Meta-Analysis*: *Correcting Error and Bias in Research Findings*, 2nd Edition, Newbury Park: Sage Publications.

JONES-LEE, Michael W. (1976). *The Value of a statistical life: An Economic Analysis*, Chicago: University Press.

KIM, Seung-Wook and Price V. FISHBACK (1999). “The Impact of Institutional Change on Compensating Wage Differentials for Accident Risk: South Korea, 1984-1990,” *Journal of Risk and Uncertainty*, vol. 18, p. 231-248.

LANOIE, Paul, Carmen PEDRO and Robert LATOUR (1995). “The Value of a Statistical Life: A Comparison of Two Approaches,” *Journal of Risk and Uncertainty*, vol. 10, p. 235-257.

LE PEN, Claude (1993). “Capital humain et la santé (valeur et qualité de la vie humaine),” Paris, Dauphine, *miméo*.

LEETH, John D. and John RUSER (2003). “Compensating Wage Differentials for Fatal and Nonfatal Injury Risk by Gender and Race,” *Journal of Risk and Uncertainty*, vol. 27, n° 3, p. 257-277.

LEIGH , Paul J. (1987). “Gender, Firm Size, Industry and Estimates of the Value-of-Life,” *Journal of Health Economics*, vol. 6, n° 3, p. 255-273.

LEIGH, Paul J. (1991). “No Evidence of Compensating Wages for Occupational Fatalities,” *Industrial Relations*, vol. 30, n° 3, p. 382-395.

LEIGH, Paul J. (1995). “Compensating Wages, Value of a Statistical Life, and Inter-industry Differentials,” *Journal of Environmental Economics and Management*, vol. 28, p. 83-97.

LEIGH, Paul J. and Roger N. FOLSOM (1984). “Estimates of the Value of Accident Avoidance at the Job Depend on the Concavity of the Equalizing Differences Curve,” *Quarterly Review of Economics and Business*, vol. 24, n° 1, p. 56-66.

LIU, Jin Tan, James K. HAMMITT and Jin Long LIU (1997). “Estimated Hedonic Wage Function and Value of a statistical life in a Developing Country,” *Economics Letters*, vol. 57, n° 3 (December), p. 353-358.

LOTT, John and Richard MANNING (2000). “Have Changing Liability Rules Compensated Workers Twice for Occupational Hazards? Earnings Premiums and Cancer Risks,” *Journal of Legal Studies*, vol. 29, p. 99-130.

LOW, Stuart A. and Lee R. MCPHETERS (1983). “Wage Differentials and Risk of Death: An Empirical Analysis,” *Economic Inquiry*, vol. 21, n° 2 (April), p. 271-280.

MARIN, Alan and George PSACHAROPOULOS (1982). “The Reward for Risk in the Labor Market: Evidence from the United Kingdom and a Reconciliation with Other Studies,” *Journal of Political Economy*, vol. 90, p. 827-853.

MARTINELLO, Felice and Ronald MENG (1992). “Workplace Risks and the Value of Hazard Avoidance,” *Canadian Journal of Economics*, vol. 25, n° 2, p. 333-345.

MELINEK, Stanley J. (1974). “A Method of Evaluating Human Life for Economic Purposes,” *Accident Analysis and Prevention*, vol. 6, p. 103-114.

MENG, Ronald (1989). “Compensating Differences in the Canadian Labor Market,” *Canadian Journal of Economics*, vol. 22, p. 413-424.

MENG, Ronald and Douglas A. SMITH (1990). “The Valuation of Risk of Death in Public Sector Decision-Making,” *Canadian Public Policy*, vol. 16, p. 137-144.

MENG, Ronald and Douglas A. SMITH (1999). “The Impact of Workers' Compensation on Wage Premiums for Job Hazards in Canada,” *Applied Economics*, vol. 31, p. 1101-1108.

MICHAUD, Pierre-Carl (2001). “Évaluation des bénéfices et choix des projets impliquant la sauvegarde de vies humaines,” Mémoire présenté en vue de l'obtention du grade de maître *ès* sciences, HEC Montréal.

MILLER, Paul, Charles MULVEY and Keith NORRIS (1997). “Compensating Differentials for Risk of Death in Australia,” *Economic Record*, vol. 73, p. 363-372.

MILLER, Ted R. (1990). "The Plausible Range for the Value of a statistical life—Red Herrings among the Mackerel," *Journal of Forensic Economics*, vol. 3, n° 3, p. 17-39.

MILLER, Ted R. (2000). "Variations between Countries in Values of Statistical Life," *Journal of Transport Economics and Policy*, vol. 34, n° 2, p. 169-188.

MINCER, Jacob (1974). *Schooling, Experience, and Earnings*, Columbia University Press, New York.

MISHAN, Ezra J. (1971). "Evaluation of Life and Limb: A Theoretical Approach," *Journal of Political Economy*, vol. 79, p. 687-705.

MOORE, Michael and W. Kip VISCUSI (1988a). "Doubling the Estimated Value of a statistical life: Results Using New Occupational Fatality Data," *Journal of Policy Analysis and Management*, vol. 7, p. 476-490.

MOORE, Michael and W. Kip VISCUSI (1988b). "The Quantity-Adjusted Value of a statistical life," *Economic Inquiry*, vol. 26, n° 3, p. 369-388.

MOORE, Michael and W. Kip VISCUSI (1989). "Rates of Time Preference and Valuations of the Duration of Life," *Journal of Public Economics*, vol. 38, n° 3, p. 297-317.

MOORE, Michael and W. Kip VISCUSI (1990a). "Discounting Environmental Health Risks: New Evidence and Policy Implications," *Journal of Environmental Economics and Management*, vol. 18, p. 51-62.

MOORE, Michael and W. Kip VISCUSI (1990b). "Models for Estimating Discount Rates for Long-Term Health Risks Using Labor Market Data," *Journal of Risk and Uncertainty*, vol. 3, 381-401.

MROZEK, Janusz R. and Laura O. TAYLOR (2002). "What Determines the Value of a statistical life? A Meta-Analysis," *Journal of Policy Analysis and Management*, Vol. 21, n° 2, p. 253-270.

NEEDLEMAN, Lionel (1980). "The Valuation of Changes in the Risk of Death by Those at Risk," *Manchester School of Economics and Social Studies*, vol. 48, n° 3, p. 229-254.

OLSON, Craig A. (1981). "An Analysis of Wage Differentials Received by Workers on Dangerous Jobs," *Journal of Human Resources*, vol. 16, p. 167-185.

PRATT, John W. and Richard J. ZECKHAUSER (1996). "Willingness to Pay and the Distribution of Risk and Wealth," *Journal of Political Economy*, vol. 104, n° 4, p. 747-763.

RAUDENBUSH, Stephen W. (1994). "Random Effects Models" in *The Handbook of Research Synthesis* , edited by COOPER, Harris and Larry V. HEDGES, Russel Sage Fundation, New York, p. 301-321.

ROOT, Norman and Deborah SEBASTIAN (1981). "BLS Develops Measure of Job Risk by Occupation," *Monthly Labor Review*, vol. 106 (October), p. 26-30.

SANDY, Robert and Robert F. ELLIOTT (1996). "Unions and Risk: Their Impact on the Compensation for Fatal Risk," *Economica*, vol 63, n° 250 (May), p. 291-309.

SANDY, Robert, Robert F. ELLIOTT, W. Stanley SIEBERT, and Xiangdong WEI (2001). "Measurement Error and the Effects of Unions on the Compensating Differentials for Fatal Workplace Risks," *Journal of Risk and Uncertainty*, vol. 23, n° 1, p. 33-56.

SHANMUGAM, K. R. (2001). "Self Selection Bias in the Estimates of Compensating Differentials for Job Risks in India," *Journal of Risk and Uncertainty*, vol. 22, n° 3, p. 263-275.

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.

SIEBERT, W. Stanley and Xiangdong WEI (1994). "Compensating Wage Differentials for Workplace Accidents: Evidence for Union and Nonunion Workers in the UK," *Journal of Risk and Uncertainty*, vol. 9, p. 61-76.

SMITH, Adam (1776). *The Wealth of Nations*, Chicago: University of Chicago Press.

SMITH, Robert S. (1974). "The Feasibility of an "Injury Tax" Approach to Occupational Safety," *Law and Contemporary Problems*, vol. 38, p. 730-744.

SMITH, V. Kerry and William H. DESVOUSGES (1987). "An Empirical Analysis of the Economic Value of Risk Changes," *Journal of Political Economy*, vol. 95, p. 89-114.

SUMMERS, Robert and Alan HESTON (1991). "The Penn World Table (Mark 5): An Expanded Set of International Comparisons, 1950-1988," *Quarterly Journal of Economics*, vol. 106, p. 327-68.

THALER, Richard and Sherwin ROSEN (1975). "The Value of Saving A Life: Evidence From The Labor Market," in *Household Production and Consumption*, by Nester Terleckyj. NBER Press, Columbia University.

THALER, Richard (1974). "The Value of Saving a Life: A Market Estimate," doctoral thesis, University of Rochester, Dept. of Economics.

VISCUSI, W. Kip (1978a). “Wealth Effects and Earnings Premiums for Job Hazards,” *Review of Economics and Statistics*, vol. 60, n° 3, p. 408-416.

VISCUSI, W. Kip (1978b). “Labor Market Valuations of Life and Limb: Empirical Evidence and Policy Implications,” *Public Policy*, vol. 26, p. 359-386.

VISCUSI, W. Kip (1993). “The Value of Risks to life and Health,” *Journal of Economic Literature*, vol. 31, p. 1912-1946.

VISCUSI, W. Kip (2000). “Risk Equity,” Discussion Paper, n° 294, Harvard Law School, Cambridge.

VISCUSI, W. Kip (2003). “Racial Differences in Labor Market Values of a Statistical Life,” *Journal of Risk and Uncertainty*, vol. 27, n° 3, p. 239-256.

VISCUSI, W. Kip (2004). “The Value of a statistical life: Estimates with Risks by Occupation and Industry,” *Economic Inquiry*, vol. 42, n° 1, p. 29-48.

VISCUSI, W. Kip (2005). “The Value of a statistical life,” Discussion Paper, n° 517, Harvard Law School, Cambridge.

VISCUSI, W. Kip and Joseph E. ALDY (2003). “The Value of a Statistical Life: A Critical Review of Market Estimates Throughout the World,” *Journal of Risk and Uncertainty*, vol. 27, p. 5-76.

VISCUSI, W. Kip and Joni HERSCH (1998). “Smoking and Other Risky Behaviors,” *Journal of Drug Issues*, vol. 28, n° 3, p. 645-661.

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.

WEISS, Peter, Gunther MAIER, and Shelby GERKING (1986). “The Economic Evaluation of Job Safety: A Methodological Survey and Some Estimates for Austria,” *Empirica*, vol. 13, n° 1, p. 53-67.

WOLF, Frederic M. (1986). *Meta-Analysis: Quantitative Methods for Research Synthesis*, Sage Publications.

WOOLDRIDGE, Jeffrey M. (2000). *Introductory Econometrics: A Modern Approach*, South-Western College Publishing.

ZHANG, Anming, Anthony E. BOARDMAN, David GILLEN, and W.G. WATERS II (2004). "Towards Estimating the Social and Environmental Costs of Transportation in Canada," a Report for Transport Canada, UBC Centre for Transportation Studies, 450 pp.