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Daniel Herrera-Araujo, Christoph Rheinberger and James K. Hammitt

Toulouse School of Economics

# Valuing non-marginal changes in mortality and morbidity risk *

Daniel Herrera-Araujo†, Christoph M. Rheinberger‡, James K. Hammitt§

**Abstract**

Many stated-preference studies that seek to estimate the marginal willingness-to-pay (WTP) for reductions in mortality or morbidity risk suffer from inadequate scope sensitivity. One possible reason is that the risk reductions presented to respondents are too small to be meaningful. Survey responses may thus not accurately reflect respondents' preferences for health and safety. In this paper we propose a novel approach to estimating the value per statistical life (VSL) or the value per statistical case (VSC) based on larger risk reductions measurable as percentages. While such non-marginal risk reductions are easier to understand, they introduce well known biases. We propose a methodology to de-bias VSL and VSC estimates derived from the evaluation of non-marginal risk reductions and present a proof of concept using simulated stated preference data.

**JEL Codes:** D10; D81; I1; Q51.

**Keywords**: Value per Statistical Life, Value per Statistical Case; non-marginal risks reductions; scope sensitivity.

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†Corresponding author (e-mail: daniel.herrera@dauphine.psl.eu), Université Paris-Dauphine, PSL Research University, LEDa (CGEMP) UMR CNRS [8007].

‡Risk Management Directorate, European Chemicals Agency (ECHA).

§Harvard University (Center for Risk Analysis) and Toulouse School of Economics, University of Toulouse Capitole.

# 1 Introduction

Evaluating policies that seek to improve risks to life and limb requires estimating the rate at which people trade money for a small change in the chance of dying or suffering an adverse health effect in a specified period. This marginal rate of substitution is commonly referred to as the value per statistical life (VSL) or the value per statistical case (VSC) of illness or injury. As these metrics enable the analyst to monetize mortality and morbidity risk reductions, they are crucial to regulatory impact analysis (Cropper et al., 2011; Cameron 2014).

In the context of environmental health and safety policies, VSL is often estimated using stated-preference (SP) studies that seek to mimic a market for mortality risk reductions. Most of these studies evaluate very small risk reductions—often as small as 1 in 100,000—to elicit VSL. The reason for choosing such small risk reductions is that VSL and VSC are marginal rates of substitution that differ from average rates of substitution for large risk changes. Moreover, under conventional assumptions, respondents' willingness-to-pay (WTP) should be nearly proportional to the risk change for such small increments (Hammitt & Graham, 1999). This near-proportionality provides a useful test of scope sensitivity. Unfortunately, many VSL studies do not pass the test. In some studies, the estimated WTP is much less than proportional to the risk reduction—a violation of *strong* scope sensitivity; in others, the estimated WTP is not even statistically related to the size of the risk reduction—a violation of *weak* scope sensitivity.[1] For example, fewer than 20% of the 405 VSL studies analyzed by Lindhjem et al. (2011) displayed at least weak sensitivity to the size of risk reduction.

There are at least two potential reasons for scope insensitivity. First, a lack of scope sensitivity may be related to the curvature of the indifference function between money and risk (Hammitt & Treich, 2007); second, it may reflect the difficulties that respondents have in understanding the small mortality risk reductions they are commonly asked to value (Baron, 1997; Hammitt & Graham, 1999; Kunreuther et al., 2001). To improve respondents' understanding, numerous risk communication aids have been employed (Corso et al., 2001). However, while such aids may help in communicating risks, they do not overcome the core problem that marginal reductions in risk are an abstract benefit that is likely to be interpreted differently by different people (Rheinberger et al., 2018).

In this paper, we propose the use of non-marginal risk reductions to improve people's understanding. The literature on risk communication suggests that, in addition to the description of risk, the size of risk changes influences understanding (Spiegelhalter, 2017). Larger risk reductions appear to be easier for researchers to explain, and for respondents to grasp and recall, than smaller risk reductions (Okan et al., 2020). For example, Garcia-Retamero and Glasic (2011) provide evidence

[1] Scope insensitivity has been seen as a major concern for the validity of preferences elicited in SP studies (Kahneman & Knetsch, 1992; Diamond et al., 1994) or a reflection of people's incapacity to form preferences over (public) goods (Kahneman et al., 1999; Hausman, 2012).

that individuals are better able to comprehend and recall (after 3 weeks) cancer risks, if these are on the order of 1 in 100 rather than 1 in 1,000. The effect is more pronounced in low-numeracy individuals than in high-numeracy individuals, suggesting that the former group has particular problems in understanding small probabilities (Peters et al., 2011). This suggests that using non-marginal risk changes in SP studies may help people to better grasp the trade-offs they are asked to evaluate.

The size of risk reduction may influence individuals' responses through a combination of various judgment processes. First, as individuals often consider small probability events too rare to pay attention to, the use of large probabilities can encourage them to take protective behavior by increasing the stakes above their threshold level of concern (Slovic et al., 1977). Second, as mortality (or morbidity) risks are often expressed on a yearly basis (e.g., as a 1 in 100,000 annual chance of dying) respondents may exhibit myopia, or narrow bracketing, in their decisions (Kahneman and Lovallo, 1993). That is, they focus on short time periods rather than recognizing the long-term impact of a cumulative annual risk. Recent evidence suggests that broad bracketing that conveys cumulative information about the distribution of possible outcomes of a gamble over a long period of time counters the narrow bracketing tendency (Chaudhry et al., 2020).

While moving to non-marginal risk reductions—i.e., risk changes in the percent range—seems promising, it comes at the cost of biasing the estimated VSL (or VSC). This is because VSL (and VSC) are defined as *marginal* rates of substitution between money and risk, which differ from *average* rates of substitution for non-marginal risk changes. Indeed, the marginal WTP for risk reduction decreases with the size of the risk reduction because of the individual's budget constraint, an income effect (Jones-Lee, 1974). In addition, eliciting WTP for a non-marginal risk reduction requires a setting in which the baseline risk is large enough to make the proposed reduction meaningful (e.g., the lifetime risk of developing cancer). This can introduce an additional bias, because WTP for a marginal risk reduction is increasing in baseline risk (Pratt & Zeckhauser, 1996).[2] This baseline risk effect arises because individuals facing a large probability of dying have little incentive to limit their spending on risk reduction, the so-called dead-anyway effect. Because of both effects, the rate of substitution for a large risk reduction does not coincide with the rate of substitution for an infinitesimally small risk reduction. Non-marginal risk reductions have therefore rarely been used to measure WTP in applied studies.

We develop a method that simultaneously corrects for income and baseline risk effects, allowing for unbiased VSL (or VSC) estimates from the evaluation of non-marginal risk reductions. The method is based on the WTP model for prevention-based and treatment-based health interventions developed by Rheinberger et al. (2016, RHH hereafter). As we assume that disease-induced mortality is conditional on suffering the disease, the model includes three health states: healthy, ill, and

[2]Zeckhauser and Viscusi (1990) propose a compelling analogy. In a game of Russian roulette, rational individuals should be willing to pay more to reduce the number of bullets in a six-chamber revolver from 5 to 4 than they should be for a reduction from 2 to 1. Although the risk reduction is the same (i.e., 1 fewer bullet), the chances of dying are obviously greater with 4 bullets remaining in the revolver than with 1 bullet.

dead. This enables us to study trade-offs between incidence rate, mortality rate, and health quality. We derive two new theoretical results. First, we extend the RHH model by decomposing the WTP for reduced disease incidence into a weighted sum of the WTP for reductions in conditional mortality and the WTP for reducing the risk of a nonfatal course of disease. Second, we show that, when an intervention exists that simultaneously reduces incidence, severity and conditional mortality of a disease, WTP cannot be simultaneously proportional to infinitesimal reductions in each of the three components. Instead, WTP is proportional to each term's contribution to the total WTP.

Based on these insights, we provide an empirically tractable method to extrapolate the incremental WTP for non-marginal risk reductions to the WTP for marginal risk reductions. This new methodology for estimating the VSL (or VSC) combines the relationship between the WTP for a risk reduction and the size of that risk reduction with information on the relationship between WTP and the individual's baseline risk and income. To test the feasibility and accuracy of our proposed appoach, we use Monte Carlo analysis to simulate a stated-preference study of WTP to decrease incidence, severity and mortality risk in a setting similar to that of Alberini and Ščasnỳ (2018). As our results demonstrate, we are able to accurately recover the marginal WTP for different types of intervention—reduced risk of developing cancer, improvements in the 5-year survival chance conditional on having cancer, or both.

The paper proceeds as follows. Section 2 introduces our workhorse model and derives the WTP for reductions in incidence, conditional mortality, and health deterioration. In Section 3 we present the setup of the Monte Carlo simulation. Section 4 reports on the accuracy with which our approach estimates the true values in the Monte Carlo simulation and Section 5 concludes. Robustness checks and alternative model specifications are presented in the Appendix.

# 2 Model

## 2.1 Notation

In our model an individual derives utility $u(W, H)$ from wealth $W$ and health $H$. We denote first (second) derivatives of the utility function with respect to wealth by the subscript 1 (11) and those with respect to health by the subscript 2 (22). Further, we make the following conventional assumptions about $u(W, H)$: non-satiation with respect to wealth, i.e., $u_1(W, H) > 0$; non-satiation with respect to health, i.e., $u_2(W, H) > 0$; weak financial risk aversion, i.e., $u_{11}(W, H) \leq 0$; weak health risk aversion, i.e., $u_{22}(W, H) \leq 0$; and weak correlation affinity, i.e., $u_{12}(W, H) \geq 0$.

The first two assumptions are the usual non-satiation assumptions. The next two assumptions state that less risk over either wealth or health is preferable to more risk. Aversion to financial risk is well supported by empirical evidence (Chetty, 2006). There is some empirical evidence for risk aversion with respect to health, but results depend on the way health is defined.[3] Correlation

[3]Several studies have investigated risk aversion with respect to longevity and have found substantial heterogeneity

affinity implies that the marginal utility of wealth does not decrease with better health (Eeckhoudt et al., 2007). This assumption is intuitively appealing since better health increases opportunities for gaining utility through consumption (with the exception of consuming some forms of health care) and there is some empirical evidence suggesting that the marginal utility of income increases with health (Viscusi & Evans, 1990; Sloan et al., 1998; Finkelstein et al., 2013; Viscusi, 2019).

Consider now an individual who faces three possible states of the world: remain in good health, contract a disease and survive in reduced health, or contract a disease and die from it.[4] The good health state $H_g$ occurs with probability $1-q$ where $q$ is the probability of falling ill. Conditional on falling ill, the individual survives in the bad health state $H_b$ with a probability $1-p$, or dies with probability $p$. We denote death as health state $H_d$. Without loss of generality, we measure health on a unit scale so that $H_g = 1$, $H_d = 0$ and $H_b = 1-h$, where $0 < h < 1$ indicates the severity of health deterioration when the disease is nonfatal.

Each of the three health conditions is associated with a state-dependent utility function that has the property $u(W,1) > u(W,1-h) > u(W,0)$ and the individual is assumed to maximize expected utility:

$$EU(W,H) = (1-q)u\left(W,1\right) + q(1-p)u\left(W,1-h\right) + qpu\left(W,0\right). \tag{1}$$

Consider now that the individual is offered an opportunity to decrease incidence probability $q$, conditional mortality probability $p$ and disease severity $h$ by the amounts $\theta_q$, $\theta_p$ and $\theta_h$, respectively. For such a risk reduction, the individual is willing to forego the compensating variation $C^* \equiv C\left(W,h,p,q,\theta_h,\theta_p,\theta_q\right)$. By definition, $C^*$ is the amount that leaves the individual as well off in terms of expected utility as the initial endowment:

$$EU(W,H) = (1-q^*)u\left(W^*,1\right) + q^*(1-p^*)u\left(W^*,1-h^*\right) + q^*p^*u\left(W^*,0\right) \tag{2}$$

where $q^* \equiv q-\theta_q$, $h^* \equiv h-\theta_h$, $p^* \equiv p-\theta_p$ and $W-C^* \equiv W^*$.[5]

with some people being risk averse, others risk seeking, and yet others who are risk neutral (Pliskin et al., 1980; Corso & Hammitt, 2001; Nielsen et al., 2010; Hammitt & Tunçel, 2015). Risk aversion with respect to health quality is often assumed in theoretical papers (e.g., Bleichrodt et al., 2003; Rheinberger et al., 2016; Herrera-Araujo et al., 2020; Bleichrodt et al., 2020), but is rarely measured. One notable exception is the experimental study by Attema et al. (2016) who reported evidence of risk aversion for both quality of life gains and losses.

[4] Alberini & Ščasnỳ (2021) add a competing risk of dying to the RHH model and show that the main results carry through.

[5] We treat baseline risk here as exogenous. However, since our proposed correction can be applied regardless of whether the WTP increases or decreases with baseline risk, it may also be applied to endogenous baseline risks (Liu and Neilson, 2006; Gerking et al., 2017); see Appendix E.

Below, we use the following notation to avoid clutter:

$$
\begin{aligned}
C\left(W,h,p,q,0,0,0\right) &\equiv C_0,\\
(1-q^*)u_1\left(W^*,1\right)+q^*(1-p^*)u_1\left(W^*,1-h^*\right)+q^*p^*u_1\left(W^*,0\right) &\equiv EU_1(W^*,H^*),\\
(1-q^*)u_{11}\left(W^*,1\right)+q^*(1-p^*)u_{11}\left(W^*,1-h^*\right)+q^*p^*u_{11}\left(W^*,0\right) &\equiv EU_{11}(W^*,H^*),\\
(1-q)u_1\left(W,1\right)+q(1-p)u_1\left(W,1-h\right)+qpu_1\left(W,0\right) &\equiv EU_1(W,H),\\
(1-q)u_{11}\left(W,1\right)+q(1-p)u_{11}\left(W,1-h\right)+qpu_{11}\left(W,0\right) &\equiv EU_{11}(W,H).
\end{aligned}
$$

## 2.2 Valuing marginal risk reductions

Assume the individual is offered an opportunity to reduce any of the three dimensions of disease risk. We focus on the slope of the WTP with respect to the risk reduction, i.e., the marginal WTP (MWTP from hereon). Three MWTP metrics can be derived: i) the MWTP for a reduction in the risk of contracting the disease, ii) the MWTP for a reduction in disease severity, and iii) the MWTP for a reduction in the conditional risk of dying from the disease.

**MWTP for a reduction in the risk of contracting the disease.** We start by differentiating Eq. (2) with respect to $\theta_q$. Isolating $\frac{\partial C^*}{\partial \theta_q}$ yields the MWTP for reductions in the risk of contracting the disease:

$$
MWTP_{\theta_q} \equiv \frac{\partial C^*}{\partial \theta_q} = \frac{u(W^*,1)-\left[(1-p^*)u(W^*,1-h^*)+p^*u(W^*,0)\right]}{EU_1(W^*,H^*)} > 0, \tag{3}
$$

where the numerator equals the gain in utility from avoiding the disease and the denominator corresponds to the individual's expected opportunity cost of spending, both evaluated after the payment of $C^*$. The VSC is thus defined as the slope of the WTP for a reduction in the risk of contracting the disease evaluated at zero risk reduction:

$$
VSC \equiv MWTP_{\theta_q}\Big|_{\theta_q=\theta_p=\theta_h=0} \equiv \frac{\partial C_0}{\partial \theta_q} = \frac{u(W,1)-\left[(1-p)u(W,1-h)+pu(W,0)\right]}{EU_1(W,H)}. \tag{4}
$$

**MWTP for a reduction in disease severity.** Next, we differentiate Eq. (2) with respect to $\theta_h$. The MWTP for a reduction in disease severity $h$ by an amount $\theta_h$ is given by:

$$
MWTP_{\theta_h} \equiv \frac{\partial C^*}{\partial \theta_h} = \frac{q^*(1-p^*)u_2(W^*,1-h^*)}{EU_1(W^*,H^*)} > 0,
$$

where the numerator equals the gain in utility due to a less severe form of the disease (equal to the marginal utility of wealth if ill multiplied by the probability of suffering the nonfatal condition)

and evaluated after the payment of $C^*$. We use $cVSR$ to denote the value of severity reduction conditional on being ill ($c$ is a mnemonic for conditional). The $cVSR$ is defined as the slope of the WTP for a reduction in disease severity evaluated at zero risk reduction:

$$cVSR \equiv MWTP_{\theta_h}\Big|_{\theta_q=\theta_p=\theta_h=0} \equiv \frac{\partial C_0}{\partial \theta_h} = \frac{q(1-p)u_2(W,1-h)}{EU_1(W,H)}. \tag{5}$$

**MWTP for a reduction in conditional mortality.** Finally, we differentiate Eq. (2) with respect to $\theta_p$. The MWTP for a reduction in conditional mortality risk $p$ by an amount $\theta_p$ is given by:

$$MWTP_{\theta_p} \equiv \frac{\partial C^*}{\partial \theta_p} = \frac{q^* \left[u(W^*,1-h^*) - u(W^*,0)\right]}{EU_1(W^*,H^*)} > 0,$$

where the numerator equals the gain in utility from avoiding mortality (the utility gain conditional on illness multiplied by the probability of disease) and the denominator is the expected marginal utility of consumption, both evaluated after the payment of $C^*$. We use $cVSL$ to denote the value per statistical life at the prevailing ill-health state (and wealth) *conditional* on contracting the disease. The $cVSL$ is defined as the slope of the WTP for a reduction in conditional mortality risk evaluated at zero risk reduction:

$$cVSL \equiv MWTP_{\theta_p}\Big|_{\theta_q=\theta_p=\theta_h=0} \equiv \frac{\partial C_0}{\partial \theta_p} = \frac{q\left[u(W,1-h) - u(W,0)\right]}{EU_1(W,H)}. \tag{6}$$

### 2.3 Deriving the unconditional VSL

Because of the compound nature of the RHH model, the three metrics—$VSC$, $cVSR$ and $cVSL$—are not independent. We exploit this dependence to derive the unconditional VSL. We start by decomposing the VSC into two components, the values of reducing the risk of falling ill and the conditional risk of dying. To this end, we re-express the VSC as:

$$VSC = \frac{u(W,1) - u(W,1-h) + p\left[u(W,1-h) - u(W,0)\right]}{EU_1(W,H)}. \tag{7}$$

Let $\psi$ denote the ratio between average utility of health and marginal utility of health *when* ill:

$$\psi = \frac{u(W,1) - u(W,1-h)}{h} \frac{1}{u_2(W,1-h)} \leq 1. \tag{8}$$

By inserting equations (5), (6) and (8) into (7), we obtain:

$$VSC = \left(\frac{\psi h}{q(1-p)}\right) cVSR + \left(\frac{p}{q}\right) cVSL. \tag{9}$$

The first term on the right hand side (RHS) of Eq. (9) corresponds to the monetized utility gain from avoiding a nonfatal health state; the second term corresponds to the contribution from the avoidance of premature death conditional on contracting the disease. A challenge for empirical work relates to the identification of each term on the RHS of Eq. (9). Indeed, survey respondents need to evaluate treatments that hold constant the likelihood of the non-relevant health states.[6]

A similar logic can be applied to derive the standard VSL defined as the slope of the WTP for an *unconditional* mortality risk reduction. A treatment that decreases incidence risk needs to hold constant the risk of experiencing the nonfatal ill-health state. However, as any reduction in incidence risk also reduces the probability of becoming ill, the treatment needs to create an additional reduction in conditional mortality risk to compensate. VSL can be derived from such a treatment, yielding the conventional definition:[7]

$$VSL = \frac{u(W,1) - u(W,0)}{EU_1(W,H)} = VSC + \left(\frac{1-p}{q}\right) cVSL. \tag{10}$$

This finding is summarized in Result I.

***Result I.*** *As a reduction in incidence risk reduces severity and mortality simultaneously, it is possible to decompose the MWTP for incidence risk reduction into a weighted sum of the MWTP for severity reduction and the MWTP for conditional mortality risk reduction. To obtain the unconditional VSL, the MWTP for incidence risk reduction must be corrected by a factor proportional to the MWTP for conditional mortality risk reduction.*

### 2.4 Risk reduction elasticity of willingness-to-pay

Let $\eta_q$, $\eta_h$, and $\eta_p$ denote the elasticities of $C^*$ with respect to reductions in incidence $q$, disease severity $h$, and conditional mortality $p$. When dealing with marginal mortality risk reduction alone, the elasticity of WTP with respect to mortality risk reduction equals one (Hammitt & Herrera-Araujo, 2018). However, in our more complex setting we have:

$$\eta_k = \frac{\frac{\partial C^*}{\partial \theta_k}\theta_k}{\frac{\partial C^*}{\partial \theta_q}\theta_q + \frac{\partial C^*}{\partial \theta_h}\theta_h + \frac{\partial C^*}{\partial \theta_p}\theta_p}, \ \ \forall\, k = \{q, p, h\}.$$

[6] To identify the first term, a treatment is required that reduces the incidence risk while holding constant the unconditional mortality risk; see Appendix A for a full derivation. Alternatively, one could isolate the second term by evaluating a treatment that reduces the conditional mortality while holding constant the incidence risk.

[7] The first equality follows from the WTP for a treatment that holds constant the risk of experiencing the nonfatal ill-health state and is derived in Appendix B. The second follows after some minor manipulations.

Thus, $\eta_q$, $\eta_h$ and $\eta_p$ are not only the elasticities with respect to WTP but also denote the relative shares of each dimension in the WTP for a simultaneous reduction in all three dimensions, i.e., $\eta_q + \eta_h + \eta_p = 1$. This finding is summarized in Result II.

***Result II.*** *WTP for a simultaneous improvement in incidence, severity and mortality is not proportional to small reductions in each of these dimensions. Instead, the elasticity of WTP for an improvement in any dimension equals its contribution to the total WTP (i.e., to* $\frac{\partial C^*}{\partial \theta_q}\theta_q + \frac{\partial C^*}{\partial \theta_h}\theta_h + \frac{\partial C^*}{\partial \theta_p}\theta_p$*). Thus, the sum of the elasticities of WTP for incidence, severity and conditional mortality risk reduction equals unity.*

## 2.5 Valuing non-marginal risk reductions

What happens if one moves from marginal to non-marginal risk reductions? To answer this question, we consider the MWTP for reductions in the risk of contracting the disease.[8] Effects for the other two risk dimensions can be derived analogously. We first illustrate the issues that arise when dealing with non-marginal risk reductions, followed by a method to correct for these issues.

### 2.5.1 Issues with non-marginal risk reductions

To understand the link between baseline risk and income effects on MWTP, consider the scenario where an individual is offered the opportunity to reduce only the incidence probability of a potentially fatal disease. The solid line in Figure 1 depicts the individual's compensating variation (or WTP) for a risk reduction of (arbitrary) size $\theta \in (0, q]$. The WTP for a risk reduction of size $\theta_q^L$ is $C(W, h, p, q, \theta_q^L, 0, 0)$. VSC is the slope of the WTP function at baseline risk, represented by the dotted line.[9] The long-dashed line is tangent to the WTP function at $\theta_q^L$. We denote the slope of this line by $VSC^*$; it corresponds to the VSC evaluated at a new income level $W^* = W - C(W, h, p, q, \theta_q^L, 0, 0)$ and a new incidence risk $q^* = q - \theta_q^L$ (and at baseline levels of $h$ and $p$). Note that VSC* is the marginal WTP for an increase in a non-marginal risk reduction $\theta_q^L$. It is not the average WTP for a non-marginal risk reduction $C(W, h, p, q, \theta_q^L, 0, 0)/\theta_q^L$.

How different is $VSC^*$ from $VSC$? Using the mean-value theorem (Hammitt, 2020), we can represent the difference between measures as

$$VSC^* = VSC - \theta_q \frac{\partial^2 C_x}{\partial \theta_q \partial q} - C_x \frac{\partial^2 C_x}{\partial \theta_q \partial W}, \tag{11}$$

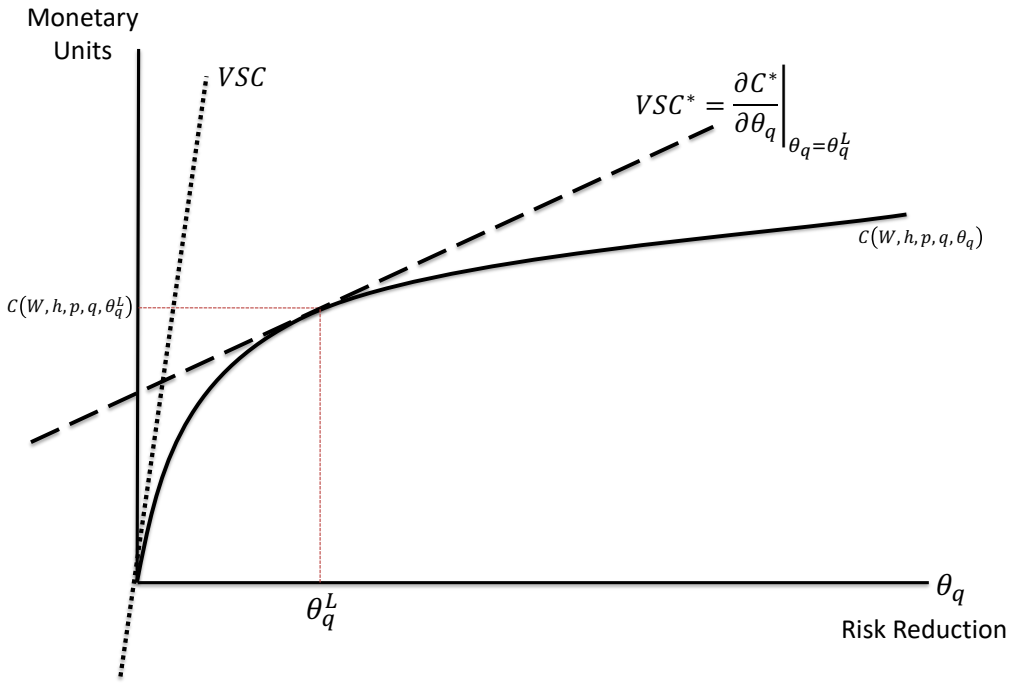
where $C_x$ is the WTP for incidence risk reduction with baseline wealth $\tilde{W}$ and incidence risk $\tilde{q}$ somewhere between $(W, q)$ and $(W^*, q^*)$. This implies that $VSC^*$ equals $VSC$ minus feedback

[8] As we focus on incidence risk, we refer to the effect of changing baseline incidence risk as the sick-anyway effect by analogy to the dead-anyway effect in mortality risk valuation.

[9] Most, if not all, SP studies of mortality or morbidity valuation approximate VSC by the ratio of $C(W, h, p, q, \theta_q^L, 0, 0)$ to $\theta_q^L$ for small values of $\theta_q^L$.

effects due to (i) the reduced risk of contracting the disease, and (ii) the reduction in disposable income. Both baseline risk and income effects decrease the VSC, but as shown in Figure 1 these effects vanish as $\theta_q^L$ tends to zero.

Figure 1: Non-marginal risk reductions bias downwards VSC estimates




*Notes:* The bold line corresponds to the compensating variation evaluated at different levels of incidence risk reduction, while holding other risk dimensions at their baseline levels. The dotted line corresponds to the $VSC$. The long-dashed line is tangent to the bold line at $\theta_q^L$. The long-dashed line, labelled $VSC^*$, corresponds to the VSC evaluated at baseline levels of $h$ and $p$, and at a new income level $W^* = W - C(W, h, p, q, \theta_q^L, 0, 0)$ and a new incidence risk $q^* = q - \theta_q^L$.

### 2.5.2 Correcting for income and baseline risk effects

The upshot of Eq. (11) is that, when estimating the VSC using non-marginal risk reductions, the feedback effects cannot be ignored. To correct the distortions introduced by non-marginal risk reductions, we follow the approach proposed by Herrera-Araujo et al. (2017). We start by differentiating Eq. (2) with respect to baseline incidence risk $q$. Upon inserting Eq. (3) and some manipulations, we have:[10]

$$\frac{\partial C^*}{\partial q} = \frac{u(W,1) - [(1-p)u(W,1-h) + pu(W,0)]}{EU_1(W^*, H^*)} - \frac{\partial C^*}{\partial \theta_q}. \tag{12}$$

[10] Appendix C provides a detailed derivation of the proposed correction for a risk reduction in incidence. Analogous derivations yield the corrections for the other two dimensions.

Differentiating Eq. (2) with respect to wealth $W$ and re-arranging some terms yields:

$$\frac{\partial C^*}{\partial W} = 1 - \frac{EU_1(W,H)}{EU_1(W^*,H^*)} \geq 0. \tag{13}$$

By inserting Eqs. (13) and (4) into Eq. (12), we have

$$\frac{\partial C^*}{\partial q} = \frac{\partial C_0}{\partial \theta_q}\left(1 - \frac{\partial C^*}{\partial W}\right) - \frac{\partial C^*}{\partial \theta_q}.$$

Finally, by isolating $\frac{\partial C_0}{\partial \theta_q}$, we obtain the following expression:

$$VSC \equiv \frac{\partial C_0}{\partial \theta_q} = \frac{\frac{\partial C^*}{\partial q} + \frac{\partial C^*}{\partial \theta_q}}{1 - \frac{\partial C^*}{\partial W}} > 0. \tag{14}$$

Correcting for the sick-anyway effect ($\frac{\partial C^*}{\partial q}$) and the income effect ($1 - \frac{\partial C^*}{\partial W}$) thus enables us to recover the theoretically correct $VSC$. Along the same lines, we can obtain:

$$cVSR \equiv \frac{\partial C_0}{\partial \theta_h} = \frac{\frac{\partial C^*}{\partial p} + \frac{\partial C^*}{\partial \theta_p}}{1 - \frac{\partial C^*}{\partial W}} > 0, \tag{15}$$

and

$$cVSL \equiv \frac{\partial C_0}{\partial \theta_p} = \frac{\frac{\partial C^*}{\partial h} + \frac{\partial C^*}{\partial \theta_h}}{1 - \frac{\partial C^*}{\partial W}} > 0. \tag{16}$$

Note that in these expressions the indirect effects of reducing one risk vs. another are accounted for through the income effect and the baseline risk effect. We summarize this as Result III.

***Result III.*** *We provide an empirically tractable method to compute $VSC$, $cVSR$ and $cVSL$ for any positive risk reduction. Proposing a larger risk reduction introduces both income and baseline risk effects that bias conventional empirical estimates. These can be corrected by applying the expressions given in Eqs. (14), (15) and (16). All terms required for the correction can, in principle, be estimated, but require specific adaptations in the survey design to allow for identification in the empirical analysis.*

## 3 Monte Carlo Simulation

As we are unaware of any SP study that has elicited WTP for non-marginal changes in incidence, severity, and conditional mortality risk needed to implement our approach, we conduct a Monte Carlo simulation of such a study to determine its feasibility and to provide a proof of concept. Specifically, we simulate a setting similar to a study by Alberini and Ščasnỳ (2018) that asked

respondents aged 45-60 years in four European countries to report their WTP for reductions in cancer risk. Respondents provided answers to a sequence of dichotomous questions that offered the choice between current cancer risk and a hypothetical program that would reduce the risk of developing cancer, improve 5-year cancer survival, or both, at a specified cost to the respondent. While this setup is close to what we require for implementing the corrections introduced in Section 2, there is no variation in the baseline risk. We therefore turn to synthetic data.

### 3.1 Data Generating Process

We consider a simple data generating process and construct 1000 different data sets for $N = 5,000$ synthetic individuals. Each individual $i$ is characterized by a level of baseline wealth $W_i$, an incidence probability $q_i$, a health deterioration if ill $h_i$, and a conditional mortality risk $p_i$. To simulate individuals' WTP we assume that utility is linear in health and displays constant relative risk aversion (CRRA) with respect to wealth. The utility function we simulate from is

$$u(W_i, 1-h_i) = \begin{cases} (1-h_i)\frac{1}{1-\gamma}W_i^{1-\gamma} & \gamma \neq 1 \\ (1-h_i)\log(W_i) & \gamma = 1, \end{cases}$$

where $\gamma$ is a measure of relative risk aversion with regard to wealth. Bequest utility is given by $u(W_i, 0) = 0$. The simulated data mimic a survey in which each individual $i$ is offered an incidence-severity-mortality risk reduction package $(\theta_{q_i}, \theta_{h_i}, \theta_{p_i})$. To illustrate how our approach can be applied to actual data, we introduce multiplicative noise in the compensating variation $C_i^*$.[11] In other words, we mimic scenarios in which the researcher has an informative, albeit, noisy measure of WTP.

We solve for the exact compensating variation $C_i^*$ using Eq. (2). For the simulated empirical study, we introduce sufficient variation in the baseline risk and the risk reduction to identify the WTP function depicted in Figure 1.[12] To do so, we need to define the parameter space and support for each of the variables in our model. Table 1 presents the supports and distributions used in the simulation. We consider a mean baseline risk of developing cancer of 25 in 1,000 over 5 years as in Alberini and Ščasnỳ (2018). The average probability of survival over 5 years is 45% and the baseline health if ill is 55%. All three dimensions and improvements in each dimension are independently and uniformly distributed. Wealth is log-normally distributed and approximates U.S. annual income in 2010 using the mean and standard deviation reported by Hammitt and Haninger (2010). We assume that all synthetic individuals have a relative risk aversion equal to one, i.e., $\gamma = 1$. As a robustness check, we created new synthetic data with $\gamma = 0.6$ and re-estimated the regressions and

[11] We do so by assuming that the measurement error $\epsilon_i$ follows a normal distribution, with mean zero and standard deviation equal to one, so that $\tilde{C}_i^* = C_i^* \exp(\epsilon_i)$.

[12] Figure 1 shows WTP for a fixed baseline risk. By varying both the baseline risk and risk reduction in our simulation study, we trace out different WTP functions corresponding to different baseline risks.

corresponding results.

This set up allows for evaluating many different scenarios. We report on two: The first scenario proposes risk reductions similar to those typically found in the SP literature, which are often (much) smaller than 50 in 10,000 for all risks (Andersson et al., 2016). As reported in Table 1, all risk reductions are on average 200 times smaller than their corresponding baseline risks. We label these as marginal risk reductions. Our second scenario proposes non-marginal reductions in incidence risk of about 1 in 1,000, disease severity of 25 in 100, and conditional mortality risk of 16 in 100. For each scenario, we simulate reductions in each risk alone, each pair of risks, and a simultaneous reduction in all three risks.

### 3.2 Empirical strategy

We begin by solving for the exact WTP corresponding to each choice in our synthetic data using Eq. (2). For the empirical counterpart, we regress the natural logarithm of the simulated (noisy) WTP $\tilde{C}_i^*$ on baseline risks and risk reductions:

$$\log(C_i^*) = \alpha + \beta_q \log(q_i) + \beta_h \log(h_i) + \beta_p \log(p_i) + \beta_W \log(W_i) + \lambda_q \log(\theta_{q_i}) + \lambda_h \log(\theta_{h_i}) + \lambda_p \log(\theta_{p_i}) + \epsilon_i, \tag{17}$$

where $\alpha$ denotes a constant and $\beta_q$, $\beta_h$, $\beta_p$, and $\beta_W$ are the empirical analogues of the elasticities of WTP with respect to baseline incidence $q$, severity $h$, conditional mortality risk $p$ and wealth $W$, respectively. The elasticities of WTP with respect to reductions in incidence risk $\theta_q$, severity $\theta_h$ and conditional mortality risk $\theta_p$ are denoted by $\lambda_q$, $\lambda_h$, and $\lambda_p$, respectively. The remaining unobserved idiosyncratic variation is captured by $\epsilon_i$.

### 3.3 Marginal willingness-to-pay estimates

Since the natural logarithm of the compensating variation is the dependent variable in Eq. (17), the standard calculation of MWTP for a risk reduction using the regression estimates is as follows:

$$\widehat{\frac{\partial C}{\partial \theta_k}} = \hat{\lambda}_k \times \frac{\overline{C}}{\overline{\theta_k}}, \tag{18}$$

where $\overline{C}$ and $\overline{\theta}_k$ correspond to the average WTP and the average reduction in a risk of type $k \in \{q, h, p\}$. The proposed correction uses the estimates from the WTP regression for a $k$-type risk reduction along with information on the relationship between the WTP for the $k$-type risk reduction and the $k$-type baseline risk, and between the WTP for the $k$-type risk reduction and the individual's income. The corrected estimates of the WTP for each $k$-type risk reduction can thus

be computed as follows:

$$\frac{\widehat{\partial C_0}}{\partial \theta_k} = \frac{\widehat{\frac{\partial C}{\partial k}} + \widehat{\frac{\partial C}{\partial \theta_k}}}{1 - \widehat{\frac{\partial C}{\partial W}}}, \tag{19}$$

where

$$\widehat{\frac{\partial C}{\partial k}} = \hat{\beta}_k \times \frac{\overline{C}}{\overline{k}}, \qquad \widehat{\frac{\partial C}{\partial W}} = \hat{\beta}_W \times \frac{\overline{C}}{\overline{W}}, \text{ and } \widehat{\frac{\partial C}{\partial \theta_k}} = \hat{\lambda}_k \times \frac{\overline{C}}{\overline{\theta_k}},$$

and where $\overline{k}$ and $\overline{W}$ correspond to the average baseline risk $k \in \{q, h, p\}$ and the average income, respectively.

# 4 Results

In Panel A of Table 2 we report the coefficients estimated by applying the model in Eq. (17) to *marginal* risk reductions. The dependent variable in all regressions is the natural logarithm of WTP for a corresponding risk reduction. All regressions are estimated using OLS and the coefficients are fully identified exploiting the variation between the proposed risk reductions. The coefficient estimates presented in the table are averaged over the 1,000 random data sets.

The first, second and third columns present estimates for a reduction in only one risk: incidence risk, mortality risk, and disease severity, respectively. Although we do not report the coefficients' standard errors, all coefficients are statistically significant, but some are economically insignificant. Baseline incidence, severity and mortality have different effects on WTP depending on the risk reduction proposed. When the baseline risk and the type of risk improvement coincide, the estimated coefficients of the baseline risk are near zero, which is consistent with theoretical predictions (Hammitt and Herrera-Araujo, 2018). Cross-baseline risks, however, do have an effect on WTP. In the case of mortality risk or severity reduction, incidence baseline risk has a proportional effect on WTP for both risk reductions. Baseline mortality (severity) risk has a negative effect on WTP for a severity (mortality) risk reduction, and has a positive effect on the WTP for incidence risk reduction. Theory suggests a positive relationship between mortality (severity) and WTP to reduce incidence risk. Under certain conditions, theory also provides guidance on the relationship between baseline mortality (severity) and WTP to reduce severity (mortality). One can unambiguously sign the effect of a higher conditional baseline mortality on the WTP for reductions in the severity if one assumes, as we do, the functional form of utility that is consistent with any life-year measure (Rheinberger et al., 2016). As expected, we find a negative relationship. Finally, we find that, as predicted by theory, WTP to reduce only one risk is proportional to the risk reduction.

The next three columns report estimates for a simultaneous reduction in two risks: incidence risk and disease severity, incidence and mortality risk, and mortality risk and disease severity, respectively. All estimated effects are statistically different from zero. WTP is larger for larger baseline incidence risk. Baseline severity has a positive effect only when incidence and severity

risk reductions are proposed. Baseline mortality risk, however, has a negative effect when a risk reduction in incidence and conditional mortality are proposed, and has a positive effect in the other two situations. For each column, all risk reduction coefficients are less than one, which implies a less than proportional effect, but their column sum is (almost) one.

The last column reports estimates for a simultaneous reduction in all three risks. The coefficients for baseline incidence and conditional mortality risk are positive, while the coefficient for the baseline severity is negative. As in the previous models, all risk reduction coefficients are less than one, while their sum is very close to one. Finally, the WTP for any combination of risk reductions is proportional to wealth.

Panel B in Table 2 reports coefficient estimates applying the model in Eq. (17) to *non-marginal* risk reductions. Again, the first three columns present estimates for a reduction in only incidence risk, mortality risk or disease severity. Nearly all coefficients are statistically significant. The results for baseline risks are very similar to those reported in Panel A. WTP is not very sensitive to own-baseline risk, but it is sensitive to cross-baseline risks. Also, WTP is nearly proportional to risk reduction. The effects on proportionality are more pronounced in the next three columns, which report estimates for a reduction in incidence risk and disease severity, a reduction in incidence risk and reduction in mortality risk, and a reduction in mortality risk and disease severity, respectively. As before, all estimated effects are statistically different from zero and all risk reduction coefficients are less than one. The sum, however, no longer equals one. In all cases the coefficients sum to less than one, except when severity and mortality risk reduction are proposed jointly for which the sum exceeds one.[13]

Table 3 reports the MWTP values derived from each of the models in Table 2. The MWTPs for incidence, mortality and severity are computed under each configuration of risk reductions proposed in Table 2 and are reported in the three panels: incidence, mortality and severity. Within each panel, we compare the exact MWTP computed with the empirical counterparts of equations (4), (5) and (6) to the standard MWTP estimates derived based on Eq. (18) and to the corrected MWTP estimates derived based on Eq. (19) using estimates from Table 2. We do so for both marginal and non-marginal risk reductions. (The exact MWTP is reported in the table notes. In the table itself, we report ratios measuring the deviation of the standard and the corrected MWTP estimates from the exact MWTP.)

Regardless of the configuration of the risk reduction program proposed, both the standard and

[13]We also ran a log-log model with the marginal unconditional mortality risk $m = pq$ as explanatory variable. As the change in unconditional mortality risk can be re-expressed as the sum of three elements $\theta_m = \theta_q p + \theta_p q - \theta_q \theta_p$ two models were tested. The first model allows the coefficients on each of the three terms of the sum to differ; the second constrains the coefficients on each of the three terms to be equal. In the unconstrained model, the product between the coefficient of the first term ($\theta_q p$) and the average WTP yields the VSC divided by the average conditional mortality probability ($VSC/p$). Similarly, the product between the coefficient of the second term ( $\theta_p q$) and the average WTP yields the $cVSL$ divided by the incidence probability ($cVSL/q$). As the second model constrains the coefficients from the three terms to be equal, the resulting coefficient is a weighted average of the unconstrained coefficients.

the corrected MWTP estimates are very close to the exact MWTP for marginal reductions to incidence, mortality, and severity risks. This suggests that both methods are able to retrieve the exact MWTP for any of the three risk reductions. For non-marginal risk reductions, the two methods to estimate MWTPs are no longer equivalent. The standard method substantially underestimates the exact MWTP for a reduction in one risk dimension and can under- or overestimate it for a reduction in multiple risk dimensions. The deviations increase with the number of risk components and the size of baseline risks to be reduced. For example, the MWTP for a reduction in incidence risk estimated using the standard approach falls short of the exact MWTP by 10% when a reduction in $q$ alone is considered but by nearly 40% when all three risks are reduced. The corrected method, however, is able to retrieve the exact MWTP regardless of the combination of risk reductions proposed.

In Table 4, we report VSL taking the empirical counterparts of Eq. 10 using the estimates from Table 3. Specifically, the table compares the VSL estimates derived using marginal and non-marginal reductions in mortality risk for two sets of simulated data. The first set assumes a relative risk aversion coefficient of $\gamma = 1$ (as do all the previous results). The second specification assumes a smaller degree of relative risk aversion ($\gamma = 0.6$). Again, we find that for marginal risk reductions the corrected and the standard VSL estimates are very close to the exact VSL. However, for non-marginal risk reductions, the standard method to estimate VSL falls short of the exact VSL by 30-37% depending on the degree of relative risk aversion considered, while the corrected VSL estimate recovers the exact VSL regardless of the specification.[14]

## 5 Conclusion

The value of health risk reductions is commonly estimated in a framework of marginal risk reductions. This paper makes a case for using risk reductions that are large enough to be meaningful to respondents of SP studies. Relying on a structural model of state-dependent preferences, we propose a novel method that allows recovering the WTP for a marginal reduction in risk from the difference in WTP for different non-marginal risk reductions. The standard method to estimate VSL or VSC assumes a linear relationship between WTP and risk reduction, which is invalid for larger risk reductions and will result in biased estimates because of income and baseline risk effects. Our method augments the standard method with additional sources of variation—namely the relationship between the WTP for a risk reduction and baseline risk, and between the WTP for a risk reduction and income—to correct for these effects. Using these additional sources of information, our correction method provides a theoretically valid means for estimating VSL or VSC while presenting respondents with meaningful risk reductions.

Although we have presented the correction method within a model that studies trade-offs be-

[14]The exact gaps are $(0.683 - 0.429)/0.683 = 37.2\%$ and $(0.152 - 0.106)/0.152 = 30.3\%$, respectively.

tween incidence rate, mortality rate, and health quality, it also applies to settings involving only one or two of these dimensions (as these simpler models are special cases of the model we present). The advantage of our method is that the variation needed for its implementation can be readily obtained from tailored surveys. It requires that researchers elicit information on how the WTP for a risk reduction in each of the intervention dimensions considered varies with baseline risk, the size of risk reduction and the respondent's income. Eliciting information on how WTP varies with the size of risk reduction and with income is standard. Creating variation in the baseline risk is more challenging. At least two strategies have been proposed in the SP literature. One method consists of providing respondents with exogenous variation in the baseline risk (Hammitt and Haninger, 2010). Another approach consists of first eliciting respondents' perceived risk, then offering them the opportunity to revise their risk assessments based on objective risk information and eliciting WTP from the revised baseline risk (Gerking et al., 2017).

In the paper, we have employed an expected utility framework ignoring that people often over-weight small probabilities and under-weight large ones in health decisions. As non-marginal risk reductions require a substantial baseline risk, which may exacerbate probability weighting effects, one might want to apply a rank dependent utility (RDU) framework to study the effect of probability weighting in our context.[15] Doing so suggests that our correction method is robust to probability weighting, but VSL itself is not robust to probability weighting because WTP for risk reductions under RDU differs from WTP under the linear-in-probabilities assumption of the EU framework (Bleichrodt and Eeckhoudt, 2006). Our method corrects for the baseline risk and income effects under probability weighting, but not for the probability weighting itself. It may, however, be possible to adjust empirical estimates of WTP to correct for probability weighting as suggested in other contexts by Bleichrodt et al. (2001) and Johansson-Stenman (2008).

In future work, we hope to collect new stated preference data that will allow us to test the procedure on real data. One key challenge consists of selecting reasonable bids in a SP study that features non-marginal risk reductions. The results of our Monte Carlo analysis suggest that the WTP for a non-marginal risk reduction should represent a sizeable proportion of income (Hammitt, 2020). Whether individuals will pay large amounts of their income is an empirical question. Another important challenge relates to ensuring sufficient variation in baseline risk and risk reduction. In the synthetic data set analyzed here we are unconstrained but in an actual SP survey one cannot present too many different scenarios without risk of confusing or tiring respondents and hampering the credibility of the scenarios. An efficient survey design along with enough sample respondents should help identify the effects. Finally, an implicit assumption of our correction method is that we can accurately elicit differences in WTP for different non-marginal risk reductions, which highlights the importance of sound risk communication. Overcoming these challenges will require close adherence to contemporary guidance for SP studies (Johnston et al., 2017) and risk communication

[15] Appendix D details the derivation of our correction method under RDU.

(Spiegelhalter, 2017).

Table 1: Simulation structural parameters

| | Distribution | Mean | Std | Min | Max |
|---|---|---|---|---|---|
| Log-wealth, $log(W)$ | Log-normal | 10.54 | 0.95 | 7.04 | 14.18 |
| **Baseline risks** | | | | | |
| Baseline incidence, $q$ | Uniform | 0.025 | 0.0058 | 0.015 | 0.035 |
| Baseline severity, $h$ | Uniform | 0.45 | 0.0866 | 0.30 | 0.60 |
| Baseline mortality, $p$ | Uniform | 0.65 | 0.0865 | 0.50 | 0.80 |
| **Marginal risk reduction** | | | | | |
| Incidence reduction, $\theta_q$ | Uniform | 0.00019 | 0.00004 | 0.00012 | 0.00025 |
| Severity reduction, $\theta_h$ | Uniform | 0.00338 | 0.00065 | 0.00225 | 0.00450 |
| Mortality reduction, $\theta_p$ | Uniform | 0.0049 | 0.0009 | 0.0032 | 0.0065 |
| **Non-marginal risk reduction** | | | | | |
| Incidence reduction, $\theta_q$ | Uniform | 0.0094 | 0.0018 | 0.0063 | 0.0125 |
| Severity reduction, $\theta_h$ | Uniform | 0.1679 | 0.0323 | 0.1123 | 0.2246 |
| Mortality reduction, $\theta_p$ | Uniform | 0.2437 | 0.0468 | 0.1626 | 0.3252 |

*Notes*: Log-wealth mean and standard deviation are taken from Hammitt & Haninger (2010). Non-marginal baseline incidence, severity and mortality risks are calibrated for cancer. Tuning parameter $\kappa$ is set to -150.

Table 2: Regression results of WTP on marginal risk reductions

| Panel A: Marginal | Log $WTP_q$ | Log $WTP_p$ | Log $WTP_h$ | Log $WTP_{qh}$ | Log $WTP_{ph}$ | Log $WTP_{qp}$ | Log $WTP_{qhp}$ |
|---|---|---|---|---|---|---|---|
| Log baseline incidence | 0.02 | 1.02 | 1.02 | 0.18 | 1.02 | 0.32 | 0.40 |
| Log baseline mortality | 0.45 | 0.01 | -1.88 | 0.07 | -0.56 | 0.31 | 0.06 |
| Log baseline severity | 0.20 | -0.80 | 0.00 | 0.16 | -0.55 | -0.10 | -0.09 |
| Log incidence reduction | 1.00 | | | 0.83 | | 0.69 | 0.60 |
| Log mortality reduction | | 1.00 | | | 0.69 | 0.30 | 0.26 |
| Log severity reduction | | | 1.00 | 0.16 | 0.31 | | 0.12 |
| Log wealth | 1.10 | 1.10 | 1.10 | 1.10 | 1.10 | 1.10 | 1.10 |
| Proportionality | 1.00 | 1.00 | 1.00 | 0.99 | 0.99 | 0.99 | 0.98 |

| Panel B: Non-marginal | Log $WTP_q$ | Log $WTP_p$ | Log $WTP_h$ | Log $WTP_{qh}$ | Log $WTP_{ph}$ | Log $WTP_{qp}$ | Log $WTP_{qhp}$ |
|---|---|---|---|---|---|---|---|
| Log baseline incidence | 0.02 | 1.00 | 1.01 | 0.18 | 0.98 | 0.34 | 0.49 |
| Log baseline mortality | 0.43 | 0.01 | -1.87 | 0.18 | -0.45 | 0.33 | 0.15 |
| Log baseline severity | 0.19 | -0.78 | 0.00 | 0.16 | -0.44 | -0.02 | -0.01 |
| Log incidence reduction | 0.95 | | | 0.78 | | 0.61 | 0.45 |
| Log mortality reduction | | 0.98 | | | 0.72 | 0.20 | 0.22 |
| Log severity reduction | | | 0.99 | 0.10 | 0.41 | | 0.12 |
| Log wealth | 1.09 | 1.09 | 1.09 | 1.09 | 1.09 | 1.09 | 1.09 |
| Proportionality | 0.95 | 0.98 | 0.99 | 0.88 | 1.12 | 0.81 | 0.79 |

*Notes:* We do not report the standard deviations as all coefficients are statistically significant. $WTP_{\theta_q}$, $WTP_{\theta_p}$, $WTP_{\theta_h}$, $WTP_{\theta_q\theta_h}$, $WTP_{\theta_p\theta_h}$, $WTP_{\theta_q\theta_p}$, and $WTP_{\theta_q\theta_h\theta_p}$ correspond to MWTP when a risk reduction in incidence, in mortality, in severity, in incidence + severity, in mortality + severity, in incidence + mortality, and incidence + severity + mortality is proposed, respectively.

Table 3: Estimates for $VSC$, $cVSR$ and $cVSL$ from marginal risk reductions

| | Marginal | Non-marginal | Marginal | Non-marginal | Marginal | Non-marginal | Marginal | Non-marginal |
|---|---|---|---|---|---|---|---|---|
| **Panel: Incidence** | Reduction only in q | | Reduction in p and q | | Reduction in h and q | | Reduction in all risks | |
| Corrected (C) | 0.549 | 0.548 | 0.545 | 0.544 | 0.544 | 0.544 | 0.544 | 0.544 |
| Standard (S) | 0.548 | 0.495 | 0.541 | 0.399 | 0.542 | 0.450 | 0.540 | 0.335 |
| C/Exact | 100% | 100% | 99.6% | 99.4% | 99.5% | 99.4% | 99.5% | 99.5% |
| S/Exact | 100% | 90.4% | 99.0% | 72.9% | 99.1% | 82.2% | 98.7% | 61.2% |
| **Panel: Mortality** | Reduction in q and p | | Reduction only in p | | Reduction in h and p | | Reduction in all risks | |
| Corrected (C) | 0.366 | 0.368 | 0.376 | 0.373 | 0.371 | 0.368 | 0.363 | 0.363 |
| Standard (S) | 0.362 | 0.201 | 0.376 | 0.356 | 0.373 | 0.446 | 0.361 | 0.252 |
| C/Exact | 97.2% | 97.3% | 100% | 99% | 98.6% | 97.8% | 98% | 96% |
| S/Exact | 96.1% | 53.2% | 100% | 94.1% | 99.1% | 118.4% | 98% | 67% |
| **Panel: Severity** | Reduction in q and h | | Reduction in p and h | | Reduction only in h | | Reduction in all risks | |
| Corrected (C) | 5.858 | 5.888 | 5.872 | 5.889 | 5.979 | 5.879 | 5.774 | 5.731 |
| Standard (S) | 5.801 | 3.324 | 5.945 | 9.154 | 5.977 | 5.769 | 5.793 | 5.178 |
| C/Exact | 99.5% | 100% | 99.7% | 100.0% | 101.5% | 99.8% | 98.0% | 97.3% |
| S/Exact | 98.5% | 56.4% | 100% | 155.4% | 101.5% | 98.0% | 98.4% | 87.9% |

*Notes:* Note: All estimates are statistically different from zero. Incidence and Mortality panels are in millions of dollars. Severity panel is in thousands of dollars. Model's exact valuation are \$0.549 millions, \$0.376 millions and \$5.889 thousands for incidence, mortality and severity, respectively. $MWTP_{\theta_q}$, $MWTP_{\theta_p}$, and $MWTP_{\theta_h}$ correspond to MWTP when a risk reduction in incidence, in mortality, and in severity is proposed, respectively. Model estimates are derived directly from equations (4), (5) and (6). Corrected are derived using the empirical estimates on WTP along with elements from Table 2 to input values in equations (14), (15) and (16). Standard corresponds to the re-transformed coefficient of the corresponding risk reduction in Table 2. MTWP values for mortality risk and severity risk reductions are unconditional.

Table 4: VSL estimates for marginal and non-marginal risk reductions and for different risk aversion coefficients

| | $\gamma = 1$ | | $\gamma = 0.6$ | |
|---|---|---|---|---|
| | Marginal | Non-marginal | Marginal | Non-marginal |
| Model (exact) | 0.683 | 0.683 | 0.152 | 0.152 |
| Corrected OLS estimate | 0.677 | 0.677 | 0.152 | 0.151 |
| Standard OLS estimate | 0.675 | 0.429 | 0.151 | 0.106 |

*Notes:* Values are in millions of dollars. All estimates are statistically different from zero. $\gamma$ corresponds to the relative risk aversion with regard to wealth.

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# Appendix

**Appendix A – The marginal willingness-to-pay for a reduction in incidence holding constant the unconditional mortality risk.**

Consider an individual that selects the decision which maximizes their expected utility given by:

$$EU(W,H) = (1-q)u\left(W,1\right) + q(1-p)u\left(W,1-h\right) + qpu\left(W,0\right).$$

Consider now that the individual is offered an opportunity to decrease incidence risk, while holding constant the unconditional mortality probability. That is, the preventive treatment reduces the incidence by $\theta_q^u$ under the constraint that

$$pq = p^{u*}q^{u*},$$

where $p^{u*} = p + \theta_p^u$ and $q^{u*} = q - \theta_q^u$. Thus, for any reduction $\theta_q^u$, we have an *increase* in the conditional mortality probability equal to

$$\theta_p^u = \frac{\theta_q^u p}{q - \theta_q^u}.$$

The intuition for this is that any reduction in incidence risk increases the survival probability. To compensate for this benefit (so that the constraint is respected), the treatment must raise $p$ to $p^{u*}$.

In return, the individual is willing to forfeit an amount $C\left(W,q,h,p,\theta_q^u,\theta_p^u\right)$. This amount is by definition one that leaves the individual's expected utility unchanged. The amount $C$ is defined as:

$$(1-q^{u*})u\left(W^*,1\right) + q^{u*}(1-p^{u*})u\left(W^*,1-h\right) + qpu\left(W^*,0\right) = EU(W,H).$$

By differentiating the above equation with respect to $\theta_q^u$ and isolating $\frac{\partial C}{\partial \theta_q^u}$, we obtain:

$$MWTP_{\theta_q^u} \equiv \frac{\partial C^*}{\partial \theta_q^u} = \frac{u(W^*,1) - u(W^*,1-h)}{EU_1(W^*,H)} > 0.$$

Therefore, the MWTP for a reduction of incidence risk holding constant the unconditional mortality risk equals the MWTP for a treatment allowing an individual to pass from the sick health state to one of perfect health.

## Appendix B – The marginal willingness-to-pay for a reduction in incidence holding constant nonfatal risk.

Consider now that the individual is offered an opportunity to decrease the incidence risk, while holding constant the nonfatal risk. The treatment reduces the incidence by $\theta_q^u$ under the constraint that:

$$q - qp = q^{u*} - q^{u*}p^{u*},$$

where $p^{u*} = p + \theta_p^u$ and $q^{u*} = q - \theta_q^u$. Thus, for any reduction $\theta_q^u$, there must be a compensating increase in the conditional mortality probability equal to

$$\theta_p^u = -\frac{(1-p)\theta_q^u}{q - \theta_q^u}.$$

The reduction in incidence risk decreases the probability of ending up in the sick state. To hold constant the probability of ending in the nonfatal state, the treatment needs to simultaneously decrease the conditional mortality risk. In return for this treatment, the individual is willing to forfeit an amount $C$ defined as:

$$(1 - q^{u*})u\left(W^*, 1\right) + q(1-p)u\left(W^*, 1-h\right) + q^{u*}p^{u*}u\left(W^*, 0\right) = EU(W, H).$$

By differentiating the above equation with respect to $\theta_q^u$ and isolating $\frac{\partial C}{\partial \theta_q^u}$, we obtain:

$$MWTP_{\theta_q^u} \equiv \frac{\partial C^*}{\partial \theta_q^u} = \frac{u(W^*, 1) - u(W^*, 0)}{EU_1(W^*, H)} > 0.$$

Therefore, the MWTP for a reduction in incidence risk holding constant the non fatal risk equals the MWTP for a treatment allowing an individual to pass from a health state equivalent to being dead to one of perfect health.

## Appendix C – Deriving the correction for income and baseline risk (dead/sick-anyway) effects.

Let us consider a risk reduction in all risk dimensions. We start by differentiating Eq. (2) with respect to baseline incidence risk and isolate $\frac{\partial C^*}{\partial q}$:

$$\frac{\partial C^*}{\partial q} = \frac{\Delta u^{1,1} - [(1-p)\Delta u^{1-h,1-h^*} + p\Delta u^{0,0}] + \theta_p \Delta u^{1-h^*,0}}{EU_1(W^*, H^*)}, \tag{20}$$

where,

$$\begin{aligned}
\Delta u^{1,1} &= u\left(W,1\right) - u\left(W^*,1\right), \\
\Delta u^{1-h,1-h^*} &= u\left(W,1-h\right) - u\left(W^*,1-h^*\right), \\
\Delta u^{0,0} &= u\left(W,0\right) - u\left(W^*,0\right), \\
\Delta u^{1-h^*,0} &= u\left(W^*,1-h^*\right) - u\left(W^*,0\right).
\end{aligned}$$

The numerator in Eq. (20) equals the change in utility arising from a change in baseline incidence risk, while holding constant both utility and the proposed risk reduction. The first and the last term in the numerator are positive, while the term in brackets may be positive or negative. However, under correlation affinity, the following inequality holds:

$$\Delta u^{1,1} \geq u\left(W,1-h\right) - u\left(W^*,1-h\right) \geq \Delta u^{0,0}. \tag{21}$$

Combined with the non-satiation assumption with respect to health, the following inequality also holds:

$$\Delta u^{1,1} \geq u\left(W,1-h\right) - u\left(W^*,1-h\right) \geq u\left(W,1-h\right) - u\left(W^*,1-h^*\right). \tag{22}$$

As the term in brackets in Eq. (20) is a convex combination of terms that are smaller than the first term, the WTP to reduce incidence risk by any amount $\theta_q > 0$ increases with baseline risk (i.e., $\frac{\partial C^*}{\partial q} \geq 0$). This baseline risk (or sick-anyway) effect pushes an individual facing a larger risk of incidence to be willing to spend more on risk reduction.

Differentiating Eq. (2) with respect to wealth yields:

$$\frac{\partial C^*}{\partial W} = \frac{\Delta u_1^{1,1}(1-q) + \Delta u_1^{1-h^*,1-h} q(1-p) + \Delta u_1^{0,0} qp + \Delta u_1^{1,1-h^*}\theta_q + \Delta u_1^{1-h^*,0}\theta_m}{EU_1(W^*,H^*)}, \tag{23}$$

where,

$$\theta_m = \theta_q p + \theta_p q - \theta_q \theta_p,$$

is the reduction in unconditional mortality risk, and

$$\begin{aligned}
\Delta u_1^{1,1} &= u_1\left(W^*, 1\right) - u_1\left(W, 1\right), \\
\Delta u_1^{1-h^*,1-h} &= u_1\left(W^*, 1-h^*\right) - u_1\left(W, 1-h\right), \\
\Delta u_1^{0,0} &= u_1\left(W^*, 0\right) - u_1\left(W, 0\right), \\
\Delta u_1^{1,1-h^*} &= u_1\left(W^*, 1\right) - u_1\left(W^*, 1-h^*\right), \\
\Delta u_1^{1-h^*,0} &= u_1\left(W^*, 1-h^*\right) - u_1\left(W^*, 0\right).
\end{aligned}$$

The numerator in Eq. (23) corresponds to the expected net gain in marginal utility of consumption from having additional income, while holding constant both utility and the proposed risk reduction. Weak financial risk aversion implies that both the first term and the third term are positive. The second term is positive due to a compound effect of weak financial risk aversion and correlation affinity, while the last two terms are positive because of weak health risk aversion.

As all five terms in the numerator are positive, WTP must be increasing in wealth. For simplicity, we may re-express equation (23) as:

$$\frac{\partial C^*}{\partial W} = 1 - \frac{EU_1(W,H)}{EU_1(W^*,H^*)} \geq 0. \tag{24}$$

Hence, under our assumptions, the derivative of WTP with respect to income is positive and bounded above by one. This income effect arises because individuals have less wealth after paying for the risk reduction.

Note that regrouping all terms with a star in the numerator of Eq. (20) yields the negative of Eq. (3). We can thus establish a theoretical link between the baseline risk (sick-anyway) effect, the income effect, and the MWTP for a reduction in incidence risk by inserting Eq. (3) into Eq. (20), which yields:

$$\frac{\partial C^*}{\partial q} = \frac{u(W,1) - [(1-p)u(W,1-h) + pu(W,0)]}{EU_1(W^*,H^*)} - \frac{\partial C^*}{\partial \theta_q}. \tag{25}$$

Given that the MWTP for an infinitesimally small incidence risk reduction is equal to:

$$\frac{\partial C_0}{\partial \theta_q} = \frac{u(W,1) - [(1-p)u(W,1-h) + pu(W,0)]}{EU_1(W,H)} > 0, \tag{26}$$

multiplying and dividing the first term on the RHS of Eq. (25) by $EU_1(W,H)$ and inserting equations (24) and (26) into (25) yields

$$\frac{\partial C^*}{\partial q} = \frac{\partial C_0}{\partial \theta_q}\left(1 - \frac{\partial C^*}{\partial W}\right) - \frac{\partial C^*}{\partial \theta_q}.$$

Finally, by isolating $\frac{\partial C_0}{\partial \theta_q}$, we obtain:

$$VSC \equiv \frac{\partial C_0}{\partial \theta_q} = \frac{\frac{\partial C^*}{\partial q} + \frac{\partial C^*}{\partial \theta_q}}{1 - \frac{\partial C^*}{\partial W}} > 0. \tag{27}$$

Correcting for the baseline risk (sick-anyway) effect, $\frac{\partial C^*}{\partial q}$, and the income effect, $1 - \frac{\partial C^*}{\partial W}$, thus yields the exact $VSC$.

## Appendix D – Allowing for Rank Dependent Utility.

VSL and other willingness-to-pay based welfare metrics are based on the assumption of linear probabilities. In this appendix, we relax this assumption and presume a common weighting function $f[.]$ for mortality risks. To ease the exposition, we will assume that conditional mortality risk equals 1—so that contracting the disease is equivalent to dying from it. The rank-dependent counterpart of the expected utility function is given by:

$$RD[U(W,H)] = f[1-q]u\left(W,1\right) + (1 - f[1-q])u\left(W,0\right).$$

Similarly, we derive WTP metrics for improvements in $q$. In particular, we can re-write Eq. (1) as:

$$f[1-q+\theta]u\left(W - C^f, 1\right) + (1 - f[1-q+\theta])u\left(W - C^f, 0\right) = RD[U(W,H)].$$

where $C^f = C(W,h,\theta,q,f[.])$ denotes the compensating variation for a reduction in the incidence rate $q$ of the target disease by an amount $\theta_q$ in the presence of probability weighting through the function $f[.]$.

The corresponding marginal WTP under probability weighting is:

$$\frac{\partial C^{f*}}{\partial \theta} = \frac{g'[1-q+\theta_q](u(W-C^f,1) - u(W-C^f,0))}{RD[U_1(W-C^f,H)]} > 0.$$

As under EU, the link between the baseline risk effect, the income effect and the MWTP for a reduction in incidence risk can be established by analyzing the relationship between the compensating variation and the baseline risk as follow:

$$\begin{aligned}
\frac{\partial C^{f*}}{\partial q} &= \frac{g'[1-q](u(W,1) - u(W,0)) + g'[1-q+\theta](u(W-C^f,1) - u(W-C^f,0))}{RD[U_1(W-C^f,H)]}, \\
\frac{\partial C^{f*}}{\partial q} &= \frac{g'[1-q](u(W,1) - u(W,0)))}{RD[U_1(W-C^f,H)]} - \frac{\partial C^{f*}}{\partial \theta} \\
\frac{\partial C^{f*}}{\partial q} &= \frac{g'[1-q](u(W,1) - u(W,0)))}{RD[U_1(W-C^f,H)]} \frac{RD[U_1(W,H)]}{RD[U_1(W,H)]} - \frac{\partial C^{f*}}{\partial \theta}.
\end{aligned}$$

which can be re-expressed as,

$$\frac{\partial C^{f*}}{\partial q} = \frac{\partial C_o^f}{\partial \theta}\left(1 - \frac{\partial C^{f*}}{\partial W}\right) - \frac{\partial C^{f*}}{\partial \theta}.$$

isolating the marginal WTP under probability weighting when $\theta = 0$, yields:

$$\frac{\partial C_o^f}{\partial \theta} = \frac{\frac{\partial C^{f*}}{\partial q} + \frac{\partial C^{f*}}{\partial \theta}}{\left(1 - \frac{\partial C^{f*}}{\partial W}\right)}.$$

We conclude that our proposed method to estimate VSL is robust to probability weighting, even though VSL itself is not robust to probability weighting.

## Appendix E – Allowing for endogenous risk control.

Assume that the probability of survival is determined by an individual's expenditure on safety improvement $I$, and an external expenditure $G$, and can be written as $S(I, G)$. The external input $G$ is exogenous to the individual, but may not be exogenous to society. The final survival probability is endogenous to the individual. This formulation allows for offsetting behavior (Liu & Neilson, 2006). Let $S_1(I, G)$ and $S_2(I, G)$ be the first order partial derivative of $S$ with respect to $I$ and $G$, respectively. Since both expenditures improve the chances of survival, $S_1(I, G) > 0$ and $S_2(I, G) > 0$. Assuming that the utility from bequest can be normalized to zero, and the individual survives in perfect quality of life, the individual chooses the safety-improving expenditure $I$ to maximize expected utility:

$$S(I, G)u\left(W - I\right).$$

As in Liu and Neilson (2006), the first order condition yielding the optimal safety investment is given by:

$$\frac{u\left(W - I\right)}{S(I, G)u_1\left(W - I\right)} = \frac{1}{S_1(I, G)}. \tag{28}$$

Let $I(W, G)$ be the individual's expenditure that solves Eq. (28). At equilibrium, the individual's expected utility is:

$$EU(W, G) = S(I(W, G), G)u\left(W - I(W, G)\right).$$

Note that Eq. (28) and the resulting equilibrium expected utility holds for any $W$ and $G$. Consider now that the individual is offered an opportunity to improve the exogenous expenditure $G$ by $\theta$.

The compensating variation $C$ for the improvement in survival probability is given by:

$$S(I(W-C,G+\theta),G+\theta)u\left(W-I(W-C,G+\theta)-C\right)=EU(W,G).$$

where $I(W-C,G+\theta)$ is the individual's new expenditure on risk control/safety improvement in equilibrium, and $C$ denotes the compensating variation for an improvement in the survival rate. Taking the derivative with respect to $\theta$ and re-arranging the terms to isolate the marginal WTP and inserting Eq. (28) yields:

$$\frac{\partial C^*}{\partial \theta}=\frac{S_2(I(W-C,G+\theta),G+\theta)}{S_1(I(W-C,G+\theta),G+\theta)}>0.$$

The marginal WTP to improve the survival probability by increasing the exogenous investment equals the marginal rate of transformation between private safety improvements and exogenous safety improvements.

Again, the link between the baseline risk effect, the income effect and the MWTP for a reduction in incidence risk can be established by analyzing the relationship between the compensating variation and the exogenous expenditure as follows:

$$\frac{\partial C^*}{\partial G}=\frac{\partial C_0}{\partial \theta}\left(1-\frac{\partial C^*}{\partial W}\right)-\frac{\partial C^*}{\partial \theta}.$$

Isolating the marginal WTP at $\theta=0$ yields:

$$\frac{\partial C_0}{\partial \theta}=\frac{\frac{\partial C^*}{\partial G}+\frac{\partial C^*}{\partial \theta}}{\left(1-\frac{\partial C^*}{\partial W}\right)},$$

where

$$\frac{\partial C_0}{\partial \theta}=\frac{S_2(I,G)}{S_1(I,G)}>0,$$

and

$$\frac{\partial C^*}{\partial W}=1-\frac{S(I(W,G)u_1\left(W-I(W,G)\right)}{S(I(W-C,G+\theta),G+\theta)u_1\left(W-I(W-C,G+\theta)\right)}>0.$$