Book Section:

Andersson, H., Hole, A.R. orcid.org/0000-0002-9413-8101 and Svensson, M. (2019) Valuation of health risks. In: Hamilton, J.H, (ed.) Oxford Research Encyclopedia of Economics and Finance. Oxford University Press .

https://doi.org/10.1093/acrefore/9780190625979.013.288

Valuation of Health Risks

Henrik Andersson[a], Arne Risa Hole[b], Mikael Svensson[c]

[a] Toulouse School of Economics, University of Toulouse Capitole

[b] Department of Economics, University of Sheffield

[c] Health Metrics, The Sahlgrenska Academy, University of Gothenburg

Summary

Many public policies and individual actions have consequences for population health. To understand if a (costly) policy undertaken to improve population health is a wise use of resources, analysts can use economic evaluation methods to assess the costs and benefits. To be able to do this, it is necessary that the costs and benefits are evaluated using the same metric, and for convenience a monetary measure is commonly used. It is well established that money measures of a reduction in health risks can be theoretically derived using the willingness to pay concept. However, since a market price for health risks is not available, analysts have to rely on analytical techniques to estimate the willingness to pay using revealed or stated preference methods. Revealed preference methods infer willingness to pay based on individuals' actual behavior in markets related to health risks and include approaches such as hedonic pricing techniques. Stated preference methods use a hypothetical market scenario where respondents make trade-offs between wealth and health risks. Using, for example, a random-utility framework, it is possible to directly estimate individuals' willingness to pay by analyzing the trade-offs individuals' make in the hypothetical scenario. Stated preference methods are commonly applied using contingent valuation or discrete choice experiment techniques. Despite criticism and shortcomings of both revealed and stated preference methods, substantial progress has been made over the last couple of decades in using both approaches to estimate the willingness to pay for health risk reductions.

Keywords: economic valuation; health risks; revealed preferences; stated preferences; cost-benefit analysis; hedonic pricing; contingent valuation; discrete choice experiments

Introduction

Does it make economic sense to implement human papillomavirus (HPV) vaccination in national child vaccination programs? What are the economic consequences of stricter vehicle emission standards that improve air quality and therefore reduces cardiovascular mortality and morbidity risks?

Public policy commonly addresses questions where the trade-offs involve comparing economic costs to the health benefits associated with investments and regulations. The input from economic analyses on the merits of such regulations are typically based on cost-effectiveness analysis (CEA) or cost-benefit analysis (CBA). In CEA, the health risks are not evaluated using monetary values and therefore these analyses cannot be (directly) used to assess the economic welfare effects of public policies.[i] The aim of a CBA is to assign monetary values to the predicted benefits and costs using a societal perspective: identifying, measuring and valuing the consequences for individuals, firms, and the public sector. If the net present value (NPV) is positive, i.e. the present value of all benefits outweighs the present value of all costs, the regulation is said to increase social welfare (The "Hicks-Kaldor" criterion).

Cost-benefit analyses of policy proposals have increased in use and importance over time. In the US, the use of CBA to inform policy makers on the consequences of policy proposals has been explicitly encouraged since the early 1980s. For proposals with an economic impact over 100 million US dollars, federal agencies are required to carry out analyses using CBA (Obama 2011). Several federal agencies, such as the Department of Transport and the Environmental Protection Agency, have also published specific guidelines on how to implement CBA in their specific domain, including recommended monetary values of e.g. mortality and morbidity health risks (EPA 2010, DoT 2016). In Europe, many national agencies also demand

and carry out CBA of major regulations and investments (Andersson 2018). The UK government outlines principles of CBA in the "Green Book", which is introduced by stating that each new policy, program or project must be assessed in terms of: "Are there better ways to achieve this objective?" and "Are there better uses for these resources?" (HM TREASURY 2003). At the level of the European Union, the European Commission (2014) has also developed a framework for how new regulations and investments can be evaluated using CBA.

To be able to carry out CBA of policies that involve improved (or worsened) population health it is necessary to value the predicted health changes in a monetary metric, e.g. US dollars, Chinese Yuan, Euros, etc. Considering that health risks are not directly traded in markets, the valuation of health risks is commonly one of the main challenges in CBA. The appropriate economic value of a health change is the willingness to pay (WTP) or the willingness to accept (WTA) for the health change. The WTP is defined as the maximum price a person is willing to give up to receive a specific good/service. The WTA is defined as the minimum amount a person is willing to accept to refrain from a good or service, or the compensation for an increase in a disamenity (e.g. health risk).

For public policy regulations and investments, the changes in average individual health risks are typically very small and the valuation exercise thus concerns individuals' WTP for a very small change in the health risk (e.g. the mortality risk). The total economic value of such a policy is then the population aggregate of each individual's WTP. Most research efforts have been devoted to WTP estimates of changes in mortality risk, which may be due to the importance of mortality risk consequences of many public policies as well as the fact that death is a relatively easy concept to define compared to many morbidity risks that are less objective. The economic term used for the trade-off between mortality risk and wealth is (commonly) the value of a statistical life (VSL). The term "statistical" highlights the fact that we are considering unidentified, rather than identified, lives.

To illustrate VSL we assume a population of 10,000 individuals where the baseline mortality risk (e.g. cancer risk) is 5/10,000, i.e. each year 5 persons in the population will die of cancer. Now imagine that a preventive treatment (e.g. a screening program) is estimated to reduce the annual mortality risk to 4/10,000, i.e. 1 person less would die each year, but it is not identified (ex-ante) who this person will be, and that everyone will benefit from the same risk reduction. We estimate the mean WTP for the screening program to \$100. This implies that the population WTP for the program and thus the VSL is *\$100×10,000 = \$1 million*, which we can interpret such that the population is in aggregate willing to pay \$1 million to reduce deaths by 1 person ("1 statistical life").

Lacking market prices for WTP estimates of mortality (and morbidity) risks, economists have developed several approaches to derive monetary values using what broadly can be classified as revealed- (RP) and stated-preferences (SP) approaches. RP approaches rely on observed market behavior, and the most common RP approach has been to assess the wage premium necessary to compensate for jobs with higher mortality and/or morbidity risks. SP studies are based on surveys and experiments where individuals are asked to make hypothetical choices between different programs or investments with varying costs and health risks.

The rest of this study will explore in more detail the theoretical foundations and empirical methods to estimate the WTP for small changes in health risks. The following sections are structured as follows. Section 2 covers the general theoretical background to the valuation of mortality risks, which can also be extended and applied to value other types of health risks. Section 3 describes the empirical approaches in more detail, with a particular focus on hedonic price regressions as the main RP approach used in valuation of health risks and the two main SP approaches of discrete choice experiments (DCE) and contingent valuation method (CVM) studies. In section 4 we present some applications in the form of empirical studies that have used hedonic pricing, DCE and CVM to estimate the WTP for small changes in mortality and/or morbidity risks. In section 5 we conclude and also discuss some of the main challenges and criticisms regarding the empirical methods to derive values of health risks. We conclude by highlighting some of our views on the most fundamental knowledge gaps in order to increase our understanding of individuals' valuation of health risks.

Theory

Monetizing Preferences

As explained, the WTP concept is considered the appropriate approach to elicit monetary values. However, at the time of Schelling (1968)'s discussion of the use of a WTP approach the human capital (HC) approach dominated as a means to estimate the social value of reducing mortality risk. The underlying assumption of the HC approach is that the market goods and services produced by an individual during his lifetime reflect his value to society (Mishan 1982). It is calculated as the expected future earnings, and hence does not consider individual preferences to reduce the risk of death. Under some (plausible) assumptions and restrictions it has been shown that the HC can serve as a lower bound for the VSL (Bergstrom 1982, Rosen 1988), but it is in general considered a poor proxy for a preference based, i.e. WTP, measure of individual risk preferences (e.g. Freeman et al. 2014).

We will in this section focus on the elicitation of preferences to reduce the risk of death. The models described below can be generalized to also cover morbidity risks (Andersson et al.

2015), but since mortality risk is a clearly defined outcome using it avoids having to address heterogeneity issues related to morbidity risks[ii]. As described the VSL is the aggregated monetary value of avoiding one statistical death in society. It is the population mean of the marginal WTP to reduce mortality risk and should not be interpreted as the value of an identified life. However, since the VSL contains the word “life” the concept leads to confusion and misunderstandings and it has been suggested to change it to something more neutral (e.g., Cameron 2010). While it is being discussed whether to change it, VSL is still the terminology used, and hence we also use it in this study.

In the following sub-section we will present the standard one-period model for VSL together with some predictions from the model and the literature. We will then describe a multiperiod model. The extension from the one- to the multiperiod model is of high relevance for examining health risks since it allows us to examine how individuals’ WTP may vary over the life-cycle, but also since many health risks are characterized by an often substantial time interval between a change in exposure and the health effect. This is usually referred to as latency and its effect on WTP can be examined in the multiperiod model.

One-Period Model

The VSL refers to the population mean of the marginal rate of substitution (MRS) between mortality risk and wealth, under the assumption that the individual MRS and the personal change in risk is uncorrelated (see e.g. Jones-Lee 2003). The theoretical model assumes that individuals maximize their utility in a state-dependent expected utility framework (Dreze 1962, Jones-Lee 1974, Rosen 1988). Let p define survival probability and $u_s(w)$ the state-dependent utilities of wealth (w), where the states are either staying alive (s=a) or dead (s=d), and individuals are assumed to maximize,

$$EU(w,p) = pu_a(w) + (1-p)u_d(w). \tag{2.1}$$

Following the standard assumptions in the literature we assume that the utility functions are twice differentiable, that utility of wealth is higher if alive than dead, that marginal utility of wealth is non-negative and higher if alive than dead, and that individuals are weakly risk averse to financial risks, i.e.,

$$u_a(w) > u_d(w),\ u_a'(w) > u_d'(w) \geq 0 \text{ and } u_s''(w) \leq 0. \tag{2.2}$$

Hence, at any wealth level both the utility and the marginal utility are higher if alive than dead and given these assumptions the indifference curves over wealth and survival probability are, as illustrated in Figure 1, decreasing and strictly convex.

Using Eq. (2.1) we can derive the compensating and equivalent surplus, i.e. the WTP and WTA, for a change in the mortality risk $\Delta p \equiv \varepsilon$ (Freeman et al. 2014). Let EU_0 be defined by Eq. (2.1) and $C(\varepsilon)$ denote the WTP for the risk reduction ε, then $C(\varepsilon)$ is given by,

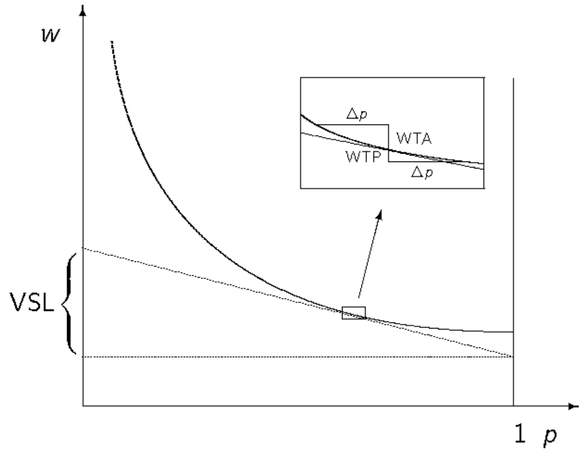
$$(p+\varepsilon)u_a(w - C(\varepsilon)) + (1-p-\varepsilon)u_d(w - C(\varepsilon)) = EU_0, \tag{2.3}$$

and similarly if we let $P(\varepsilon)$ denote the WTA for the risk increase ε, then $P(\varepsilon)$ is given by,

$$(p-\varepsilon)u_a(w + P(\varepsilon)) + (1-p+\varepsilon)u_d(w + P(\varepsilon)) = EU_0. \tag{2.4}$$

As evident from Eqs. (2.3) and (2.4), and illustrated in Figure 1, WTP and WTA will depend on the size of ε. The larger the change in the mortality risk, the larger is the WTP or WTA depending on whether it is an increase or decrease in ε. However, when eliciting WTP and WTA for changes in mortality risks the size of ε will be small. We therefore expect WTP and WTA to be nearly equal and that they are near-proportional to ε (Hammitt 2000).

Figure 1. The value of a statistical life



Source: Lectures notes, Henrik Andersson, Toulouse School of Economics, inspired by lectures notes by James Hammitt, Harvard University.

The VSL measures the WTP or WTA for an infinite small change in risk, and can be obtained by taking the limit of WTP or WTA when $\varepsilon \cong 0$. That is, as explained above it is the MRS between wealth and mortality risk and is defined as follows,

$$VSL = -\frac{dw}{dp}\bigg|_{\text{EU constant}} = \frac{u_a(w) - u_d(w)}{pu_a'(w) + (1-p)u_d'(w)}. \tag{2.5}$$

It is derived by totally differentiating Eq. (2.1) and keeping utility constant. Hence, it is the ratio between the utility difference and expected marginal utility and given by the assumptions in (2.2) VSL is always strictly positive.

Equation (2.5) can be empirically estimated as will be described and shown in sections 3 and 4. However, in empirical applications the risk reduction may be small but finite. This could be the case in surveys where it does not make sense to ask respondents about a truly marginal risk change, or in studies looking at discrete decisions in markets. In those cases, the VSL is given by the ratio between the WTP and the change in risk as shown in Eq. (2.6),

$$VSL = \frac{WTP}{\Delta p}. \tag{2.6}$$

Equation (2.6) suggests that the WTP is proportional to the change in risk. But, as explained, the true relationship between WTP and the size of Δp is only near-proportional, which is a necessary, but not sufficient, condition for WTP to be a valid measure of individuals' preferences (Hammitt 2000).

The Wealth and the Dead-Anyway Effect

For the empirical applications of the theoretical framework described in the previous section predictions are important to test the construct validity of the findings. Two standard predictions are the wealth and dead-anyway effect. First, to examine how wealth influences WTP is central to test the validity of preference estimates, not only for health risk, but also for other non-market goods (Arrow et al. 1993). The wealth effect in this scenario describes how VSL increases with wealth (Weinstein et al. 1980). The intuition is clear, i.e. that wealthier individuals (everything else equal) can pay more for a good, and in this scenario it can be broken down to: (i) the numerator in Eq. (2.5) increases in wealth, and (ii) the expected marginal utility in the denominator decreases in wealth. Both effects are assured by the assumptions in (2.2) and the results state that wealthier individuals have more to lose and that their utility cost of spending is smaller.

Second, the dead-anyway effect (Pratt and Zeckhauser 1996) suggests that WTP increases with the baseline risk, i.e. decreases with the survival probability (p). Since p only shows up in the denominator of Eq. (2.5) the dead-anyway effect does not depend on the utility difference in the numerator. Instead the effect is driven by the fact that the size of the denominator increases when p increases since $u'_a > u'_d$. The intuition is that a person at a high risk has little incentives to limit his spending on increasing his survival probabilities.

The Model and Selected Predictions

The two predictions described in the previous sections, and the one provided before on WTP and WTA being sensitive to the size of the mortality risk reduction, can be considered the basic predictions of the standard one-period VSL model. The model has also been used to provide several other predictions that are useful for understanding and testing the validity of empirical findings. For instance, the survival probability presented so far has been the overall chance of survival. However, individuals face many different types of risks, and individuals' WTP to reduce one risk may be influenced by the other risks that they face. These can be referred to as background risks and depending on whether these background risks are independent (Eeckhoudt and Hammitt 2001) or additive (Andersson 2008) to the specific risk it can be shown that VSL can either decrease or increase. Moreover, it has been shown that "Although aversion to financial risk increases VSL in definable cases, under many plausible assumptions the relationship between risk aversion and VSL is ambiguous." (Eeckhoudt and Hammitt 2004, p. 13), and that VSL increases with ambiguity aversion (Treich 2010).

Another example is the effect on health status on the VSL. Assuming that utility of wealth is higher in good than in bad health and that the marginal utility of wealth is increasing in health status, then both the numerator and denominator of Eq. (2.5) will increase, and hence, the effect on VSL will be ambiguous (Hammitt 2002, Strand 2006). We will not in this paper go into any details about these predictions. Instead we refer to the above provided references for readers interested in these topics.

Multiperiod Model

The model above is a single-period model. We here extend our model to a multiperiod model. The latter may be considered to be more realistic since individuals do have preferences for how the survival probability and consumption opportunities are distributed over their length of life. Moreover, it also allows for the examination of how age and latency affect individual WTP to reduce mortality risk.

The theoretical foundation is the life-cycle model in which individuals are assumed to maximize their expected value of the utility of consumption (see e.g. Yaari 1965, Johansson 2002). Let τ, $u(c_t)$, i, and $q_{\tau,t}=p_\tau \ldots p_{t-1}$, denote the point of reference, the utility of consumption at time t, the utility discount rate, and the probability at τ of surviving to t. The individual's expected utility is then given by,

$$EU_\tau = \sum_{t=\tau}^{\infty} q_{\tau,t} (1+i)^{\tau-t} u(c_t). \tag{2.7}$$

To simplify the description of the multi-period model we follow Hammitt and Liu (2004) and illustrate it with a two period model (assuming for simplicity that the marginal utility of a bequest is equal to zero),

$$EU = p_1 u_1(c_1) + p_1 p_2 u_2(c_2), \tag{2.8}$$

subject to the budget constraint,

$$c_1 + \frac{c_2}{1+i} = B, \tag{2.9}$$

where, as above, p, $u(c)$, and i are the survival probabilities (conditional on being alive at the beginning of each time period), utility of consumption, and the discount rate, with subscripts 1 and 2 referring to the first and second time period. In a multi-period framework the VSL will depend on the optimal consumption path and it can be shown that the optimization of consumption between periods is given by,

$$\frac{u_1'(c_1)}{u_2'(c_2)} = p_2(1+i). \tag{2.10}$$

Let $VSL_{j,k}$ denote the marginal WTP of a survival probability that appears in k, but where the consumption is given up in j (i.e. the individual pays for the risk reduction in j). By totally differentiating Eq. (2.8) we obtain

$$VSL_{1,1} = -\left.\frac{dc_1}{dp_1}\right|_{\text{EU constant}} = \frac{u_1(c_1) + p_2 u_2(c_2)}{p_1 u_1'(c_1)}, \tag{2.11}$$

which is the corresponding expression for a risk reduction that appears today and where the individual gives up other consumption (wealth) today as in Eq. (2.5). However, many health risks are characterized by a time period between exposure and the health affect, referred to as a latency period. It is therefore of interest to also estimate the WTP for latent risks and the corresponding expression for a WTP today for a future risk reduction is given by,

$$VSL_{1,2} = -\left.\frac{dc_1}{dp_2}\right|_{\text{EU constant}} = \frac{u_2(c_2)}{u_1'(c_1)}. \tag{2.12}$$

In Eqs. (2.10) and (2.11) we assume temporary risk reductions, i.e. the mortality risk is only reduced in a single time period, and we will use these two equations when we discuss predictions of age, latency, and multiperiod WTP in the next section.

Age and Latency and Multiperiod WTP

The relationship between age and preferences for health has gained a lot of attention and there is vast theoretical and empirical literature on the subject (see e.g. Huang et al. 2017). Intuitively it would make sense if WTP to reduce mortality risk would decline with age, since at older age (everything else equal) an individual has less to gain from a reduction in the risk of dying. However, it has been shown that this expectation is not necessary true. The relationship between the WTP and age will depend on the optimal consumption path over the individual's life-cycle, as shown by Eq. (2.10), which will depend on assumptions of the model. For instance, Shepard and Zeckhauser (1984) showed that in an economy where individuals can only optimize their consumption path by saving but not borrowing their VSL will have an inverted U-shape over their life, whereas in an economy where they can also borrow against future earnings their VSL declines monotonically with age. However, Johansson (2002) showed that the relationship is ambiguous since it depends on the assumptions of the model, i.e. it can in addition to the predictions above also be positive or independent.

Above we introduced the concept of latency with Eq. (2.12) showing the marginal WTP for a latent risk reduction. Intuition will tell us that WTP for a current risk should exceed that of a latent risk, since an individual would benefit from an early risk reduction also in future time periods. However, as pointed out by Hammitt and Liu (2004) this intuition is misleading, and the WTP for a future risk reduction could also be equal or greater than the WTP for a current risk reduction. They show this by subtracting Eq. (2.12) from Eq. (2.11) which results in,

$$VSL_{1,1} - VSL_{1,2} = \frac{u_1(c_1) + [p_2 - p_1]u_2(c_2)}{p_1 u_1'(c_1)}, \tag{2.13}$$

which suggests,

$$VSL_{1,2} > VSL_{1,1} \Leftrightarrow \frac{u_1(c_1)}{u_2(c_2)} < p_1 - p_2. \tag{2.14}$$

It is reasonable to assume that the survival probability will decline with age, and hence the right-hand side of the element to the right of (2.14) will be positive. The condition on the left can be satisfied if the utility of consumption in the first period is sufficiently small compared to the one in the second period, which “seems unlikely but cannot be ruled out” (Hammitt and Liu 2004, p. 78).

So far we have discussed temporary risk reductions that last one time period. The multiperiod model can also be used to estimate the WTP for risk reductions that last several time periods or are permanent, since this WTP can be calculated as the summation of the WTP for future time periods with the risk reduction (Johannesson et al. 1997). This approach has also frequently been used in the empirical literature as a mean to make the change in risk more understandable by making the risk change larger. However, as shown by Andersson et al. (2013) this approach can introduce a non-negligible bias if the time period is too long, or if the discount rate is sufficiently high.

Empirical Methods

Since no easily available market prices exist for risk reduction policies researchers instead rely on what is usually referred to as non-market valuation techniques to estimate the WTP for such policies. As explained, these techniques can broadly be classified as either RP or SP methods. The former refers to methods that use individuals’ actual decisions in markets that are related to the good of interest, while the latter is based on individuals’ responses to hypothetical choice situations. In this section we review the main approaches used in the literature and refer to additional sources for readers that are interested in learning more about a particular methodology.

Revealed Preference Methods

The most commonly used RP approach to estimate the WTP for risk reductions is the hedonic regression method (Rosen 1974), which is based on the notion that the price of a good is a function of its attributes. For example, the price of a house will depend on characteristics such as the number and size of the rooms, as well as its location (proximity to amenities, transport links etc.). The hedonic price function can then be written as:

$$P = P(Q) \tag{3.1}$$

where P is the price of the good and $Q = (q_1, q_2 \ldots, q_k)$ is a vector of attributes. Rosen showed that in a competitive market with utility maximizing individuals and profit maximising firms the marginal WTP (MWTP) for an attribute will equal its equilibrium implicit price. The implicit price of attribute q_k is given by the partial derivative of the hedonic price function with respect to that attribute:

$$MWTP_{q_k} = \frac{\partial P(Q)}{\partial q_k} \tag{3.2}$$

The hedonic wage method (Viscusi and Aldy 2003) is a variant of the hedonic regression technique which uses data on individuals' job choices to infer the tradeoff workers are prepared to make between wages and risk. Holding other characteristics of the individuals and the job constant, the increase in wages associated with an increase in workplace risk can be interpreted as the compensation needed to keep the workers' utility constant. The hedonic wage regression is typically specified along the following lines (Viscusi and Aldy 2003):

$$w_i = \alpha + X_i'\beta + W_i'\delta + \gamma_1 p_i + \gamma_2 q_i + \varepsilon_i, \tag{3.3}$$

where w_i is the wage rate of worker i, X_i is a vector of individual characteristics, W_i is a vector of job characteristics, p_i is the probability of a fatal workplace accident, q_i is the probability of a non-fatal workplace accident and ε_i is an error term. The model can be extended by including interactions between p_i and X_i, which allows the trade-off between wages and risk to vary across groups of workers depending on their characteristics, and interactions between q_i and measures to compensate workers for non-fatal accidents. Based on the wage regression the marginal WTP for a reduction in risk can be derived as the effect of a unit increase in the probability of fatal accidents on wages:

$$MWTP = \frac{\partial w_i}{\partial p_i} \tag{3.4}$$

If the model is linear the MWTP is simply given by γ_1, although it is common in the literature to compare estimates using different functional forms (such as semi-log or log-linear), or use a Box-Cox regression that nests several functional forms. A more comprehensive overview of hedonic regression methods is given in Freeman et al. (2014).

The hedonic wage method has been used extensively to estimate the WTP for risk reductions, especially in the US (EPA 2016). There is also a substantial literature utilizing data from the housing market by recognizing that housing associated with differential health risks will be capitalized in the market price. Examples include studies assessing how house prices are affected by local cancer clusters associated with increased risks of pediatric leukemia (Davis 2004) and how hazardous water pollution affects residential land prices (Leggett and Bocksstael 2000). An example of another variant of the hedonic regression method is given in Andersson (2005), who studies the relationship between car prices and fatality risks. The observation that consumers can reduce health risks by purchasing products associated with lower risks (such as safer cars, or houses in less polluted areas) is the foundation for studies on averting behavior in consumption, which also includes studies using alternatives to the hedonic regression method (see e.g. Blomquist 2004).

Stated Preference Methods

As the name suggests the SP approach is based on respondents' stated choices in hypothetical market scenarios. There exists a wide range of different SP methods, but the most commonly used approaches to elicit individual WTP are the contingent valuation method (CVM) and discrete choice experiments (DCE) (Bateman et al. 2004). SP methods have been used to evaluate a wide range of health risks, such as contaminated water (Adamowicz et al. 2011), cancer risks (Hammitt and Haninger 2010), road mortality risks (Andersson et al. 2013), and fire and drowning risks (Carlsson et al. 2010). The advantage of the SP approach is that it offers flexibility in creating specific markets of interests and allows the analysts to control the decision alternatives. Johnston et al. (2017) provide best-practice recommendations for SP studies used to inform decision making.

The Contingent Valuation Method

The CVM presents a sample of survey participants with a hypothetical policy scenario that would reduce the risk of fatalities. The respondents are also presented with background information regarding the nature of the risk that the policy would reduce. The respondents are asked to either state their maximum WTP for the policy (open-ended CVM) or they are told how much they would have to pay if the policy was introduced (the "bid" in CVM terminology) and asked whether they are willing to pay this amount or not (closed-ended CVM).[iii] See Table 1 for an example of a closed-ended CVM question which is based on the application in Andersson et al. (2016). In the influential review of the CVM method carried out by the National Oceanic and Atmospheric Administration (NOAA) panel (Arrow et al. 1993) the closed-ended approach was recommended, as it mimics a referendum in which respondents vote on whether a policy should be introduced in exchange for an increase in taxes. It is also similar to a market transaction in which consumers are presented with the price of a good and then decide whether or not to buy it.

Open-ended CVM data are straightforward to model using standard regression techniques, where the maximum WTP is specified as a function of individual characteristics. Closed-ended CVM data can be modelled using a latent variable framework, in which the latent (unobserved) WTP is specified as:

$$WTP_i^* = \alpha + X_i'\beta + \varepsilon_i \qquad (3.5)$$

where X_i is a vector of individual characteristics and ε_i is an error term which is typically assumed to be normally distributed with mean 0 and variance σ^2. The probability that respondent i accepts a bid with value r_i is then given by:

$$P(WTP_i^* > r_i) = P(\alpha + X_i'\beta + \varepsilon_i > r_i) = P(\varepsilon_i > r_i - \alpha - X_i'\beta) = 1 - \Phi\left(\frac{r_i - \alpha - X_i'\beta}{\sigma}\right) \qquad (3.6)$$

where Φ denotes the standard normal CDF. The α, β and σ parameters can be estimated by maximum likelihood in standard software using interval regression (e.g. *intreg* in Stata).[iv]

It is well established that the model specification can have a substantial impact on the estimated WTP, which indicates that analysts should conduct extensive sensitivity analyses using different specifications. It may also be advisable to estimate CVM data using distributional-free estimators such as the Turnbull estimator; see Haab and McConnel (2002) for an extensive introduction to the econometrics of CVM data.

Table 1. Example CVM question.

Introductory text
Campylobacter is a bacteria which can infect humans via food or water. Campylobacteriosis affects about 63000 people in Sweden each year, which means that 700 people are affected annually in a medium-sized city with 100,000 inhabitants. The symptoms of the disease vary from case to case, but somewhat simplified one can say that there are mild, intermediate and serious versions of the disease. It is not known which version of the disease one will get before being affected by campylobacteriosis. What we do know is that among those affected 77 out of 100 get the mild version, 22 out of 100 the intermediate version, 1 out of 100 the serious version. In very rare cases affected individuals die from the disease (less than 5 per year in Sweden).
CVM question
Assume that a government authority is considering introducing a stricter water sanitation policy that will reduce the occurrence of campylobacter. Would you be willing to pay 2000 SEK for a policy that would imply that 2 fewer persons will die in Sweden due to campylobacteriosis?

Discrete Choice Experiments

In DCEs the participants are presented with two or more hypothetical policies, and asked to choose their preferred policy or the status quo (not introducing either policy). As an example, we use a simple experiment with only two attributes; the number of fewer individuals who die when the policy is implemented and the cost of the policy (see Table 2). Respondents are asked to choose their preferred option between two hypothetical scenarios and the status-quo (the choice set). In this simple form the DCE method shares many similarities with the closed-ended CVM method, but the advantage of DCEs is that further attributes of the alternatives can easily be accommodated in the experiment. For example, we could include an additional attribute representing the reduction in non-fatal cases of campylobacteriosis, which would allow us to investigate how individuals trade off reductions in fatal and non-fatal cases (Andersson et al. 2016). The levels of the attributes presented to the participants in the experiment, i.e. the number of fatalities prevented and the cost of the policy, are varied according to an experimental design (Carlsson and Martinsson 2003). Typically, each respondent is presented with several hypothetical choice sets with different attribute levels.

Data from DCEs are typically analysed using a random utility model framework. The utility that respondent *n* derives from choosing alternative *j* in choice set *t* is given by:

$$U_{njt} = \beta_0 sq_{njt} + \beta_1 die_{njt} + \beta_2 cost_{njt} + \varepsilon_{njt} \tag{3.7}$$

where β_0, β_1 and β_2 are coefficients to be estimated, sq_{njt} is a dummy variable for the status quo alternative, die_{njt} is the number of fewer individuals who die when the policy is implemented, $cost_{njt}$ is the cost of the policy and ε_{njt} is a random error term which is assumed to be IID type I extreme value.

The MWTP for a reduction in risk equivalent to saving one life is given by the marginal rate of substitution between cost and lives saved:

$$-\frac{\partial U_{njt} / \partial die_{njt}}{\partial U_{njt} / \partial cost_{njt}} = -\frac{\beta_1}{\beta_2} \tag{3.8}$$

Given the above assumptions the probability that respondent *n* chooses alternative *j* in choice set *t* has a multinomial logit (MNL) form:

$$P_{njt} = \frac{\exp(\beta_0 sq_{njt} + \beta_1 die_{njt} + \beta_2 cost_{njt})}{\sum_{j=1}^{J} \exp(\beta_0 sq_{njt} + \beta_1 die_{njt} + \beta_2 cost_{njt})} \tag{3.9}$$

The parameters in the multinomial logit (MNL) model[v] can be estimated using maximum likelihood in standard software (e.g. *asclogit* in Stata). Lancsar et al. (2017) present a practical guide to modelling DCE data with examples using Stata and other software packages.

Other more advanced discrete choice methods which overcome the main limitations of the MNL model are commonly used in the DCE literature. In particular the assumption that respondents have the same preferences for changes in the attributes is usually regarded as being unrealistic. While this assumption can be relaxed by augmenting the MNL model with interactions between the attributes and respondent characteristics, the researcher does not typically observe all of the characteristics which are related to heterogeneity in preferences. The mixed logit model overcomes this limitation by allowing the parameters in the model to vary randomly. The vector of parameters β is specified to have a particular distribution, $f(\beta\,|\,\theta)$, whose parameters θ can be estimated. If the coefficients are normally distributed, for example, θ represents the mean and covariance of the distribution. The mixed logit probability that respondent *n* makes a particular sequence of choices is given by:

$$S_n = \int \prod_{t=1}^{T} \prod_{j=1}^{J} \left[\frac{\exp(\beta_0 sq_{njt} + \beta_1 die_{njt} + \beta_2 cost_{njt})}{\sum_{j} \exp(\beta_0 sq_{njt} + \beta_1 die_{njt} + \beta_2 cost_{njt})} \right]^{y_{njt}} f(\beta\,|\,\theta)\, d\beta \tag{3.10}$$

where y_{njt} is a dummy variable which is equal to one if alternative *j* is chosen and zero otherwise, and $\beta = (\beta_0, \beta_1, \beta_2)$. In addition to allowing for preference heterogeneity the mixed logit model allows for the fact that respondents make multiple choices, as the individual preferences are assumed to remain constant over the choices made by the same individual. The integral in Eq. (3.10) cannot be solved analytically, and it is therefore approximated using simulation methods. See Train (2009) for a comprehensive review of the mixed logit model and other advanced discrete choice methods using simulation.

An alternative to assuming that the coefficient distribution is continuous (e.g. normal or log-normal) is to specify that it is discrete. A mixed logit model with a discrete coefficient distribution is often referred to as a latent class logit model (e.g. Greene and Hensher 2003, Hole 2008). The latent class logit probability that respondent *n* makes a particular sequence of choices is given by:

$$S_n = \sum_{c=1}^{C} H_{nc} \prod_{t=1}^{T} \prod_{j=1}^{J} \left[\frac{\exp(\beta_{0c} sq_{njt} + \beta_{1c} die_{njt} + \beta_{2c} cost_{njt})}{\sum_{j=1}^{J} \exp(\beta_{0c} sq_{njt} + \beta_{1c} die_{njt} + \beta_{2c} cost_{njt})} \right]^{y_{njt}} \quad (3.11)$$

where the coefficients are given a class (*c*) subscript to indicate that preferences vary across (but not within) classes. H_{nc} is the probability that individual *n* belongs to class *c*, which is typically specified to have a multinomial logit form:

$$H_{nc} = \frac{\exp(\gamma_c' Z_n)}{\sum_{c=1}^{C} \exp(\gamma_c' Z_n)} \quad (3.12)$$

where Z_n is a vector of characteristics relating to individual *n* and γ_C is normalised to zero for identification purposes. Stata implementations of the mixed and latent class logit models are described in Hole (2007) and Pacifico and Yoo (2013).

Table 2. Example DCE question.

Introductory text as in the CVM example

Assume that a government authority is considering introducing one of the following two stricter water sanitation policies that will reduce the occurrence of campylobacter.

	Policy A	**Policy B**
Number of fewer individuals who die when the policy is implemented	1	2
Your cost	1 000 SEK	2 000 SEK

Which option do you prefer

☐ Policy A

☐ Policy B

☐ None of the suggested policies (today's situation remains and no additional cost for you)

Examples of Applications

Using Hedonic Price Regressions to Value Mortality Risks

To provide an example of a hedonic pricing study valuing mortality risks, we describe a study by Gentry and Viscusi (2016) where they specified the basic hedonic regression equation as (Gentry and Viscusi 2016, p.93):

$$\ln(w_{ijk}) = \alpha + X'_{ijk}\beta + W'_{jk}\delta + \gamma_1 p_{jk} + \gamma_2 q_{jk} + \varepsilon_{ijk} \quad (4.1)$$

The equation shows that the natural logarithm of wage (w) for an individual i in industry j and occupation k was regressed on a set of individual demographic controls (X) such as age, sex, race, years of education etc., a set of industry- and occupation-specific controls (W), the fatality (p) and injury (q) rate. The coefficient estimate of interest to value the mortality risk is γ_1, whereas γ_2 shows the impact on wage of the non-fatal injury rate. Data on wages and control variables were collected on the individual level from the Current Population Survey (CPS), whereas the fatality and injury rate data were based on average risks per industry and occupation retrieved from the US Bureau of Labor Statistics (BLS) Census of Fatal Occupational Injuries.

The fatality rate is based on average industry-occupation risks and is calculated as:

$$fatality\ rate = \frac{N}{EH} \times 2{,}000 \times 100{,}000, \tag{4.3}$$

where *N* is the number of fatal injuries and EH is total hours worked by everyone in the specific industry-occupation group. The rate is multiplied by 2,000 (hours worked per year per worker) and subsequently by 100,000 to express the rate as the annual risk per 100,000 people. The reported overall annual fatality rate was 6.23 fatalities per 100,000 employees, but this varied from e.g. 0.75 fatalities per 100,000 health care employees to 70.1 fatalities per 100,000 employees in forestry, fishing and hunting occupations. The injury rate is calculated in a similar manner, with the difference that *N* is the number of work days lost due to injury per year.

The results from estimating Eq. (4.1) showed that a higher fatality and injury rate were both statistically significantly related to lower hourly wages. An increase in the fatality rate by 1 in 100,000 was associated with a 0.16% higher hourly wage. Hence, the evidence suggest that workers are compensated to take on risk, and based on Eq. (4.1) the VSL was estimated as:

$$VSL = \hat{\gamma}_1 \times \overline{wage} \times 2{,}000 \times 100{,}000 \tag{4.3}$$

where the mean hourly wage ($\overline{wage}$) is multiplied by 2,000 to convert the hourly wage into an annual wage. The annual wage is then multiplied by 100,000 to take into account that the risk is per 100,000 workers. Based on the regression result and the mean wage for the full sample, the implicit VSL was estimated at $5.36 million.[vi]

There has been a large number of similar studies carried out using wage-risk equations to estimate the implicit VSL. Viscusi (2014) reviewed many of the wage-risk studies and updated to $2016 (based on the GDP deflator) the mean predicted VSL ranged from $7.5 million to $10.3 million in the US sample. Results from this literature has been important in policy making by influencing the recommended VSL estimates for economic evaluations especially in the US, by e.g. the US Department of Transport and the US Environmental Protection Agency (EPA 2010, DoT 2016).

Using Stated Preferences to Value Mortality Risks

Since SP methods can be tailor-made to value any specific condition they have been applied to a broader range of health risks than the RP method. For example, SP methods have been used to estimate the WTP for primary care cancer tests, insecticide treated mosquito nets to reduce malaria risks, and for genetic testing for inherited retinal disease (Biadgilign et al. 2015, Tubeuf et al. 2015, Hollinghurst et al. 2016). However, the single largest area of study has been to estimate the WTP to reduce mortality risks, i.e. comparable to the case with hedonic price regressions. A recent meta-analysis covering only a sub-set of all VSL estimates (Lindhjelm et al. 2011) includes almost 1,000 published VSL estimates using SP methods. Here we borrow from two SP studies to provide examples from this literature.

A CVM Application

Hammitt and Haninger (2017) use the CVM method to estimate the WTP for small reductions in the risk of suffering non-fatal health conditions. The survey was administered to a sample drawn randomly from a US internet panel. The survey respondents were asked to choose whether they would participate in a health protection program that would reduce the risk of developing a particular illness from exposure to environmental contaminants. The illness varied across survey versions and was described using the EQ-5D health-state descriptive system (EuroQol group 1990). In addition, half of the respondents were presented with the condition name (e.g. "Migraine headaches"). Depending on the question, the risk reduction either related to the respondent themselves, another adult living in the household or a child younger than 18 years. The baseline mortality risks and risk reductions used in the survey are shown in Table 3.

Table 3. Mortality risks and risk reductions in Hammitt and Haninger (2017)

Baseline risk	Risk if participating in the program	Risk reduction
3 in 10,000	2 in 10,000	1 in 10,000
3 in 10,000	1 in 10,000	2 in 10,000
4 in 10,000	3 in 10,000	1 in 10,000
4 in 10,000	2 in 10,000	2 in 10,000

Note: All figures are per year.

The baseline, reduction and final risk were presented using a grid containing 10,000 squares, with the number of red squares corresponding to the risk after reduction (1, 2 or 3) and the number of white squares to the risk reduction (1 or 2). The total number of red and white squares represented the baseline risk (3 or 4). The risk information was also presented numerically, as in Table 3.

The WTP elicitation format was double-bounded dichotomous choice, in which respondents are asked two sequential closed-ended CVM questions in each valuation task. The respondents were first asked if they would be willing to pay a cost $X to participate in the program, where X ranged from $10 to $2,000 per year. If they answered yes (no) to the initial

WTP question, a second question followed where they were asked if they would participate in the program if the cost was *$X×2* (*$X×0.5*). To set the range of the initial cost (bid) vector the authors assessed the implicit minimum and maximum value per statistical illness covered. With a range from $10 to $2,000 this value ranges from <$50,000 (which results from not paying $10 for the 2/10,000 risk reduction) to >$20 million (resulting from being willing to pay $2000 for the 1/10,000 risk reduction).

The authors estimated the following model using interval regression:

$$\ln\left(WTP_i\right)^* = \alpha + \gamma_1 \ln(r_i) + \gamma_2 \ln(q_i) + \gamma_3 \ln(t_i) + X_i'\beta + \varepsilon_i \tag{4.3}$$

where r_i is the reduction in the probability of illness, q_i is the reduction in health-related quality of life (HRQL) as a result of the illness (on a scale from 0 to 1) and t_i is the duration of the illness. The vector X_i includes additional control variables, such as current HRQL, and ε_i is a normally distributed error term. This model specification implies that γ_1 is the elasticity of WTP with respect to a change in the probability of illness. The standard theory implies that for small changes in the probability this elasticity should be close to 1, implying that WTP is near-proportional to small changes in risk.

The authors estimated the model in Eq. (4.3) on four different samples: including all responses or including only responses in which the target of the risk reduction was the respondent, another adult living in the household or a child younger than 18 years. In all four samples the coefficient on the reduction in the probability of illness was found to be close to (and insignificantly different from) 1, confirming the theoretical prediction that WTP is near-proportional to small changes in risk. The coefficients on the reduction in health-related quality of life and the duration of the illness were found to be positive, but less than 1, indicating that the WTP increases with these variables but not proportionally. Including dummy variables for the target type in the pooled model indicated that the respondents have a higher WTP for reducing the probability of illness for a child younger than 18 years (200% more) and another adult living in the household (150% more) than for themselves. The authors carried out various sensitivity analyses, which generally did not affect the main findings.

The modelling results can be used to estimate the WTP for different illnesses characterized by their duration and reduction in health related quality of life. The predicted WTP for a statistical illness can be calculated by predicting log(WTP) using the regression results, exponentiating the predicted value (which yields an estimate of median WTP) and dividing by the risk reduction. Some illustrative values are presented in table 4:[vii]

Table 4. Values per statistical illness (in dollars)

Duration(years)	HRQL loss	Household member at risk		
		Self	Child	Other adult
1	0.1	678,000	2,010,000	1,670,000
1	0.8	1,380,000	4,090,000	3,400,000
5	0.1	817,000	2,420,000	2,020,000
5	0.8	1,660,000	4,930,000	4,100,000

It can be seen from the table that the predicted WTP for children in the household is about 3 times as high as the value for the respondents themselves, while the WTP for another adult is about 2.5 times as high. This corresponds to the magnitudes of the estimated target type dummy coefficients. It is also apparent that while the WTP increases in the HRQL loss the increase is not proportional (the WTP of a 0.8 decrease in HRQL is less than 8 times the WTP of a 0.1 decrease), which is a result of the HRQL coefficient being positive but less than one.

A Discrete Choice Experiment Application

Adamowicz et al. (2011) used the DCE method to elicit consumers' preferences for reductions in health risks associated with tap water. A sample drawn from a panel of Canadian internet users was invited by email to complete an online survey, which presented the respondents with information about the health risks and different programs to reduce such risks before introducing the DCE choice tasks. In the DCE the tap water delivered to households was described in terms of the following attributes: two types of mortality risks (cancer and microbial), two types of morbidity risks (cancer and microbial) and the costs to the household of disinfection and treatment methods to reduce the health risks. The respondents were presented with four DCE choice tasks of the form presented in Table 5.[viii]

Table 5. Example DCE choice task from Adamowicz et al. (2011)

This is the first scenario we want you to vote on.

For every 100,000 people, the NUMBER who would…	**CURRENT SITUATION**	**PROPOSED PROGRAM A**	**PROPOSED PROGRAM B**
Get **sick** from **microbial illness** in a **35-year** period	23,000	15,000	7,500
Die from **microbial illness** in a **35-year** period	15	10	5
Get sick from **bladder cancer** in a **35-year** period	100	50	100
Die from **bladder cancer** in a **35-year** period	20	10	20
Change to your water bill starting in January, 2005	No change	Increase $75 per year ($6.25 per month)	Increase $75 per year ($6.25 per month)

If there was a referendum I would vote for…

CHECK ONE ONLY

☐ Current Situation

☐ Proposed Program A

☐ Proposed Program B

Note: the choice sets used in the actual survey also included a graphical representation of the mortality and morbidity risk attributes.

The respondents' utility function was specified to be a linear function of the attributes, i.e. the number of microbial deaths and illnesses averted ($mdie_{njt}, msick_{njt}$), the number of cancer deaths and illnesses averted ($cdie_{njt}, csick_{njt}$) and the cost of the program ($cost_{njt}$), as well as a status quo dummy variable (sq_{njt}) and an error term (ε_{njt}):

$$U_{njt} = \beta_0 sq_{njt} + \beta_1 mdie_{njt} + \beta_2 msick_{njt} + \beta_3 cdie_{njt} + \beta_4 csick_{njt} + \beta_5 cost_{njt} + \varepsilon_{njt} \tag{4.3}$$

The authors estimated the parameters in the utility function using an MNL model with and without interactions between the status-quo variable and respondent characteristics. Evidence of preference heterogeneity was explored by using a mixed logit model with lognormally distributed mortality and morbidity risk coefficients and a fixed (non-random) cost coefficient, and a latent class logit model with two classes in which the class membership was modelled as a function of individual characteristics.

Based on the results from the MNL model the authors found that the WTP for one fewer microbial death in the community was \$12.6, while the WTP for one fewer cancer death was \$10.4 (including respondent characteristics in the model made little difference to the results).[ix] The difference between these MWTP estimates was not found to be statistically significant. The difference between the MWTP estimates for morbidity risk reductions, on the other hand, was found to be statistically significant, with cancer risk reductions being valued more highly (\$2.43 vs \$0.02). The corresponding mean MWTP estimates from the mixed and latent class logit models are \$15.0/\$13.6 (microbial mortality risk), \$10.8/\$12.2 (cancer mortality risk), \$0.02/\$0.02 (microbial morbidity risk) and \$3.05/\$2.32 (cancer morbidity risk).

While the mean MWTP estimates were found to be similar across models, there is evidence of a large degree of preference heterogeneity among respondents. The results from the latent class model suggest that there are two distinct groups of respondents, one of which is reluctant to move away from the status quo and show an unwillingness to make tradeoffs for improved water quality. The authors argue that this suggests that a discrete representation of preference heterogeneity is appropriate in this context since it allows such behavior to be identified, while a continuous representation of preference heterogeneity (as in the mixed logit model) does not.

The VSL was found to be $17 million for microbial death and $14 million for cancer death according to the MNL model. The VSL estimates are derived by multiplying the MWTP estimates by the number of households in the community (38,500) over a 35-year period.[x] The estimates are in the high end of the range reported in the VSL literature, which the authors suggest may be due to the fact that their estimates are based on the WTP to reduce *public* mortality risks. This means that they include both the WTP to reduce the risk of death to oneself as well as the WTP to reduce risk of death to others in the community, including family members. This contrasts to the majority of studies in the VSL literature, which estimate the value of private mortality risk reductions.

Discussion

We have provided an overview of the valuation of health risks as carried out in economics. The WTP approach is well established as the appropriate approach to assign monetary values to health risks that reflect individual preferences. As described in section 2, the monetizing of health risks is based on well-developed theoretical models that provide predictions for the empirical applications of the WTP approach. Among economists, the valuation of health is quite uncontroversial; individuals make daily decisions in their lives that suggest that they have a finite WTP to reduce their risk of fatality, injury, illness, etc. Moreover, when health policies are implemented it is not known who will benefit from the policies, only that a certain number of deaths, injuries, etc. will be prevented (veil of ignorance). However, among non-economists it is controversial to assign monetary values to health outcomes, especially to the “value of life”. This means that the values obtained in empirical studies are often heavily scrutinized, whether from RP or SP studies, simply because they are considered to “price” health outcomes. Advocates of WTP studies for health outcomes obviously do not agree with the ethical objections to valuing health, but can agree on the fact that analysts face several difficulties when implementing health valuation studies.

Economists have traditionally been more willing to accept estimates from RP methods considering the reliance on actual behavior. A drawback with the RP approach is that markets do not always exist for the good of interest. For example, it may be that individuals have different preferences for different kinds of risks, such as the risk of dying from cancer versus the risk of a fatal workplace accident. Furthermore, the hedonic wage method depends crucially on the analyst having access to accurate measures of risk as well as all relevant individual and job-related characteristics, in order to avoid biases arising from either measurement error or omitted variables.

There is a larger literature focusing on the limitations and drawbacks of SP methods (see e.g. Hausman 2012). The main criticism of SP methods is that decisions are hypothetical, which means that respondents do not have incentives to be well informed when making their decision and that their stated response may not reveal how they would act if the decision had been real. A particular issue that has received much attention in the literature is the lack of sensitivity to scope. While most CVM studies find evidence that the WTP for risk reductions is increasing with the size of the reduction in risk, the increase is typically not near-proportional, which is a necessary validity criterion for SP-based WTP estimates (Hammitt and Graham 1999, Corso et al. 2001, Robinson and Hammitt 2015). Although there is less evidence on scope sensitivity in

DCEs, especially using between-subject designs in which different respondents are presented with different risk reductions, recent findings suggest a lack of scope sensitivity in DCEs as well (Andersson et al. 2016).[xi] This evidence implies that SP estimates of the WTP for risk reductions must be interpreted with caution. However, despite the criticism of eliciting preferences based on hypothetical scenarios there has been a large increase in the use of SP studies over the past few decades (Carson and Hanemann 2005).

Despite criticism and shortcomings of both the RP approach, e.g. non-existing markets and that the analysts may not be well informed about the decision alternatives individuals do face, and of the SP approach, as listed above, both approaches have a key role to play in eliciting preferences for health risk reductions. Since no easily available prices are available for health risk reductions non-market valuation methods are necessary to monetize these preferences. There has also been a lot of progress in estimating WTP for health risk reductions over the last couple of decades, both regarding access to data for RP studies, and methodological improvements in SP studies, resulting in improved validity and reliability of the estimated values (Viscusi 2014).

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Notes

[i] There is a very large literature on CEA and health risk metrics used in CEA, such as Quality Adjusted Life Years (QALYs) and Disability Adjusted Life Years (DALYs). These methods and metrics will not be covered in this paper, which has a focus on the welfare economics approach to health risk valuation.

[ii] Such a large variation in possible health outcomes, and context dependence related to survival when presenting the theoretical model

[iii] Other versions of the CVM method, such as the use of payment cards, have also been used in practice, although the open and closed-ended approaches are the most commonly used.

[iv] If the respondents are presented with a single bid the observations are either left- or right-censored in the interval regression terminology. If respondents are additionally presented with a follow-up bid then some observations will be intervals (if the respondent accepts one bid and rejects the other), left censored (if both bids are rejected) or right censored (if both bids are accepted).

[v] A multinomial logit model with alternative-specific attributes is often referred to as a *conditional logit* model (see e.g. Lancsar et al. (2017)

[vi] The authors also extend the basic model to incorporate what they call morbidity risks associated with a fatal injury, which captures the number of days from the injury until death. For example, some deaths occur immediately after an injury, whereas in other cases the time from injury to death (when it occurs) may stretch up to several months.

[vii] We refer interested readers to Hammitt and Haninger (2017) for information on the values chosen for the different explanatory variables when generating the predicted values of log(WTP).

[viii] Some respondents were instead randomly chosen to complete DCE tasks with only two alternatives (one program and the current situation) and DCE tasks in which the ratio of morbidity and mortality reductions were held constant. The survey also included three double-bounded CVM choice tasks, but here we focus on the DCE results.

[ix] The MWTP estimates are calculated as the ratios between the mortality risk and cost coefficients as exemplified in equation 3.8.

[x] The calculations assume that the risk of death is equally likely over the entire 35-year period. The authors also present a sensitivity analysis in which this assumption is relaxed.

[xi] Between-subject designs are considered a more stringent approach to test for scope sensitivity, as within-subject designs may lead to a failure to reject scope sensitivity due to respondents' desire to be 'internally consistent' when completing the survey.