WORKING PAPERS

N° TSE-628

February 2016

"The Value of Cancer Prevention vs Treatment"

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

Toulouse School of Economics

The Value of Cancer Prevention vs Treatment

Christoph M. Rheinberger, Daniel Herrera-Araujo, James K. Hammitt*

Abstract

We present an integrated valuation model for diseases that pose some chance of death. The model extends the standard one-period value-of-statistical-life model to three health prospects: healthy, ill, and dead. We derive willingness-to-pay values for prevention efforts that reduce a disease's incidence rate as well as for treatments that lower the corresponding health deterioration and mortality rates. We find that the demand value of prevention always exceeds that of treatment. People often overweight small risks and underweight large ones. We use the rank dependent utility framework to explore how the demand for prevention and treatment alters when people evaluate probabilities in a non-linear manner. For incidence and mortality rates associated with common types of cancers, the inverse-S shaped probability weighting found in experimental studies leads to a significant increment in the demand values of both treatment and prevention.

JEL classification: D11, D81, I10

*CMR: Toulouse School of Economics (LERNA), 21 allée de Brienne, 31000 Toulouse, France e-mail: rheinberger.cm@gmail.com; DHA: Paris School of Economics (Hospinnomics), e-mail: daniel.herrera@psemail.eu; JKH: Harvard University (Center for Risk Analysis) and Toulouse School of Economics (LERNA), e-mail: jkh@harvard.edu. This work was sponsored by an INRA Scientific Package. JKH acknowledges additional support from the European Research Council (FP7/2007–2013, grant no. 230589).

1 Introduction

How should government expenditure on health be allocated to maximize social welfare? Answers to this question require understanding people's preferences for different health interventions (Fuchs and Zeckhauser 1997). In this paper, we develop a stylized health valuation framework and apply it to the combat of cancer. Since the 1970s significant progress has been made in preventing, diagnosing, and treating cancer. However, cancer remains one of the leading causes of death.[1] Some researchers have therefore argued that society spends too much on the development of new cancer drugs and other treatment methods, and too little on prevention and diagnosis (Sporn 1996, Chabner and Roberts 2005, Faguet 2005). If that claim were true, then society would not operate at the production possibility frontier (where the good to be produced is additional life years for cancer patients) and a Pareto improvement could be achieved by re-allocating resources from R&D to prevention and screening efforts.

Efficiency concerns have been raised against the supply side of fighting cancer, but similar arguments hold for the demand side as well (Bosworth et al. 2010). Consider empirical studies that suggest people value a reduction in the risk of dying from cancer more than they value a reduction in the risk of dying from other causes (Hammitt and Liu 2004, Van Houtven et al. 2008, Viscusi et al. 2013). Such preferences should be reflected in the allocation of the health budget, as they are essential to health policy assessments; e.g. to quantifying the social value of the U.S. war on cancer (Lakdawalla et al. 2010).

In this paper, we develop willingness-to-pay (WTP) metrics for prevention-based and treatment-based health interventions to study value tradeoffs between incidence rate, mortality rate, and the life quality of cancer patients. The proposed model extends the standard economic model of preferences for mortality risk reductions (Jones-Lee 1974, Weinstein et al. 1980), which spurred the development of the value of statistical life (VSL) metric. In

[1] In 2012 cancer caused approximately 8.2 million deaths worldwide, making it the leading cause of death ahead of coronary heart diseases (Ferlay et al. 2015).

the spirit of Gerking et al. (2014), we presume that disease-induced mortality is conditional on suffering the disease. Therefore, our model includes three health states: healthy, ill, and dead. The explicit inclusion of the illness state allows us to identify the relative value of a gain in life quality when ill (Hammitt 2002).[2]

While consistent with the standard economic approach of valuing health risks, our baseline model does not capture that many people have neither a clear understanding of the risk of developing cancer, nor of the likelihoods of various outcomes of screening tests and treatment methods (Slovic et al. 2005, Peters et al. 2006). When presented with statistical information, they tend to overemphasize small probabilities and underemphasize large ones. This implies an inverse-S shaped probability weighting function (Tversky and Wakker 1995). As most cancers involve small incidence and large mortality rates, probability weighting may significantly affect how people value such risks. In order to address the non-linear weighting of probabilities, we follow Bleichrodt and Eeckhoudt (2006) and apply the rank dependent utility (RDU) framework to our model. Calibrations of the RDU version of our model to U.S. lung and skin cancer rates suggest that non-linear probability weighting significantly increases the demand value of reductions in both cancer incidence and mortality.

The paper proceeds as follows. In section 2, we introduce the baseline model and derive the WTP metrics for reductions in the incidence rate, the conditional mortality, and the health deterioration rate. We compare their relative size assuming real values of these rates for some types of cancer. In section 3, we replace the linear probability measures of the expected utility model by non-linear probability weighting and compare the rank dependent WTP metrics to those derived for the baseline model. Section 4 concludes.

[2] A previous treatment of these three states by Magat et al. (1996) used a risk-risk tradeoff framework, but did not examine monetary value-health risk tradeoffs.

2 Baseline model

In this section, we introduce the baseline model of cancer risk valuation and derive WTP values for a reduction in the incidence rate, the mortality rate and the deterioration of life quality, respectively. We loosely follow the notation of Bleichrodt et al. (2003).

2.1 Set up

Let an individual derive utility $U(W, H)$ from wealth W and health H. We denote first (second) derivatives with respect to wealth by the subscript 1 (11) and those with respect to health by the subscript 2 (22). We make the following conventional assumptions about $U(W, H)$:

- Non-satiation with respect to money: $U_1(W, H) > 0$;
- Non-satiation with respect to health: $U_2(W, H) > 0$;
- Weak financial risk aversion: $U_{11}(W, H) \leq 0$;
- Weak health risk aversion: $U_{22}(W, H) \leq 0$; and
- Correlation affinity: $U_{12}(W, H) \geq 0$.

The first two assumptions are the usual non-satiation assumptions. The next two assumptions state that less risk over either health or wealth is preferable to more risk. The last assumption implies that the marginal utility of wealth does not decrease with better health. In other words, a healthy person enjoys the benefits of an extra dollar at least as much as an ill person.[3] Viscusi and Evans (1990), Sloan et al. (1998), and more recently Finkelstein et al. (2013) provide empirical support for this assumption.

Now, consider a target disease that threatens health with probability $q = \text{pr(sick)}$. Without further knowledge about the individual's pre-condition and genetic constitution,

[3]Eeckhoudt et al. (2007) propose a straightforward way to empirically test the sign of $U_{12}(W, H)$.

it is sensible to assume that q equals the population incidence rate of the target disease. Conditional on falling ill, the individual faces a probability $p = \text{pr}(\text{death}|\text{sick})$ to die from the disease. Thus, there are three possible states of the world in our model:

1. Remaining at the current (good) health level H_G with probability $(1-q)$;
2. Developing the disease and surviving in the reduced (bad) health state H_B with probability $q(1-p)$;
3. Dying from the target disease, which implies health H_D with probability qp.

Without loss of generality, we will measure health quality on a unit scale so that $H_G = 1$, $H_D = 0$, and $H_B = 1 - h$, where $h < 1$ is the health deterioration expected from the non-fatal outcome of the disease. Each of the above health conditions is associated with a state-dependent utility function $U(W, H_G) > U(W, H_B) > U(W, H_D)$ satisfying the preferential order $H_G \succ H_B \succ H_D$, where $\succ$ indicates strict preferences. More precisely, we assume that for any given wealth endowment W utility can be normalized to $U(W, H_G) = 1, U(W, H_D) = 0$, and $0 < U(W, H_B) < 1$.

Under the assumptions made so far, $U_2(W, H_B)$ is unbounded above. Yet, since the average value of $U_2(W, H)$ between H_B and H_D is $U(W, H_B)/H_B$ and the average value between H_B and H_G is $(1 - U(W, H_B))/(1 - H_B)$, we may define an upper bound assuming that the sign of $U_{22}(W, H)$ does not change between H_D and H_G. Then, these two values bound $U_2(W, H_B)$. If we further assume $U_{22}(W, H) < 0$, then $U(W, H_B)/H_B > 1$ and $(1 - U(W, H_B))/(1 - H_B) < 1$. Based on these assumptions, which are common in the health risk literature, we argue that $U_2(W, H_B)$ is on the order of 1 and equals 1 iff the individual is risk neutral with respect to health. With risk aversion, we obtain the following bounds: $(1 - U(W, H_B))/(1 - H_B) < U_2(W, H_B) < U(W, H_B)/H_B$.

Based on the above assumptions, the individual's expected utility takes the form:

$$E[U(W, H)] = (1-q)U(W, H_G) + q[(1-p)U(W, H_B) + pU(W, H_D)]. \tag{1}$$

We are interested in how much a representative individual is willing to pay for a reduction in either the incidence rate q, the conditional mortality rate p, or the health deterioration rate h associated with a particular (cancer) disease.

Let us first define the compensating variation $C_q = C(W, H, \theta_q, p, q)$ as the amount of money the individual is willing to give up in order to reduce the incidence rate q by the amount θ_q. By definition, the payment of C_q for the risk reduction θ_q implies indifference between the utility level before and after the transfer. Hence,

$$E[U(W,H)] = (1-q+\theta_q)U(W-C_q, H_G)+(q-\theta_q)[(1-p)U(W-C_q, H_B)+pU(W-C_q, H_D)]. \tag{2}$$

Next, we differentiate Eq. (2) with respect to the risk reduction θ_q to obtain the first order condition:

$$\begin{aligned}\tfrac{\partial E[U]}{\partial \theta_q} = U(W-C_q, H_G) - [(1-p)U(W-C_q, H_B) + pU(W-C_q, H_D)]- \\ \Big[(1-q+\theta_q)\tfrac{\partial U_G}{\partial C_q}\tfrac{\partial C_q}{\partial \theta_q} - (q-\theta_q)[(1-p)\tfrac{\partial U_B}{\partial C_q}\tfrac{\partial C_q}{\partial \theta_q} + p\tfrac{\partial U_D}{\partial C_q}\tfrac{\partial C_q}{\partial \theta_q}]\Big] = 0.\end{aligned} \tag{3}$$

Solving Eq. (3) for $\frac{\partial C_q}{\partial \theta_q}$ yields the marginal WTP for reductions in the risk of contracting the disease:

$$MWTP_q \equiv \tfrac{\partial C_q}{\partial \theta_q} = \tfrac{U(W-C_q,H_G)-[(1-p)U(W-C_q,H_B)+pU(W-C_q,H_D)]}{E[U_1(W-C_q,H)]} > 0, \tag{4}$$

where the numerator equals the gain in expected utility from avoiding the disease and the denominator is the expected marginal utility of consumption, both evaluated after the payment of C_q.[4] It follows from Eq. (4) that $MWTP_q$ increases with both the risk of dying from the disease (i.e., $\frac{\partial^2 C_q}{\partial \theta_q \partial p} > 0$) and the risk of losing more life quality when surviving (i.e., $\frac{\partial^2 C_q}{\partial \theta_q \partial h} > 0$).

[4]Notice that C_q goes to zero when the reduction in the incidence of the disease becomes infinitesimally small. If contracting the disease results in certain death (or a health deterioration that is equally bad), i.e. $p = \text{pr}(\text{death}|\text{sick}) = 1$, then $(1-q)$ becomes the survival probability and Eq. (4) simplifies to the standard VSL expression (Jones-Lee 1974; Weinstein et al. 1980). This highlights the close link between our model and the VSL literature.

Similarly, we define the compensating variation $C_p = C(W, H, \theta_p, p, q)$ for a reduction in the disease-specific mortality risk p by the amount θ_p. The corresponding marginal WTP is given by

$$MWTP_p \equiv \frac{\partial C_p}{\partial \theta_p} = \frac{q[U(W-C_p,H_B)-U(W-C_p,H_D)]}{E[U_1(W-C_p,H)]} > 0, \tag{5}$$

where the numerator equals the gain in expected utility from reduced cancer mortality and the denominator is the expected marginal utility of consumption, both evaluated after the payment of C_p. A higher incidence rate increases $MWTP_p$ (i.e., $\frac{\partial^2 C_p}{\partial \theta_p \partial q} > 0$), while the prospect of a more painful course of disease may decrease or increase $MWTP_p$ depending on whether or not the effect of poorer health on the marginal utility of consumption (in the bad health state) outweighs its beneficial effect on the total utility of survival (Hammitt 2002).

Lastly, consider the compensating variation $C_h = C(W, H, \theta_h, p, q)$ for a reduction in the severity of the disease by the amount θ_h. The corresponding marginal WTP is given by

$$MWTP_h \equiv \frac{\partial C_h}{\partial \theta_h} = \frac{q(1-p)U_2(W-C_h,H_B+\theta_h)}{E[U_1(W-C_h,H)]} > 0, \tag{6}$$

where the numerator equals the gain in expected utility due to a less severe form of the disease. $MWTP_h$ rises with increasing risk of contracting the disease (i.e., $\frac{\partial^2 C_h}{\partial \theta_h \partial q} > 0$). This makes intuitive sense because a higher incidence rate of the disease makes the individual more likely to benefit from therapies that increase the life quality. In contrast, it is not possible to sign the effect of an increment in the mortality rate on the marginal WTP for reductions in h. A larger risk of dying conditional on being ill reduces the benefit of therapy (i.e. the numerator), but it simultaneously reduces the expected utility from consumption (i.e. the denominator). Again, it is an empirical question which of the two opposed effects is stronger. We summarize all of the above findings in Result I.

Result I. *Health interventions that improve any of the three health dimensions q, p, and h are valuable. However, the WTP values associated with an improvement in one of the dimensions are not independent of the other two dimensions. In particular, a higher incidence rate*

increases the WTP for reductions in p and h; a higher conditional mortality rate increases WTP for reductions in q, but its effect on the demand value of reductions in h is ambiguous; a more severe form of the disease increases WTP for reductions in q, but its effect on the demand value of reductions in p is again ambiguous.

2.2 Relative value of interventions

Result I indicates that the individual is willing to pay for interventions that ameliorate any of the three health dimensions. But which one is the most valuable dimension in terms of demand value? We compare the marginal value of improvements in the three dimensions by evaluating the WTP metrics (4–6) at the baseline level in order to identify the most efficient way to allocate a given health budget. That is, we set $\theta_\bullet = 0$ (where $\bullet$ is a placeholder for q, p, and h) implying $C_\bullet = 0$. Therefore, the three WTP metrics share a common denominator. The corresponding ratios give us the marginal rate of substitution between any two dimensions and permit assessing the relative value of prevention vs life quality vs prolongation of life.

We summarize the comparisons of the dimension-specific marginal WTP metrics in the following three results.[5]

Result II. *Reductions in q are more valuable than reductions in p iff:*

$$MWTP_q > MWTP_p \leftrightarrow \frac{1 - U(W, H_B)}{U(W, H_B)} > q - p.$$

Since severe diseases including most forms of cancer are characterized by $p \gg q$, prevention is more valuable than treatment for such diseases. This may seem counterintuitive at first sight. Notice, however, that the numerator in Eq. (5) is scaled by q, implying that it is inefficient to invest in reducing p if q is small.

[5]Detailed derivations are relegated to Appendix A.

Result III. *Reductions in h are more valuable than reductions in p iff:*

$$MWTP_h > MWTP_p \leftrightarrow (1-p)U_2(W, H_B) > U(W, H_B).$$

We know that $U_2(W, H_B) < U(W, H_B)/(1-h)$. Substituting this upper bound, we obtain $h > p$ as a necessary condition for $MWTP_h > MWTP_p$. Likewise, we can substitute the lower bound to obtain $(1-p)/h > U(W, H_B)/(1-U(W, H_B))$, which is a sufficient condition for $MWTP_h > MWTP_p$. One situation in which the latter condition is met is when $U(W, H_B) \to 0$. In words, if life quality in the bad health state is so low that the individual is indifferent between staying alive and dying, palliative actions become more valuable than prolonging life (and further suffering).

Result IV. *Reductions in q are typically more valuable than reductions in h. We obtain the following criterion:*

$$MWTP_q > MWTP_h \leftrightarrow 1-(1-p)U(W, H_B) > q(1-p)U_2(W, H_B).$$

We again substitute $U(W, H_B)/(1-h)$ for $U_2(W, H_B)$, yielding the following sufficiency condition for $MWTP_q > MWTP_h$: $1-(1-p)U(W, H_B) > q(1-p)U(W, H_B)/(1-h)$. Substituting the lower bound yields a second condition for $MWTP_q > MWTP_h$: $1-(1-p)U(W, H_B) > q(1-p)(1-U(W, H_B))/h$. These conditions are met if either q or $U(W, H_B)$ is sufficiently small, or p is sufficiently large—criteria that are commonly associated with cancer diseases.

3 Probability weighting

Results II-IV provide important insights on the relative value of the different ways to reduce the health endpoints associated with the target disease. Yet we have so far ignored that people often lack a clear understanding of health risks, particularly of the risks posed by cancer and other dreaded diseases (Peters et al. 2006). A robust finding in experiments on

risky health decisions is that people overweight small probabilities and underweight large ones (Lichtenstein et al. 1978, Bleichrodt and Pinto 2000, Abellan-Perpiñan et al. 2009, Attema et al. 2013). We follow Bleichrodt and Eeckhoudt (2006) and apply the RDU framework to study the effect of probability weighting on cancer risk valuation.

The hypothesis of RDU is that any probability measure P is evaluated as if they were transformed by a weighting function $w[P]$ such that $w[0] = 0$, $w[1] = 1$, $w[P] > P$ for P close 0, $w[P] < P$ for P close to 1, and $w[P] = P$ at some intermediate value. If $w[P]$ is differentiable, then $w' > 0$ for all P and $w' > 1$ for P in the vicinity of 0 and 1, respectively.[6] One particularly popular weighting function is Prelec's (1998) two-parameter specification $w[P] = \exp(-\beta(-\ln P)^{\alpha})$, where the parameter α governs the curvature, which indicates the patient's sensitivity to changes in risk, i.e. his ability to discriminate between different risk levels. The parameter β controls the elevation of the weighting function, which expresses the degree to which the patient is willing to take (health) risks.

Bleichrodt and Eeckhoudt (2006) made this functional choice for two reasons. First, the Prelec weighting function is continuously differentiable with:

$$\frac{\partial w[P]}{\partial P} = \frac{\beta\alpha(-\ln P)^{\alpha-1}}{P}\exp(-\beta(-\ln P)^{\alpha}).$$

Second, Bleichrodt and Pinto (2000) elicited $\hat{\alpha} = 0.534$ and $\hat{\beta} = 1.083$ in the health risk/longevity context. Below, we will use the Bleichrodt-Pinto (BP) calibration of the Prelec weighting function as a benchmark. The model can be calibrated with other probability weighting functions, however.[7] Hence, we emphasize that our results do not depend on the functional form of $w[P]$.

[6] Any such weighting function displays an inverse S-shaped form (Tversky and Wakker 1995).

[7] Fehr-Duda and Epper (2012) provide a thorough review of the probability weighting functions in use.

3.1 WTP metrics under probability weighting

We assume that each probability source is weighted separately to reflect source independence (Wakker 2010). The individual could, of course, transform the compound lottery of falling ill and surviving (dying) into a simple lottery. Yet, it seems to us that developing the disease and dying from the disease are two different risks, which the individual is likely to weight differently (Armantier and Treich 2016). In any case, the main conclusion drawn from the analysis of the RDU modeling (Result VIII below) does not depend on this assumption, see the additional analysis in Appendix C.

The rank-dependent counterpart of the expected utility function (1) is given by

$$\begin{aligned} RD[U(W,H)] \;=\; & w\left[1-q\right]U(W,H_G)+ \\ & \left(1-w\left[1-q\right]\right)\left\{w\left[1-p\right]U(W,H_B)+\left(1-w\left[1-p\right]\right)U(W,H_D)\right\}. \end{aligned} \tag{7}$$

Similar to Section 2, we derive WTP metrics for improvements in q, p, and h. In particular, we can re-write Eq. (7) as

$$\begin{aligned} & RD[U(W,H)] = w\left[1-q+\theta_q\right]U(W-C_q^w,H_G)+ \\ & \left(1-w\left[1-q+\theta_q\right]\right)\left\{w\left[1-p\right]U(W-C_q^w,H_B)+\left(1-w\left[1-p\right]\right)U(W-C_q^w,H_D)\right\}. \end{aligned} \tag{8}$$

where $C_q^w = C(W,H,\theta_q,p,q,w[.])$ denotes the compensating variation for a reduction in the incidence rate q of the target disease by the amount θ_q in the presence of probability weighting by the function $w\left[.\right]$. The corresponding marginal WTP under probability weighting is:

$$\begin{aligned} & MWTP_q^w \equiv \\ & \frac{\partial C_q^w}{\partial \theta_q} = \frac{w'\left[1-q+\theta_q\right]\left\{U(W-C_q^w,H_G)-w\left[1-p\right]U(W-C_q^w,H_B)-\left(1-w\left[1-p\right]\right)U(W-C_q^w,H_D)\right\}}{RD[U_1(W-C_q^w,H)]} > 0. \end{aligned} \tag{9}$$

In the same way, we obtain the marginal WTP for the reduction in the disease-specific mortality rate p:

$$MWTP_p^w \equiv \frac{\partial C_p^w}{\partial \theta_p} = \frac{(1-w[1-q])w'[1-p+\theta_p]\left\{U(W-C_p^w,H_B)-U(W-C_p^w,H_D)\right\}}{RD[U_1(W-C_p^w,H)]} > 0, \tag{10}$$

and the marginal WTP for the reduction in the health deterioration rate h:

$$MWTP_h^w \equiv \frac{\partial C_h^w}{\partial \theta_h} = \frac{(1-w[1-q])w[1-p]U_2(W-C_h^w,H_B+\theta_h)}{RD[U_1(W-C_h^w,H)]} > 0. \tag{11}$$

3.2 Relative value of interventions under probability weighting

Does probability weighting affect the relative value of one of the intervention channels over another? We address this question by comparing the marginal value of improvements in the three health dimensions. We do so by evaluating the WTP metrics (9–11) at the baseline level (i.e., $\theta_\bullet = 0$). Comparisons of the intervention-specific marginal WTP metrics are summarized in the following three results.

Result V. *Reductions in q are more valuable than reductions in p iff:*

$$MWTP_q^w > MWTP_p^w \leftrightarrow \frac{w'[1-q]}{(1-w[1-q])w'[1-p]+w'[1-q]\,w[1-p]} > U(W,H_B).$$

The LHS of the inequality is under very mild assumptions larger than one, so that even under probability weighting prevention of cancer is more valuable than treatment. Yet the condition is more demanding than under expected utility (Result II) as probability weighting increases the denominator for common values of q, p, and any inverse S-shaped weighting function $w[.]$.

Result VI. *Reductions in h are more valuable than reductions in p iff:*

$$MWTP_h^w > MWTP_p^w \leftrightarrow w[1-p]\,U_2(W,H_B) > w'[1-p]\,U(W,H_B).$$

By substituting $U(W,H_B)/(1-h)$ as the upper bound of $U_2(W,H_B)$, we obtain $h > 1 - \frac{w[1-p]}{w'[1-p]}$ as a necessary condition for $MWTP_h^w > MWTP_p^w$. Likewise, if we substitute $(1-U(W,H_B))/h$, we obtain the lower bound: $w\,[1-p]\,/(hw'\,[1-p]) > U(W,H_B)/(1-U(W,H_B))$, which is a sufficient condition for $MWTP_h^w > MWTP_p^w$. Comparison with Result III suggests that for commonly observed p-values the condition is more demanding under probability weighting (with an inverse-S shaped weighting function) than under linear probabilities; e.g., for the BP calibration we have that $1-p < \frac{w[1-p]}{w'[1-p]}\ \forall p > 0.24$.

Result VII. *Reductions in q are more valuable than reductions in h iff:*

$$MWTP_q^w > MWTP_h^w \leftrightarrow 1 - w\,[1-p]\,U(W,H_B) > \frac{(1-w\,[1-q])w\,[1-p]}{w'\,[1-q]}U_2(W,H_B).$$

Again, we may substitute $U_2(W,H_B)$ by $U(W,H_B)/(1-h)$ and by $(1-U(W,H_B))/h$, yielding the following two sufficiency condition for $MWTP_q^w > MWTP_h^w$:

$$1 - w\,[1-p]\,U(W,H_B) > \frac{(1-w\,[1-q])w\,[1-p]}{w'\,[1-q]}\frac{U(W,H_B)}{1-h},$$

and

$$1 - w\,[1-p]\,U(W,H_B) > \frac{(1-w\,[1-q])w\,[1-p]}{w'\,[1-q]}\frac{(1-U(W,H_B))}{h}.$$

These conditions are met if either q is sufficiently small or p is sufficiently large or both. Compared to Result IV, we find that under probability weighting (with an inverse-S shaped weighting function) the criteria are more demanding than in the baseline model.

3.3 Probability-weighted vs baseline WTP metrics

What is the bias introduced by probability weighting on the WTP metrics for different types of intervention? To address this question, we compare Eqs. (9–11) to the baseline WTP metrics (4–6). In doing so, we assume again that $\theta_\bullet = 0$ and evaluate the WTP metrics at the initial levels of q, p, and h. We compare the baseline to probability-weighted WTP

metrics by examining the following ratios:

$$\mu_q \equiv \frac{MWTP_q^w}{MWTP_q} = w'[1-q]\frac{1-w[1-p]U(W,H_B)}{1-(1-p)U(W,H_B)}\frac{E[U_1(W,H)]}{RD[U_1(W,H)]} \tag{12}$$

$$\mu_p \equiv \frac{MWTP_p^w}{MWTP_p} = \frac{(1-w[1-q])w'[1-p]}{q}\frac{E[U_1(W,H)]}{RD[U_1(W,H)]}, \text{ and} \tag{13}$$

$$\mu_h \equiv \frac{MWTP_h^w}{MWTP_h} = \frac{(1-w[1-q])w[1-p]}{q(1-p)}\frac{E[U_1(W,H)]}{RD[U_1(W,H)]}. \tag{14}$$

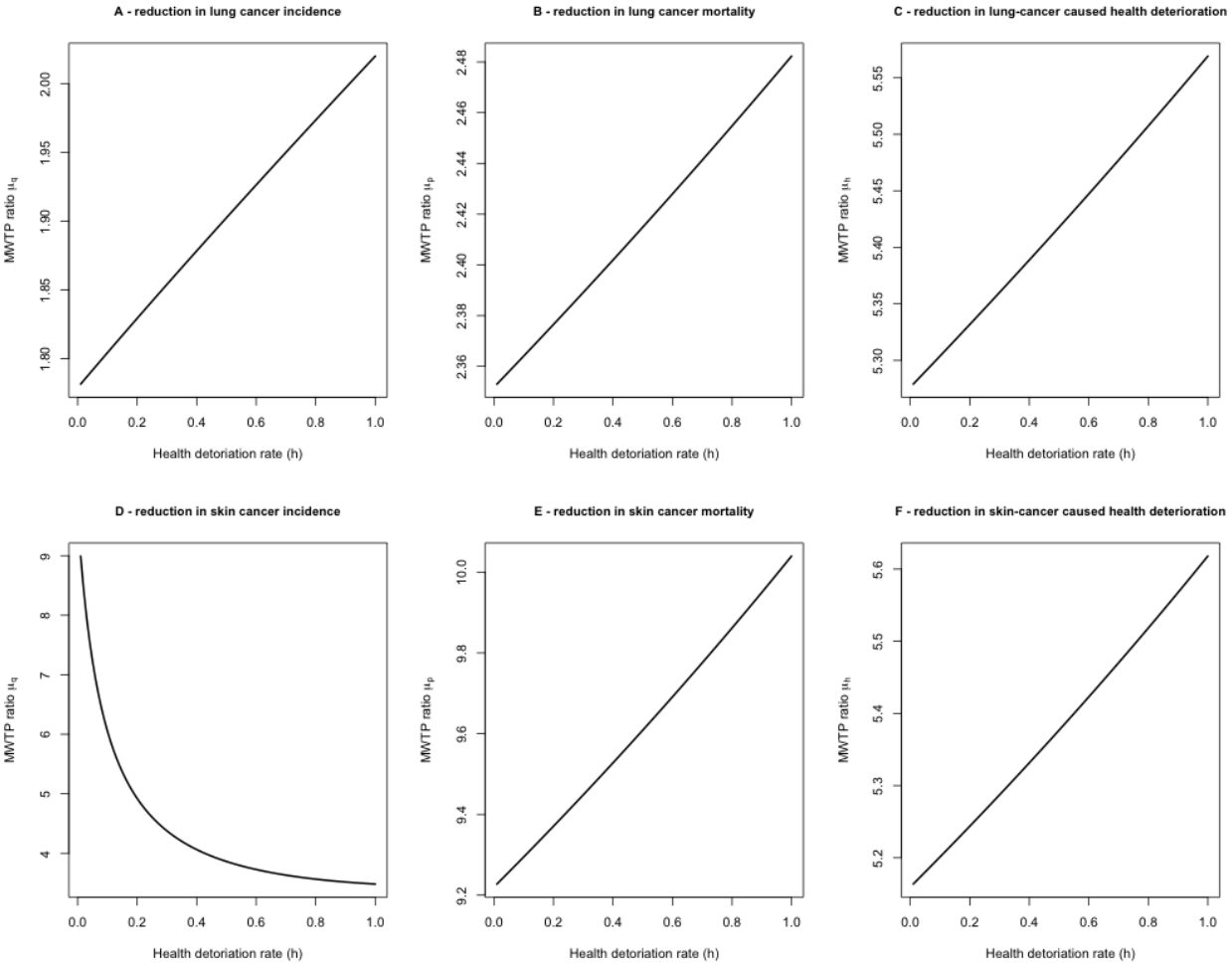
Eqs. (12–14) are not very intuitive. In order to draw meaningful conclusions, we calibrate the model using the BP calibration of the Prelec weighting function and prevailing incidence and mortality rates for lung and skin cancer in the U.S. According to the latest estimates of the U.S. National Cancer Institute about 6.6 percent of men and women will be diagnosed with lung cancer at some point during their lifetime, of which 17.4 percent will survive five years or more after the diagnosis.[8] Based on these statistics we set $q = 0.066$ and $p = 0.826$. Moreover, we normalize the utility functions so that $U(W,H_G) = 1, U(W,H_B) = 1-h, U(W,H_D) = 0$. We vary the health deterioration rate h for lung-cancer survivors from $[0,1]$, although both extremes might be somewhat unrealistic.

Panels A-C of Figure 1 show the three WTP ratios, μ_q, μ_p and μ_h, calibrated to U.S. lung-cancer incidence and mortality rates. Across the range of possible h-values the ratios are well above unity, implying that probability weighting with the BP calibration leads to up to five times higher WTP values than those derived under the baseline model. In Panels D-F of Figure 1, the same WTP ratios are displayed for current U.S. skin-cancer (melanoma) incidence and mortality rates, which imply $p = 0.085, q = 0.021$.[9] Although the survival prospects are much better for skin-cancer patients, probability weighting with the

[8] See http://www.seer.cancer.gov/statfacts.

[9] Most skin cancer is nonmelanoma, which has very high incidence and very low mortality.

Figure 1: WTP ratios for lung and skin cancer in the U.S.



Notes: Panels A-C display calibrations with current U.S. lung cancer rates; Panels D-F display calibrations with current U.S. skin cancer rates; all calibrations are based on Bleichrodt and Pinto (2006). Code for replicating the calibrations is provided in Appendix D.

BP calibration leads to up to ten times higher WTP values than those derived under the baseline model. This motivates our last result.

Result VIII. *Under a weighting function $w[.]$ that overweights small probabilities and underweights large ones, probability weighting increases the WTP for interventions that improve any of the three health dimensions:*

$$MWTP_q < MWTP_q^w, \quad MWTP_p < MWTP_p^w, \text{ and } MWTP_h < MWTP_h^w.$$

4 Conclusion

We have extended the standard VSL model to analyze the economic value of interventions that reduce either the incidence rate, the conditional mortality rate, or the health deterioration rate of severe diseases such as cancer. The valuation model we propose suggests that for commonly observed incidence and mortality rates, social investment into cancer prevention should have priority over investment into the development of new drugs and other treatments. In other words, reducing the chance to suffer from cancer is more desirable than improving survival chances. This is not to say that improvements in cancer treatment and detection methods are worthless, however. Gains in longevity and quality of life are, of course, valuable to cancer patients (Lakdawalla et al. 2010).

Many people overweight small probabilities such as those implied by cancer incidence rates, but underweight large probabilities such as those implied by the corresponding mortality rates. We have therefore employed the RDU framework to explore non-linear probability weighting in health valuations related to severe diseases.[10] We find that the WTP for reductions in any of the three rates—incidence, mortality, and health detoriation—are several

[10] An upshot of the comparison between EU-based and RDU-based WTP metrics is that the same technique can be applied to study other factors that might enter the decision maker's probabilistic reasoning. In Appendix B, we apply the approach to assess how comorbidity risks affect the relative valuation of the different intervention channels. Other applications are conceivable.

times larger than under the linear-in-probabilities assumption of the EU framework. This further supports the qualitative findings of the baseline model; even if people do not evaluate health risks using linear probabilities, prevention is more valuable than treatment.

References

Abellan-Perpiñan, J. M., Bleichrodt, H., Pinto-Prades, J. L., 2009. The predictive validity of prospect theory versus expected utility in health utility measurement. Journal of Health Economics 28 (6), 1039–1047.

Armantier, O., Treich, N., 2016. The rich domain of risk. Management Science , forthcoming.

Attema, A. E., Brouwer, W. B., l'Haridon, O., 2013. Prospect theory in the health domain: A quantitative assessment. Journal of Health Economics 32 (6), 1057–1065.

Bleichrodt, H., Crainich, D., Eeckhoudt, L., 2003. Comorbidities and the willingness to pay for health improvements. Journal of Public Economics 87, 2399–2406.

Bleichrodt, H., Eeckhoudt, L., 2006. Willingness to pay for reductions in health risks when probabilities are distorted. Health Economics 15, 211–214.

Bleichrodt, H., Pinto, J., 2000. A parameter-free elicitation of the probability weighting function in medical decision analysis. Management Science 46 (11), 1485–1496.

Bosworth, R., Cameron, T. A., DeShazo, J. R., 2010. Is an ounce of prevention worth a pound of cure? comparing demand for public prevention and treatment policies. Medical Decision Making 30 (4), 40–56.

Chabner, B. A., Roberts, T. G., 2005. Chemotherapy and the war on cancer. Nature Reviews Cancer 5 (1), 65–72.

Eeckhoudt, L., Rey, B., Schlesinger, H., 2007. A good sign for multivariate risk taking. Management Science 53 (1), 117–124.

Eeckhoudt, L. R., Hammitt, J. K., 2001. Background risks and the value of a statistical life. Journal of Risk and Uncertainty 23 (3), 261–279.

Faguet, G., 2005. The War on Cancer: An Anatomy of Failure, A Blueprint for the Future. Springer, Dodrecht.

Fehr-Duda, H., Epper, T., 2012. Probability and risk: Foundations and economic implications of probability- dependent risk preferences. Annual Review of Economics 4 (1), 567–593.

Ferlay, J., Soerjomataram, I., Dikshit, R., Eser, S., Mathers, C., Rebelo, M., Parkin, D. M., Forman, D., Bray, F., 2015. Cancer incidence and mortality worldwide: sources, methods and major patterns in globocan 2012. International Journal of Cancer 136 (5), 359–386.

Finkelstein, A., Luttmer, E. F. P., Notowidigdo, M., 2013. What good is wealth without health? the effect of health on the marginal utility of consumption. Journal of the European Economic Association 11 (S1), 221–258.

Fuchs, V., Zeckhauser, R., 1987. Valuing health–a "priceless" commodity. American Economic Review 77 (2), 263–268.

Gerking, S., Dickie, M., Veronesi, M., 2014. Valuation of human health: An integrated model of willingness to pay for mortality and morbidity risk reductions. Journal of Environmental Economics and Management 68 (1), 20–45.

Hammitt, J. K., 2002. Qalys versus wtp. Risk Analysis 22 (5), 985–1001.

Hammitt, J. K., Liu, J., 2004. Effects of disease type and latency on the value of mortality risk. Journal of Risk and Uncertainty 28 (1), 73–95.

Jones-Lee, M., 1974. Value of changes in probability of death or injury. Journal of Political Economy 82 (4), 835–849.

Lakdawalla, D. N., Sun, E. C., Jena, A. B., Reyes, C. M., Goldman, D. P., Philipson, T. J., 2010. An economic evaluation of the war on cancer. Journal of Health Economics 29 (3), 333–346.

Lichtenstein, S., Slovic, P., Fischhoff, B., Layman, M., Combs, B., 1978. Judged frequency of lethal events. Journal of Experimental Psychology: Human learning and memory 4 (6), 551–578.

Liu, L., 2004. Comorbidities and the willingness to pay for reducing the risk of a targeted disease: introducing endogenous effort for risk reduction. Health Economics 13, 493–498.

Magat, W. A., Viscusi, W. K., Huber, J., 1996. A reference lottery metric for valuing health. Management Science 42 (8), 1118–1130.

Peters, E., McCaul, K. D., Stefanek, M., Nelson, W., 2006. A heuristics approach to understanding cancer risk perception: contributions from judgment and decision-making research. Annals of Behavioral Medicine 31 (1), 45–52.

Prelec, D., 1998. The probability weighting function. Econometrica 66 (3), 497–527.

Sloan, F. A., Viscusi, W. K., Chesson, H. W., Conover, C. J., Whetten-Goldstein, K., 1998. Alternative approaches to valuing intangible health losses: the evidence for multiple sclerosis. Journal of Health Economics 17 (4), 475–497.

Slovic, P., Peters, E., Finucane, M. L., MacGregor, D. G., 2005. Affect, risk, and decision making. Health Psychology 24 (4), 35–40.

Sporn, M. B., 1996. The war on cancer. The Lancet 347 (9012), 1377–1381.

Tversky, A., Wakker, P., 1995. Risk attitudes and decision weights. Econometrica 63 (6), 1255–1280.

Van Houtven, G., Sullivan, M., Dockins, C., 2008. Cancer premiums and latency effects: A risk tradeoff approach for valuing reductions in fatal cancer risks. Journal of Risk and Uncertainty 36, 179–199.

Viscusi, W. K., Evans, W., 1990. Utility functions that depend on health status: Estimates and economic implications. American Economic Review 80 (3), 353–374.

Viscusi, W. K., Huber, J., Bell, J., 2014. Assessing whether there is a cancer premium for the value of a statistical life. Health Economics 23 (4), 384–396.

Wakker, P. P., 2010. Prospect theory: For risk and ambiguity. Cambridge University Press.

Weinstein, M. C., Shepard, D. S., Pliskin, J. S., 1980. The economic value of changing mortality probabilities - a decision-theoretic approach. Quarterly Journal of Economics 94 (2), 373–396.

Appendix A—Detailed Derivations

Derivation of Result II. We insert Eqs. (4–5) and evaluate them at $\theta_\bullet = 0$ to obtain the equivalence relationship:

$$MWTP_q > MWTP_p \leftrightarrow \frac{U(W,H_G) - [(1-p)U(W,H_B) + pU(W,H_D)]}{E[U_1(W,H)]} > \frac{q\,[U(W,H_B) - U(W,H_D)]}{E[U_1(W,H)]}.$$

The RHS can be transformed to:

$$\frac{U(W,H_G) - U(W,H_B)}{U(W,H_B) - U(W,H_D)} > q - p,$$

and, assuming $U(W,H_G) = 1$ and $U(W,H_D) = 0$, we obtain Result II.

Derivation of Result III. We insert Eqs. (5–6) and evaluate them at $\theta_\bullet = 0$ to obtain the equivalence relationship:

$$MWTP_h > MWTP_p \leftrightarrow \frac{q(1-p)U_2(W,H_B)}{E[U_1(W,H)]} > \frac{q\,[U(W,H_B) - U(W,H_D)]}{E[U_1(W,H)]}.$$

The RHS can be transformed to:

$$(1-p)U_2(W,H_B) > U(W,H_B) - U(W,H_D).$$

Next, we assume $U(W,H_D) = 0$ and replace $U_2(W,H_B)$ by the upper bound $U(W,H_B)/H_B = U(W,H_B)/(1-h)$ derived in Section 2.1:

$$(1-p)U(W,H_B)/(1-h) > U(W,H_B),$$

based on which we obtain $h > p$ as a necessary condition for $MWTP_h > MWTP_p$.

If we instead substitute $U_2(W,H_B)$ by the lower bound $(1 - U(W,H_B))/(1 - H_B) =$

$(1 - U(W, H_B))/h$, we obtain:

$$(1 - p)(1 - U(W, H_B))/h > U(W, H_B),$$

which yields the sufficiency condition for Result III.

Derivation of Result IV. We insert Eqs. (4) and (6) and evaluate them at $\theta_\bullet = 0$ to obtain the equivalence relationship:

$$MWTP_q > MWTP_h \leftrightarrow \frac{U(W, H_G) - [(1 - p)U(W, H_B) + pU(W, H_D)]}{E[U_1(W, H)]} > \frac{q(1 - p)U_2(W, H_B)}{E[U_1(W, H)]}.$$

The RHS can be transformed to:

$$U(W, H_G) - (1 - p)U(W, H_B) - pU(W, H_D) > q(1 - p)U_2(W, H_B).$$

Next, we assume $U(W, H_G) = 1$ and $U(W, H_D) = 0$ and replace $U_2(W, H_B)$ by the upper bound $U(W, H_B)/(1 - h)$ derived in Section 2.1 to obtain:

$$1 - (1 - p)U(W, H_B) > q(1 - p)U(W, H_B)/(1 - h),$$

which is the first sufficiency condition for $MWTP_q > MWTP_h$. Substituting the lower bound $(1 - U(W, H_B))/h$ instead, yields the second sufficiency condition for Result IV:

$$1 - (1 - p)U(W, H_B) > q(1 - p)(1 - U(W, H_B))/h.$$

Derivation of Result V. We insert Eqs. (9–10) and evaluate them at $\theta_\bullet = 0$ to obtain the equivalence relationship:

$$MWTP_q^w > MWTP_p^w \leftrightarrow$$

$$\frac{w'[1-q]\{U(W,H_G)-w[1-p]U(W,H_B)-(1-w[1-p])U(W,H_D)\}}{RD[U_1(W,H)]} > \frac{(1-w[1-q])w'[1-p]\{U(W,H_B)-U(W,H_D)\}}{RD[U_1(W,H)]}.$$

The RHS can be transformed to:

$$w'[1-q]\{U(W,H_G)-w[1-p]U(W,H_B)-(1-w[1-p])U(W,H_D)\} > (1-w[1-q])w'[1-p]\{U(W,H_B)-U(W,H_D)\}.$$

Assuming $U(W, H_G) = 1$ and $U(W, H_D) = 0$, this expression simplifies to Result V:

$$\begin{aligned} w'\left[1-q\right]\left\{1-w\left[1-p\right]U(W,H_B)\right\} > (1-w\left[1-q\right])w'\left[1-p\right]U(W,H_B) \quad &= \\ w'\left[1-q\right] > U(W,H_B)\left\{(1-w\left[1-q\right])w'\left[1-p\right]+w'\left[1-q\right]w\left[1-p\right]\right\} \quad &= \\ \frac{w'[1-q]}{(1-w[1-q])w'[1-p]+w'[1-q]w[1-p]} > U(W,H_B). \end{aligned}$$

Derivation of Result VI. We insert Eqs. (10–11) and evaluate them at $\theta_\bullet = 0$ to obtain the equivalence relationship:

$$MWTP_h^w > MWTP_p^w \leftrightarrow$$

$$\frac{(1-w\left[1-q\right])w\left[1-p\right]U_2(W,H_B)}{RD[U_1(W,H)]} > \frac{(1-w\left[1-q\right])w'\left[1-p\right]\left\{U(W,H_B)-U(W,H_D)\right\}}{RD[U_1(W,H)]}.$$

The RHS equals:

$$(1-w\left[1-q\right])w\left[1-p\right]U_2(W,H_B) > (1-w\left[1-q\right])w'\left[1-p\right]\left\{U(W,H_B)-U(W,H_D)\right\}.$$

Next, we assume $U(W, H_D) = 0$ and replace $U_2(W, H_B)$ by the upper bound $U(W, H_B)/(1-h)$ derived in Section 2.1:

$$\begin{aligned} (1-w\left[1-q\right])w\left[1-p\right]U(W,H_B)/(1-h) > (1-w\left[1-q\right])w'\left[1-p\right]U(W,H_B) \quad &= \\ 1-\frac{w[1-p]}{w'[1-p]} < h, \end{aligned}$$

yielding the necessary condition for Result VI.

If we instead substitute $U_2(W, H_B)$ by the lower bound $(1 - U(W, H_B))/h$, we obtain:

$$(1 - w\,[1 - q])w\,[1 - p]\,(1 - U(W, H_B))/h > (1 - w\,[1 - q])w'\,[1 - p]\,U(W, H_B) \quad = \quad \frac{w[1-p]}{w'[1-p]h} > \frac{U(W,H_B)}{1-U(W,H_B)},$$

which yields the sufficiency condition for Result VI.

*Derivation of Result VII.*We insert Eqs. (9) and (11) and evaluate them at $\theta_\bullet = 0$ to obtain the equivalence relationship:

$$MWTP_q^w > MWTP_h^w \leftrightarrow$$

$$\frac{w'[1-q]\{U(W,H_G)-w[1-p]U(W,H_B)-(1-w[1-p])U(W,H_D)\}}{RD[U_1(W,H)]} > \frac{(1-w[1-q])w[1-p]U_2(W,H_B)}{RD[U_1(W,H)]}.$$

The RHS equals:

$$w'[1-q]\{U(W,H_G)-w[1-p]U(W,H_B)-(1-w[1-p])U(W,H_D)\} > (1-w[1-q])w[1-p]U_2(W,H_B).$$

Next, we assume $U(W, H_G) = 1$ and $U(W, H_D) = 0$ and replace $U_2(W, H_B)$ by the upper bound $U(W, H_B)/(1 - h)$ and the lower bound $(1 - U(W, H_B))/h$, respectively:14

$$w'[1-q]\{1-w[1-p]U(W,H_B)\} > (1-w[1-q])w[1-p]U(W,H_B)/(1-h) \quad = \quad 1-w[1-p]U(W,H_B) > \frac{(1-w[1-q])w[1-p]}{w'[1-q]}\frac{U(W,H_B)}{1-h}.$$

and

$$w'[1-q]\{1-w[1-p]U(W,H_B)\} > (1-w[1-q])w[1-p](1-U(W,H_B))/h \quad = \quad 1-w[1-p]U(W,H_B) > \frac{(1-w[1-q])w[1-p]}{w'[1-q]}\frac{1-U(W,H_B)}{h}.$$

These are the sufficiency conditions for Result VII.

Appendix B—Comorbidity risks and WTP

Assume that the individual faces a comorbidity (Bleichrodt et al. 2003; Liu 2004) or other competing background risk (Eeckhoudt and Hammitt 2001). We introduce a mortality background risk π, which can be interpreted either as a specific competing disease or as the compound risk of dying from any other cause than the target disease.

Consider the extended form of expected utility:

$$\begin{aligned} E[U^{\pi}(W,H)] &= (1-\pi)(1-q)U(W,H_G) + \\ &\quad q[(1-\pi)(1-p)U(W,H_B) + (1-(1-\pi)(1-p))U(W,H_D)]. \end{aligned} \tag{15}$$

We derive WTP metrics for improvements in q, p, and h similarly to those in Section 2. In particular, we re-write Eq. (15) as

$$\begin{aligned} E[U^{\pi}(W,H)] &= (1-\pi)(1-q+\theta_q)U(W-C_q^{\pi},H_G) + \\ &\quad (q-\theta_q)[(1-\pi)(1-p)U(W-C_q^{\pi},H_B) + (1-(1-\pi)(1-p))U(W-C_q^{\pi},H_D)], \end{aligned} \tag{16}$$

where $C_q^{\pi} = C(W,H,\theta_q,p,q,\pi)$ denotes the compensating variation for a reduction in the incidence rate q of the target disease by the amount θ_q in the presence of the background risk π. The corresponding marginal WTP is:

$$MWTP_q^{\pi} \equiv \frac{\partial C_q^{\pi}}{\partial \theta_q} = \frac{(1-\pi)U(W-C_q^{\pi},H_G)-[(1-\pi)(1-p)U(W-C_q^{\pi},H_B)+(1-(1-\pi)(1-p))U(W-C_q^{\pi},H_D)]}{E[U_1^{\pi}(W-C_q^{\pi},H)]} > 0. \tag{17}$$

In the same way, we obtain the marginal WTP for the reduction in the disease-specific mortality rate p:

$$MWTP_p^{\pi} \equiv \frac{\partial C_p^{\pi}}{\partial \theta_p} = \frac{q(1-\pi)\left[U(W-C_p^{\pi},H_B)-U(W-C_p^{\pi},H_D)\right]}{E[U_1^{\pi}(W-C_p^{\pi},H)]} > 0, \tag{18}$$

and the marginal WTP for the reduction in the health deterioration rate h:

$$MWTP_h^{\pi} \equiv \frac{\partial C_h^{\pi}}{\partial \theta_h} = \frac{q(1-\pi)(1-p)U_2(W-C_h, H_B+\theta_h)}{E[U_1^{\pi}(W-C_h^{\pi}, H)]} > 0. \tag{19}$$

Next, we compare Eqs. (17–19) to the baseline WTP metrics given by Eqs. (4–6). We assume $\theta_\bullet = 0$ and evaluate the ratios of the corresponding WTP metrics at the baseline levels of q, p, and h:

$$\frac{MWTP_q}{MWTP_q^{\pi}} = \frac{U(W,H_G)-[(1-p)U(W,H_S)+pU(W,H_D)]}{(1-\pi)U(W,H_G)-[(1-\pi)(1-p)U_S+(1-(1-\pi)(1-p))U_D]} \quad \frac{(1-\pi)(1-q)\frac{\partial U_0}{\partial W}+q[(1-\pi)(1-p)\frac{\partial U_S}{\partial W}+(1-(1-\pi)(1-p))\frac{\partial U_D}{\partial W}]}{(1-q)\frac{\partial U_0}{\partial W}+q[(1-p)\frac{\partial U_S}{\partial W}+p\frac{\partial U_D}{\partial W}]} =$$

$$\frac{B-pU_D}{B-\frac{(1-(1-\pi)(1-p))}{(1-\pi)}U_D} \qquad \frac{A+q\frac{(1-(1-\pi)(1-p))}{(1-\pi)}\frac{\partial U_D}{\partial W}}{A+qp\frac{\partial U_D}{\partial W}} > 1.$$

$$\frac{MWTP_p}{MWTP_p^{\pi}} = \frac{(1-q)\frac{\partial U_0}{\partial W}+q[(1-p)\frac{\partial U_S}{\partial W}+\frac{(1-(1-\pi)(1-p))}{(1-\pi)}\frac{\partial U_D}{\partial W}]}{(1-q)\frac{\partial U_0}{\partial W}+q[(1-p)\frac{\partial U_S}{\partial W}+p\frac{\partial U_D}{\partial W}]} = \frac{A+q\frac{(1-(1-\pi)(1-p))}{(1-\pi)}\frac{\partial U_D}{\partial W}}{A+qp\frac{\partial U_D}{\partial W}} > 1.$$

$$\frac{MWTP_h}{MWTP_h^{\pi}} = \frac{(1-q)\frac{\partial U_0}{\partial W}+q[(1-p)\frac{\partial U_S}{\partial W}+\frac{(1-(1-\pi)(1-p))}{(1-\pi)}\frac{\partial U_D}{\partial W}]}{(1-q)\frac{\partial U_0}{\partial W}+q[(1-p)\frac{\partial U_S}{\partial W}+p\frac{\partial U_D}{\partial W}]} = \frac{A+q\frac{(1-(1-\pi)(1-p))}{(1-\pi)}\frac{\partial U_D}{\partial W}}{A+qp\frac{\partial U_D}{\partial W}} > 1.$$

The findings are summarized in the following result.

Result IX. *As long as the individual derives marginal utility from leaving a larger bequest to others, a physical background risk reduces the demand value for improvements in all three health dimensions:*

$$MWTP_q \geq MWTP_q^{\pi}, \quad MWTP_p \geq MWTP_p^{\pi}, \text{ and } MWTP_h \geq MWTP_h^{\pi}.$$

Similarly to the original why-bother effect (Eeckhoudt and Hammitt 2001), the inequalities become strict if the marginal utility of a bequest is larger than zero.

Appendix D—RDU model for compound probabilities

In case that the individual weights the compound probability of developing cancer and (not) dying from cancer, the RDU model writes:

$$\begin{gathered} RD[U(W,H)] = w\left[1-q+\theta_q\right]U(W-C_q^w,H_G)+ \\ w\left[(q-\theta_q)(1-p)\right]U(W-C_q^w,H_B)+w\left[(q-\theta_q)p\right]U(W-C_q^w,H_D). \end{gathered} \tag{20}$$

where $C_q^w = C(W,H,\theta_q,p,q,w[.])$ denotes the compensating variation for a reduction in the incidence rate q of the target disease by the amount θ_q in the presence of probability weighting by the function $w\left[.\right]$. The corresponding marginal WTP becomes:

$$\begin{gathered} MWTP_q^w \equiv \\ \frac{\partial C_q^w}{\partial \theta_q} = \frac{w'[1-q+\theta_q]U(W-C_q^w,H_G)-\left\{w'[(q-\theta_q)(1-p)]U(W-C_q^w,H_B)-w'[(q-\theta_q)p]U(W-C_q^w,H_D)\right\}}{RD[U_1(W-C_q^w,H)]} > 0. \end{gathered} \tag{21}$$

In the same way, we obtain the marginal WTP for the reduction in the disease-specific mortality rate p:

$$\begin{gathered} MWTP_p^w \equiv \\ \frac{\partial C_p^w}{\partial \theta_p} = \frac{w'[q(1-p+\theta_p)]U(W-C_p^w,H_B)-w'[q(p-\theta_p)]U(W-C_p^w,H_D)}{RD[U_1(W-C_p^w,H)]} > 0, \end{gathered} \tag{22}$$

and the marginal WTP for the reduction in the health deterioration rate h:

$$\begin{gathered} MWTP_h^w \equiv \\ \frac{\partial C_h^w}{\partial \theta_h} = \frac{w[q(1-p)]U_2(W-C_h^w,H_B+\theta_h)}{RD[U_1(W-C_h^w,H)]} > 0. \end{gathered} \tag{23}$$

The thrust of the results V-VIII still holds.

Appendix E—Code for Replication

The following R code enables replication of Figure 1.

```
##parametrization based on Bleichrodt and Pinto (2006)
alpha=0.534;beta=1.083
h=seq(0:99)/100;u=1;v=1-h

##Lung cancer calibration, data retrieved from http://seer.cancer.gov/statfacts/html/lungb.html
q=0.066;Q=1-q;p=1-0.174;P=1-p
w_Q=exp(-beta*(-log(Q))^alpha) #weighting function for incidence risk
dw_Q=beta*alpha*(-log(Q))^(alpha-1)*w_Q/Q #marginal weighting function for incidence risk
w_P=exp(-beta*(-log(P))^alpha) #weighting function for mortality risk
dw_P=beta*alpha*(-log(P))^(alpha-1)*w_P/P #marginal weighting function for mortality risk

##Eq. (12) split up in parts
rq_1=dw_Q;rq_2=(u-w_P*v)/(u-P*v);rq_3=(Q*u+(1-Q)*P*v)/(w_Q*u+(1-w_Q)*w_P*v);rq=rq_1*rq_2*rq_3

##Panel A of Figure 1
par(mfrow=c(2,3)) #graphic setting
plot(h,rq,main="A - reduction in lung cancer incidence",lwd=2,type="l",cex.main=.95,
xlab="Health detoriation rate (h)",ylab=expression("MWTP ratio"~mu[q]))

##Eq. (13) split up in parts
rp_1=((1-w_Q)*dw_P)/q;rp_2=(Q*u+(1-Q)*P*v)/(w_Q*u+(1-w_Q)*w_P*v);rp=rp_1*rp_2

##Panel B of Figure 1
plot(h,rp,main="B - reduction in lung cancer mortality",lwd=2,type="l",cex.main=.95,
xlab="Health detoriation rate (h)",ylab=expression("MWTP ratio"~mu[p]))

##Eq. (14) split up in parts
rh_1=((1-w_Q)*w_P)/(q*P);rh_2=(Q*u+(1-Q)*P*v)/(w_Q*u+(1-w_Q)*w_P*v);rh=rh_1*rh_2

##Panel C of Figure 1
plot(h,rh,main="C - reduction in lung-cancer caused health deterioration", lwd=2,type="l",
cex.main=.95,xlab="Health detoriation rate (h)",ylab=expression("MWTP ratio"~mu[h]))

##Skin cancer calibration, data retrieved from http://seer.cancer.gov/statfacts/html/melan.html
q=0.021;Q=1-q; p=1-.915;P=1-p
```

```
w_Q=exp(-beta*(-log(Q))^alpha) #weighting function for incidence risk
dw_Q=beta*alpha*(-log(Q))^(alpha-1)*w_Q/Q #marginal weighting function for incidence risk
w_P=exp(-beta*(-log(P))^alpha) #weighting function for mortality risk
dw_P=beta*alpha*(-log(P))^(alpha-1)*w_P/P #marginal weighting function for mortality risk

##Eq. (12) split up in parts
rq_1=dw_Q;rq_2=(u-w_P*v)/(u-P*v);rq_3=(Q*u+(1-Q)*P*v)/(w_Q*u+(1-w_Q)*w_P*v);rq=rq_1*rq_2*rq_3

##Panel D of Figure 1
plot(h,rq,main="D - reduction in skin cancer incidence",lwd=2,type="l",cex.main=.95,
xlab="Health detoriation rate (h)",ylab=expression("MWTP ratio" ~ mu[q]))

##Eq. (13) split up in parts
rp_1=((1-w_Q)*dw_P)/q;rp_2=(Q*u+(1-Q)*P*v)/(w_Q*u+(1-w_Q)*w_P*v);rp=rp_1*rp_2

##Panel E of Figure 1
plot(h,rp,main="E - reduction in skin cancer mortality",lwd=2,type="l",
cex.main=.95,xlab="Health detoriation rate (h)",ylab=expression("MWTP ratio"~mu[p]))

##Eq. (14) split up in parts
rh_1=((1-w_Q)*w_P)/(q*P);rh_2=(Q*u+(1-Q)*P*v)/(w_Q*u+(1-w_Q)*w_P*v);rh=rh_1*rh_2

##Panel F of Figure 1
plot(h,rh,main="F - reduction in skin-cancer caused health deterioration", lwd=2,type="l",
cex.main=.95,xlab="Health detoriation rate (h)",ylab=expression("MWTP ratio"~mu[h]))
```