Determinants of willingness-to-pay for cancer risk avoidance

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Executive summary

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Objective

Contingent valuation (CV) is a flexible non-market method that allows researchers to focus on the impact that specific causes of deaths and other relevant aspects have on people's willingness-to-pay (WTP) for mortality risk reductions. However, CV studies have often been questioned as the WTP estimates depend on the hypothetical nature of the valuation format and might be influenced by factors that should—in theory—not influence people's preferences.

This report summarizes the findings of three stated-preference studies, which were conducted in the Czech Republic in 2019 with the purpose of addressing some of the above concerns and studying preference stability over time.

The first study aimed at assessing the temporal stability of Value per Statistical Life (VSL) estimates elicited from a CV questionnaire submitted to a sample of the general population in the Czech Republic in 2014. Using a test-retest reliability approach, the same survey instrument was administered a second time to a different sample of respondents. The results of the two surveys were compared with each other as well as with other studies eliciting WTP for cancer risk reductions.

The objective of the second study was to assess whether the insensitivity to quality-of-life descriptors found in the original 2014 study was due to an artifact in the survey design or could be explained otherwise. To this end, the original survey protocol was modified by ensuring that quality of life descriptors varied not only across choice cards (as in the original survey instrument) but also within choice cards.

In the third study, the baseline cancer survival chance was modified in order to study what impact a lower cancer mortality risk has on VSL estimates. In the original study, the 5-year cancer survival chance was 60%; in the study of 2019 it was raised to 75%. The risk reductions remained similar in size—as did all other aspects of the survey—to allow isolating the effect of baseline risk on preferences for cancer risk reduction.

Key findings

Study 1. In May 2019, five years after the date of the original survey, the same survey was self-administered to a sample of individuals aged 45-60 from the general population register of the Czech Republic. As in the original study, respondents were asked to provide information on their willingness to pay (WTP) for cancer mortality risk reduction using a series of dichotomous questions.

The 2019 survey included 1,253 completed questionnaires of which 926 (74% of responses) were identified as valid, whilst the 2014 survey included 1,145 questionnaires, of which 753 (66% of responses) were included in the final sample. Over the five years, the real GDP per capita in Czech Republic increased by 19%.

Results from the test-retest reliability check reported a VSL of €4.22m (2019 PPS euro) which is about 1.4 times larger than the VSL estimate elicited from the 2014 original survey. The

higher VSL estimate in 2019 is explained by respondents' more favourable economic circumstances and to a lesser extent by the slightly lower dread of cancer reported by participants in 2019 survey.

Both samples showed good internal validity with the average WTP for reductions in cancer risk increasing significantly with the size of risk reduction. Indeed, in line with economic theory, respondents' WTP increased only slightly less than proportionately in the 2014 survey, whereas it increased in a perfectly proportionate fashion in the 2019 sample.

Finally, the VSL is positively and significantly related to income both internally within each sample and when the two samples were pooled. Income elasticity of the VSL was 0.74 in the 2014 sample and 0.52 in the 2019 sample, respectively.

With regard to criterion validity, VSL estimates from these CV studies were compared with estimates from labour market studies and other revealed preference studies, which given their limitations, might also lead to biased results. The VSL from 953 compensating wage studies from the US and other Western countries was estimated at $9.6m (2015 US dollars) with an implied income elasticity of 0.5-0.7 for the US and on just over 1.0 for non-US countries. On the basis of these income elasticities, the VSL for the Czech Republic was estimated to be $3.1m (2015 US dollars). This value is very close to those elicited from the two CV studies discussed here and consistent with earlier stated preference studies conducted in the Czech Republic. Cancer dread was positively associated with the VSL.

Study 2. The second study was conducted in the Czech Republic in May-June 2019 and the survey included 1,279 completed questionnaires, of which 936 (73% of responses) were considered valid.

The design of the choice cards was similar to the original study, with the only changes made to the variables describing quality of life (QOL) in order to assess how sensitive individuals' responses are to the severity of cancer disease. In particular, four QOL attribute levels were proposed (the best health status served as baseline).

Three conditional logit models were estimated. In the first model, mortality risk reduction and costs were the only independent variables; the corresponding VSL estimate was €6.5m (2019 PPS euro). In the second specification, quality of life (QOL) levels were entered as regressors and the implicit "pure" VSL after controlling for QOL factors was estimated at €2.6m (2019 PPS euro), suggesting that a large portion of the WTP actually was linked to improvements in quality of live aspects. In the third specification, interaction terms between QOL and the moderate pain dummy were added; the estimated coefficient implied again a "pure" VSL of €2.6m (2019 PPS euro). The same model specification was applied to restricted to subsamples of respondents who had received the reduction in mortality risk exclusively through reductions in the risk of getting cancer or exclusively through improvements in cancer survival, respectively. The implicit VSL estimates were €3.1m (2019 PPS euro) and €3.5m (2019 PPS euro), respectively.

Study 3. The objective of this study was to assess whether cancer VSL is affected by baseline cancer mortality and the corresponding chances of survival (assuming one gets the illness in first place). For this purpose, a modified version of the original survey used in the 2014 study as well as the first study in this report was self-administered to a similar sample of 1,507 individuals aged 45-60 in October 2019. 1,114 (74%) valid responses were received.

The revised version of the survey differed from first study only with respect to the baseline chance of survival (conditional on getting the illness), which was 60% in the first survey and 75% in the revised one. To analyse the impact of this difference, three separate regressions models were run; one using responses from the first study, one using responses from the third study, and one using pooled responses.

Across the studies, the results show that the larger the risk reduction the more likely are respondents to choose the risk-reducing alternative, while they are less likely to choose the risk-reducing alternative if its cost increases. Coefficients on mortality risk were not significantly different from one, indicating strict proportionality of WTP in risk reduction, while income elasticities were 0.5 and about 1 using the responses from the 1st and 3rd study, respectively.

When the two samples were pooled, the results still showed that WTP is proportional to the size of risk reduction and income elasticity was estimated at 0.7. The coefficient on the indicator of higher baseline survival chances was negative (as expected), but not statistically significant suggesting that baseline risks did not alter the WTP.

Finally, regressions were run to assess whether almost certain survival impacts the VSL estimates. The models were fit to the subsamples of responses recorded in the WTP questions where the risk-reducing alternative would lead to 5-year survival chances equal to or higher than 80%. In all models, VSL estimates were close to one another and similar to the estimates derived from the full samples.

Implications

This research project aimed at a better understanding of the determinants of WTP in the context of cancer. In particular, the three studies tackled three basic questions:

i) How stable are preferences for cancer risk reductions in a growing economy over time?
ii) Do descriptors of QOL affect people's WTP in a predictable manner?
iii) Do cancer survival rates affect the valuation in a predictable manner?

With regard to the first question, the project found that over the last five years Czech people's WTP to reduce cancer risk has grown by roughly 40%. Comparing answers across the 2014 and 2019 survey waves suggests that the increment in WTP is attributable to economic growth and a somewhat lower dread associated with cancer in the 2019 sample. This highlights the stability of preferences and underlines that stated preference studies can reliably measure preferences for cancer risk reduction.

Concerning the second question, the empirical results of the original survey suggested that respondents focused on cancer incidence and cancer mortality, and that quality-of-life impacts during and after treatment were not important. By varying the description of QOL attributes not only across but also within choice cards, this follow up study suggests that people do value QOL attributes and that improvements in these dimensions may account for more than two thirds of the VSL. However, these are preliminary findings as they rely on a series of models that assume linearity in QOL and more in-depth modeling is needed to confirm them. Importantly, it may be difficult to generalise results from a survey where the choice sets included the status quo and a proposed alternative that both reduced risks *and* improved quality-of-life. (In other words, the risk reductions and the direction of the quality-of-life impacts were not independently varied to the respondents.)

On the third question, the findings of the study suggest that WTP for mortality risk reduction is explained by the size of mortality risk reduction, while neither the baseline nor the final survival rate had a significant impact on the VSL estimates. This has important implications for policy makers when assessing the benefits of reduced exposure to chemicals associated with cancers that have relatively low mortality rates low mortality rates.

On the Validity of the Estimates of the VSL from Contingent Valuation: Evidence from the Czech Republic

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Abstract

We assess the reliability and validity of estimates of the Value per Statistical Life (VSL) from contingent valuation by administering the same contingent valuation (CV) questionnaire on samples drawn from the population of the Czech Republic five years apart. We use a novel approach in eliciting the WTP for cancer mortality risk reduction, in that we present respondents with *two* probabilities—that of getting cancer, and that of surviving it. We find that the cancer VSL is somewhat different across the two samples, but this difference is completely explained by income and cancer dread. The WTP is proportional to the size of the cancer mortality risk reduction, and increases with income and with cancer dread. The income elasticity of the VSL is 0.5 to 0.7. Our estimates of the VSL (approximately €3 - 4 mill. May 2019 PPP euro) are close to Viscusi and Masterman's prediction (2017) based on compensating wage studies, less than the estimates from compensating wage studies conducted in the Czech Republic, and similar to estimates from other stated preference studies in the Czech Republic. We conclude that the CV questionnaire and administration procedures produce reliable and stable results, and that construct and criterion validity are likewise good. We interpret these findings as providing support for an approach that expresses very small mortality risks and risk reductions as the product of two probabilities.

Keywords: VSL; VSCC; cancer risk; stated preferences; test-retest reliability; construct validity; criterion validity.

1. INTRODUCTION

The Value per Statistical Life (VSL)—a summary measure of the willingness to pay for reductions in the risk of dying—is a key metric in benefit-cost analyses of safety and environmental regulations and policies. The VSL can be estimated from compensating wage differentials (Viscusi, 2013), from the prices of otherwise similar homes, cars or other products but with different safety levels (Gayer et al., 2000, 2002; Davis, 2004; Andersson, 2005), or by asking individuals to report information about their willingness to pay (WTP) for mortality risk reductions in contingent valuation or other stated preference surveys. The latter methods are very flexible and allow researchers to focus on specific causes of death, aspects of the mortality risk reductions (for example, the fact that it will occur in the future), affected populations, and to incorporate independent experimental variation in the study design that is not often observed in labor markets or hedonic pricing studies (Alberini, 2019). They have however been subject to considerable scrutiny, in part because it is notoriously difficult to communicate risks to laypeople,[2] and in part it is sometimes feared that the hypothetical nature of the valuation questions may compromise the credibility of the results (Bishop and Boyle, 2017; Kanya et al., 2019; Rakotanarivo et al., 2016; Bryan and Jowett, 2010).

It is therefore important that the VSL obtained from stated-preference studies meet validity criteria. Validity means how well the study has measured the underlying outcome of interest, namely the true value of risk reductions. One way to check validity is to establish the degree of reliability of the survey instrument and survey procedures (Carmines and Zeller, 1979): In other words, if the survey questions were administered again in a similar setting and with the

[2] This has prompted reliance on expert assessment (Roman et al., 2012).

same type of subjects, would they produce statistically indistinguishable estimates of the metric of interest (here, the VSL)?[3]

Test-retest checks remain, to the best of our knowledge, uncommon when eliciting information about the value of mortality risk reduction. One recent exception is Hammitt et al., (2019), who administered the same contingent valuation survey questionnaire twice in Chengdu, China, 11 years apart (in 2005 and 2016).[4] Test-retest checks have been conducted with the same respondents within the same survey (Brown et al., 2008; Crossley and Kennedy, 2002), with the same respondents and a similar or identical survey instrument but at a later date (Schwappach and Strasmann, 2006; Cook et al., 2005), or with completely different subjects (e.g., Carson et al., 1997).

Another way to check the validity of the information about preferences reported by individuals in surveys is to see whether the survey responses, and the metrics based on them, are related to certain sociodemographics or vary with certain variables according to the predictions from economic theory. For example, one would expect the WTP for reducing health risks to increase with income and with the magnitude of the risk reduction. These checks are referred to as tests of internal validity in some sources (Etchegaray and Fisher, 2006) and construct validity in others (e.g., Bishop and Boyle, 2017).

[3] It is important to emphasize that reliability doesn't necessarily imply unbiasedness. It is perfectly possible for the survey instrument and study procedures to elicit a biased estimate of the true value, and yet for the bias to be stable when the study is repeated. Bishop and Boyle (2017) liken reliability to the notion of variability of the measure of value, and to the darts clustered together on a bull's eye target: They may be clustered together near the center (unbiased measure of value), or far from it, in which case the results are biased, but stable (Atker et al., 2007).

[4] Test-retest studies have been done in a variety of settings to learn about preference formation (Brown et al., 2008), the temporal stability of the WTP to protect natural resources where non-use values are likely to play an important role (Carson et al., 1997), the consistency of individual preferences for public health plans (Schwappach and Strasmann, 2006), whether specific attributes of health care plans are valued similarly when they are bundled with different health plan packages (Telser et al., 2008), and even to see whether individuals are capable of assessing their own health (Crossley and Kennedy, 2002).

Another yet validity check is criterion validity (Bishop and Boyle, 2017), where the estimate of the metric of interest from a stated preference study is compared with the estimates produced by other, generally trusted approaches. If the former is close to the latter, the stated-preference estimates would be regarded as valid.

This paper reports on the test-retest reliability, construct and criterion validity of the estimates of the VSL from contingent valuation. We ask three fundamental research questions: First, how reliable are the estimates of the VSL from stated preference studies? In order words, if we repeat the same stated preference questionnaire, study design, and mode of administration at the same locale with the same sampling frame, do we arrive at the same VSL? If not, what explains the difference in VSL between the earlier and the later study?

Second, are the estimates of the VSL internally valid? We specifically focus on the rates at which the WTP for mortality risk reductions increases with the size of the risk reduction and with respondent income. Hammitt et al. (2019), Lindhjem et al. (2011), Corso et al. (2001) and Hammitt and Graham (1999) point out that in several stated preference studies the WTP for a mortality risk reduction grows in a less than proportional fashion with the size of the risk reduction. When that is the case, the VSL is not constant with respect to the magnitude of the mortality risk reduction, complicating benefit-cost analysis recommendations and potentially raising questions about the credibility of the study.

Regarding income and the VSL, societies and individuals are expected to place higher value on mortality risk reductions as they grow wealthier. Recent literature has sought to offer predictions for the VSL for a wide range of countries, either by summarizing the relationship between the willingness to accept a riskier workplace risk and wage rates (Viscusi and

Masterman, 2017) or by reporting evidence from a variety of studies and non-market methods (Hammitt and Robinson, 2011).

Third, how do they compare with existing estimates from alternate non-market valuation methods? Policy and benefit-cost analyses in the United States, for example, rely primarily on estimates of the VSL from compensating wage studies and workplace fatalities (US EPA, 2010), and VSL figures are also available from hedonic housing price studies and consumer product safety studies (Gayer et al., 2000, 2002; Andersson, 2005; Davis, 2004; Jenkins et al., 2008).

To answer these questions, the same, identical survey instrument was self-administered online by persons aged 45-60 recruited from the general population of the Czech Republic five years apart—in March-May 2014 and in May 2019. The Czech Republic experienced considerable economic growth during those five years: Both the GDP per capita and the average household income grew in real terms by about 19%.

The questionnaire asked respondents to report information about their WTP for cancer mortality risk reductions using a series of binary questions: Would the respondent be willing to pay a specified amount for a given risk reduction, or would be rather stay with the baseline risk? A distinguishing feature of our study is that we presented respondents with *two* probabilities—the risk of developing cancer and the chance of surviving it, assuming that one got cancer in the first place. The unconditional cancer mortality risk is the product of the former times the complement to unity of the latter—but we did not present respondents with that product. Nor did we present the unconditional mortality risk *reductions* that respondents were to value. Rather, we showed them a reduction in the chance of getting cancer and an improvement in survival at 5 years, assuming that one got cancer in the first place.

In addition, in each choice question, the severity of cancer was described by pain (mild or moderate) and impacts on quality of life (ranging from no impacts to confined to bed for half of the time). These were identical across the current situation (status quo) and the risk-abating alternative.

The WTP for each risk reduction (and hence the VSL) is not directly observed, but it is inferred from fitting binary data econometric models. Our assessments of reliability and validity are implicitly seeking support for the notion that it is a good strategy to present a small mortality risk (and reduction thereof) broken down into its two components: The probability of onset of the illness, and the probability of surviving it.

Our test-retest reliability check compares the VSL figures from each wave of surveys, finding that the 2019 figure was 1.41 times larger than the 2014 figure. This difference may result from changes in the public's preferences for safety or in the economic circumstances. In our case, the difference in the VSL is completely explained by respondent income, and by the slightly lower dread of cancer reported by the participants in the 2019 wave (Olofsson et al., 2019). For comparison, Costa and Kahn (2004) examine how the VSL has changed over time in the US using Census data, and Liu et al. (1997) estimate compensating wage differentials for each year over a 16-year period to see if the valuation of workplace fatality risks has changed in Taiwan.

Both samples exhibit good internal validity, in that the WTP for the risk reductions increases significantly with the size of the risk reduction. In other words, the WTP passes the so-called scope requirement (Hammitt and Graham, 1999; Corso et al., 2001). When checking the even stronger requirement that the WTP be perfectly proportional to the size of the risk reduction, this requirement is barely missed by the 2014 sample and met easily by the 2019

sample. The responses to the WTP questions suggest that individuals were willing and able to intuitively translate the two probabilities, and reductions thereof, into the equivalent cancer mortality risk reductions.

The VSL grows with income--internally within each sample, when the samples are pooled, and across the two samples. In each case, however, the elasticity of the VSL with respect to income is less than one, and is thus well below the range from Kniesner et al. (2011) (1.23 at high income to 2.44 at low income), the income elasticity of the VSL estimated by Costa and Kahn (1.5-1.6), and that used in the current practice of the US Department of Transportation, which assumes an elasticity of one (US Department of Transportation, 2016). Our estimates of the income elasticity of the VSL also fall short of the value (1.0) used in Viscusi and Masterman (2017) to predict the VSL in countries around the world based on meta-regressions of VSL figures from compensating wage studies.

Extrapolations to the Czech Republic from other non-market methods should be interpreted with caution, due to the data and econometric limitations that often plague such studies (Alberini, 2019), and to the often different nature of the risks that they cover. Even with these caveats, the estimates of the VSL from our surveys (€2.999 million from the 2014 survey and €4.216 million from the 2019 survey; all figures in 2019 PPP euro) are within the range that would be considered acceptable for the Czech Republic based on such extrapolations.

The remainder of this paper is organized as follows. Section 2 presents background on the cancer VSL. Section 3 describes the survey. Section 4 presents the model of the responses and the hypotheses. Section 5 presents the data, section 6 the results, and section 7 concludes.

2. BACKGROUND: THE VSL

The Value per Statistical Life is defined as the WTP for a marginal change in one's risk of dying. This metric is appropriate, and often used, in ex ante analyses of safety and health regulations and programs. Since in many cases environmental and safety programs tend to protect the elderly and those in compromised health, recent research has focused on the effects of age (Krupnick, 2007), latency (Adamowicz et al., 2011), co-morbidities and competing causes of death (Eeckhoudt and Hammitt, 2001; Cameron and DeShazo, 2013) and on whether the fact that the cause of death is cancer would elicit different values than a comparable mortality risk reduction in a non-cancer setting (Hammitt and Haninger, 2010; Hammitt and Liu, 2004; Alberini and Scasny, 2013; Cameron and DeShazo, 2013; Sunstein, 2014).

In this section, we present a simple theoretical model for cancer mortality risks and examine its implications for the VSL. Assume that the individual has probability p of getting cancer, and conditional probability q of dying from it, assuming that he or she gets cancer in the first place. The unconditional probability of dying from cancer is thus $m=p\cdot q$. Further assume that the utility of income in the healthy state is $U(y)$, and the utility of income when the individual has cancer but is still alive is $V(y)=(1-h)U(y)$, where h ($0\leq h\leq 1$) is the reduction in utility with respect to the healthy state (Rheinberger et al., 2016). The utility of money when dead is, without loss of generality, set to zero. The expected utility of the individual is thus:

$$(1) \qquad EU = (1-p)\cdot U(y) + p\cdot(1-q)\cdot(1-h)\cdot U(y)\ .$$

It is straightforward to show (Alberini and Scasny, 2018) that the VSL, namely the WTP for a marginal change in the chance of dying from cancer m, is

$$(2) \qquad VSL = \frac{dy}{dm} = \frac{U(y)}{U'(y)}\cdot\frac{\left[\frac{1+(1-h)(q-1)}{q}\right]}{[(1-p)+p(1-q)(1-h)]}.$$

This is, as usual, the utility differential between the healthy state and the sick state, divided by the expected marginal utility of income. The baseline odds of getting cancer, the chance of dying

from it, and the loss of utility h when in the sick state enter in both the numerator and the denominator.

The VSL clearly increases with income,[5] but how does it depend on h? On differentiating the VSL with respect to h, we obtain

$$(3) \qquad \frac{\partial VSL}{\partial h} = \frac{U(y)}{U'(y)} \cdot \frac{\left[\frac{1-q}{q}\right]}{[(1-p)+p(1-q)(1-h)]^2},$$

which is clearly positive, implying that the worse the quality of life impacts of cancer, the higher the VSL.

In practice, the unconditional risk of dying from cancer is reduced i) when the risk of getting cancer gets smaller (holding the chance of surviving it the same), ii) when survival rates improve (and the risk of getting cancer stays unchanged), and iii) when the risk of cancer is reduced *and* the chance of survival is increased. All of these three situations are presented to the respondents in our survey.

3. STUDY DESIGN

Our questionnaire asks each respondent a total of seven dichotomous choice questions—whether or not they would be willing to pay a specified amount of money for a reduction in cancer mortality risks (see Figure 1 for an example).

When asking people to report information about the willingness to pay for a reduction in their own risk of dying, it is essential to inform the respondent about the "baseline" risk (i.e., the risk level before the reduction is offered) and the size of the risk reduction to be valued. We

[5] This is easy to see as the VSL is $U(y)/U'(y)$, times a positive term that contains p, q, and h, but does not contain income. The first derivative of the VSL with respect to income is thus proportional to $\frac{[U'(y)]^2 - U(y)U''(y)}{[U'(y)]^2}$, which is positive as long as the utility function is concave (and hence U'' is negative).

follow this approach in our questionnaire, taking care to implement three important differences with respect to previous work.

First, we presented respondents with *two* probabilities--the risk of developing cancer and the chance of surviving it, assuming that one got cancer in the first place. This is consistent with the information about cancer—the incidence and the 5-year survival rates—disseminated by public health authorities in many countries (such as the Centers for Disease Control, the World Health Organization, etc.). Clearly, the unconditional cancer mortality risk is the product of the former times the complement to unity of the latter—but we did not present respondents with that product.

The baseline probabilities were the same for all respondents. Specifically, we told respondents that their baseline risk of getting cancer was 25 in 1000 over 5 years, and that the 5-year survival odds were 60%. This means that the annual risk of getting cancer is 5 in 1000, and that the annual mortality risk, if one gets cancer, is $1-0.60^{1/5}=1-0.9029=0.0971$. The unconditional cancer mortality risk is thus $0.005\times0.0971=0.0004855$, or approximately 5 in 10,000 a year.

Second, the mortality risk reductions were likewise presented as i) reductions in the risk of getting cancer, holding the survival odds the same, or ii) improvements in the survival chance, holding the risk of getting cancer the same, or iii) simultaneous reductions in the risk of getting cancer and improvements in the survival odds. Again, we did not compute the unconditional risk reductions for the respondents. Respondents were assigned at random to combinations of options i), ii) and iii) of various sizes. About half the respondents faced three mortality risk reduction situations of type i), followed by four of type iii). The other half faced three risk reductions like those in type ii) above, followed by four of type iii).

As shown in table 1, the reductions in the risk of getting cancer offered to the respondents in the WTP questions ranged from 0 to 5 in 1000 over 5 years (equivalent to 0 to 1 in 1000 per year). The improvements in the chance of survival ranged from 0 to 20%, bringing the 5-year survival rate to a maximum of 80%. The corresponding reductions in the unconditional risk of dying from cancer thus ranged from 3.88 in 100,000 to 3.11 in 10,000 per year—but, again, we did not perform this calculation for the respondent.

Third, we recognize that the chance of survival at 5 years is only one of the possible measures of severity of cancer. Other important descriptors might be the pain and the impacts on quality of life during and after treatment. Cameron and DeShazo (2013) suggest that the course of illness may be an important determinant of WTP. Rather than following those authors' precise timelines in terms of illness, treatment and relapse, we describe four possible quality-of-life states (from perfectly normal life to being confined to bed half of the time and unable to work) and two levels of pain (mild and moderate) (see table 1).

We vary the quality-of-life impacts and pain—if one gets cancer—across the respondents and from one valuation question to the next within a respondent, but not within a valuation question. In each of the seven valuation questions, the respondents report information about their WTP to obtain the proposed risk reduction for a given quality-of-life impact and pain level. In other words, they can reduce their risk of getting cancer (and experiencing the described consequences) and dying from it, but they cannot "buy" a change in these consequences. To ensure that the bids were, in real terms, identical across the two surveys, we increased the bids used in the 2014 survey by 6%, the change in the Consumer Price Index between 2014 and May 2019.

The WTP questions were preceded by a probability tutorial. Risks were graphically depicted using a grid of squares, where the colored squares indicated the risks (see figure 1). Respondents saw the colored squares scattered on the grid to convey randomness, and then aligned at the top of grid to convey the magnitude of the risks (Ancker et al., 2006). At the end of the tutorial, respondents took a simple quiz.

After the probability tutorial, respondents were told the baseline risks for a person their age, and explained how individual actions and government programs may help reduce the risk of dying from various causes.

4. THE MODEL

We assume that the responses to the choice questions are driven by the WTP for the risk-reducing alternative, which is not directly observed. We assume that this unobserved WTP depends on the magnitude of the risk reduction as follows:

$$WTP_{ij}^{*} = \exp(\alpha) \cdot \left(\Delta mortrisk_{ij}\right)^{\gamma} \cdot \exp(\varepsilon_{ij}), \tag{7}$$

where ε is a normally distributed error term with mean zero and variance σ^2. We choose this model for three reasons. First, experience suggests that the WTP for health risks reductions and other safety and environmental programs almost always has a long right tail, and equation (7) and its assumptions imply a lognormal distribution for WTP, which is positively skewed. Second, on taking logs, equation (7) becomes

$$\ln(WTP_{ij}^{*}) = \alpha + \gamma \cdot (ln\Delta mortrisk_{ij}) + \varepsilon_{ij}. \tag{8}$$

At a minimum, γ should be positive. If γ is 1, then the WTP for a specified risk reduction is perfectly proportional to the size of the risk reduction, which in turn means that there is a single VSL value that holds at any of the risk reduction proposed to the respondents in the survey. We

can therefore let the data tell us whether the individual choice responses meet the so-called strong "scope" requirement, namely that the WTP be strictly proportional to the size of the risk reduction (Hammitt and Graham, 1999; Corso et al., 2001). We are aided in this task by the fact that our survey design (shown in table 1) implies 15 different mortality risk reduction levels ranging from approximately 2 in 10,000 over 5 years to about 1.6 in 1000 over 5 years. Third, equations (7) and (8) are easily amended to allow α to depend on the attributes of the risk reduction and/or on respondent sociodemographics or risk perceptions.

We do not observe the respondent's WTP for a specified risk reduction: All we can infer from the responses to the choice questions is whether the underlying WTP amount is greater than the cost of the risk-reducing alternative—if the respondent chooses that alternative—or otherwise. This results in a binary choice model that describes the probability of selecting the risk-reducing alternative as a function of the magnitude of its risk reduction and cost:

$$(9) \qquad \Pr(j\ is\ chosen) = \Pr\left(WTP_{ij}^{*} \geq C_{ij}\right) = \Pr\left(\ln\left(WTP_{ij}^{*}\right) \geq \ln\left(C_{ij}\right)\right) =$$

$$= \Phi(a + b \cdot ln\Delta MortRisk + c \cdot ln(C_{ij}))$$

where $\Phi(\cdot)$ denotes the standard normal cdf, a=α/σ, b=γ/σ, and c=-1/σ.

The statistical model in equation (9) is appropriate if one choice task is considered in isolation (or if the respondent only answers one WTP question), and results in a probit model that, for now, contains only one regressor—the log of cost. The original α in equation (7) is recovered as the intercept from the probit model, divided by the negative of ($\hat{c}$). The standard deviation of ε is obtained as (-1/$\hat{c}$).

In our survey, however, each respondent answered a total of seven choice WTP questions. Each respondent's seven error terms ε are likely correlated, due to unobserved characteristics of the respondent or perceptions that affect each decision task. We assume that the

correlation between any two pairs of responses is the same, which results in a random effects probit model.

If γ=1, equation (8) is simplified to

(10) $$\ln\left(\frac{WTP_{ij}^{*}}{\Delta mortrisk_{ij}}\right) \equiv \ln\left(VSL_{ij}^{*}\right) = \alpha + \varepsilon_{ij}$$

and $\ln\left(\frac{C_{ij}}{\Delta mortrisk_{ij}}\right)$, i.e., the log of the cost per unit of risk reduced, must be entered in its binary choice econometric counterpart. In its simplest variant, the binary choice model includes only the log cost per unit of risk reduced. In more complex variants α is allowed to depend on descriptions of the choice task setting, such as the quality of life experienced in this hypothetical scenario and the pain level associated with the illness or its treatment.[6] Income, education, experience with cancer and perceptions of cancer are further added to see if the VSL depends on them, and if they are sufficient to explain any differences in cancer mortality valuations across the two surveys.

In what follows we begin with fitting separate random effects probits based on model (8) for the underlying (and unobserved) willingness to pay to the samples from the 2014 and 2019 surveys, respectively. We test whether γ=1 and develop estimates of the VSL from each sample. We then pool the samples and fit the random effects probit corresponding to equation (10) to see if any differences in the VSL across the two surveys are explained by different levels of income, education, experience and perceptions of risk.

5. THE DATA

[6] We remind the reader that the quality-of-life impacts of cancer and the level of pain that would be experienced by the respondents are the same across the status quo and the risk-abating alternative, but vary from one choice question to the next, and across respondents.

The survey questionnaire was self-administered online by a sample of persons aged 45-60 drawn from internet panels of consumers in the Czech Republic in March-May 2014 ("2014 sample") and May 2019 ("2019 sample"), respectively. We instructed the respective survey firms to provide us with samples with an even number of men and women, an even number of persons with household income above and below the national median, and educational attainment that mirrors that of the Czech population in that age bracket. The surveys resulted in a total of 1145 and 1253 completed questionnaires, respectively.

The analyses in this paper are based on samples that exclude so-called "speeders," namely persons who filled out the questionnaire in less than 48% of the median completion time (13 minutes for the 2014 survey and 11 minutes for the 2019 survey; median completion times were 26 and 23 minutes, respectively).[7] We also dropped persons who did not answer the first probability quiz correctly (about 30.66% in the 2014 survey and 22.83% in the 2019 survey) to arrive at final samples comprised of N=753 and N=926 valid questionnaires, respectively.[8]

Descriptive statistics of the respondents are displayed in table 2. Clearly, despite quota sampling (or perhaps because of it), household income and the educational attainment are much higher in the 2019 survey than in the earlier one. The average household income is over 50% times larger in the 2019 survey than in the 2014 one. This difference clearly exceeds the growth in GDP per capita in the Czech Republic over the same period (15%, or 3% per annum) and that observed in the Statistics in Income and Living Conditions survey (SILC) for a sample

[7] A total of 53 and 59 respondents were classified as speeders in the 2019 and 2014 surveys, respectively.
[8] It is likely that those respondents who failed the probability quiz were simply not paying full attention to the questions, rather than exhibiting a failure of the non-satiation assumption of preferences (San Miguel et al., 2005). Ozdemir et al. (2010) investigate how individual characteristics of the respondent (gender, income, education and age) affect subject performance in stability, transitivity, and monotonicity tests via their effect on cognitive ability or effort in solving difficult tasks.

representative of the population and for a sample of persons aged 45-60 (see table 3).[9] The distribution of income in the two samples is depicted in Figure 2, which shows that the 2019 distribution is shifted to the right with respect to that of 2014, and only partially overlaps with it.

The 2019 sample is also better educated than the 2014 sample: The shares with a high school diploma or college degree (46.59% and 32.55%, respectively) are some 50% greater than their counterparts in the 2014 survey. Table 4 shows that the two samples are similar in terms of own cancer experience, having or having had a family member with cancer, and in terms of judgment of how likely cancer is to occur in the respondent's family. The 2014 sample, however, appears to dread cancer more intensely than the 2019 sample.

Random assignment to the pre-set 32 combinations of 7 choice cards each ensured that the risk reductions and attendant attributes of the choice setting were similar across the two surveys (table 5). In terms of the responses to the WTP questions, 51.46% were in favor of the risk-reducing alternative in the 2014 survey, and 57.53% in the 2019 survey.

6. RESULTS

6.1. The 2014 Sample

We begin with examining the responses from the two surveys separately. Table 6 refers to the 2014 survey data, and assumes log WTP as the latent variable driving the responses, as in

[9] We use micro data collected in compliance with the European Union's directives and implementing regulations—Statistics on Income and Living Conditions (EU-SILC)—for the Czech Republic for 2015 and 2018 to compute an estimate of the average household income of the target population (persons aged 45-60) in the Czech Republic. The CZ-SILC survey is regularly conducted by the Czech Statistical Office, using random two-stage sampling in each region. CZ-SILC records family and dwelling characteristics, earnings and income for each family member. The 2015 CZ-SILC reports earnings and income for 2014, and the 2018 CZ-SILC for 2017. Although the full CZ-SILC contains 7,914 and 8,634 households, respectively, we consider only those households with household head or partner aged between 45 and 60 at the time of the survey. This results in 2,560 and 2,686 households, respectively. Our estimates are weighted using the population weights supplied by Czech Statistical Office (CSO, 2019).

equations (7) and (8). In col. (A) we report the estimated coefficients and t statistics from the simplest random effects probit, namely one with a constant, log mortality risk reduction and log cost. Consistent with economic theory, the coefficient on log mortality risk is positive and that on log cost is negative: The larger the risk reduction, the more one is prepared to pay to obtain it, and the more expensive the risk reduction, the less likely one is to be in favor of it. This model does not control for the other attributes of the choice setting, namely quality of life and pain. Coefficient γ is estimated to be 0.7651, a value that is significantly different from one, but not far from it.

The fact that γ is less than one and is equal to 0.76 means that the implied VSL will be larger when calculated for smaller risk changes than for larger risk changes. As shown in Figure 3, when we double the size of the unconditional mortality risk reduction (from the median value assigned to the respondents in the sample, 0.0001554, to the largest value, 0.000311) the VSL decreases by some 20%, from €2,149,905 to €1,826,635 (2019 PPP euro).[10] These figures can be compared with the single VSL (€2,988,178, 2019 PPP euro) from a model that imposes that the WTP be strictly proportional to the size of the risk reduction (i.e., that γ=1), shown in col. (B) of table 6 and displayed in figure 3.

Column (C) of table 6 reports the estimation results from a model that allows for a different intercept for each of the four quality of life (QOL) scenarios that appear in the choice cards, and relaxes the restriction that γ=1 (like the model in col. (A)). The latter decision is supported by a Wald test (Wald statistic 5.70, p value 0.0170). A Wald test of the null that the four QOL intercepts are all equal to each other does not reject the null (Wald statistic 2.47, p value 0.4808). The coefficient on the moderate pain dummy is statistically insignificant. We

[10] The WTP for two risk reductions would be 436.65 and 742.46 2018 PPS euro, respectively.

conclude that, at least in the 2014 survey, the WTP for a risk-reducing alternative is not influenced by the cancer's disruption of the respondent's quality of life or pain, and that the simple model of col. (A) and its further simplified variant in col. (B) are reasonable.

Finally, col. (D) shows that the willingness to pay for the risk reductions is positively related to income: The income elasticity of the VSL—if income is known—is 0.7406 (s.e. 0.2206, t stat 3.36).[11] While the point estimate is less than one, a Wald test does not reject the null that the income elasticity is one. The Wald statistic is 1.37 and has a p-value of 0.24. Adding income in the model does not change the outcome of a Wald test of the null that the coefficients on all QOL dummies are the same (Wald statistic 2.53, p value 0.4705).[12]

In sum, the fact that the people shy away, all else the same, from more costly risk-abating alternatives, the sensitivity to the size of the risk reduction and the positive association between the WTP (and the VSL) and income suggest that responses and measures of value comply with the basic construct validity discussed in Bishop and Boyle (2017).

6.2. The 2019 Sample

Table 7 reports estimation results from the 2019 data. In all three specifications the WTP is, as suggested by economic theory, positively related to the size of the cancer risk reductions and the likelihood of selecting the risk-reducing option in a choice task negatively related to the option's cost. The differences with respect to their counterparts in table 6 are, however, striking. First, as shown in col. (A), γ is not statistically different from one (Wald statistic 0.63, p value 0.4284), leading us to wonder whether the strict proportionality of the WTP to the size of the risk

[11] We remind the reader that this figure is obtained as the coefficient on log income in the random effects probit, 0.5008, divided by the negative of the coefficient on log cost, namely 0.6762.
[12] Education does not seem to affect the WTP. The coefficients on education dummies are individually and jointly statistically insignificant, whether or not the model already controls for income (results available from the authors).

reduction is attributable to a wealthier and better educated sample (compared to that of 2014). We examine this possible explanation in more detail below.

Second, the specification of col. (B) produces an estimate of the VSL equal to €4,216,099 (2019 PPP euro), which is approximately 1.41 times its counterpart from the 2014 sample and implies a "cross-sample" income elasticity of the VSL of 0.7716.[13] Third, the coefficients on the QOL dummies (col. (C)) indicate that the heavier the impacts of cancer on quality of life, the *less* the WTP for a measure that reduces the risk of dying from it. The four coefficients are statistically different from one another (Wald statistic 32.56, p value < 0.0001). In practical terms, they mean that the VSL is €4,102,615 when QOL=0 (no impairments), €4,041,720 when QOL=1 (no heavy physical work), €3,268,066 when QOL=2 (unable to work), and €3,008,053 when QOL=3 (confined to bed for half of the time) (all figures in 2019 PPP euro). Whether pain is mild or moderate continues to be unimportant to the respondents, who probably did not see a distinction between "mild" and "moderate" pain.

Fourth, the specification of col. (D) results in an income elasticity of the VSL equal to 0.5247 (s.e. 0.1830, t stat. 2.87). This elasticity is not statistically different from that for the 2014 sample (Wald statistic 0.5659, P-value 0.4511),[14] but a Wald test finds it statistically different from one (Wald statistic 6.7459, P value less than 0.001). A Wald test of the null that the coefficient on the quality-of-life impacts are all equal to one another rejects the null soundly (Wald statistic 32.01, p value less than 0.0001).

6.3. Evidence from Pooling the Samples

[13] We compute this income elasticity as ln(1.41)/ln(1.5656), where 1.5656 is the ratio of the average household income in the 2019 sample to the average household income in the 2014 sample. This calculation follows from the simple expression $VSL_{2019} = VSL_{2014} \cdot \left(\frac{INC_{2019}}{INC_{2014}}\right)^{\theta}$, where θ is a cross-country income elasticity of the VSL.

[14] Again, the educational attainment of the respondents is not significantly associated with the WTP.

In table 8, we pool the data from the 2014 and 2019 surveys. We impose the assumption that the risk reduction elasticity of WTP is one,[15] whereby the latent variable becomes the log of the WTP per unit of mortality risk reduction, i.e., the log of the VSL. Its econometric counterpart is a random effects probit where the regressors are the log of cost per unit of mortality risk reduction (ln Cost/Δmortrisk), a dummy denoting the 2019 survey, and, in selected specifications, other characteristics of the risk and/or the individual. The specifications of columns (A)-(D) show quite clearly that the log of cost per unit of mortality risk reduced has a negative and statistically significant coefficient.

The simplest specification (column (A)) implies that the VSL is about 36% higher in the 2019 study. This effect is robust to adding the QOL and pain dummies (col. (B)), but vanishes as soon as we control for the income of the respondents (col. (C)). Education and familiarity with cancer do not explain the (log) VSL, but the VSL is higher when the respondent attaches a high level of dread to cancer. A finding that is common to cols. (B)-(D) is that the VSL appears to be greater when the cancer is *less* disruptive of one's quality of life. Wald tests reject the null that the coefficients on all QOL dummies are equal to one another in each of (B)-(D), much like with the 2019 sample. Income is a significant determinant of the VSL, and the income elasticity of the VSL is approximately 0.64.

6.4. Matched Respondents

The 2019 sample appears to be wealthier and better education than the 2014 sample. To avoid undue extrapolation and excessive reliance on the specification and functional form of the underlying WTP equation, in table 9 we report the results from fitting equation (10) to a sample

[15] Imposing this restriction may be a bit, but not much, of a stretch for the 2014 survey data, but is perfectly acceptable for the 2019 data.

comprised only of those respondents from the 2019 survey that we were able to match with similar respondents from the 2014 survey. The purpose of this exercise is to check if the VSL, income and education findings change once we remove respondents that are too dissimilar for education, income and other variables.

We used coarsened exact matching (CEM) (Iacus et al., 2012) based on up to three groups of variables to attain a more refined degree of matching. To illustrate, col. (A) refers to 2019 respondents plus their 2014 counterparts for education level. Only 1 unmatched respondent was found and excluded from the estimation sample. In column (B) we match respondents by their education and income level, losing 372 unmatched subjects.[16] For column (C) we matched respondents by education, income and cancer dread levels. This more demanding matching procedure excludes 519 unmatched persons. Despite the different sample sizes, the three columns sound a common theme: the 2019 sample dummy is insignificant and most of the coefficients are consistent with expectations. The income elasticity of the VSL is 0.62 in col. (A), 0.67 in col. (B), and 0.70 in (C). Wald tests indicate that the former two income elasticities are significantly different from one (Wald statistics 5.69 and 3.64, P values 0.0171 and 0.0563, respectively), while the latter is not different from one at the 5% significance level (Wald statistic 2.77, P value 0.0973). Education doesn't seem to matter, and the effect of quality of life during and after treatment is similar to that shown in table 8.

6.5. Criterion Validity

Some authors interpret criterion validity to mean comparison between the value elicited from a stated preference study and that observed in markets—real or simulated (Loomis, 1989).

[16] In other words, for each education level, we retain only the respondents whose income falls in the common support for that education level for the 2014 and 2019 samples.

Mortality risk reductions however are not traded on regular markets, and we are not aware of laboratory or field studies where mortality risks were bought and sold for actual cash.

We therefore assess criterion validity by comparing our estimates of the VSL with estimates from labor market studies and other revealed preference studies—with the caveat that, given data limitations and econometric difficulties, labor market studies and revealed preference studies perhaps deserve just as much scrutiny as stated preference studies (Alberini, 2019).[17]

Viscusi and Masterman (2017) adopt a base VSL of $9.6 million (2015 US dollars) and rely on 953 compensating wage studies from the US and other countries to estimate an income elasticity of the VSL of 0.5 – 0.7 for the US, and just over 1 for non-US countries. Based on these elasticities, they predict the VSL for the Czech Republic to be $3.121 million (2015 US dollars). Even adjusting for the inflation and for the exchange rate, this figure is clearly very close, and no larger than, the VSLs from our contingent valuation study.

By contrast, as shown in table 10, earlier compensating wage studies in the Czech Republic—based on both official fatal accident rates as well as perceived risks reported by the workers—arrived at much larger estimates of the VSL (up to about €18 million in May 2019 PPP euro). It is interesting that the one VSL figure that comes closest to the estimates reported in this paper relies on subjectively assessed risks, suggesting that the latter were greater than those from official statistics.

Whether conducted in the US or in the Czech Republic, compensating wage studies deal with workplace accidents and as such do not match our surveys in terms of the nature of the risk and cause of death. Estimates of the so-called Value per Statistical Case of Cancer (VSCC) from

[17] This decision blurs the distinction between convergent validity and criterion validity (Bishop and Boyle, 2017). Convergent validity means comparing the results from one non-market valuation method (in this case, contingent valuation) with those from other non-market valuation methods (compensating wage studies, housing price hedonics) applied to the same good.

the US (Gayer et al., 2002) are in the range of $4.5 to $8.3 million (2000 US $) but because they are computed from housing price differentials in the US and lifetime risks, it is not clear whether they mirror the valuation of risks in the Czech Republic and how they can be converted into an *annual* VSL.[18] Earlier *stated* preference studies from the Czech Republic (table 10) generally agree with the results from this paper.

7. CONCLUSIONS

When using stated preference methods to place a monetary value on reductions in the risk of dying, it is important to show that the metrics based on the survey responses meet validity criteria. In this paper, we focus on test-retest reliability, internal validity and criterion validity, which we put to the test by administering a questionnaire that elicits information about the WTP for cancer mortality risk reductions five years apart on a new, but similar, group of respondents in the Czech Republic.

We have found that the VSL from the 2019 survey is 1.41 times that from the 2014 survey, but this difference is completely explained by the respondents' income, which is greater (in nominal and real terms) in the 2019 survey, and somewhat more moderate assessment of cancer dread. The educational attainment of the respondent—which is higher in the 2019 sample—is not a significant determinant of the VSL.

In both waves of the survey, the responses exhibit very good internal validity. Although we described cancer mortality risks, and reductions thereof, to the respondents using *two* probabilities—the risk of getting cancer, and the 5-year chance of survival, conditional on getting cancer—the respondents seemed to have been able to process these probabilities

[18] Alberini and Ščasný (2018) show that the VSL is equal to the VSCC divided by the conditional mortality risk.

correctly, as the WTP for mortality risk reduction is perfectly proportional to the size of the risk reduction in the 2019 wave, and nearly-proportional in the 2014 wave. Unlike Hammitt et al. (2019), who find near-proportionality only with a much pared-down sample (after persons who failed a very specific internal consistency test, and those who reported zero WTP, were excluded from the sample), we arrive at these findings with only minimal data cleaning, and with a more complex breakdown of risks (into a marginal and conditional probability) than most stated preference studies.

As suggested by economic theory, the VSL increases with income—within each wave, across the two waves, and when the data from the two waves are combined. Overall, the income elasticity of the VSL appears to be less than one. The VSL is greater when the respondents dread cancer very strongly.

Recent research about the determinants of the WTP for mortality risk reduction has focused on co-morbidity (Eeckhoudt and Hammitt, 2001), and has focused on whether people should be willing to pay more to reduce cancer mortality risks than mortality risks from other causes because of the morbidity associated with it (Cameron and DeShazo, 2013). We present a simple theoretical model that shows that the VSL should increase with the loss of utility caused by cancer-associated illness, whereas the value of conditional survival should decrease with it. The empirical evidence from our surveys, however, is that either that quality of life is not important (2014 survey), or that its association with the VSL has the opposite sign than that predicted by theory (2019 survey and pooled samples).

Although alternate non-market valuation methods, such as compensating wage studies, hedonic housing price studies and other studies based on consumer product safety, do not always focus on cancer risks, and may be affected by a host of data and econometric difficulties

(Alberini, 2019), the estimates of the VSL from our 2014 and 2019 surveys (€2.999 million from the 2014 survey and €4.216 from the 2019 survey, 2019 PPP euro) are within the range that would be considered acceptable for the Czech Republic based on such alternate methods and earlier stated preference studies from the Czech Republic.

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Figure 1. Example of Choice Card.

Figure 2. Distribution of household income in the 2014 and 2019 surveys.

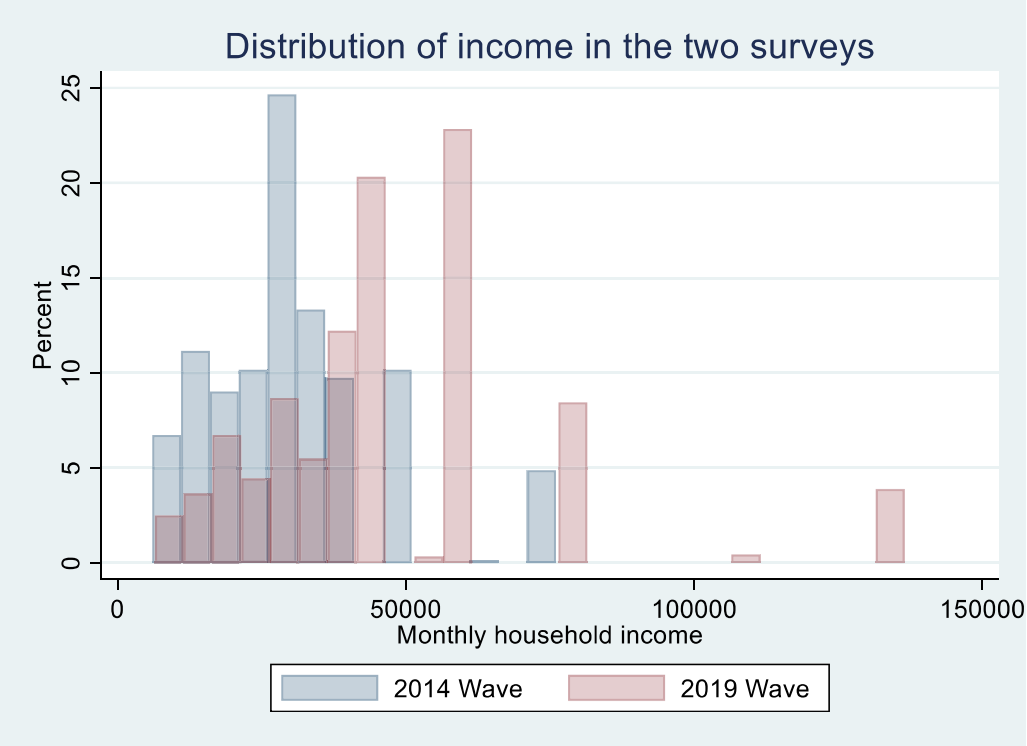

Figure 3. Median VSL from the 2014 Survey: Comparison between the model with unrestricted γ and the model with γ=1.

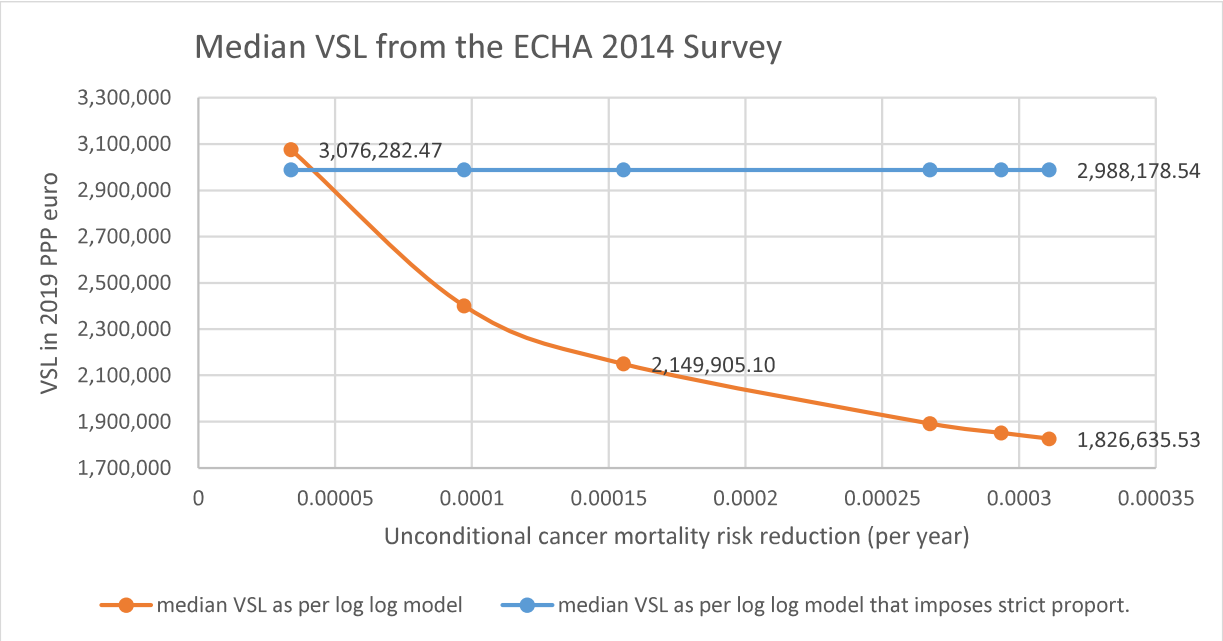

Table 1. Description of the risk reductions to be valued.

	Baseline (current situation)	**Alternative**
Chance of getting cancer	25 in 1000 over 5 years	Reduce by 0, 2, 3, 5 in 1000 over years
5-year survival chance	60%	Improve by 0%, 5%, 10%, 20% (to 60%, 65%, 70%, and 80%)
Quality of life effects	Level 0 = no impairment Level 1 = no heavy physical work Level 2 = unable to work Level 3 = confined to bed ½ of the time	The same as in the baseline
Pain	Mild Moderate	The same as in the baseline
Cost per year for each of the 5 years (CZK)		2,000 (2,200 in 2019 survey) 4,000 (4,300 in 2019 survey) 6,600 (7,000 in 2019 survey) 9,600 (10,000 in 2019 survey)

Table 2. Descriptive Statistics of the 2 Samples: Sample Mean or Percentage of the Sample.

	2014 Survey	2019 Survey
Male	48.89%	53.95%
Monthly after-tax household income		
May 2019 CZK	30,351.77	47,520.01
2019 PPP euro	1,819.88	2,849.26
Has high school diploma	31.08%	46.59%
~~P~~rofessional courses after the high school diploma, but no university degree	2.79%	1.73%
College degree	14.74%	32.55%
Post-graduate studies	0.66%	1.84%

Table 3. Comparison with population statistics. Average monthly household income (in May 2019 Czech Crowns).

	ECHA 2014 CZ sample	SILC 2015 (reports 2014 income)	ECHA 2019 CZ wave 1 sample	Prediction for 2019 based on SILC 2018 (reports 2017 income)
	30,351.77	39,292.00	47,520.00	46,310.00

Source: Authors' calculations based on this study's samples and the EU-Statistics on Income and Living Conditions.

Table 4. Familiarity with and perception of cancer: Sample Mean or Percentage of the Sample.

		2014 Survey	2019 Survey
Has or has had cancer		6.14%	4.63%
A close family member has or has had cancer		50.34%	51.46%
Cancer is likely in this family		30.95%	33.30%
A friend has or has had cancer		66.81%	74.70%
Cancer dread			
lowest	1	4.88%	6.49%
	2	8.00%	12.65%
	3	23.00%	23.68%
	4	19.62%	22.27%
highest	5	44.47%	34.92%

Table 5. Key attributes of the risk-reducing alternatives in the 2 surveys: Sample means.

		ECHA 2014 survey (Nobs=5270)	ECHA 2019 wave 1 survey (Nobs=6482)
Reduction in the risk of getting cancer (per 1000 over 5 years)	5,270	2.551423	2.559395
Improvement in the 5-year survival (%)	5,270	9.537002	9.410676
Deltamort (annual unconditional cancer mortality risk)	5,270	0.000168	0.000166

Table 6. Estimation results from ECHA 2014. Random effects probit model corresponding to the latent variable ln WTP. Nobs=5270. T statistics in parentheses.

	(A)	(B)	(C)	(D)
ln ΔMortrisk	0.5170 (12.27)	0.5889 (18.17)	0.5308 (12.40)	0.5309 (12.40)
ln Cost	-0.6757 (-14.55)	-0.5889 (-18.17)	-0.6756 (-14.50)	-0.6762 (-14.51)
Constant(s)	10.5430 (18.38)	10.4382 (18.26)		
QOL=0 dummy (no impairments)			10.7119 (18.43)	5.6142 (3.56)
QOL=1 dummy (no heavy physical work)			10.7901 (18.39)	5.6924 (3.60)
QOL=2 dummy (unable to work)			10.7069 (18.35)	5.6113 (3.55)
QOL=3 dummy (confined to bed half of the time)			10.6783 (18.48)	5.5786 (3.54)
Moderate pain			-0.0998 (-1.83)	0.0994 (-1.82)
Ln household income				0.5008 (3.42)
Missing income dummy				5.0919 (3.55)
Test of the null that γ=1	Wald statistic: 6.96 (P value 0.0083)	--	Wald statistic: 5.70 (p value 0.0170)	Wald statistic: 5.74 (p value 0.0166)
Estimate of γ	0.7651 s.e. 0.0783 (9.77)	--	0.7856 s.e. 0.0800 (9.82)	0.7851 s.e. 0.0799 (9.83)

Note: Cost is expressed in May 2019 Czech Crowns (CZK). To convert cost amounts and estimates of the VSL into May 2019 PPS euro, divide by 16.678.

Table 7. Estimation results from ECHA 2019 wave 1. Random effects probit model corresponding to the latent variable ln WTP. Nobs=6482. T statistics in parentheses.

	(A)	(B)	(C)	(D)
ln ΔMortrisk	0.6655 (16.59)	0.6856 (21.99)	0.6886 (16.72)	0.6882 (16.42)
ln Cost	-0.7112 (-15.79)	-0.6856 (-21.99)	-0.7306 (-16.06)	-0.7310 (-16.07)
Constant(s)	12.4060 (22.35)	13.365 (22.39)		
QOL=0 dummy (no impairments)			12.9815 (22.72)	8.8860 (5.92)
QOL=1 dummy (no heavy physical work)			12.8645 (22.46)	8.7679 (5.84)
QOL=2 dummy (unable to work)			12.6884 (22.40)	8.5925 (5.73)
QOL=3 dummy (confined to be half of the time)			12.6168 (22.43)	8.5200 (5.69)
Moderate pain			0.0085 (0.17)	0.0092 (0.19)
ln household income				0.3835 (2.90)
Missing income dummy				4.3820 (3.04)
Test of the null that γ=1	Wald statistic: 0.63 P value 0.4284	--	Wald statistic: 0.51 P value 0.4732	Wald statistic: 0.53 P value 0.4660
Estimate of γ	0.9357 s.e. 0.0783 (11.95)	--	0.9225 s.e. 0.0777 (12.13)	0.9416 s.e. 0.0776 (12.13)

Note: Cost is expressed in May 2019 Czech Crowns (CZK). To convert cost amounts and estimates of the VSL into May 2019 PPS euro, divide by 16.678.

Table 8. Estimation results from pooling the two samples. Random effects probit model corresponding to the latent variable ln(WTP/Δmortrisk). Nobs=11,752. T statistics in parentheses.

	(A)	(B)	(C)	(D)
ln Cost per Unit of Mortality Risk Reduction	-0.6401 (-28.51)	-0.6530 (-28.68)	-0.6531 (-28.69)	-0.6525 (-28.68)
2019 Survey Dummy	0.2328 (2.23)	0.2332 (2.23)	0.0607 (0.54)	0.0492 (0.43)
Constant	11.3335 (28.33)			
QOL=0 dummy (no impairments)		11.6787 (28.61)	7.3714 (6.96)	7.3111 (6.64)
QOL=1 dummy (no heavy physical work)		11.6693 (28.39)	7.3616 (6.94)	7.3002 (6.63)
QOL=2 dummy (unable to work)		11.5295 (28.31)	7.2228 (6.82)	7.1621 (6.51)
QOL=3 dummy (confined to bed half of the time)		11.4771 (28.42)	7.1687 (6.78)	7.1080 (6.46)
Moderate pain		-0.0432 (-1.47)	-0.0430 (-1.17)	-0.0428 (-1.16)
Ln household income			0.4212 (4.33)	0.4073 (3.99)
Missing income dummy			4.5122 (4.37)	4.4032 (4.05)
High school diploma				0.1777 (1.36)
Some college				0.3882 (1.07)
College degree or postgraduate work				0.1996 (1.31)
Cancer is highly dreaded				0.3696 (3.40)
Has or had had cancer				0.0205 (0.09)
Cancer runs in the family—Yes				-0.0530 (-0.40)
Cancer runs in the family—No				-0.1568 (-1.23)

Note: Cost is expressed in May 2019 Czech Crowns (CZK). To convert cost amounts and estimates of the VSL into May 2019 PPS euro, divide by 16.678.

Table 9. Estimation results from pooled sample with respondents matched for various characteristics. Random effects probit model corresponding to the latent variable ln(WTP/Δmortrisk). T statistics in parentheses.

	(A) match by education	(B) match by education and income*	(C) match by education, income* and cancer dread
ln Cost per Unit of Mortality Risk Reduction	-0.6524 (-28.67)	-0.6668 (-27.07)	-0.6662 (-25.14)
2019 Survey Dummy	0.0437 (0.39)	0.0336 (0.27)	0.0239 (0.19)
QOL=0 dummy (no impairments)	7.2431 (6.60)	7.0062 (5.75)	6.8390 (5.33)
QOL=1 dummy (no heavy physical work)	7.2327 (6.58)	7.0504 (5.78)	6.8647 (5.35)
QOL=2 dummy (unable to work)	7.0945 (6.47)	6.8970 (5.66)	6.7171 (5.24)
QOL=3 dummy (confined to bed half of the time)	7.0402 (6.42)	6.8335 (5.62)	6.6280 (5.17)
Moderate pain	-0.0426 (-1.16)	-0.0441 (-1.10)	-0.0450 (-1.08)
Ln household income	0.4061 (3.98)	0.4486 (3.95)	0.4660 (3.89)
Missing income dummy	4.4094 (4.06)	--	--
High school diploma	0.1714 (1.32)	0.2311 (1.65)	0.1960 (1.35)
Some college	0.3550 (0.98)	0.7070 (1.45)	0.5368 (0.95)
College degree or postgraduate work	0.1966 (1.29)	0.2707 (1.67)	0.2747 (1.55)
Cancer is highly dreaded	0.3891 (3.61)	0.2942 (2.53)	0.3234 (2.63)
Has or had had cancer	-0.0179 (-0.08)	0.0179 (0.07)	-0.0584 (-0.22)
Nobs	From 2014: 5263 From 2019: 6482 Unmatched: 1 respondent	From 2014: 4542 From 2019: 3871 Unmatched: 372 respondent	From 2014: 3968 From 2019: 3416 Unmatched: 519 respondent

*only respondents who reported income.

Note: Cost is expressed in May 2019 Czech Crowns (CZK). To convert cost amounts and estimates of the VSL into May 2019 PPS euro, divide by 16.678.

Table 10. Selected earlier VSL estimates for the Czech Republic.

Study	Data collection	Target population	Method	Type of risk	Context, Mode of risk delivery	VSL mean, million PPS Euro (2019)	monthly household income, PPS Euro (2019)
Alberini et al., 2006	2004 (Aug-Sept.)	representative 30-75 in three cities (Prague, Brno, Ostrava)	Contingent valuation	cardiovascular and respiratory illness	Overall	3.276	1683
					medical test	2.454	1683
					abstract	4.098	1683
Ščasný and Urban, 2008	2006 (Oct.)	working adults	Hedonic wage	occupational		13.427	1233
	2000 (Working Conditions Survey)	working adults	Hedonic wage	occupational		9.595	874
	aggregated (sectoral) data	labor force	Hedonic wage	occupational		9.747	1755
Melichar et al. (2010)	2007 (May)	working adults	Hedonic wage	occupational (statistical rate)		18.848	1156
			Hedonic wage	occupational (subjectively perceived rate)		4.245	1156
Alberini and Ščasný, 2011	2008 (Nov-Dec)	parents with at least one child below 18; city population (Prague, Brno, Ostrava) overrepresented	Discrete choice experiments	cancer risk	Overall	2.206	2386
				cancer risk	private initiative	1.897	2386
				cancer risk	public program	2.306	2386

Report on Wave 2 of the 2019 ECHA cancer study

By

Anna Alberini, Milan Ščasný, and Christoph Rheinberger [1]

Last revision: 3 December 2019
Last revision by: Anna

1. Introduction

Wave 2 of the 2019 ECHA cancer mortality survey was conducted in the Czech Republic in May-June 2019. A total of 1279 respondents completed the questionnaire.

The questionnaire was identical to that of wave 1 (and to the original ECHA 2014 survey questionnaire), except in one important aspect: The design of the choice cards. As in wave 1, respondents were asked to assess a total of 7 pairs consisting of a hypothetical status quo and a hypothetical alternative that, at a cost, offered a reduction in the risk of getting cancer and/or dying from it.

As in wave 1, the hypothetical status quo posited that the "current" risk of getting cancer is 25 in 1000 in 5 years (equivalent to 5 in 1000 per year), and that the 5-year survival rate is 0.60 (which is equivalent to an annual conditional mortality risk of 0.0971). These figures were the same for all subjects and for the all choice cards. What did vary across individuals and from one choice card to the next was the severity of the cancer, which we described as one of four possible degrees of impact on the quality of life (ranging from no disruption at all to unable to work and bedridden half of the time) plus either mild or moderate pain.

[1] Alberini is a professor at AREC, University of Maryland; Ščasný is a senior researcher at the Charles University Environment Center; Rheinberger is with the European Chemical Agency. This research was funded by the European Chemicals Agency under contract ECHA/2018/558—Willingness to Pay for Non-fatal Cancer. The opinions reported in this paper are solely those of the authors and do not necessarily reflect the official policy and opinions of the European Chemicals Agency.

In sharp contrast to wave 1, however, not only did the risk-reducing alternatives offer a reduction in the change of getting cancer and in the conditional probability of dying from it: They also improved prospects in terms of quality of life and pain before, during and after treatment. All of this would come at a cost ranging from 2,200 to 10,000 CZK per year for 5 years.

The purpose of this amendment to the design of wave 1 was to see whether respondents responded to the quality of life descriptions in the survey. Effectively, we converted the original choice cards to choice cards containing one health profile and a clearly better alternative in terms of health, which should be preferred to the hypothetical status quo as long as its price isn't too high. From the point of view of non-market valuation, we converted the original single-bounded dichotomous-choice contingent valuation questions into a discrete choice experiment where the size of the choice set was 2 in each choice occasion.

The remainder of this report is organized as follows. Section 2 describes the data. Section presents the model of the choice responses. Section 5 present the results and section 6 concludes.

2. The Data

A total of 53 out of 1279 respondents (4.14%) were classified as "speeders," and 310 out of 1279 (24.24%) failed the first probability quiz. For good measure, we drop these respondents from the final sample, arguing that they were probably not reading the questionnaire properly (in the case of speeders) or they were not sufficiently focused (for those who failed the first probability test).[2] This leaves us with a clean sample of 936 respondents, for a total of 6530 observations.

[2] Twenty-one respondents were classified as speeders and failed the first probability quiz.

Descriptive statistics of the respondents are displayed in table 1. The sample is clearly highly educated, as more than 30% report having a university degree or better. Income is slightly lower than that reported by wave 1 respondents, but not by much.

A total of 49 respondents (5.31% of the sample) indicated that they had or had had cancer, 487 (52.03% of the sample) reported that a close family member had been diagnosed with cancer, and 314 (33.55%) said that a friend or acquaintance had been diagnosed with cancer. Figure 1 summarizes the degree of degree that the respondents associated with cancer. As expected, the most often selected category is "very high" (33.12% of the respondents).

3. The Model

We assume that the responses to the choice questions are driven by an underlying utility function:

(1) $V_{ij} = \mathbf{x}_{ij}\boldsymbol{\alpha} + \beta \cdot (y_i - C_{ij})$,

where *i* denotes the individual, *j* the choice card, **x** is the vector of attributes of the alternative, *y* income and *C* the cost of the alternative (which means that (*y*-*C*) is residual income). $\boldsymbol{\alpha}$ is the vector of marginal utilities from the attributes and β is the marginal utility of income.

On appending an error term, ε, that is i.i.d. from the type I extreme value distribution, the probability that alternative k (k=1, 2) is selected by the respondent is:

(2) $Pr(k) = \frac{\exp(\mathbf{w}_{ik}\boldsymbol{\delta})}{\sum_{j=1}^{2}\exp(\mathbf{w}_{ij}\boldsymbol{\delta})}$,

where **w** is a vector that stacks **x** and *C*, and $\boldsymbol{\delta}$ is the vector of the corresponding marginal utilities.[3]

[3] We remind the reader that income *y* drops out and it is sufficient to simply enter *C* in the model. The coefficient on C is the negative of the marginal utility of income.

The WTP for each attribute is obtained as the coefficient on that attributed divided by the negative of the coefficient on cost. If one of the attributes is the unconditional mortality risk, then the VSL is simply obtained as the coefficient on the unconditional mortality risk divided by the negative of the coefficient on cost. This is a "pure" VSL, namely the willingness to pay for a marginal change in the unconditional mortality risk stripped out of the impacts of cancer on quality of life (QOL) and the pain associated with illness or treatment.

In principle, it is possible to see if the VSL varies with QOL or pain, but doing so requires entering in the model a total of some 18 terms (the unconditional mortality risk reduction interacted with each of the possible combinations of baseline QOL-pain and alternative QOL-pain levels). We attempted this, but it resulted in implausible and imprecisely estimated QOL- and pain-specific VSLs. For this reason we do not pursue this latter modeling and estimation strategy in this report.

4. Results

We began with a simple conditional logit model, namely one where the only regressors are the mortality risk reduction and cost. This resulted in a VSL of € 6.488 million (2019 PPS euro), a figure that is high compared to previous applications of this questionnaire but it still reasonable.[4]

Exhibit 1 displays the results from a conditional logit where all attributes are entered additively. The coefficient on mortality risk is negative, as expected, indicating that options with *lower* mortality risks are, all else the same, preferred.[5] The coefficient on cost is

[4] We divide the amounts in Czech crowns by 16.678 to obtain the corresponding 2019 PPS euro.

[5] We remind the reader that to estimate the conditional logit model we code the data as follows. For each choice card assigned to a respondent, there are two rows of data. The first row contains the attribute levels in the baseline (initial unconditional mortality risk, initial QOL and pain, and cost, which is zero). The second row contains the attribute level in the risk-reducing alternative (final unconditional mortality risk, final QOL and pain, and cost of the alternative). The dependent variable in the model ("finalchoice") takes on a value of 1 in

likewise negative, as expected. The coefficients on QOL and pain indicate that the more severe the impacts on quality of life or pain, the less likely is the respondent to choose that option (which, by design, is always the status quo). The estimated coefficients imply a "pure" VSL of € 2.640 million (2019 PPS euro). They also imply that a typical respondent would be willing to pay a total of 25,873 CZK per year (approximately € 1551 in 2019 PPS euro) to go from the initial mortality risk (0.0004856 per year, or about 5 in 10,000 per year) to 0.0003206 (the average mortality level with the risk reduction), if this change brings them from QOL=1 (no heavy physical work) and moderate pain to a situation with no impairments at all and only mild pain. This is about 5% of the average household income in the sample. Only about 28% of this amount (some € 436, in 2019 PPS euro) is accounted for by the mortality risk reduction alone. A mortality risk reduction of the same size, but accompanied by a change from QOL=2 to QOL=1 (holding the same level of pain), would elicit a WTP of 17,121 CZK, or approximately € 1027 (2019 PPS euro).

Exhibit 2 displays the results of a similar model, but with interactions between QOL and the moderate pain dummy. The estimated coefficients again imply a "pure" VSL of € 2.640 million (2019 PPS euro). The WTP for going from the initial mortality risk, QOL=1 and moderate pain to a mortality risk of 0.0003206 and no impairment and mild pain is similar to the one predicted by the model in Exhibit 1: 25,554 CZK per year, or € 1532 (2019 PPS euro), of which € 435 are accounted for by the risk reduction alone.

Exhibits 3 and 4 fit the same model to the subsamples of observations that received mortality risk reductions solely via reductions in the risk of getting cancer, and solely via improvements in cancer survival, respectively. The results are qualitatively and quantitatively similar. The VSL implicit in the responses to the choice cards that offered reduced risks of

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the first row if the respondent selected the status quo. A value of 1 in the second row means that the respondent selected the risk-reducing alternative.

getting cancer (but did not change the chance of survival at 5 years) is € 3.104 million, and that from the responses to the choice cards where only the survival odds were changed is € 3.540 million (both figures in 2019 PPS euro).

5. Discussion and Conclusions

A modification of the design of the choice cards in our cancer mortality survey allowed us to check that respondents are sensitive to the quality of life impacts and pain of cancer (during or after treatment). The cancer VSL per se—what we term the "pure" cancer VSL, stripped of QOL impacts and pain—is similar to the values estimated from the other waves of the survey and ranges between € 2 million and € 3 million, depending on the specification. The total WTP for a specified risk reduction includes the WTP for the mortality risk reduction, plus the WTP for reducing the severity of the QOL impacts and pain. These appear to account for a large portion of the total WTP.

These results should, however, be interpreted with extreme caution for a number of reasons. First, the design we chose to implement is only compatible with one statistical model—a conditional logit—where the QOL and pain attributes are entered additively. Attempts to create interactions with the mortality risk reductions, so that QOL-specific VSL figures can be obtained, were made, but with some 18 such interactions the results were implausible and imprecisely estimated, and we abandoned this type of model.

Second, risk scholars may raise the issue that the alternatives offered to the respondents in the choice cards are implausible: With respect to the baseline, they would appear to be capable of changing the etiology of the cancer, the molecular biology of the cancerous cell, the quality of cancer surgery and therapy, *and* after treatment care and recovery. Perhaps other modifications of the design may produce more credible risk reduction delivery scenarios.

Figure 1. Cancer Dread: Percent of the respondents that report the indicated category.

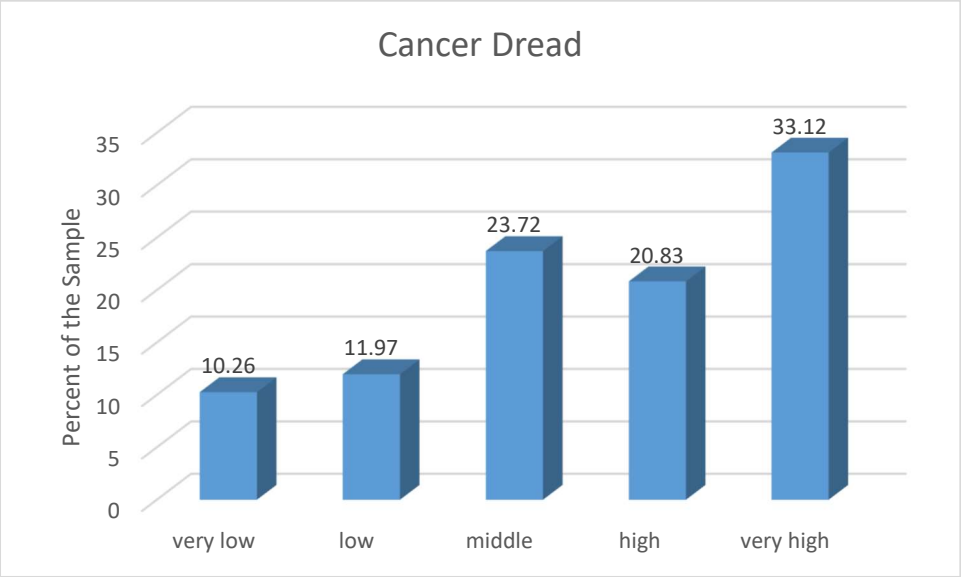

Table 1. Descriptive statistics of the respondents.

Variable	Obs	Mean	Std. Dev.	Min	Max
Household income in CZK	6,018	42510.95	22955.7	6471	135102
Did not report income (dummy)	6,530	0.078407	0.268832	0	1
High school diploma (dummy)	6,530	0.439204	0.496328	0	1
A few years of college (dummy)	6,530	0.013936	0.117233	0	1
University degree or post-graduate studies (dummy)	6,530	0.309801	0.462447	0	1

Exhibit 1. Conditional logit model results. Specification (A).

```
. clogit finalchoice mort i.qol i.pain cost, group(resppairID)
note: 4 groups (8 obs) dropped because of all positive or
      all negative outcomes.

Iteration 0:   log likelihood =  -4326.567
Iteration 1:   log likelihood = -4139.3756
Iteration 2:   log likelihood = -4135.3324
Iteration 3:   log likelihood = -4135.3318
Iteration 4:   log likelihood = -4135.3318

Conditional (fixed-effects) logistic regression

                                                Number of obs     =     13,052
                                                LR chi2(6)        =     776.29
                                                Prob > chi2       =     0.0000
Log likelihood = -4135.3318                     Pseudo R2         =     0.0858

------------------------------------------------------------------------------
 finalchoice |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        mort |  -3112.899   244.4876   -12.73   0.000    -3592.085   -2633.712
             |
         qol |
           1 |  -.7071393    .092029    -7.68   0.000    -.8875129   -.5267657
           2 |  -1.403979   .1225947   -11.45   0.000     -1.64426   -1.163698
           3 |  -2.137792    .157999   -13.53   0.000    -2.447464    -1.82812
             |
      1.pain |  -.6084578   .0605089   -10.06   0.000     -.727053   -.4898625
        cost |  -.0000707   6.73e-06   -10.51   0.000    -.0000839   -.0000575
------------------------------------------------------------------------------
```

Exhibit 2. Conditional logit model results. Specification (B).

```
. clogit finalchoice mort i.qol#i.pain cost, group(resppairID)
note: 4 groups (8 obs) dropped because of all positive or
      all negative outcomes.

Iteration 0:   log likelihood = -4326.0385
Iteration 1:   log likelihood = -4139.0367
Iteration 2:   log likelihood = -4135.0493
Iteration 3:   log likelihood = -4135.0486
Iteration 4:   log likelihood = -4135.0486

Conditional (fixed-effects) logistic regression

                                                Number of obs     =     13,052
                                                LR chi2(9)        =     776.86
                                                Prob > chi2       =     0.0000
Log likelihood = -4135.0486                     Pseudo R2         =     0.0859

------------------------------------------------------------------------------
 finalchoice |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        mort |  -3136.985   246.8258   -12.71   0.000    -3620.755   -2653.216
             |
    qol#pain |
        0 1  |  -.5971335    .097316    -6.14   0.000    -.7878693   -.4063978
        1 0  |  -.7205587   .1375145    -5.24   0.000    -.9900822   -.4510353
        1 1  |  -1.304419   .1316158    -9.91   0.000    -1.562381   -1.046456
        2 0  |  -1.376385   .1506175    -9.14   0.000     -1.67159    -1.08118
        2 1  |  -2.026221   .1599095   -12.67   0.000    -2.339638   -1.712804
        3 0  |  -2.168347   .1971698   -11.00   0.000    -2.554792   -1.781901
        3 1  |  -2.745469   .1928119   -14.24   0.000    -3.123373   -2.367564
             |
        cost |  -.0000713   6.79e-06   -10.50   0.000    -.0000846    -.000058
------------------------------------------------------------------------------

.
. nlcom (_b[mort]/_b[cost])/16.678

       _nl_1:  (_b[mort]/_b[cost])/16.678

------------------------------------------------------------------------------
 finalchoice |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _nl_1 |    2639819   193644.7    13.63   0.000      2260282     3019355
------------------------------------------------------------------------------
```

Exhibit 3. Conditional logit model. Specification (C).

```
. clogit finalchoice mort i.qol#i.pain cost if QD_DESIGN<=16 & pair<=3,
group(resppairID)
note: 1 group (2 obs) dropped because of all positive or
      all negative outcomes.

Iteration 0:   log likelihood = -951.88739
Iteration 1:   log likelihood =  -925.5454
Iteration 2:   log likelihood = -925.50464
Iteration 3:   log likelihood = -925.50464

Conditional (fixed-effects) logistic regression

                                                Number of obs     =      2,820
                                                LR chi2(9)        =     103.67
                                                Prob > chi2       =     0.0000
Log likelihood = -925.50464                     Pseudo R2         =     0.0530

------------------------------------------------------------------------------
 finalchoice |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        mort |  -4670.708    1590.46    -2.94   0.003    -7787.952   -1553.464
             |
    qol#pain |
        0 1  |  -.2169389   .3433667    -0.63   0.528    -.8899253    .4560476
        1 0  |   -.579748   .2483352    -2.33   0.020    -1.066476     -.09302
        1 1  |  -1.224668   .2855412    -4.29   0.000    -1.784318    -.665017
        2 0  |  -1.397873    .265502    -5.27   0.000    -1.918248   -.8774992
        2 1  |  -2.161847   .3267854    -6.62   0.000    -2.802335   -1.521359
        3 0  |  -2.216806   .4194824    -5.28   0.000    -3.038977   -1.394636
        3 1  |  -3.163784    .442482    -7.15   0.000    -4.031033   -2.296535
             |
        cost |  -.0000902    .000016    -5.64   0.000    -.0001216   -.0000589
------------------------------------------------------------------------------

. nlcom (_b[mort]/_b[cost])/16.678

       _nl_1:  (_b[mort]/_b[cost])/16.678

------------------------------------------------------------------------------
 finalchoice |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _nl_1 |    3103875   733458.1     4.23   0.000      1666324     4541427
------------------------------------------------------------------------------
```

Exhibit 4. Conditional logit model. Specification (D).

```
.
. clogit finalchoice mort i.qol#i.pain cost if QD_DESIGN>16 & pair<=3,
group(resppairID)
note: 1 group (2 obs) dropped because of all positive or
      all negative outcomes.

Iteration 0:   log likelihood = -928.33407
Iteration 1:   log likelihood =  -873.7508
Iteration 2:   log likelihood = -869.93131
Iteration 3:   log likelihood = -869.92949
Iteration 4:   log likelihood = -869.92949

Conditional (fixed-effects) logistic regression

                                                Number of obs     =      2,788
                                                LR chi2(9)        =     192.64
                                                Prob > chi2       =     0.0000
Log likelihood = -869.92949                     Pseudo R2         =     0.0997

------------------------------------------------------------------------------
 finalchoice |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        mort |  -3825.313   727.7694    -5.26   0.000    -5251.715   -2398.911
             |
    qol#pain |
        0 1  |  -.6452288   .2448868    -2.63   0.008    -1.125198   -.1652594
        1 0  |  -1.141255   .3741557    -3.05   0.002    -1.874587    -.407923
        1 1  |  -1.508297   .3469415    -4.35   0.000     -2.18829    -.828304
        2 0  |   -2.01895   .4067015    -4.96   0.000     -2.81607    -1.22183
        2 1  |  -2.139016    .395235    -5.41   0.000    -2.913663    -1.36437
        3 0  |  -2.888642   .4433344    -6.52   0.000    -3.757561   -2.019723
        3 1  |  -2.713189   .4476756    -6.06   0.000    -3.590617   -1.835761
             |
        cost |  -.0000648   .0000171    -3.79   0.000    -.0000983   -.0000313
------------------------------------------------------------------------------

.
. nlcom (_b[mort]/_b[cost])/16.678

       _nl_1:  (_b[mort]/_b[cost])/16.678

------------------------------------------------------------------------------
 finalchoice |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
       _nl_1 |    3539802   708377.3     5.00   0.000      2151408     4928196
------------------------------------------------------------------------------
```

Part III: Wave 1 – Wave 3 comparison chapter

The Effect of Baseline and Close to Non-fatal Cancer

By

Anna Alberini and Milan Ščasný[1]

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Last revision by: Anna

1. Introduction and Motivation

While no cancer can be considered 100% safe, there is no doubt that some forms of cancer are less aggressive than others, and, if diagnosed early and treated appropriately, have lower mortality rates than others. Should the Value of a Statistical Case of Cancer, and the cancer VSL, to be used in policy analyses adjusted to reflect that? Or is only consequence for policy analysis purpose the fact that the expected number of fatalities will be lower?

The purpose of this chapter is to begin investigating two key aspects related to the above questions. First, is the (cancer) VSL affected by the baseline (cancer) mortality risk? Second, when we value mortality risk reduction using stated preference methods, is the size of the risk reduction all that matters, or does the "final" chance of dying exert an additional effect on the willingness to pay? Specifically, is the VSL different when the chance of survival, conditional on getting the illness in the first place, approaches one?

We seek to answer these questions through the comparison of the results from the "base" cancer mortality questionnaire developed for ECHA (see Alberini and Ščasný, 2018, 2019) and a modified version that differed from the former solely in the baseline chance of survival, conditional on getting the illness. As we discussed below, this simple modification

[1] This research was funded by the European Chemicals Agency under contract ECHA/2018/558—Willingness to Pay for Non-fatal Cancer. The opinions reported in this paper are solely those of the authors and do not necessarily reflect the official policy and opinions of the European Chemicals Agency. We thank Christoph Rheinberger for his helpful comments.

changes the baseline unconditional cancer mortality risk and baseline and final survival, conditional on the illness, with respect to the "base" version.

The "base" version of the questionnaire was self-administered using CAWI by a sample of 45-60 year-olds living in the Czech Republic and members of a nationally representative panel of consumers. This is what we term "wave 1," which took place in May 2019. The modified version was self-administered by similar persons in late October 2019. Analysis of the Consumer Price Index in the months between and including the times of the two waves of survey shows that the cost of living was unchanged in the Czech Republic, which allows to merge the data from the two waves without needing to adjust incomes and costs of the hypothetical risk reduction measures in the questionnaire.

2. Study Design.

Table 1 summarizes the experiment design in wave 1 and wave 3. As can be seen in tables 1 and 3, the baseline risk of getting cancer is the same for all respondents and in both waves. The unconditional risk of dying in the status quo is however different across the two waves, mirroring the different baseline chances of survival at 5 years, conditional on getting cancer in the first place (60% and 80%, respectively). The implied baseline annual conditional mortality risk is almost twice as large in wave 1 than in wave 3. Wave 3 offers proportionally larger reductions in the conditional mortality risk.

The *reduction* in the unconditional cancer mortality risk is on average larger in wave 1, and indeed the two waves do not completely overlap in terms of unconditional risk reductions. The unconditional mortality risk reductions shown to the respondents in the survey fall in the common support between the two waves for 10,829 of the 14,280 observations—about three-quarters of the total.

3. Econometric Model and Hypotheses

A. Econometric Models

We assume that the responses to the choice questions are driven by the WTP for the risk-reducing alternative, which is not directly observed. We assume that this unobserved WTP depends on the magnitude of the risk reduction as follows:

(1) $$WTP_{ij}^{*} = \exp(\alpha) \cdot \left(\Delta mortrisk_{ij}\right)^{\gamma} \cdot \exp(\varepsilon_{ij}),$$

where ε is a normally distributed error term with mean zero and variance σ^2. We choose this model for three reasons. First, experience suggests that the WTP for health risks reductions and other safety and environmental programs almost always has a long right tail, and equation (1) and its assumptions imply a lognormal distribution for WTP, which is positively skewed. Second, on taking logs, equation (1) becomes

(2) $$\ln(WTP_{ij}^{*}) = \alpha + \gamma \cdot (ln\Delta mortrisk_{ij}) + \varepsilon_{ij}.$$

If coefficient γ is 1, then the WTP for a specified risk reduction is perfectly proportional to the size of the risk reduction, which in turn means that there is a single VSL value that holds at any of the risk reduction proposed to the respondents in the survey. We can therefore let the data tell us whether the individual choice responses meet the so-called strong "scope" requirement, namely that the WTP be strictly proportional to the size of the risk reduction (Corso et al., 2001). At a minimum, γ should be positive. Third, equations (1) and (2) are easily amended to allow α to depend on the attributes of the risk reduction or to test for systematic differences across the two waves.

We do not observe the respondent's WTP for a specified risk reduction: All we can infer from the responses to the choice questions is whether the underlying WTP amount is greater than the cost of the risk-reducing alternative—if the respondent chooses that alternative—or otherwise. This results in a binary choice model that describes the probability of selecting the risk-reducing alternative as a function of the magnitude of its risk reduction and cost:

$$(3) \qquad \Pr(j\ is\ chosen) = \Pr\left(WTP_{ij}^{*} \geq C_{ij}\right) = \Pr\left(\ln\left(WTP_{ij}^{*}\right) \geq \ln\left(C_{ij}\right)\right) =$$

$$= \Phi(a + b \cdot ln\Delta MortRisk + c \cdot ln(C_{ij}))$$

where $\Phi(\cdot)$ denotes the standard normal cdf, a=α/σ, b=γ/σ, and c=-1/σ.

The statistical model of equation (3) is appropriate if one choice task is considered in isolation (or if the respondent only answers one WTP question), and results in a probit model that, for now, contains only one regressor—the log of cost. The original α in equation (1) is recovered as the intercept from the probit model, divided by the negative of ($\hat{c}$). The standard deviation of ε is obtained as (-1/$\hat{c}$).

In our survey, however, each respondent answered a total of seven choice WTP questions. Each respondent's seven error terms ε are likely correlated, due to unobserved characteristics of the respondent or perceptions that affect each decision task. We assume that the correlation between any two pairs of responses is the same, which results in a random effects probit model.

If γ=1, equation (2) is simplified to

$$(4) \qquad \ln\left(\frac{WTP_{ij}^{*}}{\Delta mortrisk_{ij}}\right) \equiv \ln\left(VSL_{ij}^{*}\right) = \alpha + \varepsilon_{ij}$$

and $\ln\left(\frac{C_{ij}}{\Delta mortrisk_{ij}}\right)$, i.e., the log of the cost per unit of risk reduced, must be entered in its binary choice econometric counterpart. In its simplest variant, the binary choice model includes only the log cost per unit of risk reduced. In more complex variants α is allowed to depend on descriptions of the choice task setting, such as the quality of life experienced in this hypothetical scenario and the pain level associated with the illness or its treatment.[2]

[2] We remind the reader that the quality-of-life impacts of cancer and the level of pain that would be experienced by the respondents are the same across the status quo and the risk-abating alternative, but vary from one choice question to the next, and across respondents.

The random effects probit models corresponding to equations (2) and (4) can be fit to the data from wave 1 and wave 3 separately, as well as to the combined samples and specific subsets thereof.

B. Hypotheses

In addition to testing whether $\gamma=1$, we wish to see whether the WTP for mortality risk and the VSL vary with the baseline risk. One would expect that the larger the baseline mortality risk, the greater the VSL. This can be shown using a simple expected utility model: The larger the baseline risk, the lower the expected marginal utility of income. Since the latter is the denominator in the expression for the VSL, it follows that the VSL must increase, all else the same, with the baseline risk. This expectation is also consistent with one of the possible interpretations of the "dead anyway effect" in Pratt and Zeckhauser (1996).

A simple way to test this hypothesis is to fit the random effects probit corresponding to the latent dependent variable log VSL, augmented with a "wave 3" dummy. Since the baseline unconditional mortality is always lower in wave 3, the coefficient on the wave 3 dummy should be negative if the difference in baselines is sufficiently pronounced to be detected in such an external test.

We also wish to see whether the WTP for a mortality risk reduction, and the VSL, is different when the hypothetical improvement has made the probability of surviving very close to one. To see if this is the case, we consider the subset of observations with final survival at 5 years equal to or greater than 80%, and check whether the WTP is still proportional to the size of the risk reduction, whether valuations appear to be systematically different in wave 3, and whether the proposed increases in conditional survival have a different effect in the two waves.

4. Data and Results

A. The Data

Descriptive statistics of the samples are displayed in table 3a. The two waves contain roughly the same percentage of "speeders" and virtually identical shares of persons who failed the first probability quiz. Table 3b shows that the two samples are similar in terms of income and education, although wave 3 respondents were more likely to decline to report income. Table 4 indicates that there are no substantial differences in terms of experience with cancer and cancer dread across the two waves.

B. Results: Basic Regressions

Using the clean samples, we fit separate random effects models to the responses from wave 1 and wave 3. The results displayed in table 5 are based on latent log WTP, which means that the random effects probit must include, at a minimum, the log of the unconditional mortality risk reduction and log cost. Such base specification is displayed in col. (A) for wave 1 and col. (D) for wave 3. Cols. (B) and (E) add income variables, and cols. (C) and (F) further control for quality of life and pain.

The results show clearly that the larger the risk reduction, the more likely is a respondent, all else the same, to choose the risk-reducing alternative. The higher the latter's cost, the less likely is the respondent to choose the risk-reducing alternative. The estimates of γ are indistinguishable from one in all specifications and in both waves. Household income is positively associated with the WTP for the risk reduction, although the exact magnitude of this effect is rather different across the two waves. The income elasticity of the WTP is 0.5 in wave 1 and about 1 in wave 3.

In both waves is the WTP for the mortality risk reduction greater when the quality-of-life (QOL) impacts of cancer are less disruptive. Respondents do not seem to distinguish between mild and moderate pain. This is not surprising, as these patterns were observed in

the ECHA 2014 study (Alberini and Ščasný, 2018) and in wave 1 of the ECHA 2019 survey (Alberini and Ščasný, 2019). They are also consistent with the respondents' ratings of the importance they attach to the different aspects of the risk-reducing alternatives and to the frequency with which they paid attention to them during the valuations tasks (tables A.1 and A.2 of the Appendix).

C. Results: Pooled Samples

We pool the two samples and fit random effects models that assume that the latent dependent variable is log WTP. The random effects probit include, at a minimum, the log mortality risk and log cost, plus a "wave 3" dummy. Results are reported in table 6. It is clear that the WTP is still proportional to the size of the risk reduction, and that the coefficient on the wave 3 dummy is always insignificant. When we trim the sample, retaining only the observations from the mortality risk reductions common support, the point estimate of γ is slightly lower, but still statistically indistinguishable from one. Column (C) further suggests that the income elasticity of the WTP (and VSL) is about 0.7.

In the models of table 7 we impose the restriction that γ=1. The VSL is estimated to be just about € 4 million (2019 PPS euro)—for wave 1 separately, wave 3 separately, and when the samples are combined, in which case the coefficient on the wave 3 dummy is statistically insignificant (cols. (C) and (D)).

The story is qualitatively the same when income and QOL controls are entered in the model. The VSL is estimated to be almost € 5.5 million when QOL=0 (no restrictions), about € 4.9 million when QOL=1 (no heavy physical work), just about € 4 million if QOL=2 (unable to work), and € 3.5 million if QOL=3 (confined to bed for half of the time) (col (E).

The fact that, once the size of the mortality risk reduction is controlled for, the coefficient on wave 3 is almost always negative is consistent with expectations from theory.

It is however in all cases insignificant, suggesting that the baselines are not sufficiently different to affect valuation meaningfully.

D. Results: When Survival is Almost Certain

Table 8 displays the results from fitting random effects probit to the subsample of responses recorded in the WTP questions where the risk-reducing alternative would bring the probability of survival at 5 years to 0.80 or higher. A total of 1849 such observations come from wave 1. The remaining 6146 come from wave 3, for a total of 7995 observations that meet this "high chance of survival" criterion.

Column (A) displays the estimation results from fitting the random effects model corresponding to latent equation (2). The sample is restricted to wave 3, showing that once again the WTP appears to be perfectly proportional to the size of the risk reduction.[3] In col. (B) we use observations from both waves, and obtain that γ is approximately equal to one, and that respondent valuations are not statistically different across the two waves.

In col. (C), we further restrict the sample to the responses to alternatives that would deliver a final probability of survival just about equal to 0.80 (greater than 0.75 and less than or equal to 0.81). This ensures a more balanced split between wave 1 and wave 3 observations, but still results in an estimated γ that is not statistically different from one, and in a negative but statistically insignificant coefficient on the wave 3 dummy. Even more important, the VSL is € 4.287 million (2019 PPS euro) and is thus virtually the same as that for the entire sample, or specifically for wave 1 and wave 3 but based on all valuation questions.

[3] Wave 1 contains too few observations with final probability of survival greater than or equal to 0.80 for us to be able to fit a separate model to it.

In Col. (D) we return to the sample with final survival probability greater than or equal to 0.80, impose the restriction that $\gamma=1$ (which means that our latent model is that of equation (4)), and enter one dummy denoting that the final probability of survival is 0.85, and one dummy denoting that the final probability of survival is 0.90. The remaining possible value of the final probability of survival (0.80) is absorbed into the intercept. We find that the coefficient on the 0.85-dummy is negative and significant at the 5% level, and that on the 0.90-dummy is negative and statistically insignificant at the conventional levels. In practice, however, the VSL associated with each of the three final levels of the odds of survival are very close to one another, statistically indistinguishable from one another, and similar to those estimated for the full samples.

5. Discussion and Conclusions

We designed wave 3 of this study to test whether the VSL is different when the baseline, pre-reduction mortality risk is different. Our results were consistent with the expected sign of this effect (lower WTP when the baseline risk is lower), but this effect was not statistically significant. We speculate that it might take a much more dramatic contrast in baseline mortality risk across samples, or much larger baseline risks, to observe such an effect.

The design of wave 3 also allows us to check whether the final survival odds delivered by a program affect the WTP for a mortality risk reduction and the VSL. This question is important for the European Chemicals Agency when it must conduct benefit-cost analyses of policies that would reduce exposure to chemicals linked with cancers that have relatively low mortality rates. We found that the WTP for mortality risk reductions in this setting is completely explained by the size of the mortality risk reduction itself, and that

neither the baseline nor the final survival level made an appreciable difference in terms of the WTP or the cancer VSL.

Finally, a finding in common with other chapters of this report is that, contrary to what predicted by a simple theoretical model based on expected utility, the VSL appears to be greater when the quality of life impacts and pain during and after treatment are less disruptive. Respondent debriefs indicate that these impacts were less important to them than the chance of getting cancer and the chance of surviving it, despite the fact that our questionnaire dedicated just about as much space to them (number of screens and questions) as it did to the risks and the ways risks can be reduced.

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Table 1. Design Summary

	Baseline (wave 1)	**Baseline (wave 3)**	**Alternative (both waves)**
Chance of getting cancer	25 in 1000 over 5 years	25 in 1000 over 5 years	Reduce by 0, 2, 3, 5 in 1000 over years
5-year survival chance	60%	75%	Improve by 0%, 5%, 10%, 20%
Quality of life effects	Level 0 = no impairment Level 1 = no heavy physical work Level 2 = unable to work Level 3 = confined to bed ½ of the time	Level 0 = no impairment Level 1 = no heavy physical work Level 2 = unable to work Level 3 = confined to bed ½ of the time	The same as in the baseline
Pain	Mild Moderate	Mild Moderate	The same as in the baseline
Cost per year for each of the 5 years (CZK)			2200 4300 7000 10000

Table 2. Risk features in wave 1 and wave 3.

	Wave 1	Wave 3
Baseline risk of getting cancer	25 in 1000 over 5 years (or 5 in 1000 per year)	25 in 1000 over 5 years (or 5 in 1000 per year)
Conditional mortality risk in the 5 years since getting cancer—baseline	0.0971 per year	0.0559 per year
Conditional mortality risk in the 5 years since getting cancer—after the improvement	0.0713 per year (average)	0.0339 per year (average)
Unconditional mortality—baseline	0.0004856 (approx. 5 in 10,000) per year	0.0002796 (approx. 3 in 10,000) per year
Unconditional mortality risk reduction—after the improvement	Avg. 0.0001664 per year Min. 0.0000388 per year Max. 0.0003110 per year	Avg. 0.0001278 per year Min. 0.0000224 per year Max. 0.0002387 per year

Table 3. Sample sizes and characteristics of the respondents (Average or percent of the sample).

a. Sample sizes

	Wave 1	Wave 3
Completed questionnaires	1253	1507
Speeders	53	73
Failed probability quiz 1	292	352
Clean sample (no speeder or respondents who failed the probability quiz)	926	1114

b. Characteristics of the respondents in the clean samples.

	Wave 1	Wave 3
Male	53.95%	52.60%
Net monthly household income (if reported)	47,250 CZK	43,987 CZK
Did not report income	5.40%	15.08%
Has high school diploma	46.65%	44.61%
Some years of college	1.73%	1.35%
College degree or post-graduate studies	34.34%	31.06%

Table 4. Familiarity with and perceptions of cancer. Clean samples.

	Wave 1	Wave 3
Has or has had cancer	4.93%	5.66%
Family members have or have had cancer	51.40%	51.08%
Close friends or acquaintance have or have had cancer	74.73%	70.83%
Cancer dread		
1 (lowest)	6.48%	9.61%
2	12.74%	12.57%
3	23.65%	23.88%
4	22.25%	20.29%
5 (highest)	34.68%	33.66%

Table 5. Basic regressions. Random effects probit models corresponding to equation (2). Unless otherwise indicated, the number in each cell are the coefficient (top number) and the t statistic (bottom number).

	wave 1 (N=6482)			wave 3 (N=7798)		
	A	B	C	D	E	F
_cons	12.40602	8.35046		10.7497	4.51574	
	22.354	5.634		22.018	3.335	
ldeltamort	0.66553	0.66506	0.68824	0.58534	0.58641	0.59947
	16.594	16.589	16.719	17.545	17.579	17.638
lcost	-0.71125	-0.71138	-0.73096	-0.60519	-0.60495	-0.61286
	-15.789	-15.793	-16.068	-14.793	-14.785	-14.908
lhincd		0.37964	0.38353		0.58938	0.59175
		2.898	2.898		4.84	4.837
hincmiss		4.32099	4.38205		6.32571	6.35456
		3.027	3.039		4.86	4.86
qqol0			8.88599			4.80089
			5.925			3.525
qqol1			8.7679			4.75563
			5.842			3.49
qqol2			8.59249			4.66394
			5.735			3.424
qqol3			8.52001			4.57745
			5.69			3.365
painmod			0.00929			-0.02893
			0.185			-0.616
gamma	0.9357	0.9349	0.9416	0.9672	0.9694	0.9781
s.e	0.0782	0.0782	0.0776	0.0824	0.0825	0.0826
t stat	11.95	11.95	12.14	11.74	11.75	11.83
wald test that						
gamma=1	0.67	0.69	0.57	0.16	0.14	0.07
p value	0.4116	0.4052	0.4515	0.6906	0.7104	0.7917
income elasticity		0.5337	0.5247		0.9743	0.9656
s.e.		0.1863	0.183		0.2098	0.2079
t stat		2.86	2.87		4.64	4.64

Table 6. Pooled data samples: Initial Regressions. Random effects models corresponding to equation (2). Selected coefficients and estimates.

	A	B	C
	simple model, just ldeltamort and lcost (N=14,280)	same but common support (N=10,829)	add income QOL painmod, common support (N=10,829)
gamma	0.9454	0.8706	0.8823
s.e.	0.0565	0.0727	0.0731
t stat	16.75	11.98	12.07
coeff on wave 3	-0.0424	-0.016	0.0111
s.e.	0.1009	0.1033	0.0343
t stat	-0.42	-0.15	0.11
VSL	2,627,497	1,221,828	
s.e.	1,407,724	838957.1	
t stat	1.87	1.46	
income elasticity			0.712
s.e.			0.1399
t stat			5.09

Table 7. Pooled samples. Further regressions. Selected results from random effects probit model corresponding to equation (4). All models impose that γ=1. Unless otherwise indicated, the top number in each cell is the coefficient or estimate, and the bottom number is the standard error.

	(A) wave 1 only; model includes only lcost_per_unit	(B) wave 2 only; model includes only lcost_per_unit	(C) Pooled samples; model includes only lcost_per_unit	(D) same as (C) but common support	(E) same as (C) but add income, QOL and painmod	(F) same as (E) but common support
coeff on wave 3			-0.0378	-0.0239	-0.0362	0.004182
s.e.			0.1007	0.1032	0.1014	0.1046
income elasticity						0.7499***
s.e.						0.1455
VSL	4,000,177	4,023,630	4,357,801	4,084,358		
s.e.	460,693.20	487,545	518,065.8	501,073.80		
t stat	8.68	8.25	8.41	8.15		
VSL if QOL=0					5,484,783	
s.e.					711,043.40	
t stat					7.71	
VSL if QOL=1					4,891,437	
s.e.					623,698	
t stat					7.84	
VSL if QOL=2					4,000,418	
s.e.					510,703.40	
t stat					7.83	
VSL if QOL=3					3,525,599	
s.e.					453,583.10	
t stat					7.77	

Note: * = significant at the 10% level; ** = significant at the 5% level; ***=significant at the 1% level. All of the estimates of VSL are statistically significant at the 1% level or better, and we refrain from using asterisks to mark their significant to avoid clutter.

Table 8. Random effects probit models that use only observations where the final probability of survival is greater than or equal to 0.80. Selected coefficients and results.

	wave 3 only	both waves	both waves, final prob survival about 0.80 (b/w 0.75 and 0.81)	Model that imposes that γ=1
nobs	6146	7995	3854	7995
γ	1.0617***	1.0292***	0.8354***	1
s.e.	0.1077	0.0993	0.36	
wwave 3		-0.2274*	-0.1491	--
s.e.		0.1387	0.4199	
Final surv=0.85				-0.1489**
				0.0670
Final surv=0.90				-0.0500
				0.0714
VSL			4,286,594***	
se			671,943.50	
VSL if final surv=0.80				4,533,182***
				445,069.50
VSL if final surv=0.85				3,717,325***
				437,803.50
VSL if final surv=0.90				4,239,378***
				549,439.30

Note: * = significant at the 10% level; ** = significant at the 5% level; ***=significant at the 1% level.

Appendix.

Table A.1. Importance of the attributes of the risk-reducing alternative. Percentage of respondents for each rating category, where 1="not important at all" and 5="very important."

	Wave 1					Wave 3				
	1	2	3	4	5	1	2	3	4	5
Chance of getting cancer	2.05	4.86	23.22	28.40	41.47	2.78	4.76	25.31	26.93	40.22
Chance of surviving cancer	1.62	2.92	13.71	30.35	51.40	2.15	3.32	16.88	28.46	49.19
Effects on everyday life	1.08	4.64	23.00	39.09	32.18	1.53	5.92	27.47	35.28	29.80
Pain	1.08	7.78	28.19	32.07	30.89	1.97	7.81	27.38	33.30	29.53
Cost	10.48	14.47	28.08	23.43	23.54	10.41	12.93	26.03	23.07	27.56

Table A.2. Attention paid by the respondents to the attributes of the risk-reducing alternative during the choice tasks. Percentage of the respondents who selected each attention level, where 1=never and 5=always.

	Wave 1					Wave 3				
	1 never	2	3	4	5 always	1 never	2	3	4	5 always
Chance of getting cancer	3.89	13.17	24.62	26.78	31.53	5.39	14.36	22.80	26.48	30.97
Chance of surviving cancer	3.78	8.75	20.30	21.32	35.85	4.94	10.32	19.57	28.46	36.71
Effects on everyday life	3.56	11.99	28.29	32.72	23.43	4.94	11.76	28.90	30.97	23.43
Pain	4.10	14.69	26.57	30.35	24.30	5.66	13.20	26.39	29.53	25.22
Cost	14.90	14.25	24.84	22.25	23.65	14.63	14.45	22.08	20.74	28.10