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Demand for health risk reductions ☆

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ABSTRACT

A choice model based on utility in a sequence of prospective future health states permits us to generalize the concept of the value of statistical life (*VSL*). Our representative national survey asks individuals to choose between costly risk-reducing programs and the status quo in randomized stated choice scenarios. Our model allows for separate marginal utilities for discounted net income and avoided illness years, post-illness years, and lost life-years. Our estimates permit calculation of overall willingness to pay to reduce risks for a wide variety of different prospective illness profiles. These can be benchmarked against the standard *VSL* as a special case.

1. Introduction

Policies to reduce health, environmental, and safety risks are often intended to reduce the incidence of major illnesses or injuries that develop in future years. We present a new approach to the measurement of individual-specific benefits that result from reductions in future patterns of morbidity and mortality risks. Measures of such benefits are important to researchers and policy-makers in many fields. For example, this information helps us understand the benefits of expenditures on medical research or the benefits from costly environmental regulations. It can also help us decide upon appropriate levels of regulations for road, workplace, and household safety, or how much we should spend on publicly supported health care (e.g., OECD [55]).

The conventional approach to measuring the benefits of health risk reductions relies upon estimates of the marginal rate of substitution between mortality risk and income in the current period. This approach has arisen as a matter of empirical necessity. Benefit measures based on observable choices have tended to come from estimates of current-period wage-risk tradeoffs (Jones-Lee [38], Viscusi [67], Tolley et al. [63]). These measures of people's willingness to pay (*WTP*) for a small reduction in risk are typically used to construct what is known as "the value of a statistical life" (*VSL*). The *VSL* scales, proportionally, the dollar-risk tradeoffs for small individual marginal risk changes into an aggregate *WTP*, across individuals, for an *aggregate* risk change of 1.00.

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Policy applications of the *VSL* typically involve one of two cases. In the first case, a one-size-fits-all *VSL* is multiplied by an expected overall number of "deaths avoided" to produce an estimate of overall expected benefits.[1] In the second case, researchers require an estimate of the value of avoiding just a single year of premature mortality, for example when valuing advances in medical research that may extend life. To answer this particular need, it has been standard to calculate the "value of a statistical life-year" (*VSLY*) by dividing a standard one-size-fits-all *VSL* by the population average number of (discounted) expected remaining life-years (Cutler and Richardson [23], Cutler and Richardson [24]; Murphy and Topel [52]).[2]

Our new approach to measuring the values people assign to health risk reductions represents an improvement over conventional empirical strategies. We begin with a structural model of utility in future periods of an individual's life as a function of the health status they will experience in those future periods. We differentiate these future health states as "current health," "sickness," "recovered/remission years," and "lost life-years." In our stated choice survey (also known as a conjoint analysis or a discrete-choice experiment), each subject is presented with several opportunities either to purchase one of two illness-specific health-risk reduction programs or to stick with their status-quo health risks.[3] These risk reduction "programs" involve diagnostic screening and, when risks are high, medical therapies that would reduce, but not eliminate, the subject's chance of experiencing that particular future illness with its associated pattern of health states. We use the tradeoffs embodied in people's stated choices to infer their *WTP* for a given-*sized* reduction in their baseline risk of experiencing a specified future illness profile. However, these given-sized risk reductions are heterogeneous. The implicit value of an *incremental* sick year or lost life-year can then be inferred, as in a hedonic model, by taking the derivatives of this overall *WTP* with respect to the number of sick-years or lost life-years involved.[4]

Our strategy overcomes several limitations of the conventional *VSL* approach. These limitations have long been recognized by researchers, but have been unavoidable due to the constraints of existing empirical data and methods. We introduce two main innovations. First, we generalize the conventional strategy by more comprehensively defining the good to be valued. Instead of valuing a single mortality risk reduction in the current period, we value risk reductions for a time profile of possible adverse future health states. Individuals express their *WTP* to reduce their risks of entire time profiles of adverse health states over their remaining lifespans. We do not have to extrapolate these future estimates from only current-period data. Importantly, we can identify inter-temporal substitutability or complementarity among future health states. This is possible because we estimate demands for a much wider range of health risks than usual. Our model subsumes myriad patterns of illness, recovery, and lost life-years across the individual's remaining lifespan. This generalization is needed because the majority of benefits from many health, environmental and safety policies accrue in future years of the individual's life, as opposed to solely in the current period.[5]

Second, our structural random utility model for our subjects' discrete choices makes it very clear how *WTP* estimates for reductions in the risks of sick-years and lost life-years depend upon the individual's age, income, marginal utility of other consumption, and discount rate. Informed by the lifecycle model of Ehrlich [27], our structural model also recognizes and builds upon a growing empirical literature which has explored various sources of heterogeneity within traditional *VSL* estimates.[6] While we make advances in structural modeling in terms of the most important variables in this paper, we cannot comprehensively explore all alternative assumptions or all possible sources of *VSL* heterogeneity in one paper. For example, we leave to related and future papers a more-detailed exploration of the roles played by, for example, age, current health status, specific-illness effects, subjective risk beliefs, choice set complexity and alternative discounting assumptions.

Conceptually, we focus on the individual's *WTP* for a "microrisk" reduction (where "micro-" means "one-millionth," as in Howard [36]). We prefer the microrisk metric to the more-typical *VSL* terminology for aggregated risks. Our model is based fundamentally on discounted expected per-year utility in distinct future health states. No arbitrary conversion of a standard *VSL* to a per-year *VSLY* is necessary. For example, our model makes it straightforward to assess *WTP* for a reduction in the risk of an illness profile that involves dying just one or two years prematurely. Normalization on a small risk change also helps avoid the all-too-common episodes of public outrage when people misinterpret the *VSL* as an arbitrary government dictum about the intrinsic worth of a specific human life (see Cameron [14]).

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[1] A one-size-fits-all *VSL* has been politically expedient since policy-makers have difficulty explaining the logic for differentiated values to their constituents. Baker et al. [8] outline the restrictions on the underlying social welfare function that would be necessary to justify a one-size-fits-all *VSL*.

[2] For an alternative and more sophisticated approach to calculating the *VSLY* see Moore and Viscusi [50].

[3] In the past, stated preference methods generated controversy because of concerns that respondents would overstate their willingness to pay for a public risk reduction. However, over the last two decades, important strides have been made in understanding and minimizing concerns about the incentive compatibility of these choice situations (e.g., List [47]). Indeed, a recent meta-analysis shows that stated preference estimates of the *VSL* are systematically lower than those produced by revealed preference data from wage-risk studies (Kochi et al. [44]).

[4] Strand [62] also considers both mortality and morbidity, but his is a theoretical treatment which emphasizes continuous time.

[5] Van Houtven et al. [66] use a survey that asks respondents to consider a forced relocation, for one year, to one of two other cities, where the two locations differ only in their relative and absolute frequencies of fatal stomach, liver, or brain cancer versus car accident deaths. They randomly describe the illness profiles for the cancer as having 5, 15, or 25 years of latency and either two or five years of morbidity. Dow et al. [26] discuss the importance of competing health risks when one considers the demand for a risk-reducing intervention. Other researchers have valued risk reductions at selected times in the future (e.g., Krupnick et al. [46], Alberini et al. [1], Hammitt and Liu [35], and Van Houtven et al. [66]) but not the reduction of risks involving time patterns of several different adverse health states.

[6] Various other researchers have explored the influence of each of these factors on *VSLs* but not in a comprehensive structural model of intertemporal demand. For age, see Krupnick [45] and Viscusi and Aldy [68]. For income, see Mrozek and Taylor [51], Viscusi and Aldy [69], and Costa and Kahn [22]. For future health states, see (Krupnick et al. [46] and Alberini et al. [1]).

Ideally, we would use market-based data to estimate our model using actual demands for risk-mitigating interventions. However, revealed-preference data of the type needed to identify the relevant intertemporal tradeoffs do not exist.[7] Thus, we administer a representative national survey wherein 2407 U.S. adults make choices over alternative risk-mitigation programs in a stated choice survey. Each health risk in our study is described as a time pattern of health states that the individual might experience in the future. Each illness profile is randomly generated but tailored to the individual's known gender and current age. Each illness profile is described in terms of a baseline risk and a description of the individual's most-likely age when symptoms would begin (namely, the delayed onset or the "latency" the illness). The illness profile also describes the severity and duration of the illness, the likely need for hospitalization or surgery, the individual's likely age at recovery (if recovery occurs), and the number of lost life-years (if the illness shortens the individual's lifespan). We describe an optional intervention program that would reduce this risk by a specified amount and at a given cost.[8]

It is important that our sample reflects the overall population of U.S. adults aged 25 and older. Many of the samples used in past revealed- and stated-preference studies have not been general-population samples. For example, wage-risk studies are limited to samples of wage-earners. We undertake a wide array of robustness checks, validity assessments and sensitivity analyses. Survey development also involved extensive pretesting, expert review, and numerous revisions to minimize hypothetical bias, incentive incompatibility and a number of other biases that are of concern in any stated choice survey. We use the resulting data to estimate a flexible translog-type indirect utility function with income and age-wise heterogeneity, using 11,385 different choices.[9]

The most-typical *VSL* approach yields a single summary measure for one type of risk reduction for all individuals. The value-added from our approach stems from our ability to produce estimates of *WTP* for reductions in risk for a virtual continuum of different time patterns of future illness and lost life-years. To illustrate, we evaluate a set of five different "benchmark" illness profiles commencing in the current period. Second, we consider the same health threats, but with a variety of different latencies and for individuals of different current ages. Finally, we consider a major illness that starts one year prior to the end of the individual's nominal expected lifespan and results in death coming six months earlier than otherwise, again for individuals of different current ages. These various examples demonstrate how our model can be used to value both the short-term and long-term benefits of many different types of health, environment and safety programs and how these vary with the age and income of the affected populations.

Finally, for the special case of sudden death in the current period, our approach lends itself readily to cross-validation with existing empirical estimates. This bolsters our confidence in the reliability of our *WTP* estimates for all of the other types of illness profiles that our new approach can be used to value. For our first "benchmark" case, our data suggest a *WTP* corresponding to a *VSL* of approximately $6.74 million. This is very close to the roughly $6 million *VSL* employed by the U.S. Environmental Protection Agency (USEPA) around the time of our survey.

This paper is the flagship for a "fleet" of papers that further explore various sources of heterogeneity in the data. Within the space constraints of a single journal article, it is not possible to entertain all of these dimensions in one model. In our conclusions section, we outline some of these auxiliary analyses.

2. Survey methods and data

As noted, it is very difficult to identify market data that would adequately illustrate differences in individuals' demands for reductions in the wide variety of health risks that may come to bear across their remaining years of life.[10] Therefore, in 2003, we conducted a representative survey of adults in the United States using the premium consumer panel maintained by Knowledge Networks, Inc. The centerpiece of the survey is an extensively randomized set of five conjoint choice tasks that present individuals with specific illness profiles appropriate to their particular age and gender, along with programs to reduce these illness risks by specified amounts at specified costs. The randomized design of our choice sets means that the attributes of each alternative risk-reduction program presented to our survey subjects are orthogonal to any of the individual's characteristics (except for their current age, for which we employ extensive controls). This means than any omitted variables create minimal bias, especially when fixed effects methods are employed in estimation. Our response rate for panelists invited to participate was 79 percent. See the more than 300-page online Handbook which accompanies our analyses of these data (Cameron and DeShazo [16], available at the journal's repository of online material, which can be accessed via www.aere.org/journals) for a detailed description of the Knowledge Networks panel and a thorough discussion the properties of our sample.[11]

[7] Manski [49] encounters a similar paucity of data concerning consumer expectations and likewise resorts to eliciting this critical information by using a consumer survey; Blass et al. [9] elicit respondents' subjective probabilities of choosing each alternative, rather than the usual discrete stated choices, to characterize preferences for electricity reliability.

[8] Tsuge et al. [64] use choice experiments to value mortality risk reductions, but do not introduce illness profiles.

[9] Two other significant studies in this area, Krupnick et al. [46] and Alberini et al. [1], survey only people aged forty and older.

[10] Most market data characterize only one source of risk (e.g., hedonic wage data and job-based risk) and are often missing essential variables such as the baseline risk, risk reduction, the latency of the programs or the costs of programs. For example, using the Health and Retirement Survey, Picone et al. [57] explore how time preferences, expected longevity and other demand shifters affect women's propensities to get mammograms or pap-smears and to conduct regular breast self-exams. However, missing data on program costs, baseline risks, and latency of program benefits prevented a fuller demand analysis.

[11] In brief, panelists are recruited into the Knowledge Network sample using standard RDD techniques. At the time of our survey, recruits without home computers were equipped with WebTV technology that enabled them also to receive and answer web-based surveys. More information about Knowledge Networks is available from their website at knowledgenetworks.com. On top of the usual benefits of Knowledge Networks panel membership

2.1. The survey

We designed our sample and survey to overcome several limitations of existing risk valuation methods. First, many studies have focused on non-representative sub-populations (e.g., working-age males) while our sample is of the general population of both men and women, including a wide range of ethnicities, age groups, and income groups. Second, many studies focus upon mortality risks only, ignoring individuals' marginal rates of substitution between morbidity (sick-time) and mortality states.[12] Furthermore, many other stated-preference studies focus on only one, or just a few, types and sizes of risk reductions. To enhance representativeness of our estimates of *WTP* for health risk reductions, we assess 12 common major health risks over range of different-sized risk reductions. The illnesses we ask respondents to consider are labeled as prostate cancer (for males), breast cancer (for females), colon cancer, lung cancer, skin cancer, heart disease, heart attack, stroke, respiratory disease, diabetes and Alzheimer's disease. There is also a safety program to reduce the risk of traffic accidents.[13]

2.2. Overview of survey modules

Here, we review the structure of the survey very briefly. Our online Handbook provides a comprehensive discussion of our survey instrument and its development.

Module 1

The first module of our survey prepares the respondent to think about a wide variety of threats to life and health. This module evaluates the individual's subjective risk assessments for the major illnesses we address in our survey, their familiarity with each illness, and any current mitigating and averting behavior they may undertake.

Module 2

The second module consists of an extensive tutorial that introduces individuals to the idea of an illness profile and to programs that may manage these illness-specific risks. This module prepares the respondent, attribute by attribute, for the information to be summarized in the upcoming choice scenarios. The attribute levels used in the tutorial section are unique to each individual, but are identical to those used in the first choice scenario for that person.

Each illness profile is a description of a time sequence of health states associated with a major illness that the individual is described as facing with some existing probability over the course of his or her remaining lifetime. These illness profiles are hypothetical.[14] Each major illness is described in terms of its period(s) of moderate and/or severe pain and disability (with the interpretation of the terms "moderate" and "severe" pain and disability described during the tutorial portion of the survey). We also indicate the treatments that could be expected to be necessary, such as hospitalization and minor or major surgery. Each illness profile involves specific intervals of time in each future health state (implicitly the vector of expected values for the actual joint distribution of these durations). The attributes of the illness profiles are randomly varied, subject to a few plausibility constraints for each illness type.[15] Just one example of the 11,385 different randomized choice sets used in our main survey is shown in the short appendix included with this paper. Based on each respondent's age and gender, we construct 22,770 essentially unique randomized illness profiles. Up to eleven attributes characterize each illness profile and program, although we concentrate here on just the main attributes (sick-years, recovered-years, lost life-years, the size of the risk reduction and program cost).[16] (See our online Handbook for more details about the randomization of these illness profiles).

In other work, we explore heterogeneity in the marginal utilities associated with future health states according to the type of illness. Given that the illness attributes were randomly assigned, however, omitted variables bias will be minimal and the preference parameters we estimate here can be viewed as averages across the wide range of different types of major health threats covered by our study. In terms of their number and variety of attributes, the complexity of our choice scenarios is comparable to that of several existing health valuation studies (Viscusi et al. [70]; O'Conor and Blomquist [54]; Sloan et al. [60]; Johnson et al. [37]).[17] We should be clear, however, that we seek to estimate demand for health risk reductions *conditional* on people's *ex ante* information about all of these health risks.[18]

(*footnote continued*)
(which included free internet access in return for completing a small number of surveys each month), respondents were paid an additional ten dollars for completing our survey.

[12] Van Houtven et al. [65], however, have undertaken a meta-analysis of estimates of the value of reduced morbidity.

[13] The value of traffic safety improvements has long been an important policy question (see Jones-Lee et al. [39]).

[14] Causes of *death* are recorded as vital statistics but only a few specific non-fatal illnesses are reportable.

[15] Each illness is randomly assigned a particular name, although we took great care to avoid having individuals reject the scenario because it was completely implausible (e.g., one does not recover from Alzheimer's or die suddenly from diabetes).

[16] Our selection of these attributes was guided by a focus on those attributes that seem most likely to affect the utility of individuals and could also span all of the different illnesses that the individual would be asked to consider.

[17] Throughout the survey design process, we were sensitive to respondents' cognitive constraints and choice-task complexity. See the online Handbook for descriptions of specific preventative steps and ex post evaluations we have undertaken.

[18] Prior to the choice experiments, we ask individuals questions about their subjective assessment of their risk of each illness, their personal experience with each illness, and the experience of friends and family with each illness. This information ensures that we have established a broad context for the upcoming risk reduction choices.

After presenting an illness profile in the tutorial section, we next explain to individuals that they might be able to purchase new early diagnostic programs that would be coming on the market that would help to reduce their risk of experiencing specific major illnesses over future periods of their lives. These programs are described as involving annual diagnostic testing and, if needed, associated drug therapies and recommended life-style changes. We choose this class of interventions because pretesting showed that individuals view this combination of programs (diagnostic tests, followed by drug therapies) as feasible, potentially effective and familiar for a wide range of illnesses.[19]

The risk-reducing effectiveness of the health programs is described in four ways. In the tutorial section, for the first choice scenario, risks are described (i) graphically, with a 25×40-cell "risk grid" (Corso et al. [21]; Krupnick et al. [46]); (ii) as a qualitative textual description of the risk reduction; (iii) in terms of before-and-after risk probabilities; and (iv) in terms of the percentage risk reduction. The latter two formats are used in all subsequent choice sets for each individual. The payment vehicle for each program is presented as a co-payment that would have to be paid by the respondent for as long as the diagnostic testing and medication are needed.[20] For the sake of concreteness, we ask respondents to assume that, to reap the health risk reductions offered, these payments would be needed annually for the remainder of their lifespan (although test subjects assumed they would not need the program during the time they actually experienced the illness, should they suffer from it despite the program). These indicated costs are also hypothetical and are randomly varied across alternatives.

Module 3

The third module of the survey contains the five main choice sets, each offering the individual two programs, each of which reduces their risk of a specific illness profile.[21] We explain to individuals that they have the option to choose neither program if they do not feel that either risk reduction is worth its cost. We point out several possible explanations why a reasonable person might choose neither program in some cases.[22] If individuals choose the "Neither Program" alternative, we assume that they prefer their status quo risks of these illness profiles to either of the two costly risk-reducing programs in that choice set.

Module 4

The fourth module contains various debriefing questions, including several that are used to document the individual's degree of acceptance of the choice scenarios posed in our survey.

Module 5

This module was administered by Knowledge Networks, separate from our survey. Knowledge Networks collects a standard panelist profile that contains household sociodemographic information, as well as a health profile, which provides a detailed self-reported medical history for the panelist.

During the course of our study, we undertook several *ex ante* measures to minimize biases via our survey's design. We also evaluate, *ex post*, the presence of any remaining biases in our data and correct for differences both within and across respondents in the degree of choice scenario adjustment or rejection. Our online Handbook gives the details concerning the *ex ante* criteria used to exclude certain choices from the estimating sample in some of our simpler models. The Handbook also describes our efforts at risk comprehension verification and mitigation of biases associated with the hypothetical nature of the willingness to pay questions, omitted substitutes, order effects in the choice questions, and yea-saying. Also described is the comprehensive nature of our "external scope test" as well as a general evaluation of the validity of our results from the perspective of economic theory. We also examine concerns about (and the available evidence on) any choice inconsistency that might result from fatigue, informational complexity and respondents' potential use of choice heuristics.[23]

[19] Depending upon their gender and age, many individuals were familiar with comparable diagnostic tests such as mammograms, pap smears, the prostate-specific antigen (PSA) test, or the C-reactive protein (CRP) test for heart disease.

[20] Costs were expressed in both monthly and annual terms. The interventions (diagnosis and treatment regimens) were selected to be as minimally invasive (or onerous) as possible, while still remaining credible.

[21] Importantly, the objects of choice are risk reduction programs which will commence immediately, so the distinction between immediate versus future consumption (as in Salisbury and Feinberg [59]) is not relevant here. The onset of the potential illness is delayed, but every risk-reduction program, if chosen, commences in the current period. Also, while it is typically desirable to employ carefully blocked designs in conjoint choice experiments, this is prohibitively difficult in the current context. Possible illness profiles must be unique to each age and gender, because these two characteristics define gender-specific remaining normative life-years to be allocated across four possible health states. There are typically fewer than two dozen people in each age-gender bin, and about 135 such bins in play.

[22] Legitimate economic reasons include that the individual (i) cannot afford either program, (ii) does not believe they face these illness risks, (iii) would rather spend the money on other things, or (iv) believes they would be affected by another illness first. If the individual chooses "Neither Program," we ask them why they did so in a follow-up question.

[23] A wide variety of non-parametric internal consistency tests can be applied to stated-preference data in some types of applications. The VALIDTST program by F. Reed Johnson permits six types of internal consistency tests for conjoint choice data. In the Handbook, we describe these tests in greater detail and explain why the VALIDTST program cannot be implemented with our data. This is because our data involve no repetitions of alternatives within individuals, there are no instances of strict dominance in any choice set, and we include attributes for which utility is not necessarily monotonic in the attribute level.

3. A utility-theoretic choice model

Our structural choice model interprets individuals' preferred alternatives as revealing their option prices, in the sense of Graham [32], for programs that reduce the risks of future adverse health states. This concept of an option price differs from the one commonly used in the financial literature. It is defined as the maximum certain payment, regardless of the uncertainty yet to be resolved, that makes the individual just indifferent between paying for the program and enjoying the risk reduction, or not paying for the program and not enjoying the risk reduction.

3.1. Marginal (dis)utilities from different future health states

While program choices have inter-temporal consequences, our model is one of static decision-making, with future expected costs and benefits first converted into the appropriate present values.[24] Let i index individuals and let t index time periods. We focus on four distinct health states: (i) an existing pre-illness healthy state, also called the "latency" period ($pre\text{-}illness_{it}$), (ii) a period of pain and/or disability ($illness_{it}$), (iii) a post-illness recovered/remission state (if the illness is non-fatal) ($recovered_{it}$), and (iv) premature mortality ($lost\ life\text{-}year_{it}$). Let the set of mutually exclusive and exhaustive 0,1 indicator variables, $1(pre\text{-}illness_{it})$, $1(illness_{it})$, $1(recovered_{it})$, and $1(lost\ life\text{-}year_{it})$, describe individual i's health state in each future time period t.[25] Let α_0, α_1, α_2, and α_3 be the undiscounted marginal utilities associated with one period in each health state.[26] In its simplest linear form, the individual's indirect utility function in period t might be specified as:

$$V_{it} = f(Y_{it}) + \alpha_0 1(pre\text{-}illness_{it}) + \alpha_1 1(illness_{it}) + \alpha_2 1(recovered_{it}) + \alpha_3 1(lostlife\text{-}year_{it}) + \eta_{it} \quad (1)$$

where $f(Y_{it})$ is some additively separable function of current net income so that $\partial f(Y_{it})/\partial Y_{it}$ gives the undiscounted marginal utility of net income. What follows is merely a sketch of the model. A comprehensive derivation is contained in Section 5 of the online Handbook.

3.2. Choices among programs to reduce risks of future illness profiles

In our data, individuals face choices that involve three alternatives: Program A, Program B, or Neither Program (labeled A, B, and N). As we outline our estimating specification, however, we shall describe our choice model in terms of just two alternatives: Program A versus No Program (just A and N). The three-alternative case is completely analogous. Individuals are informed that they have an existing baseline risk of suffering from the illness or injury in question. Their choice is *not* between suffering from the illness and enjoying perfect health, since there is a specified chance of suffering the illness both with and without the program. Instead, their choice concerns whether to purchase a program that will *reduce* their risk of suffering from the illness in question by a specified amount.[27] This risk reduction is also described in the survey as coming at a specified cost. We assume that the stated cost of achieving the advertised risk reduction subsumes all market and non-market opportunity costs perceived by the respondent.[28]

Given the *ex ante* uncertainty about future health states, we need to calculate *expected* utilities to derive the individual's option price for any given program. Let V_{it}^{jk} denote undiscounted indirect utility for the ith individual in period t, where $j=A$ if Program A is chosen and $j=N$ if the program is not chosen. The necessary expectation is taken across the binary uncertain outcome of getting sick, $k=S$, or remaining healthy, $k=H$. The probability of illness or injury differs according to whether the respondent participates in the risk-reducing intervention program. Let the baseline probability of getting sick be π_i^{NS} if the individual opts out (i.e., chooses "no program"), and let the reduced probability be π_i^{AS} if the individual opts to participate in Program A. The risk change accomplished by Program A is therefore $\Delta\pi_i^{AS} = \pi_i^{AS} - \pi_i^{NS}$, a negative number.

From the perspective of program choices being made today, before the respondent knows whether they will suffer the future illness or injury, individuals are assumed to *discount* the streams of expected future utility derived from each health state. We assume a simple exponential discount factor, $\delta^t = (1+r)^{-t}$, and employ it to calculate the present discounted expected indirect utility from these profiles of future health states.[29] This present discounted value (PDV) of expected

[24] The literature has identified a number of behavioral anomalies that cannot be explained by conventional expected utility models and exponential discounting formulas, but these simple specifications can serve as a useful starting point for our analysis. Subsequent research with these data may explore non-expected utility models and different types of discounting.

[25] Algebraically, the indicators for each health state will play a role that is equivalent to adjusting the limits of the summations used in calculating the present value of future continued good health, future intervals of illness, post-illness time, and life-years lost.

[26] We interpret the net disutility of each adverse health state as equivalent to the utility associated with avoiding it.

[27] In the survey's tutorial about program choices, respondents are reminded (for example) that "If you DO NOT choose Program A, your risk of [respiratory disease] will remain at [4] in 1000 over this time period."

[28] Non-market costs might include the inconvenience of visiting the doctor once a year, although this test might be performed in conjunction with a regular annual checkup. More problematic is the unknown extent to which the individual may have balked at the possibility of being asked to take medicines or make "lifestyle changes" in conjunction with the information provided by the test, to achieve the stated risk reduction. Limits on average panelist survey duration unfortunately required tradeoffs about which issues we should raise explicitly.

[29] When discounting, we assume the individual uses the same discount rate, r, to discount both future money costs and health states. The discounting process in our model is greatly simplified by the assumption that income in real terms, and utilities from different health states, are

utility differs according to whether the individual selects Program A or "No Program" (N), and we introduce the following simplifying notation in each case:

$$PDV(E[V_i^A]) = PDV(\pi_i^{AS}V_{it}^{AS} + (1-\pi_i^{AS})V_{it}^{AH})$$
$$PDV(E[V_i^N]) = PDV(\pi_i^{NS}V_{it}^{NS} + (1-\pi_i^{NS})V_{it}^{NH}) \quad (2)$$

It is the *difference* in these two present discounted expected utilities, under Program A versus "No Program" (N), that is assumed to drive the individual's choice.

As we outline our stochastic specification for this difference, we will use the shorthand notation $\Delta PDV(E[V_i^A]) = PDV(E[V_i^A]) - PDV(E[V_i^N])$, and we will also make use of a number of other abbreviations. The first is a basic discounting summation to be applied to anything which is constant ("c") over the time, T_i, between now and the end of the individual's nominal life expectancy. Let this term be $pdvc_i^A = \sum_{t=1}^{T_i} \delta^t$, which will depend upon the individual's life expectancy, but not upon the choice of program. Given the four discrete health states we consider, the other relevant discounted time-in-health-state terms, also summed from $t=1$ to $t=T_i$, include $pdve_i^A = \sum \delta^t 1(pre\text{-}illness_{it})$, $pdvi_i^A = \sum \delta^t 1(illness_{it})$, $pdvr_i^A = \sum \delta^t 1(recovered_{it})$, and $pdvl_i^A = \sum \delta^t 1(lost\ life\text{-}year_{it})$. In our illness profiles, the four different future health states are mutually exclusive and exhaustive, so $pdvc_i = pdve_i^A + pdvi_i^A + pdvr_i^A + pdvl_i^A$. Finally, since individuals are assumed to anticipate paying ("p") program costs only when they are neither sick nor dead, it is convenient to define an additional term—$pdvp_i^A = pdve_i^A + pdvr_i^A$—a measure of total discounted pre-illness and recovered/remission time under the illness profile to be addressed by Program A.

3.3. The estimating specification

The discounted expected utility difference that drives the individual's choice between Program A and the "No Program" alternative can then be expressed in terms of the quantities defined above to produce the most basic version of our estimating specification.[30] The net income term (with and without the program) is more complicated than usual, however, because income and program costs are assumed to depend upon whether the individual turns out to suffer from the health risk in question. We assume that the individual expects to retain approximately their current income in real terms through a major illness, but not after death. We also assume that the individual does not expect to pay the cost of the program if they are currently experiencing that illness or if they die from the illness.[31]

To accommodate the complexity of probabilistic net income as a consequence of probabilistic future health states, we further simplify the upcoming notation by letting $cterm_i^A = [(1-\pi_i^{AS})pdvc_i^A + \pi_i^{AS}pdvp_i^A]$. This is the discounted expected number of future healthy years (over which the cost of the program will be paid, if Program A is chosen).[32] Also let $yterm_i^A = [pdvc_i^A - \pi_i^{AS}pdvi_i^A - \pi_i^{NS}pdvl_i^A] = [(1-\pi_i^{NS})pdvc_i^A + \pi_i^{NS}pdvp_i^A - \Delta\pi_i^{AS}pdvi]$. This term consists of the discounted expected number of future healthy years *without* Program A, minus the change in the discounted expected number of sick years due to Program A. Both $cterm_i^A$ and $yterm_i^A$ reflect the pattern of net income with and without the program, and with and without getting sick (where the details of their derivation are provided in the online Handbook). Normalizing on the individual's current health status, the difference in discounted expected utilities that drives the individual's program choice can then be written as:

$$\Delta PDV(E[V_i^A]) = \{f(Y_i - c_i^A)cterm_i^A - f(Y_i)yterm_i^A\} + [\alpha_1 pdvi_i^A + \alpha_2 pdvr_i^A + \alpha_3 pdvl_i^A]\Delta\pi_i^{AS} + \varepsilon_i^A \quad (3)$$

Eq. (3) emphasizes how the net discounted expected utility difference from Program A depends on two key things: first, it depends on Program A's net impact on the individual's income (the term in the curly braces) and, second, it depends on the size of the risk reduction, $\Delta\pi_i^A$, that Program A would achieve (which is multiplied by the term in square brackets). In the special case of sudden death in the current period (i.e., the illness profile associated with most wage-risk studies of mortality risk valuation), $pdvl_i^A = pdvc_i$ and $pdvi_i^A = pdvr_i^A = 0$, so the expression $\{f(Y_i - c_i^A)cterm_i^A - f(Y_i)yterm_i^A\}$ reduces to $\{f(Y_i - c_i^A)\pi_i^{AH} - f(Y_i)\pi_i^{NH}\}pdvc_i$. Assuming that net income and program costs after death are zero, this is just the present discounted value over the individual's remaining nominal lifespan of the difference in the expected utility of future net income with and without the program.

Eq. (3) also emphasizes that the *marginal* discounted expected utility difference, from each unit of risk reduction $\Delta\pi_i^{AS}$, is given by $[\alpha_1 pdvi_i^A + \alpha_2 pdvr_i^A + \alpha_3 pdvl_i^A]$. This marginal utility thus depends on the time profile of the health threat for

(*footnote continued*)
approximately constant over time within each type of health state. Had it been feasible to elicit each individual's expected time profile of future income, and to convey smoothly changing health states over time, the model could of course be much richer.

[30] In the three-alternative case, there will be an analogous utility difference for Program B versus the "Neither Program" alternative.

[31] The online Handbook reports sensitivity analyses with respect to this assumption. The effects on our *WTP* estimates are minimal. Note that assumptions about the future stream of income and program costs can be different during model estimation versus simulations of *WTP*, to capture the difference between private and public risk reductions.

[32] The expectation is taken across the chance, $(1-\pi_i^{AS})$, of staying healthy (whereupon the cost would be paid in all future years) and the chance, π_i^{AS}, of suffering the illness in question (so that the cost would be paid only when neither sick nor prematurely dead).

which the risk is being reduced. This form emphasizes that if the illness profile being considered was identical in every case, as in much of the previous *VSL* research, all that could be identified would be a single scalar marginal utility of the risk reduction, $\overline{\alpha}=[\alpha_1 pdvi_i^A+\alpha_2 pdvr_i^A+\alpha_3 pdvl_i^A]$, rather than the three distinct marginal (dis)utilities for each type of adverse health state which can be identified here.

Eq. (3) can be rewritten slightly to emphasize the estimating specification:

$$\Delta PDV(E[V_i^A])=\{f(Y_i-c_i^A)cterm_i^A-f(Y_i)yterm_i^A\}+\alpha_1\{\Delta\pi_i^{AS}pdvi_i^A\}+\alpha_2\{\Delta\pi_i^{AS}pdvr_i^A\}+\alpha_3\{\Delta\pi_i^{AS}pdvl_i^A\}+\varepsilon_i^A \tag{4}$$

The ingredients for the four terms in curly braces can be constructed from the data, given specific assumptions about the discount rate and about respondents' perceptions of the time profiles of future income and program payments. The basic utility parameters include any implicit parameters involved in the function $f(Y_i)$ as well as α_1, α_2, and α_3, which are the same marginal utilities appearing back in Eq. (1). These parameters are the focus of our empirical illustration. The right-hand side of Eq. (4) can be expressed as a linear-in-parameters "index" (i.e., the $x_i\beta$ term) that enters into a standard fixed-effects conditional logit choice model. The fixed-effects variant of the specification is relevant because each respondent considers five independent stated choice scenarios, making this a form of panel data.[33]

3.4. Calculating WTP Estimates

To outline how to impute willingness to pay estimates, it is convenient to abbreviate the set of illness profile terms in Eq. (3) as $pterm_i^A=[\alpha_1 pdvi_i^A+\alpha_2 pdvr_i^A+\alpha_3 pdvl_i^A]\Delta\pi_i^{AS}$. The annual option price in the sense of Graham [32] that will make $\Delta PDV(E[V_i^A])$ exactly zero, here called $\hat{c}_i^A$, can be calculated as:

$$\hat{c}_i^A=Y_i-f^{-1}\left(\frac{f(Y_i)yterm_i^A-pterm_i^A-\varepsilon_i^A}{cterm_i^A}\right) \tag{5}$$

The payment $\hat{c}_i^A$ is the maximum *annual* payment the individual is willing to make, but these payments are necessary for the rest of the individual's life as long as they are neither sick from this illness nor dead, so their present value must be calculated. In this context, however, there is uncertainty over just what will constitute "the rest of the individual's life," since this may differ according to whether the individual suffers the illness. We thus use the discounted *expected value* of this time profile of costs, which conveniently involves the same $cterm_i^A$ construct:

$$PDV(E[\hat{c}_i^A])=cterm_i^A\left[Y_i-f^{-1}\left(\frac{f(Y_i)yterm_i^A-pterm_i^A-\varepsilon_i^A}{cterm_i^A}\right)\right] \tag{6}$$

For comparison with the rest of the empirical literature, we can scale our present-value expected option price for a risk change of just $\Delta\pi_i^A$ to produce a construct that could have, as a special case, an analog to the conventional value of a statistical life (*VSL*). This requires that we take our estimated *WTP* for the number of microrisk reductions in the stated choice scenario and scale it up to an aggregate risk reduction of 1.00. This can be done by dividing this *WTP* by the absolute size of the risk reduction in question: $PDV(E[\hat{c}_i^A])/|\Delta\pi_i^A|$. Our actual estimating specification will involve a slightly diminishing marginal utility of income, but to illustrate using the easier case where indirect utility is merely linear in net income (i.e., $f(Y_i)=\beta Y_i$, so that $f^{-1}=1/\beta$), this construct can be written as[34]:

$$\frac{PDV(E[\hat{c}_i^A])}{|\Delta\pi_i^A|}=Y_i pdvl_i^A-\frac{\alpha_1}{\beta}pdvi_i^A-\frac{\alpha_2}{\beta}pdvr_i^A-\frac{\alpha_3}{\beta}pdvl_i^A-\frac{\varepsilon_i^A}{\beta|\Delta\pi_i^{AS}|} \tag{7}$$

To obtain an estimate of *WTP* for simply a *microrisk* reduction, the result in Eq. (7) needs to be multiplied by 0.000001.[35]

This simpler linear case illustrates clearly how this scaled *WTP* measure will depend inextricably on income, as well as on the different marginal (dis)utilities of sick-time, α_1, periods in a post-illness recovered/remission state, α_2, and lost life-years, α_3. Scaled *WTP* also depends on the time profiles for each of these health states as embedded in the three discounted time-in-health-state terms $pdvi_i^A$, $pdvr_i^A$, and $pdvl_i^A$, on the individual's current age (since this age defines the possible combinations of future health state durations), and upon the individual's discount rate (implicit in these *pdv*

[33] The online Handbook provides the full details of the estimator. This is the standard packaged **clogit** algorithm within the widely used Stata econometrics program, so we do not reproduce the full log-likelihood function here. Since this analysis represents a first foray into the modeling of preferences over illness profiles, the error term in Eq. (4) is assumed to conform to the maintained hypotheses for a fixed effects logit specification. In current work in progress, we relax this assumption about the stochastic term and to explore some of the generalizations suggested by our Invitational Choice Symposium team in Louviere et al. [48].

[34] Here, we make use of the insight that $cterm_i^A-yterm_i^A=-\Delta\pi_i^{AS}pdvl_i^A$, and note that division by the negative-valued $\Delta\pi_i^{AS}$ is the same as multiplying through by -1 and dividing by the absolute value of this risk change (which we can view as a positive-sized *reduction* in risk).

[35] The error term ε is assumed to be identically distributed across observations in a manner appropriate for conditional logit estimation. Given the transformation needed to solve for the willingness to pay measure, however, the error term in the $\hat{c}_i^A$ formula will be heteroskedastic, with smaller error variances corresponding to cases with larger absolute risk reductions, $|\Delta\pi_i^{AS}|$. However, in our calculation of *WTP*, we use the zero mean of this error.

terms).[36] Heterogeneity in preferences can be related to the *type* of health threat (as opposed to its likely profile over time, as captured by the *pdv* terms) by allowing the indirect utility parameters associated with each type of future health state, α_1, α_2, and α_3, to depend upon illness names or on other individual characteristics, notably age.[37]

3.5. Benchmarking against conventional VSL estimates

If we desire a measure that is comparable to the conventional *VSL*, we can consider an illness profile that consists of sudden death in the current period, with no period of illness and no post-illness recovery/remission. The terms in $pdvi_i^A$ and $pdvr_i^A$ will both be zero. The remainder of the individual's nominal life expectancy would be experienced simply as lost life-years. If we assume that $E[\varepsilon_i^A]=0$, our analog to the conventional *VSL* formula, in the simplest linear case, would be $[Y_i-(\alpha_3/\beta)]pdvl_i^A$. The summation in the $pdvl_i^A$ term runs from now until the end of the person's nominal life expectancy, so this interval still depends inextricably upon the individual's current age. Our *VSL*-type measure will thus vary with age even in a model with homogeneous preferences. The overall monetized value of avoiding *one* discounted lost life-year, $[Y_i-(\alpha_3/\beta)]$, is given by the chance to enjoy continued current real income (i.e., other consumption) in that year, Y_i, minus the monetized value, (α_3/β), of the (dis)utility from that prospective lost life-year (which is negative).[38]

3.6. Functional form considerations for net income

The linear-in-net-income form is simple and convenient, but it is typically important to allow for a diminishing marginal utility of income. A line-search across possible Box-Cox transformations of net income—denoted $f(Y_i)=(Y_i^{\lambda}-1)/\lambda$, to allow for non-linearity of a general form—reveals that $\lambda=0.45$ maximizes the log-likelihood function. Given the vastly greater convenience of a fixed transformation parameter in terms of the estimation, we elect to approximate preferences using this particular transformation, which is close to a square root function. This function is less flexible than a quadratic form in net income. However, it allows for risk aversion with respect to net income but still guarantees monotonicity, which is also desirable.[39]

3.7. Practical application

The range of fitted *WTP* estimates for each health risk reduction program in our data set corresponds merely to these stylized illness profiles generated at random for our stated choice survey, rather than the real-world distribution of actual illnesses. Two things are needed to produce an estimate of the distribution of *WTP* for a specific reduction in the risk of a particular illness profile in a particular population. First, for the illness in question, one must have an approximate joint distribution for the illness profile (possible ages at onset, possible reductions in lifespans, and possible outcomes (recovery, sudden death, limited morbidity, chronic morbidity). Second, for the population affected by this health threat, one must have an approximate joint distribution of age and income levels.[40]

One would then need to make a large number of random draws from the distribution of relevant health risks and the distribution of ages and incomes in the affected population, and then, for each draw, to calculate the *WTP* formulas outlined above. Across a large number of random draws, one could then build up a sampling distribution for the implied *WTP* measure. The central tendency of this distribution would be interpreted as our model's prediction about willingness to pay to reduce the risk of this type of health threat affecting this particular population.

In the simple linear case, our model would retain the usual assumption that *WTP* is exactly proportional to the size of the risk reduction, which would allow *WTP* to be scaled to any arbitrarily sized risk change. Given the nonlinearity in net income of our preferred model, however, some attention must be paid to the size of the risk reduction unless specific assumptions are made about how people view their future incomes and future program costs.[41]

While most previous researchers quote their *WTP* estimates in terms of *VSLs*, we will quote *WTP* estimates for one microrisk reduction for a range of illustrative health risks. Most risk reduction policies will concern some larger number of microrisk reductions for each affected individual, so our estimates will need to be scaled accordingly. Nevertheless,

[36] The online Handbook includes a specification that preserves individual discount rates as systematically varying parameters that depend upon respondent characteristics. For a separate sample from the Knowledge Networks consumer panel, we elicited choices that allow us to specify a model for individual-specific financial discount rates. In our main models here, however, discount rates are presumed to be exogenous and constant across individuals although our empirical analyses explore the sensitivity of our results to different assumed discount rates. We will note results based on individual financial discount rates, where $r=0.05$ is imposed as an over-ride when calculating *WTP*.

[37] For example, illness characteristics might be expected to shift the value of α_1, the marginal (dis)utility of a sick-year, and possibly the marginal utility of each period in the post-illness state, α_2, since the type of illness may connote the degree of "health" that nominal recovery from that illness actually implies. We explore heterogeneity by type of illness in a separate paper.

[38] This could be recast as "*plus* the monetized value of *avoided* disutility" by *averting* a lost life-year.

[39] Risk aversion in the context of the value of a statistical life has been examined by Kaplow [41].

[40] The illness distributions may be based on expert judgment combined with exposure and epidemiological data for different groups. The age and income data could be drawn from census records for the geographic region in question, if the risk has a spatial character.

[41] For the *WTP* estimates provided in this paper, we benchmark the risk changes as being from 0.004 down to 0.001. Section 5.6.12 and Tables 5–17 in the online Handbook demonstrate the near-proportionality of *WTP* to the size of the risk change, even in our model where utility is slightly non-linear in net income.

we contend that "*WTP* for a microrisk reduction" is less likely to court misinterpretation than the *VSL*. We preserve heterogeneity in benefits estimates at the individual level. This stands in contrast to the more-usual approach, which involves aggregation of physical risk reductions across the affected populations to produce some number of "statistical lives" saved, followed by the application of a one-size-fits-all *VSL* to monetize these benefits.

4. Empirical estimates and comparisons to existing research

As noted, fixed effects conditional logit methods are appropriate in this context. Our basic model in Eq. (1) is couched in terms of the individual's undiscounted per-period indirect utility, where future-period health status is captured only by a set of mutually exclusive and exhaustive dummy variables. Our estimation method is discussed in detail in Section 5 of the online Handbook.[42] The Handbook also describes our results for a number of preliminary specifications that confirm the robustness of the estimated coefficients associated with the basic features of each offered program (i.e., cost and the size of the risk reduction) and the main attributes of each illness profile (i.e., sick-time and lost life-years). Details concerning essential tasks such as external scope tests are also described there.

4.1. Models in terms of discounted time in each future health state

At the moment of the individual's program choice, however, it is possible that each alternative could be perceived simply in terms of the *present value* of the mix of expected future health states it represents. We focus on richer models that allow for diminishing, rather than constant, marginal utilities from discounted health-state years, and interactions between the numbers of discounted years in different health states.

The final line in Eq. (3) can easily be adapted to be non-linear in $pdvi_i^A$, $pdvr_i^A$, and $pdvl_i^A$. To accommodate scenarios with zero durations for illness or recovery (including the case of sudden death), we shift all of the data for each *pdv* term by one unit, then take logarithms. The resulting alternative logarithmic form for the terms in square brackets on the second line of Eq. (3) becomes $\alpha_1\log(pdvi_i^A+1)+\ \alpha_2\log(pdvr_i^A+1)+\alpha_3\log(pdvl_i^A+1)$. In Table 1, estimates for a specification using this adjustment are presented as Model 1. This specification produces a more than 12-point improvement in the log-likelihood function compared to a additively separable structural model that is merely linear in discounted health-state years. This suggests diminishing marginal utility in both net income and avoided discounted expected time in degraded future health states.[43]

Whenever a linear-in-logs form is a better predictor of consumer choices than a linear form, the researcher is typically inspired to explore even more-general logarithmic forms. In particular, the translog form represents a second-order local approximation to any arbitrary functional relationship. The translog-type form is fully quadratic in all of the log terms and includes all of their pairwise interactions. We have explored the inclusion of all these terms. The two robustly significant additional terms, which we retain, are the squared term in lost life-years, $\log(pdvl_i^A+1)$, and an interaction between the sick-years term, $\log(pdvi_i^A+1)$, and the lost life-years term, $\log(pdvl_i^A+1)$.

In this application, however, there is a further complication. No respondent was asked to consider illnesses that could strike at an age younger than their current age, so current age defines the maximum duration of any illness profile. The result is a degree of multicollinearity between the respondent's remaining nominal life expectancy and the range of sick-years, recovered/remission years, and lost life-years he or she was eligible to consider. In particular, when including interactions between the sick-years term, $pdvi_i^A$, and the lost life-years term, $pdvl_i^A$, occasional large values of these interaction terms were closely associated with the youth of the respondent. This interaction term is important, since it allows for the possibility that some illnesses may represent "fates worse than death." If the disutility from a lost life-year falls as prior illness-years increase, it is possible that the disutility from an additional illness-year could surpass that from an additional lost life-year. Or, a lost life-year could actually come to be perceived as a good thing (if the subject believes *ex ante* that, in these extreme circumstances, they would be "better off dead" than suffering an additional year of serious illness).

We thus allow each of the translog indirect utility coefficients to vary systematically with the respondent's current age, age_{i0}, and with age_{i0}^2, since earlier empirical research has suggested the presence of quadratic age effects in *VSLs*.[44] The age shifters on the sick-years term, $\log(pdvi_i^A+1)$, are not statistically significantly different from zero. However, there are significant quadratic-in-age shifters on the linear and quadratic terms in the shifted logarithms of lost life-years ($pdvl_i^A$)

[42] Randomization, however, renders fixed effects methods considerably less important since program attributes will be uncorrelated with respondent characteristics (other than weakly with age, which is controlled for in estimation).

[43] In the online Handbook, Section 5.6.2 discusses the effects of alternative transformations of the discounted health state years. Note that Model 1 in this paper is based on a reduced sample that simply excludes respondents who failed to answer correctly our risk comprehension question, or who chose Neither Program and gave as their sole reason the opinion that they did not believe that programs would work. Model 2 restores these problematic respondents or choices, by making use of appropriate controls to neutralize the effects of scenario adjustment, scenario rejection, and a variety of other departures from ideal choice conditions that respondents admit to making. This strategy is a more comprehensive version of the types of corrections we first examined in Cameron et al. [18].

[44] See for example Jones-Lee et al. [40], Krupnick et al. [46], and Aldy and Viscusi [5]. The specification with just linear age effects on the linear-in-logarithms terms in discounted health-state years produces a substantial improvement in the log-likelihood function, but leads to some implausible outliers in the simulation results when we use the parameter estimates to predict *WTP* measures for specific illness profiles. Quadratic forms in age, where warranted by the data, appear necessary to more fully accommodate nonlinearities in these relationships.

Table 1
Logarithmic and translog-type fixed effects conditional logit models.

Parameter	Constructed variable	Simple logs (1)	Interactions (2)
Main variables and their coefficients:			
β_0	$\left[\frac{(Y_i-c_i^j)^{0.45}-1}{0.45}\right]cterm_i^j-\left[\frac{(Y_i)^{0.45}-1}{0.45}\right]yterm_i^j$	0.0139 (10.47)***	0.01344 (8.59)***
α_{10}	$\Delta\pi_i^{jS}\log(pdvi_i^j+1)$	−26.4 (4.61)***	−27.14 (2.22)**
α_{20}	$\Delta\pi_i^{jS}\log(pdvr_i^j+1)$	−22.5 (2.41)**	27.87 (0.87)
α_{21}	$\ldots age_{i0}\times\Delta\pi_i^{jS}\log(pdvr_i^j+1)$	–	−1.228 (2.07)**
α_{30}	$\Delta\pi_i^{jS}\log(pdvl_i^j+1)$	−27.7 (5.60)***	−1680 (4.03)***
α_{31}	$\ldots age_{i0}\times\Delta\pi_i^{jS}\log(pdvl_i^j+1)$	–	66.45 (3.91)***
α_{32}	$\ldots age_{i0}^2\times\Delta\pi_i^{jS}\log(pdvl_i^j+1)$	–	−0.6199 (3.72)***
α_{40}	$\Delta\pi_i^{jS}[\log(pdvl_i^j+1)]^2$	–	789.9 (3.69)***
α_{41}	$\ldots age_{i0}\times\Delta\pi_i^{jS}[\log(pdvl_i^j+1)]^2$	–	−31.6 (3.59)***
α_{42}	$\ldots age_{i0}^2\times\Delta\pi_i^{jS}[\log(pdvl_i^j+1)]^2$	–	0.2921 (3.35)***
α_{50}	$\Delta\pi_i^{jS}[\log(pdvi_i^j+1)]\times[\log(pdvl_i^j+1)]$	–	−188.1 (3.18)***
α_{51}	$\ldots age_{i0}\times\Delta\pi_i^{jS}[\log(pdvi_i^j+1)]\times[\log(pdvl_i^j+1)]$	–	3.657 (3.27)***
α_{51}	1(no program)="status quo" indicator	–	−0.09183 (1.56)
Scenario adjustment/rejection interactions (see Appendix Table A.1)[a]		No	Yes
Number of choices		7,250[b]	11,385[c]
Maximized log-likelihood		−11,719.76	−14,841.337

Notes: **=statistically significant at the 1 percent level; ***=statistically significant at the 5 percent level. Parameter estimates produced by Stata's clogit algorithm with respondent-level fixed effects due to the usual five choices per respondent. Absolute asymptotic t-test statistics in parentheses. See text for definitions of net-income-related *cterm* and *yterm* expressions. Variables *pdvi*, *pdvr*, *pdvl* are present discounted illness-years, recovered/remission years, and lost life-years. $\Delta\pi^{jS}$=reduction in the specified health risk due to participation in program *j* at a cost of *c* per year (unless sick with this illness, or dead).

[a] Observations that would otherwise be dropped can be salvaged if respondents' admitted assumptions or choice behaviors that conflict with the stated choice scenario can be controlled for in the model and then netted out of the willingness-to-pay calculations via counterfactual simulation of full compliance with the desired conditions.

[b] For Model 1, we drop choices where individuals chose the "no program" alternative and indicated, as their *only* reason for this choice, that they did not think the program would work. We also dropped all individuals who failed the risk comprehension question and those 1 percent of choices for which a programming error meant that the illness actually increased life expectancy.

[c] The only choices dropped from Model 2 are the tiny fraction where life expectancy was subject to the programming error mentioned in footenote b. Due to differences in sample size, the log-likelihoods are not comparable across these two models.

and there are linear-in-age effects on the shifted logarithm of discounted recovered/remission years, $pdvr_i^A$, and on the interaction term between the shifted logarithms of discounted sick-years, $pdvi_i^A$, and discounted lost life-years, $pdvl_i^A$. Therefore, we prefer Model 2 in Table 1.[45]

[45] There is no robust evidence, in these models, of age heterogeneity in the marginal utility of income. Note that Model 2 also includes forty additional terms (described in the Appendix) that control for evidence of scenario adjustment/rejection, for systematic sample selection, and for evidence of cognitive difficulty on the part of respondents, among other things. The online Handbook explains in detail our efforts to identify and control for any systematic selection that may produce a different set of estimated preferences from our estimating sample than may be present in the general population of the U.S.

One caveat concerning the models in this paper is that the parameter estimates in our models have the potential to be biased by our assumption of a common error variance. Salisbury and Feinberg [59] illustrate the possibility that suppressed heterogeneity in error dispersions may manifest itself as distortions in the systematic portion of a choice model. We have explored a simplification of Model 1 that allows for alternative-specific error dispersions that vary systematically with illness labels, for example, but none of these shifters is individually statistically significant and the relative magnitudes of the coefficients in the systematic portions of the model remain qualitatively similar. Given the diversity of our illness profiles (as an artifact of the need to match durations in different future health states to individuals according to their gender and current age), the dimensionality of our parameter space grows rapidly as we entertain alternative forms of heteroscedasticity as a function of profile attributes. Given that these more-elaborate models must be estimated using general nonlinear function optimizing software, estimation complexity quickly becomes problematic.[46]

To our knowledge, these are the first attempts to estimate, within a single framework, age-varying marginal utilities of avoiding present discounted time in multiple different prospective adverse health states. We next assess the validity of our estimates by exploring whether they vary systematically in a manner that economic theory (or simple intuition) would predict.[47]

4.2. Fitted distributions for WTP

In Tables 2, 3, and 4, we examine how our estimates vary with assumptions about time preferences, as well as with the data concerning each individual's income, and with current age and prospective disease latency. We employ the estimated parameters from Model 2 to characterize the implied *WTP* for a microrisk reduction for selected combinations of years of morbidity, years in a post-illness recovered/remission state, and years of premature mortality. A vast range of different illness profiles can potentially be considered, but for initial illustrative purposes, we report in Table 2 our model's results for five "benchmark" examples of zero-latency illness profiles: (1) sudden death in the current period (the most common profile considered in standard *VSL* calculations), (2) a period of shorter-term morbidity followed by recovery/remission, (3) a period of longer-term morbidity followed by recovery/remission, (4) a combination of shorter-term morbidity followed by premature mortality, and (5) a combination of longer-term morbidity followed by premature mortality. These alternative illness profiles highlight the ability of our model to accommodate morbidity as well as mortality. This capability means it may now be less necessary to appeal to the cost-effectiveness literature on quality-adjusted life years (*QALYs*, e.g., Gold et al. [31]) to fill the many gaps in the morbidity valuation literature. (See the discussion by Dickie and List [25]).

4.2.1. Five different illness profiles

Consider the center column of results in Table 2, for the 0.05 discount rate assumption, and illness profile 1 (corresponding to the standard "sudden death" illness profile). The estimates from Model 2 suggest that, for an individual who is 45 years old and has a household income of $42,000, mean *WTP* is about $6.74 for a microrisk reduction for sudden death in the current period. Across 1000 random draws from the joint distribution of the estimated maximum likelihood parameters, this mean and the corresponding 90 percent interval summarize the calculated *WTP* estimates from a formula analogous to Eq. (6), normalized on a microrisk reduction.[48]

In our model, average *WTP* per microrisk reduction varies slightly across different sizes of risk reductions when utility is not perfectly linear in net income. In this paper, we preserve the characterization of the risk reduction as a private good and base our *WTP* estimates on a case where the initial risk is 0.004 and the reduced risk is 0.001. While our model is estimated using private risk-reduction choices, it can certainly be used to simulate *WTP* in a public goods context, where individuals do *not* assume that they would be excused from paying the cost of the risk reduction program should they fall ill. If we were to further assume that individuals completely ignore the fact that both their income and their cost obligations will disappear should they die, so that they expect their net income under the program to continue until the end of their nominal life expectancy, *WTP* again becomes strictly proportional to the size of the risk reduction. In the case of Model 2, under these "public risk reduction, naïve net income" assumptions, *WTP* under the conditions in the previous paragraph would be adjusted only to $6.73 (from $6.74).

For illness profile 1, our estimates can be benchmarked against conventional *VSL* estimates, after dividing the *VSL* by one million. Contemporaneous *VSL* estimates of roughly $6–$7 million used by the U.S. EPA and roughly $3–$4 million used by the U.S. Department of Transportation thus correspond to $6–$7 and $3–$4 for a microrisk reduction. Of course, these numbers apply to a reduction in the risk of sudden death in the current period, on average, without regard to age or income. The literature review by Viscusi [67] suggests that "most of the reasonable estimates of the value of life are

[46] For example, we failed to achieve convergence for a specification where the scale factor depends upon both a set of indicators for our twelve different illness labels and the individual's subjective risks for these same illnesses. With further extensive specification searching, it may be possible to turn up some systematic differences in the error dispersions by some illness profile attribute. However, we leave this effort for subsequent research.

[47] In separate papers that extend this basic model, we explore how these utility parameters vary with (1) the respondent's current health status and subjective risk expectations across illnesses, (2) the disease labels which are randomly associated with each illness profile, subject to a few exclusions for plausibility, and (3) household structure. The average WTP amounts, across the heterogeneity explored in those papers, are consistent with the baseline estimates identified in this paper. There are no surprises, just greater degrees of generality.

[48] The mean of the theoretical distribution is undefined, since it pertains to a ratio of asymptotically normal quantities where zero is a possible value of the denominator. Thus we describe only the finite-sample means and 90 percent ranges to convey a sense of the precision of the parameter estimates and the implications of this precision for fitted *WTP*.

Table 2
WTP for microrisk reductions, different discounting assumptions.

Illness profile: age 45 now; …at 45:		$r_i=r=0.03$	$r_i=r=0.05$	$r_i=r=0.07$	Individual r_i; simulate 0.05
1.	Sudden death	$8.33 (4.45, 12.46)	**$6.74 (3.12, 10.68)**	$5.48 (1.44, 9.62)	$6.82 (2.20, 11.78)
2.	1 year sick; nonfatal	2.58 (0.40, 4.85)	**2.42 (0.51, 4.49)**	2.25 (0.54, 4.13)	2.05 (0.20, 3.92)
3.	5 years sick; nonfatal	3.39 (1.13, 5.77)	**3.05 (1.15, 5.07)**	2.74 (0.98, 4.55)	2.47 (0.67, 4.32)
4.	1 year sick; then die	9.22 (5.58, 13.11)	**8.09 (4.60, 11.82)**	7.12 (3.26, 11.19)	8.55 (4.12, 13.46)
5.	5 years sick; then die	9.75 (5.84, 13.83)	**9.09 (5.33, 13.44)**	8.35 (4.28, 12.60)	10.11 (5.40, 15.25)

Notes: Units are in 2003 US dollars per microrisk reduction for each of five illustrative illness profiles (rows), and for four different assumptions about the discount rate (columns). The fourth set of results stems from a model that employs calculated individual discount rates based on a model using a separate survey with another sample from the same population. Individual discount rates are used in estimation, but we simulate *WTP* under a common discount rate of 0.05 for all, since this discount rate is commonly used in policy analyses. Values are based on the specification for Model (2) in Table 1. Entries reflect 1000 random draws from the joint distribution of estimated parameters. We report the mean, 5th and 95th percentiles for the sampling distribution of calculated *WTP* based on the appropriate version of Eq. (7). Our "main" estimates are those for a 0.05 discount rate (the second column of estimates). For alternative fixed discount rate assumptions, *WTP* estimates are different because the constructed variables differ, and hence the estimated indirect utility parameters differ as well. Household income is set at $42,000. Illness profile 1 corresponds most closely to the scenario implicit in many wage-risk *VSL* studies (sudden death in the current period for a mid-career blue-collar male worker).

Table 3
WTP for microrisk reductions, different household income levels.

Illness profile: age 45 now; …at 45:		$y=$$25,000	$\boldsymbol{y=}$**$42,000**	$y=$$67,500	$y=$$42,000; none if sick
1.	Sudden death	$4.81 (2.09, 7.76)	**$6.74 (3.12, 10.68)**	$9.26 (4.56, 14.39)	$6.73 (3.14, 10.49)
2.	1 year sick; nonfatal	1.82 (0.39, 3.37)	**2.42 (0.51, 4.49)**	3.14 (0.66, 5.83)	2.38 (0.52, 4.44)
3.	5 years sick; nonfatal	2.29 (0.86, 3.81)	**3.05 (1.15, 5.07)**	3.96 (1.48, 6.59)	2.97 (1.07, 4.98)
4.	1 year sick; then die	5.83 (3.21, 8.63)	**8.09 (4.60, 11.82)**	10.99 (6.44, 15.85)	7.91 (4.52, 11.38)
5.	5 years sick; then die	6.63 (3.81, 9.88)	**9.09 (5.33, 13.44)**	12.19 (7.30, 17.86)	8.86 (5.02, 12.82)

Notes: See notes to Table 2. The first three sets of estimates in this table assume full current income while sick, a 0.05 discount rate, and they use the estimated indirect utility parameters for Model 2 in Table 1. The last set of estimates assumes that respondent anticipates zero income while sick, which affects estimation variables and simulation settings. *WTP* reflects the entire illness profile, including recovered/remission time associated with the illness (i.e., for illness profile 2, this is not simply the value of one sick-year).

Table 4
WTP for microrisk reductions, different disease latencies.

Illness profile: Age no; onset	1. Sudden death	2. 1 years sick, nonfatal	3. 5 years sick, nonfatal	4. 1 year sick, then die	5. 5 years sick, then die
Now 35 years old—symptoms start:					
Now	$0.72 (−4.30, 5.92)[a]	$1.92 (−0.29, 4.27)	$2.68 (0.50, 4.89)	$4.47 (−0.13, 9.06)	$9.66 (5.12, 14.86)
At age 40	1.17 (−2.79, 5.14)	1.74 (−0.30, 3.87)	2.42 (0.44, 4.41)	4.07 (0.55, 7.65)	8.49 (4.88, 12.61)
At age 50	1.91 (−0.61, 4.44)	1.38 (−0.26, 3.11)	1.92 (0.35, 3.49)	3.55 (1.52, 5.79)	6.48 (4.46, 8.88)
At age 60	2.30 (0.32, 4.37)	1.06 (−0.17, 2.35)	1.45 (0.34, 2.59)	3.13 (1.46, 5.01)	4.77 (3.22, 6.60)
At age 70	2.19 (0.43, 4.00)	0.77 (−0.05, 1.62)	1.01 (0.33, 1.72)	2.54 (0.87, 4.28)	3.10 (1.67, 4.67)
At age 80	1.40 (0.21, 2.63)	0.47 (0.11, 0.86)	0.60 (0.31, 0.90)	1.42 (0.34, 2.53)	1.04 (0.47, 1.63)
Now 65 years old—symptoms start:					
Now	$5.91 (1.61, 10.24)	$3.83 (1.70, 6.24)	$3.85 (1.77, 6.07)	$3.67 (−0.45, 8.06)	$0.15 (−4.45, 4.52)
At age 70	4.37 (1.40, 7.29)	3.33 (1.42, 5.44)	3.28 (1.51, 5.16)	2.73 (−0.04, 5.45)	−0.05[a] (−2.98, 2.90)
At age 80	1.73 (−0.07, 3.49)	2.14 (0.86, 3.52)	1.81 (0.77, 2.90)	0.98 (−0.51, 2.54)	−0.28 (−1.78, 1.16)

Notes: See notes to Table 2. Assumes discount rate=0.05, income=$42,000. Signs of parameter estimates are unconstrained.

[a] Negative simulated values of the *WTP* for a microrisk reduction can be interpreted as zero. Negative values can result when there is a random draw from the fitted distribution of the marginal utility of income that is negative, or for the marginal (dis)utility of an adverse health state that is positive. The quadratic-in-age forms for marginal (dis)utilities of adverse health states also do not preclude negative draws for extreme values of age. To keep the estimation algorithm simple, we do not attempt to impose sign restrictions on the utility parameters (many of which are systematically varying).

clustered in the $3 million to $7 million range" (in 1990 dollars). Mrozek and Taylor [51] conduct a meta-analysis of labor-market studies that suggests a *VSL* range from about $1.5 million to $2.5 million. A meta-analysis by Kochi et al. [44] using empirical Bayes pooling to combine the data from forty selected studies between 1974 and 2002, containing 197 *VSL* estimates, suggests that *VSL* has a mean of $5.4 million and a standard deviation of $2.4 million. More recently, Kniesner et al. [42] use panel methods with wage data and devote very careful attention to a wide range of econometric issues. Using data from 1993–2001 , they estimate the *VSL* to lie in the range of $4 million to $10 million, which they describe as a "comparatively narrow range." Our model produces, as a special case, a *VSL*-type point estimate of $6.7 million with 5th

and 95th percentiles of $3.2 million and $10.7 million (in 2003 dollars). Thus our *VSL* estimates conform well where they overlap with the most sophisticated existing estimates.[49]

However, our results (as shown in Table 2) do not merely validate previous studies. They also generate new information for which there are no comparable *WTP* estimates in the existing literature. For example, consider the other types of illness profiles in Table 2. Continuing to focus on the estimates in the middle column, for a 0.05 discount rate, we see that a microrisk reduction for "one year of a major illness, followed by recovery/remission with no decrease in life expectancy" (illness profile 2) is valued at $2.42. In illness profile 3, "five years of a major illness," however, is not valued five times as much, in part because of discounting. The same small risk reduction for this illness profile (with four more years of illness, but also with four fewer years of recovered/remission time) is valued only at $3.05. Simulation 4 considers "one full year of a major illness, followed by death," for which *WTP* is actually somewhat larger than *WTP* to avoid sudden death. Finally, in Simulation 5, *WTP* to reduce the risk of being sick for five years, followed by death, is $9.09. However, all of the 90 percent intervals overlap to some degree.[50]

4.2.2. Assumptions about discount rates

Our sensitivity analysis with respect to the discounting assumption used in our models is provided in first and third columns of results in Table 2. All three columns of estimates apply to the same type of individual (45 years old with an income of $42,000), for the same baseline risk and risk reduction. The parameter estimates for Models 1 and 2 in Table 1 were derived under the assumption that $r=0.05$. We recalculated all of the discounted health-state intervals using two other discount rate assumptions ($r=0.03$ and $r=0.07$) and re-estimated Model 2 with the revised constructed variables.[51] As expected, the fitted *WTP* estimates vary inversely with the assumed discount rate. While the 0.05 discount rate assumption implies a *WTP* of roughly $6.74 per microrisk reduction for the sudden death scenario, the mean estimates for the 0.03 and 0.07 discount rates are about $8.33 and $5.48.

The final column of estimates in Table 2 uses a formula for individual discount rates derived for a different sample of Knowledge Networks panelists in Bosworth et al. [12]. The mean fitted financial discount rate for the sample used in the present paper is 0.084, with a range between 0.03 and 0.48. We estimate the other preference parameters for a model analogous to Model 2 using these individual predicted financial discount rates, but we then simulate WTP based on these revised preference parameters and a 0.05 discount rate, for comparability to the constant 0.05 discount rate estimates in the second column of Table 2, since a 0.05 discount rate is common in policy analyses.[52]

4.2.3. WTP as a function of income

The relationship between *WTP* and income level has also been of great policy interest, especially for forecasting changes in *WTP* as real incomes grow (Evans and Smith [29]; Kniesner et al. [43]). Table 3 reverts to a discount rate of $r=0.05$ and again reports, in bold face in the center column, the simulated *WTP* distribution for an individual who is now 45 years old, with an income of $42,000, for each of these five illness profiles. In contrast, the first and third columns show *WTP* simulations for arbitrarily selected alternative income levels of $25,000 and $67,500.[53] As expected, *WTP* is larger when income is greater. For our 45-year-old and the common scenario of sudden death (in the first row of the table), the mean *WTP* at $25,000 income is only about $4.81 per microrisk reduction, whereas the mean *WTP* at $67,500 income is about $9.26 per microrisk reduction.

Over the interval between $25,000 and $42,000 of income, therefore, our arc income elasticity of *WTP* to reduce the risk of sudden death in the current period is about 0.66. Between $42,000 and $67,500, it is 0.68. Based upon market estimates, the meta-analysis by Viscusi and Aldy [69] finds an income elasticity of the value of a statistical life between 0.5 and 0.6. Newhouse [53] reports income elasticities for observed health spending substantially less than one. Empirically, in a survey conducted in the UK, Italy, and France, Alberini et al. [2] find that income elasticities of *WTP* "increase gradually with income levels and are between 0.15 and 0.5 for current income levels in EU countries."[54]

[49] In other contexts, Gayer et al. [30] find tradeoffs in housing prices as a function of environmental risk implying an aggregate *WTP* to avoid a statistical cancer case of $4.3 to $8.3 million. Valuing time savings at the wage rate, Ashenfelter and Greenstone [7] find that increased speed limits on rural interstate roads in 1985 imply a willingness to accept risk in the adopting states of about $1.54 million (in 1997 dollars) per highway fatality. Ashenfelter [6] reports *VSL* estimates between $1.6 million and $6 million for the same data, depending upon functional form.

[50] Each of these simulations is somewhat of an out-of-sample forecast in that no illness profile in our survey involved immediate onset of symptoms, since healthy individuals tended to find these profiles implausible. Except for traffic accidents, the shortest latency period in our scenarios was 2 years.

[51] In the online Handbook the underlying sets of parameter estimates for the different models are provided in Section 5.6.5. Also, Figures 5–8 and 5–9 in the Handbook show the age profiles of *WTP* for two different types of risk reductions under each of the three fixed discount rate assumptions.

[52] We have been cautioned against assuming that financial discount rates are the same as discount rates for health. We have also been cautioned that high discount rates in financial contexts may be artifacts of capital market constraints, which may not be binding in the intertemporal health care choices considered here. The maximized value of the log-likelihood is higher under the 0.07 discount rate assumption, consistent with the finding that fitted individual-specific financial discount rates average 0.084. The online Handbook goes into greater detail concerning the use of alternative discounting assumptions.

[53] These correspond roughly to the 25th percentile and median of the household income distribution according to the 2000 Census ($25,000 and $42,000), as well as for the 75th percentile of individual income for our sample ($67,500).

[54] Hall and Jones [33] argue that income elasticities should be substantially greater than one and note that health insurance limits people's choices and may mask income effects. However, the interventions in our study were described as not covered by insurance, so this qualification does not apply in our case.

The final column of results in Table 3 illustrates the consequences of a different supposition about how much of current real income would be received if the individual were to get sick. Our basic model in column 2 assumes that real income would continue through illness, perhaps based on insurance coverage. The final model in Table 3 assumes that respondents expected to earn none of their current income if they were to get sick, although their normal income would be earned while healthy.[55]

4.2.4. WTP as a function of disease latency.

WTP to reduce the risk of latent illnesses has been addressed only in a piecemeal fashion across the existing literature. Table 4 explores the effect of illness latency (the time in the current health state before the illness or injury occurs) on *WTP* to avoid health risks, for a subject with an assumed 0.05 discount rate, household income of $42,000 and for whom the lifetime risk is to be reduced from 0.004 to 0.001. In this table, we array our five basic examples of different illness profiles across the top of the table. In the body of the table, we display sets of mean *WTP* estimates (and 90 percent ranges) for one individual aged 35 now, and for another individual aged 65 now. The age at onset of each illness is varied to include immediate onset, as well as onset at decade intervals starting five years from now.

Focusing first on the "sudden death now" scenario in the first column of Table 4, our point estimates suggest that the 65-year-old has a considerably higher *WTP* ($5.91) to reduce the risk of sudden death now than the 35-year-old ($0.72), although the 90 percent intervals overlap. From Table 2 and Fig. 1, we see that a 45-year-old has a *WTP* of 6.74 and that *WTP* for this type of risk reduction peaks around age 50-55, dropping to about half that peak amount by age 70. These estimates put in context the U.S. EPA's controversial attempt, in 2002, to use a *VSL* for seniors that was only 2/3 of the *VSL* employed for other adults. Our results suggest that the sign and size of the difference depends greatly upon the specific age groups that one compares. Our findings, however, are in line with other life-cycle modeling results (Ehrlich [27]) that suggests that *WTP* by seniors to reduce risks is less than that for middle-aged adults—at least for the risk of sudden death in the current period.

In looking forward to future illnesses, however, as in the subsequent rows of Table 4, both 35-year-olds and 65-year-olds seem to have a lower *WTP* to avoid the same illness profile when symptoms commence at a later age. Our selection of disease latency results can be compared to just a small number of extant empirical studies. Hammitt and Liu [35] find that *WTP* declines at a 1.5 percent annual rate for a 20-year latency period, while Hammitt and Haninger [34] (p. 71) find that *WTP* does not vary significantly with latency. From our Table 4, delaying by twenty years the time at which sudden death might occur (from five years to 25 years hence) actually *increases WTP* by 96 percent for 35-year-olds. For 65-year-olds, however, a similarly 20-year delay (postponing the risk of sudden death from five years to 25 years hence) does reduce *WTP*, in this case from $4.37 to essentially zero (not shown in the table). Comparing these results to the existing empirical literature on latency, Alberini et al. [2] find that for respondents aged 40 to 60 years, delaying the "time at which the risk reduction occurs" from 10 years to 30 years reduces *WTP* by more than 60 percent in samples from both Canada and the U.S. This may reflect the fact that their youngest respondents are forty years old, whereas ours range down to 25 years of age.

4.2.5. WTP to reduce risk of sudden death as a function of age

Fig. 1 provides a convenient visual summary of the effect of the respondent's current age on *WTP* for a reduction in the risk of sudden death in the current period. This graph shows the simulated mean and 90 percent interval for this fitted *WTP* as a function of the individual's age at the time they are making their program choices. Recall that age has a statistically significant linear or quadratic effect on four of the utility parameters of our model. The graph displays the *combined* influence of these four different types of age effects on fitted *WTP*.[56]

While there is a growing stock of evidence concerning the relationship between the *VSL* and age, Smith et al. [61] and Evans and Smith [28] point out that the theoretical results are ambiguous and the empirical results are mixed. Krupnick [45] and Aldy and Viscusi [4] review the stated- and revealed-preference literatures, respectively.[57]

Our stated-preference results for a *VSL*-type sudden death scenario suggest that younger people between 25 and 35 (including both workers and those not employed for pay) have a mean *WTP* between zero and about $0.72. For the general population aged 45–55 , like Aldy and Viscusi [3], we find the highest mean *WTP* amounts, varying between $6.74 and $8.15. As ages progress to 55–65 , our sample suggests that *WTP* drops from about $8.15 down to about $5.91. Finally, after normal retirement age, in the interval between 65 and 75, mean *WTP* drops from about $5.91 down to about $2.05. In contrast, Smith et al. [61] find results which suggest that the oldest and most risk-averse *workers* require significantly

[55] As expected, this distinction makes little difference in the "sudden death" scenario, where no sick-years are involved.

[56] Any instance of negative *WTP* predicted by the model is depicted as zero, since there was no opportunity to pay a negative amount for any risk reduction program. The worst people could do was to choose "Neither Program".

[57] Among the earliest age-related results, Alberini et al. [1] find, for survey respondents aged 40 years and older in Canada and the U.S., that there is weak support for a decline with age in *WTP* to reduce the risk of sudden death in the current period, but only for the oldest respondents. In a Canadian sample, described in more detail in Krupnick et al. [46], *WTP* is about 30 percent lower for persons aged 70 or more. The hedonic wage study of Viscusi and Aldy [68] suggests that younger workers have a *WTP* for this type of risk reduction of $6.40, whereas workers aged 35–44 value this same risk reduction at $9.00, but the numbers decline to about $3.80 for workers aged 55-62. Aldy and Viscusi [3] find that *WTP* rises from $3.70 in the youngest group (ages 18–24), peaks at $9.70 between 35–44 , and declines to $3.40 by the 55–62 age group. Controlling for birth-year cohort effects, they find a peak at $7.80 at age 46 and a flatter profile. Blomquist et al. [10] model *WTP* for asthma mortality risk reductions as a reduced-form cubic function of age with a local minimum at age 30 and a local maximum at age 66. Hammitt and Haninger [34] also used reduced-form models where WTP is a function of respondent age and age squared. Their coefficient on the age-squared term is only statistically significant when the person in the household who is at risk is a child, and then only at the 10 percent level. Based on their point estimates, however, *WTP* is monotonically decreasing in the age of the affected child, peaks near age 55 when the respondent is at risk, and peaks near age 70 when another adult is at risk.

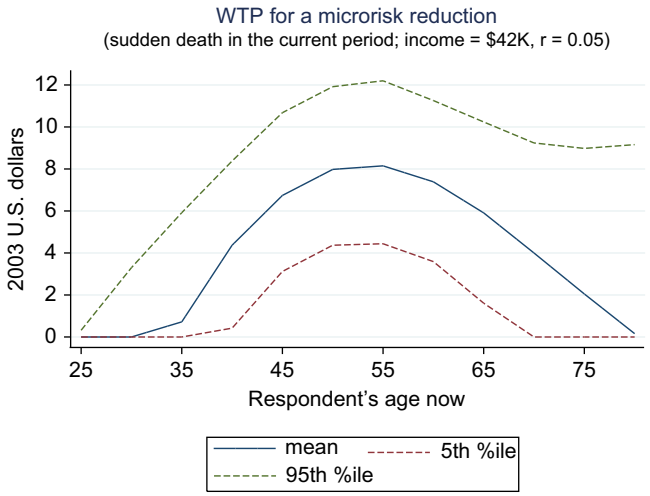

Fig. 1. Sudden death now.

higher compensation, rather than lower compensation, to accept increases in job-related fatality risks. Our data, however, include non-workers and retired persons, and do not apply solely to job-related fatality risks.

4.2.6. WTP to reduce risk of other illness profiles as a function of age

Figs. 2 through 4 illustrate age patterns in *WTP* to avoid three other illustrative illness profiles. It is for *other types* of illness profiles, such as these, where our model offers great advantages over other approaches. Fig. 2 shows a non-fatal year of major illness from which the individual recovers, with no change in life expectancy. *WTP* begins at about $1.28 at age 25 and increases with age, growing to a *WTP* of $7.00 by age 80. Fig. 3 shows an illness that lasts five years, ending in death, but with ten years of latency prior to onset. *WTP* to reduce the risk of this illness profile also differs systematically with age, but with a very different pattern. In contrast, the illness profile illustrated in Fig. 4 may be relevant to many environmental health risks which might cause modest changes in life expectancies. In this case, the individual gets sick just one year before the end of his or her expected lifespan. After six months of major illness, death occurs six months sooner than it would have otherwise. At a 0.05 discount rate, 25- to 60-year-olds have a *WTP* that is less than $0.56 per microrisk reduction to avoid this scenario. Respondents 45 to 65 years old place little value on reducing these risks, but *WTP* begins to increase quickly after age 65. Here we see a noticeable *increase*, rather than a decrease, in *WTP* among seniors. This stands in sharp contrast to the results for the "sudden death now" scenario addressed in most studies of the *VSL* as a function of age.[58]

5. Discussion and conclusions

No other single study subsumes the broad range of major illnesses addressed within a single structural model in this paper. Extant research by other authors has addressed the implicit value of a statistical on-the-job injury, motor-vehicle injury, or to avoid symptom-days of various specific types (see Viscusi [67] for an early comprehensive review). To evaluate the social benefits of a policy change that alters the incidence of a particular illness, however, there are great advantages to being able to estimate *WTP* corresponding to the types of illness profiles associated with that particular illness. Our approach offers the flexibility to evaluate changes in the type, future timing, and duration of heterogeneous illness profiles. Additionally, it does so within a consistent theoretical and empirical model, rather than requiring researchers to cobble together estimates based mostly on *WTP* to reduce current-period morbidity and mortality risks, derived from separate valuation methods and studies.

Our model is a generalization of prior approaches, so we can produce new and important types of economic information: distinct estimates of the marginal utilities of avoiding a discounted year of morbidity and a discounted lost life-year (as distinct "hedonic" characteristics of an illness profile) within a single model. We also confirm that these marginal utilities are not simple constants. From these heterogeneous marginal values, which depend upon the mix of health states in an illness profile and the individual's age, we have illustrated how to construct average *WTP* values for reductions in the risks of a wide range of illness profiles, for individuals of different ages and different income levels.

[58] An early inquiry into the valuation of changes in life expectancy is contained in Rosen [58]. Philipson et al. [56] explain four main reasons why the value of end-of-life care to an elderly individual may be larger than most models would predict (i.e., the opportunity cost of expenditure is minimal if there is no strong bequest motive, there is a chance of surviving until a newly discovered treatment becomes available, the social value of terminal care may exceed the private value in many cases, and the frail elderly may value additional life-years at least as highly as an ordinary healthy adult).

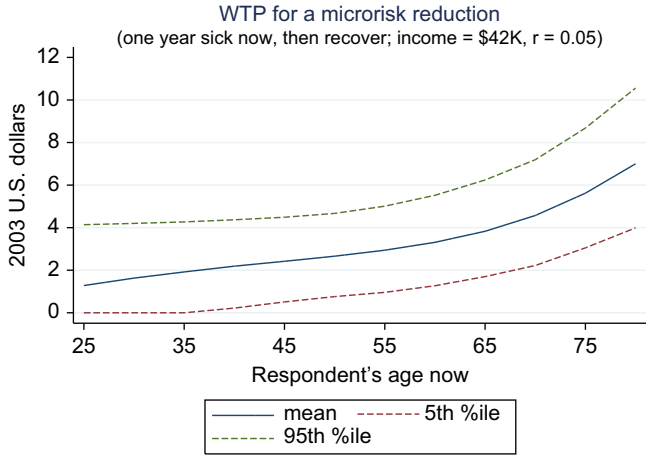

Fig. 2. 1 year sick now, recovery/remission, life-span not affected.

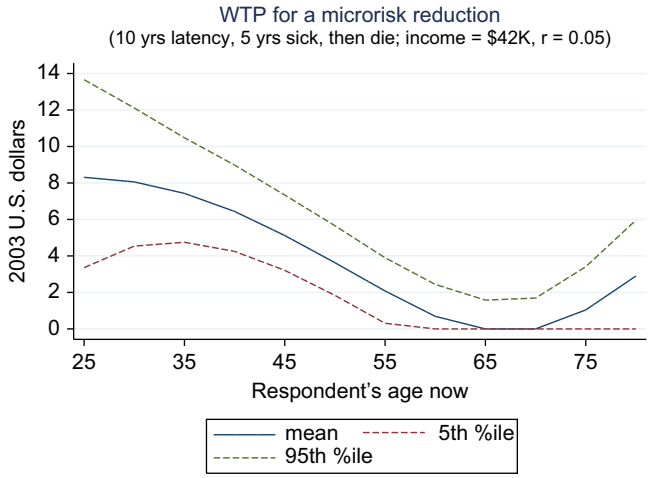

Fig. 3. 10 years latency, 5 years sick, THEN DIE.

Policy changes that affect the prevalence and severity of a given illness will shift the joint distribution of the duration of morbidity and premature mortality, for specified populations. Our model also permits assessment of the benefits of *reductions* in the risk of one type of illness profile, combined with *increases* in the risk of another. In this paper, however, we demonstrate the model's simulation capabilities with only a selection of illustrative illness profiles.

Our results strongly reinforce the growing body of evidence that a single one-size-fits-all *VSL*, however convenient it may be, is probably misguided. The use of a single number may continue to be dictated by political concerns, but willingness to pay to reduce health risks should clearly be viewed as an inverse demand *function* (rather than as a *scalar* that is merely proportional to the magnitude of the risk reduction). Given that willingness to pay for risk reductions represents an inverse demand, the prospect of systematic variation in willingness to pay—according to the attributes of the good in question, and with indicators of individual preferences—should not be at all surprising.

Our basic model and data have been used to explore other sources of heterogeneity in risk reduction valuations. In Cameron et al. [17], we have explored adults' willingness to pay to reduce their own risks of suffering adverse future health profiles as a function of the numbers and ages of children currently in their household. In Cameron et al. [20], we combine these data with an analogous survey for Canada to explore systematic differences between WTP for health risk reductions across the U.S. and Canada. Research by Cameron et al. [19] allows the marginal utilities of avoided sick-years and lost life-years to vary systematically with the type of illness. In other work, still in progress, we consider two distinct types of age effects that appear to be relevant to WTP for health risk reductions. We also explore the influence of current same-illness or other-illness morbidity and individual subjective risks of the illnesses in question and subjective risks of other illnesses. Finally, we have used the consumer choices from the survey employed in the present paper as an example in a general theoretical and methodological inquiry about respondents' attention to attributes in complex choice sets in Cameron and DeShazo [15].

This research on individuals' willingness to pay for their own private risk reduction measures sets aside the distinction between willingness to pay for private risk reductions and willingness to pay for risk reductions for other people. What to

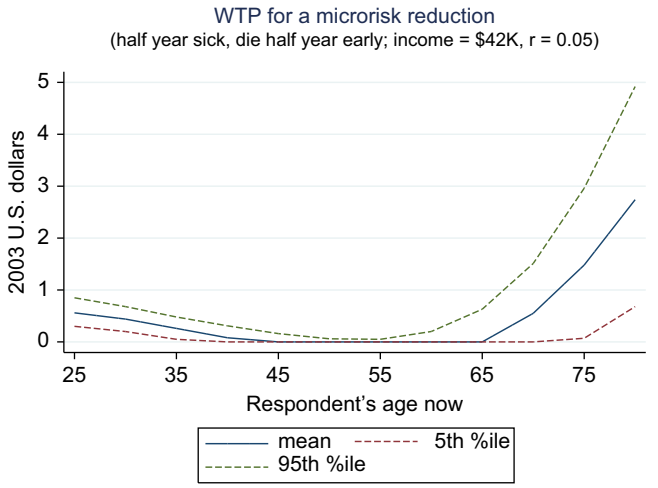

Fig. 4. End-of-life effects; half year sick, die half-year early.

do about these differences is still an open question. In other survey-based research described in Bosworth et al. [11], however, we explore the question of individuals' willingness to pay for public policies that address environmental, health and safety threats as a way to reduce morbidity and mortality risks for everyone in their community, rather than simply for themselves. In yet other work, we also explore the willingness of individuals to bear the costs of treating illnesses for individuals who are already sick, reducing morbidity by increasing recoveries and reducing premature mortality by delaying deaths. This vein of research, based upon yet another survey sample, is described in Bosworth et al. [13].

Appendix A

Example: One of the 11,385 randomized choice sets.

Choose the program that reduces the illness that you most want to avoid. But think carefully about whether the costs are too high for you. If both programs are too expensive, then choose Neither Program.

If you choose "neither program", remember that you could die early from a number of causes, including the ones described below.

	Program A for Heart Disease	**Program B for Colon Cancer**
Symptoms/ Treatment	Get sick when 71 years old 2 weeks of hospitalization No surgery Moderate pain for remaining life	Get sick when 68 years old 1 month of hospitalization Major surgery Severe pain for 18 months Moderate Pain for 2 years
Recovery/ Life expectancy	Chronic heart condition Die at 79	Recover at 71 Die of something else at 73
Risk Reduction	5% From 40 in 1,000 to 38 in 1,000	50% From 4 in 1,000 to 2 in 1,000
Costs to you	$15 per month [= $180 per year]	$4 per month [= $48 per year]
Your choice	**Reduce my chance of heart disease**	**Reduce my chance of colon cancer**

Neither Program

Table A1
Coefficients on scenario adjustment/rejection interaction terms in Model (2) in Table 1.

Base coef.	Shifter→	1	2	3	4	5	6	7	8
	Main Constructed Variable ↓	Would never benefit?	Log(pos. life expect. diff+1)	Log(neg. life expect. diff+1)	Shortens life most? incorrect	Failed risk comp. test	Status quo b/c reject scenario	Ingored affordab.	Dev. from median select. prob
β_0	$\left[\frac{(Y_i-c_i^j)^{0.45}-1}{0.45}\right] cterm_i^j - \left[\frac{(Y_i)^{0.45}-1}{0.45}\right] yterm_i^j$	−.01002 (1.97)**	–	–	–	–	.6498 (21.83)***	−.009186 (4.76)***	–
α_{10}	$\Delta\pi_i^{jS}\log\left(pdvi_i^j+1\right)$	420.9 (8.18)***	–	–	–	–	–	−26.88 (1.75)*	190 (2.23)**
α_{20}	$\Delta\pi_i^{jS}\log\left(pdvr_i^j+1\right)$	–	–	12.5 (1.65)*	–	–	–	–	–
α_{21}	… $age_{i0}\times\Delta\pi_i^{jS}\log\left(pdvr_i^j+1\right)$	–	–	–	–	–	–	–	–
α_{30}	$\Delta\pi_i^{jS}\log\left(pdvl_i^j+1\right)$	–	672.9 (2.62)***	592.3 (3.14)***	247.6 (2.91)***	347.9 (2.62)***	–	–	–
α_{31}	… $age_{i0}\times\Delta\pi_i^{jS}\log\left(pdvl_i^j+1\right)$	–	−29.49 (2.67)***	−26.03 (3.37)***	−5.352 (3.23)***	−11.98 (2.25)**	–	–	–
α_{32}	… $age_{i0}^2\times\Delta\pi_i^{jS}\log\left(pdvl_i^j+1\right)$	.1406 (4.01)***	.2929 (2.55)**	.2591 (3.41)***	–	.1365 (2.74)***	–	–	–
α_{40}	$\Delta\pi_i^{jS}\left[\log\left(pdvl_i^j+1\right)\right]^2$	1200 (10.44)***	−321.8 (2.41)**	−302.9 (3.14)***	−131.2 (2.85)***	–	–	–	–
α_{41}	… $age_{i0}\times\Delta\pi_i^{jS}\left[\log\left(pdvl_i^j+1\right)\right]^2$	−18.52 (7.19)***	13.57 (2.35)**	12.97 (3.25)***	3.154 (3.47)***	–	–	–	–
α_{42}	… $age_{i0}^2\times\Delta\pi_i^{jS}\left[\log\left(pdvl_i^j+1\right)\right]^2$	–	−.1313 (2.18)**	−.128 (3.23)***	–	−.01305 (2.12)**	–	–	–
α_{50}	$\Delta\pi_i^{jS}\left[\log\left(pdvi_i^j+1\right)\right]\times\left[\log\left(pdvl_i^j+1\right)\right]$	−699.7 (4.45)***	104.7 (2.75)***	56.41 (2.13)**	–	–	–	23.3 (1.92)*	–
α_{51}	… $age_{i0}\times\Delta\pi_i^{jS}\left[\log\left(pdvi_i^j+1\right)\right]\times\left[\log\left(pdvl_i^j+1\right)\right]$	6.885 (2.57)**	−2.037 (2.63)***	−.9817 (1.92)*	–	–	–	–	–
α_{61}	1(no program)="status quo" indicator	–	.09247 (2.40)**	–	.099 (2.36)**	–	–	.1104 (1.72)*	–

Appendix B. Controls for scenario adjustment and scenario rejection by respondents, and systematic sample selection

In stated preference surveys, it is rare for everyone in the sample to cooperate fully and adopt or comply with all of the conditions that the researcher asks them to assume are true as they consider the choices they are being asked to make. If the researcher does not follow up by explicitly checking the extent to which each respondent was able to adopt the assumptions that are specified by the researcher, there is no way to assess the extent of any non-compliance or its potential implications for the findings of the study.

Our survey includes a number of important follow-up and debriefing questions designed to provide evidence about the extent to which our respondents' assumptions conformed with the stylized choice scenarios that were presented. Rather than throwing away information by simply dropping those choices (or those respondents) where the assumptions made in our model are violated in some way, we endeavor to retain as much demand information as possible by using control variables to net out the effects of scenario adjustments, outright scenario rejection, and systematic sample selection.[59]

We permit each one of the coefficients in the main specification in Table 1 to vary systematically with control variables that have been normalized to take on zero values if every respondent conforms to every assumption that we wish to make in our analysis. Our first additional control, included in Table 1 in the text where it fits more conveniently, is a "status quo" indicator variable (which will be zero for any offered program and one for the "no program" alternative). Then we permit the estimated coefficients on every one of the main variables in Table 1 in the text to differ systematically with the levels of eight other variables. Potentially, this means 104 additional interaction terms in our model. We trim the list of potential interaction terms by dropping those with persistently insignificant coefficients.

As indicated, the scenario adjustment/rejection and sample selection variables are constructed so that under the desired conditions, their values are zero. Thus the basic model coefficients in Table 1 are the coefficients that would be relevant if no one in the sample violated any of a number of important conditions that would ideally be met. Appendix Table A1 shows the extent to which the basic coefficients in Table 1 are changed when these controls are not zero. The control variables are as follows:

1. "Would never benefit?"—After each choice, we ask the respondent about when they thought they would begin to experience the benefits of each program in the preceding choice set. If they checked the box to say "Never (Program would not benefit me)," this indicator takes on a value of one. However, we will simulate it for a value of zero.[60]
2. "Log(pos life expect diff+1)"—The final question in our survey asked the respondent "Until what age do you expect to live?" We compared this number to the age we used, beginning on Form 9 of the survey, to characterize that person's nominal life expectancy. If the subjective life expectancy was greater than the number we used, we added one to the absolute difference and took logarithms (to reduce sensitivity to outliers).
3. "Log(neg life expect diff+1)"—Analogously, if the respondent's expected age at death was lower than the age we used in the survey, this absolute difference was non-zero. We again add one so that the transformation goes through (0,0) and take logarithms to reduce the effects of outliers.
4. "Shortens life most? Incorrect"—In the context of the survey's tutorial, respondents were asked to look at the prognosis, should they suffer each of the two illnesses featured in their tutorial. They were asked "Which one shortens your life the most?"[61] If the respondent gets the answer wrong, this indicator takes the value of one. We will simulate it at zero, implying a correct answer to this tutorial question.
5. "Failed risk comp. test"—Also during the tutorial, respondents were invited to consider the risk (and risk reduction) information for each health threat and its associated risk reduction program. They were asked "Which program reduces your risk the most?" If the respondent answered this question incorrectly, this variable was set to one. We desire to simulate conditions where it takes a value of zero (i.e., under which the respondent appears to understand these probabilities).
6. "Status quo b/c reject scenario"—If the individual chose the status quo outcome, they were presented with a list of possible reasons why someone might choose the "no program" alternative. If one of the reasons checked was "I did not believe these programs would reduce my risks," this indicator takes on a value of one. For our corrected coefficients, we wish to simulate conditions under which nobody in our sample would say this. The desired value of this variable is zero.
7. "Ignored affordab."—Our debriefing questions also asked respondents to reflect upon whether they treated their budget constraints as binding. "Did you consider whether you could actually afford to pay for these programs over your

[59] In previous papers using these data, we have dropped more observations. For example, in Cameron et al. [17] and Cameron et al. [20], we exclude respondents who failed the risk comprehension test, as well as those who chose the status quo and gave as their *only* reason for doing so as the fact that they did not believe the programs would work. These two criteria were also used to exclude respondents in Model 1 in Table 1, since it is inappropriate to include them without controlling for this information. We used the same earlier exclusion restrictions in Cameron et al. [18], where we first illustrated the potential importance of scenario adjustment corrections such as these.

[60] This was one of the scenario adjustment variables featured in Cameron et al. [18]. With the reinstatement of observations previously dropped due to controls 5 and 6 (below), and further reflection upon the second control used in that paper (called the "minimum overestimate of the latency"), we have been persuaded that it is unreasonable to expect respondents to interpret the benefits of the program as beginning only when a spell of moderate to severe pain begins. Thus we no longer use this overestimate as a control, and argue that the broader controls used in this paper are probably superior.

[61] In retrospect, we should probably have phrased the question as "Which health problem causes you to die sooner?"

lifetime?'' If the respondent selected anything other than ''Yes'' as their answer (i.e., ''Somewhat'' or ''No''), this indicator was set to one. We desire conditions under which everyone responds ''Yes,'' so we simulate a value of zero for subsequent use of the model.

8. ''Dev. from median select. prob.''—In a separate comprehensive sample selection analysis described in the online Handbook, we estimate/explain the probability that each of the over 500,000 potential panelists recruited to Knowledge Networks ends up in our final estimating sample. We wish to simulate the same ''typical'' response propensity for everyone, so we simulate everyone having the median response probability.

First of all, we note that the simple status quo indicator variable in Table 1 in the body of the paper is itself a type of scenario adjustment variable. Ideally, the attributes of the health risks and the programs designed to address them, in conjunction with respondent characteristics such as income and age, would fully explain individual's choices among the available alternatives. The coefficient on an alternative-specific dummy variable captures the systematic influence of unmeasured attributes of that alternative on choice probabilities. A ''status quo'' dummy variable is commonly used in choice models such as these. The coefficient on this variable records whether respondents tend to have some systematic preference for or against the ''neither program'' alternative that appears in every choice set.

When we control for all of the types of scenario adjustment/rejection and systematic sample selection variables outlined above, we find that the status quo effect in our models is not statistically significantly different from zero. Without these corrections, we find a negative status quo effect in some specifications, suggesting that something for which we fail to control in those simpler specifications makes respondents more inclined to choose a program than the observed program attributes would suggest. This sort of outcome is often interpreted as ''yea-saying.'' In cases where the payment vehicle is a tax, there is often a positive coefficient on the status quo variable, consistent with payment vehicle rejection. Here, however, when we are careful to control for cases where respondent's admitted behaviors violate ideal conditions, no statistically significant status quo effect remains. This means that program cost, the size of the risk reduction, and the nature of the risk to be reduced (as captured by the illness profile), in conjunction with respondent income and current age, may actually do a good job of explaining respondent's choices, not only across the offered programs, but between each pair of programs and the ''neither program'' alternative.

B.1. Results

Control 1 (''Would never benefit?'') varies across respondents, across choices, and across alternatives for each choice scenario, since respondents were asked this question separately for each offered program. Not surprisingly, the conviction that a particular program, for some reason, was irrelevant to the respondent makes a huge difference to the implied marginal utilities of different adverse health states.

Controls 2 and 3 pertain to any lack of alignment between the respondent's own subjective life expectancy and the ''nominal life expectancy'' assigned in their survey instrument for a typical person of their gender and current age. We allow for different effects for cases where the respondent's subjective life expectancy is greater than what the survey asserted, and for cases where it is less. Due to the presence of a number of outliers, both positive and negative, we elected to use a log transform of the absolute difference to reduce somewhat the influence of these outliers. The results are qualitatively similar either way, however, for either the linear version or the logged version.

Controls 4 (''Shortens life most?'') and 5 (''Failed risk comp. test'') make use of the results of the two ''skill-testing questions'' that were posed to respondents during the tutorial portion of the survey. It is generally a good idea to keep the respondent engaged during the learning phase by asking them to interact in some way while crucial information about the choice exercise is being conveyed. Incorrect answers to these questions can have two interpretations, however. The respondent may be truly unable to understand the concepts involved. Alternatively, they did not pay sufficient attention to the way the question was posed (or we did not pose the question in a sufficiently straightforward fashion) so that they selected the wrong answer even though they get the basic idea and will do fine when they know they are in the part of the survey that actually involves risk-reduction program choices. Failure to answer these questions correctly is associated with a bias towards zero in all of the coefficients involving lost life-years for which the control variables bear persistently significant coefficients. As discussed in Cameron and DeShazo [15], a coefficient that is smaller in absolute value can easily reflect lesser attention to an attribute instead of a lower marginal (dis)utility associated with that health state. It is possible that incorrect answers to one or both of these skill-testing questions are proxies for lower levels of attention to the survey in general. However, if these outcomes reflect lower cognitive ability, this lower cognitive ability could also lessen attention to the finer details of each illness profile.

Control 6 (''Status quo b/c reject scenario'') allows us to salvage many choice sets that we previously excluded from the estimating sample. Some of our other papers using this survey excluded choices where the individual chose the ''neither program'' alternative and checked as their only reason the fact that they did not believe either of the two programs would work. They had been specifically asked to accept that the programs would work, so these were unambiguous cases of ''scenario rejection.'' Reinstating these choice sets in the estimating sample, but using this particular control, allows the implied preference parameters to differ if the individual checked as at least one of the reasons for choosing ''neither program'' that they did not believe either of the programs would work. This coefficient has a huge effect on the coefficient for the term in net income, making it vastly larger. Since this net income coefficient enters the denominator of the *WTP*

expression, it is clear that this type of scenario rejection vastly decreases the individual's *WTP* for the programs in any choice set where they chose "neither program" and listed this inadmissible justification as one of their reasons for this choice.

The coefficients for the interaction terms relating to Control 7 ("Ignored affordability") indicate that if the individual concedes that they did not fully keep in mind whether they could afford the programs, the coefficient on their net income term is too small, corresponding to an implied *WTP* that is too large.

Finally, the systematic sample selection adjustment (Control 8) is found to have an effect only on the coefficient on discounted sick-years. Among the over 500,000 random-digit-dialed individuals Knowledge Networks attempted to recruit to their panel, those who were relatively more likely to show up in our estimating sample derived lesser disutility from the number of discounted sick-years in any given illness profile. Correspondingly, those who were less likely to appear in our sample tend to derive greater disutility from discounted sick-years. While the coefficient on this control variable is large, the magnitudes of the deviations are generally very small. Among the 11,385 choice sets in the estimating sample, the mean value of this deviation is 0.0112 (with a minimum of -0.003450 and a maximum of 0.2965). Thus the average value of the correction is less than $+2$ on a base coefficient of roughly -27, so we infer that selection effects are likely to be modest. Nevertheless, our *WTP* estimates are normed on the case of median response probabilities.

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