A Generalized Empirical Model of Demand for Health Risk Reductions

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November 2008

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JEL Classifications: I1, H43, Q51

Keywords: health risks, value of a statistical life, VSL, mortality, morbidity, illness profile

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Abstract

We develop a structural model of utility defined over a sequence of prospective future health states which permits us to generalize the concept of the Value of Statistical Life (VSL). We use a large representative national survey involving stated choice experiments where individuals choose between three options: two programs to reduce major health risks, and the status quo. We estimate the marginal (dis)utilities of discounted prospective illness years, recovered/remission years, and lost life-years. For an individual of a given age and income, these estimates permit calculation of overall WTP to avoid a wide variety of arbitrarily specified illness profiles.

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1 Introduction

Most health, environmental, and safety programs reduce some specific health risk that individuals face, with some type of time profile, over their remaining lifespan. Accurate estimates of the schedules of improvements in expected utility associated with these programs, for different individuals, are important for several reasons. In the fields of health, public and environmental economics, this information is essential to value accurately the benefits from medical research (Cutler and Richardson, 1998; Murphy and Topel, 2006), or from environmental, health and safety regulations (Viscusi, 1993). Labor economists are also interested how these policies or programs improve individuals' expected future health states because these expectations affect widely studied life-cycle decisions related to consumption and savings, as well as participation in labor and health insurance markets. In this paper, we present the first attempt to estimate individual-specific schedules of expected utilities for morbidity and mortality risk reductions in each year of an individual's remaining life.

Our approach represents an important improvement over the conventional approach to measurement of the social benefits associated with health, environmental and safety programs. The conventional approach is based on a simple conceptual measure of the benefits of risk reductions: the current-period measure of the marginal rate of substitution between mortality risk and income.[1] This approach has arisen as a matter of empirical necessity since observable benefits measures have tended to come from estimates of current-period wage-risk or wealth-risk tradeoffs (Viscusi, 1993). When evaluating a health, environment or safety program, this current period estimate of a dollar-risk tradeoff is normalized on a vast risk change of 1.00, and the result is known as the "value of a statistical life" (VSL). When a regulatory policy results in a small reduction in average mortality risk for each member of a specified population, the VSL is multiplied by expected number of deaths to produce a monetized estimate of overall expected benefits. If researchers need to calculate the value of avoiding just one lost life-year, which is often necessary when assigning prospective values to advances in medical research, they use the VSL to impute a per-year estimate, often by arbitrarily dividing the standard VSL by the population average number of expected remaining life-years. This measure is called the value of a statistical life-year (VSLY) (Moore and Viscusi, 1988; Cutler and Richardson, 1997; Murphy and Topel, 2006, Hammitt, 2007).

[1] For early research, see Jones-Lee (1974) and Jones-Lee et al. (1985).

Our approach addresses, simultaneously, several limitations of the conventional VSL approach. Researchers have long recognized these limitations, but have been unable to overcome them because of the constraints of existing empirical data and methods. The improvements identified in this paper take the form of 1) enhanced construct validity (i.e. that the measure varies systematically, in ways we would expect, with attributes of the health threat and characteristics of the individual), 2) utilization of illness profile information that is omitted from the conventional estimation framework, 3) enhanced transparency of the determinants of demand through an explicitly structural model, and 4) replacement of the concept of a one-size-fits-all VSL with a measure of heterogeneous individual benefits: willingness to pay (WTP) for a "microrisk" reduction for a specified health threat.[2]

First, our approach generalizes the conventional strategy in that we directly estimate the individual's marginal utility from a risk reduction—not just for the current period, but for their remaining lifespan. This generalization is needed because the vast majority of health, environmental and safety policies serve to reduce the risk of death across several future years of the individual's life. By more completely defining the difference in the relevant pattern of future states of the world that can be expected to result from a policy change (from the perspective of the individual), we enhance the construct validity of the resulting empirical estimates of demand for these policies.

Second, our approach utilizes several new types of information. Researchers can recover individuals' expressed preferences over time profiles of health states over future periods, rather than having to transfer current period preference estimates to future period risk reductions. In addition, we allow the marginal utility of health risk reduction in one period to dependent explicitly upon prospective health states in other periods. Thus the marginal utility of avoiding a death in a given future period can depend upon whether that period is preceded by a specified period of morbidity or good health, thus capturing information on inter-temporal complementarities or substitutability across health states.[3]

Third, our structural estimating model makes explicit how the schedule of estimated utilities depends upon the individual's expectations about income flows, health states, the marginal utility of consumption, and discount rates in future years (Ehrlich, 2001). In contrast, conventional VSL studies yield empirical benefit estimates that researchers typically treat as independent of income, discount rates, or the number of avoided lost life-years

[2]See Baker et al. (2008) for a discussion of the restrictions on the underlying social welfare function that would be required to justify the use of a single common VSL for any hazard affecting any population within a given society.

[3]Strand (2006) develops an intriguing theoretical model with both morbidity and mortality effects, in the context of enviromental risks. In his paper, the values for the healthy and ill states are derived from two Bellman dynamic programming equations.

(Viscusi and Aldy 2003, and Mrozek and Taylor, 2002). In most contemporary policy evaluations, researchers typically assign the same estimate of marginal benefit to both the young and the old, and the rich and the poor, by using a single one-size-fits-all VSL. Of course, our approach places new burdens upon researchers involved in policy evaluation to make explicit their assumptions about individuals' current and future income flows, the number of illness-years and/or lost life-years avoided, and appropriate discount rates.

Fourth, our approach should help to reduce the public's perennial semantic confusion about the VSL. We focus on the individual's willingness to pay for a one-in-a-million risk reduction (a "microrisk" reduction, with "micro-" meaning one-millionth) for a specified pattern of future morbidity and premature mortality (Howard, 1984). For the special case of sudden death in the current period, this risk change has been termed a "micromort" (where "mort" signifies mortality risk).[4] Moving away from the VSL terminology has the benefit of avoiding repeated episodes of public outrage caused when people misinterpret the VSL as an arbitrary government dictum about the intrinsic value of a specific human life to be lost with certainty in the current period. In addition, our model is based fundamentally on per-year utility in distinct health states, so no arbitrary conversion of a standard VSL to a per-year VSLY is necessary. Finally, our approach lends itself readily to cross-validation with empirical estimates from conventional approaches since we can consider a special case of our model that corresponds to the scenario of sudden death in the current period represented by a standard VSL.

Ideally, we would prefer to estimate our model with actual demands for risk-mitigating interventions based on market data. However, revealed-preference data of the type needed to identify the relevant tradeoffs do not exist. Thus, we have chosen to administer a nationally representative survey that elicits individuals' choices over alternative risk-mitigation programs in a stated-preference experiment.[5] Each health risk in our study (e.g. the threat of heart disease) is presented as an illness profile that describes a time pattern of health states that the individual could experience with a given probability. Based upon each individual's gender and current age, each health profile is randomly assigned and consists of a description of the individual's most-likely age at future onset (i.e. conveying the "latency" or delayed onset of the illness or injury), the severity and duration of associated morbidity and any treatments, the individual's age at recovery (if recovery occurs), and the number of lost life-years (if the major illness in question can be expected to shorten the individual's

[4] Kneisner and Viscusi (2005) report an average fatality risk in their wage-risk sample of 4/100,000, which would be 40 micromorts. The range across industries and occupations between 1992 and 1997 was 0.6/100,000 to 25/100,000–between 6 and 250 micromorts altogether.

[5] Manski (2004) encounters a similar paucity of data concerning consumer expectations and likewise resorts to eliciting this critical information by using a consumer survey.

lifespan).[6]

After a long preamble and training exercises, our survey presents respondents with sets of illness-specific health-risk reduction programs that involve diagnostic screening and, if necessary, remedial measures that would reduce their probability of experiencing that particular future illness profile. Individuals must pay an annual fee to participate in each risk-reducing program. They are invited to choose one of two risk-reducing programs (each associated with a different illness profile) or to reject both programs. Via their choice, individuals reveal the kinds of trade-offs they are willing to make across specific illnesses and a full continuum of health states of different durations. Rather than attempting to value morbidity and mortality risks separately, as has been done in many other studies, we model the relevant health states simply as different aspects of an overall illness profile. Respondents make choices that reveal their willingness to pay to reduce the risk of suffering a specified illness profile. The implicit value of a sick-year or a lost life-year is determined as in a hedonic model, via the derivatives of the overall willingness to pay with respect to time periods spent in each type of adverse health state.

Our estimates are based on a sample of over 1800 individuals that is more representative of the U.S. population than many of the samples used in past revealed and stated preference studies (especially wage-risk studies, where the sample is limited to those in the workforce). Using our survey data, we assess the most prevalent types of potentially fatal health threats and consider a range of different risk reductions. We also undertake a very wide array of robustness and validity checks, as well as sensitivity analyses. We empirically assess risk comprehension, scope effects, order effects, scenario rejection and sample selection biases. Through careful use of pretesting and numerous revisions to our trial survey instrument, we have also worked hard to mitigate hypothetical bias associated with incentive incompatibility and biases associated with the omission of relevant substitute risks and alternative future health states.

To analyze individuals' program choices, we estimate a translog indirect utility function with heterogeneity such that the utility parameters are permitted to be quadratic in the respondent's current age. We analyze over 7500 choices made by our sample of U.S. adults aged 25 and older.[7] While one goal of this initial analysis is to estimate willingness to pay for

[6] An appendix to this paper provides diagrammatic examples of the concept of different illness profiles used here. In contrast to illness profiles, Van Houtven, Sullivan, and Dockins (2008) use a survey that asks respondents to consider a forced relocation for one year to one of two other cities, where the 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 2 or 5 years of morbidity.

[7] Two other significant studies, Krupnick et al. (2002) and Alberini et al. (2004) survey only people aged 40 and older.

a standardized reduction in mortality risk (i.e. sudden death in the current period,as for a conventional VSL measure), our model also allows us to estimate the implied marginal utility of avoiding a year spent in each of the other two main health states in many illness profiles: morbidity and a post-morbidity recovered/remission state. This is important because we find that individuals value a given reduction in the probability of a lost life-year by less if the lost life-years are preceded by a longer period spent in a state of morbidity associated with a major life-threatening illness.

By way of sensitivity analysis, we illustrate how an estimated willingness to pay for a standardized mortality risk reduction varies, in ways that conform to economic intuition, according to the individual's age and income, as well as the discount rate. Since willingness to pay is merely an inverse demand, it is important to know how this inverse demand differs with both the characteristics of the individual and the attributes of the good in question, which in this case is a modest reduction in the risk of an adverse future health profile.[8]

As noted, to compare our estimates most directly to the vast literature on the VSL, we can easily tailor our willingness to pay estimates for a VSL-type illness profile. However, to illustrate the roles of both latency and a prior period of morbidity, we can also readily use our model to produce a selection of more-general willingness-to-pay estimates. We consider microrisk reductions for the case of a one-year illness followed by recovery/remission, and five years of illness prior to recovery. We also consider the same two profiles followed by death. We also demonstrate WTP as a function of current age, to avoid sudden death, illness with latency followed by death, and a half-year of illness followed by death that is premature by only six months. Thus, rather than just the special case of mortality in the current period, we illustrate how our model can be used to generate willingness-to-pay estimates of the benefits of reducing the risk of suffering a wide variety of illness profiles across an individual's remaining lifespan. For the benchmark VSL-type scenario of sudden death for a 45-year-old with $42,000 in income and a 5% discount rate, however, our data suggest a willingness to pay that would correspond to a VSL of approximately $5.35 million. This is slightly lower than the roughly $6 million VSL employed by the EPA around the time of our survey, although the EPA estimate falls within our approximate 90% interval estimate for this number ($3.56 million to $7.43 million). It is somewhat higher, however, than the number used contemporaneously by the U.S. Department of Transportation.

[8] In this basic paper, space constraints prevent us from illustrating all possible dimensions of heterogeneity, but we offer these few examples and address others in a suite of related papers, currently in preparation.

2 Survey Methods and Data

It is very difficult to identify market data that would adequately illustrate how individuals allocate risk mitigation expenditures across competing risks and across their remaining years of life.[9] Therefore, we have 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 a set of conjoint choice experiments that present individuals with specific illness profiles and programs to mitigate these illness risks. Knowledge Networks administered the final version of this demand survey and the health-profile survey to a sample of 2,439 of their panelists.[10] Our response rate for those panelists contacted was 79 percent. (See our discussion of sample selection assessment techniques below.)

We designed this survey to ameliorate several limitations of existing risk valuation methods. First, many studies have focused on non-representative sub-populations (e.g., working age men) while our sample is of the general population of men and women, including a wide range of ethnicities, age groups, and income groups. Second, many studies focus upon mortality risks from only one source, often ignoring indivduals' marginal rates of substitution between morbidity and mortality states. Furthermore, many of these stated preferences studies focus on only one, or at most two, risk reductions. To enhance representativeness of our estimates of willingness to pay to for health risk reductions, we assess twelve common major health risks over range of different-sized risk reductions. Third, the results of many revealed and stated preference studies may be subject to a biases because they omit relevant substitute risks and mitigating programs from the individual's choice set. In contrast, we strive to establish in the individual's mind a more complete health risk decision environment before asking for tradeoffs with respect to different subsets of these risks.

Here, we review the structure of the survey only briefly.[11] The first module induces the respondent to begin thinking about a wide variety of threats to life and health. This module evaluates the individual's subjective risk assessments for the major illnesses they face, their familiarity with each illness, and any current mitigating and averting behavior they may

[9] Most market data characterize at best only one source of risk (e.g. hedonic wage data) 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, Sloan and Taylor (2004) explored 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.

[10] Panelists are recruited in the Knowledge Network sample using standard RDD techniques. Recruits without home computers are equipped with WebTV technology that enables them also to receive and answer our web-based surveys. More information about Knowledge Networks is available from their website: www.knowlegdenetworks.com. Respondents were paid 10 dollars for completing our survey, in addition to the usual benefits of Knowledge Networks panel membership.

[11] An annotated version of the survey instrument is available from the authors.

undertake. The second module consists of an extensive tutorial that introduces individuals to the idea of an illness profile and programs that may manage these illness-specific risks. It prepares them, attribute by attribute, for the information to be summarized in the upcoming choice sets. The attribute levels in the tutorial are unique to each individual but are identical to those used in the first choice set for that person. The illnesses we describe are labeled as prostate cancer, breast cancer, colon cancer, skin cancer, lung cancer, heart disease, heart attack, stroke, respiratory diseases, diabetes and Alzheimer's disease.[12]

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 lifetime. Each major illness is described in terms of the period(s) of moderate to severe pain and disability that would be involved (with the interpretation of the terms "moderate" and "severe" pain and disability described during the tutorial portion of the survey). This illness profile involves specific intervals of time (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.[13] We summarize the key attribute levels employed in our choice set in Table 1, including the frequencies with which each of the twelve randomly assigned illness names appeared in the choice sets. Up to eleven attributes characterize each illness profile and program, although we concentrate on just the main attributes in this paper.[14] In other work, we explore heterogeneity in the marginal utilities associated with future health states according to the illness names used in the choice scenarios. Here, we assume homogeneity in preferences along these dimensions and focus primarily on the timing and duration in each health state. Given that these other attributes were randomly assigned, the preference parameters we estimate here can be viewed as the averages across the types of major health threats covered by our study. In terms of the number and type of attributes, our design is comparable to existing state-of-the-art health valuation studies (Viscusi et al., 1991; O'Connor and Blomquist, 1997; Sloan et al., 1998; Johnson, et al., 2000). It should also be made clear that we seek to estimate demand conditional in this case on the range, across all individuals, in people's

[12] There is also an adaptation for traffic accidents.

[13] Each illness was randomly assigned a particular name, although we then 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). In this paper, we rely on the extensive randomization of this assignment to minimize omitted variables bias in the specifications we consider here.. Controlling for illness names would of course reduce the error variances in the model. We explore the systematic effects of illness labels in a separate paper.

[14] These illness profiles included the illness name, the age of onset, medical treatments, duration and level of pain and disability, and a description of the outcome of the illness. Our selection of these attributes was guided by a focus on those attributes that 1) most affected the utility of individuals and 2) spanned all the illnesses that individuals evaluated (Moxey et al. 2003).

ex ante information sets about each health risk.[15] Appendix A provides one example of a choice set from our main survey instrument.

After presenting an illness profile, we next explain to individuals that they could 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 current and future periods of their life. 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.[16] The effectiveness of these programs is described in four ways: 1) graphically, with a risk grid, 2) in terms of risk probabilities, 3) in terms of measures of relative risk reduction across the two illness profiles and 4) as a qualitative textual description of the risk reductions (Corso et al., 1999; Krupnick et al., 2002). 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.[17] For the sake of concreteness we ask respondents to assume that to reap the health risk reduction offered, these payments would be needed each year for the remainder of their lifespan (although test subjects assumed they would not need the program during the time they actually experienced the illness).

The third module contains the five main choice sets, each offering the individual two programs that reduced the risk of two distinct illness profiles. We carefully 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 reasonable people might choose neither program in some cases.[18] If individuals choose "neither program," we assume that they prefer their status quo risks of these illness profiles to either of the two costly risk-reducing programs in each choice set.[19]

The fourth module contains various debriefing questions that are used to document the individual's status quo health profile and to cross-check the validity of the responses (Baron

[15] Prior to the choice experiments, we ask individuals questions about their subjective assessment of: 1) various background environmental risks, 2) their risk of each illness, 3) their personal experience with illness, and 4) 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.

[16] Depending upon their gender and age, individuals were familiar with comparable diagnostic tests such as mammograms, pap smears and prostate exams, or the new C-reactive protein tests for heart disease.

[17] 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.

[18] These reasons include that they 1) cannot afford either program, 2) did not believe they faced these illness risks, 3) would rather spend the money on other things, 4) believed 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.

[19] Tsuge et al. (2005) use choice experiments to value mortality risk reductions, but do not introduce illness profiles.

and Ubel, 2002). Module five was administered separately from the choice experiments. It collects a detailed medical history of the individual, as well as household socioeconomic information.

Of course, data gathered using a stated preference survey that is hastily developed, poorly designed, or insufficiently validated is rightfully suspect. To ensure data quality, the development of our survey instrument involved 36 cognitive interviews, three pretests (n=100 each) and an unusually large pilot study (n=1,100). The instrument was approximately sixteen months in development, went through several major revisions, and benefitted from expert external review.[20] We also subjected individuals' responses to an extensive set of robustness and validity checks. Due to space limitations, we merely summarize our quality assurance efforts in what follows.

Risk Comprehension Verification. After we administer an extensive risk tutorial and present the risk changes in three forms (textually, graphically and mathematically), we test the individual's risk comprehension. This comprehension test requires individuals to rank the sizes of the risk reductions associated with two risk mitigation programs. Approximately eighty percent of the individuals demonstrate adequate comprehension of the relative risk size reductions of the programs, which is a rate consistent with risk comprehension levels documented in other surveys (Alberini, et al., 2004 and Krupnick et al., 2002).[21]

Mitigation of Biases Associated with Omitted Substitutes. In contrast with many valuation studies that focus on just one or two risks and their associated risk-reduction programs, we endeavor to reduce biases associated with so-called bracketing (Read, et al, 1999) via inclusion of nearly all major competing health risks (and specific programs to reduce them) in at least one of each individuals' choice sets.[22] Presentation of a broad spectrum of major health threats and mortality risks increases the generality of our estimates. Of course, a potential disadvantage of this approach is the cognitive complexity associated with the choice task, which we seek to minimize through careful survey design, and which we evaluate carefully ex post.[23]

[20] We thank Vic Adamowicz, Richard Carson, Maureen Cropper, Baruch Fischhoff, Jim Hammitt, Alan Krupnick, and V. Kerry Smith for their careful reviews of the second of four versions of this instrument, although any remaining errors are our own.

[21] As Harrison and Rutstrom (2006) argue, reliable estimates of the monetary value of risk reductions hinge on respondents' comprehension of mortality risks. Their research suggests that it is indeed possible to elicit subjective beliefs about mortality risks from individuals. We discuss the effects on the estimated parameters of including and excluding individuals from the sample based on their risk comprehension in an appendix.

[22] Ashenfelter and Greenstone (2004) also address the problem of omitted variables and other biases in measuring the value of a statistical life. Competing risks are addressed in Dow et al. (1999).

[23] We assess this concern directly in the survey. After each choice set we ask individuals how difficult each choice was. On a scale of 1 to 5 (very easy to very difficult), the average response for the first choice set was 3.2. This rating fell with each subsequent choice set, suggesting that the choice task became easier with increasing familiarity.

Mitigation of Hypothetical Bias. At the beginning of the valuation module, we include a "cheap talk" reminder–to ensure that respondents carefully consider their budget constraints and to discourage them from overstating their willingness to pay (Cummings and Taylor, 1999; List, 2001). Individuals are instructed, "In surveys like this one, people sometimes do not fully consider their future expenses. Please think about what you would have to give up to purchase one of these programs. If you choose a program with too high a price, you may not be able to afford the program when it is offered. . . ."[24]

Mitigation of Distortions from Provision Rules and Order effects. In order to clarify provision rules for each choice set (Taylor, et al, 2005) and to avoid potential choice set order effects (Ubel et al., 2002; de Bruin and Keren, 2003), we instructed individuals to assume that every choice is binding and to evaluate each choice set independently of the other choice sets. Our empirical analyses show that the first four choice sets appeared largely free of choice task order effects. Individuals did exhibit a slightly higher propensity to select a program from the last choice set, an effect that has also been demonstrated in other similar settings (Bateman, et al, 2004).

Tests for the Effects of Scope on Willingness to Pay. We explore whether individual choices are sensitive to the scope of the illness profile and the scope of the risk mitigating program (Hammitt and Graham, 1999; Yeung et al., 2003). We show, even in the simplest possible choice models, that individuals readily pass the "scope test." Our subjects are highly sensitive to differences in the scope of our key choice-scenario attributes. In Table 2, Model 1 demonstrates that even minimal conditional logit choice models, in terms of the raw program attributes, produce intuitively plausible and strongly significant coefficients on the two most crucial aspects of each program: i.e. a lower cost and a greater risk reduction make a program more attractive. Model 2 shows that the other two most important dimensions of the illness profiles, the number of sick-years and the number of lost life-years for which the risk will be reduced, are also strongly significant determinants of respondents' choices among programs. Respondents are systematically more likely to choose programs which address more serious health threats. (Model 3 will be discussed later.)

Other Validity Checks on Willingness to Pay. We also show that individuals' willingness to pay for these programs varies with several factors as economic theory would predict it should. It rises with income, as shown in the analysis in this paper. For any given age, it rises with the expected incidence of health risks in future years (DeShazo and Cameron, 2005b). It also varies systematically as predicted by economic theory with same-

[24]For a complete description, see the annotated survey instrument available from the authors. We note that Hakes and Viscusi (2007) have demonstrated that the value of a statistical life implied by stated preference survey estimates is not statistically significantly different from estimates of the same quantity derived from seatbelt usage.

illness and other-illness morbidity (DeShazo and Cameron, 2005a)

The Representativeness of Our Estimating Sample. Our estimating sample is very close to being representative of the U.S. population in terms of standard demographic characteristics. Appendix B compares the characteristics of the individuals in our estimating sample with the corresponding population characteristics (e.g., age, income, and gender) from the 2000 Decennial Census. Our final estimating sample consists of 7,520 choices involving 22,560 alternatives. We arrived at this sample after cleaning the data based on two primary quality control criteria. We exclude individuals if they failed to answer correctly the simple risk comprehension question at the end of the survey's risk tutorial. We also exclude individuals if they explicitly rejected the choice scenario.[25] Sensitivity analyses with respect to these conservative data exclusion criteria are presented in Appendix C.

3 A Utility-Theoretic Choice Model

Our structural model interprets individuals' choices as revealing their option prices, in the sense of Graham (1981), for programs that mitigate the risks of future adverse health states. This concept of an option price differs from the one used in the financial literature. Instead, it is defined as the maximum common 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.

While program choices have inter-temporal consequences, our model is one of static decision-making, with future costs and benefits converted into the appropriate present values. We focus on four distinct health states: (1) a existing pre-illness healthy state, also called the latency period (pre), (2) an illness state (ill), (3) a post-illness recovered/remission state (if the illness is non-fatal) (rcv), and (4) a lost life-year (lyl). Let i index individuals and let t index time periods.[26] Let $1\left(pre_{it}\right)$, $1\left(ill_{it}\right)$, $1\left(rcv_{it}\right)$, and $1\left(lyl_{it}\right)$ be a set of mutually exclusive and exhaustive 0,1 indicators for individual i's health state in time period t.[27] Let α_0, α_1, α_2, and α_3 be the undiscounted marginal utilities from one period in each health

[25] We excluded 2,236 choices because the respondent selected "Neither Program" and indicated as the *only* explanation, "I did not believe the programs would work." If any other (economic) reason was also given, however, we retained the choice.

[26] Time is measured in years or months, as needed. Three examples of illness profiles are presented in Table A1, in an appendix available from the authors.

[27] 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.

state.[28] In its simplest form, the individual's indirect utility function in period t might be specified as:

$$V_{it} = f(Y_{it}) + \alpha_0\ 1\left(pre_{it}\right) + \alpha_1\ 1\left(ill_{it}\right) + \alpha_2\ 1\left(rcv_{it}\right) + \alpha_3\ 1\left(lyl_{it}\right) + \eta_{it} \tag{1}$$

where $f(Y_{it})$ is some function of current net income and the $\partial f(Y_{it})/\partial Y_{it}$ gives the undiscounted marginal utility of net income.

In our data, individuals face choices that involve three alternatives: Program A, Program B, or Neither Program (labeled A, B, and N). As we explain our estimating specification, however, we will describe our choice model in terms of just two choices: Program A versus no program (just A and N). The three-alternative case is completely analogous. A key point is that individuals are informed that they have an existing 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.[29] 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.[30]

Let undiscounted indirect utility be V_{it}^{jk} for the i^{th} individual in period t, where $j = A$ if Program A is chosen and $j = N$ if the program is not chosen. The superscript k will be S (denoting "sick") if the individual suffers the illness and H (denoting "healthy") if the individual does not suffer the illness. From the perspective of a program choice made today, individuals will discount the streams of utility derived from each future health state.[31] Let the discount factor be $\delta^t = (1+r)^{-t}$, and employ it to calculate the present discounted indirect utility from these profiles of future health states, which we will denote $PDV(V_i^{jk})$. The discounting process in our model is greatly simplified by the assumption that income in real terms, and utilities from different health states, are constant over time within health

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

[29] 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 1,000] over this time period."

[30] Non-market costs might include the inconvenience of getting to 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 to raise explicitly.

[31] When discounting, we assume the individual uses the same discount rate, r, to discount both future money costs and health states.

states.[32]

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. In this case, the expectation is taken across the binary uncertain outcome of getting sick, S, or remaining healthy, 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 illness be Π_i^{NS} if the individual opts out of the 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 $\Delta\Pi_i^A = \Pi_i^{AS} - \Pi_i^{NS}$, a negative number.

Expected utility (taken across the uncertain sick (S) and healthy (H) states) differs according to whether the individual selects Program A or "no program" (N):

$$\begin{aligned} PDV\left(E\left[V_i^A\right]\right) &= PDV\left(\Pi_i^{AS}V_i^{AS} + \left(1-\Pi_i^{AS}\right)V_i^{AH}\right) \\ PDV\left(E\left[V_i^N\right]\right) &= PDV\left(\Pi_i^{NS}V_i^{NS} + \left(1-\Pi_i^{NS}\right)V_i^{NH}\right) \end{aligned} \tag{2}$$

The difference in present discounted expected utility under Program A versus "No Program" (N) will be assumed to drive the individual's choice. In presenting this measure to be discussed next, denoted using the shorthand notation $\Delta PDV\left(E[V_i^A]\right) = PDV\left(E\left[V_i^A\right]\right) - PDV\left(E\left[V_i^N\right]\right)$, we will make use of a number of abbreviations. The basic discounting term to be applied to anything which is constant over time ("c") between now and the individual's nominal life expectancy, T_i, is $pdvc_i^A = \sum_{t=1}^{T_i}\delta^t$. Given the four discrete health states we consider, the other relevant discounted terms, also summed from $t=1$ to $t=T_i$ include $pdve_i^A = \sum \delta^t 1\left(pre_{it}^A\right)$, $pdvi_i^A = \sum \delta^t 1\left(ill_{it}^A\right)$, $pdvr_i^A = \sum \delta^t 1\left(rcv_{it}^A\right)$, and $pdvl_i^A = \sum \delta^t 1\left(lyl_{it}^A\right)$. These four different health states are mutually exclusive and exhaustive, so $pdvc_i = pdve_i + pdvi_i + pdvr_i + pdvl_i$. 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, $pdvp_i^A = pdve_i^A + pdvr_i^A$.

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. (There will be an analogous utility difference for Program B versus the "Neither Program" alternative in the three-alternative case.) To simplify the notation in what follows, let $cterm_i^A = \left[\left(1-\Pi_i^{AS}\right)pdvc_i^A + \Pi_i^{AS}pdvp_i^A\right]$, the expected number of present-discounted years over which the cost of the program will be paid, given that Program A is chosen. The expecta-

[32] 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.

tion is taken across the chance, $\left(1-\Pi_i^{AS}\right)$, 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). Also let $yterm_i^A = \left[pdvc_i^A - \Pi_i^{AS} pdvi_i^A - \Pi_i^{NS} pdvl_i^A\right]$. This term appears to have no correspondingly intuitive explanation, but it also reflects the pattern of net income with and without the program and with and without getting sick. Then

$$\begin{aligned} \Delta PDV\left(E[V_i^A]\right) &= \left\{f(Y_i - c_i^A)\ cterm_i^A - f(Y_i)\ yterm_i^A\right\} \\ &\quad + \left[\alpha_1 pdvi_i^A + \alpha_2 pdvr_i^A + \alpha_3 pdvl_i^A\right]\ \Delta\Pi_i^{AS} + \varepsilon_i^A \end{aligned} \tag{3}$$

$$\begin{aligned} \Delta PDV\left(E[V_i^A]\right) &= \left\{f(Y_i - c_i^A)\ cterm_i^A - f(Y_i)\ yterm_i^A\right\} \\ &\quad + \alpha_1\left\{\Delta\Pi_i^{AS} pdvi_i^A\right\} + \alpha_2\left\{\Delta\Pi_i^{AS} pdvr_i^A\right\} + \alpha_3\left\{\Delta\Pi_i^{AS} pdvl_i^A\right\} + \varepsilon_i^A \end{aligned} \tag{4}$$

In equation (3), we emphasize the dependence of the net discounted expected utility difference from Program A versus "Neither Program" on (a) the program's implications for the individual's net income (the first term, in the braces) and (b) the size of the risk reduction, $\Delta\Pi_i^{AS}$, that it would achieve. In the special case of sudden death in the current period, $pdvl_i^A = pdvc_i^A$ and $pdvi_i^A = pdvp_i^A = 0$, so the expression $f(Y_i - c_i^A)cterm_i^A - f(Y_i)yterm_i^A$ reduces to $\left\{f(Y_i - c_i^A)\Pi_i^{AH} - f(Y_i)\Pi_i^{NH}\right\} pdvc_i^A$. This just the present discounted value of the difference, due to the program, in expected utility from future net income.

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

In equation (4), all four terms in 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.[33] The basic utility parameters include any parameters β involved in the function $f(Y_i)$ as well as α_1, α_2, and α_3, which are the same marginal utilities appearing in equation (1). These parameters are the focus of our empirical illustration. In what follows, however, it is convenient also to abbreviate the set of terms in equation (3) that involve the discounted health states in the illness profile: $pterm_i^A = \left[\alpha_1 pdvi_i^A + \alpha_2 pdvr_i^A + \alpha_3 pdvl_i^A\right] \Delta\Pi_i^{AS}$.

[33] The underlying complexity of the first term in braces is entirely an artifact of the need to acknowledge different time profiles of income and program costs in the sick and healthy states. Different assumptions would result in different expressions for *cterm* and *yterm*.

The annual option price in the sense of Graham (1981) that will make $\Delta PDV\left(E[V_i^A]\right)$ exactly zero, here called $\widehat{c_i^A}$, can be calculated as:

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

While the payment $\widehat{c_i^A}$ is the maximum *annual* payment the individual is willing to make, these payments are necessary for the rest of the individual's life, so the present value of these payments 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 use the expected present value of this time profile of costs:

$$PDV\left(E\left[\widehat{c_i^A}\right]\right) = cterm_i^A\left[Y_i - f^{-1}\left(\frac{f(Y_i)yterm_i^A - pterm_i^A - \varepsilon_i^A}{cterm_i^A}\right)\right]$$

For comparisons with the rest of the literature, we can scale our present-value expected option price for a risk change of $\Delta\Pi_i^A$ up to a construct that could have, as a special case, an analog to the value of a statistical life. This requires that we normalize arbitrarily on an extremely large 1.00 risk change by dividing this WTP by the absolute size of the risk reduction to produce something which could be dubbed the "value of a statistical illness profile": $VSIP = PDV\left(E\left[\widehat{c_i^A}\right]\right)/\left|\Delta\Pi_i^A\right|$. In a special case where indirect utility is merely linear in net income (i.e. $f(Y_i) = \beta Y_i$, so that $f^{-1} = 1/\beta$), the $VSIP$ is just:

$$VSIP = Y_i pdvl_i^A - \frac{\alpha_1}{\beta}pdvi_i^A - \frac{\alpha_2}{\beta}pdvr_i^A - \frac{\alpha_3}{\beta}pdvl_i^A - \frac{\varepsilon_i}{\beta\left|\Delta\Pi_i^{AS}\right|} \tag{6}$$

where use is made of the fact that $cterm_i^A - yterm_i^A = -\Delta\Pi_i^{AS}pdvl_i^A$, and that division by the negative quantity that is $\Delta\Pi_i^{AS}$ 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*).

This linear case illustrates clearly how the $VSIP$ depends on income as well as the different marginal (dis)utilities of periods of illness, α_1, periods in a post-illness recovered/remission state, α_2, and lost life-years, α_3. The $VSIP$ also depends on the time profiles for each of these states as embedded in the discounted-time terms $pdvi_i^A$, $pdvr_i^A$, and $pdvl_i^A$, and upon the individual's discount rate (implicit in these pdv terms).[34] Heterogeneity in preferences and in the type of health threat (as opposed to its time profile) can be accom-

[34]Subsequent work will preserve 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 infer individual specific discount rates. Here, however, discount rates are presumed to be exogenous and constant across individuals although our empirical analyses explores the senstivity of our results to different discount rates.

modated by making the indirect utility parameters α_1, α_2, and α_3, and even β, depend upon other individual characteristics, notably age.[35,36]

To calculate a measure closest to the conventional VSL, one would assume sudden death in the current year, with no period of illness or post-illness recovered/remission status. 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 as lost life-years. If we assume that $E[\varepsilon_i] = 0$, our analog to the conventional VSL formula in the linear case will be $VSIP = (Y_i - \alpha_3/\beta)\, pdvl_i^A$. Note that the summation in the $pdvl_i^A$ term, in this case, runs from now until the end of the person's nominal life expectancy, and this interval depends upon the individual's current age. Thus, the $VSIP$ will 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, *plus* the monetized value, α_3/β, of the *avoided* disutility from those lost life-years (keeping in mind that the marginal utility from a lost life-year, α_3, is *negative*).

The linear-in-net-income form is simple and convenient, but in this paper we use a model with a square-root relationship indirect utility and net income. A line-search across Box-Cox transformation parameters revealed that the value 0.42 maximized the log-likelihood function and there is a negligible difference between the maximized log-likelihood values for parameters values 0.42 and 0.50. Given the vastly greater convenience of a fixed transformation parameter in terms of the estimation, we elected to approximate preferences using the implied square root function. While this function is less flexible than a quadratic form in net income, it also allows for risk aversion with respect to net income but guarantees monotonicity, which is desirable.[37]

The fitted $VSIP$s from our estimating specification correspond to sets of stylized illness attributes designed into our choice experiments, rather than those associated with the real-world distribution of actual illnesses. Table 1 summarizes the distribution of artificial (and randomized) health profiles used in our survey. To produce estimates of the distribution of willingness to pay for a specific reduction in the risk of a particular illness profile in the population, two things are needed. For the illness in question, one must have an approximate

[35] For example, illness characteristics can 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. Many dimensions of heterogeneity are explored in detail in other papers related to this project.

[36] 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 $VSIP$, however, the error term in the $VSIP$ formula will be heteroscedastic, with smaller error variances corresponding to cases with larger absolute risk reductions, $\left|\Delta\Pi_i^{AS}\right|$.

[37] Risk aversion in the context of the value of a statistical life has been examined by Kaplow (2005).

joint distribution for the illness profile (possible ages of onset, possible reductions in lifespans, and possible outcomes (recovery, sudden death, limited morbidity, chronic morbidity). Also, for the population affected by this health threat, one must have an approximate joint distribution of age and income levels.[38]

With these two joint distributions in hand, one would need to make a large number of random draws from this pair of joint distributions and combine the illness profiles and individual characteristics for each draw using the willingness to pay formulas outlined above. Across a large number of random draws, one could then build up a sampling distribution for the implied $VSIP$. The mean of this distribution would be interpreted as our model's prediction about the average willingness to pay to reduce the risk of this type of health threat affecting this particular population. An overall estimate of willingness to pay, estimated in this fashion and calculated for a given policy by simulation methods, would allow the researcher to more fully capture the policy choice context for the risk in question. The $VSIP$ for a particular illness and a particular affected population could then be scaled down to the relevant sized risk reduction for each individual to produce an estimate of individual willingness to pay for that particular risk reduction. While most previous research quotes estimates of the value of a statistical life in millions of dollars, in this paper we quote willingness to pay for the corresponding microrisk reduction (i.e. a one-in-one-million reduction in a specified type of risk) which can typically be measured simply in dollars.

4 Empirical Estimates

We begin this analysis by using fixed effects three-alternative conditional logit algorithms to estimate choice models to explain respondents' preferred alternatives among risk reduction Program A, risk reduction Program B, and the status quo.[39] The utility-theoretic specifications labeled as Model 3 through Model 7 (in Tables 2 and 3) focus on the marginal (dis)utilities of discounted prospective years spent in each of three health states: morbidity (sick-months or sick-years), a post-illness recovered/remission state, and lost life-years. We also explore interactions between years of morbidity and lost life-years in order to assess the assumption of additive separability that characterizes our most basic model. Using the implied marginal rates of substitution between illness profiles and money, we then construct individual measures of willingness to pay to avoid five archetypical illness profiles. Our

[38] 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.

[39] Fixed effects are employed because each respondent makes five independent choices, although randomization renders fixed effects methods somewhat less important since program attributes will be uncorrelated with most respondent characteristics (other than age).

underlying structural model requires (for now) that we make specific assumptions about individuals' time preferences and about their income expectations if they get sick.

Our basic square-root-of-net-income structural model, which assumes homogeneous preferences, produces the four parameter estimates shown as Model 3 in Table 2.[40] These homogenous-preferences specifications are estimated without sign restrictions and show robust significance and the expected signs on all four primary parameters.[41] The estimated marginal utility of income is positive and declines with the level of income. The marginal utilities of discounted sick-years, post-illness recovered/remission-years, and lost life-years are all negative and very strongly significantly different from zero.

While simple intuition might suggest that death should be far "worse" than illness and recovery/remission, it is important to keep in mind that the units involved are *discounted years* in each health state. In many illness profiles, there are many more life-years lost than there are sick-years, and the lost life-years are always further into the future, so they are discounted more heavily. Thus the marginal utility per discounted health-state year does not convey the overall disutility of total time in that state. Also, the relatively large (dis)utility associated with recovered/remission state reflects the seriousness of the major illnesses our survey describes. Rightfully, respondents do not interpret being recovered or in remission from any of this list of major illnesses as being equivalent to the pre-illness "healthy" state. In fact, there seems to be considerable disutility from the prospect of living, for example, as a cancer or heart-attack survivor. Most people seem to associate recovered/remission status relative to any of these major health threats as involving considerable limitations. For cancers, there is certainly the continued fear of recurrence. The evidence about the marginal (dis)utility of a discounted recovered/remission-year also do not involve diabetes or Alzheimer's disease, since it was not possible to describe credible scenarios with recovery from these diseases.

We now relax the maintained hypothesis in Model 3 that the marginal utilities from each state are independent of the duration of that state and the durations of other health states that characterize the illness profile in question. Our original model was developed in terms of the individual's undiscounted *per-period* indirect utility, where current-period health status is captured only by a set of mutually exclusive and exhaustive dummy variables. At the moment of the individual's program choice, however, each alternative is likely to be

[40] The square-root-of-net-income form allows for risk aversion to financial risk. Eeckhoudt and Hammitt (2004) find that this type of risk aversion increases willingness to pay for risk reductions in definable cases, but that in general, the relationship is theoretically ambiguous.

[41] Not surprisingly, the additional structure in Model 3, as opposed to Models 2, produces a lower maximized value of the log-likelihood function. This is a common tradeoff. The structure is required for a rigorous utility-theoretic interpretation of the results, but the ad hoc model provides a better fit to the data.

perceived in terms of the present value of the sequence of expected future health states it represents. These present values reflect the mix of future health states in each illness profile. If they capture the relevant attributes of each alternative in the individual's choice set, we can consider richer models that allow for diminishing, rather than constant, marginal utilities from present discounted health-state years, and for interactions between the numbers of present discounted years in different health states. In contrast, Model 3 constrains the marginal utility of each health state to be constant and imposes a constant marginal rate of substitution between different health-state-years.

The final line in equation (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 the data for each pdv term by one unit, then we take logarithms. The resulting alternative logarithmic form for the final substantive term in the estimating equation becomes $\{\alpha_1 \log\left(pdvi_i^A + 1\right) + \alpha_2 \log\left(pdvr_i^A + 1\right) + \alpha_3 \log\left(pdvl_i^A + 1\right)\}\Delta\Pi_i^{AS}$. Estimates for a specification using this form are presented as Model 4 in Table 3, which produces a six-point improvement in the log-likelihood function compared to the linear and additively separable structural specification in Model 3. This suggests diminishing marginal utility in avoided present discounted degraded health-state years.

We have noted that systematic selection into a survey sample is a common concern. Model 5 illustrates the consequences of allowing the parameters of the model to vary according to the fitted probability that each respondent appears in our estimating sample. Full-fledged selectivity correction models in multiple-choice conditional logit models are challenging, so we do not attempt them in this paper, although we do estimate a response/non-response model that produces fitted response probabilities for each individual in our sample.[42] We have explored what happens when we allow each basic parameter of our model to vary systematically with the deviation of that individual's fitted response propensity from the median response propensity among all 500,000-plus members of the random-digit-dialed initial Knowledge-Networks recruiting sample. Only the coefficient on the discounted sick-years term differs significantly with the fitted probability that the respondent shows up in our estimating sample. The greater the probability of being in our sample, relative to the median probability, the lesser the disutility the individual appears to experience from a percentage increase in discounted sick-years. While the shift is statistically significant, comparison of

[42] Our selection model takes the over 525,000 original random-digit dialed recruiting contacts for the Knowledge Networks panel and fits a probit model to explain the presence or absence of each household in our final estimating sample. As explanatory variables, we use a set of 15 orthogonal factors derived from a factor analysis of almost 100 census tract characteristics, county voting records, county mortality from each major disease over the previous decade as a fraction of 2000 census population, and the number of hospitals in the same census tract(s) as the address (or telephone exchange) of the contacted household. Discussion of this response/nonresponse model constitutes a separate manuscript, currently under preparation.

Model 5 and Model 4 reveals the relatively minor difference in the magnitude of this key sick-years coefficient across individuals with different response propensities.[43]

Whenever a linear-in-logs form is a better predictor of consumer choices than a linear form, the researcher is typically inclined to explore even more general logarithmic forms. In particular, the translog form represents a second-order local approximation to any arbitrary functional relationship. This form is fully quadratic in all of the log terms and includes all of their pairwise interactions. We have explored the inclusion of all three squared terms and all three interaction terms. The only robustly significant terms are the squared term in $pdvl_i^A$ and an interaction between the $pdvi_i^A$ and $pdvl_i^A$ terms. This more-general specification is presented as Model 6. This specification produces a further eleven-point improvement in the log-likelihood. Our estimates suggest that the *dis*utility of an additional discounted lost life-year shrinks as the number of discounted lost life-years increases. They also suggest that the *dis*utility of an additional discounted lost life-year is lessened by increases in the number of discounted illness-years that precede it (e.g., as the number of years of morbidity preceding death increases, dying earlier becomes less bad).

In this application, however, there is a further complication. The illness profiles that were eligible to be considered by each respondent were constrained by the respondent's current age. No respondent considered 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 $pdvi_i^A$ terms and the $pdvl_i^A$ terms, 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 the number of 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).

To control for the effect of current age on the apparent marginal utility of each health state, we need to allow current age, age_{i0}, to shift the marginal utility parameters. We allow each of the translog coefficients to vary systematically with both age_{i0} and age_{i0}^2 since earlier

[43] We employ differences from the median response probability so that the estimated utility parameters correspond to the simulated case where all response probabilities are exactly equal to the median in the population. We employ the median because the distribution is skewed, with a number of large positive outliers.

empirical research has suggested the presence of quadratic age effects in VSLs.[44] The age shifters on the sick-years and post-illness recovered/remission years terms ($pdvi_i^A$ and $pdvr_i^A$) are statistically insignificant. However, allowing for the significant quadratic-in-age shifters on the linear and quadratic lost life-years terms ($pdvl_i^A$) and on the interaction between the $pdvi_i^A$ term and the $pdvl_i^A$ term, prevents counter-intuitive negative fitted $VSIP$ point estimates for some illness profiles for young respondents. Therefore, we prefer Model 7 in Table 3 (even though the two lower-order age effects on the interaction between the $pdvi_i^A$ and $pdvl_i^A$ terms are not individually statistically significant).[45] To our knowledge, these are the first attempts to estimate, within a single framework, both the age-varying marginal utilities of avoiding a present discounted sick-year and a present discounted lost life-year. 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.[46]

It is relevant to 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 reported for Model 7 in Table 3 to characterize the implied WTP for a microrisk reduction (i.e. a 0.000001 risk 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 illustrative purposes, we tabulate our model's results for just five representative 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, seamlessly, to accommodate morbidity as well as mortality, meaning that it will be less necessary to appeal to the cost-effectiveness literature on quality adjusted life years (QALYs, e.g. Gold et al., 1996) to fill the many gaps in the morbidity valuation literature. (See the discussion by Dickie and List, 2006).

[44] See for example Jones-Lee et al. (1993), Krupnick et al. (2002), and Aldy and Viscusi (2003). 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 $VSIP$s for specific illness profiles. Quadratic forms in age for each of the systematically varying parameters appear necessary to accommodate nonlinearities in these relationships.

[45] There is no robust evidence, in these models, of age heterogeneity in the marginal utility of income.

[46] The only other ordinal-utility benefits measure expressed "per year" is the concept of the value of a statistical life year (the $VSLY$). However, this is not a measure of marginal utility, rather it is constructed by dividing a VSL estimate by the remaining number of expected life-years.

Consider the center column of results in Table 4, for the 5% discount rate assumption, and Simulation 1 (corresponding to the standard "sudden death" illness profile). The estimates from Model 7 suggests that for an individual who is now 45 years old and has income of $42,000, median willingness to pay for a "micromort" is $5.35. Across 1000 random draws from the joint distribution of the estimated parameters, this summarizes the calculated WTP estimate from an equation like equation (6), normalized on a microrisk reduction. The figures in square brackets give the 90% interval fo these simulated values, reflecting the precision of parameter estimation.[47]

The existing willingness to pay estimates (*VSL*s) against which we might compare this number would be the contemporaneous roughly $6-$7 willingness to pay used by the U.S. EPA and the roughly $3-$4 willingness to pay used by the U.S. Department of Transportation– in both cases just for reductions in the risk of sudden death in the current period, on average, without regard to age or income. Remember: WTP for a microrisk reduction is comparable to a VSL divided by one million. The literature review by Viscusi (1993) found that "most of the reasonable estimates of the value of life are clustered in the $3 million to $7 million range" (in 1990 dollars). Mrozek and Taylor (2002) conduct a meta-analysis of labor-market studies that suggests a VSL range from about $1.5 million to $2.5 million. Gayer et al (2002) find tradeoffs in housing prices as a function of environmental risk implying willingness to pay to avoid a statistical cancer case of $4.3 to $8.3 million. Valuing time savings at the wage rate, Ashenfelter and Greenstone (2004) 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, although the sampling error is about one-third of this amount. Ashenfelter (2006) reports VSL estimates between $1.6 million and $6 million for the same data, depending upon functional form. A recent meta-analysis by Kochi et al. (2006) using empirical Bayes pooling to combine the data from forty selected studies between 1974 and 2002, containing 197 VSL estimates for the standard special case, suggest that VSL has a mean of $5.4 million and a standard deviation of $2.4 million. Thus our model produces VSL-type estimates which are squarely in the range produced by other studies.

Our other four simulated distributions of willingness to pay, however, represent new information for which there exist no comparable willingness-to-pay estimates in the existing literature. In Table 4, each of the illness profiles in Simulations 2 through 5 is characterized by onset in the current period. Continuing to focus on the estimates in the middle column,

[47] We acknowledge that the mean of the theoretical distribution of a ratio of asymptotically normal quantities, like these maximum likelihood parameter estimates, is undefined. Thus we describe only the finite-sample medians and 90% ranges to convey a sense of the precision of the parameter estimates and the implications of this precision for fitted WTP.

for a 5% 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 (Simulation 2) is valued at $2.77. In Simulation 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 is valued only at $4.21. Simulation 4 considers one full year of a major illness, followed by death, for which willingness to pay is roughly the same as willingness to pay to avoid sudden death. Finally, in Simulation 5, willingness to pay to reduce the risk of being sick for five years, followed by death, is somewhat less, at $5.04.

The other two columns of results in Table 4 constitute our sensitivity analysis with respect to the discounting assumption used in our models. All three columns of simulated WTP estimates in Table 4 apply to the same individual (45 years old with an income of $42,000), for a microrisk reduction. While the parameter estimates for Models 3 through 7 were all derived under the assumption that $r = 0.05$ we recalculated all of the discounted health-state intervals using two alternative discount rate assumptions and re-estimated Model 7 with the revised constructed variables. The different estimated models are displayed in Appendix Table C2. As expected, fitted willingness-to-pay estimates vary inversely with the assumed discount rate. While the 5% discount rate assumption implies a WTP of roughly $5.35 per microrisk reduction for the sudden death scenario, the median estimates for 3% and 7% rates are about $6.47 and $4.28. Since the maximized value of the log-likelihood is higher and differs minimally for the 3% and 5% estimates, we infer (cautiously) that the average willingness to pay for a microrisk reduction for sudden death, for this type of individual, is more likely to be on the order of $5.35 to $6.47 than $4.28.

The relationship between WTP and income level has also been of great policy interest, especially for forecasting changes in WTP as real incomes grow.. Table 5 reverts to a discount rate of $r = 0.05$ and again reports in bold face in the center column the simulated willingness to pay 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 willingness to pay for arbitrarily selected alternative income levels of $25,000 and $67,500.[48] As expected, willingness to pay 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 fitted median willingness to pay at $25,000 income is only about $3.82 per microrisk reduction, whereas the fitted median willingness to pay at $67,500 income is about $7.34 per microrisk reduction.

Over the interval between $42,000 and $67,500 of income, therefore, the arc elasticity

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

of willingness to pay with respect to income is about 0.76. Based upon market estimates, the meta-analysis by Viscusi and Aldy (2003) finds an income elasticity of the value of a statistical life between 0.5 and 0.6. Newhouse (1992) reports income elasticities for observed health spending substantially less than one, but Hall and Jones (2007) argue that income elasticities should be substantially greater than one and note that health insurance limits people's choices and may mask income effects. They argue that their model "makes a strong prediction that if one looks hard enough and carefully enough, one ought to be able to see income effects in the micro data. Future empirical work will be needed to judge this prediction." The interventions in our study were described as not covered by insurance, so that qualification does not apply in our case. Nevertheless, we still do not see much evidence of support for their prediction that "The value of a statistical life should rise faster than income." Empirically, in a survey conducted in the UK, Italy, and France, Alberini et al. (2006) find that income elasticities of the willingness to pay "increase gradually with income levels and are between 0.15 and 0.5 for current income levels in EU countries."

Table 6 explores the effect of illness latency (the time in the current health state before the illness or injury occurs) on willingness to pay to avoid health risks, for a subject with an assumed 5% discount rate and an income of $42,000. 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 fitted median willingness to pay estimates and 90% ranges for one individual aged 35 now, and for another 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. Considerable variability is present.

Focusing first on the sudden death (now) scenario, our point estimates suggest that the 65-year-old is willing to pay less ($3.48) to avoid sudden death now than the 35-year-old ($5.31), although the 90% intervals for the two willingness-to-pay amounts overlap. Coincidentally, the 65-year-old is willing to pay about 34% less. This number appears to support the U.S. EPA's controversial decision, in 2002, to attempt to use a VSL for seniors that was only 2/3 of the VSL employed for other adults. This decision was reversed in the face of public outcry over the "senior death discount" and the misperception that the agency was arbitrarily asserting that the worth of a human being was less if that person was a senior. Our findings, however, are in line with other evidence that suggests that seniors are willing to pay less than younger adults to reduce risks–at least the risk of sudden death in the current period.

In looking forward to future illnesses, however, both the 35-year-old and 65-year-old individuals are willing to pay less to avoid the same illness profile when it commences at a later age. In contrast to other empirical efforts, our model allows willingness to pay to reflect the duration of each type of health state. The numbers of prospective sick-years and

life-years lost in the illness profile in question can be expected to have a substantial effect on willingness-to-pay to avoid that illness profile.

The results in Table 6 can be compared to just a small number of extant empirical studies. Hammitt and Liu (2004) find that willingness to pay declines at a 1.5 percent annual rate for a twenty-year latency period. From our Table 6, delaying the time at which sudden death might occur from 5 years to 25 years reduces willingness to pay by 23 percent for 35-year-olds and by 76 percent for 65-year-olds. Comparing this to the existing empirical literature on latency, Alberini et al. (2006) 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 willingness to pay by more than 60% in samples from both Canada and the U.S.

As a visual summary of the effect of the respondent's age now on willingness to pay for a reduction in the risk of sudden death, we offer Figure 1, which shows the simulated median and 90% confidence interval for this fitted willingness to pay as a function of age now. Recall that age has a statistically significant nonlinear effect on three of the parameters of our model. The combined influence of these three different types of quadratic age effects on the fitted willingness to pay produces an age profile for willingness to pay as displayed in Figure 1, where we note than any instance of negative willingness to pay predicted by the model can be interpreted 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."

There is a growing stock of evidence concerning the relationship between the VSL and age. Aldy and Viscusi (2007) and Krupnick (2007) review the revealed and stated-preference literatures, respectively. Smith et al. (2004) and Evans and Smith (2006) point out that the theoretical results are ambiguous and the empirical results are mixed. Alberini et al. (2004) find that among survey respondents aged 40 years and older, in Canada and the U.S., there is weak support for a decline in willingness to pay with age, but only for the oldest respondents (in the Canadian sample, described in more detail in Krupnick et al. (2002), willingness to pay is about 30 percent lower for persons aged 70 or more). The hedonic wage study of Vicusi and Aldy (2007) suggests that younger workers have a willingness to pay 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 (2008) finds that willingness to pay rises from $3.70 in the youngest group (ages 18-24), peaks at $9.7 between 35-44 (which is also the interval where our maximum occurs), 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.

Our stated preference results suggest for the VSL-type scenario that younger people between 25 and 35 (both workers and those not employed for pay) are willing to pay an

average amount between about $4.90 and $5.80. The general population aged 35-44 are willing to pay somewhere between $5.80 up to $5.95. As ages progress to 55-62, our sample suggests that willing to pay drops from about $5.05 down to about $4.00, and past normal retirement age, between 65 and 80, fitted willingness to pay drops from about $3.70 down to about $2.30. In contrast, Smith et al. (2004) find results which suggest that the oldest and most risk-averse workers require significantly 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.

For comparison, Figures 2 and 3 illustrate age patterns in WTP to avoid two other possible illness profiles. Figure 2 shows an arbitrary illness that lasts five years, ending in death, but with ten years of latency prior to onset. Willingness to pay to reduce the risk of this illness profile also differs systematically with age, but it has a different pattern from the sudden death scenario. (Again, we interpret any negative fitted WTP values as zero.)

The illness profile in Figure 3 may be relevant to many environmental health risks which might cause small 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 5% discount rate, 25- to 60-year-olds are willing to pay less than $0.50 per microrisk reduction to avoid this scenario, but WTP begins to increase quickly after sixty-five. 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.[49]

Finally, we note that due to the space constraints of a single journal article, we do not take advantage of the information in our survey conerning the labels associated with each illness profile, or the many other observable dimensions of heterogeneity across respondents. This omission of illness labels is not expected to lead to much omitted variables bias because the illness labels and other program attributes were randomized to the extent permitted by plausibility. 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, 1993, for an early comprehensive review). However, we know of no single other study which subsumes the broad range of major illnesses addressed symmetrically in this paper.[50]

When evaluating the social benefits of a policy change that alters the incidence of a

[49] Appendix Figure A2 reveals the sensitivity of this pattern to different assumptions about discounting. An early inquiry into the valuation of changes in life expectancy is contained in Rosen (1988).

[50] A study of the different WTP estimates for microrisk reductions of specific named illnesses forms one chapter of a Ph.D. dissertation by [name suppressed for anonymity].

particular illness, there are great advantages to being able to estimate willingness to pay corresponding to a broad spectrum illness profiles associated with any 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 for current period morbidity and mortality from separate valuation methods and studies.

5 Discussion and Conclusions

Unlike many previous empirical efforts to measure willingness to pay to reduce mortality risks, our model does not produce just a single best estimate for the Value of a Statistical Life (VSL) for use in all policy contexts. Instead, our model is best understood as a generalization of the standard single-period, single-risk valuation model. It explicitly allows the individual to allocate risk-reduction expenditures across health risks that come to bear across different future time periods. Our model allows for substitution across different health risks with different time profiles that more-completely characterize the duration of morbidity and the eventual health outcomes that result from those risks.

Rather than focusing on only a single risk of death in the current period, or separately on symptom-days for short-term acute episodes of illness, as has been done in many prior studies, our model considers entire future illness profiles as an individual's objects of choice. Even our most basic estimates of willingness to pay depend fundamentally upon the subject's current age and income. The most significant advantages of this generalization are that it allows us to accommodate (a) varying latencies for different health risks, (b) the severe prior morbidity that may be associated with many mortality risks, and (c) non-fatal as well as fatal risks. Along these three dimensions, our model represents a major departure from previous empirical specifications.

Since our model is a generalization, it produces a new and important type of economic information: distinct estimates of the marginal utilities of avoiding a discounted year of morbidity and a discounted lost life-year (as distinct 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 current age of the respondent (and therefore possibly upon other factors which are correlated with age) and the mix of health states in an illness profile, we have illustrated how to construct average values for a wide range of illness profiles, for individuals of different ages and income levels.

To further enhance the evaluation process for specific risk-reducing programs or policies, we organize our analysis around the task of estimating willingness to pay for a microrisk

reduction for a given illness profile. For validation against existing empirical estimates in the special case of sudden death in the current period, we can specialize our model to produce a simplified construct that is analogous to the more-traditional value of statistical life (VSL). Our more-general $VSIP$ is an analogous willingness-to-pay measure, scaled up to a vast 1.00 risk reduction for the specified illness profile. Policy changes that affect the prevalence and severity of that illness will shift the joint distribution of the duration of morbidity and premature mortality, for specified populations, and our model is capable of assessing the benefits of such broad shifts, although we do not pursue in this paper any combinations of increases in some types of health risks and decreases in others.

Our empirical analyses and simulations illustrate some initial results concerning how marginal utility of risk mitigation varies systematically across individuals. Specifically, we evaluate how the demand for mortality risk reduction varies with the individual's current age and the disease latencies that dictate the future ages at which degraded health states would be experienced. Our results suggest that, however convenient it may be, the presumption that there should be a single one–size-fits-all VSL is probably misguided. While the use of a single number may continue to be dictated by political concerns, the willingness to pay to reduce health risks should be viewed as an inverse demand function (rather than a scalar that is merely proportional to the magnitude of the risk reduction).

Since 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. Just as people of different ages have different demands for many types of consumer goods, they may have different demands for risk reductions. Willingness to pay for risk reductions can furthermore be expected to vary across people or over time according to their income levels. While there is an occasional assertion in the popular press that risk reductions should be valued equally for everyone, some commentators fail to notice that regulations to improve safety, for example, are not gifts to those who are so protected. Instead, the regulation will impose costs upon them in the form of higher prices or taxes, lower wages and/or reduced investment returns. What matters for fairness is the distribution of *net* benefits. Net benefits for different groups in society will depend upon their willingness to pay for any risk reductions and what costs will be imposed upon them in order to achieve these gains. Using an identical average willingness-to-pay estimate for everyone can obscure these important equity considerations.

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Table 1 – Range of Attributes used for Stylized Illness Profiles, by Label Assigned to Health Threat, Means and Standard Deviations (Estimating Sample = 1801 different individuals, 7520 completed choice occasions, 15040 illness profiles, 22560 alternatives)

Health Threat:	Breast Cancer	Prostate Cancer	Colon Cancer	Lung Cancer	Skin Cancer	Heart Attack	Heart Disease	Stroke	Resp. Disease	Traffic Accident	Diabetes	Alzheim. disease
# profiles	697	676	1357	1368	1353	1406	1423	1424	1337	1295	1357	1347
Monthly cost ($)	30.78 (30.09)	28.12 (26.09)	29.35 (28.37)	30.4 (28.7)	30.19 (28.81)	29.85 (29.62)	29.87 (28.63)	30.85 (29.43)	29.77 (29.41)	29.72 (27.92)	29.17 (28.07)	29.84 (28.54)
Risk reduction	0.0033 (0.0016)	0.0034 (0.0017)	0.0034 (0.0017)	0.0034 (0.0017)	0.0035 (0.0017)	0.0035 (0.0017)	0.0034 (0.0017)	0.0034 (0.0017)	0.0034 (0.0017)	0.0034 (0.0017)	0.0033 (0.0016	0.0033 (0.0016)
Latency (pre-illness years)	17.0 (11.0)	18.5 (11.2)	18.4 (11.6)	19.4 (11.5)	17.6 (11.7)	20.5 (12.5)	19.4 (11.9)	21.8 (12.7)	21.4 (12.2)	18.2 (12.3)	18.2 (10.8)	22.6 (12.5)
Illness years	4.9 (3.5)	4.9 (3.9)	8.5 (8.3)	8.3 (7.7)	7.5 (7.3)	3.4 (6.6)	10.2 (8.8)	3.6 (6.4)	7.4 (6.5)	4.0 (7.6)	6.8 (5.8)	6.8 (4.7)
Lost life-years	11.5 (11.4)	12.0 (11.5)	8.9 (9.7)	10.3 (9.8)	10.3 (10.8)	13.5 (11.3)	7.4 (8.4)	12.0 (10.1)	8.0 (7.8)	14.5 (12.5)	13.4 (10.7)	8.8 (6.4)
1(Sudden death)	0	0	0	0	0	0.52	0	0.51	0	0.51	0	0
1(Recovery/remission)	0.60	0.64	0.39	0.23	0.40	0.19	0.26	0.19	0.38	0.19	0	0

Table 2 – Ad Hoc Models; Linear Additively Separable Structural Model (Individuals = 1801, completed choice sets = 7520; no selection correction, fixed effects conditional logit estimates)[a]

	Model 1 Ad hoc	Model 2 Ad hoc	Model 3 Structural
Monthly Cost of Program	-.007581 (9.63)***	-.007491 (9.48)***	-
Risk Reduction: $\left\|\Delta\Pi_i^A\right\|$	89.27 (9.95)***	57.64 (5.77)***	-
Sick-Years	-	.008795 (3.85)***	-
Lost Life-Years	-	.01139 (7.12)***	-
$(\beta_0)\left[\text{term in } \sqrt{\text{net income}}\right]$	-	-	0.01133 (9.75)***
$(\alpha_{10})\Delta\Pi_i^{jS}\, pdvi_i^j$	-	-	-9.124 (-5.53)***
$(\alpha_{20})\Delta\Pi_i^{jS}\, pdvr_i^j$	-	-	-8.606 (-2.67)***
$(\alpha_{30})\Delta\Pi_i^{jS}\, pdvl_i^j$	-	-	-7.889 (-6.01)***
Log-likelihood	-11735.125	-11706.105	-11726.019

[a] Asymptotic t-test statistics in parentheses (***=statistically significant at the1% level; **=statistically significant at the 5% level)

Table 3 – Evolution of Fixed Effects Conditional Logit Estimating Specification (Individuals = 1801, Completed choice sets = 7520)

	Model 4	Model 5	Model 6	Model 7
(Parameter) Variable	Simple Logs	w/ P(select)	Translog	Quad in Age
$(\beta_0)\left[\text{term in } \sqrt{\text{net income}}\right]$	.01285 (10.48)***	.01281 (10.45)***	.01459 (11.13)***	.01288 (9.46)***
$(\alpha_{10})\Delta\Pi_i^{jS}\log\left(pdvi_i^j+1\right)$	-27.13 (4.71)***	-29.45 (5.04)***	-53.11 (6.08)***	-50.52 (5.76)***
$\ldots(\alpha_{13})\left[P(sel_i)-\overline{P}\right]\Delta\Pi_i^{jS}\left[\log\left(pdvi_i^j+1\right)\right]$	-	3.267 (2.27)**	3.25 (2.26)**	3.358 (2.33)**
$(\alpha_{20})\Delta\Pi_i^{jS}\log\left(pdvr_i^j+1\right)$	-22.81 (2.45)**	-22.87 (2.46)**	-20.11 (2.16)**	-17.09 (1.82)*
$(\alpha_{30})\Delta\Pi_i^{jS}\log\left(pdvl_i^j+1\right)$	-29.23 (5.88)***	-29.15 (5.86)***	-71.62 (3.91)***	-560.9 (3.14)***
$\ldots\ (\alpha_{31})age_{i0}\cdot\Delta\Pi_i^{jS}\log\left(pdvl_i^j+1\right)$	-	-	-	19.57 (2.70)***
$\ldots\ (\alpha_{32})age_{i0}^2\cdot\Delta\Pi_i^{jS}\log\left(pdvl_i^j+1\right)$	-	-	-	-.1802 (2.60)***
$(\alpha_{40})\Delta\Pi_i^{jS}\left[\log\left(pdvl_i^j+1\right)\right]^2$	-	-	11.56 (1.42)	193.6 (2.35)**
$\ldots(\alpha_{41})age_{i0}\cdot\Delta\Pi_i^{jS}\left[\log\left(pdvl_i^j+1\right)\right]^2$	-	-	-	-7.481 (2.23)**
$\ldots(\alpha_{42})age_{i0}^2\cdot\Delta\Pi_i^{jS}\left[\log\left(pdvl_i^j+1\right)\right]^2$	-	-	-	.07147 (2.20)**
$(\alpha_{50})\Delta\Pi_i^{jS}\left[\log\left(pdvi_i^j+1\right)\right]\cdot\left[\log\left(pdvl_i^j+1\right)\right]$	-	-	35.69 (4.42)***	104.7 (1.43)
$\ldots\ (\alpha_{51})age_{i0}\cdot\Delta\Pi_i^{jS}\left[\log\left(pdvi_i^j+1\right)\right]\cdot\left[\log\left(pdvl_i^j+1\right)\right]$	-	-	-	-4.494 (1.58)
$\ldots\ (\alpha_{52})age_{i0}^2\cdot\Delta\Pi_i^{jS}\left[\log\left(pdvi_i^j+1\right)\right]\cdot\left[\log\left(pdvl_i^j+1\right)\right]$	-	-	-	.0561 (2.10)**
Log L	-11720.22	-11717.53	-11706.67	-11685.48

Table 4 – Simulations: Discount Rate Sensitivity Analysis[a]
(WTP for a microrisk reduction for each benchmark illness profile)

Model 7 Specification; fixed effects conditional logit

	45 years old now; …at 45:	r=3%	**r=5%**	r=7%
1.	Sudden death	$ 6.47 (4.66, 8.41)	**$ 5.35 (3.56, 7.43)**	$ 4.28 (2.52, 6.33)
2.	1 yr sick; recovery/ remission	3.11 (1.58, 4.71)	**2.77 (1.49, 4.18)**	2.63 (1.24, 4.00)
3.	5 yrs sick; recovery/ remission	4.64 (3.12, 6.34)	**4.21 (2.92, 5.65)**	3.96 (2.64, 5.40)
4.	1 yr sick; then die	6.58 (4.92, 8.52)	**5.30 (3.59, 7.24)**	4.06 (2.43, 5.89)
5.	5 yrs sick; then die	6.54 (4.66, 8.76)	**5.04 (3.27, 7.11)**	3.72 (2.02, 5.84)

[a] Across 1000 random draws from the joint distribution of estimated parameters: median, 5th and 95th percentiles of the sampling distribution of calculated *VSIP*. Estimated parameters differ somewhat with the discount rate assumption employed in the construction of the estimating variables. Income = $42,000.

Table 5 – Income Sensitivity Analysis[a]
(WTP for a microrisk reduction for each benchmark illness profile)

Model 7 Specification; fixed effects conditional logit

	45 years old now; …at 45:	y=$25,000	**y=$42,000**	y=$67,500
1.	Sudden death	$ 3.82 (2.49, 5.46)	**$ 5.35 (3.56, 7.43)**	$ 7.34 (5.06, 9.72)
2.	1 yr sick; recovery/ remission	2.16 (1.11, 3.31)	**2.77 (1.49, 4.18)**	3.54 (1.81, 5.39)
3.	5 yrs sick; recovery/ remission	3.27 (2.18, 4.46)	**4.21 (2.92, 5.65)**	5.35 (3.68, 7.16)
4.	1 yr sick; then die	3.82 (2.51, 5.38)	**5.30 (3.59, 7.24)**	7.25 (5.13, 9.47)
5.	5 yrs sick; then die	3.70 (2.28, 5.39)	**5.04 (3.27, 7.11)**	6.83 (4.59, 9.47)

[a] Across 1000 random draws from the joint distribution of estimated parameters: median, 5th and 95th percentiles of the sampling distribution of calculated *VSIP*. Estimated parameters are identical across simulations. Discount rate = 5%.

Table 6 – Latency Effects[a] (*WTP* for a microrisk reduction for each type of illness profile)

	Selected Illness Profiles (Model 7 Specification; fixed effects conditional logit)				
Age: Onset	Sudden death	1 year sick, recovery/ remission	5 years sick, recovery/ remission	1 year sick, then die	5 years sick, then die
Now 35 years old:					
Now	$ 5.31 (2.97, 7.58)	$ 2.92 (1.51, 4.37)	$ 4.39 (2.98, 5.98)	$ 5.28 (3.27, 7.28)	$ 5.31 (3.01, 7.85)
At age 40	5.08 (3.21, 6.91)	2.60 (1.3, 3.93)	3.92 (2.67, 5.36)	5.12 (3.51, 6.68)	5.22 (3.49, 7.2)
At age 50	4.53 (3.34, 5.79)	2.03 (0.97, 3.08)	3.06 (2.09, 4.2)	4.67 (3.63, 5.71)	4.88 (3.81, 6.14)
At age 60	3.89 (2.88, 4.99)	1.52 (0.75, 2.33)	2.29 (1.58, 3.09)	4.01 (3.1, 4.99)	4.15 (3.35, 5.16)
At age 70	2.97 (2.09, 3.93)	1.06 (0.57, 1.59)	1.57 (1.15, 2.07)	3.01 (2.19, 3.93)	3.00 (2.32, 3.84)
At age 80	1.61 (1.06, 2.24)	0.63 (0.42, 0.86)	0.92 (0.75, 1.14)	1.57 (1.07, 2.13)	1.25 (0.98, 1.59)
Now 65 years old:					
Now	$ 3.48 (1.54, 5.43)	$ 2.74 (1.44, 3.97)	$ 3.81 (2.52, 5.07)	$ 1.51 (-0.27, 3.27)	$-0.85[b] (-3.05, 1.04)
At age 70	3.07 (1.78, 4.45)	2.4 (1.26, 3.49)	3.37 (2.27, 4.42)	1.74 (0.58, 2.88)	0.08 (-1.27, 1.27)
At age 80	2.25 (1.36, 3.18)	1.71 (0.95, 2.47)	2.37 (1.76, 3)	1.80 (1.07, 2.51)	1.37 (0.69, 2.03)
At age 90	0.73 (0.16, 1.25)	0.71 (0.39, 1.01)	1.44 (1.07, 1.81)	0.71 (0.39, 1.01)	-[c]

[a] Across 1000 random draws from the joint distribution of estimated parameters: median, 5th and 95th percentiles of the sampling distribution of calculated *VSIP*. Signs of parameters are unconstrained.

[b] For our square-root-in-net-income model, negative point estimates for the VSIP can result when there is a random draw from the fitted distribution of the marginal utility of income that is negative, even if the estimated marginal (dis)utilities of health states have the right signs. However, the quadratic-in-age forms for marginal (dis)utilities can produce negative draws for extreme values of age.

[c] 95 years is beyond the nominal life expectancy of 65-year-olds, so this simulations is not appropriate

Figure 1: Sudden death

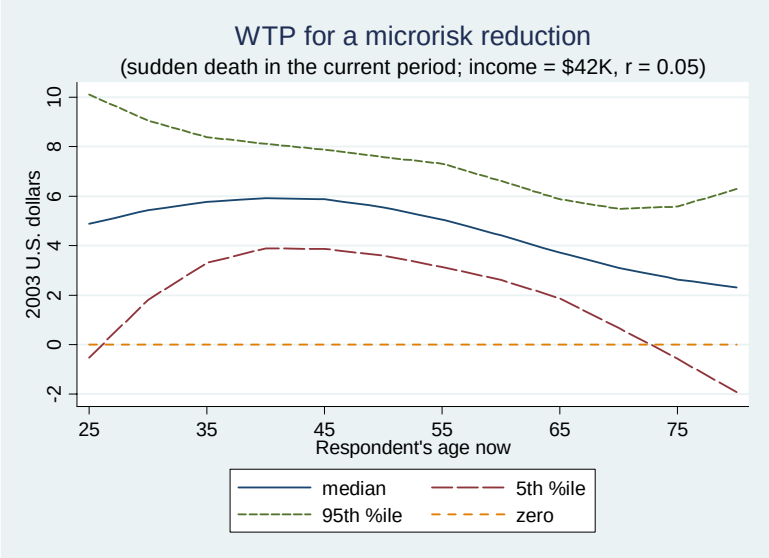


Figure 2: 10 years latency,
5 years sick,
then die

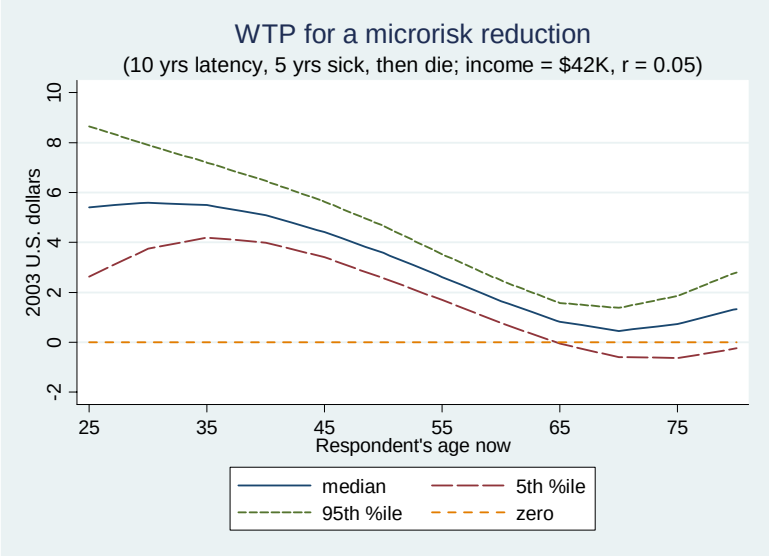
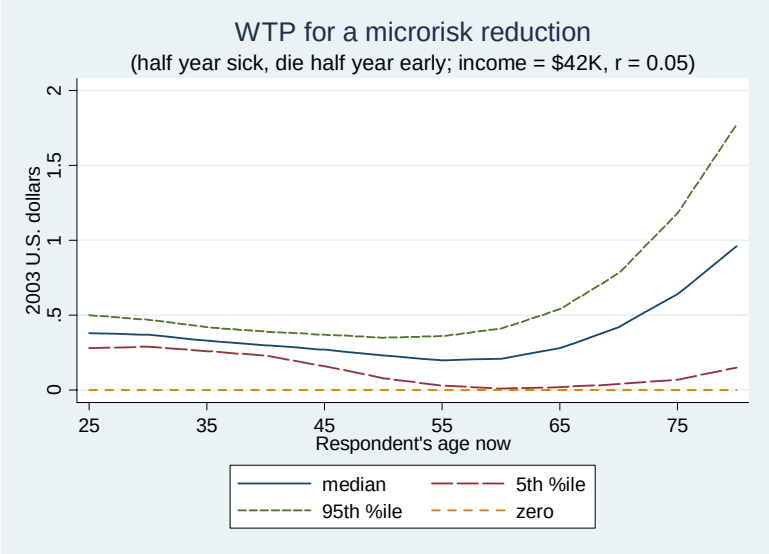
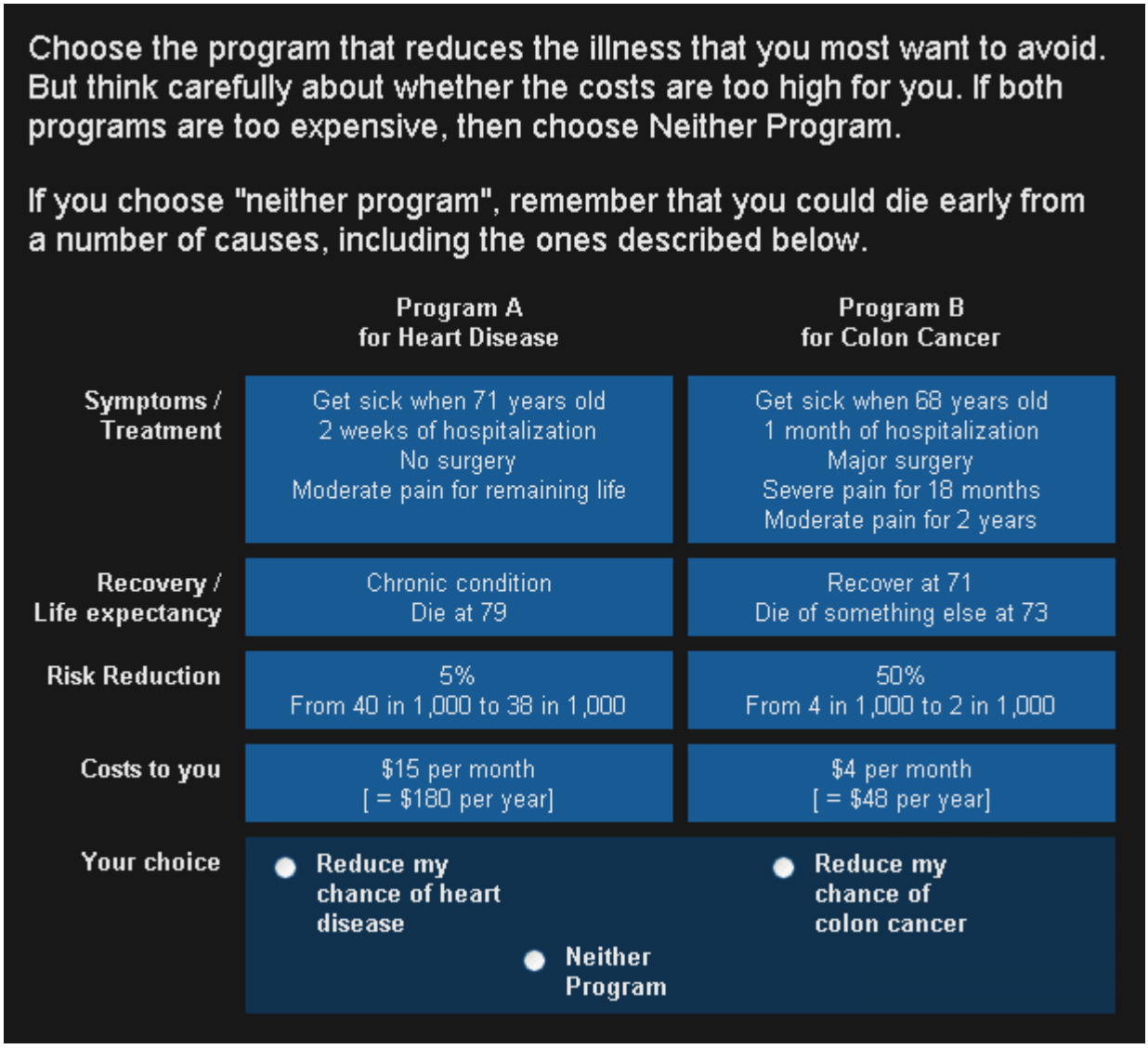


Figure 3: End-of-life effects



Appendix A

Example: One Randomization of a Conjoint Choice Set



Appendix B – Available from the Authors

Table B1 – Sample versus Population Characteristics (percent)

	Sample (n=1801 Individuals)	2000 U.S. Census
Age		% of 25+ pop
25 to 34	16.7	22
35 to 44	22.8	25
45 to 54	21.5	21
55 to 64	17.7	7
65 to 74	14.3	6
75 and older	6.9	10
Income		% of hhlds
Less than $10,000	5.7	9.5
$10,000 to $15,000	6.1	6.3
$15,000 to $20,000	5.1	6.3
$20,000 to $25,000	6.4	6.6
$25,000 to $30,000	6.6	6.4
$30,000 to $40,000	16.2	6.4
$40,000 to $50,000	13.2	5.9
$50,000 to $60,000	11.3	10.7
$60,000 to $75,000	10.9	9.0
$75,000 to $100,000	10.2	10.4
$100,000 to $125,000	4.1	10.2
More than $125,000	4.3	5.2
Female	**0.52**	0.51

Appendix C. Available from the authors

Table C1 - Assessing the Impact of Sample Inclusion Criteria; Estimating sample = (4)

Parameter	(1) none	(2) by	(3) by,cr	**(4) by,cr,wk**	(5) by,cr,wk,60	(6) by,cr,wk,80	(7) by,cr,wk,100
β_0	.01758	.01745	.01859	**.01288**	.01304	.01292	.01298
	(14.99)***	(14.51)***	(13.75)***	**(9.46)*** **	(9.44)***	(9.21)***	(9.01)***
α_{10}	25.79	24.32	10.85	**-50.52**	-54.91	-53.43	-54.11
	(3.40)***	(3.16)***	(1.28)	**(5.76)*** **	(6.18)***	(5.91)***	(5.84)***
α_{13}	.9532	1.058	1.715	**3.36**	3.22	3.604	3.195
	(0.69)	(0.75)	(1.21)	**(2.33)** **	(2.22)**	(2.35)**	(2.05)**
α_{20}	-.1017	-1.677	-2.407	**-17.09**	-18.28	-19.57	-20.02
	(0.01)	(0.20)	(0.26)	**(1.82)***	(1.93)*	(2.04)**	(2.02)**
α_{30}	-143	-140.2	-337	**-560.9**	-634.9	-645.8	-632.5
	(0.95)	(0.92)	(2.00)**	**(3.14)*** **	(3.51)***	(3.48)***	(3.32)***
α_{31}	9.157	9.185	15.89	**19.57**	21.76	21.48	20.7
	(1.49)	(1.48)	(2.32)**	**(2.70)*** **	(2.97)***	(2.87)***	(2.70)***
α_{32}	-.08259	-.08393	-.1459	**-.1802**	-.1961	-.19	-.1842
	(1.40)	(1.40)	(2.22)**	**(2.60)*** **	(2.80)***	(2.67)***	(2.53)**
α_{40}	83.7	78	126.2	**193.6**	220.7	230.7	230.3
	(1.20)	(1.11)	(1.62)	**(2.35)** **	(2.64)***	(2.70)***	(2.62)***
α_{41}	-4.431	-4.279	-5.953	**-7.48**	-8.327	-8.438	-8.334
	(1.56)	(1.48)	(1.87)*	**(2.23)** **	(2.45)**	(2.44)**	(2.35)**
α_{42}	.04106	.04024	.05626	**.07146**	.07775	.07728	.07692
	(1.48)	(1.43)	(1.82)*	**(2.20)** **	(2.37)**	(2.31)**	(2.26)**
α_{50}	-16.59	-13.18	14.79	**104.7**	98.88	95.1	69.93
	(0.27)	(0.21)	(0.21)	**(1.43)**	(1.34)	(1.25)	(0.89)
α_{51}	-1.388	-1.526	-2.364	**-4.494**	-4.266	-4.17	-3.333
	(0.58)	(0.63)	(0.88)	**(1.58)**	(1.48)	(1.42)	(1.10)
α_{52}	.02469	.02669	.03532	**.0561**	.05478	.05401	.04739
	(1.10)	(1.17)	(1.40)	**(2.10)** **	(2.03)**	(1.96)**	(1.68)*
Alternatives	35151	34155	27795	**22560**	21855	21030	19881
Log L	-18261.826	-17681.838	-14443.724	**-11685.473**	-11308.813	-10882.637	-10287.318

continued…

Parameter	(1) none	(2) by	(3) by,cr	**(4) by,cr,wk**	(5) by,cr,wk,60	(6) by,cr,wk,80	(7) by,cr,wk,100
Sample 5th % [a]	0.00	0.00	0.00	**0.36**	0.37	0.39	0.44
Sample 25th %	0.00	0.00	0.00	**1.32**	1.39	1.45	1.56
Sample 50th %	**0.00**	**0.00**	**0.00**	**2.29**	**2.43**	**2.53**	**2.65**
Sample 75th %	0.00	0.00	0.00	**3.70**	3.95	4.13	4.29
Sample 95th %	0.00	0.00	0.73	**6.12**	6.64	6.92	7.20

Key to inclusion criteria: "by" = choice did not involve an (erroneously designed) life extension from the illness experience; "cr" = passed simple risk comprehension question at end of risk tutorial; "wk" = choice of Neither Program not explained solely by "I did not believe the programs would work" (i.e. scenario rejection); "60" = aggregate time on all five program choice tasks at least 60 seconds (e.g. average time at least 12 seconds per choice set); analogously for "80" and "100." The most substantial incremental impact is associated with the "wk" (weak scenario rejection) criterion.

[a] For the distribution of point estimates for fitted *WTP* for a 1/1,000,000 reduction in the risk of each specified illness profile, calculated across the estimating sample (as opposed to "at the means of the data"). The variation in fitted *WTP* values stems from differences in the illness profiles we specify in our survey (for which the distribution does not match the "real" distribution, but spans approximately the same range) and differences in respondents' ages. Our models do not constrain fitted *WTP* amounts to be non-negative, but there is likewise no opportunity for any respondent to convey a negative willingness to pay. At most, they may prefer the status quo, at zero net cost, to any offered program. In these descriptive statistics, we set any individual negative fitted *WTP* estimates to zero.

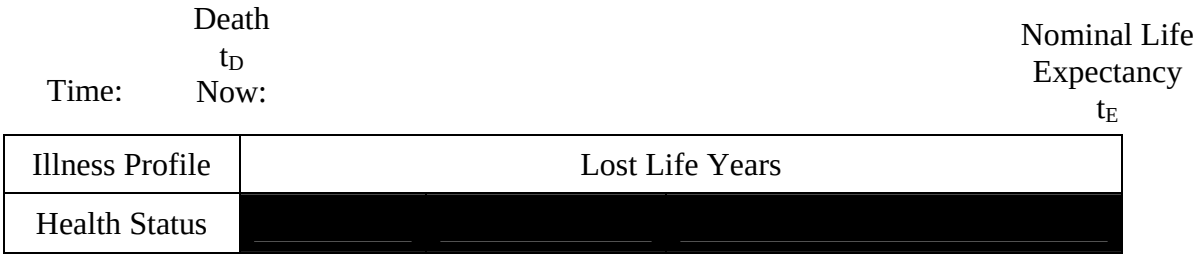
Table C2 – Effect of Discounting Assumption on Parameter Estimates

(1801 Individuals, 7520 completed choice sets, 22560 alternatives)

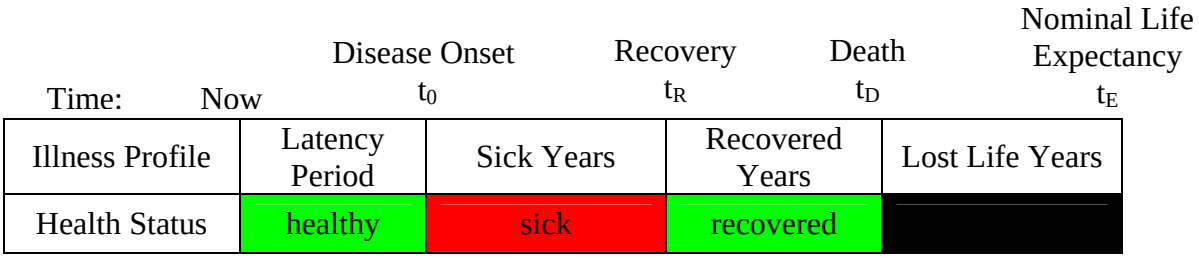
(Parameter) Variable	Model 7	**Model 7**	Model 7
…assuming	r=.03	**r=.05**	r=.07
$(\beta_{00}\times 10^5)[\text{first income term}]$	.01033 (9.48)***	**.01288** **(9.46)*** **	.01518 (9.33)***
$(\alpha_{10})\Delta\Pi_i^{jS}\log(pdvi_i^j+1)$	-42.36 (5.30)***	**-50.52** **(5.76)*** **	-58.67 (6.09)***
$(\alpha_{13})[P(sel_i)-P^*]\Delta\Pi_i^{jS}\left[\log(pdvi_i^j+1)\right]$	2.766 (2.31)**	**3.358** **(2.33)** **	3.989 (2.32)**
$(\alpha_{20})\Delta\Pi_i^{jS}\log(pdvr_i^j+1)$	-13.39 (1.79)*	**-17.09** **(1.82)***	-21.2 (1.81)*
$(\alpha_{30})\Delta\Pi_i^{jS}\log(pdvl_i^j+1)$	-342.4 (2.28)**	**-560.9** **(3.14)*** **	-863.3 (3.94)***
$(\alpha_{31})age_{i0}\Delta\Pi_i^{jS}\log(pdvl_i^j+1)$	12.33 (2.01)**	**19.57** **(2.70)*** **	29.49 (3.37)***
$(\alpha_{32})age_{i0}^2\Delta\Pi_i^{jS}\log(pdvl_i^j+1)$	-.1196 (2.02)**	**-.1802** **(2.60)*** **	-.2612 (3.16)***
$(\alpha_{40})\Delta\Pi_i^{jS}\left[\log(pdvl_i^j+1)\right]^2$	92.68 (1.58)	**193.6** **(2.35)** **	371.7 (3.18)***
$(\alpha_{41})age_{i0}\Delta\Pi_i^{jS}\left[\log(pdvl_i^j+1)\right]^2$	-3.909 (1.60)	**-7.481** **(2.23)** **	-13.63 (2.94)***
$(\alpha_{42})age_{i0}^2\Delta\Pi_i^{jS}\left[\log(pdvl_i^j+1)\right]^2$	.04032 (1.67)*	**.07147** **(2.20)** **	.1232 (2.80)***
$(\alpha_{50})\Delta\Pi_i^{jS}\left[\log(pdvi_i^j+1)\right]\times\left[\log(pdvl_i^j+1)\right]$	75.94 (1.61)	**104.7** **(1.43)**	144.2 (1.32)
$(\alpha_{51})age_{i0}\Delta\Pi_i^{jS}\left[\log(pdvi_i^j+1)\right]\times\left[\log(pdvl_i^j+1)\right]$	-3.393 (1.78)*	**-4.494** **(1.58)**	-5.915 (1.42)
$(\alpha_{52})age_{i0}^2\Delta\Pi_i^{jS}\left[\log(pdvi_i^j+1)\right]\times\left[\log(pdvl_i^j+1)\right]$	.04303 (2.34)**	**.0561** **(2.10)** **	.07231 (1.89)*
Log L	-11684.947	-11685.48	-11688.197
Age at max. of 1st age profile: on $\log(pdvl_i^j+1)$	51.5	54.3	56.5
Age at min. of 2nd age profile: on $\left[\log(pdvl_i^j+1)\right]^2$	48.5	52.3	55.3
Age at min. of 3rd age profile: on $\left[\log(pdvi_i^j+1)\right]\times\left[\log(pdvl_i^j+1)\right]$	39.4	40.1	40.9

Figure A1: Three examples of illness profiles

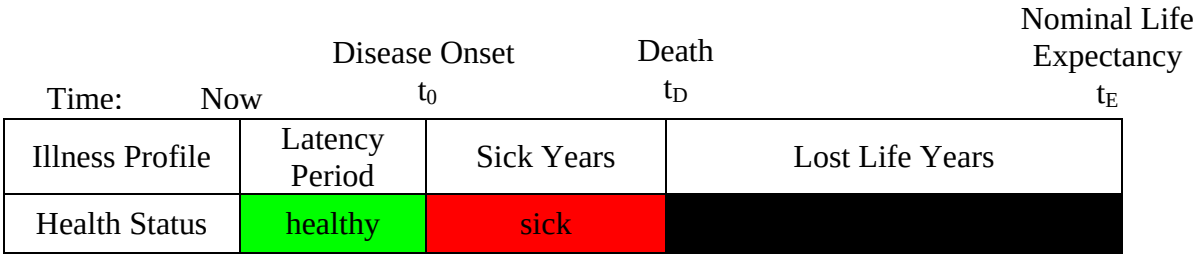
Illness Profile 1: Sudden death in the current period (usual VSL illness profile)



Illness Profile 2: A nonfatal illness (with recovery) that reduces life expectancy



Illness Profile 3: A fatal illness (no recovery)



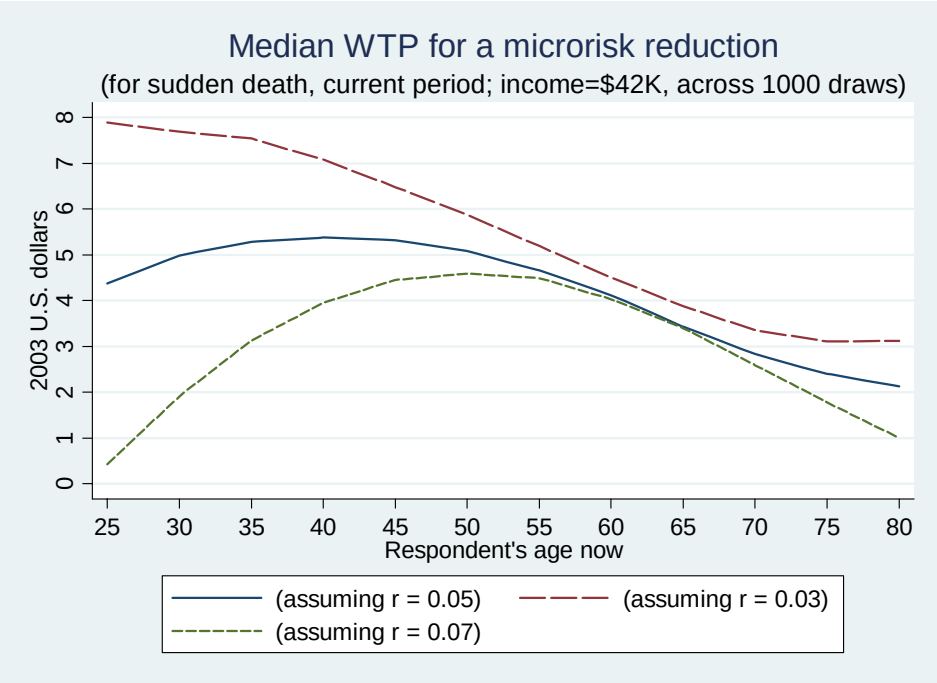


Figure A2 – *WTP* for a microrisk reduction for sudden death now, as a function of respondent age now, for three different discount rate assumptions

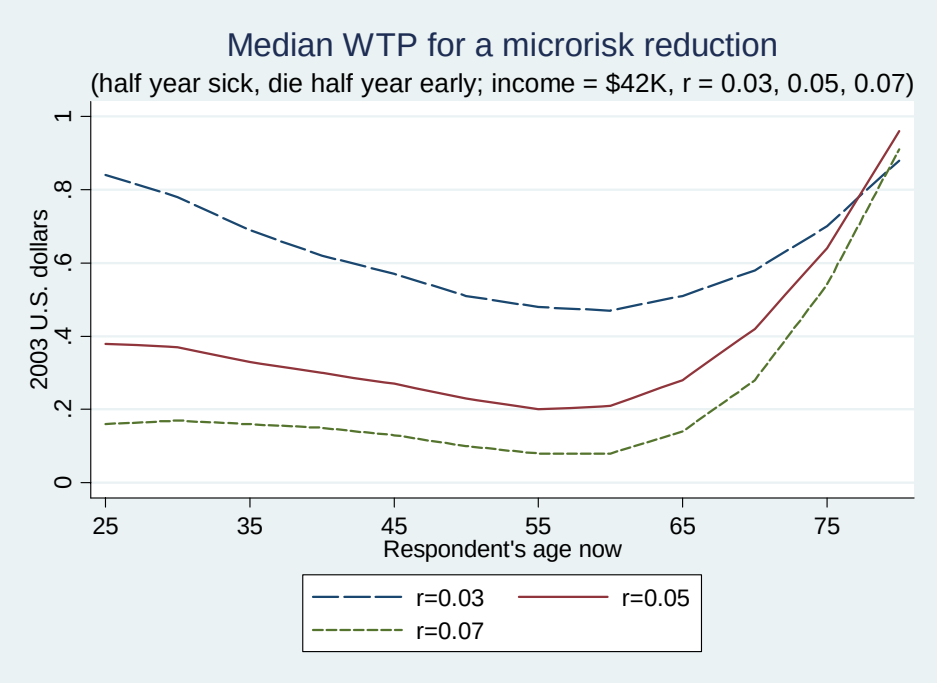


Figure A3 – WTP for a microrisk reduction for six month reduction in life expectancy, preceeded by six months of major illness, as a function of age now, for three different discount rate assumptions

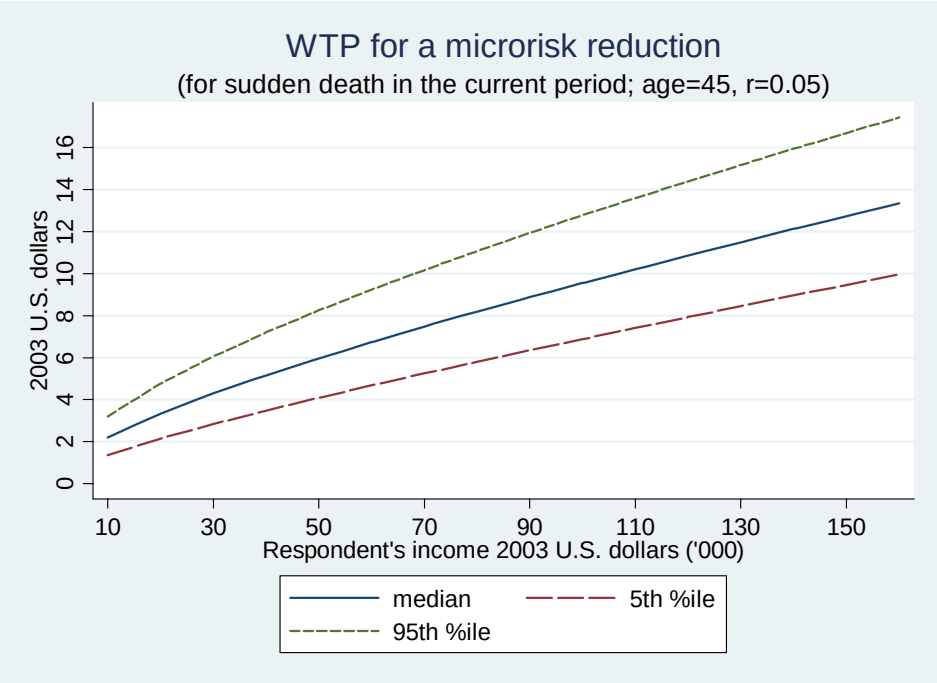


Figure A4 – *WTP* for 1/1,000,000 reduction in risk of sudden death in the current period, as a function of respondent income now in $'000, for a 45-year-old