Demand for Health Risk Reductions

By Trudy Ann Cameron and J.R. DeShazo*

A choice model based on utility in each of a sequence of prospective future health states permits us to generalize the concept of the Value of Statistical Life (VSL). Our representative national survey asks individuals to choose between costly risk-reducing programs and the status quo in randomized stated choice scenarios. We estimate separate marginal utilities for discounted net income and avoided illness years, post-illness years, and lost life-years. Our estimates permit calculation of overall willingness to pay to reduce risks for a wide variety of different prospective illness profiles. These can be benchmarked against the VSL as a special case. (JEL I1, H43, Q51)

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

The conventional approach to measuring the benefits of health risk reductions relies upon

* Cameron: Department of Economics, University of Oregon, Eugene, OR 97403-1285 (e-mail: cameron@uoregon.edu); DeShazo: Department of Public Policy, School of Public Affairs, 3250 Public Policy Building, UCLA, Los Angeles, CA 90095-1656 (e-mail: deshazo@ucla.edu). We thank Kip Viscusi, Vic Adamowicz, Richard Carson, Maureen Cropper, Baruch Fischhoff, Jim Hammitt, Alan Krupnick, and V. Kerry Smith as well as numerous conference and seminar participants for helpful comments. Rick Li implemented our survey very capably. Ryan Bosworth, Graham Crawford, Dan Burghart and Ian McConnaha have provided able assistance. This research has been supported by the US Environmental Protection Agency (R829485), Health Canada (H5431-010041/001/SS), the National Science Foundation (SES-0551009), and the Mikesell Foundation at the University of Oregon. This work has not been formally reviewed by any of these entities. Any remaining errors are our own.
estimates of the marginal rate of substitution between mortality risk and income in the current period. This approach has arisen as a matter of empirical necessity. Benefit measures based on observable choices have tended to come from estimates of current-period wage-risk tradeoffs (Michael W. Jones-Lee 1974, W. Kip Viscusi 1993, George Tolley, Donald Kenkel, and Robert Fabian 1994). These measures of people’s willingness to pay (WTP) for a small reduction in risk are typically used to construct what is known as the Value of Statistical Life (VSL). The VSL scales, proportionally, the dollar-risk tradeoff for a marginal risk change into an aggregate WTP, across individuals, for an aggregate risk change of 1.00.

Policy applications of the VSL typically involve one of two cases. In the first case, a one-size-fits-all VSL is multiplied by an expected overall number of “deaths avoided” to produce an estimate of overall expected benefits.1 In the second case, researchers require an estimate of the value of avoiding just a single year of premature mortality, for example when valuing advances in medical research that may extend life. To answer this need, it has been standard to calculate the “Value of a Statistical Life-Year” (VSLY) by dividing a standard one-size-fits-all VSL by the population average number of expected remaining life-years (David M. Cutler and Elizabeth Richardson 1997, 1998; Kevin M. Murphy and Robert H. Topel 2006).2

Our new approach to measuring the values people assign to health risk reductions represents an improvement over conventional empirical strategies. We begin by modeling utility in future periods of an individual’s life as a function of the health status they will experience in those future periods. We differentiate these future health states as “current health,” “sickness,” “recovered/remission years,” and “lost life-years.” In our stated choice survey (also known as a

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1 A one-size-fits-all VSL has been politically expedient since policy-makers have difficulty explaining the logic for differentiated values to their constituents. Rachel Baker et al. (2008) outline the restrictions on the underlying social welfare function that would be necessary to justify a one-size-fits-all VSL.

2 For an alternative and more sophisticated approach to calculating the VSLY see Michael J. Moore and Viscusi (1988).
conjoint analysis or a discrete-choice experiment), each subject is presented with several opportunities either to purchase one of two illness-specific health-risk reduction programs or stick with their status-quo health risks. These risk reduction “programs” involve diagnostic screening and, when risks are high, medical therapies that would reduce, but not eliminate, their chance of experiencing that particular future illness with its associated pattern of health states. We use the tradeoffs embodied in people’s stated choices to infer their WTP for a given-sized reduction in their baseline risk of experiencing a specified future illness profile. However, these given-sized risk reductions are heterogeneous. The implicit value of an incremental sick year or lost life-year can then be inferred, as in a hedonic model, by taking the derivatives of this overall WTP with respect to the number of sick-years or lost life-years involved.

Our strategy overcomes several limitations of the conventional VSL approach. These limitations have long been recognized by researchers, but have been unavoidable due to the constraints of existing empirical data and methods. We introduce three main innovations. First, we generalize the conventional strategy by more comprehensively defining the good to be valued. Instead of valuing a single mortality risk reduction in the current period, we value risk reductions for a time profile of possible adverse future health states. We can derive benefits measures for a range of health risks that is much wider than usual because our model subsumes myriad patterns of illness, recovery, and lost life-years across the individual’s remaining lifespan. This generalization is needed because the majority of benefits from most health, 

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3 In the past, stated preference methods generated controversy because of concerns that people would overstate their willingness to pay for a public risk reduction. However, over the past ten years, important strides have been made in understanding and minimizing concerns about the incentive compatibility of these choice situations (John List 2001). Indeed, a recent meta-analysis shows that stated preference estimates of the VSL are systematically lower than those produced by revealed preference data (Ikuho Kochi, Bryan Hubbell, and Randall Kramer 2003). We discuss additional validity checks in Appendix C.

4 Jon Strand (2006) considers both mortality and morbidity, but his is a theoretical treatment which emphasizes continuous time.
environmental and safety policies accrue in future years of the individual’s life as opposed to solely in the current period.5

Second, our approach provides direct information on individuals’ preferences over risk reductions in future years of their lives. Individuals express their WTP to reduce their risks of entire time profiles of adverse health states over their remaining lifespans. We do not have to forecast these future estimates from only current-period data. Importantly, we can identify inter-temporal substitutability or complementarity among future health states. This is possible because we estimate demands for health risk reductions that involve many different patterns of illness and lost life-years. For example, the marginal utility of an avoided lost life-year can depend upon whether death is preceded by a period of chronic illness or good health.6,7

Third, our structural random utility model for our subjects’ discrete choices makes it very clear how WTP for reductions in the risk of certain types of health threats depends upon specific variables. WTP depends explicitly on the nature of the health threat, as well as the individual’s age, income, marginal utility of other consumption, and discount rate, reflecting several of the insights offered by Isaac Ehrlich (2000).8

We focus on the individual’s WTP for a “microrisk” reduction (where “micro-” means “one-millionth,” as in Ronald A. Howard 1984). For the special case of sudden death in the current

5 Other researchers have valued risk reductions at one time in the future (e.g. Alan Krupnick et al. 2002, Anna Alberini et al. 2004, James K. Hammitt and Jin-Tan Liu 2004, and George Van Houtven, Melonie B. Sullivan, and Chris Dockins, 2008) but not the reduction of risks involving time patterns of several different adverse health states.
6 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 two locations differ only in their relative and absolute frequencies of fatal stomach, liver, or brain cancer versus car accident deaths. They randomly describe the illness profiles for the cancer as having 5, 15, or 25 years of latency and either 2 or 5 years of morbidity.
7 William H. Dow, Tomas J. Philipson, and Xavier Sala-I-Martin (1999) discuss the importance of competing health risks when one considers the demand for a risk-reducing intervention.
8 Various other researchers have explored the influence of each of these factors on VSLs but not in a comprehensive structural model of intertemporal demand. For age, see Krupnick (2007) and Viscusi and Joseph E. Aldy (2007). For income, see Janusz R. Mrzoez and Laura O. Taylor (2002), Viscusi and Aldy (2003), and Dora L. Costa and Matthew E. Kahn (2004). For future health states, see (Krupnick et al. 2002 and Alberini et al. 2004).
period, this is called *WTP* for a “micromort,” where “mort” signifies mortality risk specifically.\(^9\) We prefer the microrisk metric to the more-typical *VSL* terminology for aggregated risks. Normalization on a smaller risk change retains the assumption of proportionality between *WTP* and the size of the risk reduction but helps avoid the all-too-common episodes of public outrage when people misinterpret the *VSL* as an arbitrary government dictum about the intrinsic worth of a specific human life.

An additional advantage of our model is that it is based fundamentally on per-year utility in distinct health states. Thus no arbitrary conversion of a standard *VSL* to a per-year *VSLY* is necessary. For example, our model makes it straightforward to assess *WTP* for a reduction in the risk of an illness profile that involves dying just one or two years prematurely.

Ideally, we would use market data to estimate our model with actual demands for risk-mitigating interventions. However, revealed-preference data of the type needed to identify the relevant intertemporal tradeoffs do not exist.\(^10\) Thus, we administer a representative national survey wherein 1,801 U.S. adults make choices over alternative risk-mitigation programs in a stated choice survey. Each health risk in our study is described as a time pattern of health states that the individual might experience in the future. Each illness profile is randomly generated but tailored to the individual’s known gender and current age. Each illness profile consists of a description of the individual’s most-likely age when symptoms would begin, known as the “latency” or delayed onset of the illness. The illness profile also describes the severity and duration of the illness, the likely need for hospitalization or surgery, the individual’s age at recovery (if recovery occurs), and the number of lost life-years (if the illness shortens the

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\(^9\) Thomas J. Kneisner and Viscusi (2005) report an average fatality risk in their wage-risk sample of 4/100,000, which would be 40 micromorts. The reported range across industries and occupations between 1992 and 1997 was 0.6/100,000 to 25/100,000 or between 6 and 250 micromorts.

\(^10\) Charles F. Manski (2004) encounters a similar paucity of data concerning consumer expectations and likewise resorts to eliciting this critical information by using a consumer survey.
individual’s lifespan). The individual is informed about what to assume is their baseline risk of experiencing this illness profile as we describe an optional intervention program that would reduce this risk by a specified amount and at a given cost.\textsuperscript{11}

It is important that our sample reflects the overall population of U.S. adults. Many of the samples used in past revealed- and stated-preference studies have not been general-population samples. For example, wage-risk studies are limited to samples of wage-earners. We undertake a wide array of robustness checks, validity assessments and sensitivity analyses. Survey development also involved extensive pretesting, expert review, and numerous revisions to minimize hypothetical bias, incentive incompatibility and a number of other biases that are of concern in any stated choice survey. We use the resulting data to estimate a flexible translog-type indirect utility function with age-wise heterogeneity, using over 7,500 different choices.\textsuperscript{12}

The most-typical VSL approach yields a summary measure for one type of risk for all individuals. The value-added from our approach stems from our ability to produce estimates of $WTP$ for reductions in risk for a virtual continuum of different patterns of future illness and lost life-years. We illustrate the capabilities of our model with a selection of empirical $WTP$ estimates for microrisk reductions for a variety of different health threats. First, we consider a set of five different illness profiles commencing in the current period. Second, we consider the same health threats, but with a variety of different latencies and for individuals of different current ages. Finally, we consider a major illness that starts one year prior to the end of the individual’s nominal expected lifespan and results in death coming six months earlier than otherwise, again for individuals of different current ages. These three kinds of examples demonstrate how our model can be used to value the benefits of a wide range of health risk reductions. This capability

\textsuperscript{11} Takahiro Tsuge, Atsuo Kisimoto and Kenju Takeuchi (2005) use choice experiments to value mortality risk reductions, but do not introduce illness profiles.

\textsuperscript{12} Two other significant studies in this area, Krupnick et al. (2002) and Alberini et al. (2004), survey only people aged 40 and older.
is important when we wish to value both the short-term and long-term benefits of many different types of health, environment and safety programs. Furthermore, these benefits can be differentiated according to the age and income characteristics of the affected populations.

Finally, for the special case of sudden death in the current period, our approach lends itself readily to cross-validation with empirical estimates of the \( VSL \) from earlier approaches, and this bolsters our confidence in the reliability of our \( WTP \) estimates for all of the other types of illness profiles that our new approach can be used to value. Our data suggest a \( WTP \) corresponding to a \( VSL \) of approximately $5.82 million. This is very close to the roughly $6 million \( VSL \) employed by the U.S. Environmental Protection Agency (EPA) around the time of our survey, and the EPA estimate certainly falls within the range of our 5th through 95th percentiles for this number ($3.78 million to $7.79 million).

**I. Survey Methods and Data**

It is very difficult to identify market data that would adequately illustrate differences in individuals’ demands for reductions in the wide variety of health risks that may come to bear across their remaining years of life.\(^{13}\) 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 along with programs to reduce these illness risks by specified amounts. Knowledge Networks administered the final version of our stated choice survey concerning the demand for health risk reductions, as well as their own standard socio-

\(^{13}\) Most market data characterize at best only one source of risk (e.g. hedonic wage data and job-based risk) and are often missing essential variables such as the baseline risk, risk reduction, the latency of the programs or the costs of programs. For example, using the Health and Retirement Survey, Gabriel Picone, Frank Sloan and Donald Taylor Jr. (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.
demographic and health-history surveys, to a sample of 2,439 of their panelists. Our response rate for those panelists invited to participate was 79 percent. (We provide a separate set of detailed appendices to accompany this paper. See Appendix D for a detailed description of the Knowledge Networks panel and a thorough discussion the properties of our sample.)

A. The Survey

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

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14 In brief, panelists are recruited into 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 web-based surveys. More information about Knowledge Networks is available from their website at knowlegdenetworks.com. On top of the usual benefits of Knowledge Networks panel membership (which include free internet access in return for completing a small number of surveys each month), respondents were paid an additional ten dollars for completing our survey.

15 George van Houtven et al. (2003), however, have undertaken a meta-analysis of estimates of the value of reduced morbidity.

16 The value of traffic safety improvements has long been an important policy question (see Jones-Lee et al. 1985).
B. Overview of Survey Modules

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

(i) Module 1.—The first module of our survey 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 we address, their familiarity with each illness, and any current mitigating and averting behavior they may undertake.

(ii) Module 2.—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. This module prepares the respondent, attribute by attribute, for the information to be summarized in the upcoming choice scenarios. The attribute levels used in the tutorial section are unique to each individual, but are identical to those used in the first choice scenario for that person.

Each illness profile is a description of a time sequence of health states associated with a major illness that the individual is described as facing with some existing probability over the course of his or her remaining lifetime. These illness profiles are hypothetical.17 Each major illness is described in terms of its period(s) of moderate and/or severe pain and disability (with the interpretation of the terms “moderate” and “severe” pain and disability described during the tutorial portion of the survey). We also indicate the treatments that could be expected to be necessary, such as hospitalization and minor or major surgery. Each illness profile involves specific intervals of time in each future health state (implicitly the vector of expected values for the actual joint distribution of these durations). The attributes of the illness profiles are randomly

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17 Causes of death are recorded as Vital Statistics but only a few specific illnesses are actually reported.
varied, subject to a few plausibility constraints for each illness type. Just one example of the 7,520 different randomized choice sets used in our main survey is shown in the short appendix included with this paper.

Appendix C provides details about of the randomization of illness profiles. In Table C1 in Appendix C, we summarize the frequency with which each named illness appears among the 15,040 essentially unique randomized illness profiles described in the choice sets used in this study. Table C1 also provides the main types and ranges of the attributes that we used to describe each illness. Up to eleven attributes characterize each illness profile and program, although we concentrate on just the main attributes (sick-years, recovered-years, lost life-years, and program cost) in this paper.

Here, we focus primarily on the timing and duration of each health state. 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. Given that the illness attributes were randomly assigned, however, omitted variables bias will be minimal and the preference parameters we estimate here can be viewed as averages across the different types of major health threats covered by our study.

In terms of its numbers and types of attributes, the complexity of our survey is comparable to that of several existing health valuation studies (Viscusi et al., 1991; Richard M. O'Connor and Glenn C. Blomquist, 1997; Frank A. Sloan et al., 1998; F. Reed Johnson, Melissa Ruby Banzhaf, and William H. Desvousges 2000). We should be clear, however, that we seek to estimate

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

19 Our selection of these attributes was guided by a focus on those attributes that seem most to affect the utility of individuals and could also span all of the different illnesses that individual would be asked to consider.
demand for health risk reductions *conditional* on people's *ex ante* information about each health risk.  

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

The risk-reducing effectiveness of the health programs is described in four ways. In the tutorial section, for the first choice scenario, risks are described (i) graphically, with a 25x40-cell “risk grid” (Phaedra Corso, Hammitt and John D. Graham 1999; Krupnick et al., 2002); (ii) as a qualitative textual description of the risk reduction; (iii) in terms of before-and-after risk probabilities; and (iv) in terms of the percentage risk reduction. The latter two formats are used in all subsequent choice sets for each individual. The payment vehicle for each program is presented as a co-payment that would have to be paid by the respondent for as long as the diagnostic testing and medication are needed. For the sake of concreteness, we ask respondents to assume that, to reap the health risk reductions offered, these payments would be needed annually for the remainder of their lifespan (although test subjects assumed they would not need

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

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

22 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.
the program during the time they actually experienced the illness, should they suffer from it despite the program). These indicated costs are also hypothetical and are randomly varied across alternatives.

(iii) Module 3.—The third module contains the five main choice sets, each offering the individual two programs, each of which reduces their risk of a specific illness profile. We explain to individuals that they have the option to choose neither program if they do not feel that either risk reduction is worth its cost. We point out several possible explanations why a reasonable person might choose neither program in some cases. If individuals choose the “Neither Program” alternative, we assume that they prefer their status quo risks of these illness profiles to either of the two costly risk-reducing programs in that choice set.

(iv) Module 4.—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.

(v) Module 5.—Module five was administered by Knowledge Networks, separate from our survey. Knowledge Networks collects a standard panelist profile that contains household sociodemographic information, as well as a health profile, which provides a detailed medical history for the panelist.

During the course of our study, we undertook several *ex ante* measures to minimize biases via our survey’s design. We also evaluate, *ex post*, the presence of any remaining biases in our data. Appendix D gives the details concerning three *ex ante* criteria used to exclude certain respondents and/or choices from the estimating sample. In Appendix B, we describe our efforts at risk comprehension verification and mitigation of biases associated with the hypothetical

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23 Legitimate economic reasons include that the individual (i) cannot afford either program, (ii) does not believe they face these illness risks, (iii) would rather spend the money on other things, or (iv) believes they would be affected by another illness first. If the individual chooses “Neither Program,” we ask them why they did so in a follow-up question.
nature of the willingness to pay questions, omitted substitutes, order effects in the choice questions, and yea-saying. Also described is the nature of our “external scope test” as well as a general evaluation of the validity of our results from the perspective of economic theory. We also examine concerns about (and the available evidence on) any choice inconsistency that might result from fatigue, informational complexity and respondents’ use of heuristics.  

II. A Utility-Theoretic Choice Model

Our structural choice model interprets individuals’ preferred alternatives as revealing their option prices, in the sense of Daniel A. Graham (1981), for programs that reduce the risks of future adverse health states. This concept of an option price differs from the one commonly used in the financial literature. It is defined as the maximum certain payment, regardless of the uncertainty yet to be resolved, that makes the individual just indifferent between paying for the program and enjoying the risk reduction, or not paying for the program and not enjoying the risk reduction.

A. Marginal (Dis)Utilities from Different Future Health States

While program choices have inter-temporal consequences, our model is one of static decision-making, with future expected costs and benefits first converted into the appropriate present values. Let \( i \) index individuals and let \( t \) index time periods. We focus on four distinct health states: (i) an existing pre-illness healthy state, also called the “latency” period.

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

25 The literature has identified a number of anomalies that cannot be explained by conventional expected utility models and exponential discounting formulas, but these simple specifications can serve as a useful starting point for our analysis. Subsequent research with these data may explore non-expected utility models and different types of discounting.
(pre-illness\textsubscript{i}), (ii) a period of pain and/or disability (illness\textsubscript{i}), (iii) a post-illness recovered/remission state (if the illness is non-fatal) (recovered\textsubscript{i}), and (iv) premature mortality (lost life-year\textsubscript{i}). Let the set of mutually exclusive and exhaustive 0,1 indicator variables, \(1(\text{pre-illness}\textsubscript{i}), 1(\text{illness}\textsubscript{i}), 1(\text{recovered}\textsubscript{i}), \text{and } 1(\text{lost life-year}\textsubscript{i})\), describe individual \(i\)'s health state in each future time period \(t\).\textsuperscript{26} Let \(\alpha_0, \alpha_1, \alpha_2, \text{and } \alpha_3\) be the undiscounted marginal utilities associated with one period in each health state.\textsuperscript{27} In its simplest linear form, the individual’s indirect utility function in period \(t\) might be specified as:

\[
V_i = f(Y_i) + \alpha_0 1(\text{pre-illness}\textsubscript{i}) + \alpha_1 1(\text{illness}\textsubscript{i}) + \alpha_2 1(\text{recovered}\textsubscript{i}) + \alpha_3 1(\text{lost life-year}\textsubscript{i}) + \eta_i
\]

where \(f(Y_i)\) is some additively separable function of current net income so that \(\partial F(Y_i)/\partial Y_i\) gives the undiscounted marginal utility of net income. What follows is merely a sketch of the model. Additional details concerning the development of this model are contain in Section 2 of Appendix E.

**B. Choices Among Programs to Reduce Risks of Future Illness Profiles**

In our data, individuals face choices that involve three alternatives: Program A, Program B, or Neither Program (labeled \(A, B, \text{and } N\)). As we outline our estimating specification, however, we shall describe our choice model in terms of just two alternatives: Program A versus no program (just \(A\) and \(N\)). The three-alternative case is completely analogous. Individuals are informed that they have an existing baseline risk of suffering from the illness or injury in question. Their choice is not between suffering from the illness and enjoying perfect health, since

\textsuperscript{26} 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.

\textsuperscript{27} We interpret the disutility of each adverse health state as equivalent to the utility associated with avoiding it.
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.\textsuperscript{28} 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.\textsuperscript{29}

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

\[ \Delta \Pi_i^{AS} = \Pi_i^{AS} - \Pi_i^{NS}, \text{ a negative number.} \]

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

\textsuperscript{28} 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.”

\textsuperscript{29} Non-market costs might include the inconvenience of visiting the doctor once a year, although this test might be performed in conjunction with a regular annual checkup. More problematic is the unknown extent to which the individual may have balked at the possibility of being asked to take medicines or make “lifestyle changes” in conjunction with the information provided by the test, to achieve the stated risk reduction. Limits on average panelist survey duration unfortunately required tradeoffs about which issues we should raise explicitly.
from these profiles of future health states. This present discounted value (PDV) of expected utility differs according to whether the individual selects Program A or “No Program” (N), and we introduce the following simplifying notation in each case:

\[
PDV \left( E \left[ V_i^A \right] \right) = PDV \left( \Pi_i^{AS} V_{it}^{AS} + \left( 1 - \Pi_i^{AS} \right) V_{it}^{AH} \right) \\
PDV \left( E \left[ V_i^N \right] \right) = PDV \left( \Pi_i^{NS} V_{it}^{NS} + \left( 1 - \Pi_i^{NS} \right) V_{it}^{NH} \right)
\]

(2)

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

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

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30 When discounting, we assume the individual uses the same discount rate, \( r \), to discount both future money costs and health states. The discounting process in our model is greatly simplified by the assumption that income in real terms, and utilities from different health states, are constant over time within each type of health state. Had it been feasible to elicit each individual’s expected time profile of future income, and to convey smoothly changing health states over time, the model could of course be much richer.
an additional term—\( pdvp_i^A = pdve_i^A + pdvr_i^A \)—a measure of total discounted pre-illness and recovered/remission time under the illness profile to be addressed by Program A.

\[ C. \hspace{1em} \text{The Estimating Specification} \]

The discounted expected utility difference that drives the individual’s choice between Program A and the “No Program” alternative can then be expressed in terms of the quantities defined above to produce the most basic version of our estimating specification.\(^{31}\) The net income term (with and without the program) is more complicated than usual, however, because income and program costs are assumed to depend upon whether the individual turns out to suffer from the health risk in question. We assume that the individual expects to retain approximately their current income in real terms through a major illness, but not after death. We also assume that the individual does not expect to pay the cost of the program if they are currently experiencing that illness or if they die from the illness. To accommodate the complexity of probabilistic net income as a consequence of probabilistic future health states, we further simplify the upcoming notation by letting \( cterm_i^A = \left[ \left(1 - \Pi_i^{4S} \right) pdve_i^A + \Pi_i^{4S} pdvp_i^A \right] \). This is the discounted expected number of future healthy years (over which the cost of the program will be paid, if Program A is chosen).\(^{32}\) Also let \( yterm_i^A = \left[ pdve_i^A - \Pi_i^{4S} pdvi_i^A - \Pi_i^{NS} pdvl_i^A \right] \)

\[ = \left[ \left(1 - \Pi_i^{NS} \right) pdve_i^A + \Pi_i^{NS} pdvp_i^A - \Delta \Pi_i^{4S} pdvi \right]. \] This term consists of the discounted expected number of future healthy years without Program A, minus the change in the discounted expected number of sick years due to Program A. Both \( cterm_i^A \) and \( yterm_i^A \) reflect the pattern of net

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\(^{31}\) In the three-alternative case, there will be an analogous utility difference for Program B versus the “Neither Program” alternative.

\(^{32}\) The expectation is taken across the chance, \(1 - \Pi_i^{4S}\), of staying healthy (whereupon the cost would be paid in all future years) and the chance, \(\Pi_i^{4S}\), of suffering the illness in question (so that the cost would be paid only when neither sick nor prematurely dead).
income with and without the program, and with and without getting sick (and more detail on
their derivation is provided in Appendix E). Normalizing on the individual’s current health
status, the difference in discounted expected utilities that drives the individual’s program choice
can then be written as:

\[
\Delta PDV \left( E \left[ V_i^A \right] \right) = \left\{ f \left( Y_i - c_i^A \right) cterm_i^A - f \left( Y_i \right) yterm_i^A \right\} + \left[ \alpha_1 pdvl_i^A + \alpha_2 pdvr_i^A + \alpha_3 pdvl_i^A \right] \Delta \Pi_i^{AS} + \varepsilon_i^A
\]

Equation (3) emphasizes how the net discounted expected utility difference from Program A
depends on two key things: first, it depends on Program A’s net impact on the individual’s
income (the first term, in the braces) and, second, it depends on the size of the risk reduction,
\( \Delta \Pi_i^A \), that Program A would achieve. In the special case of sudden death in the current period
(i.e., the illness profile associated with most wage-risk studies of mortality risk valuation),
\( pdvl_i^A = pdvc_i \) and \( pdvr_i^A = 0 \), so the expression \( \left\{ f \left( Y_i - c_i^A \right) cterm_i^A - f \left( Y_i \right) yterm_i^A \right\} \)
reduces to merely \( \left\{ f \left( Y_i - c_i^A \right) \Pi_i^{III} - f \left( Y_i \right) \Pi_i^{III} \right\} pdvc_i \). This is just the present discounted value
of the difference, due to the program, in expected utility from net income over the individual’s
remaining lifespan.

Equation (3) also emphasizes that the marginal discounted expected utility difference, from
each unit of risk reduction \( \Delta \Pi_i^{AS} \), is given by \( \left[ \alpha_1 pdvl_i^A + \alpha_2 pdvr_i^A + \alpha_3 pdvl_i^A \right] \). This marginal
utility thus 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
marginal utility of the risk reduction, \( \overline{\alpha} = \left[ \alpha_1 pdvl_i^A + \alpha_2 pdvr_i^A + \alpha_3 pdvl_i^A \right] \), rather than the three
distinct marginal (dis)utilities for each type of adverse health state which can be identified here.
Equation (3) can be rewritten slightly to emphasize the estimating specification:

\[
\Delta PDV \left( E \left[ V_i^A \right] \right) = \left\{ f \left( Y_i - c_i^A \right) cterm_i^A - f \left( Y_i \right) yterm_i^A \right\} \\
+ \alpha_1 \left\{ \Delta \Pi_i^{4S} pdvi_i^A \right\} + \alpha_2 \left\{ \Delta \Pi_i^{4S} pdvr_i^A \right\} + \alpha_3 \left\{ \Delta \Pi_i^{4S} pdvl_i^A \right\} + \epsilon_i^A
\]

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. The basic utility parameters include any implicit parameters \( \beta \) involved in the function \( f \left( Y_i \right) \) as well as \( \alpha_1, \alpha_2, \) and \( \alpha_3 \), which are the same marginal utilities appearing back in equation (1). These parameters are the focus of our empirical illustration. The right-hand side of equation (4) is a linear-in-parameters “index” (i.e. the \( x, \beta \) term) that enters into a standard fixed-effects conditional logit choice model. The fixed-effects variant of the specification is relevant because each respondent considers five independent stated choice scenarios, making this a form of panel data.\(^{33}\)

**D. Calculating WTP Estimates**

To outline how to impute willingness to pay estimates, however, it is convenient to abbreviate the set of illness profile terms in equation (3) as \( pterm_i^A = \left[ \alpha_1 pdvi_i^A + \alpha_2 pdvr_i^A + \alpha_3 pdvl_i^A \right] \Delta \Pi_i^{4S} \). The annual option price in the sense of Graham (1981) that will make \( \Delta PDV \left( E \left[ V_i^A \right] \right) \) exactly zero, here called \( \hat{c}_i^A \), can be calculated as:

\[
\hat{c}_i^A = Y_i - f^{-1} \left( \frac{f \left( Y_i \right) yterm_i^A - pterm_i^A - \epsilon_i^A}{cterm_i^A} \right)
\]

\(^{33}\) Appendix E provides the full details of the estimator. This is a standard packaged \texttt{clogit} algorithm within the widely used Stata econometrics program, so we do not reproduce the full log-likelihood function here.
The payment $\hat{\text{A}}$ is the maximum annual payment the individual is willing to make, but these payments are necessary for the rest of the individual’s life, so their present value must be calculated. In this context, however, there is uncertainty over just what will constitute “the rest of the individual’s life,” since this may differ according to whether the individual suffers the illness. We use the discounted expected value of this time profile of costs, which conveniently involves the same $\text{cterms}^4$ construct:

$$PDV \left( E \left[ \hat{\text{A}}^4 \right] \right) = \text{cterms}^4 \left[ Y_i - f^{-1} \left( \frac{f(Y_i) \text{yterms}^4 - \text{pterms}^4 - e_i^A}{\text{cterms}^4} \right) \right]$$

For comparison with the rest of the empirical literature, we can scale our present-value expected option price for a risk change of just $\Delta \Pi_i^4$ to produce a construct that could have, as a special case, an analog to the conventional Value of a Statistical Life ($VSL$). This requires that we take our estimated $WTP$ for the number of microrisk reductions in the stated choice scenario and scale it up to an aggregate risk reduction of 1.00. This can be done by dividing this $WTP$ by the absolute size of the risk reduction in question: $PDV \left( E \left[ \hat{\text{A}}^4 \right] \right) / |\Delta \Pi_i^4|$. Our actual estimating specification will involve a diminishing marginal utility of income, but to illustrate using the easier case where indirect utility is merely linear in net income (i.e. $f(Y_i) = \beta Y_i$, so that $f^{-1} = 1/\beta$), this construct can be written as:

$$PDV \left( E \left[ \hat{\text{A}}^4 \right] \right) \left| \Delta \Pi_i^4 \right| = Y_i pdv_{i}^{A} - \frac{\alpha_1}{\beta} pdv_{i}^{A} - \frac{\alpha_2}{\beta} pdrv_{i}^{A} - \frac{\alpha_3}{\beta} pdvl_{i}^{A} - \frac{\epsilon_{i}^{A}}{\beta |\Delta \Pi_i^{AS}|}$$

34 Here, we make use of the insight that $cterms^4 - yterms^4 = -\Delta \Pi_i^{AS} pdvl_{i}^{A}$, and note that division by the negative-valued $\Delta \Pi_i^{AS}$ is the same as multiplying through by -1 and dividing by the absolute value of this risk change (which we can view as a positive-sized reduction in risk).
To obtain an estimate of WTP for a microrisk reduction, the result in equation (7) needs to be multiplied by 0.000001.

This simpler linear case illustrates clearly how this scaled WTP measure will depend inextricably on income, as well as on the different marginal (dis)utilities of periods of illness, $\alpha_i$, periods in a post-illness recovered/remission state, $\alpha_2$, and lost life-years, $\alpha_3$. Scaled WTP also depends on the time profiles for each of these health states as embedded in the three discounted time-in-health-state terms $pdvi_t^A$, $pdvr_t^A$, and $pdv_t^A$, on the individual’s current age (since this age defines the possible combinations of future health state durations), and upon the individual’s discount rate (implicit in these $pdv$ terms). Heterogeneity in preferences related to the type of health threat (as opposed to its likely profile over time, as captured by the $pdv$ terms) can be accommodated by allowing the indirect utility parameters associated with each type of future health state, $\alpha_i$, $\alpha_2$, and $\alpha_3$, to depend upon other individual characteristics, notably age.

E. Benchmarking Against Conventional VSL Estimates

If we desire a measure that is comparable to the conventional VSL, we can consider an illness profile that consists of sudden death in the current period, with no period of illness and no post-illness recovery/remission. The terms in $pdvi_t^A$ and $pdvr_t^A$ will both be zero. The remainder of

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35 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 financial discount rates. Here, however, discount rates are presumed to be exogenous and constant across individuals although our empirical analyses explore the sensitivity of our results to different assumed discount rates.

36 For example, illness characteristics might be expected to shift the value of $\alpha_i$, the marginal (dis)utility of a sick-year, and possibly the marginal utility of each period in the post-illness state, $\alpha_2$, since the type of illness may connote the degree of “health” that nominal recovery from that illness actually implies.

37 The error term $\epsilon$ is assumed to be identically distributed across observations in a manner appropriate for conditional logit estimation. Given the transformation needed to solve for the willingness to pay measure, however, the error term in the $\hat{C}_i^A$ formula will be heteroscedastic, with smaller error variances corresponding to cases with larger absolute risk reductions, $\left|\Delta\Pi_i^{AS}\right|$. 


the individual’s nominal life expectancy would be experienced simply as lost life-years. If we assume that $E \left[ e_i^4 \right] = 0$, our analog to the conventional $VSL$ formula, in the simplest linear case, would be $\left[ Y_i - (\alpha_3 / \beta) \right] pdv t_i^4$. The summation in the $pdv t_i^4$ term runs from now until the end of the person’s nominal life expectancy, so this interval still depends inextricably upon the individual’s current age. Our $VSL$-type measure will thus vary with age even in a model with homogeneous preferences. The overall monetized value of avoiding one discounted lost life-year, $\left[ Y_i - (\alpha_3 / \beta) \right]$, is given by the chance to enjoy continued current real income (i.e. other consumption) in that year, $Y_i$, minus the monetized value, $(\alpha_3 / \beta)$, of the utility from that lost life-year, which is negative.38

F. Functional Form Considerations for Net Income

The linear-in-net-income form is simple and convenient, but it is typically important to allow for a diminishing marginal utility of income. A line-search across possible Box-Cox transformations of net income—denoted $Y_i^{(\lambda)} = (Y_i^\lambda - 1) / \lambda$, to allow for non-linearity of a general form—reveals that $\lambda = 0.42$ maximizes the log-likelihood function. Given the vastly greater convenience of a fixed transformation parameter in terms of the estimation, we elect to approximate preferences using this particular transformation, which is close to a square root function. This function is less flexible than a quadratic form in net income. However, it allows for risk aversion with respect to net income but still guarantees monotonicity, which is also desirable.39

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38 This can be recast as “plus the monetized value of avoided disutility” by averting a lost life-year.
39 Risk aversion in the context of the value of a statistical life has been examined by Louis Kaplow (2005).
G. Practical Application

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

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

Our model retains the usual assumption that \( WTP \) is proportional to the size of the risk reduction, which allows \( WTP \) to be scaled to any arbitrarily sized risk change. While most previous researchers quote their \( WTP \) estimates in terms of \( VSLs \), we will quote \( WTP \) estimates for one microrisk reduction for a range of illustrative health risks. Most risk reduction policies will concern some larger number of microrisk reductions for each affected individual, so our

\(^{40}\) The illness distributions may be based on expert judgment combined with exposure and epidemiological data for different groups. The age and income data could be drawn from census records for the geographic region in question, if the risk has a spatial character.
estimates will need to be scaled up by that number. Nevertheless, we contend that “WTP for a
microrisk reduction” is less likely to court misinterpretation than the VSL. We preserve
heterogeneity in benefits estimates at the individual level. This stands in contrast with the more-
usual approach, which involves aggregation of physical risk reductions across the affected
populations to produce some number of “statistical lives” saved, followed by the application of a
one-size-fits-all VSL to monetize these benefits.

III. Empirical Estimates and Comparisons to Existing Research

Fixed effects conditional logit methods are appropriate in this context, and our estimation
method is discussed in detail in Appendix E. Appendix E also describes our results for a
number of preliminary specifications that confirm the robustness of the basic features of each
offered program (i.e. cost and the size of the risk reduction) and the main attributes of each
illness profile (i.e. sick-time and lost life-years). Our basic model in equation (1) is couched in
terms of the individual’s undiscounted per-period indirect utility, where future-period health
status is captured only by a set of mutually exclusive and exhaustive dummy variables. Model E3
in Appendix E complies by constraining the marginal utility of time in each health state to be
constant, which also implies a constant marginal rate of substitution between different types of
discounted health-state-years.

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

At the moment of the individual’s program choice, however, it is possible that each
alternative could be perceived simply in terms of the present value of the mix of expected future
health states it represents. We focus on richer models that allow for diminishing, rather than

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41 Randomization, however, renders fixed effects methods somewhat less important since program attributes
will be uncorrelated with respondent characteristics (other than weakly with age and gender).
constant, marginal utilities from discounted health-state years, and for interactions between the numbers of discounted years in different health states.

The final line in equation (3) can easily be adapted to be non-linear in \( pdvi_t^A \), \( pdvr_t^A \), and \( pdvl_t^A \). To accommodate scenarios with zero durations for illness or recovery (including the case of sudden death), we shift all of the data for each \( pdv \) term by one unit, then take logarithms. The resulting alternative logarithmic form for the terms in square brackets on the second line of equation (3) becomes \( \alpha_1 \log (pdvi_t^A + 1) + \alpha_2 \log (pdvr_t^A + 1) + \alpha_3 \log (pdvl_t^A + 1) \). In Table 1, estimates for a specification using this adjustment are presented as Model 1. This specification produces a more than twelve-point improvement in the log-likelihood function compared to the linear and additively separable structural specification given in equation and reported as Model E3 in Appendix E. This suggests diminishing marginal utility in both net income and avoided discounted expected time in degraded health states.\(^{42}\)

Whenever a linear-in-logs form is a better predictor of consumer choices than a linear form, the researcher is typically inspired to explore more-general logarithmic forms. In particular, the translog form represents a second-order local approximation to any arbitrary functional relationship. The translog-type form is fully quadratic in all of the log terms and includes all of their pairwise interactions. We have explored the inclusion of all these terms. The two robustly significant additional terms, which we retain, are the squared term in lost life-years, \( pdvl_t^A \), and an interaction between the sick-years term, \( pdvi_t^A \), and the lost life-years term, \( pdvl_t^A \).\(^{43}\)

In this application, however, there is a further complication. No respondent was asked to consider illnesses that could strike at an age younger than their current age, so current age

\(^{42}\) Appendix E, Figure E2 depicts the effects of alternative transformations of the discounted health state years.\(^{43}\) The results for this specification are not presented separately, although it produces a further improvement in the log-likelihood.
defines the maximum duration of any illness profile. The result is a degree of multicollinearity between the respondent’s remaining nominal life expectancy and the range of sick-years, recovered/remission years, and lost life-years he or she was eligible to consider. In particular, when including interactions between the sick-years term, \( pdvi^i \), and the lost life-years term, \( pdvl^i \), occasional large values of these interaction terms were closely associated with the youth of the respondent. This interaction term is important, since it allows for the possibility that some illnesses may represent “fates worse than death.” If the disutility from a lost life-year falls as prior illness-years increase, it is possible that the disutility from an additional illness-year could surpass that from an additional lost life-year. Or, a lost life-year could actually come to be perceived as a good thing (if the subject believes \textit{ex ante} that in these extreme circumstances, they would be “better off dead” than suffering an additional year of serious illness).

We thus allow each of the translog indirect utility coefficients to vary systematically with the respondent’s current age, \( age_{i0} \), and with \( age_{i0}^2 \), since earlier empirical research has suggested the presence of quadratic age effects in \( VSLs \).\textsuperscript{44} The age shifters on the sick-years and post-illness recovered/remission years terms, \( pdvi^i \) and \( pdvr^i \), are not statistically significantly different from zero. However, there are significant quadratic-in-age shifters on the linear and quadratic terms in the shifted logarithms of lost life-years (\( pdvl^i \)) and on the interaction term between the shifted logarithms of discounted sick-years, \( pdvi^i \), and discounted lost life-years, \( pdvl^i \).

Therefore, we prefer Model 2, even though the baseline coefficient and the lower-order age

\textsuperscript{44} See for example Jones-Lee et al.\textit{(1993)}, Krupnick et al.\textit{(2002)}, and Aldy and Viscusi \textit{(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 \textit{WTP} measures for specific illness profiles. Quadratic forms in age for each of the systematically varying parameters appear necessary to accommodate nonlinearities in these relationships.
effect on the interaction term involving sick-years and lost life-years are not individually statistically significant.45,46

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

\textit{B. Fitted distributions for WTP}

In Tables 2, 3, and 4, we examine how our estimates vary with assumptions about time preferences, as well as with the data concerning each individual’s income, and with current age and prospective disease latency. We employ the estimated parameters from Model 2 to characterize the implied WTP for a microrisk reduction for selected combinations of years of morbidity, years in a post-illness recovered/remission state, and years of premature mortality. A vast range of different illness profiles can potentially be considered, but for illustrative purposes, we report in Table 2 our model’s results for just five arbitrarily selected 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. This capability means it will now be less necessary to appeal to the cost-effectiveness literature on quality-adjusted life years (QALYs,

\footnote{45 There is no robust evidence, in these models, of age heterogeneity in the marginal utility of income. \footnote{46 Model 2 includes a final term designed to offset a small degree of systematic selection in terms of the marginal disutility of illness. Appendix D explains our efforts to identify and control for any systematic selection that may produce a different set of estimated preferences from our estimating sample than may be present in the general population of the U.S.}
e.g. Marthe R. Gold, Louise B. Russell, Joanna E. Siegel, and Milton C. Weinstein, 1996) to fill the many gaps in the morbidity valuation literature. (See the discussion by Mark Dickie and List, 2006).

(i) Five different illness profiles.—Consider the center column of results in Table 2, for the 0.05 discount rate assumption, and illness profile 1 (corresponding to the standard “sudden death” illness profile). The estimates from Model 2 suggest that, for an individual who is now 45 years old and has a household income of $42,000, median \( WTP \) is about $5.82 for a microrisk reduction for sudden death in the current period. Across 1000 random draws from the joint distribution of the estimated maximum likelihood parameters, this median and the corresponding 90 percent interval summarize the calculated \( WTP \) estimates from a formula analogous to equation (6), normalized on a microrisk reduction.\(^{47}\)

For illness profile 1, our estimates can be benchmarked against conventional \( VSL \) estimates, after dividing the \( VSL \) by one million. Contemporaneous \( VSL \) estimates of roughly $6-$7 million used by the U.S. EPA and roughly $3-$4 million used by the U.S. Department of Transportation thus correspond to $6.00-$7.00 and $3.00-$4.00 for a microrisk reduction. Of course, these numbers apply to a reduction in the risk of sudden death in the current period, on average, without regard to age or income. The literature review by Viscusi (1993) suggests 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. 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

\(^{47}\) The mean of the theoretical distribution is undefined, since it pertains to a ratio of asymptotically normal quantities where zero is a possible value of the denominator. Thus we describe only the finite-sample medians and 90 percent ranges to convey a sense of the precision of the parameter estimates and the implications of this precision for fitted \( WTP \).
\( VSL \) has a mean of $5.4 million and a standard deviation of $2.4 million. Thus our model produces, as a special case, \( VSL \)-type estimates which are squarely in the range produced by other studies.\(^{48}\)

Illness profiles 2 through 5 in Table 2, however, represent new information for which there are no comparable \( WTP \) estimates in the existing literature. Each of these illness profiles in is characterized by onset in the current period. Continuing to focus on the estimates in the middle column, for a 0.05 discount rate, we see that a microrisk reduction for “one year of a major illness, followed by recovery/remission with no decrease in life expectancy” (illness profile 2) is valued at $2.96. In illness profile 3, “five years of a major illness,” however, is not valued five times as much, in part because of discounting. The same small risk reduction for this illness profile (with four more years of illness, but four fewer years of recovered/remission time) is valued only at $4.47. Simulation 4 considers “one full year of a major illness, followed by death,” for which \( WTP \) is roughly the same as \( WTP \) to avoid sudden death. Finally, in Simulation 5, \( WTP \) to reduce the risk of being sick for five years, followed by death, is somewhat less, at $5.43. However, all of the 90 percent intervals overlap to some degree.

(ii) Assumptions about discount rates.—Our sensitivity analysis with respect to the discounting assumption used in our models is provided in first and third columns of results in Table 2. All three columns estimates apply to the same type of individual (45 years old with an income of $42,000), for the same sized risk reduction. The parameter estimates for Models 1 and 2 (and models E1 through E3 reported in Appendix E) were derived under the assumption that \( r=0.05 \). We recalculated all of the discounted health-state intervals using two other plausible

\(^{48}\) In other contexts, Ted Gayer, James T. Hamilton, and Viscusi (2002) find tradeoffs in housing prices as a function of environmental risk implying an aggregate \( WTP \) to avoid a statistical cancer case of $4.3 to $8.3 million. Valuing time savings at the wage rate, Orley Ashenfelter and Michael 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. Ashenfelter (2006) reports \( VSL \) estimates between $1.6 million and $6 million for the same data, depending upon functional form.
discount rate assumptions \( (r=0.03 \text{ and } r=0.07) \) and re-estimated Model 2 with the revised constructed variables.\(^{49}\) As expected, the fitted \( WTP \) estimates vary inversely with the assumed discount rate. While the 0.05 discount rate assumption implies a \( WTP \) of roughly $5.82 per microrisk reduction for the sudden death scenario, the median estimates for the 0.03 and 0.07 discount rates are about $6.97 and $4.74.\(^{50}\)

(iii) \( WTP \) as a function of income.—The relationship between \( WTP \) and income level has also been of great policy interest, especially for forecasting changes in \( WTP \) as real incomes grow. Table 3 reverts to a discount rate of \( r = 0.05 \) and again reports in bold face in the center column the simulated \( WTP \) distribution for an individual who is now 45 years old, with an income of $42,000, for each of these five illness profiles. In contrast, the first and third columns show \( WTP \) simulations for arbitrarily selected alternative income levels of $25,000 and $67,500.\(^{51}\) As expected, \( WTP \) is larger when income is greater. For our 45-year-old and the common scenario of sudden death (in the first row of the table), the median \( WTP \) at $25,000 income is only about $3.97 per microrisk reduction, whereas the median \( WTP \) at $67,500 income is about $8.18 per microrisk reduction.

Over the interval between $42,000 and $67,500 of income, therefore, the arc elasticity of \( WTP \) with respect to income is about 0.72. 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. Empirically, in a survey conducted in the UK, Italy, and France, Alberini et al.

\(^{49}\) In Appendix E, the underlying sets of parameter estimates for the different models are displayed in Table E1 and the implications of the different discount rate assumptions for the age profile of \( WTP \) are depicted in Figure E3.

\(^{50}\) The maximized value of the log-likelihood is higher and differs minimally for the 0.03 and 0.05 discount rate estimates, so we infer (cautiously) that the average \( WTP \) for a microrisk reduction for sudden death, for this type of individual, is more likely to be on the order of $5.87 to $6.97 than $4.74.

\(^{51}\) 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).
(2006) find that income elasticities of WTP “increase gradually with income levels and are between 0.15 and 0.5 for current income levels in EU countries.”

(iv) WTP as a function of disease latency.—Table 4 explores the effect of illness latency (the time in the current health state before the illness or injury occurs) on WTP to avoid health risks, for a subject with an assumed 0.05 discount rate and household 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 median WTP estimates (and 90 percent ranges) for one individual aged 35 now, and for another individual aged 65 now. The age at onset of each illness is varied to include immediate onset, as well as onset at decade intervals starting five years from now.

Focusing first on the “sudden death now” scenario in the first column of Table 4, our point estimates suggest that the 65-year-old has a lower WTP ($3.73) to avoid sudden death now than the 35-year-old ($5.78), although the 90 percent intervals overlap. WTP by the 65-year-old is about 35 percent less. This estimate appears to support the U.S. EPA’s controversial attempt, in 2002, to use a VSL for seniors that was only 2/3 of the VSL employed for other adults. 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 WTP by seniors to reduce risks is less than that for younger adults—at least for the risk of sudden death in the current period.

In looking forward to future illnesses, however, as in the subsequent rows of Table 4, both 35-year-olds and 65-year-olds seem to have a lower WTP to avoid the same illness profile when

52 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. However, the interventions in our study were described as not covered by insurance, so this qualification does not apply in our case.
it commences at a later age. Our selection of disease latency results can be compared to just a small number of extant empirical studies. Hammitt and Liu (2004) find that \textit{WTP} declines at a 1.5 percent annual rate for a twenty-year latency period. From our Table 4, delaying the time at which sudden death might occur from 5 years to 25 years reduces \textit{WTP} by 24 percent for 35-year-olds and by 78 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 \textit{WTP} by more than 60 percent in samples from both Canada and the U.S.

\textit{(v) \textit{WTP} to reduce risk of sudden death as a function of age.}—Figure 1 provides as a visual summary of the effect of the respondent’s current age on \textit{WTP} for a reduction in the risk of sudden death in the current period. This graph shows the simulated median and 90 percent interval for this fitted \textit{WTP} as a function of the individual’s age at the time they are making their program choices. Recall that age has a statistically significant nonlinear effect on three of the utility parameters of our model. The graph displays the \textit{combined} influence of these three different types of quadratic age effects on fitted \textit{WTP}.\footnote{Any instance of negative \textit{WTP} 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.”}

While there is a growing stock of evidence concerning the relationship between the \textit{VSL} and age, Smith et al. (2004) and Evans and Smith (2006) point out that the theoretical results are ambiguous and the empirical results are mixed. Krupnick (2007) and Aldy and Viscusi (2007) review the stated- and revealed-preference literatures, respectively. Among the earliest age-related results, Alberini et al. (2004) find for survey respondents aged 40 years and older, in Canada and the U.S., there is weak support for a decline in \textit{WTP} with age, but only for the oldest respondents. In a Canadian sample, described in more detail in Krupnick et al. (2002), \textit{WTP} 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 $WTP$ for this type of risk reduction of $6.40,$ whereas workers aged 35-44 value this same risk reduction at $9.00, but the numbers decline to about $3.80 for workers aged 55-62. Aldy and Viscusi (2008) find that $WTP$ rises from $3.70$ in the youngest group (ages 18-24), peaks at $9.70$ between 35-44, and declines to $3.40$ by the 55-62 age group. Controlling for birth-year cohort effects, they find a peak at $7.80$ at age 46 and a flatter profile.

In comparison, our stated-preference results for a $VSL$-type sudden death scenario suggest that younger people between 25 and 35 (including both workers and those not employed for pay) have a median $WTP$ between about $4.74$ and $5.77.$ For the general population aged 35-45, like Aldy and Viscusi (2008), we find the highest median $WTP$ amounts, varying between $5.73$ and $5.82.$ As ages progress to 55-65, our sample suggests that $WTP$ drops from about $4.95$ down to about $3.70.$ Finally, after normal retirement age, in the interval between 65 and 80, median $WTP$ drops from about $3.70$ down to about $2.38.$ 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.

(vi) $WTP$ to reduce risk of other illness profiles as a function of age.—Figures 2 and 3 illustrate age patterns in $WTP$ to avoid two other possible illness profiles. It is for other types of illness profiles, such as these, were our model offers great advantages over other approaches. Figure 2 shows an illness that lasts five years, ending in death, but with ten years of latency prior to onset. $WTP$ to reduce the risk of this illness profile also differs systematically with age, but
with a different pattern.\textsuperscript{54} In contrast, the illness profile illustrated in Figure 3 may be relevant to many environmental health risks which might cause modest changes in life expectancies. In this case, the individual gets sick just one year before the end of his or her expected lifespan. After six months of major illness, death occurs six months sooner than it would have otherwise. At a 0.05 discount rate, 25- to 60-year-olds have a \textit{WTP} that is less than $0.50 per microrisk reduction to avoid this scenario, but \textit{WTP} begins to increase quickly after age 65. Here we see a noticeable increase, rather than a decrease, in \textit{WTP} among seniors. This stands in sharp contrast to the results for the “sudden death now” scenario addressed in most studies of the \textit{VSL} as a function of age.\textsuperscript{55}

We know of no single other study which subsumes the broad range of major illnesses addressed symmetrically in this paper. Extant research by other authors has addressed the implicit value of a statistical on-the-job injury, motor-vehicle injury, or to avoid symptom-days of various specific types (see Viscusi, 1993, for an early comprehensive review). To evaluate the social benefits of a policy change that alters the incidence of a particular illness, however, there are great advantages to being able to estimate \textit{WTP} corresponding to the 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 based mostly on \textit{WTP} to reduce current-period morbidity and mortality risks, derived from separate valuation methods and studies.

\textsuperscript{54} Again, we interpret any negative fitted \textit{WTP} values as zero.

\textsuperscript{55} An early inquiry into the valuation of changes in life expectancy is contained in Rosen (1988).
IV. 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. We explicitly allow individuals to express different demands for reductions in different types of health risks that come to bear across different future time periods. Our model also allows for substitution across different types of health risks with different time profiles because we 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 explicit attributes of the objects of choice (i.e. the risk reductions available at a cost) that individuals are asked to consider. 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 include 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 of prior approaches, we can produce new and important types of economic information: distinct estimates of the marginal utilities of avoiding a discounted year of morbidity and a discounted lost life-year (as distinct characteristics of an illness profile) within a single model. We also confirm that these marginal utilities are not simple constants. From these heterogeneous marginal values, which depend upon the mix of health
states in an illness profile and the individual’s age, we have illustrated how to construct average 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 selection of arbitrarily specified illness profiles. For the benchmark case of sudden death in the current period, we can specialize our model to produce a \( WTP \) for a microrisk reduction that can be scaled up to an aggregate 1.00 risk reduction to render it comparable to a traditional Value of a Statistical Life (\( VSL \)). Alternatively, policy changes that affect the prevalence and severity of a given illness will shift the joint distribution of the duration of morbidity and premature mortality, for specified populations. Our model also permits assessment of the benefits of reductions in the risk of one type of illness profile, combined with increases in the risk of another. In this paper, however, we illustrate the model’s simulation capabilities with only a handful of representative illness profiles.

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. The use of a single number may continue to be dictated by political concerns, but 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).

Given that willingness to pay for risk reductions represents an inverse demand, the prospect of systematic variation in willingness to pay—according to the attributes of the good in question,
and with indicators of individual preferences—should not be at all surprising. 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.
REFERENCES


### TABLE 1—LOGARITHMIC AND TRANSLOG-TYPE FIXED EFFECTS CONDITIONAL LOGIT MODELS

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Constructed Variable</th>
<th>Simple logs</th>
<th>Interactions</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td><strong>Main variables and their coefficients:</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\beta_0$</td>
<td>$(Y_{j} - c_{j}^{i})^{0.42}$ cterm$^j - (Y_{j})^{0.42}$ yterm$^j$</td>
<td>0.0139</td>
<td>0.0139</td>
</tr>
<tr>
<td>$\alpha_{10}$</td>
<td>$\Delta \Pi_{j}^{IS} \log \left( pdvi_{j} + 1 \right)$</td>
<td>(10.47)***</td>
<td>(9.44)***</td>
</tr>
<tr>
<td>$\alpha_{20}$</td>
<td>$\Delta \Pi_{j}^{IS} \log \left( pdvr_{j} + 1 \right)$</td>
<td>(4.61)***</td>
<td>(5.64)***</td>
</tr>
<tr>
<td>$\alpha_{30}$</td>
<td>$\Delta \Pi_{j}^{IS} \log \left( pdvl_{j} + 1 \right)$</td>
<td>(2.41)**</td>
<td>(1.79)*</td>
</tr>
<tr>
<td>$\alpha_{31}$</td>
<td>$\ldots age_{i0} \times \Delta \Pi_{j}^{IS} \log \left( pdvl_{j} + 1 \right)$</td>
<td>-</td>
<td>19.6</td>
</tr>
<tr>
<td>$\alpha_{32}$</td>
<td>$\ldots age_{i0}^{2} \times \Delta \Pi_{j}^{IS} \log \left( pdvl_{j} + 1 \right)$</td>
<td>-</td>
<td>-0.180</td>
</tr>
<tr>
<td>$\alpha_{40}$</td>
<td>$\Delta \Pi_{j}^{IS} \left[ \log \left( pdvl_{j} + 1 \right) \right]^2$</td>
<td>-</td>
<td>195.</td>
</tr>
<tr>
<td>$\alpha_{41}$</td>
<td>$\ldots age_{i0}^{2} \times \Delta \Pi_{j}^{IS} \left[ \log \left( pdvl_{j} + 1 \right) \right]^2$</td>
<td>-</td>
<td>-7.50</td>
</tr>
<tr>
<td>$\alpha_{42}$</td>
<td>$\ldots age_{i0}^{3} \times \Delta \Pi_{j}^{IS} \left[ \log \left( pdvl_{j} + 1 \right) \right]^2$</td>
<td>-</td>
<td>0.0714</td>
</tr>
<tr>
<td>$\alpha_{50}$</td>
<td>$\Delta \Pi_{j}^{IS} \left[ \log \left( pdvi_{j} + 1 \right) \times \log \left( pdvl_{j} + 1 \right) \right]$</td>
<td>-</td>
<td>104.</td>
</tr>
<tr>
<td>$\alpha_{51}$</td>
<td>$\ldots age_{i0} \times \Delta \Pi_{j}^{IS} \left[ \log \left( pdvi_{j} + 1 \right) \times \log \left( pdvl_{j} + 1 \right) \right]$</td>
<td>-</td>
<td>-4.50</td>
</tr>
<tr>
<td>$\alpha_{52}$</td>
<td>$\ldots age_{i0}^{2} \times \Delta \Pi_{j}^{IS} \left[ \log \left( pdvi_{j} + 1 \right) \times \log \left( pdvl_{j} + 1 \right) \right]$</td>
<td>-</td>
<td>0.0561</td>
</tr>
<tr>
<td><strong>Systematic selection correction term:</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\alpha_{13}$</td>
<td>$\ldots \left[ P(\text{sel}<em>j) - \overline{P} \right] \times \Delta \Pi</em>{j}^{IS} \left[ \log \left( pdvi_{j} + 1 \right) \right]$</td>
<td>-</td>
<td>3.37</td>
</tr>
</tbody>
</table>

**Maximized log-likelihood**

-11719.76 -11685.12

**Notes:** Parameter estimates produced by Stata’s clogit algorithm. Absolute asymptotic t-test statistics in parentheses. Sample includes 1,801 individuals and 7,250 different choices. The Box-Cox transformation on the income terms is denoted as $Y^{0.42} = (Y^{0.42} - 1)/0.42$. Variables $pdvi$, $pdvr$, $pdvl$ are present discounted illness-years, recovered/remission years, and lost life-years. $\Delta \Pi_{j}^{IS} = \text{reduction in the risk of getting sick due to participation in testing program } j \text{ at a cost of } c \text{ per year (unless sick with this illness, or dead). Ordinary logarithmic transformations involve first adding one to the level of the variable for all values of the variable, so that } \log(X + 1) = 0 \text{ when } X = 0. $ Appendix E provides estimates for simpler ad hoc specifications, as well as a structural model that corresponds to equation (4). Our selection correction measure, $P(\text{sel}_j) - \overline{P}$, is explained in detail in Appendix D.

*** = significant at the 1 percent level, ** = statistically significant at the 5 percent level.
### Table 2—WTP for Microrisk Reductions, Different Discount Rates

<table>
<thead>
<tr>
<th>Illness profile: age 45 now; …at 45:</th>
<th>r=0.03</th>
<th>r=0.05</th>
<th>r=0.07</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Sudden death</td>
<td>$6.97  (4.90, 9.32)</td>
<td>$5.82  (3.78, 7.79)</td>
<td>$4.74  (2.80, 6.97)</td>
</tr>
<tr>
<td>2. 1 yr sick; nonfatal</td>
<td>3.28  (1.69, 5.18)</td>
<td>2.96  (1.47, 4.64)</td>
<td>2.75  (1.35, 4.22)</td>
</tr>
<tr>
<td>3. 5 yrs sick; nonfatal</td>
<td>4.88  (3.37, 6.83)</td>
<td>4.47  (3.06, 6.18)</td>
<td>4.16  (2.86, 5.67)</td>
</tr>
<tr>
<td>4. 1 yr sick; then die</td>
<td>7.18  (5.21, 9.31)</td>
<td>5.76  (3.84, 7.75)</td>
<td>4.50  (2.71, 6.62)</td>
</tr>
<tr>
<td>5. 5 yrs sick; then die</td>
<td>7.10  (5.02, 9.51)</td>
<td>5.43  (3.53, 7.71)</td>
<td>4.24  (2.04, 6.51)</td>
</tr>
</tbody>
</table>

**Notes:** Units are in 2003 US dollars per microrisk reduction for each of five arbitrarily selected illness profiles (rows), and for three different assumptions about the discount rate (columns). Values are based on the parameter point estimates and the parameter variance-covariance matrix for Model (2) in Table 1. Entries reflect 1000 random draws from the joint distribution of estimated parameters. We report the median, 5th and 95th percentiles for the sampling distribution of calculated WTP based on the appropriate analog to equation (6). Main estimates are for a 0.05 discount rate (in center column). For alternative discount rate assumptions, WTP estimates are different because the constructed variables differ, and hence the estimated indirect utility parameter estimates, as detailed in Appendix E. Household income is set at $42,000. Illness profile 1 corresponds most closely to the scenario implicit in many wage-risk VSL studies (sudden death in the current period for a mid-career blue-collar male worker).

### Table 3—WTP for Microrisk Reductions, Different Household Income Levels

<table>
<thead>
<tr>
<th>Illness profile: age 45 now; …at 45:</th>
<th>y=$25,000</th>
<th>y=$42,000</th>
<th>y=$67,500</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Sudden death</td>
<td>$3.97  (2.60, 5.66)</td>
<td>$5.82  (3.78, 7.79)</td>
<td>$8.18  (5.60, 10.88)</td>
</tr>
<tr>
<td>2. 1 yr sick; nonfatal</td>
<td>2.19  (1.10, 3.40)</td>
<td>2.96  (1.47, 4.64)</td>
<td>3.93  (1.95, 5.99)</td>
</tr>
<tr>
<td>3. 5 yrs sick; nonfatal</td>
<td>3.33  (2.19, 4.58)</td>
<td>4.47  (3.06, 6.18)</td>
<td>5.88  (4.00, 7.95)</td>
</tr>
<tr>
<td>4. 1 yr sick; then die</td>
<td>3.99  (2.64, 5.62)</td>
<td>5.76  (3.84, 7.75)</td>
<td>8.12  (5.73, 10.64)</td>
</tr>
<tr>
<td>5. 5 yrs sick; then die</td>
<td>3.88  (2.41, 5.63)</td>
<td>5.43  (3.53, 7.71)</td>
<td>7.70  (5.15, 10.63)</td>
</tr>
</tbody>
</table>

**Notes:** See notes to Table 2. All estimates in this table assume a 0.05 discount rate and use the estimated indirect utility parameters for Model 2 in Table 1.
## Table 4—WTP for Microrisk Reductions, Different Disease Latencies

<table>
<thead>
<tr>
<th>Illness profile:</th>
<th>1. Sudden death</th>
<th>2. 1 year sick, nonfatal</th>
<th>3. 5 years sick, nonfatal</th>
<th>4. 1 year sick, then die</th>
<th>5. 5 years sick, then die</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Age no; onset</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Now 35 years old – symptoms start:</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>now</td>
<td>$5.78 (3.48, 8.36)</td>
<td>$3.11 (1.52, 4.70)</td>
<td>$4.64 (3.09, 6.35)</td>
<td>$5.81 (3.70, 8.31)</td>
<td>$5.84 (3.44, 8.65)</td>
</tr>
<tr>
<td>at age 40</td>
<td>5.48 (3.60, 7.60)</td>
<td>2.76 (1.32, 4.22)</td>
<td>4.16 (2.76, 5.70)</td>
<td>5.57 (3.92, 7.55)</td>
<td>5.69 (3.92, 7.93)</td>
</tr>
<tr>
<td>at age 50</td>
<td>4.87 (3.61, 6.42)</td>
<td>2.14 (0.96, 3.32)</td>
<td>3.25 (2.17, 4.47)</td>
<td>5.02 (3.95, 6.27)</td>
<td>5.24 (4.08, 6.72)</td>
</tr>
<tr>
<td>at age 60</td>
<td>4.15 (3.12, 5.32)</td>
<td>1.60 (0.72, 2.49)</td>
<td>2.42 (1.64, 3.32)</td>
<td>4.26 (3.35, 5.33)</td>
<td>4.46 (3.59, 5.51)</td>
</tr>
<tr>
<td>at age 70</td>
<td>3.15 (2.30, 4.12)</td>
<td>1.12 (0.55, 1.70)</td>
<td>1.66 (1.18, 2.20)</td>
<td>3.21 (2.41, 4.15)</td>
<td>3.21 (2.49, 4.06)</td>
</tr>
<tr>
<td>at age 80</td>
<td>1.70 (1.16, 2.36)</td>
<td>0.66 (0.42, 0.93)</td>
<td>0.98 (0.77, 1.20)</td>
<td>1.67 (1.17, 2.24)</td>
<td>1.33 (1.03, 1.66)</td>
</tr>
<tr>
<td>Now 65 years old – symptoms start:</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>now</td>
<td>$3.73 (1.67, 5.76)</td>
<td>$2.86 (1.47, 4.31)</td>
<td>$3.98 (2.65, 5.41)</td>
<td>$1.66 (-0.31, 3.60)</td>
<td>$-0.91 (3.13, 1.12)</td>
</tr>
<tr>
<td>at age 70</td>
<td>3.27 (1.75, 4.72)</td>
<td>2.51 (1.29, 3.78)</td>
<td>3.50 (2.37, 4.70)</td>
<td>1.85 (0.52, 3.09)</td>
<td>0.03 (-1.29, 1.34)</td>
</tr>
<tr>
<td>at age 80</td>
<td>2.30 (1.38, 3.26)</td>
<td>1.77 (0.97, 2.64)</td>
<td>2.47 (1.79, 3.18)</td>
<td>1.83 (1.03, 2.61)</td>
<td>1.38 (0.61, 2.08)</td>
</tr>
<tr>
<td>at age 90</td>
<td>0.72 (0.13, 1.30)</td>
<td>0.73 (0.41, 1.06)</td>
<td>1.50 (1.12, 1.89)</td>
<td>0.73 (0.41, 1.06)</td>
<td>-b</td>
</tr>
</tbody>
</table>

**Notes:** See notes to Table 2. Assumes discount rate = 0.05, income = $42,000. Signs of parameter estimates are unconstrained.  
*a Negative simulated values of the WTP for a microrisk reduction can 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 expected signs. The quadratic-in-age forms for marginal (dis)utilities also do not preclude negative draws for extreme values of age.  
*b 95 years is beyond the nominal life expectancy of 65-year-olds, so this simulation is not appropriate.
**Figure 1. Sudden death now**

**Figure 2. 10 years latency, 5 years sick, then die**

**Figure 3. End-of-life effects**
Appendix

Example: One of the 7,520 randomized choice sets

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

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

<table>
<thead>
<tr>
<th></th>
<th>Program A for Heart Disease</th>
<th>Program B for Colon Cancer</th>
</tr>
</thead>
<tbody>
<tr>
<td>Symptoms/Treatment</td>
<td>Get sick when 71 years old 2 weeks of hospitalization</td>
<td>Get sick when 68 years old 1 month of hospitalization</td>
</tr>
<tr>
<td></td>
<td>No surgery</td>
<td>Major surgery</td>
</tr>
<tr>
<td></td>
<td>Moderate pain for remaining life</td>
<td>Severe pain for 18 months Moderate Pain for 2 years</td>
</tr>
<tr>
<td>Recovery/Life expectancy</td>
<td>Chronic heart condition Die at 79</td>
<td>Recover at 71</td>
</tr>
<tr>
<td></td>
<td>Die of something else at 73</td>
<td></td>
</tr>
<tr>
<td>Risk Reduction</td>
<td>5% From 40 in 1,000 to 38 in 1,000</td>
<td>50% From 4 in 1,000 to 2 in 1,000</td>
</tr>
<tr>
<td>Costs to you</td>
<td>$15 per month [ = $180 per year]</td>
<td>$4 per month [ = $48 per year]</td>
</tr>
<tr>
<td>Your choice</td>
<td>Reduce my chance of heart disease</td>
<td>Reduce my chance of colon cancer</td>
</tr>
<tr>
<td></td>
<td>Neither Program</td>
<td></td>
</tr>
</tbody>
</table>