An Empirical Model of Demand for Future Health States when Valuing Risk-Mitigating Programs

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Abstract

We develop a structural option price model in which individuals choose among competing risk-mitigating programs to alter their probability of experiencing future years in various degraded health states. The novel aspects of this model include separate estimates of the marginal utilities of avoiding years of morbidity and lost life-years. With these marginal utilities, we may evaluate a broad spectrum of probabilistic health outcomes over any period of an individual's future life. The model also reduces potential biases associated with single-period, single-risk models typically used to produce estimates of the Value of a Statistical Life (VSL) by allowing individuals to substitute risk mitigation across competing sources of risk and across future years of their lives. We evaluate this model using data from a national survey that contains a choice experiment on demand for the mitigation of illness-specific risks.

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1 Introduction

Individuals face a portfolio of distinct health risks such as heart disease, accidents, cancers, strokes, respiratory disease and many others. Individuals and policymakers may mitigate these risks through expenditures on privately available preventative care and medical therapies and publicly provided environmental, safety and health programs. The consumer's problem is to optimally allocate expenditures to each risk-mitigating program for each future year of their life. An important dimension of this problem is that the severity of each health risk will vary over an individual's lifespan. Furthermore, the majority of these risk-mitigating programs involve multiple periods of costs and yield uncertain future benefits.

In empirical analyses, researchers have tended to simplify this consumer problem to render it more tractable. They estimate the wage-risk or the wealth-risk trade-off by assuming the individual considers a single health risk that is reduced with certainty in the current period (Dreze, 1962; Jones-Lee, 1974). Missing are multiple risks and inter-temporal decision-making under uncertainty. These traditional single-risk, single-period models have motivated hundreds of empirical demand analyses, including many of those currently used to evaluate the social benefits of life-saving public policies (Viscusi, 1993). The central contribution of the present paper is an empirical model that not only generalizes the traditional model but also provides previously unavailable demand information.

Our choice model assumes that individuals face a portfolio of competing sources of risks, each with a different time profile of health states. The consumer's problem is to choose the set of risk mitigation programs that maximizes the present discounted value of the expected utility that each individual derives from his or her remaining lifespan, subject to the usual income constraint, a discount rate, and stated program prices. This is a multi-period model of demand, based on the individual's indirect utility function in each future year of life.

The individual's fundamental element of choice is the probability of alternative health-states in future years. To accommodate the probabilistic nature of both health states and program benefits, we recast the traditional model in an option price framework (Graham, 1981). Our parameter estimates for the marginal disutilities of avoided degraded health-state years depend explicitly upon the latency of the program benefits, the stream of program costs, and the individual's discount rate and future income.

This model generalizes the traditional single-risk, single-period model in several ways. First, it allows individuals to substitute risk-mitgating expenditures across different sources of risk. Omitting relevant substitutes (and the prices of these risk-mitigation programs) from the individual's choice set may bias the estimates of marginal utility (Rosen, 1988; Dow et al., 1999).[3] Second, it permits individuals to allocate risk-mitigating expenditures across current and future years of their lives. Assuming the individual's allocation of risk-mitigation expenditures is a one-period problem, when in fact it is a multi-period problem, may also yield biased estimates.[4] Third, rather than addressing risk reduction with certainty, we recast demand in a formal option price framework.

Most importantly, our model permits us to estimate both the marginal utility of avoiding a future year of morbidity and the marginal utility of avoiding a lost life-year. Most actual programs do not "save" lives; rather they extend life by deferring the future onset of morbidity or the event of death. Both policymakers and scholars have long sought a tractable and theoretically consistent empirical model that would describe how the marginal value of avoiding a year of morbidity or a lost life-year varies across an individual's remaining

[3]Recently, scholars have sought to allow for substitution between pairs of risks (Liu and Hammitt, 2003).

[4]One might argue that hedonic wage studies are exempt from this critique, since wage contracts may be interpreted as one-period contracts. However, when choosing across occupations, individuals may, in effect, choose across time-paths of risk-wage premia that implicitly embody inter-temporal substitution of risk mitigation (Aldy and Viscusi, 2003).

lifespan.[5] To the best of our knowledge, we provide the first such estimates in the literature.

Ideally, we would estimate our model of demand for risk mitigating programs using market data. However, given the absence of market data, we have chosen to administer a national survey that elicits individuals' choices over alternative risk-mitigation programs. Each health risk is presented as an illness profile that describes a probabilistic time pattern of health states that the individual could experience. Each profile is cast in terms of a specific major illness: heart disease, various cancers, stroke, respiratory diseases, diabetes, Alzheimer's, etc. For each illness, the profile describes the individual's future age at the time of onset, the severity and duration of treatments and morbidity, the age at recovery (if there is any), and the number of lost life-years (if there are any).

We then present individuals with an illness-specific health-risk reduction program that involves diagnostic screening, remedial medications, and life-style changes that would reduce their probability of experiencing that illness profile. Individuals must pay an annual fee to participate in each risk-reducing program. They are asked to choose between one of two risk reducing programs (each associated with a different illness profile) or to reject both programs. An advantage of this choice setting is that the individual faces a portfolio of health risks that resemble those they actually face. Through their choices, individuals reveal trade-offs across specific illnesses and a full continuum of health states of different durations. We also observe them strategically allocating expenditures for risk mitigating programs across the current year and future years of their remaining life. To analyze individuals' program choices, we estimate a modified translog indirect utility function using 7,520 choices by respondents to a representative national survey of approximately 2,439 U.S. citizens. Our estimated model

[5]Several popular per-year estimates have been developed to meet this need, but none of these describes the marginal utility of avoiding a year of morbidity or premature death. For Quality-Adjusted Life Years (QALYs) see Gold et al., (1996) and for the Value of a Statistical Life Year (VSLY) , see Moore and Viscusi (1988).

recovers estimates of the marginal utility of avoiding a year spent in each of three health states: morbidity, post-morbidity and mortality.

To illustrate the implications of our model, we focus on willingness to pay to avoid five archetypical illness profiles: 1) shorter-term morbidity with recovery, 2) longer-term morbidity with recovery, 3) a combination of shorter-term morbidity and premature mortality, 4) a combination of longer-term morbidity and premature mortality, and 5) immediate mortality. This exercise illustrates the way in which our model generalizes the concept of the Value of a Statistical Life (VSL). Rather than representing only the special case of mortality in the current year, our model describes the value of avoiding a wide variety of statistical illness profiles and characterizes how that Value of a Statistical Illness (VSI) will vary across an individual's remaining lifespan. By way of sensitivity analysis, we illustrate how different conditions–with respect to (1) discount rates, (2) income levels and (3) program latency for individuals of different ages–affect the marginal value of risk mitigation and, in turn, the value of avoiding different types of statistical illnesses.

We present our basic structural model in Section 2, showing that the traditional concept of a VSL is a special case of the more general Value of Statistical Illness. To illustrate our model with an empirical application, we outline our survey methods in Section 3, and our model's parameter estimates in Section 4, along with some sensitivity analyses. Section 5 concludes.

2 A Structural Option Price Model

Our structural model interprets individuals' choices as revealing their option prices for programs that mitigate the risks of uncertain future health states. The model allows a great deal of flexibility in characterizing how future health states impact future income and program

costs in each future year. Program choices have inter-temporal consequences. However, our model remains one of static decision-making, with future costs and benefits converted into equivalent present values.

2.1 Indirect Utility of Health State Years

We focus on four distinct health states: 1) a pre-illness healthy state, 2) an illness state, 3) a post-illness state (if the illness is non-fatal) and 4) death. Let i index individuals and let t index time periods.[6] In its simplest form the individual's indirect utility function might be:

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

This form allows the undiscounted marginal utility of some function of current income, $f(Y_{it})$, to be some parameter β, which we generalize right away to be a function of the individual's income, $\beta_0 + \beta_1 Y_{it}$, to allow for diminishing marginal utility of income. In the current paper, we will assume simply that $f(Y_{it}) = Y_{it}$. Let the undiscounted utility from the pre-illness status quo health state ($pre_{it} = 1$) be α_0, and let the (dis)utility from each future year of illness ($ill_{it} = 1$) be defined as α_1, from each year of the post-illness state (i.e. "recovered," $rcv_{it} = 1$) be α_2, and from each year of premature death (i.e. "life-year lost," $lyl_{it} = 1$) be α_3. The indicators for each health state, ill_{it}, rcv_{it}, and lyl_{it}, 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. In this paper, the disutility of each of these states will be interpreted as being the same as the utility associated with avoiding them.

[6] Time is measured in years, months, or even smaller units of time, depending on the degree of resolution needed to conform with the illness profile in question.

2.2 Present Discounted Values of Indirect Utility

We next develop a structural model of the ex ante option price that individuals are willing to pay for a program that reduces their risk of a future illness profile. Define the present discounted value of indirect utility V_i^{jk} for the i^{th} individual when $j = A$ if the program is chosen and $j = N$ if the program is not chosen. The superscript k will be S (denoting "sick") if the individual suffers the illness and H (denoting "healthy") if the individual does not suffer the illness. When discounting, we assume the individual uses the same discount rate, r, to discount both future money costs and health states.[7] Let the discount factor be $\delta^t = (1+r)^{-t}$.

The present value of indirect utility if the individual *does* choose the program and *does* suffer the illness takes the following form. All summations below run from 0 to T_i, the remaining number of years in the individual's nominal life expectancy:

$$\begin{aligned} PDV(V_i^{AS}) &= \beta_0 \sum \delta^t f(Y_{it}^* - c_{it}^{A*}) + \beta_1 \sum \delta^t (Y_{it}^* - c_{it}^{A*}) f(Y_{it}^* - c_{it}^{A*}) \\ &\quad + \alpha_1 \sum \delta^t ill_{it}^A + \alpha_2 \sum \delta^t rcv_{it}^A + \alpha_3 \sum \delta^t lyl_{it}^A + \varepsilon_i^{AS} \end{aligned} \tag{2}$$

where $Y_{it}^* = Y_i \left(pre_{it}^A + \gamma_1 ill_{it}^A + rcv_{it}^A + \gamma_2 lyl_{it}^A \right)$, and $c_{it}^{A*} = c_i^A \left(pre_{it}^A + \gamma_3 ill_{it}^A + rcv_{it}^A + \gamma_4 lyl_{it}^A \right)$.

Effective incomes and costs, Y_{it}^* and c_{it}^{A*}, are sufficiently general to allow for a number of different assumptions about how individuals view the implications of illness for their income stream and how they view their cost obligations under each program in different health states. Exactly what individuals assume about their future income and program

[7] Empirically estimated discount rates for future money as opposed to future health states are suspected to differ to some extent. Discount rates also differ across individuals and across choice contexts, time horizons and sizes and types of outcomes at stake. No comprehensive empirical work has been undertaken that conclusively demonstrates the relationships between money and health discount rates. If we were to choose hyperbolic discounting for our specification, all of the discount factors in the expressions for present discounted value would need to be changed from $1/(1+r)^t$ to $1/(1+t)^\lambda$.

costs, if they choose the program or not, has implications for the formulas we develop in later sections. We define γ_1 as the fraction of the individual's income that will be earned while the individual is sick, should he suffer the illness in question. Our default assumption will be that individuals expect constant real annual income Y_i in each future year until the expected time of death if the individual gets the illness. When $\gamma_1 = 1$ and $\gamma_2 = 0$, the term $pre_{it}^A + \gamma_1 ill_{it}^A + rcv_{it}^A + \gamma_2 lyl_{it}^A = \left(1 - lyl_{it}^A\right)$ in equation (2) will be nonzero in those periods when the individual is still alive. Let γ_2 be the fraction of income received if the individual is no longer living because they suffered from the illness. We assume this parameter is zero in our empirical models, but a non-zero value could be invoked to activate a bequest motive.

For program costs, we assume that the annual costs of the risk-management program in question are incurred in the years leading up to the onset of the illness or injury, but are not paid while the individual is sick or injured.[8] Therefore, the parameter γ_3, the fraction of the cost of the program that must be paid while the individual is suffering from the illness in question, is zero. Likewise, the individual would not participate in the program if dead, so we will assume that $\gamma_4 = 0$ is inferred by respondents. If the individual recovers from the illness or injury, rather than dying from it, they will again participate in the risk-management program until their death. When $\gamma_3 = \gamma_4 = 0$, the term $pre_{it}^A + \gamma_3 ill_{it}^A + rcv_{it}^A + \gamma_4 lyl_{it}^A = pre_{it}^A + rcv_{it}^A$ in equation (2) will be non-zero only prior to the onset of the illness or during the post-illness state.

The present value of indirect utility, if the individual *does* choose the program but *does not* suffer the illness, involves no illness, no post-illness state, and no reduced lifespan. Thus, the expression for indirect utility takes the following form:

$$PDV(V_i^{AH}) = \beta_0 f(Y_i - c_i^A) \sum \delta^t + \beta_1 (Y_i - c_i^A) f(Y_i - c_i^A) \sum \delta^t + \varepsilon_i^{AH}$$

[8] While the individual is sick, the health testing program would provide no valuable information.

In this case, both income and the annual costs of the program will continue until the end of the individual's nominal life expectancy. However, there are no benefits in the form of avoided illness-years, post-illness-years or lost life-years.

Present value of indirect utility, if the individual *does not* choose the program but *does* suffer the illness, is given by:

$$\begin{aligned} PDV(V_i^{NS}) &= \beta_0 \sum \delta^t f(Y_{it}^*) + \beta_1 \sum \delta^t (Y_{it}^*) f(Y_{it}^*) \\ &\quad + \alpha_1 \sum \delta^t ill_{it}^A + \alpha_2 \sum \delta^t rcv_{it}^A + \alpha_3 \sum \delta^t lyl_{it}^A + \varepsilon_i^{NS} \end{aligned} \tag{3}$$

Present value of indirect utility, if the individual *does not* choose the program and *does not* suffer the illness, is:

$$PDV(V_i^{NH}) = \beta_0 f\left(Y_i\right) \sum \delta^t + \beta_1 \left(Y_i\right) f\left(Y_i\right) \sum \delta^t + \varepsilon_i^{NH} \tag{4}$$

2.3 Expected Indirect Utility

Given the ex ante uncertainty about future health states, we need to calculate *expected utilities* to derive the individual's option price for any given program. In this case, the expectation is taken across the binary uncertain outcome of getting sick, S, or remaining healthy, H. The probability of illness or injury differs according to whether the respondent participates in the risk-reducing intervention program. Let the baseline probability of illness be Π_i^{NS} if the individual opts out of the program, and let the reduced probability be Π_i^{AS} if the individual opts to participate in the program.

Expected utility if the individual *buys* program A is:

$$E\left[PDV\left(V_i^A\right)\right]_{S,H} = \Pi_i^{AS} \times PDV(V_i^{AS}) + \left(1 - \Pi_i^{AS}\right) \times PDV(V_i^{AH})$$

Expected utility if the program is *not* purchased (i.e. "no program", N) is:

$$E\left[PDV\left(V_i^N\right)\right]_{S,H} = \Pi_i^{NS} \times PDV(V_i^{NS}) + \left(1 - \Pi_i^{NS}\right) \times PDV(V_i^{NH})$$

We will make use of a number of notational abbreviations in presenting the expected utility difference formula, $E\left[PDV\left(V_i^A\right)\right]_{S,H} - E\left[PDV\left(V_i^N\right)\right]_{S,H}$, to be discussed next. First, the risk change due to program participation, $\Delta\Pi_i^{AS} = \left(\Pi_i^{AS} - \Pi_i^{NS}\right)$, is presumed to be negative. Then, there are several distinct present discounted value terms to accommodate. We abbreviate each of these as follows:

$$\begin{aligned}
pdvc_i^A &= \sum \delta^t, \\
pdve_i^A &= \sum \delta^t pre_{it}^A, \quad pdvi_i^A = \sum \delta^t ill_{it}^A \\
pdvr_i^A &= \sum \delta^t rcv_{it}^A, \quad pdvl_i^A = \sum \delta^t lyl_{it}^A
\end{aligned}$$

The indicator variables for each health state are mutually exclusive and exhaustive, so $pdvc_i = pdve_i + pdvi_i + pdvr_i + pdvl_i$.

To accommodate the different time profiles of income and program costs over the indi-

vidual's remaining lifespan, it is convenient to define five additional terms:

$$
\begin{aligned}
pdvy_i^A &= \sum \delta^t \left(pre_{it}^A + \gamma_1 ill_{it}^A + rcv_{it}^A + \gamma_2 lyl_{it}^A\right) = pdve_i^A + \gamma_1 pdvi_i^A + pdvr_i^A + \gamma_2 pdvl_i^A \\
pdvp_i^A &= \sum \delta^t \left(pre_{it}^A + \gamma_3 ill_{it}^A + rcv_{it}^A + \gamma_4 lyl_{it}^A\right) = pdvev + \gamma_3 pdvi_i^A + pdvr_i^A + \gamma_4 pdvl_i^A \\
pdvyy_i^A &= \sum \delta^t \left(pre_{it}^A + \gamma_1 ill_{it}^A + rcv_{it}^A + \gamma_2 lyl_{it}^A\right)^2 = pdvev + \gamma_1^2 pdvi_i^A + pdvr_i^A + \gamma_2^2 pdvl_i^A \\
pdvpp_i^A &= \sum \delta^t \left(pre_{it}^A + \gamma_3 ill_{it}^A + rcv_{it}^A + \gamma_4 lyl_{it}^A\right)^2 = pdve_i^A + \gamma_3^2 pdvi_i^A + pdvr_i^A + \gamma_4^2 pdvl_i^A
\end{aligned}
$$

$$
pdvyp_i^A = \sum \delta^t \left[\begin{array}{c} \left(pre_{it}^A + \gamma_1 ill_{it}^A + rcv_{it}^A + \gamma_2 lyl_{it}^A\right) \times \\ \left(pre_{it}^A + \gamma_3 ill_{it}^A + rcv_{it}^A + \gamma_4 lyl_{it}^A\right) \end{array} \right] = pdve_i^A + \gamma_1\gamma_3 pdvi_i^A + pdvr_i^A + \gamma_2\gamma_4 pdvl_i^A
$$

The expected utility difference driving the individual's choice between Program A and the "Neither Program" alternative can then be written as follows (there will be an analogous utility difference for Program B versus the "Neither Program" alternative). This version of the formula emphasizes that it is a quadratic form in annual program cost c_i^A. This is a consequence of the manner in which we allow for a diminishing marginal utility of income (via $\beta_1 \neq 0$).

$$
\begin{aligned}
& E\left[PDV(V_i^A)\right] - E\left[PDV(V_i^N)\right] = A[c_i^A]^2 + B[c_i^A] + C + \varepsilon_i \qquad (5) \\
= \; & [c_i^A]^2 \quad \left\{\beta_1 \left[\left(1 - \Pi_i^{AS}\right) pdvc_i^A + \Pi_i^{AS} pdvpp_i^A\right]\right\} \\
& \left[c_i^A\right] \left\{ \begin{array}{ll} -\beta_0 & \left[\left(1 - \Pi_i^{AS}\right) pdvc_i^A + \Pi_i^{AS} pdvp_i^A\right] \\ -\beta_1 2Y_i & \left[\left(1 - \Pi_i^{AS}\right) pdvc_i^A + \Pi_i^{AS} pdvyp_i^A\right] \end{array} \right\} \\
& + \left\{ \begin{array}{c} \beta_0 Y_i \Delta\Pi_i^{AS}\left(pdvy_i^A - pdvc_i^A\right) + \beta_1 Y_i^2 \Delta\Pi_i^{AS}\left(pdvyy_i^A - pdvc_i^A\right) \\ +\alpha_1 \Delta\Pi_i^{AS} pdvi_i^A + \alpha_2 \Delta\Pi_i^{AS} pdvr_i^A + \alpha_3 \Delta\Pi_i^{AS} pdvl_i^A + \varepsilon_i \end{array} \right\}
\end{aligned}
$$

For estimation using a conventional linear-index conditional logit multiple choice model,

the terms must be rearranged into a form that isolates the five key parameters in the underlying indirect utility function:

$$
\begin{aligned}
&E\left[PDV(V_i^A)\right] - E\left[PDV(V_i^N)\right] = \\
&\beta_0 \left\{ \begin{array}{c} -\left[c_i^A\right] \quad \left[\left(1-\Pi_i^{AS}\right) pdvc_i^A + \Pi_i^{AS} pdvp_i^A\right] \\ +Y_i \Delta\Pi_i^{AS}\left(pdvy_i^A - pdvc_i^A\right) \end{array} \right\} \\
&+\beta_1 \left\{ \begin{array}{c} [c_i^A]^2 \quad \left[\left(1-\Pi_i^{AS}\right) pdvc_i^A + \Pi_i^{AS} pdvpp_i^A\right] \\ -[c_i^A]\ 2Y_i \left[\left(1-\Pi_i^{AS}\right) pdvc_i^A + \Pi_i^{AS} pdvyp_i^A\right] \\ +Y_i^2 \Delta\Pi_i^{AS}\left(pdvyy_i^A - pdvc_i^A\right) \end{array} \right\} \\
&+\alpha_1 \left\{\Delta\Pi_i^{AS} pdvi_i^A\right\} + \alpha_2 \left\{\Delta\Pi_i^{AS} pdvr_i^A\right\} + \alpha_3 \left\{\Delta\Pi_i^{AS} pdvl_i^A\right\} + \varepsilon_i
\end{aligned}
\tag{6}
$$

The five terms in braces in equation (6) can be constructed from the data, given an assumption about the discount rate and the γ parameters that define the time profiles of income and program costs. We estimate the five parameters β_0, β_1, α_1, α_2, and α_3 in our base model in our empirical illustration

2.4 From maximum annual payment to PDV of payment stream

The option price for the program is the common certain payment 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. This annual option price, $\widehat{c_i^A}$, will make $E\left[PDV(V_i^A)\right] - E\left[PDV(V_i^N)\right]$ exactly zero. This amount of money $\widehat{c_i^A}$ is the maximum constant annual payment that the individual will be willing to make, regardless of whether he suffers the illness, in order to purchase the program that reduces his probability

of suffering the illness from Π_i^{NS} to Π_i^{AS}.

To simplify the exposition, although our empirical illustration involves a dimininishing marginal utility of income, we will outline the special case where the marginal utility of income does not depend upon the level of income (i.e. $\beta_1 = 0$). The formulas are analogous, but somewhat more complicated, when the marginal utility of income is non-constant. In this special case, equation (5) reduces to be linear in c_i^A:

$$\begin{aligned} & E\left[PDV(V_i^A)\right] - E\left[PDV(V_i^N)\right] \\ = \; & -\left[c_i^A\right] \;\; \beta_0 \;\; \left[\left(1-\Pi_i^{AS}\right) pdvc_i^A + \Pi_i^{AS} pdvp_i^A\right] \\ & +\beta_0 Y_i \Delta\Pi_i^{AS}\left(pdvy_i^A - pdvc_i^A\right) \\ & +\alpha_1 \Delta\Pi_i^{AS} pdvi_i^A + \alpha_2 \Delta\Pi_i^{AS} pdvr_i^A + \alpha_3 \Delta\Pi_i^{AS} pdvl_i^A + \varepsilon_i \end{aligned} \tag{7}$$

Setting equation (7) equal to zero and solving for the implied value of $\widehat{c_i^A}$ yields

$$\widehat{c_i^A} = \frac{\left[\begin{array}{c} \beta_0 Y_i \Delta\Pi_i^{AS}\left(pdvy_i^A - pdvc_i^A\right) \\ +\alpha_1 \Delta\Pi_i^{AS} pdvi_i^A + \alpha_2 \Delta\Pi_i^{AS} pdvr_i^A + \alpha_3 \Delta\Pi_i^{AS} pdvl_i^A + \varepsilon_i \end{array}\right]}{\beta_0 \;\; \left[\left(1-\Pi_i^{AS}\right) pdvc_i^A + \Pi_i^{AS} pdvp_i^A\right]} \tag{8}$$

While the payment $\widehat{c_i^A}$ is the maximum *annual* payment the individual is willing to make, these payments are necessary for the rest of the individual's life, so the present value of these payments must be calculated. In this context, however, there is some 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 or not. We will use the expected present value of this time profile of costs, with the expectation taken over whether or not the individual

suffers the illness when they are participating in the program.

$$\begin{aligned} E\left[PV(\widehat{c_i^A})\right] &= \left(1-\Pi_i^{AS}\right)(\widehat{c_i^A})pdvc_i^A + \left(\Pi_i^{AS}\right)(\widehat{c_i^A})pdvp_i^A \\ &= (\widehat{c_i^A})\left[\left(1-\Pi_i^{AS}\right)pdvc_i^A + \Pi_i^{AS}\left(pdvp_i^A\right)\right] \end{aligned} \tag{9}$$

In this simplified case where the marginal utility of income is constant, capitalizing forward this payment in equation (8) over the rest of the individual's life by multiplying by the probability-weighted average of $pdvc_i^A$ and $pdvp_i^A$ allows this term to cancel the identical term in the denominator of equation (8). If we also factor out $\Delta\Pi_i^{AS}$ from the numerator of equation (8), the formula for the present value of the stream of annual maximum payments willingly made to avoid a specified degraded health profile therefore reduces to:

$$\begin{aligned} & E\left[PV(\widehat{c_i^A})\right] \\ = \; & \Delta\Pi_i^{AS}\left[Y_i\left(pdvy_i^A - pdvc_i^A\right) + \frac{\alpha_1}{\beta_0}pdvi_i^A + \frac{\alpha_2}{\beta_0}pdvr_i^A + \frac{\alpha_3}{\beta_0}pdvl_i^A + \varepsilon_i\right] \end{aligned} \tag{10}$$

If the marginal utility of income is constant across the population, therefore, the expected present value of the lifetime stream of maximum annual payments is merely proportional to the size of the risk reduction, given individual preferences, income and the illness profile in question.[9] In our more general specification (i.e. allowing for diminishing marginal utility

[9]The assumption of strict proportionality between willingness to pay and the size of the risk reduction is typically maintained in order to construct the Value of a Statistical Life. If the risk reduction involved, and the cost of the program, pertained only to a single year (as is the case in most VSL studies) there would be no difference between $pdvy_i$ and $pdvc_i$, so that the first term inside the square brackets in equation (10) would disappear. If all illness profiles were to be treated as identical, all of the terms involving our differentiated α parameters would collapse into a single constant parameter, α, multiplying by a dummy variable, say D_i^A, that indicates whether the health state occurs in alternative A. This new parameter would describe the marginal utility of the generic health outcome to be avoided. For most existing studies this health outcome is "sudden death this year." In this case, we would have just a single point estimate of the option price that would be proportional to the size of the risk change due to the program:

of income via $\beta_1 \neq 0$) the formulas are somewhat more complex because equation (5) is quadratic in c_i^A, rather than conveniently linear in c_i^A.

2.5 Value of a statistical illness (VSI)

The option price that we estimate represents a willingness to pay to reduce an illness-specific risk that jointly determines several health state outcomes, not just the mortality outcomes upon which a conventional VSL is based. To convert our expected present-value option price to the "value of a statistical illness" (VSI), we normalize arbitrarily on a 1.00 risk change by dividing this WTP by the absolute size of the risk reduction.[10] Use the same abbreviations B and C for the detailed expressions defined in equation (5), but consider again the simpler case where the marginal utility of income is simply a constant ($\beta_1 = 0$) so that $A = 0$. If the researcher desires measures of a quantity that is comparable to traditional VSL estimates, the effective formula for the value of a statistical illness will be

$$VSI = \frac{E\left[PV(\widehat{c_i^A})\right]}{|\Delta\Pi_i^{AS}|} = \frac{C\ \left[\left(1-\Pi_i^{AS}\right) pdvc_i^A + \Pi_i^{AS}\left(pdvp_i^A\right)\right]}{B\ \ |\Delta\Pi_i^{AS}|} \tag{11}$$

$$\begin{aligned} E\left[PV(\widehat{c_i^A})\right] &= \Delta\Pi_i^{AS}\beta_0^{-1}\left[\alpha D_i^A\right] \\ &= (\alpha/\beta_0)\Delta\Pi_i^{AS} \qquad \text{to avoid death } (D_i^A = 1) \\ &= 0 \qquad \text{for "no program," where } (D_i^A = 0) \end{aligned}$$

[10] In our study, all the probability changes $\Delta\Pi_i^{AS}$ are negative, while the absolute magnitude of these changes will be positive. The ratios that result, $\Delta\Pi_i^{AS}/\left|\Delta\Pi_i^{AS}\right|$, will amount to multiplying by -1, which will change the effective sign on each of the terms involving this ratio.

In this special case, the formula for VSI simplifies to

$$VSI = Y_i pdvl_i^A - \frac{\alpha_1}{\beta_0} pdvi_i^A - \frac{\alpha_2}{\beta_0} pdvr_i^A - \frac{\alpha_3}{\beta_0} pdvl_i^A - \frac{\varepsilon_i}{\beta_0 \left|\Delta \Pi_i^{AS}\right|} \tag{12}$$

where we take advantage of the fact that $pdvy_i^A + pdvl_i^A = pdvc_i^A$ so that $\left(pdvy_i^A - pdvc_i^A\right) = -pdvl_i^A$.

How does the magnitude of the estimated VSI vary with changes in it components? In this simple model with a constant marginal utility of income, increases in income Y_i will increase the predicted point estimate of the VSI. The effect of income on VSI_i^A is given by $\partial VSI_i^A / \partial Y_i = pdvl_i^A$, which is non-negative. The effect of an increase in income on the predicted VSI will be larger (i.) as more life-years are lost and (ii.) as the individual is older, so that life-years lost come sooner in time.[11]

The VSI will also will depend upon the different marginal utilities of avoided periods of illness, post-illness status, and premature death. It will also depend upon the time profiles for each of these states as embedded in the terms $pdvi_i^A$, $pdvr_i^A$, and $pdvl_i^A$, and (implicit in this model) upon the individual's own discount rate.[12] This heterogeneity can be accommodated by making the indirect utility parameters α_1, α_2, and α_3 depend upon other individual

[11]Nothing in this specification precludes negative point estimates of the VSI. The key undiscounted marginal utility parameters are not presently constrained to be strictly positive (for income) and strictly negative (for episodes of undesirable health profiles). This is especially a concern when these marginal utilities are permitted to vary systematically with of the attributes of the illness profile and/or the characteristics of the individual in question. The marginal utility of income, the scalar parameter β in our simplest models, bears a point estimate that is robustly positive, but positive values for the important systematically varying parameters capturing the marginal utility of an illness-year (α_1) or a lost life-year (α_3) can push an individual fitted value of the VSI for a particular morbidity/mortality profile, for a respondent of a particular age, into the negative range.

[12]Subsequent work will preserve individual discount rates as systematically varying parameters that depend upon respondent characteristics. In a separate subsample for our survey, we elicited choices that allow us to infer individual specific discount rates. Here, however, discount rates are presumed to be exogenous and constant across individuals although our empirical analyses explores the senstivity of our results to different discount rates.

characteristics.[13]

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

2.6 VSIs versus Conventional VSLs

In our framework, the VSL is but one possible variant of the more general concept of the VSI. To isolate the VSL associated with particular illness, one would assume death in the current year, with no period of illness or post-illness status. The remainder of the individual's nominal life expectancy would be experienced as lost life-years. Since the terms in $pdvi_i^A$ and $pdvr_i^A$ will be zero, our analog to the conventional VSL formula in the simplified case where the marginal utility of income is a constant ($\beta_1 = 0$), will be:

$$E[VSL] = \left|\Delta\Pi_i^{AS}\right|^{-1} E\left[PV(\widehat{c_i^A})\right] = \left(Y_i - \frac{\alpha_3}{\beta_0}\right) pdvl_i^A \tag{13}$$

where $pdvl_i^A = \sum \delta^t lyl_{it}^A$.

The summation in the formula for $pdvl_i^A$ is from the present until the end of the individual's nominal life expectancy. This interval depends upon the individual's current age, so even in a model with homogeneous preferences, the VSI will vary with age. The term α_3/β_0 is the monetized disutility of a lost life-year. We assume that avoiding a lost life-year means avoiding disutility equivalent to this amount of money (which accounts for the negative sign)

[13]For example, illness characteristics can be expected to shift the value of α_1, the marginal (dis)utility of a sick-year, and possibly the marginal utility of each period in the post-illness state, α_2, since the type of illness may connote the degree of "health" that nominal recovery from that illness actually implies. Also, the marginal utility of a lost life-year may depend upon the health state prior to death. Many of these dimensions of heterogeneity will be explored in detail in subsequent papers.

and preserving future income.

2.7 Calculating Policy-Relevant VSIs

The fitted VSIs that we will estimate are based on the sets of illness attributes generated for the choice experiment rather than those actually associated with specific illnesses. Therefore, the distribution of our fitted VSIs cannot be expected to match the actual distribution of VSIs in the general population that faces a real range of illness profiles. To be clear on what is needed to construct fitted VSIs using our present results, we offer the following checklist of needs and tasks:

1. For the illness in question: 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). In practice, this joint distribution will be constructed using expert judgment and its validity will in part determine the validity of the eventual VSI estimates our model will produce.

2. For the population affected by this health threat: An approximate joint distribution of age, gender, and income level. The distribution of these characteristics may be based on expert judgment combined with exposure and epidemiological data. Again, the validity of the assumptions underlying this approximate joint distribution will in part determine the validity of the resulting VSI estimates.

3. Make a large number of random draws from the joint distribution of illness profiles and affected population characteristics and combine these illness profiles and individual characteristics with our formulas for the value of a statistical illness.

6. Build up a sampling distribution for the implied VSIs. The mean of this distribution can be interpreted as our model's prediction about the average of VSIs for this type of health threat affecting this particular population.

The overall Value of a Statistical Illness, estimated in this fashion and calculated for a given policy by simulation methods, will allow the researcher to more fully capture the policy choice context for the risk in question.

3 Survey Methods and Data

Market data that adequately illustrate how individuals allocated risk mitigation expenditure across competing risks and across their remaining years of life are not available.[14] Therefore, we have conducted a survey of over 2400 randomly chosen adults in the United States. The centerpiece of the survey is a conjoint choice experiment that presents individuals with specific illness profiles and programs that mitigated these illness risks. In this section we briefly describe the five modules of this survey instrument. (Appendix A provides one example of a choice set from the primary survey instrument.[15])

The first module evaluates the individual's subjective risk assessment of the major illnesses they face, their familiarity with each illness, and current mitigating and averting behavior they may be undertaking. The second module consists of a tutorial that intro-

[14]Most market data characterize at best only one source of risk (e.g. hedonic wage data) and are often missing essential variables such as the baseline risk, risk reduction, the latency of the programs or the costs of programs. For example, using the Health and Retirement Survey, Picone, Sloan and Taylor (2004) expertly explored how time preferences, expected longevity and other demand shifters affect individuals' propensity to get mammograms, pap-smears and regular breast self-exams. However missing data on program costs, baseline risks, and latency of program benefits prevented a fuller demand analysis.

[15]Readers who wish to peruse the actual survey instrument used for this study may access and example at: http://darkwing.uoregon.edu/~cameron/vsl/DeShazo_Cameron_Private_Survey_US_example.pdf . An annotated version is available at http://darkwing.uoregon.edu/~cameron/vsl/Annotated_survey_DeShazo_Cameron.pdf .

duces individuals to the idea of an illness profile and programs that may manage these illness-specific risks.

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 probability over the course of his or her lifetime. The attributes of the illness profiles are randomly varied, subject to some plausibility constraints for each illness type.[16] We summarize the key attribute levels employed in our choice set in Table 1. The first row in this table presents the frequency with which each of the twelve illnesses appeared in the choice sets. Up to eleven attributes characterize each illness profile and program, although we concentrate on just the main attributes in this paper.[17] In terms of the number and type of attributes, our design is comparable to existing state of the art health valuation studies (Viscusi et al., 1991; O'Connor and Blomquist, 1997; Sloan et al., 1998; Johnson, et al., 2000). However, unlike some studies, we choose not to give individuals extensive background information on illnesses that might make one illness risk appear more salient than others. We seek to estimate demand conditional on the individual's ex ante information set.[18]

There are several reasons why we choose to include illness labels as an attribute. As shown in Table 1 these labels include prostate cancer, breast cancer, colon cancer, skin cancer, lung cancer, heart disease (i.e., heart attack, angina), stroke (e.g., blood clot, aneurysm), respiratory diseases (i.e., asthma, bronchitis, emphysema) as well as diabetes and Alzheimer's. A

[16]We took great care to try to ensure individuals did not reject the scenario because it was implausible (e.g., one does not recover from Alzheimer's or die suddenly from diabetes). See the on-line Appendix A for more details.

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

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

major advantage of using these labels is that our pre-testing showed that individuals think in terms of specific illnesses when identifying hereditary risks and when planning for the mitigation of future risks. Second, the inclusion of the twelve major illnesses meant that our estimates of the marginal utility of avoiding a year of morbidity and premature mortality were broadly representative of the leading lifetime illness risks. Finally, including diverse illnesses enabled us to motivate a wide range of health outcomes, (e.g., some associated with sudden death (heart attack and stroke) and others associated with chronic morbidity (such as diabetes and Alzheimer's disease)).[19] The major disadvantage of specific illness names is that individuals may implicitly assume the presence of attributes that we did not explicitly include in the illness profile description.[20]

After presenting an illness profile, we next explain to individuals that they could purchase a new program that would be coming on the market that would reduce their risk of experiencing specific illnesses over current and future periods of their life. These programs are described as involving annual diagnostic testing and, if needed, associated drug therapies and recommended life-style changes. We choose this class of interventions because pretesting showed that individuals view this combination of programs (diagnostic tests, followed by drug therapies) as feasible, potentially effective and familiar for a wide range of illnesses.[21] The effectiveness of these programs is described in four ways: 1) graphically, with a risk grid, 2) in terms of risk probabilities, 3) in terms of measures of relative risk reduction across the

[19]Gender specific illnesses (e.g., breast and prostate cancer) are chosen to comport with the respondent's gender. We aggregated some illness labels based on the cognitive labels individuals used in our pretests. These included heart disease (i.e., heart attack, angina), stroke (e.g., blood clot, aneurysm), and respiratory diseases (i.e., asthma, bronchitis, emphysema). Each of these illnesses was described in greater detail in its illness profile.

[20]In empirical analysis, one could address this potential disadvantage by using illness-specific dummy variables to control for these effects. We reserve these considerably more-complex models for a subsequent paper.

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

two illness profiles and 4) as a qualitative textual description of the risk reductions (Corso et al., 1999; Krupnick et al., 2000). 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.[22] For the sake of concreteness we ask respondents to assume that these payments would be needed for the remainder of their life span unless they actually experienced that illness.[23]

We implement several measures to avoid potential biases.[24] First, at the beginning of this survey section, we include a "cheap talk" reminder to ensure that respondents carefully consider their budget constraint and to discourage them from overstating their willingness to pay (Cummings and Taylor, 1999; List, 2001).[25] Second, we carefully explain to individuals that they can choose neither program. We also point out several possible explanations why reasonable people might choose neither program in some cases.[26] If individuals choose "neither program," we assume that they prefer their status quo illness profile to either of the costly illness-reducing programs. We obtain a great deal of information on each individual's status quo health profile that enables us to characterize his or her future health state expectations.[27]

[22]Costs were expressed in both monthly and annual terms.

[23]As result of respondents' experience with co-payments and finely designed insurance premiums for different levels of service, focus group subjects found this annual cost assumption entirely plausible.

[24]Targeted biases include hypothetical and incentive compatibility biases as well as yea-saying behavior. Other biases that we address are discussed in the on-line Appendix 1; these include order and sequencing effects, Weber's law in risk perception and various framing and anchoring concerns.

[25]This screen began "In surveys like this one, people sometimes do not fully consider their future expenses. Please think about what you would have to give up to purchase one of these programs. If you choose a program with too high a price, you may not be able to afford the program when it is offered..." (form 22-private). See online Appendix A for a complete description of this section.

[26]These reasons include that they 1) cannot afford either program, 2) did not believe they faced these illness risks, 3) would rather spend the money on other things, 4) believed they would be affected by another illness first. If the individual did choose neither program we ask them why they did so in a follow-up question.

[27]We elicited individuals' subject risk levels for illness as well as their age when each illness risk would be a threat to their life. We also elicited their subjective life expectancy, documented their current health status with respect to over 16 illnesses and evaluated their current risk averting and mitigating activities.

The third module contains the five main choice sets, each offering the individual two programs that reduced the risk of two distinct illness profiles.[28] Presenting individuals with a large array of illness risks has advantages and disadvantages. The greatest advantage is that individuals consider a more-complete choice set, allowing us to observe how they substitute across programs associated with these competing illness risks. Second, presenting a range of major illnesses increases the representativenss of our estimates and makes the motivation of a fuller range of illness profiles plausible, and thus possible. One disadvantage is that this format, in conjunction with survey length and time limitations, limits that background information that we can provide about each illness. A second potential disadvantage is the cognitive complexity associated with the choice task, which we seek to minimize through the survey design and evaluate ex post.[29]

The fourth module contains various debriefing questions that are used to document the individual's status quo health profile and to cross-check the validity of the responses (Baron and Ubel, 2002). Module five was administered separately from the choice experiment. It collects a detailed medical history of the individual, as well as household socioeconomic information.

We need this information on the individual's status quo health profile to fully interpret individuals' stated choices.

[28]To avoid potential order effects, we were careful to ask individuals to evaluate each pair of alternatives independent of previous choice sets (Ubel et al., 2002; de Bruin and Keren, 2003). Our empirical evaluation showed that the first four choice sets appeared largely free of order effects. Individuals did exhibit a slightly higher propensity to select a program from the last choice set.

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

3.1 Sample Characteristics and Scope Tests

The development of this survey instrument involved 36 cognitive interviews, three pretests (n=100 each) and an unusually large pilot study (n=1,400).[30] Knowledge Networks administered the final version of the demand survey and the health-profile survey to a sample of 2439 of their panelists.[31] Respondents were paid an incentive for completing the survey.[32] Our response rate for those panelists contacted was 79 percent. For these respondents, there were 11,717 choices, although only 7,520 choices (22,560 alternatives) were deemed admissible for estimation. Appendix Table B1 compares the individuals in our estimating sample with corresponding population characteristics (e.g., age, income, and gender) from the 2000 Decennial Census.[33] Among the full set of 11,717 choices, 332 were excluded because an undetected error our randomization algorithm produced for one of the illness profiles in the choice set the characteristic that the illness would slightly prolong the individual's life span. While this is perhaps remotely possible, we elect to exclude these choices as having been potentially confusing to respondents. A further 2,236 choices were excluded because the respondent selected "Neither Program" and indicated as the only explanation "I did not believe the programs would work." This is clear evidence of scenario rejection. If any other (economic) reason was given, we retained the choice. Finally, we excluded 1,629 choices because the individual failed to answer correctly the simple risk comprehension question at

[30]We thank Vic Adamowicz, Richard Carson, Maureen Cropper, Baruch Fischhoff, Jim Hammitt, Alan Krupnick, and V. Kerry Smith for their careful reviews of the second of four versions of this instrument.

[31]Respondents are recruited in the Knowledge Network sample from standard RDD techniques. They are then equipped with WebTV technology that enables them to receive and answer our surveys. More information about Knowledge Networks is available from their website: www.knowlegdenetworks.com.

[32]Respondents were paid 10 dollars for completing our survey, in addition to the usual benefits of Knowledge Networks panel membership.

[33]Although our sample characteristics are generally representative of the US population, we also control for systematic survey participation in our empirical analysis described in Section 4. Our response/nonrespondent model to predict survey participation propensities uses data on Knowledge Networks' initial RDD panel recruitment sample.

the end of the survey's risk tutorial.[34]

To evaluate construct validity of the study, we explore whether individual choices are sensitive to the scope of the illness profile and risk-mitigating program (Hammitt and Graham, 1999; Yeung et al., 2003). In Models 1 and 2 in Table 2, we show using a simple ad hoc conjoint choice analysis that individuals were highly sensitive to changes in the scope or level of our central attributes. These attributes include the two most crucial attributes of the program, its cost and the size of the risk reduction, as well as the two most important dimensions of the illness profiles, the number of years spent in a morbid condition, and the number of lost life-years. As will be the case for all models presented in this paper, these estimates are obtained using a fixed effects conditional logit estimator.[35]

4 Empirical Analysis

In our empirical analysis, we first illustrate the new types of demand information that our model yields by estimating the marginal utilities of avoiding a year in each of our three undesirable health states. We show how these marginal utilities may be combined with sequences of health states to construct what is essentially a continuum of statistical illness profiles and their associated utility consequences. Second, we show that the empirical evidence concerning individuals' demand behavior warrants the generalizations that we entertain. We do this by demonstrating within our structural model that when choosing risk reducing programs, individuals substitute across illness risks and also appear to substitute intertemporally across their remaining lifespans.

[34]We believe these to be the minimal a priori justifiable exclusions from the estimating sample. Sensitivity analyses with respect to these successive sample exclusions are provided in Appendix B2, available from the authors. By far the greatest difference in results stems from the scenario rejection criterion.

[35]We use the clogit algorithm in Stata 8, with groups defined as the individual making the choice, and up to five choices per individual when all conjoint choice questions were answered.

4.1 Marginal Utility of a Health-State Year

We begin this analysis by estimating the marginal utility of year spent in each of three health states: morbidity, a post-illness state, and a lost life-year. We also explore interactions between years of morbidity and lost life years in order to assess the assumption of additive separability that characterizes our most basic model. Using the implied marginal rates of substitution between illness profiles and money, we then construct individual measures of willingness to pay to avoid five archetypical illness profiles: 1) shorter-term morbidity with recovery, 2) longer-term morbidity with recovery, 3) a combination of short term morbidity and mortality, 4) a combination of longer-term morbidity and mortality and 5) immediate mortality. Our underlying structural model requires (for now) that we make assumptions about individuals' time preferences and future expected income levels. Thus, in Section 4.2, we explore how our implied VSIs vary systematically with these two factors.

Our basic structural model, which assumes homogeneous preferences (except for income differences), takes the form presented in equation (6), and produces the five parameter estimates shown as Model 3 in Table 2. These homogenous-preferences specifications are estimated without sign restrictions and show robust significance and the expected signs on all five primary parameters.[36] The marginal utility of income is positive, but declines with the level of income (yet does not go negative within the range of incomes in our sample). The marginal utilities of sick-years, post-illness years, and lost life-years are all negative and very strongly significantly different from zero.[37] While simple intuition might suggest that death should be "worse" than illness and recovery, it is important to keep in mind that the

[36]Not surprisingly, the additional structure in Model 3, as opposed to Models 1 and 2, produces a lower maximized value of the log-likelihood function. This is a common tradeoff. The structure is required for a rigorous utility-theoretic interpretation of the results, but the ad hoc model provides a better fit to the data.

[37]A positive marginal utility associated with a lost life-year might be expected only when the illness is question constitutes a "fate worse than death."

units involved are *years* in each health state. The relatively large (dis)utility associated with recovered state probably reflects the general seriousness of the illnesses our survey describes. (For example, respondents seem not to interpret being recovered from lung cancer, heart attack, or respiratory disease as being equivalent to the pre-illness state.)

We now relax the maintained hypothesis in Model 3 that the marginal utilities from each state are independent of the duration of that state and the durations of other health states that characterize the profile in question. Our original model was developed in terms of the individual's undiscounted *per-period* indirect utility, where current-period health status is captured only by a set of mutually exclusive and exhaustive dummy variables. At the moment of the individual's program choice, however, each alternative is likely to be perceived in terms of the present value of the sequence of future health states it represents. These present values reflect the mix of health states in each illness profile. It is therefore reasonable to take as a starting point for our choice models the indirect utility expressions such as $PDV(V_i^{AS})$ in equation (2). If these present discounted values capture the relevant attributes of each alternative in the individual's choice set, we can consider richer models that allow for diminishing, rather than constant, marginal utilities from present discounted health-state years, and for interactions between the numbers of present discounted years in different health states. In contrast, Model 3 constrains the marginal utility of each health state to be constant and imposes a constant marginal rate of substitution between different health-state-years.

The final line in the estimating specification in equation (6), $\alpha_1 \Delta\Pi_i^{AS} pdvi_i + \alpha_2 \Delta\Pi_i^{AS} pdvr_i + \alpha_3 \Delta\Pi_i^{AS} pdvl_i$, can easily be adapted to be non-linear in $pdvi_i^A$, $pdvr_i^A$, and $pdvl_i^A$. We first factor out the common $\Delta\Pi_i^{AS}$ term. Then original form of the term involving the present

discounted health states is:

$$\Delta\Pi_i^{AS}\left\{\alpha_1 pdvi_i^A + \alpha_2 pdvr_i^A + \alpha_3 pdvl_i^A\right\} \tag{14}$$

We then shift each present discounted health-state term by one unit to accommodate the absence of some health states in some health profiles. Then we take logarithms. The resulting alternative logarithmic form for the final term in equation (6) is:

$$\Delta\Pi_i^{AS}\left\{\alpha_1 \log\left(pdvi_i^A + 1\right) + \alpha_2 \log\left(pdvr_i^A + 1\right) + \alpha_3 \log\left(pdvl_i^A + 1\right)\right\} \tag{15}$$

Estimates for this form are presented as Model 4 (presented in Table 3), which produces an improvement in the log-likelihood function compared to the linear and additively separable structural specification in Model 3. This implies diminishing marginal utility in avoided present discounted degraded health-state years.

Model 5 then illustrates the consequences of allowing the parameters of the model to vary according to the fitted probability that each respondent appears in our estimating sample. Full-fledged selectivity correction models in multiple-choice conditional logit models are complex, so we do not attempt them in this paper, although we do estimate a response/nonresponse model that produces fitted response probabilities for each individual in our sample.[38] Only the coefficient on the lost life-years term differs significantly with the fitted probability that the respondent shows up in our estimating sample. The greater the probability of being

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

in our sample, relative to the mean probability, the lesser the disutility the individual appears to experience from a percentage increase in discounted lost life-years. While the shift is statistically significant, comparison of Model 5 and Model 4 reveals that the difference in the magnitude of this key coefficient across these two specifications is minimal. We employ differences from the mean response probability so that the estimated utility parameters correspond to the simulated case where all response probabilities are exactly equal to the mean (i.e. identical response probabilities across the entire sample).

Of course, whenever a linear-in-logs form is a better predictor of consumer choices than a linear form, the researcher is typically inclined to explore even more general logarithmic forms. In particular, the translog form represents a second-order local approximation to any arbitrary functional relationship. This form is fully quadratic in all of the log terms and their pairwise interactions. We have explored the inclusion of all three squared terms and all three interaction terms. Only the squared term in $pdvl_i^A$ and the interaction term between $pdvi_i^A$ and $pdvl_i^A$ are robustly significant. This more general specification is presented as Model 6. Again, it produces a substantial improvement in the log-likelihood. The estimates suggest that the disutility of an additional discounted lost life-year shrinks as the number of discounted lost life-years increases. They also suggest that the disutility of an additional discounted lost life-year is reduced by increases in the number of discounted illness-years that precede it.

In this application, however, there is a further complication. The illness profiles that were eligible to be considered by each respondent were constrained by the respondent's current age. No respondent considered illnesses that could strike at an age younger than their current age, so current age defines the maximum duration of any illness profile. The result is a degree of multicollinearity between the respondent's remaining nominal life expectancy and

the range of sick-years, post-illness years, and lost life-years they were eligible to consider. In particular, when including interactions between the $pdvi_i^A$ terms and the $pdvl_i^A$ terms, large values of these interaction terms were closely associated with the youth of the respondent.

It is not possible to include current age as a factor that might have an additively separable effect on the individual's level of utility, since terms such as these drop out of the utility-difference calculation across alternatives. To control for the effect of current age on the apparent marginal utility of each health state, we need to allow current age, age_{i0}, to shift the marginal utility parameters. An intermediate model, not shown in Table 3, assessed the consequences of allowing age_{i0} to shift only the coefficients on each of the linear terms in the logs of discounted years in each adverse health state. Each of the additional coefficients, α_{11}, α_{21}, and α_{31}, was statistically significant. Older respondents appear to anticipate lesser disutility from discounted sick-years and discounted lost life-years, but greater disutility from discounted post-illness years.

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 odd simulation results when we use the parameter estimates to predict VSIs for specific illness profiles. Our recourse is to allow all of the translog coefficients to vary systematically with age_{i0} and age_{i0}^2 since earlier empirical research has suggested the presence of quadratic age effects in VSLs.[39] The age shifters on the sick-years and post-illness years terms ($pdvi_i^A$ and $pdvr_i^A$) become statistically insignificant. However, the presence of significant quadratic-in-age shifters on the linear and quadratic lost life-years terms ($pdvl_i^A$) and on the interaction between the $pdvi_i^A$ term and the $pdvl_i^A$ term, prevents counter-intuitive negative fitted VSI estimates for some illness profiles for young respondents. Therefore, we

[39]See for example Jones-Lee et al. (993) or Krupnick et al. (2002).

prefer the specification presented as Model 7 in Table 3, even though two coefficients (on the level and linear age effects on the interaction between the $pdvi_i^A$ and $pdvl_i^A$ terms) are not individually statistically significant.

For Model 7, if we simulate identical response probabilities for all participants, the final term in equation (6) is specified as follows:

$$+\Delta\Pi_i^{AS}\left\{\begin{array}{c}(\alpha_{10})\log\left(pdvi_i^A+1\right)\\+(\alpha_{20})\log\left(pdvr_i^A+1\right)\\+(\alpha_{30}+\alpha_{31}age_{i0}+\alpha_{32}age_{i0}^2)\log\left(pdvl_i^A+1\right)\\+(\alpha_{40}+\alpha_{41}age_{i0}+\alpha_{42}age_{i0}^2)\left[\log\left(pdvl_i^A+1\right)\right]^2\\+(\alpha_{50}+\alpha_{51}age_{i0}+\alpha_{52}age_{i0}^2)\left[\log\left(pdvi_i^A+1\right)\right]\left[\log\left(pdvl_i^A+1\right)\right]\end{array}\right\} \tag{16}$$

To our knowledge, these are the first attempts to estimate the age-varying marginal utilities of avoiding a present discounted year of morbidity and a present discounted lost life-year within a common model. We evaluate the validity of our estimates by assessing whether they vary systematically in a manner that economic theory or simple intuition would predict.[40] We examine next how these estimates vary with assumptions about average time preferences, as well as with the data concerning each individual's income, and with current age and disease latency.

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

4.2 Statistical Illness Profiles with Varying Time Preferences and Income

We now employ the estimated parameters reported for Model 7 in Table 3 to characterize the Value of a Statistical Illness (VSI) associated with selected combinations of years of morbidity, years in post-illness status, and years of premature mortality. For illustrative purposes, we examine five representative illness profiles: 1) a period of shorter-term morbidity followed by recovery, 2) a period of longer-term morbidity followed by recovery, 3) a combination of shorter-term morbidity followed by premature mortality, 4) a combination of longer-term morbidity followed by premature mortality, and 5) immediate mortality.

Our models currently require that the researcher specify each individual's time preferences. In Table 4, we consider an individual who is now 45 years old with an income of $42,000 and calculate the fitted VSI (in millions of dollars) for each of five illness profiles to illustrate the sensitivity of our models to our choice of discount rate. In Table 3, the results for Model 7 were derived under the assumption that $r = 0.05$. The middle column of Table 4 shows the medians and 90% ranges of simulated point estimates of the VSI for our five different illness profiles assuming a current age of 45 and immediate onset.[41] The first and third columns of results in Table 4 are produced by re-estimating Model 7 having constructed the present discounted value terms using two alternative discounting assumptions: $r = 0.03$, and $r = 0.07$. Table 4 shows that fitted VSI estimates vary inversely with the assumed discount rate. For our 45-year-old, the case of sudden death (most common in the conventional VSL context) the 5% discount rate produces a VSI of roughly $4.5 million, whereas the median

[41] These simulations are taken across 1000 draws from the joint distribution of the estimated parameters. We acknowledge that the mean of the theoretical distribution of a ratio of asymptotically normal quantities is undefined. However, we present finite-sample medians and 90% ranges to convey a sense of the precision of the parameter estimates and the implications of this precision for fitted VSIs.

estimates for 3% and 7% rates and about $5.5 million and $3.8 million.

Table 5 reverts to a discount rate of $r = 0.05$ and again reports the results of simulating VSIs for an individual who is now 45 years old and faces each of our five representative illness profiles with immediate onset. The middle column reproduces the results for our baseline income of $42,000. The first and third columns demonstrate the sensitivity of VSIs to income levels. We arbitrarily select alternative income levels of $25,000 and $67,500 for illustration.[42] As expected, VSI is larger when income is greater. For our 45-year-old and the case of sudden death, the fitted median VSI at $25,000 income is only about $3.5 million, whereas the fitted median VSI at $67,500 income is $7.0 million.

Table 6 explores the effect of illness latency on willingness to pay to avoid health risks. In this table, we array the five different illness profiles across the top of the table. In the body of the table, we display fitted median VSI estimates and 90% ranges for one respondent aged 35 now and another aged 65 now. The age at onset of each illness is varied to include immediate onset, as well as onset at decade intervals starting five years from now. Considerable variability is present. Focusing again on the sudden death scenario, our model suggests that the 65-year-old respondents are willing to pay less to avoid sudden death than the 35-year-old respondent. Looking forward, however, both individuals are willing to pay less to avoid the same illness profile when it commences at a later age. Our model allows VSIs to reflect the duration of each type of health state. The numbers of prospective sick-years and life-years lost can be expected to have a substantial effect on willingness-to-pay to avoid each illness profile.

As a more detailed summary of the effect of the respondent's age now on the VSI for

[42]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 ($65,000).

sudden death, we offer Figure 1, which shows the simulated median and 90% confidence interval for this fitted VSI as a function of age now. As the term in (16) indicates, age has an nonlinear effect on several of the parameters of the model. The combined influence of these three different types of quadratic age effects on the fitted VSI for this particular illness profile is captured by Figure 1. Figure 2 illustrates one other possible illness profile. In this case, it is an illness that lasts five years, ending in death, but with ten years of latency prior to onset. Willingness to pay to avoid this illness profile also differs systematically with age.

When evaluating the social benefits of a policy change that alters the incidence of a particular illness, there are great advantages to being able to estimate the continuum of statistical illness profiles associated with that particular illness. Our approach offers the flexibility to evaluate changes in the type, future timing, and duration of heterogeneous illness profiles. Additionally, it does so within a consistent theoretical and empirical model, rather than requiring researchers to cobble together estimates for current period morbidity and mortality from separate valuation methods and studies.

5 Discussion and Conclusions

Unlike many previous empirical efforts to measure willingness to pay to reduce mortality risks, our model does not produce a single best estimate or confidence interval for the Value of a Statistical Life (VSL) for use in all policy contexts. Instead, our model is best understood as a generalization of the standard single-period, single-risk valuation model. It explicitly allows the individual to allocate risks across multiple future time periods. Across those multiple periods, it allows for an explicit and very general treatment of future income streams, costs streams, probabilistic benefits, and time preferences. Importantly, it also allows for substitution across competing sources of risks and more completely characterizes the type

and duration of health outcome results from those risks. Rather than focusing on only a single risk of death in the current period, the model takes as its objects of choice a continuum of future health-state years. These generalizations may mitigate several sources of bias associated with single-period, single-risk analyses.

Although the model is a generalization, it nonetheless produces a new and important type of economic information: distinct estimates of the marginal utilities of avoiding a year of morbidity and a lost life year within a single model. It appears that these marginal utilities are *not* simple constants. From these heterogeneous marginal values, which appear to depend upon the current age of the respondent and the mix of health states in an illness profile, we have illustrated how to construct the values for a full range of statistical illness. This may significantly enhance the construct validity of previous measures of demand used in public policy analysis. Estimates such as these may diminish the need for policy analysts to piece together disparate estimates morbidity and mortality from different valuation methods. To further enhance program and policy evaluation, we organize our analysis around estimating the value of a statistical illness (VSI), although we allow for the identification of a concept that is similar to the more-traditional value of statistical life (VSL). The VSI evaluates the set of heterogeneous health outcomes associated with a given illness risks. Policy changes that affect the prevalence and severity of that illness will shift the joint distribution of the duration of morbidity and premature mortality, for specified populations, and our model is capable of assessing the benefits of such shifts.

Our analyses illustrate some initial results concerning how marginal utility of risk mitigation varies systematical across individuals. Specifically, we evaluate how the demand for mortality risk reduction varies with assumed individual discount rates, incomes, 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 the presumption that there should be a single number for the VSL is misguided. While the use of a single number may continue to be dictated by political concerns, economically the VSL should be viewed as a multi-dimensional schedule of values. Since it is ultimately a type of inverse demand function, this heterogeneity should not be surprising.

6 References

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Table 1 – Main Illness Profile Attributes, by Label Assigned to Health Threat, Means and Standard Deviations (Estimating Sample = 1619 individuals, 7520 choice sets, 15040 illness profiles, 22560 alternatives)

Health Threat:	Breast Cancer	Prostate Cancer	Colon Cancer	Lung Cancer	Skin Cancer	Heart Attack	Heart Disease	Stroke	Resp. Disease	Traffic Accident	Diabetes	Alzheim. disease
# profiles	697	676	1357	1368	1353	1406	1423	1424	1337	1295	1357	1347
Monthly cost (dollars)	30.78 (30.09)	28.12 (26.09)	29.35 (28.37)	30.4 (28.7)	30.19 (28.81)	29.85 (29.62)	29.87 (28.63)	30.85 (29.43)	29.77 (29.41)	29.72 (27.92)	29.17 (28.07)	29.84 (28.54)
Risk difference	-0.0033 (0.0016)	-0.0034 (0.0017)	-0.0034 (0.0017)	-0.0034 (0.0017)	-0.0035 (0.0017)	-0.0035 (0.0017)	-0.0034 (0.0017)	-0.0034 (0.0017)	-0.0034 (0.0017)	-0.0034 (0.0017)	-0.0033 (0.0016	-0.0033 (0.0016)
Latency (years)	16.97 (10.95)	18.52 (11.2)	18.37 (11.57)	19.35 (11.46)	17.6 (11.68)	20.48 (12.54)	19.42 (11.94)	21.79 (12.67)	21.39 (12.18)	18.21 (12.32)	18.23 (10.82)	22.63 (12.51)
Illness years	4.861 (3.481)	4.917 (3.853)	8.546 (8.295)	8.294 (7.681)	7.478 (7.322)	3.421 (6.649)	10.239 (8.84)	3.593 (6.429)	7.37 (6.529)	4.036 (7.596)	6.798 (5.817)	6.805 (4.661)
Lost life-years	11.54 (11.4)	12.03 (11.5)	8.88 (9.71)	10.32 (9.75)	10.33 (10.79)	13.54 (11.26)	7.41 (8.42)	12 (10.07)	7.99 (7.81)	14.49 (12.51)	13.44 (10.72)	8.8 (6.42)
Sudden death	0	0	0	0	0	0.52	0	0.51	0	0.51	0	0
Recover	0.60	0.64	0.39	0.23	0.40	0.19	0.26	0.19	0.38	0.19	0	0
Die within 6 years	0.40	0.36	0.22	0.36	0.30	0.08	0.11	0.07	0.21	0.07	0.85	0.84
Chronic effects	0	0	0.37	0.41	0.30	0.21	0.63	0.24	0.41	0.23	0.15	0.16

Table 2 – Ad Hoc Models; Linear Additively Separable Structural Model (No selection correction, Fixed effects conditional logit)[a]

	Model 1 Ad hoc	Model 2 Ad hoc	Model 3 Structural
Monthly Cost of Program	-0.007581 (-9.63)***	-0.007491 (-9.48)***	-
Risk Reduction	89.27 (9.95)***	57.64 (5.77)***	-
Sick-Years	-	0.0879 (3.85)***	-
Lost Life-Years	-	0.01138 (7.13)***	-
$\left(\beta_{00}\times 10^{5}\right)$[first income term]	-	-	4.88 (8.60)***
$\left(\beta_{10}\times 10^{9}\right)$[second income term]	-	-	-0.220 (-4.71)***
$(\alpha_{10})\Delta\Pi_i^{AS}\, pdvi_i^A$	-	-	-8.390 (-5.00)***
$(\alpha_{20})\Delta\Pi_i^{AS}\, pdvr_i^A$	-	-	-8.02 (-2.48)***
$(\alpha_{30})\Delta\Pi_i^{AS}\, pdvl_i^A$	-	-	-8.08 (-6.04)***
Alternatives	22560	22560	22560
Log-likelihood	-11735.13	-11706.11	-11733.47

[a] Asymptotic t-test statistics in parentheses (***=statistically significant at better than 1% level)

Table 3 – Evolution of Estimating Specification (Alternatives = 22560)

	Model 4	Model 5	Model 6	Model 7
(Parameter) Variable	Simple Logs	w/ P(select)	Translog	Quad in Age
$(\beta_{00}\times 10^{5})[\text{first income term}]$	5.35	5.34	5.89	5.19
	(9.20)***	(9.18)***	(9.79)***	(8.31)***
$(\beta_{10}\times 10^{9})[\text{second income term}]$	-0.2155	-0.2159	-0.2094	-0.1991
	(4.61)***	(4.61)***	(4.46)***	(4.22)***
$(\alpha_{10})\Delta\Pi_i^{AS}\log(pdvi_i^A+1)$	-24.7	-26.8	-51.3	-47.8
	(4.22)***	(4.52)***	(5.75)***	(5.32)***
$(\alpha_{13})\left[P(sel_i)-\overline{P}\right]\Delta\Pi_i^{AS}\left[\log(pdvi_i^A+1)\right]$		3.181	3.153	3.280
		(2.13)**	(2.12)**	(2.19)**
$(\alpha_{20})\Delta\Pi_i^{AS}\log(pdvr_i^A+1)$	-21.52	-21.54	-19.59	-16.45
	(2.29)**	(2.30)**	(2.09)**	(1.74)*
$(\alpha_{30})\Delta\Pi_i^{AS}\log(pdvl_i^A+1)$	-30.59	-30.48	-68.62	-582.4
	(6.00)***	(5.98)***	(3.66)***	(3.26)***
$(\alpha_{31})age_{i0}\Delta\Pi_i^{AS}\log(pdvl_i^A+1)$	-	-	-	20.58
				(2.84)***
$(\alpha_{32})age_{i0}^2\Delta\Pi_i^{AS}\log(pdvl_i^A+1)$	-	-	-	-0.1888
				(2.72)***
$(\alpha_{40})\Delta\Pi_i^{AS}\left[\log(pdvl_i^A+1)\right]^2$	-	-	9.263	200.6
			(-1.13)	(2.43)**
$(\alpha_{41})age_{i0}\Delta\Pi_i^{AS}\left[\log(pdvl_i^A+1)\right]^2$	-	-	-	-7.848
				(2.33)**
$(\alpha_{42})age_{i0}^2\Delta\Pi_i^{AS}\left[\log(pdvl_i^A+1)\right]^2$	-	-	-	0.0746
				(2.29)**
$(\alpha_{50})\Delta\Pi_i^{AS}\left[\log(pdvi_i^A+1)\right]\times\left[\log(pdvl_i^A+1)\right]$	-	-	34.71	102.1
			(4.25)***	(-1.40)
$(\alpha_{51})age_{i0}\Delta\Pi_i^{AS}\left[\log(pdvi_i^A+1)\right]\times\left[\log(pdvl_i^A+1)\right]$	-	-	-	-4.47
				(-1.57)
$(\alpha_{52})age_{i0}^2\Delta\Pi_i^{AS}\left[\log(pdvi_i^A+1)\right]\times\left[\log(pdvl_i^A+1)\right]$	-	-	-	0.056
				(2.10)**
Alternatives	22560	22560	22560	22560
Log L	-11729.021	-11726.662	-11716.989	-11694.991
Sample mean fitted VSI ($ million) [a]	7.15	7.47	0.9	2.59

[a] The survey provides no opportunity for respondents to express a negative willingness to pay. At worst, they can merely prefer the status quo alternative. In this table, we interpret individual negative fitted VSI estimates as zero values.

Table 4 – Simulations: Discount Rate Sensitivity Analysis[a] (VSI in $million)

Model 7 Specification

45 years old now; at 45:	r=3%	**r=5%**	r=7%
1 yr sick, non-fatal	2.55 [1.19, 3.88]	**2.35** **[1.1, 3.69]**	2.29 [1.11, 3.7]
5 yrs sick, non-fatal	3.83 [2.51, 5.24]	**3.58** **[2.28, 4.91]**	3.46 [2.29, 4.87]
1 yr sick; then die	5.59 [4.01, 7.53]	**4.52** **[3.01, 6.22]**	3.68 [1.98, 5.74]
5 yrs sick; then die	5.57 [3.94, 7.71]	**4.39** **[2.79, 6.37]**	3.40 [1.66, 5.61]
Sudden death	5.49 [3.76, 7.43]	**4.48** **[2.85, 6.44]**	3.82 [2.13, 5.67]

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

Table 5 – Income Sensitivity Analysis[a] (VSI in $million)

Model 7 Specification

45 years old now; at 45	y=$25,000	y=$42,000	y=$67,500
1 yr sick; non-fatal	1.99 [0.87, 3.14]	2.35 [1.1, 3.69]	3.34 [1.61, 5.76]
5 yrs sick; non-fatal	3.02 [1.92, 4.21]	3.58 [2.28, 4.91]	5.04 [3.17, 7.87]
1 yr sick; then die	3.55 [2.31, 5.02]	4.52 [3.01, 6.22]	7.05 [4.59, 10.89]
5 yrs sick; then die	3.53 [2.15, 5.08]	4.39 [2.79, 6.37]	6.74 [4.15, 10.99]
Sudden death	3.51 [2.22, 5.10]	4.48 [2.85, 6.44]	7.01 [4.56, 10.63]

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

Table 6 – Latency Sensitivity Analysis[a] (VSI in $million) fixed effects specification

Selected Illness Profiles (Model 7 Specification)

Age: Onset	1 year sick, non-fatal	5 years sick, non-fatal	1 year sick, then die	5 years sick, then die	Sudden death
Now 35 years old:					
Now	2.47 [1.19, 3.87]	3.75 [2.42, 5.11]	4.59 [2.82, 6.62]	4.73 [2.83, 7]	4.47 [2.41, 6.64]
At age 40	2.2 [1.05, 3.49]	3.36 [2.18, 4.6]	4.44 [3.06, 6.09]	4.65 [3.17, 6.49]	4.29 [2.61, 6.09]
At age 50	1.71 [0.79, 2.73]	2.63 [1.72, 3.6]	4.03 [3.1, 5.22]	4.29 [3.35, 5.53]	3.9 [2.82, 5.2]
At age 60	1.28 [0.59, 2.04]	1.95 [1.31, 2.67]	3.43 [2.68, 4.48]	3.6 [2.88, 4.67]	3.34 [2.52, 4.45]
At age 70	0.89 [0.44, 1.4]	1.34 [0.95, 1.79]	2.56 [1.86, 3.51]	2.58 [1.98, 3.43]	2.51 [1.8, 3.46]
At age 80	0.52 [0.33, 0.75]	0.78 [0.62, 0.99]	1.34 [0.89, 1.9]	1.06 [0.82, 1.38]	1.37 [0.87, 1.99]
Now 65 years old:					
Now	2.22 [1.06, 3.43]	3.16 [2.01, 4.28]	1.21 [-0.28, 2.85]	-0.86 [-2.69, 0.8]	2.88 [1.32, 4.82]
At age 70	1.95 [0.92, 3]	2.79 [1.81, 3.72]	1.38 [0.42, 2.48]	-0.06 [-1.25, 0.97]	2.53 [1.4, 3.88]
At age 80	1.38 [0.7, 2.08]	1.94 [1.38, 2.53]	1.4 [0.69, 2.03]	1.01 [0.33, 1.58]	1.8 [0.98, 2.6]
At age 90	0.54 [0.26, 0.82]	1.07 [0.73, 1.42]	0.54 [0.26, 0.82]	-[b]	0.53 [0.02, 1.02]

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

[b] 95 years is beyond the nominal life expectancy of 65-year-olds, so simulations are not conformable

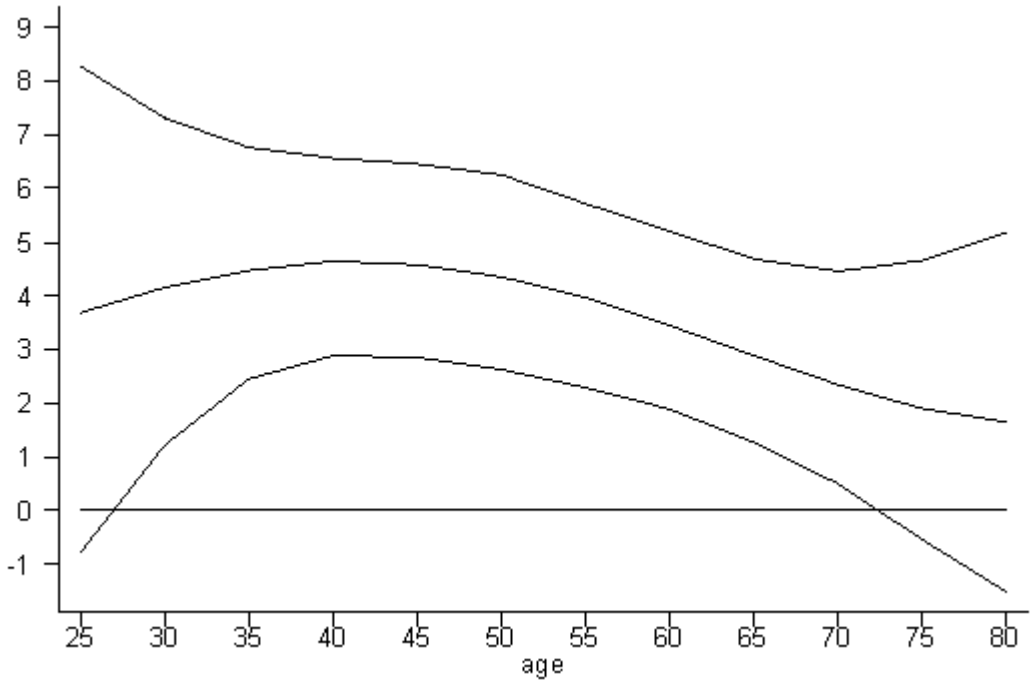


Figure 1 – Implicit VSL associated with sudden death now, as a function of respondent age ($ million) Estimated without sign constraints.

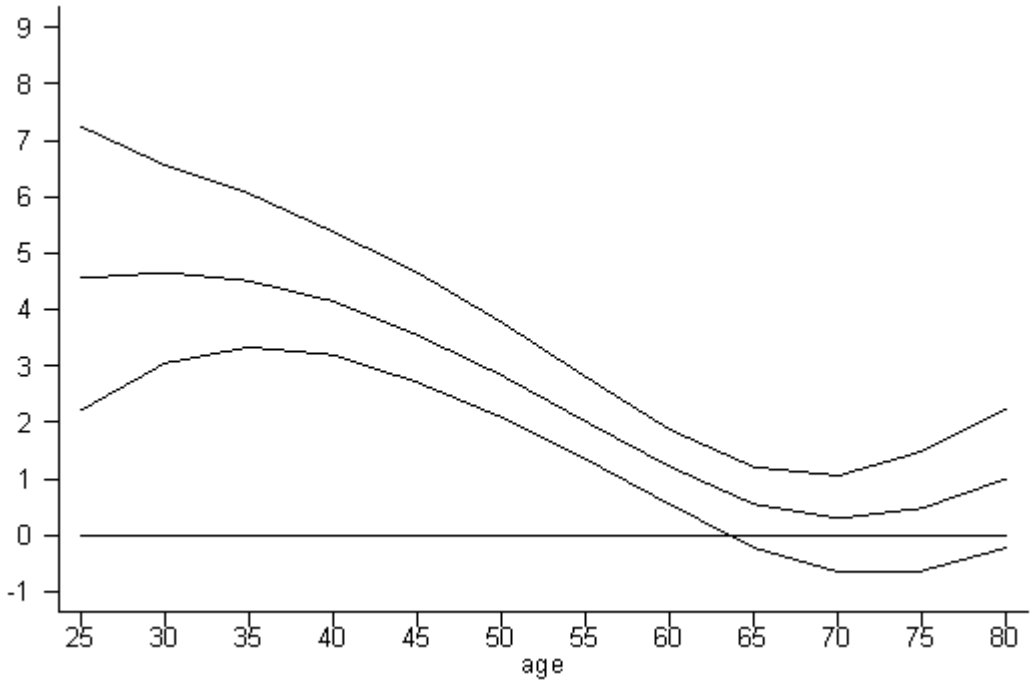
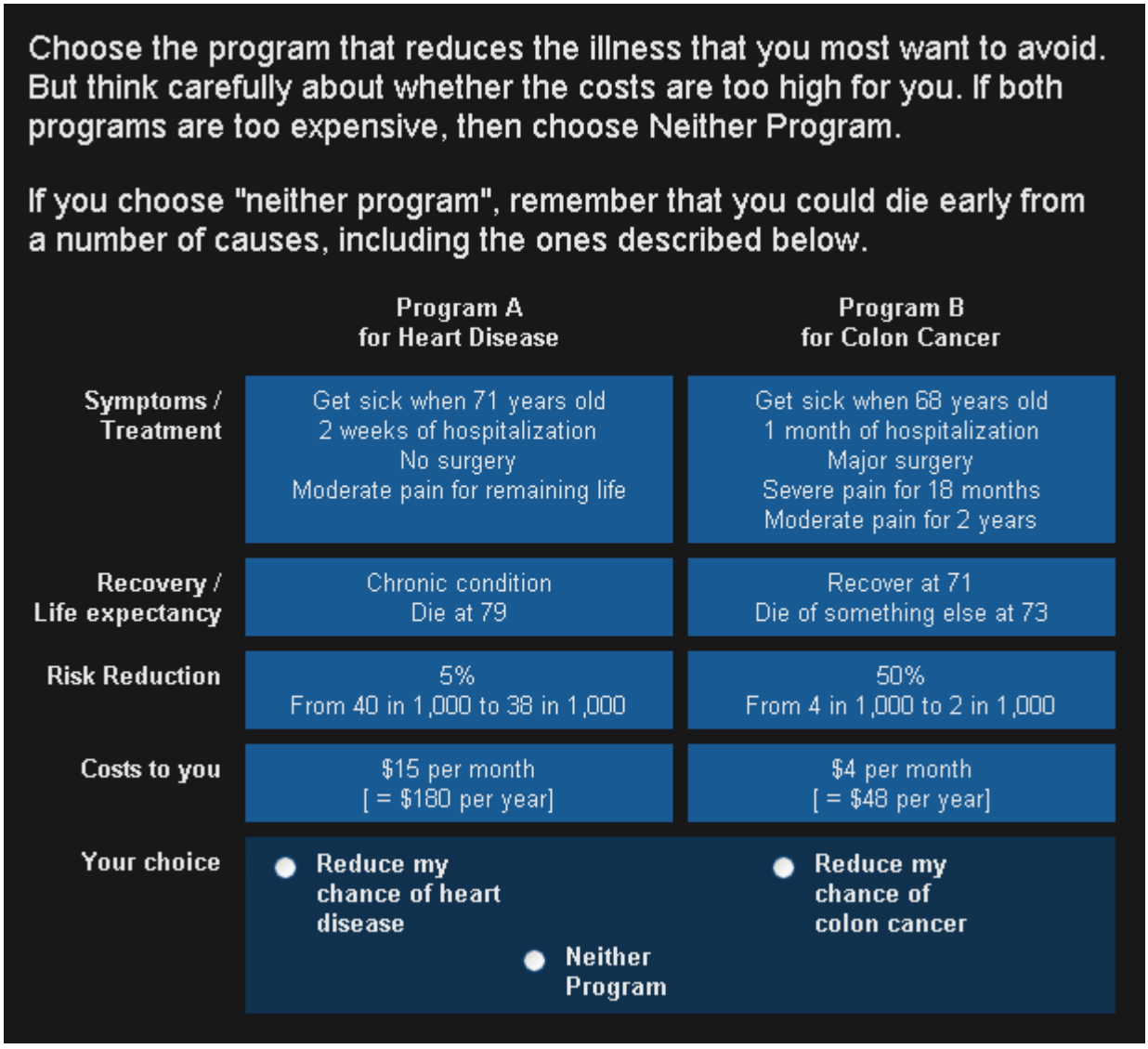


Figure 2 – Implicit VSL for ten years of latency, five years of illness, death in 15 years, as a function of respondent age now ($ million) Estimated without sign constraints.

Appendix A

Example: Conjoint Choice Set



Appendix B – Supplementary Tables

B.1 To be included with paper

Table B1 – Sample versus Population Characteristics (percent)

	Sample n=1619 individuals	2000 U.S. Census
Age		% of 25+ pop
25 to 34	**18**	22
35 to 44	**23**	25
45 to 54	**21**	21
55 to 64	**17**	7
65 to 74	**14**	6
75 and older	**7**	10
Income		% of hhlds
Less than $10,000	**5.7**	9.5
$10,000 to $15,000	**6.1**	6.3
$15,000 to $20,000	**4.9**	6.3
$20,000 to $25,000	**6.1**	6.6
$25,000 to $30,000	**6.6**	6.4
$30,000 to $40,000	**7.4**	6.4
$40,000 to $50,000	**8.6**	5.9
$50,000 to $60,000	**13.3**	10.7
$60,000 to $75,000	**11.1**	9.0
$75,000 to $100,000	**11.1**	10.4
$100,000 to $125,000	**10.4**	10.2
More than $125,000	**4.2**	5.2
Female	**0.51**	0.51

B2. Available from the authors

Table B2 - Assessing the Impact of Sample Inclusion Criteria

Parameter	(1) 100, wk,cr,by	(2) 80, wk,cr,by	(3) 60, wk,cr,by	**(4) wk,cr,by**	(5) wk,by	(6) by	(7) none
$\beta_0 \times 10^5$	5.343	5.250	5.402	**5.208**	5.376	7.513	7.582
	(8.14)***	(8.18)***	(8.53)***	**(8.34)*** **	(9.57)***	(13.68)***	(14.14)***
$\beta_1 \times 10^9$	-0.2332	-0.215	-0.2271	**-0.199**	-0.2241	-0.2279	-0.2327
	(4.64)***	(4.39)***	(4.72)***	**(4.22)*** **	(5.26)***	(5.53)***	(5.74)***
α_{10}	-47.93	-47.80	-49.26	**-45.57**	-37.03	21.29	22.67
	(5.09)***	(5.20)***	(5.45)***	**(5.11)*** **	(4.58)***	(2.72)***	(2.94)***
α_{11}	-19.18	-18.84	-17.43	**-16.45**	-17.18	-2.09	-0.57
	(1.92)*	(1.95)*	(1.83)*	**(1.74)* **	(2.01)**	-0.25	-0.07
α_{20}	-656.2	-669.1	-663.1	**-585.0**	-434.6	-153.7	-155.1
	(3.44)***	(3.61)***	(3.66)***	**(3.28)*** **	(2.71)***	-1.01	-1.03
α_{21}	21.89	22.61	23.13	**20.70**	15.04	9.73	9.65
	(2.86)***	(3.02)***	(3.15)***	**(2.85)*** **	(2.29)**	-1.56	-1.57
α_{30}	-0.1943	-0.1997	-0.2083	**-0.1901**	-0.1341	-0.0915	-0.0896
	(2.67)***	(2.80)***	(2.97)***	**(2.74)*** **	(2.12)**	-1.52	-1.51
α_{31}	238.7	238.7	230.9	**202.0**	172.2	80.6	85.6
	(2.71)***	(2.79)***	(2.77)***	**(2.45)** **	(2.33)**	-1.14	-1.23
α_4	-8.789	-8.870	-8.856	**-7.912**	-6.646	-4.471	-4.593
	(2.48)**	(2.56)**	(2.61)***	**(2.35)** **	(2.19)**	-1.55	-1.61
α_{50}	0.0808	0.081	0.0825	**0.07528**	0.06138	0.04291	0.04342
	(2.37)**	(2.43)**	(2.51)**	**(2.31)** **	(2.08)**	-1.52	-1.56
α_{51}	67.76	94.45	98.17	**104.57**	51.73	-8.08	-11.78
	-0.87	-1.25	-1.33	**-1.44**	-0.79	-0.13	-0.19
Alternatives	19881	21030	21855	**22560**	27447	34155	35151
Log L	-10296.949	-10894.039	-11319.506	**-11697.495**	-14224.012	-17681.197	-18260.971

continued…

Parameter	(1) 100, wk,cr,by	(2) 80, wk,cr,by	(3) 60, wk,cr,by	**(4) wk,cr,by**	(5) wk,by	(6) by	(7) none
Sample mean VSI	6.61	3.31	3.52	**2.5**	2.52	0.05	0.05
Sample 5th %	0	0	0	**0**	0	0	0
Sample 25th %	1.28	1.16	1.11	**1.07**	0.76	0	0
Sample 50th %	2.33	2.19	2.08	**1.94**	1.54	0	0
Sample 75th %	4.15	3.82	3.63	**3.23**	2.71	0	0
Sample 95th %	12.94	9.69	9.95	**6.95**	7.24	0.03	0

Key to inclusion criteria: "100" = aggregate time on all five program choice tasks at least 100 seconds (e.g. average time 20 seconds per choice set); analogously for "80" and "60"; "wk" = choice of Neither Program not explained solely by "I did not believe the programs would work" (i.e. scenario rejection); "cr" = passed simple risk comprehension question at end of risk tutorial; "by" = choice did not involve an (erroneously designed) life extension from the illness experience. The most substantial impact is associated with the "wk" (scenario rejection) criterion.

Table B3 – Effect of Discounting Assumption on Parameter Estimates

(Parameter) Variable	Model 1	Model 2	Model 3
	r=.03	r=.05	R=.07
$\left(\beta_{00}\times 10^{5}\right)\left[\text{first income term}\right]$	4.14 (8.31)***	5.19 (8.31)***	6.17 (8.21)***
$\left(\beta_{10}\times 10^{9}\right)\left[\text{second income term}\right]$	-0.1499 (4.02)***	-0.1991 (4.22)***	-0.2524 (4.39)***
$(\alpha_{10})\Delta\Pi_i^{AS}\log\left(pdvi_i^A+1\right)$	-40.6 (4.96)***	-47.8 (5.32)***	-54.8 (5.57)***
$(\alpha_{13})\left[P(sel_i)-\overline{P}\right]\Delta\Pi_i^{AS}\left[\log\left(pdvi_i^A+1\right)\right]$	2.664 (2.14)**	3.280 (2.20)**	3.925 (2.20)**
$(\alpha_{20})\Delta\Pi_i^{AS}\log\left(pdvr_i^A+1\right)$	-13.00 (1.72)*	-16.45 (1.74)*	-20.21 (1.72)*
$(\alpha_{30})\Delta\Pi_i^{AS}\log\left(pdvl_i^A+1\right)$	-358.9 (2.39)**	-582.4 (3.26)***	-888.4 (4.05)***
$(\alpha_{31})age_{i0}\Delta\Pi_i^{AS}\log\left(pdvl_i^A+1\right)$	13.11 (2.13)**	20.58 (2.84)***	30.69 (3.51)***
$(\alpha_{32})age_{i0}^2\Delta\Pi_i^{AS}\log\left(pdvl_i^A+1\right)$	-0.1265 (2.13)**	-0.1888 (2.72)***	-0.2711 (3.28)***
$(\alpha_{40})\Delta\Pi_i^{AS}\left[\log\left(pdvl_i^A+1\right)\right]^2$	96.80 (1.64)*	200.6 (2.43)**	381.5 (3.26)***
$(\alpha_{41})age_{i0}\Delta\Pi_i^{AS}\left[\log\left(pdvl_i^A+1\right)\right]^2$	-4.149 (1.70)*	-7.848 (2.33)**	-14.13 (3.04)***
$(\alpha_{42})age_{i0}^2\Delta\Pi_i^{AS}\left[\log\left(pdvl_i^A+1\right)\right]^2$	0.0425 (1.76)*	0.0746 (2.29)**	0.1274 (2.90)***
$(\alpha_{50})\Delta\Pi_i^{AS}\left[\log\left(pdvi_i^A+1\right)\right]\times\left[\log\left(pdvl_i^A+1\right)\right]$	74.48 (-1.58)	102.1 (-1.4)	140.1 (-1.28)
$(\alpha_{51})age_{i0}\Delta\Pi_i^{AS}\left[\log\left(pdvi_i^A+1\right)\right]\times\left[\log\left(pdvl_i^A+1\right)\right]$	-3.372 (1.78)*	-4.47 (-1.57)	-5.899 (-1.42)
$(\alpha_{52})age_{i0}^2\Delta\Pi_i^{AS}\left[\log\left(pdvi_i^A+1\right)\right]\times\left[\log\left(pdvl_i^A+1\right)\right]$	0.0429 (2.34)**	0.056 (2.10)**	0.0723 (1.89)*
Alternatives	22560	22560	22560

Log L	-11694.154	-11694.991	-11697.598
Sample mean fitted VSI ($ million) [a]	3.20	2.59	2.28
Sample 5th %	0	0	0
Sample 25th %	1.51	1.12	0.78
Sample 50th %	2.64	2	1.53
Sample 75th %	4.25	3.33	2.69
Sample 95th %	8.52	7.14	6.67
Age at maximum of first age profile on $\log\left(pdvl_i^A+1\right)$ term	51.8	54.5	56.6
Age at minimum of second age profile on $\left[\log\left(pdvl_i^A+1\right)\right]^2$ term	48.9	52.6	55.4
Age at minimum of third age profile $\left[\log\left(pdvi_i^A+1\right)\right]\times\left[\log\left(pdvl_i^A+1\right)\right]$ term	39.3	39.9	40.8