The Effect of Health Status on Willingness to Pay for Morbidity and Mortality Risk Reductions

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Abstract

Both actual and expected morbidity systematically affect individuals' demands for both life-saving policies and preventative health care. Using a large general-population sample, we estimate a utility-theoretic model of consumer preferences across risk reduction programs targeted at a wide variety of major health threats with differing illness profiles. Individuals' demands for programs targeting a particular illness are higher when there is a history of that illness and when subjective risks are higher. A history of other illnesses and greater other-illness subjective risks decrease demand. These comorbidity effects operate through the marginal utilities of both (i) adverse health states and (ii) income.

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1 Introduction

The probability that individuals will suffer from an illness varies dramatically over their lives. Ultimately, most individuals will experience some type of chronic illness, spending up to a quarter of their lifetimes suffering from some type of morbidity. Yet empirically, researchers know little about how changes in actual and expected morbidity affect individuals' health-seeking and risk-mitigating behavior. These changes can bias benefits estimates for life-saving policies, such as the Value of a Statistical Life (VSL).[3]

The question of how to accommodate differences in current health status across individuals has also been raised in the Quality Adjusted Life Years (QALY) literature.[4] In particular, there has been a debate about how to deal with the perceived discrimination against disabled people implied by assigning lower values to their life-years gained through treatments (see Ubel, et al. (2000), Johannesson (2001), Nord, et al. (2003)). In calculating the QALYs gained from treating a specific condition, some researchers argue that one should assume that a previously disabled person will be restored to perfect health if they are treated for this new illness. Others point to a down-side of this strategy: it reduces to zero the implied utility gains from treating the pre-existing disability itself. This has been called the "QALY trap."

Failure to consider prior morbidity in assessing the benefits of reduced health risks may result in poorly designed public policies. Failing to account for the effects of prior morbidity or subjective morbidity risks may also lead to models of health-seeking behavior that poorly predict individuals' investments in their own health and their utilization of exist-

[3] VSLs are used in benefit cost-analyses for reductions in mortality risks. A VSL is calculated merely by taking an estimate of willingness to pay (WTP) for a tiny change in risk (e.g. Δr=0.000001) and scaling that WTP to a 1.00 risk change, assuming proportionality. This normalization strategy renders comparable a variety of WTP estimates based on risk changes of different magnitudes. The averages represented by VSL estimates are widely used as a basis for calculating the approximate social benefits of other small risk changes of different arbitrary sizes.

[4] QALYs are used in cost-effectiveness analysis of alternative medical therapies. They focus on physical measures of health status and involve the standardization of health decrements relative to a year of perfect health (where death is 0 and perfect health is normalized as 1). For a brief overview, see Appendix C, available from the authors.

ing preventive and remedial health programs. In this paper, we develop and offer the first empirical tests of how actual and expected morbidity affect individuals' health-seeking and risk-mitigating behaviors.

Recent theoretical analyses of comorbidity and background risks have made important advances. Eeckhoudt and Hammitt (2001) explore the effects of two sequential risks, finding that demand for the first risk falls as the second risk rises because of a "why bother" effect. Evans and Smith (2001) consider two simultaneous risks, highlighting the ambiguity that results from the "why bother" effect and the "dead anyway" effect attributed to Pratt and Zeckhauser (1996). When considering the risk of two illnesses, Bleichrodt et al., (2003) assume that if individuals experience one illness, they face no further risk from that illness. They predict that morbidity from a background illness will increase individuals' demands for reducing the risk of the targeted illness. For example, having diabetes increases individuals' demands for prostate cancer prevention.

In contrast with Bleichrodt et al. (2003), we consider the scenario in which the onset of morbidity signals an increase in the probability of a recurrence of that same illness. Having had an episode of breast cancer or heart disease, for example, increases the morbidity-mortality risk associated with that same disease. Our theoretical model extends the Bleichrodt et al. framework by evaluating the effects of actual or expected morbidity on the demand for both same-illness and other-illness prevention. Once an individual experiences an illness, he or she faces a new set of state-dependent illness probabilities. The individual will now face a higher probability of a further worsening of their health due to that same illness. We hypothesize that a previous episode of a particular illness likely increases demand for preventing a same-illness recurrence, potentially causing the individual to allocate resources away from the prevention of other illnesses. This contrasts sharply with the hypothesis of Bleichrodt et al. (2003), which implies that individuals who experience one illness will increase their demand for programs that reduce their risks of other illnesses. A second novel hypothesis that emerges from this framework is that individuals in a relatively

degraded health state will become relatively more risk-averse, on average.

We test these hypotheses using data from an innovative survey that elicits individuals' demands for programs that reduce their risks of eleven different major health threats. Using a nationally representative sample of over 1,600 individuals, we estimate the parameters of an indirect utility-difference function that explains stated preferences over alternative risk-reduction programs. We allow the marginal utilities associated with reducing the risk of each particular illness profile to vary systematically as a function of whether the individual has experienced 1) a previous episode of that illness, 2) previous episodes of other major illness(es) or 3) no prior major illnesses. We then explore an alternative specification. We allow individual demands to vary systematically with the individual's subjective risk assessments for the same (and other) illnesses. Both of these estimated models are very general, allowing demand to vary with income and the age of the individual, as well as with the latency of the illness and the types of health states avoided (i.e. sick-years, post-illness years, and lost life-years).

Our findings advance several literatures in a number of ways. First, methodologically, our approach evaluates the effects of both actual and expected morbidity when valuing changes in the risks of different types of illnesses. This approach will have wide application in assessing both the value of reductions in morbidity and mortality risks, and the value of preventative and remedial therapies. Second, we evaluate the effects of this actual and expected morbidity for an unusually large range of health state outcomes, including non-fatal short-term or long-term morbidity, periods of morbidity followed by mortality, and for sudden death. Thus our models subsume the special case that is usually considered (a reduction in the risk of death in the current period, e.g. Jones-Lee, 1974). However, we also generalize this framework to a much wider array of health outcomes than is usually considered in the risk mitigation literature.

Third, our hypotheses tests are the first of their kind in the literature to show that morbidity may have a very large impact on individuals' demands for health risk mitigation.

Having had an illness previously can more than triple an individual's demand for programs that reduce a risk of a recurrence of that same illness. Having had some other major illness does not appear to increase demand for mitigating the risk of the targeted illness. On the contrary, when the individual subjective risk assessment for some other major illness is high relative to the targeted illness, then the individual's demand for the targeted illness actually decreases, on average. These results generally hold for all types of health outcomes: non-fatal morbidity, a period of morbidity followed by mortality, and sudden death. Behaviorally, these results suggest that individuals aggressively substitute investments in risk mitigation in response to their perceived relative risk levels.

2 A Utility-Theoretic Choice Model

Our model interprets individuals' choices as revealing their option prices, in the sense of Graham (1981), for programs that mitigate the risks of uncertain future health states.[5] The underlying model allows a great deal of flexibility in characterizing how individuals assume that future health states will impact their future income and program costs. While program choices have inter-temporal consequences, our model remains one of static decision-making, with future costs and benefits converted into the appropriate 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 "recovered" state (if the illness is non-fatal) and 4) premature death. Let i index individuals and let t index time periods.[6] In its simplest form, the individual's indirect

[5] Cameron (2005) employs a less-elaborate model in a similar vein to the problem of climate change mitigation programs, where costs must be incurred starting now to reduce the chance of adverse consequences many years into the future.

[6] Time is measured in years or months, as needed.

utility function might be:

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

We generalize the undiscounted marginal utility, β, of some function of current income, $f(Y_{it})$, to be a linear function of income itself: $\beta = \beta_0 + \beta_1 Y_{it}$. This accommodates a diminishing marginal utility of income. In the current paper, we will also assume simply that $f(Y_{it}) = Y_{it}$. The variables pre_{it}, ill_{it}, rcv_{it}, and lyl_{it} are a set of mutually exclusive and exhaustive 0,1 variables that capture individual i's basic health state in time period t. Let α_0 be the undiscounted utility from the pre-illness status quo health state ($pre_{it} = 1$); let α_1 be the (dis)utility from each future period of illness ($ill_{it} = 1$); let α_2 correspond to each period of the post-illness state (i.e. "recovered," $rcv_{it} = 1$); and let α_3 correspond to each period of premature death (i.e. "life-year lost," $lyl_{it} = 1$). Algebraically, 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. We interpret the disutility of each of these states as being the same as the utility associated with avoiding them.

In our data, individuals will face choices that involve three alternatives: Program A, Program B, or neither program (labeled A, B, and N). In developing our estimating specification, however, we will describe our model in terms of just two choices: Program A versus no program (just A and N). The three-alternative case is completely analogous.

Let undiscounted indirect utility be V_{it}^{jk} for the i^{th} individual in period t, where $j = A$ if Program A is chosen and $j = N$ if the program is not chosen. The superscript k will be S (denoting "sick") if the individual suffers the illness and H (denoting "healthy") if the individual does not suffer the illness. From the perspective of a program choice made today, individuals will discount the streams of utility derived from each future health state. 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 $\delta^t = (1+r)^{-t}$, and assume it can be used to calculate the present discounted values of these profiles of future health states for individual i, which we will denote $PDV(V_i^{jk})$, where $j = A, N$ and $k = S, H$.

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.

If the individual selects Program A, then expected utility (with the expectation taken across the uncertain sick (S) and healthy (H) states, is:

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

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

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

In presenting the explicit form of the expected utility difference formula, $E_{S,H}\left[PDV\left(V_i^A\right)\right] - E_{S,H}\left[PDV\left(V_i^N\right)\right]$, to be discussed next, we will make use of a number of notational abbreviations. The basic discounting term to be applied to any constant stream of payments between now and the individual's nominal life expectancy, T_i, is $pdvc_i^A = \sum_{t=1}^{T_i} \delta^t$. Other discounted terms, also summed from $t = 1$ to $t = T_i$ include $pdve_i^A = \sum \delta^t pre_{it}^A$, $pdvi_i^A = \sum \delta^t ill_{it}^A$,

[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 $1/(1+t)^\lambda$.

$pdvr_i^A = \sum \delta^t rcv_{it}^A$, and $pdvl_i^A = \sum \delta^t lyl_{it}^A$ (for pre-illness years, sick-years, recovered years, and lost life-years). We also abbreviate by defining $pdvy_i^A = pdve_i^A + pdvi_i^A + pdvr_i^A$, which captures the time intervals over which the individual is assumed to anticipate earning his or her current real income, and $pdvp_i^A = pdve_i^A + pdvr_i^A$, which captures the time intervals over which the individual is assumed to understand that the stated costs of the program will be paid. Recall that the indicator variables for each health state are mutually exclusive and exhaustive, so that we can define $pdvc_i = pdve_i + pdvi_i + pdvr_i + pdvl_i$.

If the marginal utility of income is presumed to depend linearly on income, the expected utility difference that drives the individual's choice between Program A and the "No Program" alternative can then be written as follows (there will be an analogous utility difference for Program B versus the "Neither Program" alternative in the three-alternative case):

$$E_{S,H}\left[PDV(V_i^A)\right] - E_{S,H}\left[PDV(V_i^N)\right] = A[c_i^A]^2 + B[c_i^A] + C + \varepsilon_i \qquad (2)$$

where

$$\begin{aligned} A &= \beta_1 \left[\left(1 - \Pi_i^{AS}\right) pdvc_i^A + \Pi_i^{AS} pdvp_i^A\right] \\ B &= -(\beta_0 + \beta_1 2Y_i) \ \left[\left(1 - \Pi_i^{AS}\right) pdvc_i^A + \Pi_i^{AS} pdvp_i^A\right] \\ C &= (\beta_0 Y_i + \beta_1 Y_i^2)\Delta\Pi_i^{AS}\left(pdvy_i^A - pdvc_i^A\right) \\ &\quad + \alpha_1 \Delta\Pi_i^{AS} pdvi_i^A + \alpha_2 \Delta\Pi_i^{AS} pdvr_i^A + \alpha_3 \Delta\Pi_i^{AS} pdvl_i^A + \varepsilon_i \end{aligned}$$

This model pertains to the case where respondents are assumed to anticipate that they will sustain their current income in real terms while sick, but not if they die, and that they will incur the costs of the risk reduction program only if they are neither sick nor dead. This pair of assumptions accounts for the complexity of the terms in equation (2) that involve $pdvc_i^A$, $pdvp_i^A$, and $pdvy_i^A$.

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

the terms in equation (2) must be rearranged into a form that isolates the five key parameters, β_0, β_1, α_1, α_2, and α_3, in the underlying indirect utility function:

$$\begin{aligned} & E_{S,H}\left[PDV(V_i^A)\right] - E_{S,H}\left[PDV(V_i^N)\right] = \\ & \beta_0 \ \{\text{first income term}\} + \beta_1 \ \{\text{second income term}\} \\ & +\alpha_1\left\{\Delta\Pi_i^{AS} pdvi_i^A\right\} + \alpha_2\left\{\Delta\Pi_i^{AS} pdvr_i^A\right\} + \alpha_3\left\{\Delta\Pi_i^{AS} pdvl_i^A\right\} + \varepsilon_i \end{aligned} \tag{3}$$

If we impose a single common discount rate, the five terms in braces in equation (3) can be constructed from the data. We focus on estimates of these fundamental indirect utility parameters in our empirical illustration, although we are careful to generalize the model, as warranted, to accommodate nonlinearities, interaction terms, and systematically varying versions of these parameters.

2.2 The "Value of a Statistical Illness Profile" ($VSIP$)

The Graham-type 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. Once the parameters β_0, β_1, α_1, α_2, and α_3 have been estimated from a conditional logit model based on equation (3), the annual option price that will make $E_{S,H}\left[PDV(V_i^A)\right] - E_{S,H}\left[PDV(V_i^N)\right]$ exactly zero, $\widehat{c_i^A}$, can be solved from equation (2).

To convert the present value of this annual willingness-to-pay into something we call the "value of a statistical illness profile" ($VSIP$), we adopt a strategy just like that used with VSLs. We normalize arbitrarily on a 1.00 risk change by dividing this WTP by the absolute size of the risk reduction.[8] In the empirical section in this paper, we use an adaptation of the model in equation (2), where the marginal utility of income is a function of income itself.

[8] In our study, all the probability changes $\Delta\Pi_i^{AS}$ are negative, while the absolute magnitudes 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.

However, the intuition of arriving at the $VSIP$ is obscured less by the algebra if we show the steps in terms of a slightly simpler model where indirect utility is only linear in income (i.e. where $\beta_1 = 0$). In this case, in equation (2), $A = 0$ and B and C simplify to:

$$\begin{aligned} B &= -\beta_0 \left[\left(1 - \Pi_i^{AS}\right) pdvc_i^A + \Pi_i^{AS} pdvp_i^A\right] \\ C &= \beta_0 Y_i \Delta\Pi_i^{AS} \left(pdvy_i^A - pdvc_i^A\right) \\ &\quad + \alpha_1 \Delta\Pi_i^{AS} pdvi_i^A + \alpha_2 \Delta\Pi_i^{AS} pdvr_i^A + \alpha_3 \Delta\Pi_i^{AS} pdvl_i^A + \varepsilon_i \end{aligned}$$

Dividing by the absolute value of the risk change produces:

$$VSIP = \frac{E\left[PV(\widehat{c_i^A})\right]}{|\Delta\Pi_i^{AS}|} = \frac{C \left[\left(1 - \Pi_i^{AS}\right) pdvc_i^A + \Pi_i^{AS} \left(pdvp_i^A\right)\right]}{B \ |\Delta\Pi_i^{AS}|} \tag{4}$$

How does the magnitude of the estimated $VSIP$ vary with changes in its 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 $VSIP$. The effect of income on $VSIP_i^A$ is given by $\partial VSIP_i^A / \partial Y_i = pdvl_i^A$, which is non-negative. The effect of an increase in income on the predicted $VSIP$ will be larger (i.) as more life-years are lost and (ii.) as the individual is older, so that any life-years lost come sooner in time and less discounting is involved.[9]

The $VSIP$ will also depend upon the different marginal utilities of avoided periods of illness, post-illness status, and premature death. It will further 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.[10] This heterogeneity can

[9] Nothing in this specification precludes negative point estimates of the $VSIP$. 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 can be a concern when these marginal utilities are permitted to vary systematically with some of the attributes of the illness profile and/or the characteristics of the individual in question.

[10] 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 sensitivity of our results to different discount rates.

be accommodated by making the indirect utility parameters α_1, α_2, and α_3 depend upon other individual characteristics.[11]

In our framework, an analog to a conventional VSL is but one possible variant of our more-general concept of a $VSIP$. To isolate the quantity most akin to a conventional VSL (for benchmarking against existing VSL estimates), 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:

$$E[VSL] = \left|\Delta\Pi_i^{AS}\right|^{-1} E\left[PV(\widehat{c_i^A})\right] = \left(Y_i - \frac{\alpha_3}{\beta_0}\right) pdvl_i^A \tag{5}$$

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 $VSIP$ 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), in addition to preserving future income.[12]

3 Survey Methods and Data

Market data that adequately illustrate how individuals allocate risk mitigation expenditures across competing risks and across their remaining years of life are not available.[13] Therefore,

[11] 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.

[12] Our program choice data reject the restriction that $\beta_1 = 0$, so the formulas employed for the $VSIP$ in this paper are somewhat more complex (although completely analogous).

[13] 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

we have surveyed a large sample of 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 to mitigate these illness risks.

The development of this survey instrument involved 36 cognitive interviews, three pretests (n=100 each) and an unusually large pilot study (n=1,100).[14] Knowledge Networks Inc. administered the final version of the demand survey, and the health-profile survey, to a sample of 2439 of their panelists.[15] Our response rate for those panelists contacted was 79 percent.[16] (A brief summary of sample versus population characteristics is provided in Table A1 of Appendix A. We control for sample selection probabilities in our empirical estimates.)

We designed this survey to ameliorate several limitations of existing risk valuation methods. First, many studies have focused on non-representative sub-populations (e.g., working-age men). In contrast, our sample is of the general population of men and women 25 years and older, including a wide range of ethnicities, age groups, and income groups. Second, many studies focus upon only mortality risks from one source, often ignoring indivduals' marginal rates of substitution between morbidity and mortality states. Here, pre-mortality morbidity is an integral part of the model. Furthermore, many earlier stated preference studies focus on only one, or at most two, risk reduction(s), whereas here, to enhance the representativeness of the $VSIP$ and VSL estimates we derive, we assess the most common health and mortality risks over a wide range of risk reductions. Third, the results of many revealed and stated preference studies may be subject to biases because they omit relevant substitute risks and mitigating programs from the individual's choice set. In contrast, we

costs of programs. For example, using the Health and Retirement Survey, Picone, Sloan and Taylor (2004) explore how time preferences, expected longevity and other demand shifters affect women's propensities to get mammograms or pap-smears and to conduct regular breast self-exams. However, missing data on program costs, baseline risks, and latency of program benefits prevented a fuller demand analysis.

[14]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.

[15]Households are recruited to the Knowledge Networks panel 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: www.knowlegdenetworks.com.

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

strive to establish, in the individual's mind, a more complete health risk decision environment before valuing a reduction in any one given risk.

We review the structure of the survey only briefly in the body of this paper.[17] Module 1 of the survey evaluates the individual's subjective risk assessment for the major illnesses they face, their familiarity with each illness, and any current mitigating and averting behavior they may be undertaking. Module 2 consists of a tutorial that introduces individuals to the idea of an illness profile and some programs that may manage these illness-specific risks. As shown in Appendix A, Table A2, these illnesses and injuries include breast cancer, prostate cancer, colon cancer, lung cancer, skin cancer, heart disease (i.e., heart attack, angina), stroke (e.g., blood clot, aneurysm), respiratory diseases (i.e., asthma, bronchitis, emphysema), and traffic accidents, as well as chronic diseases such as diabetes and Alzheimer's.

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 a few plausibility constraints for each illness type).[18] Table A2 also summarizes the key attribute levels employed in our choice sets. The first row in this table presents the frequency with which each of the twelve randomly assigned illness names appears. Up to eleven attributes (rows) characterize each illness profile and program, although we concentrate on just the most important attributes in this paper.[19] 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.,

[17] An annotated example of one realization of the randomized survey design is available at: http://darkwing.uoregon.edu/~cameron/vsl/Annotated_survey_DeShazo_Cameron.pdf

[18] Each illness was randomly assigned a particular name so that we could match responses to the individual's subjective risk of each disease. We took care to avoid scenarios that were implausible (e.g., one does not recover from Alzheimer's or die suddenly from diabetes). In this paper, we rely on the essential randomness of this assignment to minimize any potential omitted variables bias in the specifications we employ here. Controlling for illness names would of course reduce the error variances in the model, but should not make much difference to the point estimates. We explore the systematic effects of illness names in a separate paper.

[19] 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 decision to include these particular attributes was guided by a focus on those attributes that (1) most affected the utility of individuals and (2) could be characterized for all the illnesses that individuals evaluated (Moxey et al. 2003).

1991; O'Connor and Blomquist, 1997; Sloan et al., 1998; Johnson, et al., 2000). We seek to estimate demand conditional on the individual's ex ante information set about each health risk.[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 an annual pin-prick diagnostic blood test and, if needed, associated drug therapies and recommended life-style changes. We choose this class of interventions because pretests 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 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 copayment that would have to be paid by the respondent for as long as the diagnostic testing and medication are needed, and is expressed in both monthly and annual terms. For 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.

Module 3 of the survey contains the five main choice sets, each offering the individual two specific programs, each designed to reduce the risk of a different specific illness profile. We carefully explain to individuals that they can choose neither program. We also point out several possible explanations why a reasonable person might choose neither program in some cases.[22] If individuals choose "neither program," we assume that they prefer their status quo

[20] 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.

[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. For traffic accidents, the intervention is described as additional safety equipment with a specified annualized cost.

[22] These reasons include that they 1) cannot afford either program, 2) did not believe they faced these

illness profile to either of the two costly illness-reducing programs in each choice set. Figure 1 provides one example of a full choice set from the primary survey instrument. The two illness profiles in this example include one non-fatal illness and one fatal illness.

Module 4 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 5 was administered separately from the choice experiment. It collects a detailed medical history for the individual, as well as household socioeconomic information.

For the present paper, we are particularly interested in each individual's current morbidity. From Module 5 of the survey, we know whether the individual reports having been diagnosed (by a doctor) as having any of a wide range of illnesses. We match this information with the illness name used to label each illness profile and create a dummy variable, $samorbid_i^j$ equal to one if the individual has already had this illness. We also create a count variable that enumerates how many of the other major illnesses that our survey asks about have been experienced by the individual. This variable, $comorbid_i^j$, is zero if the individual has no other major illnesses on our list, but it can take a number of integer values according to the health history of the individual.[23] Table 1 shows the distribution of these two additional variables, $samorbid_i^j$ and $comorbid_i^j$, across the 15,040 illness profiles in our estimating sample. Since the incidence of "same illness" and "number of other major illnesses" differs with the illness being considered in any particular illness profile, the values of the dummy variable and the count variable differ across illness profiles for the same person.

If the individual has already been diagnosed with the disease in question, they are instructed in our survey to consider the diagnostic tests as reducing the risk of a recurrence of that ailment. These individuals can be expected to be more willing to pay for that program. In contrast, the individual may not have experienced the disease that the program addresses,

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.

[23] Experience with traffic accidents is always counted as zero, due to the general perception that these events are random and exogenous. If we had reliable information on numbers of prior injury auto accidents for each individual, we could use these data analogously.

but may have experienced other major diseases. The relative salience of this program will decline with the number of other diseases because its relative importance will decline compared to other more-urgently relevant programs or health-maintenance activities to which the individual may prefer to devote his or her resources.

We are also interested in each individual's subjective assessment of different types of morbidity/mortality risks. In Module 1 of the survey, we asked respondents to rate their subjective risk from each of seven classes of health risks on a five-point scale from "low risk" to "high risk." To conserve on survey length and complexity when eliciting these subjective risks, it was necessary to aggregate all cancers (breast, prostate, colon, lung, and skin) and both types of heart problems (heart attack and heart disease).[24] The frequencies of subjective same-illness ratings, $sasubrsk_i^j$, (corresponding to each of the 14,109 illness profiles for which sufficient subjective risk data are available) are given in Table 2. For other-illness subjective risks, we assign to all cancers the same subjective cancer risk, and to both heart-related profiles the common subjective risk for heart ailments. We then calculate the average subjective risk rating for all illnesses other than the one featured in each illness profile. Due to averaging, this variable, $cosubrsk_i^j$, is more nearly continuous. Table 2 also provides the mean and standard deviation, across the sample, of these individual-average other-illness ratings.

4 Empirical Analysis

The most basic utility-theoretic model takes the form presented in equation (3), assumes homogeneous preferences, and produces five parameter estimates for a simple additively separable specification.[25] This specification, even when estimated without sign restrictions, produces robust statistical significance and the expected signs on all five primary parameters. The marginal utility of income is positive, but declines with the level of income (yet does not

[24] Despite the potential value of greater resolution among cancers and heart problems, we faced binding constraints in reducing the average elapsed time for our survey to an acceptable level.

[25] Table A3 in Appendix A gives results for some even-simpler ad hoc models.

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.[26]

We immediately reject one important hypothesis embodied in our simplest utility-theoretic specification in equation (3), namely 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. We then acknowledge that, at the moment of the individual's ex ante program choice, each alternative is likely to be perceived in terms of the *present value* of the sequence of health states it represents. These present values reflect the mix of future health states in each illness profile. It is therefore reasonable to take as a starting point for our choice models the indirect utility expressions in terms of present discounted health states. 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.

4.1 Nonlinear models: logarithmic specifications

The systematic portion of the final line in our simplest estimating specification in equation (3), $\alpha_1 \Delta\Pi_i^{AS} pdvi_i + \alpha_2 \Delta\Pi_i^{AS} pdvr_i + \alpha_3 \Delta\Pi_i^{AS} pdvl_i$, can be easily adapted to produce a specification that is 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 the original form of the term involving the present discounted health states is:

$$\Delta\Pi_i^{AS} \left\{ \alpha_1 pdvi_i^A + \alpha_2 pdvr_i^A + \alpha_3 pdvl_i^A \right\} \tag{6}$$

We then shift each present discounted health-state term by 1 to accommodate the absence of some health states in some health profiles (e.g. there are no sick-years or post-illness years

[26] 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."

in cases of sudden death). Then we take logarithms. The resulting logarithmic form for the final substantive term in equation (3) is:

$$+\Delta\Pi_i^{AS}\left\{\alpha_1 \log\left(pdvi_i^A+1\right)+\alpha_2 \log\left(pdvr_i^A+1\right)+\alpha_3 \log\left(pdvl_i^A+1\right)\right\} \tag{7}$$

Estimates for this form produce a substantial improvement in the log-likelihood function compared to the preliminary linear and additively separable specification. However, an even more general translog-based form proves to be warranted by the data, and its parameters vary systematically with the age of the individual. It is important to control for the respondent's age because long-latency illness profiles can only realistically be offered to younger respondents. In this paper, we take as our baseline specification the final form established in Cameron and DeShazo (2004a). In comparison to the model in equation (3), our baseline translog-based model, with some utility parameters quadratic in age, can be expressed as:

$$\begin{aligned} & E_{S,H}\left[PDV(V_i^A)\right]-E_{S,H}\left[PDV(V_i^N)\right] \qquad (8)\\ = \;& \beta_0\ \{\text{first income term}\}+\beta_1\ \{\text{second income term}\}\\ & +\Delta\Pi_i^{AS}\left\{\begin{array}{c} (\alpha_{10})\log\left(pdvi_i^A+1\right)\\ +(\alpha_{20})\log\left(pdvr_i^A+1\right)\\ +(\alpha_{30}+\alpha_{31}age_{i0}+\alpha_{32}age_{i0}^2)\log\left(pdvl_i^A+1\right)\\ +(\alpha_{40}+\alpha_{41}age_{i0}+\alpha_{42}age_{i0}^2)\left[\log\left(pdvl_i^A+1\right)\right]^2\\ +(\alpha_{50}+\alpha_{51}age_{i0}+\alpha_{52}age_{i0}^2)\left[\log\left(pdvi_i^A+1\right)\right]\left[\log\left(pdvl_i^A+1\right)\right] \end{array}\right\} \end{aligned}$$

We retain only those age-related shifters which prove to be robustly statistically significant. The coefficients on the three terms involving lost life-years prove to be most affected by the respondent's current age. Estimates for this specification are reported as Model 1 in Table 3.

In all of the models reported in Table 3, we employ one additional preference-heterogeneity

variable that proves to be statistically significant only as a shifter on the sick-years term, $\Pi_i^{jS} \log(pdvi_i^j + 1)$. Nonrandom sample selection is always a potential concern in survey data. In other work (Cameron and DeShazo, 2005b) we have modeled non-random selection, across several types of attrition, in the Knowledge Networks panel recruitment process. Our estimating specification in the present paper is a conditional logit model, so there do not exist convenient packaged algorithms for Heckman-type selectivity corrections that recognize correlations between the error terms in the sample selection process and the choice model. However, we employ as an additional measure of heterogeneity the fitted participation probabilities from a selection model that undertakes to explain the presence or absence from our estimating sample of each of 525,188 initial random-digit dialed contacts with potential Knowledge Networks panelists.

Note in Table 3 that the baseline coefficient, α_{10}, on $\Pi_i^{jS} \log(pdvi_i^j + 1)$ is on the order of -50. When this coefficient is allowed to shift with the differences between individual fitted participation probabilities and their median level, this baseline coefficient shifts by only about 3 to 4 for a one-unit change in this difference. The vast bulk of fitted participation probabilities lie between 0.001 and 0.01, so this correction, while statistically significant, is barely detectible in practice. If the typical value of $[P(sel_i) - P*]$ is no larger than about 0.005, the typical distortion in the estimated value of α_{10} will be on the order of only 0.02 (on a base of about -50).[27]

4.2 Introducing Comorbidity Effects

Model 2 in Table 3 introduces systematic variation in demands for health risk reductions according to whether the individual has already suffered, or is currently suffering, from the same illness used to label the intervention program for the alternative in question.

At first blush, it might seem reasonable to introduce the comorbidity terms as potential

[27] Of course, the finding that the within-sample effects of overall response probabilities is tiny does not necessarily imply that the out-of-sample effects are also tiny, but this result increases our confidence that they may be small.

shifters only on the marginal disutilities of adverse health states, anticipating that prior experience with an illness should affect the marginal (dis)utility associated with a recurrence of sick-time from that illness or the (dis)utility of future life-years lost due to that illness. However, due to the discussion in the literature of complementarities between health status and income or wealth, we also entertain comorbidity shifters on the two parameters in our model that capture the marginal utility of income. In Equation (8), we generalize the previously scalar version of the linear marginal-utility-of-income coefficient (β_0) to ($\beta_{00} + \beta_{01} samorbid_i^A + \beta_{02} comorbid_i^A$). We do the same for β_1, the quadratic marginal-utility-of-income coefficient, and for each of the health-state marginal utilities. The version reported as Model 2 retains only those morbidity and comorbidity shifters that are robustly statistically significant. Having the named disease ($samorbid_i^A = 1$), regardless of what that disease may be, renders more-negative the base coefficient on $\log\left(pdvl_i^A + 1\right)$, the lost life-years term. By increasing the disutility associated with lost life-years from the named disease, this effect will tend to increase WTP for the program. But this same-illness morbidity also appears to increase the rate at which the marginal utility of income declines with income. Individuals thus appear to become more risk-averse with respect to other consumption. At higher incomes, this will make the marginal utility of income relatively lower and this heterogeneity will therefore amplify WTP for the program relatively more at these higher income levels.[28]

Having major diseases other than the one associated with the program in question, however, has a different effect. When this count variable, $comorbid_i^A$, is allowed to shift only the marginal disutilities associated with adverse health states, it is difficult to discern any robustly significant effects. However, when $comorbid_i^A$ is permitted to shift the two parameters that describe the marginal utility of income, there are strongly significant effects. Thus the other-illness comorbidity effect appears to operate substantially through its effects on

[28] If $samorbid_i$ is prevented from shifting the coefficient on the lost life-years term, its effect shows up as a statistically significant decrease in the baseline marginal utility of income. Via this pathway, it would increase WTP similarly for all income levels. Models that allow both effects reveal that the $samorbid_i$ shifter on the lost life-years term is significant but the shifter on the baseline marginal utility of income, β_0, is not. Thus we retain only the shifter on the lost life-years term.

the marginal utility of income, rather than any shift in preferences with respect to different health states. The marginal utility of income captures the marginal utility of a dollar spent on all other goods and services besides health risk reductions. When one's health is compromised, one apparently draws less enjoyment from increments to the consumption of other things.

Each additional other major illness raises the baseline marginal utility of income, β_0, an effect that will tend to reduce WTP (proportionately) for the program in question. However, each additional other major illness also causes the marginal utility of income to decline more quickly as income is larger, since it shrinks β_1. This is an increase in risk-aversion with respect to other consumption. This effect will tend to increase WTP for the program at high incomes more than at low incomes. The relative magnitudes of these two effects will determine the overall effect of $comorbid_i^A$ on WTP. However, it appears that the number of other illnesses suffered is more likely to reduce demand for the program in question at low incomes than at high incomes, so the distributional implications of this tendency will be important.

4.3 Introducing Subjective Morbidity Risks

Model 3 in Table 3 shows the consequences of a further generalization. Subjective risks do not have any statistically significant effect on the marginal utilities of income, but they do affect the marginal (dis)utility of both discounted sick-years and discounted lost life-years. Greater same-illness subjective risk, $sasubrsk_i^j$, significantly increases the disutility of a sick-year and appears to increase the disutility of a lost life-year by an even greater amount, leading to a much greater WTP to avoid any given illness profile.

Holding same-illness subjective risks constant, the greater the individual's average other-illness subjective risk, $cosubrsk_i^j$, the less is the individual's expected disutility from a sick-year or lost life-year due to the illness in question. This effect is also strongly significant (and of roughly comparable magnitude for both of these adverse health states).

Note that inclusion of the subjective risk variables causes the sole significant coefficient on the interaction between the sick-years and lost life-years term (α_{52} in Table 3) to become statistically insignificant, although it retains the same sign and order of magnitude. This is because subjective risks of illness appear to be quadratic in age. For each of the seven categories of illness for which we elicited subjective risks, we have crudely modeled individuals' risk ratings as quadratic functions of the individual's current age. Ordinary least squares regression estimates are presented in Table A4 in Appendix A. With the exception of traffic accidents, for which the perceived risk seems to decline monotonically with age, and possibly for Alzheimer's disease, for which it may increase monotonically with age, all subjective risks seem to first rise with age and then decline. Table A4 also reports point estimates of the age at which the average subjective risk seems to peak for each health threat.[29]

We speculate that individuals experience a growing sense of health vulnerability with age that may initially be higher for traffic accidents but relatively uniform across most major diseases. However, around their middle years, they begin to get indications of which specific diseases are most likely to affect them and which are less likely to be their greatest concern. Some support for this conjecture can be garnered from the skewness in the distribution of risk ratings across our seven disease categories, for individuals of different ages. For each individual, we can calculate this skewness statistic. Modeling skewness in subjective risk ratings as a function of age reveals the following regression:

$$\begin{aligned} Skewness_i &= 0.8426 - 0.02678\ age_i + 0.0002536\ age_i^2 + e_i \qquad (9) \\ &\qquad\quad (4.02) \qquad (3.23) \qquad\qquad (3.28) \quad (absolute\ t-ratios) \end{aligned}$$

This quadratic form has its minimum at age 52.8 years. Fitted skewness is everywhere positive, suggesting outliers in the higher-risk range. As a function of age, fitted skewness ranges from a low of 0.1357 (at age 52.8) to a high of 0.5459, suggesting that individuals tend,

[29] The age range in our sample was from 25 through 93 years. A histogram for the complete age distribution is presented in Figure B2 in Appendix B, available from the authors.

on average, to perceive more lower-risk illnesses or injuries and fewer higher-risk illnesses or injuries. The outlying larger subjective risk for younger people seems to be a shared concern about traffic accidents. As they age, however, different people focus on different subsets of illnesses. The declining average across individuals of the subjective risk associated with *any given illness* is an artifact of the subjective risk being higher for some individuals, but relatively lower for most others, instead of moderate for all.

Despite the statistical insignificance of α_{52} in Model 3, we retain the interaction terms between $log(pdvi_i^j + 1)$ and $log(pdvl_i^j + 1)$ so that simulations using this model will be comparable with those for Model 2, without subjective risks. Furthermore, the only instances where respondents were eligible to see illness profiles with very high values for both sick-years and lost life-years were cases when the individual was young. As noted above, failing to control for age in estimating the effects of this log-interaction term will bias the apparent coefficients.

4.4 Values of Statistical Illness Profiles

To our knowledge, our efforts are the first attempts to estimate separately the marginal utility of avoiding a year of morbidity and a lost life-year within a common utility-theoretic model. We now evaluate the validity of the corresponding $VSIP$ estimates by assessing whether they vary systematically in a manner that economic theory or simple intuition would predict.[30] We examine first how these $VSIP$ estimates vary with respect to the explanatory variables that are the focus of this paper: current health status and subjective health risks. We then report upon sensitivity analyses with respect to assumptions about average time preferences and about income (see Appendix A). Sensitivity of our $VSIP$ estimates with respect to age and assumed disease latency is the subject of a separate paper.

We employ the estimated parameters for Model 3 in Table 3 to characterize what we

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

term the Value of a Statistical Illness Profile ($VSIP$) associated with arbitrarily designated combinations of years of morbidity, years in post-illness status, and years of premature mortality. Unlike the traditional concept of the Value of a Statistical Life (VSL), this $VSIP$ is not a one-size-fits-all constant. The $VSIP$ depends on the illness profile, income, and the current age of the individual. For illustrative purposes, we examine just five representative illness profiles, for a 45-year-old individual with income of $42,000: 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) sudden death in the current period.[31] We specifically consider the sudden death profile because it is closest to the implicit profile considered in many hedonic wage-risk studies designed to reveal the VSL. The other profiles are offered to emphasize the usefulness of being able to model sick-years as well as lost life-years, as well as different time profiles of illness.

Descriptive statistics for the $VSIP$ values implied by Model 1, Model 2, and Model 3 are presented at the foot of Table 3. In this case, our baseline example is for a 45-year-old individual with income of $42,000, no current morbidity, and sample-wide average levels of own-illness and other-illness subjective risk.[32] The marginal utility parameters are estimated by maximum likelihood using a packaged algorithm for McFadden's conditional logit model with fixed effects.[33] The fitted $VSIP$ values are nonlinear functions of these estimated parameters. We randomly draw vectors of possible parameter values from the approximately joint-normal distribution of these maximum-likelihood estimated parameters and use these parameter draws to calculate different possible point estimates of the $VSIP$. The $VSIP$ formulas involve marginal utility of income terms in the denominator which

[31] A much wider variety of illness profiles could of course be considered. We consider many other profiles in other papers associated with this project.

[32] These averages are taken across all the individuals in the sample, not just the 45-year-olds. Because our baseline individual in this study has no current morbidity, our baseline VSL estimates in this paper are slightly lower than those derived in Cameron and DeShazo (2005a) where we did not control for current morbidity.

[33] We use Stata's *clogit* algorithm, with individual fixed effects across the five choice occasions presented to each respondent.

are not constrained to be strictly positive, so the theoretical mean of the distribution is technically undefined. Thus, we report the median value of these simulated point estimates as well as the 5th and 95th percentiles of the distribution (across 1000 random draws).

The parameters of Model 3 suggest that the $VSIP$ for sudden death for a 45-year-old (our closest approximation to the conventional hedonic-wage VSL estimate) is about \$4.4 million, with a 90% interval ranging from about \$2.6 million to about \$6.4 million. This interval contains the \$6.2 million figure currently employed by the U.S. EPA in many of its benefit-cost analyses of environmental regulations. It also contains the roughly \$3 million figure preferred by the U.S. Department of Transportation

Our simulated VSIPs for illnesses other than sudden death reveal the disutility suffered from morbidity that may be overlooked in many other studies that consider just mortality risks (or just sudden death scenarios). The $VSIP$ for a profile involving one year of serious non-fatal illness is more than half of the $VSIP$ for one year of illness that is fatal. Five years of serious non-fatal illness has a $VSIP$ at least three-quarters as great as the $VSIP$ for sudden death. After five years of serious illness, there is not much difference in the $VSIP$ according to whether the illness is fatal or not.

Having established these baselines, Table 4 displays examples of the key findings for this paper. The table shows the results of analogous simulations to illustrate the estimated effects of individual morbidity status and subjective morbidity risk on the estimated $VSIP$ for our five illustrative illness profiles. Again, we use the parameter estimates and parameter variance-covariance matrix for Model 3 in Table 3. The top panel of Table 4 first reproduces our baseline simulation results for a 45-year-old with \$42,000 in income, zero current morbidity and sample average levels of subjective morbidity. The table then shows what happens to the simulated distribution of the $VSIP$ as same-illness morbidity is set to one with comorbidity held at zero. This corresponds to the case of an individual having the named illness, but no other illnesses. (Recall from Table 2 that for only about 4 percent of profiles has the individual already experienced the major illnesses that is the subject of the

risk reduction program.) Having already experienced the illness in question is confirmed to increase dramatically the individual's willingness to pay for a program that reduces the risk of a recurrence.[34]

The top panel of Table 4 also shows the consequences of holding same-illness morbidity at zero and counterfactually simulating one "other illness" for this individual. Recall from Table 1 that about 24 percent of profiles were considered by respondents who had at least one other major illness besides the one that is the subject of that illness profile. Having one other major illnesses does indeed tend to decrease the $VSIP$ for a program to reduce the illness named in a particular illness profile.[35]

The lower panel of Table 4 again begins by providing for easy comparison the baseline simulation results for a healthy 45-year-old with sample average subjective risk levels. But now we hold all current morbidity at zero and permute subjective risks. Lowering same-illness subjective risk by one rating unit dramatically decreases the $VSIP$ for a program to reduce the risk from the illness in question. Increasing same-illness subjective risk by an equal amount greatly increases the $VSIP$ for the program to control that risk. We then consider similar changes in other-illness subjective risk and find that decreasing average other-illness subjective risk serves to increase $VSIP$ for the illness in question, but increasing average other-illness subjective risk correspondingly lowers $VSIP$ for the illness in question. These results are plausible and fully consistent with the underlying theory.

Appendix A also describes the consequences of different assumptions about the discount rate (Table A5) and provides some simulations to illustrate the effect of income on our

[34] If a draw from the asymptotic joint distribution of the estimated parameters produces a very tiny negative point value of the marginal utility of income, a huge negative value will result for the $VSIP$. This is because the marginal utility of income is in the denominator of the WTP calculation.

[35] Corresponding results for simulations for *samorbid* and *comorbid* for the specification in Model 2 of Table 5 are presented for comparison in Appendix Table B2, available from the authors. The baseline $VSIP$s for this specification differ only minimally. Results for the simulation with respect to *comorbid* are almost identical. Results for the *samorbid* simulation differ more noticeably because of the markedly different estimates for the α_{33} parameter in these two specifications. For Model 2, the medians in the five simulations range between 11 percent lower and 80 percent higher than the corresponding values for Model 3. We emphasize the results for Model 3 because of the overwhelming statistical significance of the subjective risk coefficients.

estimates for $VSIP$s (Table A6).

5 Discussion and Conclusions

Unlike many previous empirical efforts to measure willingness to pay to reduce mortality risks, the model developed in Cameron and DeShazo (2005a) and extended in this paper does not produce a single best estimate or confidence interval for the Value of a Statistical Life (VSL). Intead, 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, our model 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 types and durations of health outcomes 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.

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 calculate $VSIP$s for a wide variety of illness profiles that could be 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.

Our model can produce, as a special case, a construct that is similar to a traditional VSL estimate. However, it also produces a new and important type of economic information: explicit and distinct estimates of the marginal utilities of avoiding a year of significant morbidity and a lost life-year. It is apparent that these marginal utilities are *not* simple constants. From these heterogeneous marginal values, which appear to depend upon many

factors (including the current age of the respondent, their income, their current health status, and the mix of health states in an illness profile) we have illustrated how to construct values for a wide range of statistical illness profiles.

Estimates such as ours may diminish the need for policy analysts to piece together disparate estimates for the value of morbidity and mortality risk reductions from different valuation methods and studies. To further enhance program and policy evaluation, we have organized our model around estimating the value of a statistical illness profile ($VSIP$), although we allow for the identification of a concept that is roughly similar to the more-traditional value of statistical life (VSL). The $VSIP$ evaluates the set of heterogeneous health outcomes associated with a given illness risk. Policy changes that affect the prevalence and severity of that illness will shift the joint distribution of the duration of morbidity and extent of premature mortality.

Our analyses illustrate some initial results concerning how the marginal utility of risk mitigation varies systematically across individuals according to one category of individual characteristics. Specifically, we illustrate how the demand for mortality risk reduction varies with the individual's current current health status (same-illness and other-illness morbidity) and subjective health risks. We do this for a selection of archetypical illness profiles. Our results certainly 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 actual demand function for morbidity and mortality risk reductions should be viewed as a multi-dimensional schedule of values exhibiting a great deal of systematic heterogeneity.

Particularly thought-provoking with respect to the comorbidity effects uncovered here is the result that current same-illness morbidity and other-illness morbidity seem to act very strongly through their effects on the marginal utility of income and that this impact differs by income level. If we fail to control for subjective health risks, current morbidity also appears to increase significantly the disutility associated with a life-year lost to that

same illness. However, when the model controls for the subjective risk of (a recurrence of) the same illness, this apparent effect disappears. What remains is the insight that same-illness morbidity reduces the value to the individual of other consumption opportunities. Same-illness morbidity increases risk aversion with respect to other consumption (i.e. the rate at which the marginal utility of income diminishes with income). This implies that compromised health states inhibit our abilities to enjoy other things in life (and moreso as our incomes are greater) rather than increasing the perceived disutilities of future adverse health states. This change in relative utilities makes us willing to spend more to reduce the health risk, especially when we have higher incomes.

Current other-illness morbidity ("comorbidity"–being already a victim of other major health problems) increases the baseline marginal utility of income but also decreases the rate at which this marginal utility diminishes with income. This effect will tend to decrease demand for the reduction of other types of health risks for lower-income individuals, but will produce a lesser effect at higher incomes. The more resource-constrained the individual, the greater will be the impact of reduced health on demand for programs that will prevent other serious illnesses. The equity implications of this effect should therefore be a particular policy concern.

In other work, we have examined more closely the relationship between demand for health risk reductions and age. We, and other researchers, have identified a tendency for this demand to vary non-monotonically over the life-cycle. Our models in this present paper allow all the main parameters that capture the marginal disutilities of sick-years and lost life-years to vary quadratically with the individual's current age. In this paper, however, it is apparent that some of this quadratic tendency stems from systematic variation over the life-cycle in the distribution of subjective health risks.

The distinction between current morbidity/comorbidity and subjective risk perceptions appears to be an important one. Whereas the individual's current health state appears to act through its effects on the marginal utility of income (i.e. other goods and services),

subjective risks have their greatest impacts upon the apparent disutility associated with sick-years and life-years lost due to prospective health risks. Subjective risks are endogenous, however. It is very useful to confirm that the relative marginal disutilities of sick-years and life-years lost vary with the relative subjective risk ratings for different diseases. However, it is an open question whether it is truly the marginal utilities that differ, or whether ex ante subjective risks are merely used by respondents to update the stated risks in our choice scenarios before their program choice is made. In the current analysis, these completing hypotheses are observationally equivalent.

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Table 1 - Frequency of morbidity status (across 15,040 profiles)

	Frequency	Percent
samorbid (=1 if r has had illness named in profile)		
0	14,432	95.96
1	608	4.04
comorbid (=# of other named illnesses r has had)		
0	11,409	75.86
1	2,854	18.98
2	619	4.12
3	158	1.05

Table 2 – Frequency of subjective morbidity/mortality risk ratings

sasubrsk (same-illness risk ratings, centered at 0)	Frequency	Percent
-2 – Low Risk	3,092	20.94
-1	3,112	21.08
0	4,417	29.92
1	2,613	17.70
2 – High Risk	1,529	10.36
Profiles with complete data	14,763	100.00
cosubrsk (other-illness risk ratings, centered at 0)	Mean	Std. Dev.
Individual means across eleven "other" risks[a]	-0.2531	0.8674
Profiles with complete data	14,109	

[a] Cancers (breast, prostate, lung, colon, skin), heart disease (and heart attack), stroke, respiratory disease, traffic accidents, diabetes, Alzheimer's disease.

Table 3 – Generalizations involving Actual Morbidity and Comorbidity, and Subjective Morbidity and Comorbidity Risk

(Parameter) Variable	Model 1	Model 2	Model 3
	Baseline Model: Translog, Quad in Age	Add Actual Morbidity, Comorbidity	Add Subjective Morbidity, Comorbidity Risk
$(\beta_{00}\times 10^{5})$[first income term]	5.183	4.461	4.777
	(8.30)***	(6.30)***	(6.37)***
$(\beta_{02}\times 10^{5})\,comorbid_i^j$ [first income term]	-	**.1835**	**.1344**
		(2.41)**	**(1.63)**
$(\beta_{10}\times 10^{9})$[second income term]	-1.992	-1.249	-1.598
	(4.22)***	(2.26)**	(2.75)***
$(\beta_{11}\times 10^{9})\,samorbid_i^j$ [second inc term]	-	**-0.4035**	**-0.3649**
		(3.42)***	**(2.97)*****
$(\beta_{12}\times 10^{9})\,comorbid_i^j$ [second inc term]	-	**-0.1517**	**-0.1255**
		(2.16)**	**(1.70)***
$(\alpha_{10})\Delta\Pi_i^{jS}\log(pdvi_i^j+1)$	-47.90	-49.10	-47.52
	(5.35)***	(5.47)***	(4.99)***
$(\alpha_{11})\,sasubrsk_i^j\,\Delta\Pi_i^{jS}\log(pdvi_i^j+1)$	-	-	**-28.76**
			(5.23)***
$(\alpha_{12})\,cosubrsk_i^j\,\Delta\Pi_i^{jS}\log(pdvi_i^j+1)$	-	-	**25.38**
			(3.12)***
$(\alpha_{13})\left[P(sel_i)-\overline{P}\right]\Delta\Pi_i^{jS}\left[\log(pdvi_i^j+1)\right]$	3.378	3.706	3.016
	(2.35)**	(2.54)**	(2.00)**
$(\alpha_{20})\Delta\Pi_i^{jS}\log(pdvr_i^j+1)$	-16.49	-17.01	-13.94
	(1.76)*	(1.81)*	(1.42)
$(\alpha_{30})\Delta\Pi_i^{jS}\log(pdvl_i^j+1)$	-580.1	-573.1	-693.4
	(3.25)***	(3.20)***	(3.71)***
$(\alpha_{31})\,age_{i0}\Delta\Pi_i^{jS}\log(pdvl_i^j+1)$	20.46	20.16	24.97
	(2.82)***	(2.77)***	(3.28)***
$(\alpha_{32})\,age_{i0}^2\Delta\Pi_i^{jS}\log(pdvl_i^j+1)$	-0.1874	-0.1824	-0.2322
	(2.70)***	(2.61)***	(3.18)***
$(\alpha_{33})\,samorbid_i^j\,\Delta\Pi_i^{jS}\log(pdvl_i^j+1)$	-	**-83.25**	**-17.18**
		(3.77)***	**(0.70)**
$(\alpha_{33})\,sasubrsk_i^j\,\Delta\Pi_i^{jS}\log(pdvl_i^j+1)$	-	-	**-43.79**
			(8.48)***
$(\alpha_{33})\,cosubrsk_i^j\,\Delta\Pi_i^{jS}\log(pdvl_i^j+1)$	-	-	**22.9305**
			(3.08)***

(Parameter) Variable (continued)	Model 1	Model 2	Model 3
	Baseline Model: Translog, Quad in Age	Add Actual Morbidity, Comorbidity	Add Subjective Morbidity, Comorbidity Risk
$(\alpha_{40})\Delta\Pi_i^{jS}\left[\log\left(pdvl_i^j+1\right)\right]^2$	199.3 (2.41)**	193.6 (2.34)**	268.1 (3.07)***
$(\alpha_{41})age_{i0}\Delta\Pi_i^{jS}\left[\log\left(pdvl_i^j+1\right)\right]^2$	-7.786 (2.32)**	-7.581 (2.25)**	-10.58 (2.96)***
$(\alpha_{42})age_{i0}^2\Delta\Pi_i^{jS}\left[\log\left(pdvl_i^j+1\right)\right]^2$	0.0739 (2.27)**	0.0718 (2.19)**	0.1019 (2.94)***
$(\alpha_{50})\Delta\Pi_i^{jS}\left[\log\left(pdvi_i^j+1\right)\right]\times\left[\log\left(pdvl_i^j+1\right)\right]$	102.5 (1.40)	102.2 (1.39)	67.07 (0.87)
$(\alpha_{51})age_{i0}\Delta\Pi_i^{jS}\left[\log\left(pdvi_i^j+1\right)\right]\times\left[\log\left(pdvl_i^j+1\right)\right]$	-4.484 (1.57)	-4.461 (1.56)	-2.861 (0.95)
$(\alpha_{52})age_{i0}^2\Delta\Pi_i^{jS}\left[\log\left(pdvi_i^j+1\right)\right]\times\left[\log\left(pdvl_i^j+1\right)\right]$	0.0561 (2.10)**	0.0560 (2.08)**	0.0395 (1.39)
Alternatives	22560	22560	21314
Log L	-11694.647	-11662.924	-10868.419
Simulated *VSIP*s: archetypical profiles (*y*=$42,000, *samorbid*=0, *comorbid*=0, *sasubrsk*=-0.25, *cosubrsk*=-0.25)			
Simulate: 45, 1 yr sick, non-fatal ($ million)	2.37 [1.13, 3.71]	2.48 [1.20, 3.87]	2.21 [0.84, 3.76]
Simulate 45, 5 yrs sick, non-fatal ($ million)	3.61 [2.34, 4.96]	3.76 [2.51, 5.26]	3.44 [2.05, 5.06]
Simulate 45, 1 yr sick, then die ($ million)	4.63 [2.92, 6.50]	4.51 [2.97, 6.69]	4.21 [2.40, 6.03]
Simulate 45, 5 yrs sick, then die ($ million)	4.49 [2.71, 6.52]	4.43 [2.57, 6.71]	3.73 [1.88, 5.98]
Simulate 45, sudden death ($ million)	4.57 [2.88, 6.48]	4.53 [2.82, 6.74]	4.40 [2.60, 6.42]

[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. Simulated *VSIP*s for a 45-year-old, for specified illness profiles, are medians and 5% and 95% levels of fitted values across 1000 random draws from the joint distribution of the parameters.

Table 4 – Simulations:[a] based on Model 3 (both actual morbidity/comorbidity and subjective risks (*VSIP* in $million; with y=$42,000, discount rate=0.05)

Sensitivity to actual morbidity levels (samorbid and comorbid)

45 years old now; At 45:	***samorbid*=0** ***comorbid*=0** ***sasubrsk*=-0.25** ***cosubrsk*=-0.25**	***samorbid*=1** *comorbid*=0 *sasubrsk*=-0.25 *cosubrsk*=-0.25	*samorbid*=0 ***comorbid*=1** *sasubrsk*=-0.25 *cosubrsk*=-0.25
1 yr sick; non-fatal	**2.21** **[0.84, 3.76]**	4.25 [-lots, 55.90]	2.01 [0.85, 3.32]
5 yrs sick; non-fatal	**3.44** **[2.05, 5.06]**	7.01 [-lots, 90.29]	3.09 [2.00, 4.54]
1 yr sick; then die	**4.21** **[2.40, 6.03]**	11.95 [-lots, 140.68]	3.81 [2.31, 5.61]
5 yrs sick; then die	**3.73** **[1.88, 5.98]**	10.35 [-lots, 125.76]	3.34 [1.67, 5.41]
Sudden death	**4.40** **[2.60, 6.42]**	12.54 [-lots, 146.50]	4.05 [2.47, 6.05]

Sensitivity to subjective risk levels (mean-1 and mean+1 for sasubrsk and cosubrsk)

45 years old now; At 45:	***samorbid*=0** ***comorbid*=0** ***sasubrsk*=-0.25** ***cosubrsk*=-0.25**	*samorbid*=0 *comorbid*=0 ***sasubrsk*=-1.25** *cosubrsk*=-0.25	*samorbid*=0 *comorbid*=0 ***sasubrsk*=0.75** *cosubrsk*=-0.25	*samorbid*=0 *comorbid*=0 *sasubrsk*=-0.25 ***cosubrsk*=-1.25**	*samorbid*=0 *comorbid*=0 *sasubrsk*=-0.25 ***cosubrsk*=0.75**
1 yr sick; non-fatal	**2.21** **[0.84, 3.76]**	1.40 [0.05, 2.79]	2.95 [1.63, 4.37]	2.71 [1.35, 4.27]	1.60 [0.28, 3.00]
5 yrs sick; non-fatal	**3.44** **[2.05, 5.06]**	1.81 [0.39, 3.20]	4.99 [3.63, 6.83]	4.66 [3.18, 6.54]	2.07 [0.62, 3.69]
1 yr sick; then die	**4.21** **[2.40, 6.03]**	-0.21 [-2.03, 1.45]	8.37 [6.17, 11.40]	6.55 [4.48, 9.60]	1.63 [-0.28, 3.57]
5 yrs sick; then die	**3.73** **[1.88, 5.98]**	-1.22 [-3.36, 0.69]	8.50 [6.08, 11.74]	6.63 [4.48, 9.70]	0.63 [-1.35, 2.62]
Sudden death	**4.40** **[2.60, 6.42]**	0.52 [-1.36, 2.45]	8.06 [5.92, 11.10]	6.42 [4.20, 9.31]	2.28 [0.23, 4.49]

[a] Across single samples of 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. Coincidentally, the sample means for both *sasubrsk* and *cosubrsk* round to -0.25 on a scale of -2 to +2. Notation "-lots" means that for some draws, the marginal utility of income, shifted by *samorbid*, is very small and negative. This marginal utility forms the denominator of the formula for willingness-to-pay. Very tiny positive or negative values produce VSI estimates with large absolute values.

Figure 1 – One example of a choice set

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

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

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

○ Neither Program

Next Question

APPENDIX A

Table A1 – 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

Table A2 – Main illness profile attributes, by label assigned to health threat

(estimating sample = 15040 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 A3 – Simple ad hoc conjoint choice specifications
(alternatives = 22560, no selection, no fixed effects)

	Model 1	Model 2
Monthly Cost of Program	-0.0078 (-9.84)***	-0.0081 (-10.14)***
Risk Reduction	88.99 (10.05)***	72.14 (7.60)***
Sick-Years	-	0.0158 (2.46)***
Lost Life-Years	-	0.0265 (4.88)***
Alternatives	22560	22560
Log-likelihood	-8203.94	8189.46

Table A4 - Dependence of subjective risk ratings[a] on age

	Cancers	Heart Disease	Stroke	Resp. Disease	Traffic Accident	Diabetes	Alzheim. Disease
Quadratic Specifications							
Age	0.03110	0.04970	0.04967	0.04838	0.01358	0.04806	0.02463
	(2.32)**	(3.67)**	(3.77)**	(3.31)**	(1.13)	(3.18)**	(2.17)**
Age^2	-0.3262	-0.04737	-0.04211	-0.05178	-0.01952	-0.05036	-0.01895
	(2.59)**	(3.72)**	(3.40)**	(3.76)**	(1.72)*	(3.55)**	(1.78)*
Constant	-0.7346	-1.184	-1.685	-1.563	-0.54576	-1.466	-1.735
	(2.19)**	(3.49)**	(5.11)**	(4.28)**	(1.81)*	(3.88)**	(6.11)**
Peak Age	47.7	52.5	59.0	46.7	34.8	47.7	65.0
Linear Specifications (where suspected)							
Age	-	-	-	-	-0.006941	-	.0047037
					(3.84)**		(2.75)**
Constant	-	-	-	-	-.0526	-	-1.25679
					(-0.55)		(14.01)
n	1594	1595	1596	1583	1588	1591	1564

[a] Subjective risk scale is low risk through high risk (-2, -1, 0, 1, 2) in these data.

Table A5 – Simulations: sensitivity to discount rate assumption[a]
(*VSIP* in $million; *y*=$42,000, *samorbid*=0, *comorbid*=0,
sasubrsk=-0.25, *cosubrsk*=-0.25)

45 years old now; At 45:	r=3%	**r=5%**	r=7%
1 yr sick, non-fatal	2.24	**2.21**	2.17
	[0.73, 3.81]	**[0.84, 3.76]**	[0.79, 3.86]
5 yrs sick, non-fatal	3.53	**3.44**	3.34
	[2.09, 5.16]	**[2.05, 5.06]**	[1.93, 5.05]
1 yr sick; then die	5.17	**4.21**	3.28
	[3.49, 7.13]	**[2.40, 6.03]**	[1.64, 5.41]
5 yrs sick; then die	4.84	**3.73**	2.76
	[3.00, 7.10]	**[1.88, 5.98]**	[0.79, 5.13]
Sudden death	5.24	**4.40**	3.69
	[3.48, 7.36]	**[2.60, 6.42]**	[1.90, 5.86]

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

Table A6 – Simulations: Sensitivity to income based on Model 3[a]
(*VSIP* in $million; *r*=0.05, *samorbid*=0, *comorbid*=0, *sasubrsk*=-0.25, *cosubrsk*=-0.25)

Sensitivity to income level			
45 years old now: At 45	***y*=$25,000**	***y*=$42,000**	***y*=$67,500**
1 yr sick; non-fatal	1.88 [0.77, 3.09]	**2.21 [0.84, 3.76]**	2.85 [1.12, 5.13]
5 yrs sick; non-fatal	2.93 [1.74, 4.2]	**3.44 [2.05, 5.06]**	4.46 [2.69, 7.18]
1 yr sick; then die	3.22 [1.83, 4.98]	**4.21 [2.40, 6.03]**	5.73 [3.5, 10.03]
5 yrs sick; then die	2.89 [1.35, 4.71]	**3.73 [1.88, 5.98]**	5.07 [2.73, 9.02]
Sudden death	3.42 [1.86, 5.2]	**4.40 [2.60, 6.42]**	6.13 [3.65, 10.51]

Implied arc elasticity of VSIP with respect to income		
	$25,000 to $42,000	**$42,000 to $67,000**
1 yr sick; non-fatal	0.32	0.54
5 yrs sick; non-fatal	0.32	0.55
1 yr sick; then die	0.53	0.66
5 yrs sick; then die	0.50	0.65
Sudden death	0.49	0.71

[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%.

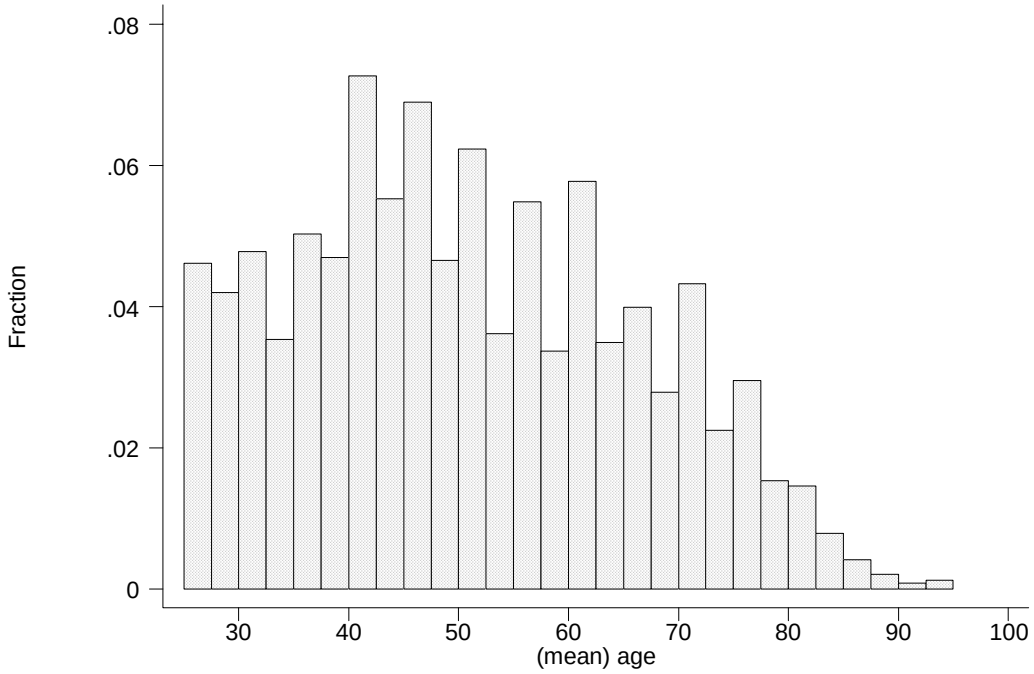

Figure A1 - Age Distribution in Estimating Sample (Alternatives = 25,560)

APPENDIX B

Table B1 - Impact of exclusion criteria
(Estimates differ from main results for Model 3 due to absence of $\left[P(sel_i)-\overline{P}\right]\Delta\Pi_i^{AS}\left[\log\left(pdvi_i^A+1\right)\right]$ term for probability of selection from RDD recruitment to survey sample.)

	(1)	(2)	(3)	**(4)**
Parameter	None	by	by, wk	**by, wk, cr**
$\left(\beta_{00}\times10^5\right)$[first income term]	0.723	0.7132	0.4848	**0.4834**
	(11.14)***	(10.75)***	(7.15)***	**(6.45)*** **
$\left(\beta_{03}\times10^5\right)comorbid_i^A$[first income term]	0.1756	0.1834	0.1579	**0.1247**
	(2.46)**	(2.52)**	(2.09)**	**(1.52)**
$\left(\beta_{10}\times10^9\right)$[second income term]	-0.1749	-0.1668	-0.1517	**-0.165**
	(3.46)***	(3.24)***	(2.88)***	**(2.85)*** **
$\left(\beta_{11}\times10^9\right)samorbid_i^A$[second inc term]	-0.2893	-0.3237	-0.4207	**-0.3593**
	(2.97)***	(3.23)***	(3.60)***	**(2.92)*** **
$\left(\beta_{12}\times10^9\right)comorbid_i^A$[second inc term]	-0.1682	-0.1728	-0.1584	**-0.1124**
	(2.65)***	(2.69)***	(2.30)**	**(1.53)**
$(\alpha_{10})\Delta\Pi_i^{AS}\log\left(pdvi_i^A+1\right)$	16.88	15.32	-38.68	**-45.32**
	(2.05)**	(1.83)*	(4.45)***	**(4.79)*** **
$(\alpha_{11})sasubrsk_i^A\Delta\Pi_i^{AS}\log\left(pdvi_i^A+1\right)$	-31.64	-31.29	-29.44	**-28.87**
	(6.60)***	(6.44)***	(5.78)***	**(5.26)*** **
$(\alpha_{12})cosubrsk_i^A\Delta\Pi_i^{AS}\log\left(pdvi_i^A+1\right)$	12.76	11.97	26.70	**25.45**
	(1.83)*	(1.69)*	(3.61)***	**(3.13)*** **
$(\alpha_{20})\Delta\Pi_i^{AS}\log\left(pdvr_i^A+1\right)$	3.242	1.792	-13.64	**-13.92**
	(0.38)	(0.21)	(1.52)	**(1.42)**
$(\alpha_{30})\Delta\Pi_i^{AS}\log\left(pdvl_i^A+1\right)$	-207.0	-213.6	-493.8	**-695.6**
	(1.31)	(1.34)	(2.93)***	**(3.73)*** **
$(\alpha_{31})age_{i0}\Delta\Pi_i^{AS}\log\left(pdvl_i^A+1\right)$	10.74	11.18	16.78	**25.07**
	(1.66)*	(1.71)*	(2.43)**	**(3.30)*** **
$(\alpha_{32})age_{i0}^2\Delta\Pi_i^{AS}\log\left(pdvl_i^A+1\right)$	-0.0996	-0.1051	-0.1499	**-0.2335**
	(1.60)	(1.66)*	(2.25)**	**(3.20)*** **
$(\alpha_{33})samorbid_i^A\Delta\Pi_i^{AS}\log\left(pdvl_i^A+1\right)$	-10.12	-4.01	-17.63	**-17.27**
	(0.50)	(0.19)	(0.78)	**(0.71)**
$(\alpha_{33})sasubrsk_i^A\Delta\Pi_i^{AS}\log\left(pdvl_i^A+1\right)$	-43.32	-44.05	-43.04	**-43.81**
	(9.56)***	(9.62)***	(9.05)***	**(8.49)*** **
$(\alpha_{33})cosubrsk_i^A\Delta\Pi_i^{AS}\log\left(pdvl_i^A+1\right)$	10.48	10.46	20.73	**22.95**
	(1.64)	(1.62)	(3.08)***	**(3.08)*** **
$(\alpha_{40})\Delta\Pi_i^{AS}\left[\log\left(pdvl_i^A+1\right)\right]^2$	109.5	108.5	204.3	**269.1**
	(1.47)	(1.44)	(2.58)***	**(3.08)*** **
$(\alpha_{41})age_{i0}\Delta\Pi_i^{AS}\left[\log\left(pdvl_i^A+1\right)\right]^2$	-5.284	-5.329	-7.755	**-10.63**
	(1.73)*	(1.73)*	(2.39)**	**(2.98)*** **

$(\alpha_{42})age_{i0}^2\Delta\Pi_i^{AS}\left[\log\left(pdvl_i^A+1\right)\right]^2$	0.0505 (1.70)*	0.0516 (1.72)*	0.0723 (2.28)**	**0.1025** **(2.96)*** **
$(\alpha_{50})\Delta\Pi_i^{AS}\left[\log\left(pdvi_i^A+1\right)\right]\times\left[\log\left(pdvl_i^A+1\right)\right]$	-25.11 (0.39)	-23.84 (0.36)	35.30 (0.51)	**69.27** **(0.90)**
$(\alpha_{51})age_{i0}\Delta\Pi_i^{AS}\left[\log\left(pdvi_i^A+1\right)\right]\times\left[\log\left(pdvl_i^A+1\right)\right]$	-0.4777 (0.19)	-0.5698 (0.22)	-1.691 (0.62)	**-2.939** **(0.97)**
$(\alpha_{52})age_{i0}^2\Delta\Pi_i^{AS}\left[\log\left(pdvi_i^A+1\right)\right]\times\left[\log\left(pdvl_i^A+1\right)\right]$	0.01409 (0.59)	0.01598 (0.66)	0.02789 (1.09)	**0.04011** **(1.41)**
Alternatives	32842	31898	25578	**21314**
Log L	-16798.945	-16251.229	-13027.459	**-10870.494**
Within-sample fitted VSI estimates, for actual illness profiles used in survey				
Sample mean VSI	0.34	0.63	4.79	**2.89**
Sample 5th %	0	0	0	**0**
Sample 25th %	0	0	0.04	**0.14**
Sample 50th %	0	0	1.29	**1.56**
Sample 75th %	0.04	0.06	3.16	**3.55**
Sample 95th %	1.96	2.01	8.86	**8.5**

Key to inclusion criteria: "by" = choice did not involve "bad year" for death (i.e. did not involve a random and erroneously designed small life extension due to the illness experience); "cr" = passed simple risk comprehension question at end of risk tutorial; "wk" = choice of Neither Program not explained solely by "I did not believe the programs would work" (i.e. unequivocal scenario rejection). The most substantial impact is associated with the "wk" (scenario rejection) criterion.

The fitted within-sample VSI statistics are not comparable to those given in the body of the paper because we did not retain fitted selection probabilities for alternatives not included in the 21,314-alternative estimating sample, but present in the 32,842-alternative full sample (with complete data) used if no exclusion criteria are applied. Note that negative fitted VSI values in these sampling distributions are set to zero, since respondents are not able to express negative willingness to pay.

Table B2 – Simulations:[a] based on Model 2 rather than Model 3; actual same-illness morbidity and comorbidity
(*VSIP* in $million; *y*=$42,000, *r*=0.05)

45 years old now; At 45	***samorbid*=0 *comorbid*=0**	***samorbid*=1** *comorbid*=0	*samorbid*=0 ***comorbid*=1**
1 yr sick; non-fatal	**2.48** **[1.20, 3.87]**	3.77 [-lots,96.63]	2.14 [1.07, 3.39]
5 yrs sick; non-fatal	**3.76** **[2.51, 5.26]**	6.32 [-lots,138.77]	3.24 [2.20, 4.61]
1 yr sick; then die	**4.51** **[2.97, 6.69]**	20.01 [-lots,395.47]	3.96 [2.66, 5.78]
5 yrs sick; then die	**4.43** **[2.57, 6.71]**	18.86 [-lots,370.65]	3.82 [2.28, 5.71]
Sudden death	**4.53** **[2.82, 6.74]**	20.33 [-lots,402.27]	4.00 [2.60, 5.86]

[a] Across 1000 random draws from the joint distribution of estimated parameters: median, 5th and 95th percentiles of the sampling distribution of calculated *VSIP*. Estimated parameters are identical across simulations. Discount rate = 5%. Notation "-lots" means that for some draws, the marginal utility of income, shifted by *samorbid*, is very small and negative. This marginal utility forms the denominator of the formula for willingness-to-pay. Very tiny positive or negative values produce VSI estimates with large absolute values.

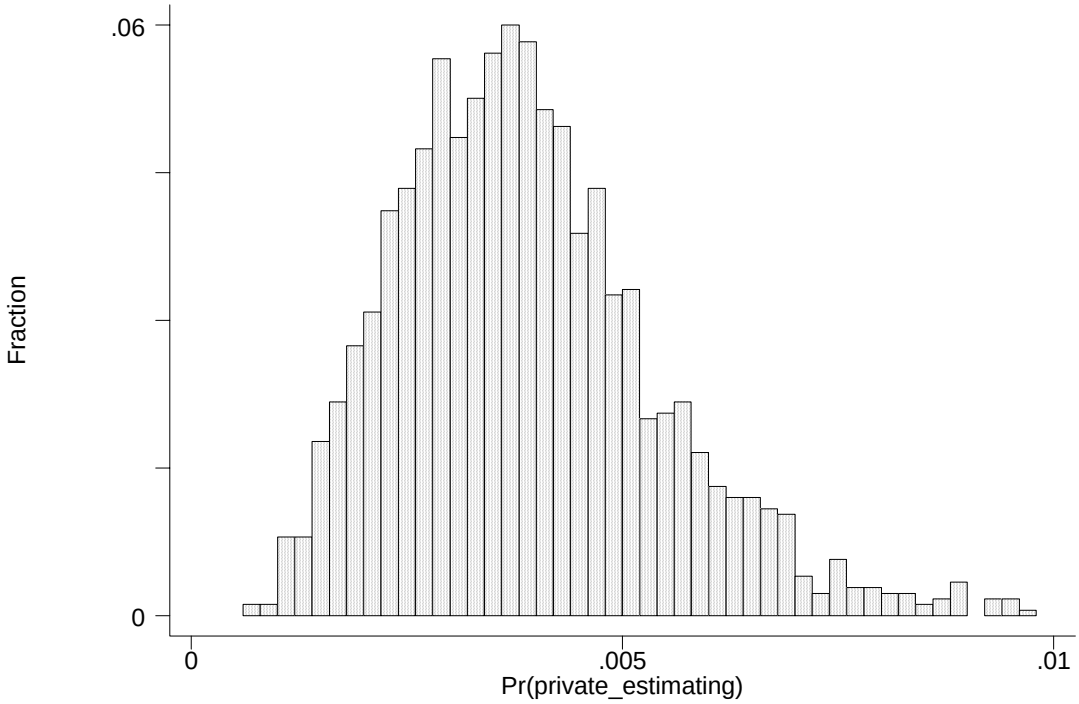

Figure B1 – Fitted sample selection probability in estimating sample if probability is less than .01. (1750 respondents; histogram omits 84 respondents with outlying fitted response probabilities between .010 and 0.183 (mean=0.155)). Selection Model based on 525,188 random-digit-dialed initial recruiting contacts for Knowledge Networks. Outliers lead to use of median, rather than mean selection probability in deviation calculations.

Appendix A
Robustness, Validation Checks and Bias Mitigation

For this survey, we have subjected individuals' responses to an extensive set of robustness and validity checks. Because of space limitations, we merely summarize our results here.

Risk Comprehension Verification. After administering an extensive risk tutorial and presenting the risk changes in three forms (textually, graphically and mathematically), we tested each individual's risk comprehension. This comprehension test required individuals to rank the sizes of the risk reductions associated with the first pair of risk mitigation programs. Approximately eighty percent of the individuals demonstrated a comprehension of the relative risk reductions of the programs, which is a rate consistent with risk comprehension levels documented in other surveys (Alberini, et al., 2004 and Krupnick et al., 200?).[36]

Mitigating Bracketing Biases Associated with Omitted Substitutes. In contrast with many valuation studies that focus on only one risk and one risk-mitigating program, we endeavor to reduce the biases that can be associated with bracketing (Read, et al., 1999) by ensuring that nearly all relevant substitute risks and programs were included in individuals' choice sets. Presenting essentially the full set of major mortality risks also increases the representativeness of our estimates and makes the motivation of a fuller range of illness profiles plausible, and thus, possible. A potential disadvantage of this approach stems from the cognitive complexity of the choice task, which we sought to minimize through careful survey design, and which we also evaluate ex post.[37]

Mitigating Hypothetical Bias. At the beginning of the valuation module we include a "cheap talk" reminder, to ensure that respondents carefully consider their budget constraints and to discourage them from overstating their willingness to pay (Cummings and Taylor,

[36] In Table B1 of Appendix B, available from the authors, we show the effects on the estimated parameters of excluding individuals from the estimating sample based on inadequate risk comprehension and other defensible criteria.

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

1999; List, 2001). Individuals are advised that "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..." (See the Online Annotated Survey at http://darkwing.uoregon.edu/~cameron/vsl/Annotated_survey_DeShazo_Cameron.pdf for a complete description.)

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

Testing for the Effects of Scope on Willingness to Pay. 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). 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. (See Models 1 and 2 in Table A3 in Appendix A.) These models evaluate 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. All coefficients are strongly statistically significant and bear the expected signs.

Other Validity Checks on Willingness to Pay. We also show that individuals' willingness to pay for these programs varies with several factors as economic theory would predict it should. It rises with income, as shown in the simulations reported in Table A6. For any given age, it also rises with future age at which each period in an adverse health

state would be experienced (DeShazo and Cameron, 2005).

Validating the Representativeness of Our Estimating Sample. Our estimating sample is reasonably representative of the U.S. population in terms of standard demographic characteristics. Table A2 compares the marginal distributions of age, income and gender for our initial estimating sample against corresponding population characteristics from the 2000 Decennial Census. Our estimating sample consists of 7,520 choices involving 22,560 alternatives. We arrived at this sample after cleaning the data based on minimal quality control criteria. We excluded individuals if they failed to answer correctly the simple risk comprehension question at the end of the survey's risk tutorial. We also excluded individuals if they rejected the program scenario–choosing "neither program" and stating as their sole explanation, "I did not believe the programs would work." If any other (economic) reason was given, we retained the choice.[38] In Appendix B, Table B1, we show how the parameter estimates and fitted $VSIP$s for the profiles used in estimation vary with these exclusion criteria. Not surprisingly, including choices for which the individual acknowledges explicitly that they rejected the choice scenario tends to decrease fitted $VSIP$s. Including people who answered the risk comprehension question incorrectly decreases the median fitted $VSIP$ slightly but also widens the distribution, consistent with the notion that confusion about the risk metric increases the noise in people's choices.

Sensitivity Analyses. Our models currently require that the researcher specify (a) each individual's time preferences, (b) their assumed future trajectory of income, and (c) their assumed future trajectory of program costs. Thus each estimated marginal utility of avoiding an undesirable health state, and the associated illness profiles, will depend upon these three maintained hypotheses.

The cost commitment and income maintenance assumptions that we use in this paper

[38] An inadvertent failure to truncate values to the nearest integer also produced a fraction of illness profiles wherein the illness produced a slight extension of life expectancy (in about 1% of profiles). These design errors were random across individuals and profiles, but we delete all choice sets with this feature because they did not convey the information we intended.

appear to be the most defensible.[39] The 5% individual discount rate assumption in our main results is open to question, however. In Table A5 in this Appendix, we consider the same individual who is now 45 years old with an income of $42,000 and calculate the fitted $VSIP$ (in millions of dollars) for each of our five illness profiles to illustrate the sensitivity of our models to our choice of discount rate. The middle column of results again reproduces the baseline simulations, derived under the assumption that $r = 0.05$. The first and third columns are produced by re-estimating Model 3 after having constructed the present discounted value terms that form the regressors using two alternative discounting assumptions: $r = 0.03$, and $r = 0.07$. Our fitted $VSIP$ estimates vary inversely with the assumed discount rate. For our 45-year-old and the case of sudden death (most common in the conventional VSL context) the 5% discount rate produces a $VSIP$ of roughly $4.4 million, whereas the median estimates at 3% and 7% discount rates are about $5.2 million and $3.7 million.

Table A6 in this Appendix presents the results from simulations across alternative assumptions about income levels. These simulations all assume a discount rate of $r = 0.05$ and again report the results of simulating $VSIP$s for an individual who is now 45 years old and faces each of our five representative illness profiles. The middle column again reproduces the results for our baseline income of $42,000. The first and third columns demonstrate results for alternative income levels of $25,000 and $67,500 for illustration.[40] As expected, $VSIP$ is larger when income is greater. For our 45-year-old and the case of sudden death, the fitted median $VSIP$ at $25,000 income is only about $3.4 million, whereas the fitted median $VSIP$ at $67,500 income is about $6.1 million.

These simulations of the sensitivity of $VSIP$ to income automatically invite cursory consideration of the implied arc elasticities of the $VSIP$ with respect to income. The second

[39] To have elicited assumptions used by each respondent about how their income might vary with alternative future health states would have been desirable. However, this would have extended the average completion time of the survey by an unacceptable amount.

[40] These corresponding roughly to the 25 percentile and median of the household income distribution according to the 2000 Census ($25,000 and $42,000), as well as for the 75th percentile of individual income for our sample ($65,000).

panel of Table A6 reports these arc elasticities, which range between 0.3 and 0.7 over different intervals of income and for different illness profiles.

Caveats. In the models described in this paper, we have opted to express the marginal utility of income as a linear function of income itself, which renders indirect utility quadratic in income. This creates a risk that the quadratic form that provides the best fit to capture the diminishing marginal utility of income within the body of the data may produce negative point estimates of the marginal utility of income at the highest income levels. This eventuality can be precluded by the use of a strictly monotonic function for the relationship between indirect utility and income, such as a logarithmic transformation. However, this limits the flexibility of the model.

In this paper, we have opted to preserve the flexibility of the quadratic form. As a consequence, however, the predictions of these particular models at higher incomes may be less reliable than for lower income levels. In other work, we impose sign restrictions on the marginal utility of income, either by making indirect utility logarithmic in income, or by using nonlinear-in-parameters methods to estimate not the level, but the logarithm, of the marginal utility of income as a systematic function of income and other variables.

Another possible option for managing this side-effect of the quadratic form is to borrow a strategy used in the estimation and interpretation of Tobit models. In a Tobit specification, the research invokes a latent propensity variable behind the observed (strictly non-negative) dependent variable that typically exhibits heaping at zero. If this continuous conditionally normal variable is positive, we observe its actual value. If it is negative, its value is manifested as zero.

A similar device could be used to interpret the estimated marginal utility of income in the models used in this paper. The marginal utility of income is a latent dimension of individual preferences that we estimate from observed choices. The estimated single parameter (or function of estimated parameters and data) that captures this marginal utility of income is assumed to be asymptotically normally distributed with support consisting of the entire

real line. Suppose our conviction is strong that the marginal utility of income should not be negative. We could move to zero the cumulative density associated with the negative portion of distribution of the fitted marginal utility. Then, as in a Tobit model, the expected marginal utility would correspond to the expected value of the corresponding truncated normal distribution, and would be strictly positive. The more negative the point estimate of marginal utility, the less of the density would lie in the positive domain, but the expected value of the truncated distribution would remain positive.

While this fix is feasible, and no less reasonable than the same strategy as it is applied in Tobit models, we do not pursue it in the present paper.

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Appendix B
Sample Properties

In the sample selection model reported in much more detail in Cameron and DeShazo (2005x), we report the results of a number of alternative sample selection models. As explanatory variables, we use a set of fifteen orthogonal factors that collectively capture almost 90 percent of the variation in sociodemographic categories across census tracts. We also use county-level voting results from the year 2000 Presidential election, recent death rates for major diseases in the county, and the density of hospitals in each county as a measure of the accessibility of medical services. From this model we save the fitted survey participation probabilities. Figure B1 shows the bulk of the distribution of these fitted probabilities for the estimating sample used in this paper.

For each of the models reported in the body of this paper, we explored whether our estimated marginal utility parameters were sensitive to departures of fitted participation probabilities from the sample median participation probability, $[P(sel_i) - P*]$. We use the median rather than the mean because of the presence of a number of extreme outliers (about 4% of the sample). The only place where this type of heterogeneity seems to matter is for the coefficient on the sick-years term.

Appendix C
Relevant QALY Literature

Researchers in the health care field may be relatively more familiar with the standard approaches to cost-effectiveness analysis (CEA) used in that literature than they are with the willingness-to-pay (WTP) measures for benefit-cost analysis that are considered here. The main tradition in cost-effectiveness analysis uses quality-adjusted life years (QALYs) or its analogs (see Gold, et al. (1996), or a review of methods in Green, et al. (2000)). Rather than using money as a metric, the QALY approach focuses on physical measures of health status and involves the standardization of health decrements relative to a year of perfect health (where death is 0 and perfect health is normalized as 1). The two main methods for eliciting these standardizations are the time trade-off (TTO) method and the standard gamble (SG) method.[41]

Cost-effectiveness using QALYs can be very helpful when the alternatives to be compared are, for example, different treatments for patients with the same illness. However, QALY analysis is more difficult to implement when the health-risk management alternatives to be compared are more different. QALY analysis is also difficult to apply when there are benefits other than human health benefits that need to be taken into account (such as ecosystem benefits). These additional benefits must typically be subtracted from the costs in the numerator of the cost-effectiveness ratio. QALYs are also unsuited to the analysis of allocation decisions where the resources in question are to be allocated not only to the management of health risks, but also to other programs.

Nevertheless, QALY researchers have certainly raised some of the issues we deal with here. In a public choice context, Dolan and Tsuchiya (2005) find preferences for treating younger patients over older ones, and some evidence that past health levels for the group in question can influence these preferences.

[41] The visual analog scale (VAS) method and the magnitude estimation (ME) methods are not choice-based methods and are less widely relied upon. The person trade-off method is used primarily for assessing preferences over the health status of others (as may be relevant for public health programs).

We argue here that the perspective of the individual will influence demand (WTP) for health-risk reductions. The QALY literature tends to emphasize treatment choices, and therefore generally focuses on the ex post utility levels for patients with specified diseases. There has been considerable debate in that literature whether it is appropriate to use the perceptions of actual patients, or the perceptions of the general public, about different adverse health states (see Damschroder, et al. (2005). In contrast, our research supports ex ante policy-making, mostly for preventive measures, where the relevant preferences are arguably ex ante. Resource allocation decisions must be made in advance of knowing which members of society will eventually fall victim to the health risks in question. However, in the present work, we find that patients with a past history of the same affliction, or with other afflictions, appear to have preferences which differ systematically from those of non-patients. Likewise, subjective risks for the health threat in question, versus other health threats, also appear to be relevant.

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