Valuing Environmental Health Risk Reductions to Children

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SESSION IV-PM: AGE-SPECIFIC VALUE OF STATISTICAL LIFE ESTIMATES (CONT'D)

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An Empirical Life-cycle Model of Demand for Mortality and Morbidity Risk Reduction

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Abstract

This paper explores empirically the way that demand for health-enhancing and life-extending programs varies over the life-cycle for individuals. We test the hypothesis that, at any given current age, an individual's schedule of marginal utility for future risk reductions rises on average with the age at which the future adverse health status would be experienced. However, as individuals age, we also hypothesize that there is a systematic downward shift in these schedules of marginal utility for risk reductions at future ages. Using data from a representative national sample of US households, we estimate the net effect of these two offsetting age effects for various risk-reducing policies. We identify the systematic age-varying determinants that explain why demand for some programs varies significantly with age, while demand for other programs does not.

[1] Senior authorship is not assigned. Nominal lead authorship will rotate though the series of papers associated with this project.

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1 Introduction

Empirically, scholars know little about how demand varies, over individuals' life-cycles, for programs that reduce the risk of morbidity and mortality. These programs include publicly provided environmental, safety and health programs as well as privately available preventative care and medical therapies. Understanding how demands for these programs vary with age has become increasingly important to several fields in economics.

Environmental and regulatory economists measure the social benefits of publicly mandated environmental, health and safety regulations. At the prompting of policymakers, they are now seeking to determine whether the sizes of the social benefits from these programs vary by age group (Smith and Evans, 2003; Alberini, et al., 2003).

Health economists have a longstanding focus on how individuals' investments in their health vary throughout their lifecycle. While this literature has made considerable theoretical advances in understanding the life-cycle determinants of demand for health (Grossman, 1972, Chuma and Erhlich, 1990, Johannsson, 1997; Erhlich, 2002) there has been a shortage of empirical analyses that test the hypotheses implied by these theories.

Finally, we are in the midst of a number of major demographic shifts, including a general aging of the population. Public economists have become interested in how changes in health and longevity affect individuals' consumption of government programs such as Social Security, Medicare, Medicaid (Hamermesh, 1995; Hurd et al., 1995, 1995, Gan et al., 2003).

The central contribution of this paper is an empirical exploration of the way individual demand for health-enhancing and life-extending programs varies with age. We test two hypotheses about how individuals will value risk-reductions over their life cycle. We motivate these hypotheses though a [stochastic dynamic optimization] model in which the individual chooses a quantity of a risk-reducing program in each period throughout her life cycle (Ehrlich, 2000). Our first hypothesis is that, at any age, individuals will derive

increasing marginal utility from reducing risks that come to bear later in life. This comports with the intuition that marginal value of health investments rises with age and concurrently that life-saving programs will grow more valuable with age.

Our second hypothesis is that as individuals age, there is systematic downward shift in their schedule of marginal utility for risk reductions at future ages. Our second hypothesis is based in the assumption that there are strong complementarities between health and other commodities. Individuals only learn about the extent of these complementarities as they age. With greater age, the declining quality of health begins to have appreciable affect on the marginal utility of consumption. Such age-induced learning causes individuals to decrease their expected value of future consumption. In response, individuals intertemporally adjust by shifting their consumption forward in time. As the value of future consumption declines, so does the shadow value of investment in life-extension. The effect of this process is to diminish the value of investment in current and future life-saving programs.

While this model illustrates these two countervailing dynamics, the net effect on age-varying demand for risk reductions is ultimately an empirical question. To evaluate these two hypotheses and to assess this empirical question, we develop an estimating specification that enables individuals to express their demands for risk-reduction programs that will alter the time-pattern of risk faced during their remaining life cycle. This empirical model makes several contributions to the existing empirical literature (Krupnick et al., 2002; Alberini et al., 2003; Evans and Smith, 2003).

First, we cast the demand for risk reducing programs in an option price framework (Graham, 1982). This approach is appropriate for the vast majority of public and private life-saving programs, since they involve a stream of certain costs and uncertain future benefits. Second, this model recovers the individual's marginal utility of avoiding a year spent in a morbid condition, the marginal utility of a year spent in a recovered state, if the condition is not fatal, and the marginal value of avoiding a lost life-year. Our specification allows these marginal values to shift with both the individual's current age and the future age at which the risk of

each particular health state is reduced. For each age cohort, we are able to estimate the schedule of marginal values associated with reducing risks over all future ages.

We estimate this model using data from an innovative national survey of over 1,300 U.S. citizens. In the survey, individuals were asked to choose between programs that reduced the probability of experiencing a future time profile of undesirable health states. The time profiles for these health states were described in the context of the individual's current age and nominal life expectancy. Each profile described the future age of onset of an illness, the level and duration of pain and disability that could be expected to follow, including surgery and hospitalization, and the number of life-years lost relative to nominal life expectancy. The risk-reducing programs consisted of an ongoing annual diagnostic test for a specific illness. If the individual is found to be at risk for the illness, they would be given drug therapies, and prescribed lifestyle changes, that would reduce their risk of experiencing the illness profile. These data enable us to evaluate how individual demand for avoiding a future year of morbidity and premature mortality varies with each individual's current age and with their age during each future period of reduced health (or they age that they would have been, had they not experienced premature mortality).

Controlling for the individual's current age, we find that the marginal utility of avoiding a future lost life-year rises with age. Controlling for the age at which the undesirable future health states would potentially be experienced, we find that as individuals grow older, their marginal value of current and future risk reductions declines. Together, these effects produce distinct schedules of marginal utility for each age cohort. To evaluate the present value of these future risk reductions, these marginal values must be discounted, and the risk reduction normalized to 1.00, to obtain the present value benefits of avoiding a "statistical" case of a particular morbidity/mortality health profile.

We conclude our analysis by exploring how a number of selected types of risk-reducing programs will be valued by different age groups. Most previous empirical studies (notably wage-risk studies) have focused on the risk of sudden death, so we emphasize these health profiles here. Through simulations, we evaluate

the social benefits of a program that reduces the risk of sudden death for five age groups: 25-, 35-, 45-, 55-, and 65-year-olds. Because the individuals enjoy the risk reduction immediately, any differences that are observed are determined exclusively by the age-specific declines in the marginal value of risk reductions. We find in models with no explicit age effects, and in models with linear age effects, that our inferred values of statistical lives (VSLs) decline by age cohort. In more general models with quadratic age effects, the pattern is non-monotonic. First one effect dominates, then the other.

Our second policy simulation, a latency period of five years is hypothesized before the risk of sudden death would materialize so that benefits would begin to accrue. In this context, discounting becomes important when calculating the VSL, but the discounted latency period (five years) is constant across age groups. As should be expected, we find differences in age-specific VSLs that are roughly comparable to the first simulation.

Our third policy simulation considers how all age cohorts would value a reduction in the risk of death at the common age of 70. A model with no explicit age effects suggest strongly that the VSL increases as the respondent's age gets closer to 70. In models with age effects, however, the pattern of VSLs is non-monotonic due to the competing influences of the two types of age variables in our models. For models with age effects, we find no clear differences in the VSL for this policy which is consistent with the findings of Krupnick et al., (2002) and Alberini et al., (2003). Our results suggest that the reason for no apparent age effect may be the existence of offsetting effects of discounting and downward shifts in the marginal utility of risk reduction with age. Younger cohorts have a higher marginal utility for the risk reduction but this value is discounted over a longer time period. Older cohorts express a lower marginal utility for the risk reduction but discount it over a shorter period.

In our final policy simulation, we hold the age group constant (focusing only on 25 year olds) in order to evaluate the implied VSLs for policies with latency periods that vary by 5, 15, 25, 35 and 45 years. In this simulation, we utilize only the upward sloping schedule of marginal utility for future risk reduction

associated with 25 year olds. Therefore, any difference in VSLs results from differences in (1.) the slope of the marginal utility schedule for future risk reduction, (2.) the discount rate, and (3.) the latency period over which discounting occurs. In a specification that ignores age effects, there in an apparent strong decline in the VSL as the latency period for the mortality risk increases. In a model with linear age effects, this pattern persists but is somewhat attenuated. In a model with quadratic age effects, however, the pattern becomes again non-monotonic.

2 Theoretical Model of Life-Cycle Demand

This model follows Ehrlich (2002) who develops a life-cycle model of demand for risk reduction programs.[3] To maximize lifetime utility, individuals choose quantities of a risk-reducing program, $I(t)$, and a composite consumption activitiy, $Z(t)$, in each period, t.[4] Demand for risk reduction arises because individuals face a conditional per-period arrival frequency, $f(t)$, of life-threatening events (such as major illnesses) that lead to mortality.

Individuals control the flow of $f(t)$ though the purchase of risk reducing programs in the following way:

$$\begin{aligned} f(t) &= j(t) - I(t) \qquad (1) \\ \text{where } I(t) &= I(m(t),\, M(t);\, e(t),\, t), \end{aligned}$$

and where $j(t) > 0$ is the exogenous conditional probability of a major illness, which is determined by heredity in conjunction with biological and environmental risks. $I(t)$ defines the difference between the exogenous risk and the individual's actual risk, $j(t) - f(t)$.[5] These risk-reducing programs are produced using inputs of time,

[3] This model generalizes similar life-cycle models by Conley (1976), Shepard and Zeckhauser (1984), Rosen (1988), and Johansson (2001).

[4] For simplicity, we assume that individuals habor no bequest motives. Nor do individuals participate in insurance markets that are designed to protect against "living too long" (by purchasing guaranteed annuuities) or "living too short" (by purchasing life insurance).

[5] This formulation simplifies the derivation of the time path for $I^*(t)$.However, it abstracts from the possibility that current period expenditures on risk reduction could affect the the conditional risks in future periods.

$m(t)$, and market goods $M(t)$. Production of these programs is also determined by efficiency parameters, $e(t)$ (reflecting the individual's human capital or education level), and their current age, t. In keeping with theories of aging (Kirkwood, 1977; Kirkwood and Rose, 1997; Sozou and Seymour, 2003), health risks are assumed to rise at an increasing rate throughout the remaining lifespan $(\dot{j}(t)) \equiv dj(t)/dt > 0$.

The cost function for $I(t)$ is given by

$$C(I(t)) = c(t)\ I(t)^{\alpha} \text{ where } \alpha > 1 \text{ and } c(t) = c(w(t), P(t), e(t), t), \tag{2}$$

where w is the wage rate per unit of human capital. The wage rate also represents the opportunity cost of time, where $w \equiv \dot{w}(e)/e$. All prices, $P(t)$, and efficiency parameters, $e(t)$, are held constant across the life cycle. For simplicity, assume that $\alpha = 2$ so that the cost function for the risk-reducing program is $C(I(t)) = c\,I(t)^2$. The production function for risk reductions is subject to diminishing returns to scale because of the fixed scale of the human body.

In each period the individual will consume a flow of health-state denominated time, $h(t)$, and a flow from a composite consumption activity, $Z(t)$. We treat the risks of morbidity and mortality as independent risks in our empirical analysis. However, we assume here, for simplicity, that they are monotonically related to one another.[6] Health-state denominated time is assumed to be a decreasing and concave function of $f(t)$ to capture the positive correlation between the risk of a life-threatening illness and associated morbidity. Health denominated time, $h(\cdot)$, may range from perfect health to acute morbidity as function of :

$$h(t) = (h\,f(t), \beta) \text{ with } h'(\cdot) < 0 \text{ and } h''(\cdot) < 0. \tag{3}$$

The argument β represent shifts in medical technologies that reduce the levels of morbidity associated with

[6] As a practical matter this assumption limits us only in that we cannot theoretically explore the determinants of individuals' marginal rate of substitution between morbidity and mortality as health states. Such tradeoffs are not the focus of this paper; see Cameron and DeShazo (2004) for an exploration of these issues.

$h(f(t))$. We assume that this measure of health-state denominated time perfectly exhausts each individual's time constraint.

The consumption activity $Z(t)$ is produced by combining purchased market goods, $M(t)$, at constant unit prices (P) and the individual's time, $m(t)$. The individual purchases these market goods subject to an instantaneous wealth constraint:

$$\dot{A}\,(t) = r\,A\,(t) + w\,h\,(f\,(t)) - cI^2\,(t) - Z\,(t)\,, \tag{4}$$

where $\dot{A}(t) \equiv dA(t)/dt$ is the rate of change in savings in period t.[7] Parameters r and w denote the market interest rate and the wage rate, $h\,(t)$ represents healthy labor time, and the full price of consumption, $P_z = 1$, is the numeraire. The individual knows her terminal condition (age of death) only stochastically, which represents an innovation on Ehrlich and Chuma (1990). In the following equation, E represents the expectation operator which applies to the stochastic length of life, D, while ρ denotes the individual's subjective discount rate.

Individuals choose optimal time paths for Z and I to maximize[8]:

$$J(A(t), t; \alpha) = \underset{Z,I}{Max}\; E\left[\int_t^D \exp\left[-\rho(s-t)\right] U\left(Z(s),\, h(s),\, h(f(s))\right)\, ds\right]. \tag{5}$$

The individual maximizes (5) subject to equations (1) and (3), $A(t) > 0$, as well as a vector of exogenous parameters: $\alpha = w, e, P, \rho, j$. The terminal conditions, $A(D) > 0$ and $J(A(D), D; \alpha) = 0$ must hold. The optimal time paths for $\{Z^*(t), I^*(t)\}$ are found by applying the stochastic dynamic programming approach

[7] To avoid any discontinuity, which occurs whenever $A(t)$ assumes its boundary value, the individual optimizes subject to $A(t) > 0$. Furthermore, without an insurance market, it is impossible for the individual to die with negative wealth.

[8] The instantaneous utility function (.) is to be concave and possess other standard properties (Judd, 1998).

(Judd, 1998) as determined by the Hamilton-Bellman-Jacobi condition:

$$-J_t = -(\rho + f^*)J + U(Z^*, h(f^*)) + J_A\left[rA + wh(f^*) - cI^{*2} - Z^*\right] \tag{6}$$

where $J_t \equiv \partial J(A(t), t; \alpha)/\partial t$ and where Z* and I* satisfy the optimality conditions:

$$U_z(Z^*, h(f^*)) = J_A \tag{7}$$

$$2cI^* = J/J_A + [w + (1/J_A)U_h(Z^*, h(f^*))][-h'(f^*)] \equiv v_0^* \tag{8}$$

Equation (8) describes the conditions that shape the optimal time path of investment in risk reductions over individuals' life cycles. On the left hand side is the marginal cost of the risk-reducing program. On the right-hand side is the *complete* value of the risk reduction which consists of two terms. The first term, (J/J_A), describes the value of the individual's remaining life span. The second term, $[w + (1/J_A)U_h(Z^*, h(f^*))][-h'(f^*)]$, characterizes the change in utility derived from this remaining life span as a result of reducing morbidity.

2.1 Marginal Value of Future Risk Reduction

This model predicts that the time path of investment in risk reduction will rise with the conditional probability of risk. To see this explicitly, assume (for the sake of expositional ease only) that the individual's utility function is separable in healthy time and consumption. From equation (8) we can show the path of risk reduction investment depends upon two countervailing influences:

$$\begin{aligned} \dot{I^*}(t) &= (\frac{1}{\Delta})\left\{ \begin{array}{l} [d(J/J_A)/dt + (U_h/J_A)(-h')(r - \rho - f(t^*))] \\ -\left[(w + (U_h/J_A))h'' + (U_{hh}/J_A)(h')^2\right]\dot{j}(t) \end{array} \right\} \\ &\equiv \dot{v}^*(t), \end{aligned} \tag{9}$$

where $\Delta \equiv 2c - [w + (U_h/J_A)h'' - (U_{hh}/J_A)(h')^2 > 0$ and $\dot{X} \equiv dX/dt$. Examining the first term, the time path of investment in risk reduction depends upon the rate of increase in exogenous risks, $\dot{j}(t)$, associated with aging. Concurrently, the marginal value of improving health-denominated time rises with $j(t)$ and t. The aging process raises the marginal benefits of investment in risk reductions. Concurrently, the marginal value of improving health-denominated time rises with $j(t)$ and t. Therefore, we hypothesize that individuals will express a higher marginal value for risk reductions that occur at later ages. This should be true even though there are diminishing returns to increasing investments in risk reduction. The first two terms inside the braces (9) illustrate how the value of protective investments rises with the value of reducing the risk of mortality, $d(J/J_A)/dt$, plus morbidity, $(U_h/J_A)\,(-h')\,(r - \rho - f(t^*))$. We discuss the time path of these two terms in more detail below.

2.2 Health and Consumption Complementarities

Traditional theoretical expositions of this class of models leave open the question of whether utility from the consumption activity $Z(t)$ and health $h(t)$ are separable, i.e., whether $U_{zh}(t) = 0$ (see Grossman, 1972; Chuma and Ehrlich, 1990; Ehrlich, 2000). While the modeling exercise is less complicated if the separability assumption is invoked, such an a priori assumption seems unwarranted. To begin with, the production function for $Z(t)$ is assumed to require the individual's non-market time, $m(t)$ (Ehlrich, p. 345, 2000). The health quality of this input should affect the level of utility that the individual derives from the consumption activity. It is much more likely that the individual's time, $m(t)$, and market goods, $M(t)$, are complements in consumption, rather than perfect substitutes. As the level of morbidity $h(f(t))$ rises, the quality of the individual's time input, $m(t)$, should fall. So should the utility derived from the consumption activity, $Z(t)$. These theoretical relationships are supported by a large body of literature on the physiological and cognitive effects of aging (Kenney, 1989; Gfellner, 1989; Posner, 1995). As individuals age, their ability to derive utility from market goods declines. With increasing age, individuals begin to have trouble driving a car, for

example, or enjoying the same recreational activities as they did in their youth or middle age. With age, the level of utility they derive from basic market goods declines. They may eventually experience difficulty in feeding themselves, dressing, and moving about freely.

To see the theoretical importance of this separability assumption, consider the individual's optimal consumption path:

$$\begin{aligned} \dot{Z}(t) &= -\left[U_Z(t)/U_{zz}\right](r-\rho-f^*(t)) \\ &\quad -[(U_{Zh}(t)/U_{zz}(t)]h'(f^*(t))\dot{f}^*(t) \end{aligned} \tag{10}$$

If $U_{Zh}(t) = 0$, the second term in (10) drops out. Examining the first term, we get the well-known result due to Yaari (1965) that lifetime consumption rises only if the market discount rate exceeds the subjective discount rate and the conditional rate of mortality. Both theoretically (Sozou and Seymour, 2003) and empirically (DeShazo and Cameron, 2003), scholars have shown that subjective discount rates rise with age. Therefore, even with the assumption of separability, the quantity of consumption is likely to fall with age. However, once the assumption of complementarities between health-denominated time and commodities is made (i.e. that $U_{Zh}(t) > 0$), the rate of decline with age will be even greater. As shown by equation (8) this decline in the value of future consumption will, in turn, lower the marginal value of current and future risk reduction.

2.3 Learning with age and shifts in the marginal value of future risk reductions

This model assumes that individuals have perfect information on all parameters over the course of their life cycle. But what would be the implications if, instead, individuals learned about the aging process as they aged? Current-period expectations about the future values of parameters are likely to be biased towards their current-period value. Through learning, however, individuals might update their future expectations by assessing trends in key parameters over their recent life histories. Candidate parameters for updating might

include the individual's conditional risk of a life-threatening illness, $j(t)$, the individual's subjective discount rate, her future wealth constraint or the extent of complementarities between health and consumption (i.e. if $U_{Zh}(t) > 0$). While the effect of learning about any of these parameters is likely to cause individuals to revise their future time path of consumption downward, we argue that the possibility of learning about complementarities between health and consumption is the most plausible, since such knowledge is most likely to be acquired though the personal experience of aging.[9]

If individuals do progressively learn, as they age, that health and consumption commodities are strong complements, the exogenous rise in $j(t)$ with age will cause the value of consumption in future periods to fall. Intertemporally, individuals will respond to this knowledge by reallocating consumption to earlier time periods where it will yield more utility. This action, in turn, reduces the value of investment in risk reduction in future periods; from equation (8) the remaining value of reducing mortality risk (J/J_A) and morbidity, $[w + (1/J_A)U_h(Z^*, h(f^*))][-h'(f^*)]$ will decline. Based on our conjecture of age-driven learning, we hypothesize that as individuals age, their schedule of marginal utility for future risk reduction will decline with their current age. A related (and empirically testable) consequence of this conjecture is that individuals' projected schedules of future marginal utility of consumption should vary systematically with their current age. Specifically these schedules of future marginal utilities of consumption should be steeper and turn down later in life for younger age groups relative to those of older age groups.

3 Data and Survey Methods

Our data were collected in a national random survey of U.S. adults in 2002. The innovative feature of our survey consisted of a conjoint choice exercise wherein individuals could purchase a program that reduced their risk of experiencing specific illnesses over future periods of their life. These programs were described

[9] Ehrlich (2003) provides comparative static analysis for all of these parameters except for changes in the complementarity between health and consumption.

as involving annual diagnostic testing and, if needed, associated drug therapies and recommended life-style changes. Each program required a constant annual payment in return for reducing the risk of an illness profile. 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. We briefly describe the development, design and administration of this survey instrument below. A fuller description is available in Appendix A.

3.1 Survey Development and Design

In order to effectively describe the illness profiles, the associated risk, and the programs that reduced these risks, we conducted extensive one-on-one interviews (i.e., cognitive interviews) and pre-testing. We conducted 36 cognitive interviews over the nine-month development period. During this period the survey went through four significant revisions. We pretested the last three versions. These three pretests involved a total of 1,500 respondents over a three-month period. We also benefited greatly from a peer review panel that evaluated the second of the four versions of the instrument.

The final conjoint survey is structured around four modules: 1) the introductory module, 2) a tutorial for the illness profile and the risk-reducing program, 3) the presentation of the choice sets, and 4) a debriefing and follow-up module. For the sake of brevity, we focus below on only the risk-reducing program and the design of the illness profiles in the context of the conjoint choice set.

For the risk reduction programs in our survey, we specified combinations of diagnostic testing and drug therapies because respondents viewed these as technically feasible and potentially effective. Respondents were familiar with comparable and pre-existing diagnostic tests such as mammograms, pap smears and prostrate exams, or the new C-reactive protein tests for heart disease. Important from our perspective was the fact that this class of interventions could plausibly be applied to all of the illnesses upon which we focused. The effectiveness of these programs was described using a risk grid (Krupnick, et al., 2002).

The payment vehicle for each program was presented as a co-payment that would have to be paid by the respondent for as long as the diagnostic testing and medication was needed. For the sake of concreteness we asked the respondents to assume the payments would be needed for the remainder of his or her lifespan unless they actually experienced that illness. Costs were expressed in both monthly and annual terms. To ensure that respondents carefully considered their budget constraint, we included a "cheap talk" reminder as well as language to discourage overstating their willingness to pay.

3.2 Illness Profiles in Choice Sets

Each conjoint choice set presents the respondent with the attributes of two illness profiles: 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. This is followed by a description of the cost and effectiveness of the risk-reducing program. Subject to several plausibility constraints, we randomly varied these attributes across each illness profile. Both the age of onset and the final stage of each illness are determined by the respondent's current age. Gender specific illnesses (e.g., breast and prostate cancer) are chosen to comport with the respondent's gender.

We summarize the results of the choice set design process in Table 2. The first row in this table presents the frequency with which each of the twelve illnesses appeared in the choice sets. The remainder of the table presents the mean levels of each of the risk, morbidity, and mortality attributes associated with that illness. While the mean levels of the costs, baseline risk, and risk change are very comparable across all of the illnesses, the average levels of the other attributes vary greatly across illnesses. For example, heart attacks are associated with much shorter periods of pain, hospitalization, and death than is lung cancer.

3.3 Sample and Survey Administration

Our conjoint choice survey and a separate health-profile survey were administered by Knowledge Networks to approximately 1,800 panelists. Each survey required about 30 minutes to complete. Respondents were paid an incentive for completing the conjoint choice survey. Respondents' ages ranged from 25 to over 90 years of age. Our response rate for those panelists contacted was 79 percent. Attrition response bias may be present between the point when Knowledge Networks made their initial contact to join their panel and the point when we initially contacted each panelist. To address potential sample selection bias, we are preparing to implement sample selection correction procedures using the Knowledge Networks database of initial telephone contacts and other attrition data.

4 An Empirical Option Price Model of Life Cycle Risk Reductions

We now turn to develop an empirical model in which individuals can express their option price for a program that intertemporally redistributes their investment in risk reductions over their remaining life span.(See Cameron and DeShazo (2003) for a more general discussion of this model.)

4.1 Indirect utility from health states

We develop a simple model of the individual's future undiscounted indirect utility as a function of their health state in that future period. We expand upon most earlier empirical treatments by considering four distinct health states: 1) a pre-illness healthy state, 2) illness state, 3) a post-illness recovered state and 4) a dead state.[10] We define each of these states as a time segment. Within each segment, the individual's health status is assumed (for now) to be relatively homogeneous.

To capture an illness profile, we use sets of dummy variables that collectively exhaust the period of time

[10] Within our empirical model, the illness states are further differentiated into one of twelve specific illnesses, each of which can exhibit a wide variety of different symptom-treatment profiles that may last from zero to six years. In appropriate cases, the illness may also be chronic, lasting for more than six years.

between the individual's present age and the end of his nominal life expectancy. In Figures 1 and 2, we depict examples of these four discrete health states. Let i index individuals and let t index time periods[11]. The dummy variable Pre-illness_year$_{it}$ take a value of 1 in years when the individual enjoys a healthy state. When the health state ends, the value of Pre-illness_year$_{it}$ changes to 0 and remains there for the rest of the individual's expected lifespan. At the end of the healthy period the individual may die suddenly or become sick. Let the dummy variable Illness_year$_{it}$ take on a value of 1 at this point and remain equal to 1 for the years during which the individual is ill. When he is not sick, it takes a value of zero. The dummy variable labeled Recover_year$_{it}$ takes on value of 1 in the years between the conclusion of the illness and the individual's expected time of death. Finally, we define Lifeyear_lost$_{it}$ to distinguish the extent to which death is premature (that is, the time between death and what would otherwise have been the individual's nominal life expectancy).

Next we define the future undiscounted indirect utilities per unit of time in each health state. Let these marginal utilities be denoted as δ_s for an episode of type s, where s in our model can be illness, recovered status, or a life-year lost to premature death. Let the undiscounted utility from each future year in a particular health state be defined relative to no new illness. In other words, we normalize utility on the level of utility being experienced by the individual in their current health state. We abbreviate Pre-illness_year$_{it}$ to pre$_{it}$, Illness_year$_{it}$ to ill$_{it}$, Recover_year$_{it}$ to rcv$_{it}$ and Lifeyear_lost$_{it}$ to lyl$_{it}$ to allow more-compact notation.

$$V_{it} = \beta f(Y_{it}) + \delta_0 pre_{it} + \delta_1 ill_{it} + \delta_2 rcv_{it} + \delta_3 lyl_{it} + \eta_{it} \tag{11}$$

Let the undiscounted marginal utility of some function of current income, $f(Y_{it})$, be the parameter β. Let the undiscounted (dis)utility from each future year of illness be defined as δ_1, from each year of the post-illness recovered state be δ_2, and from each year of being prematurely dead be δ_3.

[11] Time may be measured in years, months, or even a smaller units of time, depending on the degree of resolution needed.

Our basic specification assumes that the undiscounted (dis)utility of a year of illness or injury is a constant (in the homogeneous specification). Let age_{i0} denote the current age of respondent i. This is distinct from the age of respondent i in future period t, which we will denote age_{it}. The individual's current age is just another personal characteristic that we can allow to shift the marginal (dis)utility of a sick-year and the marginal (dis)utility of a lost life-year.

We allow the indirect utility in each future period to depend upon the age of the individual while they are experiencing the health state corresponding to that period. Age in period t may shift the marginal utility of transformed income and of each health status:

$$\begin{aligned} V_{it} &= \left[\beta_0 + \beta_1 age_{it} + \beta_2 age_{it}^2 + \beta_3 Y_{it}\right] f(Y_{it}) \\ &\quad + \left[\delta_{10} + \delta_{11} age_{it} + \delta_{12} age_{it}^2\right] ill_{it} \\ &\quad + \left[\delta_{20} + \delta_{21} age_{it} + \delta_{22} age_{it}^2\right] rcv_{it} \\ &\quad + \left[\delta_{30} + \delta_{31} age_{it} + \delta_{32} age_{it}^2\right] lyl_{it} + \eta_{it}. \end{aligned} \tag{12}$$

Or,

$$\begin{aligned} V_{it} &= \beta_0 f(Y_{it}) + \beta_1 age_{it} f(Y_{it}) + \beta_2 age_{it}^2 f(Y_{it}) + \beta_3 Y_{it} f(Y_{it}) \\ &\quad + \delta_{10} ill_{it} + \delta_{11} age_{it} ill_{it} + \delta_{12} age_{it}^2 ill_{it} \\ &\quad + \delta_{20} rcv_{it} + \delta_{21} age_{it} rcv_{it} + \delta_{22} age_{it}^2 rcv_{it} \\ &\quad + \delta_{30} lyl_{it} + \delta_{31} age_{it} lyl_{it} + \delta_{32} age_{it}^2 lyl_{it} + \eta_{it} \end{aligned}$$

The disutility of each of these states will be interpreted as being the same as the utility associated with avoiding them. The dummy variables, ill_{it} , rcv_{it}, and lyl_{it} adjust the limits of the summations used for the present value of future continued good health, future intervals of illness, recovered time, and life-years lost. In this paper we assume that the individual uses the same discount rate, r, to discount both future money

costs and health states. [12]

With this set-up, we can develop a structural model of the ex ante option price that an individual will be willing to pay for a program that reduces his/her risk of a morbidity/mortality profile over the future. Define the present discounted value of indirect utility V_i^{jk} for the ith individual when $j = A$ if the program is chosen and $j = N$ if the program is not chosen. The superscript k will be S if the individual suffers the illness (or injury) and H if the individual does not suffer the illness.

The pattern of income and program costs under the four different health states will be relevant to the individual's indirect utility in each state. We define γ_1 as the fraction of the individual's income that will be earned while the individual is sick, should he suffer the illness in question. With adequate disability insurance or sick leave, this fraction might be assumed to be 1.00. Let γ_2 be the fraction of income received if the individual is no longer living, but would have been, had they not suffered the illness. This parameter will be assumed to be zero in our empirical models, but a non-zero value could be invoked to activate a bequest motive. The parameter γ_3 is the fraction of the cost of the program that must be paid while the individual is suffering from the illness in question. Logically, the program would be unnecessary in this health state, so we will assume that γ_3 is typically zero. Likewise, the individual would not participate in the program if dead, so we will be assuming that $\gamma_4 = 0$.

4.2 Present Discounted Values of Indirect Utility

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

[12] 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, below, would need to be changed from $1/(1+r)^t$ to $1/(1+t)^\lambda$. Other than this, the formulas will be the same.

individual's nominal life expectancy:

$$
\begin{aligned}
PDV(V_i^{AS}) \;=\;& \beta_0 \sum \frac{f(Y_{it}^* - c_{it}^{A*})}{(1+r)^t} + \beta_1 \sum \frac{age_{it} f(Y_{it}^* - c_{it}^{A*})}{(1+r)^t} \\
&+\beta_2 \sum \frac{age_{it}^2 f(Y_{it}^* - c_{it}^{A*})}{(1+r)^t} + \beta_3 \sum \frac{(Y_{it}^* - c_{it}^{A*}) f(Y_{it}^* - c_{it}^{A*})}{(1+r)^t} \\
&+\delta_{10} \sum \frac{ill_{it}^A}{(1+r)^t} + \delta_{11} \sum \frac{age_{it} ill_{it}^A}{(1+r)^t} + \delta_{12} \sum \frac{age_{it}^2 ill_{it}^A}{(1+r)^t} \\
&+\delta_{20} \sum \frac{rcv_{it}^A}{(1+r)^t} + \delta_{21} \sum \frac{age_{it} rcv_{it}^A}{(1+r)^t} + \delta_{22} \sum \frac{age_{it}^2 rcv_{it}^A}{(1+r)^t} \\
&+\delta_{30} \sum \frac{lyl_{it}^A}{(1+r)^t} + \delta_{31} \sum \frac{age_{it} lyl_{it}^A}{(1+r)^t} + \delta_{32} \sum \frac{age_{it}^2 lyl_{it}^A}{(1+r)^t} + \varepsilon_i^{AS}
\end{aligned} \tag{13}
$$

where $Y_{it}^* = Y_i \left(pre_{it}^A + \gamma_1 ill_{it}^A + rcv_{it}^A + \gamma_2 lyl_{it}^A \right)$ and $c_{it}^{A*} = c_i^A \left(pre_{it}^A + \gamma_3 ill_{it}^A + rcv_{it}^A + \gamma_4 lyl_{it}^A \right)$. Y_{it}^* and c_{it}^{A*} are sufficiently general to allow for a number of different assumptions about how individuals view their potential income and how they view their cost obligations under each program in different health states.

What individuals assume about their future income and program costs, if they choose the program, has implications for the formulas we develop in later sections. For their future income, our default assumption will be that individuals expect constant real annual income Y_i in each future year until the expected time of death if the individual gets the illness. When $\gamma_1 = 1$ and $\gamma_2 = 0$, the term $pre_{it}^A + \gamma_1 ill_{it}^A + rcv_{it}^A + \gamma_2 lyl_{it}^A = \left(1 - lyl_{it}^A\right)$ in equation (13) will be nonzero in those periods when the individual is still alive. While earned income is likely to suffer if the individual gets the illness, we assume that their annual income can be sustained through insurance coverage. For program costs, we assume that the annual costs of the risk-management program in question are incurred in the years leading up to the onset of the illness or injury, but are not paid while the individual is sick or injured.[13] If the individual recovers from the illness or injury, rather than dying from it, they will again participate in the risk-management program until their death. When $\gamma_3 = \gamma_4 = 0$, the term $pre_{it}^A + \gamma_3 ill_{it}^A + rcv_{it}^A + \gamma_4 lyl_{it}^A = pre_{it}^A + rcv_{it}^A$ in equation (13) will be non-zero only prior to the onset

[13] While the individual is sick, the health testing program would provide no further information, and we assume that the major traffic accident is likely to result in the vehicle being "totaled" so that a new vehicle, with its safety features, would not be acquired until the individual has recovered from his or her injuries.

of the illness or during the recovered state.

The present value indirect utility, if the individual does choose the program but does not suffer the illness, involves no illness, recovery, or reduced lifespan. Thus, the expression for indirect utility takes the following form:

$$\begin{aligned} PDV(V_i^{AH}) &= \beta_0 f(Y_i - c_i^A) \sum \frac{1}{(1+r)^t} \\ &\quad +\beta_1 f(Y_i - c_i^A) \sum \frac{age_{it}}{(1+r)^t} \\ &\quad +\beta_2 f(Y_i - c_i^A) \sum \frac{age_{it}^2}{(1+r)^t} \\ &\quad +\beta_3 (Y_i - c_i^A) f(Y_i - c_i^A) \sum \frac{1}{(1+r)^t} + \varepsilon_i^{AH} \end{aligned} \tag{14}$$

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

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

$$\begin{aligned} PDV(V_i^{NS}) &= \beta_0 \sum \frac{f(Y_{it}^*)}{(1+r)^t} + \beta_1 \sum \frac{age_{it} f(Y_{it}^*)}{(1+r)^t} \\ &\quad +\beta_2 \sum \frac{age_{it}^2 f(Y_{it}^*)}{(1+r)^t} + \beta_3 \sum \frac{(Y_{it}^*) f(Y_{it}^*)}{(1+r)^t} \\ &\quad +\delta_{10} \sum \frac{ill_{it}^A}{(1+r)^t} + \delta_{11} \sum \frac{age_{it} ill_{it}^A}{(1+r)^t} + \delta_{12} \sum \frac{age_{it}^2 ill_{it}^A}{(1+r)^t} \\ &\quad +\delta_{20} \sum \frac{rcv_{it}^A}{(1+r)^t} + \delta_{21} \sum \frac{age_{it} rcv_{it}^A}{(1+r)^t} + \delta_{22} \sum \frac{age_{it}^2 rcv_{it}^A}{(1+r)^t} \\ &\quad +\delta_{30} \sum \frac{lyl_{it}^A}{(1+r)^t} + \delta_{31} \sum \frac{age_{it} lyl_{it}^A}{(1+r)^t} + \delta_{32} \sum \frac{age_{it}^2 lyl_{it}^A}{(1+r)^t} + \varepsilon_i^{NS} \end{aligned} \tag{15}$$

The individual's lifespan is potentially reduced, so future income continues only until the time of death, and the disutility of the illness, any recovery period, and any life-years lost will be relevant.

Present value indirect utility, if the individual does not choose the program and does not suffer the illness,

is:

$$
\begin{aligned}
PDV(V_i^{NH}) \quad = \quad & \beta_0 f\left(Y_i\right) \sum \frac{1}{\left(1+r\right)^t} + \beta_1 f\left(Y_i\right) \sum \frac{age_{it}}{\left(1+r\right)^t} \\
& + \beta_2 f\left(Y_i\right) \sum \frac{age_{it}^2}{\left(1+r\right)^t} \\
& + \beta_3 \left(Y_i\right) f\left(Y_i\right) \sum \frac{1}{\left(1+r\right)^t} + \varepsilon_i^{NH}
\end{aligned} \tag{16}
$$

Recall, the individual assumes that his current income level will be sustained until the end of his lifespan in the absence of premature mortality.

4.3 Expected indirect utility

In deriving the individual's option price for the program, given the ex ante uncertainty about future health states, we need to calculate expected utilities. 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 in. The risk change due to program participation, $\Delta\Pi_i^{AS}$, is presumed to be negative.

Expected utility if the individual buys program A is:

$$E\left[V_i^A\right]_{S,H} = \Pi_i^{AS} \times PDV(V_i^{AS}) + \left(1 - \Pi_i^{AS}\right) \times PDV(V_i^{AH}) \tag{17}$$

$$= \Pi_i^{AS} \left[\begin{array}{c} \beta_0 \sum \frac{f(Y_{it}^* - c_{it}^{A*})}{(1+r)^t} + \beta_1 \sum \frac{age_{it} f(Y_{it}^* - c_{it}^{A*})}{(1+r)^t} \\ +\beta_2 \sum \frac{age_{it}^2 f(Y_{it}^* - c_{it}^{A*})}{(1+r)^t} + \beta_3 \sum \frac{(Y_{it}^* - c_{it}^{A*}) f(Y_{it}^* - c_{it}^{A*})}{(1+r)^t} \\ +\delta_{10} \sum \frac{ill_{it}^A}{(1+r)^t} + \delta_{11} \sum \frac{age_{it} ill_{it}^A}{(1+r)^t} + \delta_{12} \sum \frac{age_{it}^2 ill_{it}^A}{(1+r)^t} \\ +\delta_{20} \sum \frac{rcv_{it}^A}{(1+r)^t} + \delta_{21} \sum \frac{age_{it} rcv_{it}^A}{(1+r)^t} + \delta_{22} \sum \frac{age_{it}^2 rcv_{it}^A}{(1+r)^t} \\ +\delta_{30} \sum \frac{lyl_{it}^A}{(1+r)^t} + \delta_{31} \sum \frac{age_{it} lyl_{it}^A}{(1+r)^t} + \delta_{32} \sum \frac{age_{it}^2 lyl_{it}^A}{(1+r)^t} + \varepsilon_i^{AS} \end{array} \right]$$

$$+ \left(1 - \Pi_i^{AS}\right) \left[\begin{array}{c} \beta_0 f(Y_i - c_i^A) \sum \frac{1}{(1+r)^t} + \beta_1 f(Y_i - c_i^A) \sum \frac{age_{it}}{(1+r)^t} \\ +\beta_2 f(Y_i - c_i^A) \sum \frac{age_{it}^2}{(1+r)^t} + \varepsilon_i^{AH} \end{array} \right]$$

Expected utility if the program is not purchased (i.e. "no program", N), with the expectation taken over

uncertainty about whether the individual will suffer the illness, is:

$$E\left[V_i^N\right]_{S,H} = \Pi_i^{NS} \times PDV(V_i^{NS}) + \left(1 - \Pi_i^{NS}\right) \times PDV(V_i^{NH}) \tag{18}$$

$$= \Pi_i^{NS} \left[\begin{array}{c} \beta_0 \sum \frac{f(Y_{it}^*)}{(1+r)^t} + \beta_1 \sum \frac{age_{it} f(Y_{it}^*)}{(1+r)^t} \\ +\beta_2 \sum \frac{age_{it}^2 f(Y_{it}^*)}{(1+r)^t} + \beta_3 \sum \frac{(Y_{it}^*) f(Y_{it}^*)}{(1+r)^t} \\ +\delta_{10} \sum \frac{ill_{it}^A}{(1+r)^t} + \delta_{11} \sum \frac{age_{it} ill_{it}^A}{(1+r)^t} + \delta_{12} \sum \frac{age_{it}^2 ill_{it}^A}{(1+r)^t} \\ +\delta_{20} \sum \frac{rcv_{it}^A}{(1+r)^t} + \delta_{21} \sum \frac{age_{it} rcv_{it}^A}{(1+r)^t} + \delta_{22} \sum \frac{age_{it}^2 rcv_{it}^A}{(1+r)^t} \\ +\delta_{30} \sum \frac{lyl_{it}^A}{(1+r)^t} + \delta_{31} \sum \frac{age_{it} lyl_{it}^A}{(1+r)^t} + \delta_{32} \sum \frac{age_{it}^2 lyl_{it}^A}{(1+r)^t} + \varepsilon_i^{NS} \end{array} \right]$$

$$+ \left(1 - \Pi_i^{NS}\right) \left[\begin{array}{c} \beta_0 f\left(Y_i\right) \sum \frac{1}{(1+r)^t} + \beta_1 f\left(Y_i\right) \sum \frac{age_{it}}{(1+r)^t} \\ +\beta_2 f\left(Y_i\right) \sum \frac{age_{it}^2}{(1+r)^t} \\ +\beta_3 \left(Y_i\right) f\left(Y_i\right) \sum \frac{1}{(1+r)^t} + \varepsilon_i^{NH} \end{array} \right]$$

Details concerning the simplification of the expected utility difference $E\left[V_i^A\right]_{S,H} - E\left[V_i^N\right]_{S,H}$ are provided in an Appendix. Concerning the time paths of future income and program costs, we will maintain the hypothesis that $(\gamma_1, \gamma_2, \gamma_3, \gamma_4) = (1, 0, 0, 0)$. In words, usual income is sustained through illness by insurance, but not after death (there are no bequests), and program costs are only paid while alive and healthy.

We make use of a number of notational abbreviations in getting to the expected utility difference formula. First, let $\Delta\Pi_i^{AS} = \left(\Pi_i^{AS} - \Pi_i^{NS}\right)$. Then, there are many distinct present discounted value terms. We

abbreviate each of these as follows:

$$
\begin{aligned}
pdvc_i^A &= \sum \frac{1}{(1+r)^t} \qquad agepdvc_i^A = \sum \frac{age_{it}}{(1+r)^t} \qquad age2pdvc_i^A = \sum \frac{age_{it}^2}{(1+r)^t} \\
pdve_i^A &= \sum \frac{pre_{it}^A}{(1+r)^t} \qquad agepdve_i^A = \sum \frac{age_{it} pre_{it}^A}{(1+r)^t} \qquad age2pdve_i^A = \sum \frac{age_{it}^2 pre_{it}^A}{(1+r)^t} \\
pdvi_i^A &= \sum \frac{ill_{it}^A}{(1+r)^t} \qquad agepdvi_i^A = \sum \frac{age_{it} ill_{it}^A}{(1+r)^t} \qquad age2pdvi_i^A = \sum \frac{age_{it}^2 ill_{it}^A}{(1+r)^t} \\
pdvr_i^A &= \sum \frac{rcv_{it}^A}{(1+r)^t} \qquad agepdvr_i^A = \sum \frac{age_{it} rcv_{it}^A}{(1+r)^t} \qquad age2pdvr_i^A = \sum \frac{age_{it}^2 rcv_{it}^A}{(1+r)^t} \\
pdvl_i^A &= \sum \frac{lyl_{it}^A}{(1+r)^t} \qquad agepdvl_i^A = \sum \frac{age_{it} lyl_{it}^A}{(1+r)^t} \qquad age2pdvl_i^A = \sum \frac{age_{it}^2 lyl_{it}^A}{(1+r)^t}
\end{aligned}
$$

Notice that the following two relationships hold, since the indicator variables for each health status are mutually exclusive and exhaustive:

$$
\begin{aligned}
pdvc_i^A &= pdve_i^A + pdvi_i^A + pdvr_i^A + pdvl_i^A \\
agepdvc_i^A &= agepdve_i^A + agepdvi_i^A + agepdvr_i^A + agepdvl_i^A \\
age2pdvc_i^A &= age2pdve_i^A + age2pdvi_i^A + age2pdvr_i^A + age2pdvl_i^A
\end{aligned}
$$

To accommodate the different time profiles of income and program costs over the individual's remaining lifespan, we must also define two additional terms

$$
\begin{aligned}
pdvy_i^A &= \sum \frac{\left(pre_{it}^A + \gamma_1 ill_{it}^A + rcv_{it}^A + \gamma_2 lyl_{it}^A\right)}{(1+r)^t} = pdve_i^A + \gamma_1 pdvi_i^A + pdvr_i^A + \gamma_2 pdvl_i^A \\
pdvp_i^A &= \sum \frac{\left(pre_{it}^A + \gamma_3 ill_{it}^A + rcv_{it}^A + \gamma_4 lyl_{it}^A\right)}{(1+r)^t} = pdve_i^A + \gamma_3 pdvi_i^A + pdvr_i^A + \gamma_4 pdvl_i^A \\
pdvyy_i &= \sum \frac{\left(pre_{it}^A + \gamma_1 ill_{it}^A + rcv_{it}^A + \gamma_2 lyl_{it}^A\right)^2}{(1+r)^t} = pdve_i + \gamma_1^2 pdvi_i + pdvr_i + \gamma_2^2 pdvl_i \\
pdvpp_i &= \sum \frac{\left(pre_{it}^A + \gamma_3 ill_{it}^A + rcv_{it}^A + \gamma_4 lyl_{it}^A\right)^2}{(1+r)^t} = pdve_i + \gamma_3^2 pdvi_i + pdvr_i + \gamma_4^2 pdvl_i \\
pdvyp_i &= \sum \frac{\left(pre_{it}^A + \gamma_1 ill_{it}^A + rcv_{it}^A + \gamma_2 lyl_{it}^A\right)\left(pre_{it}^A + \gamma_3 ill_{it}^A + rcv_{it}^A + \gamma_4 lyl_{it}^A\right)}{(1+r)^t} \\
&= pdve_i + \gamma_1\gamma_3 pdvi_i + pdvr_i + \gamma_2\gamma_4 pdvl_i
\end{aligned}
$$

The Appendix shows that the expected utility difference driving the individual's choice between Program A and the Neither Program aternative can then be written as follows (there will be an analogous utility-

difference for the B program versus the Neither Program alternative).

$$
\begin{aligned}
E\left[V_i^A\right] - E\left[V_i^N\right] \quad = \quad & \left[c_i^A\right](-1)\,\beta_0\left[\left(1-\Pi_i^{AS}\right)pdvc_i + \Pi_i^{AS}pdvp_i\right] \\
& + \left[c_i^A\right](-1)\,\beta_1\left[\left(1-\Pi_i^{AS}\right)agepdvc_i + \Pi_i^{AS}agepdvp_i\right] \\
& + \left[c_i^A\right](-1)\,\beta_2\left[\left(1-\Pi_i^{AS}\right)age2pdvc_i + \Pi_i^{AS}age2pdvp_i\right] \\
& + [c_i^A](-1)\,\beta_3 2Y_i\left[\left(1-\Pi_i^{AS}\right)pdvc_i + \Pi_i^{AS}pdvyp_i\right] \\
& + [c_i^A]^2\beta_3\left[\left(1-\Pi_i^{AS}\right)pdvc_i + \Pi_i^{AS}pdvpp_i\right] \\
& + \beta_0 Y_i\Delta\Pi_i^{AS}\left(pdvy_i - pdvc_i\right) \\
& + \beta_1 Y_i\Delta\Pi_i^{AS}\left(agepdvy_i - agepdvc_i\right) \\
& + \beta_2 Y_i\Delta\Pi_i^{AS}\left(age2pdvy_i - age2pdvc_i\right) \\
& + \beta_3 Y_i^2\Delta\Pi_i^{AS}\left(pdvyy_i - pdvc_i\right) \\
& + \delta_{10}\Delta\Pi_i^{AS}pdvi_i + \delta_{11}\Delta\Pi_i^{AS}agepdvi_i + \delta_{12}\Delta\Pi_i^{AS}age2pdvi_i \\
& + \delta_{20}\Delta\Pi_i^{AS}pdvr_i + \delta_{21}\Delta\Pi_i^{AS}agepdvr_i + \delta_{22}\Delta\Pi_i^{AS}age2pdvr_i \\
& + \delta_{30}\Delta\Pi_i^{AS}pdvl_i + \delta_{31}\Delta\Pi_i^{AS}agepdvl_i + \delta_{32}\Delta\Pi_i^{AS}age2pdvl_i + \varepsilon_i
\end{aligned} \tag{19}
$$

4.4 Ex ante option prices

The respondent's implied ex ante option price for program A can be determined by setting the expected utility difference equal to zero and solving for the vale of c_i^A that makes the equality hold. First however, the unknown utility parameters must be estimated. For parameter estimation, all terms involving the same β parameter must be combined. These constructed variables, listed according to their corresponding parameters, are:

$$
\begin{aligned}
\beta_0 \quad : \quad & \left[c_i^A\right](-1)\left[\left(1-\Pi_i^{AS}\right) pdvc_i + \Pi_i^{AS} pdvp_i\right] \\
& + Y_i \Delta\Pi_i^{AS}\left(pdvy_i - pdvc_i\right) \\
\beta_1 \quad : \quad & \left[c_i^A\right](-1)\left[\left(1-\Pi_i^{AS}\right) agepdvc_i + \Pi_i^{AS} agepdvp_i\right] \\
& + Y_i \Delta\Pi_i^{AS}\left(agepdvy_i - agepdvc_i\right) \\
\beta_2 \quad : \quad & \left[c_i^A\right](-1)\left[\left(1-\Pi_i^{AS}\right) age2pdvc_i + \Pi_i^{AS} age2pdvp_i\right] \\
& + Y_i \Delta\Pi_i^{AS}\left(age2pdvy_i - age2pdvc_i\right) \\
\beta_3 \quad : \quad & \left[c_i^A\right](-1)\, 2Y_i\left[\left(1-\Pi_i^{AS}\right) pdvc_i + \Pi_i^{AS} pdvyp_i\right] \\
& + \left[c_i^A\right]^2\left[\left(1-\Pi_i^{AS}\right) pdvc_i + \Pi_i^{AS} pdvpp_i\right] \\
& + Y_i^2 \Delta\Pi_i^{AS}\left(pdvyy_i - pdvc_i\right)
\end{aligned}
$$

4.5 Solving for option prices from estimated models

Once the parameters have been estimated, we can solve for the payment c_i^A that would make the utility-difference exactly zero. This yields a quadratic form of the type $0 = Ax^2 + Bx + C$, where $x = c_i^A$. The squared term in c_i^A will be activated only if $\beta_3 \neq 0$, and will bear the coefficient:

$$
A = \beta_3\left[\left(1-\Pi_i^{AS}\right) pdvc_i + \Pi_i^{AS} pdvpp_i\right]
$$

The linear coefficient on c_i^A will be.

$$B = \begin{bmatrix} \beta_0 (-1) \left[\left(1 - \Pi_i^{AS}\right) pdvc_i + \Pi_i^{AS} pdvp_i \right] \\ +\beta_1 (-1) \left[\left(1 - \Pi_i^{AS}\right) agepdvc_i + \Pi_i^{AS} agepdvp_i \right] \\ +\beta_2 (-1) \left[\left(1 - \Pi_i^{AS}\right) age2pdvc_i + \Pi_i^{AS} age2pdvp_i \right] \\ +\beta_3 (-1) 2Y_i \left[\left(1 - \Pi_i^{AS}\right) pdvc_i + \Pi_i^{AS} pdvyp_i \right] \end{bmatrix}, \text{ or}$$

$$-B = \begin{bmatrix} \beta_0 \left[\left(1 - \Pi_i^{AS}\right) pdvc_i + \Pi_i^{AS} pdvp_i \right] \\ +\beta_1 \left[\left(1 - \Pi_i^{AS}\right) agepdvc_i + \Pi_i^{AS} agepdvp_i \right] \\ +\beta_2 \left[\left(1 - \Pi_i^{AS}\right) age2pdvc_i + \Pi_i^{AS} age2pdvp_i \right] \\ +\beta_3 2Y_i \left[\left(1 - \Pi_i^{AS}\right) pdvc_i + \Pi_i^{AS} pdvyp_i \right] \end{bmatrix}$$

Finally, the terms not involving c_i^A can be collected as:

$$\begin{aligned} C = \quad & \beta_0 \, Y_i \Delta\Pi_i^{AS} \left(pdvy_i - pdvc_i\right) \\ & +\beta_1 \, Y_i \Delta\Pi_i^{AS} \left(agepdvy_i - agepdvc_i\right) \\ & +\beta_2 \, Y_i \Delta\Pi_i^{AS} \left(age2pdvy_i - age2pdvc_i\right) \\ & +\beta_3 \, Y_i^2 \Delta\Pi_i^{AS} \left(pdvyy_i - pdvc_i\right) \\ & +\delta_{10} \, \Delta\Pi_i^{AS} pdvi_i + \delta_{11} \, \Delta\Pi_i^{AS} agepdvi_i + \delta_{12} \, \Delta\Pi_i^{AS} age2pdvi_i \\ & +\delta_{20} \, \Delta\Pi_i^{AS} pdvr_i + \delta_{21} \, \Delta\Pi_i^{AS} agepdvr_i + \delta_{22} \, \Delta\Pi_i^{AS} age2pdvr_i \\ & +\delta_{30} \, \Delta\Pi_i^{AS} pdvl_i + \delta_{31} \, \Delta\Pi_i^{AS} agepdvl_i + \delta_{32} \, \Delta\Pi_i^{AS} age2pdvl_i + \varepsilon_i \end{aligned}$$

where $\Delta\Pi_i^{AS} = \Pi_i^{AS} - \Pi_i^{NS}$ is a negative number for each of our risk reduction scenarios. If the error term can be considered to be zero, the systematic portion of the difference in expected utilities can be solved to yield point estimates of the option price.

Many practitioners currently use samples drawn from the joint distribution of the maximum likelihood parameter estimates to generated simulated 90% confidence intervals for the option price predictions. In this exercise, it is possible either to ignore the error term, or to replace it with a random draw from a unit logistic distribution before computing the value of the C term for each replication. As usual for a quadratic formula, fitted values of option price for each simulation will be given by:

$$c_i^A = \frac{-B \pm \sqrt{B^2 - 4AC}}{2A}$$

If $B^2 - 4AC > 0$, the equation has two distinct real roots. In cases where only one of these roots is positive, the correct solution will be obvious. In models where $\beta_3 = 0$, the formula for c_i^A is simply linear, rather than a quadratic form. The A term is zero, and the B term loses its component in β_3 so that $c_i^A = -C/B$

4.6 Fully quadratic marginal utilities

The discrete choice among program alternatives can thus be modeled as depending upon the marginal utility of income and the marginal (dis)utilities of time in each health state. The marginal utility of income may involve up to four parameters, β_0, β_1, β_2, and β_3, depending upon whether it is allowed to depend on both the linear and squared values of the respondent's age in the future period when the income is to be enjoyed, and on the level of income itself. Further generality will also be explored in this paper. In particular, the age of the respondent at the time he or she is being asked to make these tradeoffs will be allowed to influence the indirect utility function. The baseline marginal utility parameters $\beta_0, \delta_{10}, \delta_{20}$, and δ_{30} will be allowed to shift with age_{i0} and with age_{i0}^2, making indirect utility potentially fully quadratic in the respondent's current age. Also, β_1, δ_{11}, δ_{21}, and δ_{31} can be allowed to shift with age_{i0}, which will allow for an interaction

between current age and the age at which income or a particular health status is to be experienced. While we do not expect, a priori, that each undiscounted marginal utility in our model will be fully quadratic in both age now and age-at-event, we wish to allow the data to reveal nonlinearities, including maxima or minima over the range of current ages or ages when income or health status is to be experienced.

From the simple undiscounted indirect utility function in equation ( ), it is necessary to go through several steps to achieve the estimating form that can be used to explain respondent's choices among risk-reduction programs. We see from equation ( ) that the difference in expected present value indirect utilities associated with choosing a risk-reduction program is a function of the illness profile as captured by the $pdvi_i^A$, $pdvr_i^A$,and $pdvl_i^A$ terms, as well as a function of the individual discount rate r_i assumed for each respondent. In this analysis, we assume $r_i = r$, the same for each respondent, and we conduct sensitivity analyses with respect to the magnitude of this discount rate.

In our empirical application, equation (19) is the basis for estimation of the random utility choice model that explains individuals' choices among the three alternatives presented in each choice scenario: Program A, Program B, or Neither Program. There is an analogous difference in expected utilities between Program B and the Neither Program choice. All choices posed to respondents were three-way choices, so the models will be estimated using McFadden's conditional logit estimator (or appropriate modifications of this model).

4.7 From maximum annual payment to PDV of payment stream

The option price for the program that accomplishes this decrease in illness probabilities is the common certain payment, regardless of which way the uncertainty about contracting the illness is resolved, that makes the individual just indifferent between paying for the program and enjoying the risk reduction, or not paying for the program and not enjoying the risk reduction. This payment, c_i^{A*}, will make $E\left[V_i^A\right] - E[V_i^N\big] = 0$. The amount of money c_i^{A*} is the maximum constant annual payment that the individual will be willing to make, regardless of whether he suffers the illness, in order to purchase the program that reduces his probability of

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

While the payment $\widehat{c_i^A}$ is the maximum annual payment the individual is willing to make, these payments are necessary for the rest of the individual's life, so the present value of these payments must be calculated. In this context, however, there is some uncertainty over just what will constitute "the rest of the individual's life," since this may differ according to whether the individual suffers the illness or not. We will use the expected present value of this time profile of costs, with the expectation taken over whether or not the individual suffers the illness when they are participating in the program.

$$\begin{aligned} & E\left[PV(\widehat{c_i^A})\right] \\ = \; & \left(1-\Pi_i^{AS}\right)(\widehat{c_i^A})pdvc_i^A + \left(\Pi_i^{AS}\right)(\widehat{c_i^A})pdvp_i^A \\ = \; & (\widehat{c_i^A})\left[\left(1-\Pi_i^{AS}\right)pdvc_i^A + \Pi_i^{AS}\left(pdvp_i^A\right)\right] \end{aligned} \tag{20}$$

In the case where the marginal utility of income is constant, so that $\beta_1 = \beta_2 = \beta_3 = 0$, the denominator of the option price formula is just $\beta_0\left[\left(1-\Pi_i^{AS}\right)pdvc_i^A + \Pi_i^{AS}\left(pdvp_i^A\right)\right]$, so that capitalizing this payment over the rest of the individual's life allows the terms in square brackets to cancel. The formula for the present value of the streams of annual maximum payments willingly made to avoid a specified health profile reduces

to:

$$
\begin{aligned}
E\left[PV(\widehat{c_i^A})\right] &= \beta_0^{-1}\left[\begin{array}{c}
\beta_0 Y_i \Delta\Pi_i^{AS}\left(pdvy_i - pdvc_i\right) \\
+\delta_{10}\Delta\Pi_i^{AS} pdvi_i + \delta_{11}\Delta\Pi_i^{AS} agepdvi_i + \delta_{12}\Delta\Pi_i^{AS} age2pdvi_i \\
+\delta_{20}\Delta\Pi_i^{AS} pdvr_i + \delta_{21}\Delta\Pi_i^{AS} agepdvr_i + \delta_{22}\Delta\Pi_i^{AS} age2pdvr_i \\
+\delta_{30}\Delta\Pi_i^{AS} pdvl_i + \delta_{31}\Delta\Pi_i^{AS} agepdvl_i + \delta_{32}\Delta\Pi_i^{AS} age2pdvl_i + \varepsilon_i
\end{array}\right] \\
&= \Delta\Pi_i^{AS}\beta_0^{-1}\left[\begin{array}{c}
\beta_0 Y_i\left(pdvy_i - pdvc_i\right) \\
+\delta_{10} pdvi_i + \delta_{11} agepdvi_i + \delta_{12} age2pdvi_i \\
+\delta_{20} pdvr_i + \delta_{21} agepdvr_i + \delta_{22} age2pdvr_i \\
+\delta_{30} pdvl_i + \delta_{31} agepdvl_i + \delta_{32} age2pdvl_i + \varepsilon_i
\end{array}\right]
\end{aligned}
$$

From this result, it is clear that if the marginal utility of income is constant across the population, the expected present value of the lifetime stream of maximum annual payments is merely proportional to the size of the risk reduction, given individual preferences, income and the illness profile in question.

4.8 Proportionality to risk differences

This proportionality is a common assumption in much empirical work on WTP to avoid health risks and this proportionality has been used to justify the normalization across different risk reductions inherent in the concept of the valuation of a "statistical" life. Indeed, if the risk reduction involved and the cost of the program pertained only to a single year (as is the case in a number of existing VSL studies) there would be no difference between $pdvy_i$ and $pdvc_i$, so that the first term in the square brackets would disappear. Furthermore, if all illness profiles were to be treated as identical and no dependency on age was being assumed, all of the terms involving δ parameters would collapse into a single constant parameter, δ, multiplying a

dummy variable, say D_i^A, that indicates whether the health state occurs in alternative A. This new parameter would describe the marginal utility of the generic health outcome to be avoided. This health outcome is "sudden death this year" in many existing empirical studies. In this case, we would have:

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

When the marginal utility of income is heterogeneous across individuals, these simplifications are not possible. The process of calculating the expected present value of program costs does not produce a term that cancels with everything but β_0. The expected present value can still be calculated, but the formulas will remain functions of both $\left(1-\Pi_i^{AS}\right)$ and Π_i^{AS} and the other arguments of the B term above.

4.9 Value of a statistical illness (VSI)

The expected present discounted value in equation (20) pertains to the maximum annual willingness to pay for a small risk reduction, $\Delta\Pi_i^{AS}$. There is a tradition in the mortality valuation literature of ignoring the size of the risk difference involved, $\Delta\Pi_i^{AS}$, and scaling each expected present value option price to the amount that would correspond to a 100% risk difference. To convert our expected present value option price to something that might be termed the "value of a statistical illness" (VSI), we could divide by the absolute size of the risk reduction. In our study, all probability changes $\Delta\Pi_i^{AS}$ are negative, while the absolute magnitude of these changes will be positive. Multiplication by $\Delta\Pi_i^{AS}/\left|\Delta\Pi_i^{AS}\right|$ will amount to multiplying by -1, which will change the effective sign on each of the terms involving this ratio. Using the same abbreviations B and C for the detailed expressions defined above, if the researcher desires measures of a quantity that is comparable to traditional VSL estimates, the effective formula for the value of a statistical illness, in the

case where $\delta_3 = 0$, will be:

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

In the special case where the marginal utility of income is simply a constant, this formula simplifies to:

$$\frac{E\left[PV(\widehat{c_i^A})\right]}{\left|\Delta\Pi_i^{AS}\right|} = \beta_0^{-1}\begin{bmatrix} \beta_0 Y_i pdvl_i \\ -\delta_{10}pdvi_i - \delta_{11}agepdvi_i - \delta_{12}age2pdvi_i \\ -\delta_{20}pdvr_i - \delta_{21}agepdvr_i - \delta_{22}age2pdvr_i \\ -\delta_{30}pdvl_i - \delta_{31}agepdvl_i - \delta_{32}age2pdvl_i + \frac{\varepsilon_i}{\left|\Delta\Pi_i^{AS}\right|} \end{bmatrix} \tag{21}$$

where we take advantage of the fact that $pdvy_i + pdvl_i = pdvc_i$ so that $(pdvy_i - pdvc_i) = -pdvl_i$.

Across the distribution of the logistic error term, ε_i, the expectation is zero, so the expected value of a statistical illness depends only on the systematic portion of equation (21). The VSI in this case will depend upon the different marginal utilities of avoided periods of illness, recovered status, and premature death and on the way these marginal utilities vary with age at the time each health status is experienced. It will also depend upon the time profiles for each of these states as embedded in the terms $pdvi_i^A$, $pdvr_i^A$, and $pdvl_i^A$, as well as $agepdvi_i^A$, $agepdvr_i^A$, $agepdvl_i^A$ and potentially $age2pdvi_i^A$, $age2pdvr_i^A$, $age2pdvl_i^A$, and (implicit in this model) upon the individual's own discount rate.[14]

In this simple model with a constant marginal utility of income, increases in income Y_i will increase the predicted point estimate of the VSI. The effect of income on VSI_i^A is given by $\partial VSI_i^A/\partial Y_i = pdvl_i^A$ which is non-negative. Thus the effect of an increase in income on the predicted VSI will be larger (i.) as more

[14] Subsequent work will preserve individual discount rates as systematically varying parameters, to be estimated with reference to the individual's responses to a hypothetical "how to take your lottery winnings" question. Here, discount rates are presumed to be exogenous and constant across individuals. Our empirical work explores the consequences of using different discount rate assumptions.

life-years are lost, (ii.) as the individual is older, so that life-years lost come sooner in time. The effect of income on VSI can be estimated more generally if the marginal utility of income is not constant.[15]

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

In expectation, the fitted value of a statistical illness can potentially vary systematically across types of illnesses according to the labels assigned to the illnesses, the symptoms and treatment associated with them, the individual's characteristics besides just age now and age-at-event, perceptions of risks associated with the type of illness, and prior experience with that illness. This heterogeneity can be accommodated by making the indirect utility parameters δ_1, δ_2, and δ_3 depend upon other individual characteristics. In future empirical models, the addition of illness labels and a symptom-treatment profile (within the illness state) will convey to the respondent some information about what health consequences might ensue from each illness we describe. These illness characteristics can be expected to shift the value of δ_1, the marginal (dis)utility of a sick-year. The marginal utility of each period of recovered health status, δ_2, could be allowed also to vary by type of illness as well, since the illness labels may connote the degree of "health" that nominal recovery from that illness actually implies. Finally, the marginal utility of a lost life-year may depend upon the health state prior to death. In the meantime, readers should keep in mind that the essentially randomized design of the illness profiles, conditional only on the individual's age and gender (and excluding nonsensical combinations), ensures that omitted variables bias concerning attributes of each illness profile

[15] Nothing in this specification precludes negative point estimates of the VSI. A positive VSI estimate will result if the estimated value of the marginal utility of income, β, is positive and there are negative values for the marginal utilities of illness-years, recovered-years, and lost life-years (the δs).

The key undiscounted marginal utility parameters are not presently constrained to be strictly positive (for income) and strictly negative (for episodes of undesirable health profiles). This is especially a concern when these marginal utilities are permitted to vary systematically with of the attributes of the illness profile and/or the characteristics of the individual in question. The marginal utility of income, the scalar parameter β in our simplest models, bears a point estimate that is robustly positive, but positive values for one or both of the systematically varying parameters capturing the marginal utility of an illness-year (δ_1) or a lost life-year (δ_3) can push an individual fitted value of the VSI for a particular morbidity/mortality profile into the negative range.

will be minimized in this analysis.

4.10 VSIs versus Conventional VSLs

The existing literature, especially the hedonic wage-risk literature, focuses on society's willingness to pay for incremental reductions in the chance of a sudden accidental death in the current period. In general, there are no age effects, and age_{i0} is the same thing as "age-at-event" (age_{it}). In the framework of our illness profiles, such an event would be captured by zero years of morbidity and death in the current year, with the remainder of the individual's nominal life expectancy 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 will be simply:

$$\begin{aligned} E[VSL] &= \frac{E\left[PV(\widehat{c_i^A})\right]}{\left|\Delta\Pi_i^{AS}\right|} = \left(\frac{-\delta_{30}}{\beta} + Y_i\right) pdvl_i^A \qquad (22) \\ \text{where} \quad pdvl_i^A &= \sum \frac{lyl_{it}^A}{(1+r)^t} \end{aligned}$$

The summation in the formula for $pdvl_i^A$ is from the present until the individual's nominal life expectancy. This interval depends upon the individual's current age, so even in a model with homogeneous preferences, the VSI will vary with age. The VSI also depends upon the individual's income, and of course, the individual's discount rate will also matter. See Cameron and DeShazo (2003) for discussion of calculating policy-relevant VSLs with this model.

5 Results and Discussion

For this paper, we examine the model in equation (19) and a number of its special cases. Our estimating sample consists of stated preferences for 5 sets of three-way program choices provided by roughly 1320 respondents from an originally representative sample of roughly 2000 from the US population. [16]

[16] For this analysis we have dropped the choices of individuals who appear to have spent too little total time on the five choice tasks to have allowed fully-considered selections. An Appendix details the consequences for parameter estimates in our

Table 1 compiles estimation results for three different specifications estimated for three different assumptions about individual discount rates: 3%, 5%, and 7%. These rates were chosen based on the official range of values recommended for benefit-cost analysis by the Science Advisory Board of the US EPA. For each discount rate, we calculate the various present discounted value terms (capturing the time profiles of morbidity and mortality) employed in the construction of variables for use in the estimating specification.[17]

5.1 Estimating Specifications

Our baseline model allows for the level of income to affect the marginal utility of additional income, but excludes any age effects on the marginal (dis)utilities of health states. Our "No Age Effects" specification is

$$
\begin{aligned}
E\left[V_i^A\right] - E\left[V_i^N\right] \quad = \quad & \beta_0 \left\{ \begin{array}{c} \left[c_i^A\right](-1)\left[\left(1-\Pi_i^{AS}\right) pdvc_i + \Pi_i^{AS} pdvp_i\right] \\ +Y_i \Delta\Pi_i^{AS}\left(pdvy_i - pdvc_i\right) \end{array} \right\} \\
& +\beta_3 \left\{ \begin{array}{c} \left[c_i^A\right](-1)\, 2Y_i\left[\left(1-\Pi_i^{AS}\right) pdvc_i + \Pi_i^{AS} pdvyp_i\right] \\ +\left[c_i^A\right]^2\left[\left(1-\Pi_i^{AS}\right) pdvc_i + \Pi_i^{AS} pdvpp_i\right] \\ +Y_i^2 \Delta\Pi_i^{AS}\left(pdvyy_i - pdvc_i\right) \end{array} \right\} \\
& +\delta_{10}\Delta\Pi_i^{AS} pdvi_i + \delta_{20}\Delta\Pi_i^{AS} pdvr_i + \delta_{30}\Delta\Pi_i^{AS} pdvl_i + \varepsilon_i
\end{aligned}
\tag{23}
$$

Our "Linear Age Effects" model allows the marginal utility of income to be shifted by the respondent's current age (age_{i0}), and allows the marginal (dis)utility of a sick-year, a recovered-year and a lost life-year to shift with both the respondent's current age (age_{i0}) and the respondent's age at the time that health state

preferred specification as our criteria for rejecting observations are successively weakened, leaving more and more respondents in the estimating sample. We focus on a subset of people we will characterize as "careful choosers who do not explicitly reject the choice scenarios." Selectivity correction exercises are pending.

[17] In current models, we lean heavily on linearities that allow us to estimate our parameters using packaged software algorithms for McFadden's conditional logit models.

is being experienced (i.e. the "age-at-event," age_{it}):

$$
\begin{aligned}
E\left[V_i^A\right] - E\left[V_i^N\right] \quad = \quad & (\beta_{00} + \beta_{01} age_{i0}) \left\{ \begin{array}{c} \left[c_i^A\right](-1)\left[\left(1-\Pi_i^{AS}\right) pdvc_i + \Pi_i^{AS} pdvp_i\right] \\ +Y_i \Delta\Pi_i^{AS}\left(pdvy_i - pdvc_i\right) \end{array} \right\} \\
& +\beta_3 \left\{ \begin{array}{c} \left[c_i^A\right](-1)\, 2Y_i \left[\left(1-\Pi_i^{AS}\right) pdvc_i + \Pi_i^{AS} pdvyp_i\right] \\ +\left[c_i^A\right]^2 \left[\left(1-\Pi_i^{AS}\right) pdvc_i + \Pi_i^{AS} pdvpp_i\right] \\ +Y_i^2 \Delta\Pi_i^{AS}\left(pdvyy_i - pdvc_i\right) \end{array} \right\} \\
& +(\delta_{100} + \delta_{101} age_{i0}) \Delta\Pi_i^{AS} pdvi_i + \delta_{11} \Delta\Pi_i^{AS} agepdvi_i \\
& +(\delta_{200} + \delta_{201} age_{i0}) \Delta\Pi_i^{AS} pdvr_i + \delta_{21} \Delta\Pi_i^{AS} agepdvr_i \\
& +(\delta_{300} + \delta_{301} age_{i0}) \Delta\Pi_i^{AS} pdvl_i + \delta_{31} \Delta\Pi_i^{AS} agepdvl_i + \varepsilon_i
\end{aligned}
\tag{24}
$$

The most general model described in Table 1 is our "Quadratic Age Effects" model. This model retains the same formulation for the marginal utility of income, but allows for each of the (dis)utilities of the three

different health states to be fully quadratic in the respondent's age now (age_{i0}) and age-at-event (age_{it}).

$$
\begin{aligned}
E\left[V_i^A\right] - E\left[V_i^N\right] \quad = \quad & (\beta_{00} + \beta_{01} age_{i0}) \left\{ \begin{array}{c} \left[c_i^A\right](-1)\left[\left(1-\Pi_i^{AS}\right) pdvc_i + \Pi_i^{AS} pdvp_i\right] \\ +Y_i \Delta\Pi_i^{AS}\left(pdvy_i - pdvc_i\right) \end{array} \right\} \\
& +\beta_3 \left\{ \begin{array}{c} \left[c_i^A\right](-1)\, 2Y_i\left[\left(1-\Pi_i^{AS}\right) pdvc_i + \Pi_i^{AS} pdvyp_i\right] \\ +[c_i^A]^2\left[\left(1-\Pi_i^{AS}\right) pdvc_i + \Pi_i^{AS} pdvpp_i\right] \\ +Y_i^2 \Delta\Pi_i^{AS}\left(pdvyy_i - pdvc_i\right) \end{array} \right\} \\
& +(\delta_{100} + \delta_{101} age_{i0} + \delta_{102} age_{i0}^2)\Delta\Pi_i^{AS} pdvi_i \\
& +\delta_{110}\Delta\Pi_i^{AS} agepdvi_i + \delta_{111}\Delta\Pi_i^{AS} agepdvi_i age_{i0} + \delta_{12}\Delta\Pi_i^{AS} age2pdvi_i \\
& +(\delta_{200} + \delta_{201} age_{i0} + \delta_{202} age_{i0}^2)\Delta\Pi_i^{AS} pdvr_i \\
& +\delta_{210}\Delta\Pi_i^{AS} agepdvr_i + \delta_{211}\Delta\Pi_i^{AS} agepdvr_i age_{i0} + \delta_{22}\Delta\Pi_i^{AS} age2pdvr_i \\
& +(\delta_{300} + \delta_{301} age_{i0} + \delta_{302} age_{i0}^2)\Delta\Pi_i^{AS} pdvl_i \\
& +\delta_{310}\Delta\Pi_i^{AS} agepdvl_i + \delta_{311}\Delta\Pi_i^{AS} agepdvl_i age_{i0} + \delta_{32}\Delta\Pi_i^{AS} age2pdvl_i + \varepsilon_i
\end{aligned}
\tag{25}
$$

The marginal utility of income should be positive, but is not constrained to be so. Our competing specifications also involve several parameters that describe the marginal (dis)utility of a sick year, a recovered year, and a lost life-year. Intuitively, the marginal utility of a sick-year should be negative, but we do not enforce this restriction. The estimated marginal utility of a lost life-year may also depend on several parameters, and these parameters are also estimated freely from the observed choices, without sign restrictions. In general, one would expect that the marginal utility of a lost-life-year would be negative.[18] For our two models with age effects, we will provide figures that show the systematic variation in these two marginal utilities as a function of age-at-event, for each of a 25, 35, 45, 55, and 65-year-olds.

[18] 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." For certain illnesses, such as severe Alzheimers' disease, we might expect that death would "come as a blessing." In any situation where the pre-death state was less onerous, however, we would expect death to be unwelcome, and hence that the marginal utility of a lost life-year would be negative.

5.2 Parameter Estimates

In Table 4 which present our parameter estimates, we will emphasize the middle set of three models, for the 5% discount rate assumption. Our "No Age Effects" specification shows robust significance and the expected signs on all five core parameters. The marginal utility of income is positive, but declines with the level of income. The marginal utilities of sick-years, recovered years, and lost life-years are all negative, and (somewhat surprisingly) each has a similar point value. The surprising result is that recovered years are not interpreted by respondents to be equivalent to health pre-illness years. Despite our having intended respondents to view these years as equivalent to health years, they do not. They seem to be imputing reduced health or reduced function to these recovered years. The similarity in the magnitude of the marginal utility of a sick-year and a recovered-year, however, may be due to the fact that the illnesses are described as major life-threatening illnesses, including cancers, respiratory disease, and stroke, for example.

The "Linear Age Effects" model makes the main empirical point in this paper. In this model, the respondent's current age is permitted to shift his or her marginal utility of income (see Figure 3A), and the marginal utility of each health status is allowed to depend on the respondent's current age and on the age at which they would experience each year of each health status. The marginal utility of income declines with the current age of the respondent.[19] The marginal utilities of sick-years and lost life-years are less negative, the greater the current age of the respondent, but more negative with the age at which these health states would be experienced, controlling for current age. These findings are fully consistent with the two main hypotheses discussed in the theoretical section of this paper. For recovered years, the results are somewhat less precise. Age-at-event makes the marginal utility of a recovered year significantly more negative, but the respondent's age now has no statistically discernible effect upon the marginal utility of a recovered year. The anticipated marginal utility of a recovered-year appears to be independent of the current age of the

[19] We have explored the consequences of allowing the marginal utility of income to depend upon age-at-event. However, a noticeable proportion of fitted MU(Y) estimates are then negative. Negative MU(Y) produces nonsensical results for the implied WTP for an avoided sick-year, recovered-year, or lost life-year, since the marginal utility of income acts as the denominator of the WTP formula.

respondent in these data.

One troubling feature of the Linear Age Effects models is the persistence of positive values for the marginal utilities of all three health states for some future ages. These positive marginal utilities lead to negative WTP estimates in those early future years and will tend to bias downward the present value employed as an estimate of the Value of a Statistical Illness (VSI). Figures 3B, 3C, and 3D show that, for example, WTP to avoid a statistical sick-year, recovered-year, and lost life-year for a currently 25-year-old respondent (the line tagged with "25") appear to be negative for the first few years into the future. We suspect that many respondents, feeling currently rather healthy, doubt that the health risk we describe will actually affect them in the next 5-10 years, although the possibility of becoming ill in the years beyond that is more credible. It is not clear whether this should be interpreted as a form of scenario rejection in response to our stated preference choice scenarios, or whether this is a legitimate property of people's preferences.

Recall that there is no opportunity for any respondent to express a negative willingness to pay explicitly. At a minimum, respondents can imply that the value they place on a program is zero (i.e. no greater than the cost of the Neither Program alternative, available at zero net cost). To determine whether these negative fitted WTP estimates in the linear models are merely an artifact of a too-restrictive functional form, we estimate a specification that allows the marginal utilities associated with all three health states to be fully quadratic in both age now and age-at-event.

It would be desirable, in our quadratic model, also to allow the marginal utility of income to be a fully quadratic function of both age now and age-at-event. However, as Figure 4A reveals, generalizing the marginal utility of income in this way leads to occasional negative fitted values for the marginal utility of income. Since this marginal utility serves as the denominator in WTP calculations, negative and zero values are particularly problematic. Pending further exploration of models that restrict the marginal utility of income to be strictly positive, we revert to the simpler specification where the marginal utility of income depends only upon current age.

For the 5% discount rate, the "Quadratic Age Effects" model reveals individually statistically significant point estimates on the quadratic and interaction terms in age-at-event for sick-years. It also reveals statistically significant point estimates on the age-now term and the interaction term for lost life-years. None of the additional parameters for recovered-years is individually statistically significant, but the maximized log-likelihood increases by almost seven.

Figures 4B, 4C, and 4D reveal the consequences of allowing a more general functional form. For each current age, the only relevant portions of these curves lie to the right of that current age. These diagrams strongly suggest that most respondents place zero value on avoiding a sick-year that will occur prior to their 50s. They may tend to believe, on average, that they will remain healthy until their 50s. Respondents who are currently younger place higher value on avoiding future sick-years at specified ages than do currently older respondents (for those same specified ages). Similar patterns, to a greater or lesser degree, are apparent for recovered-years and lost life-years.

5.3 Potential Extension

The Quadratic Age Effects specification creates a strong impression that it will be desirable to break away from linear-in-parameters models, in spite of their extremely attractive properties for ease of estimation. In particular, our next task is to specify a non-linear model wherein we estimate the logarithms of the marginal utilities of income and years in each health state, rather than their absolute levels. The logarithmic transformation will prevent the fitted marginal utility of income from going negative and will prevent the marginal utility of a sick-year, a recovered-year, and a lost life-year from being positive. In the simple case with no age effects, it seems appropriate to specify a model of undiscounted utility of the form:

$$\begin{aligned} V_{it} &= \exp\left[\beta_0 + \beta_3 Y_{it}\right]\ f(Y_{it}) \\ &\quad - \exp\left[\delta_{10}\right]\ ill_{it} - \exp\left[\delta_{10}\right]\ rcv_{it} - \exp\left[\delta_{30}\right]\ lyl_{it} + \eta_{it}. \end{aligned} \tag{26}$$

This form constrains the marginal utility of income to be positive, equal to $\exp\left[\beta_0 + \beta_3 Y_{it}\right]$. It also constrains to be negative the marginal utility from each health state $[ill_{it}, rcv_{it}, lyl_{it}]$ in each year. In the more general case where all marginal utilities are fully quadratic in the respondent's current age, age_{i0}, and the respondent's future age-at-event, age_{it},the undiscounted utility will be of the form:

$$\begin{aligned} V_{it} \quad = \quad & \exp\left[\beta_{00} + \beta_{01} age_{i0} + \beta_{02} age_{i0}^2 + \beta_{10} age_{it} + \beta_{11} age_{it} age_{i0} + \beta_2 age_{it}^2 + \beta_3 Y_{it}\right] \; f(Y_{it}) \\ & - \exp\left[\delta_{100} + \delta_{100} age_{i0} + \delta_{100} age_{i0}^2 + \delta_{110} age_{it} + \delta_{111} age_{it} age_{i0} + \delta_{12} age_{it}^2\right] \; ill_{it} \\ & - \exp\left[\delta_{200} + \delta_{200} age_{i0} + \delta_{200} age_{i0}^2 + \delta_{210} age_{it} + \delta_{211} age_{it} age_{i0} + \delta_{22} age_{it}^2\right] \; rcv_{it} \\ & - \exp\left[\delta_{300} + \delta_{300} age_{i0} + \delta_{300} age_{i0}^2 + \delta_{310} age_{it} + \delta_{311} age_{it} age_{i0} + \delta_{32} age_{it}^2\right] \; lyl_{it} \\ & + \eta_{it}. \end{aligned} \tag{27}$$

This specification precludes the eventuality of "fates worse than death" (positive marginal utility of a lost life-year following a particularly unpleasant illness). However, prior to differentiating by the types of illnesses addressed in our survey, it may be plausible to assume that the average marginal utility of a prematurely lost life-year is negative.

5.4 Fitted VSIs

Table 5 gives summary statistics concerning the marginal distribution of fitted VSIs in the estimating sample. However, these VSI estimates reflect the artificial range of illness profiles generated for use in eliciting individual choices. They do not reflect the true joint distribution, in the real world, of illnesses, symptoms and treatments, and prognoses. In particular, there are may short-term and non-fatal illnesses among the programs we presented to respondents. Thus, we do not expect to see the usual $6.1 million VSL estimate in these distributions. For the 5% discounting assumption, for the Linear Age Effects model and the Quadratic Age Effects model, median VSI is around $2.0-$2.1 million. It is slightly higher for the 3% discount rate

assumption ($2.6-$2.8 million). For the 7% discount rate model, it is lower ($1.6-$1.65 million).

How do the WTP results from our model compare to those of earlier VSL results? Many hedonic wage estimates of "the" VSL estimate wage-risk tradeoffs for middle-aged white males in blue collar jobs. For comparison with earlier results, we should consider just the VSI for an illness profile consisting of sudden death at age 45 for a 45-year-old. However, in order to highlight the generality of our WTP models, compared to earlier VSL models, we will consider four classes of simulations:

Simulation 1. How would a 25-, 35-, 45-, 55-, and 65-year-old value a reduction in the chance of sudden death starting now?

Simulation 2. How would a 25-, 35-, 45-, 55-, and 65-year-old value a reduction in the chance of sudden death starting 5 years from now?

Simulation 3: How would a 25-, 35-, 45-, 55-, and 65-year-old value a reduction in the chance of sudden death starting at age 70?

Simulation 4. How would a 25-year-old value a reduction in the chance of sudden death starting 5, 15, 25, 35 and 45 years from now?

Table 6 summarizes the results of these four classes of simulations for the No Age Effects model, the Linear Age Effects model and the Quadratic Age Effects model. For each simulation, we make 1000 random draws from the joint distribution of the maximum likelihood conditional logit parameters. For each set of parameter values, we calculate the desired VSI. We report the median of this distribution, as well as the 5th and 95th percentiles.

The No Age Effects model in Table 6 is our model that conforms as closely as possible to most previous studies. This model does not differentiate the marginal utility of a lost life-year according to the age of the respondent now or the age the respondent would have been during each life-year lost. The median VSI can be expected to differ with the respondents current age, however, because our model emphasizes life-years and involves discounting. Remarkably, despite these differences from previous models, our median VSI for

sudden death for a 45-year-old is $6.82 million, with simulated 90% confidence bounds of ($5.34 million to $8.83 million). This range of estimates compares very closely to the $6.1 million estimate used routinely by the US EPA in their major benefit-cost analysis. Evidence for any sort of a "senior death discount" is sparse in simulations 1 and 2. The medians decline monotonically with the current age of the respondent, but the differences are small. In Simulations 3 and 4, there are larger effects. In Simulation 3, we see substantial increases in the VSI for sudden death at age 70 as the respondent is closer to 70 in age. In Simulation 4, where 25-year-olds are asked to consider risks of sudden death at increasingly distant future times, the VSI falls substantially and significantly.

However, our data emphatically reject the No Age Effects model in favor of a model that acknowledges the systematic variation of WTP for risk reductions with respect to the respondent's age now and the age at which they would experience future lost life-years. The second column of VSI results in Table 6 reveals, for the Linear Age Effects model, a considerably lower median VSI of $2.08 million for sudden death this year for a 45-year-old. The bootstrapped confidence interval is wide, and admits for values as low as $50,000 and as high as $4.42 million. However, one must keep in mind that fitted WTP for avoided adverse health states is negative during the "early future" for the inflexible Linear Age Effects models. These spurious negative values will tend to bias downward our estimates of VSI for each age group.[20]

In Table 6, for simulation 1 under the Linear Age Effects model, the decline in WTP with the respondent's current age is evidenced in the lesser VSI associated with increasing current age. These calculations suggest the presence of a "senior discount" in WTP to avoid sudden death.[21] This same decline with current age is exhibited in simulation 2 (sudden death in 5 years). In simulation 4, because of discounting, WTP to avoid sudden death in more remote future years also falls. The progression in WTP is non-monotonic, however, for simulation 3 which pertains to sudden death at age 70 for people of different ages now.

[20] Less biased estimates await constrained estimation of a model featuring a positive marginal utility of income and negative marginal utilities of adverse health states.

[21] Perhaps, however, sudden death is viewed as less likely for older respondents. It is possible that respondents substitute lower risks than the survey instrument suggests, interpreting their own risk to be lower than the "average" that they assume is being quoted in the survey.

For the Quadratic Age Effects model in Table 6, however, the situation is rather different. First of all, the bootstrapped confidence intervals are even wider because of the greater number of statistically insignificant parameter estimates in this specification. The quadratic models also allow WTP for avoided sick-years, recovered-years, and lost life-years to increase much more quickly with age-at-event than they do in the Linear Age Effects models. This can lead the positive effect of age-at-event to dominate the negative effect of age-now on VSIs over some parts of the range of simulations. However, one must keep in mind that the estimated VSIs may be biased (ambiguously) because the quadratic forms can fit slighted negative or slightly positive values for the undiscounted WTP for avoided sick-years, recovered-years, and lost life-years when the true value probably ought to be positive but very close to zero.

In Table 6, none of the simulated VSI progressions based on the Quadratic Age Effects model are monotonic. This is a consequence of the countervailing positive effect of age-at-event, and the negative effect of age now, on undiscounted WTP for future years in each health state. These processes are further confounded by the discounting process.

6 Conclusions

Policy analysis with respect to risk-management programs requires detailed information about consumer demand for these programs. We begin with a concise theoretical model, adapted from Ehrlich (2001) that produces two key insights. First, individuals will derive increasing marginal utility from reducing risks that they will face later in life, which implies that individuals will be willing to pay more to reduce risks that will afflict them when they are older (and correspondingly less to reduce risks that will afflict them when they are younger). The second insight is that health and other consumption goods are likely to be complements. As individuals age, they learn more about the extent of complementarity between health and other goods–in particular, they learn that future consumption will provide less utility because of declining physical well-being. Hence they are inclined to shift more consumption forward in time and their willingness to pay for

health risk reductions will fall as they are older.

Which of these two countervailing effects will dominate is an empirical question, so we have set out to build a formal utility-theoretic model that captures the relevant considerations in private ex ante consumer choices about incurring ongoing expenditures to reduce risks to life and health. Most past studies have focused on current-period costs and current-period benefits. In contrast, our model recognizes the future time profiles of illnesses and injuries for which individuals may choose to act to reduce their risks. Intertemporal consumer optimization requires explicit treatment of the interaction between disease latencies and individual discount rates. Our model permits us to derive option prices for programs that reduce well-defined types of risks. Option prices are the appropriate theoretical construct for decision-making under uncertainty, where the uncertainty in this case concerns whether the individual will actually suffer the illness or injury that the proposed risk reduction measure addresses.

While we believe that it is important to preserve information about the nature of the risk reduction involved (its size, and perhaps the baseline risk), we show that our option price WTP formulas lead naturally to what we have labeled as the "value of a statistical illness" (VSI). The VSI is the present discounted value of the stream of maximum annual payments that the individual would be willing to pay for the specified (typically small) risk reduction, scaled up proportionately to correspond to a risk reduction of 100%. This construct is analogous to the more familiar, but more-limited, concept of the value of a statistical life (VSL). A VSL is typically constructed by looking simply at the static single-period willingness to pay for a specified risk reduction, and scaling this willingness to pay up to a 100% risk reduction. However, static VSL estimates do not typically vary with important morbidity/mortality attributes such as latency, time profiles of illness, symptoms and treatments, outcomes, or life-years lost.

In the empirical analysis presented in this paper, we first consider a model wherein preferences are considered to be homogenous across all types of individuals and where the marginal (dis)utility of a sick-year or a lost life-year is independent of the respondent's age now and his or her age at the time he or she would

be experiencing that health state (or the age that they would have been, had they not died prematurely). Even these very simple models can be used to display the sensitivity of option prices to the timing of events in an illness profile. The pattern of future health states in question matters for willingness to pay to avoid different types of risks to life and health..

Our empirical analysis also demonstrates conclusively that the current age of the respondent, as well as the prospective age at which they will experience illness or premature death, will have a systematic effect on willingness to pay for programs that reduce health risks. These findings are relevant to the current debate about whether there should be a "senior death discount" in assessing the health benefits of costly risk reductions. The choices made by the individuals in our sample strongly suggest that, ceteris paribus, the older an individual is when asked to begin paying for a particular health risk reduction, the less he or she will be willing to pay. However, this tendency can be confounded by the fact that for individuals of a given age, willingness to pay for health risk reductions increases with the age at which these health risks would be experienced. Any given individual, looking forward, may feel that they would be willing to pay more to reduce risks to their health that materialize when they are older. This tendency may feed the intuition that the benefits of risk reductions should be, if anything, higher for older persons. However, across individuals of different ages, individuals who are older seem willing to pay less to reduce risks to their health.

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Appendices A and B are available from the authors upon request.

Table 1

Descriptive statistics for Risk Reduction Programs

Variable	Mean	Std. Dev.	Min	Max
Risk Reduction Programs				
Present discounted sick-years	2.236	2.525	0	16.277
Present discounted recovered-years	0.4746	1.356	0	14.589
Present discounted lost life-years	2.596	2.938	0	17.803
Monthly cost	$ 31.03	29.46	2	140
Risk change	-.0034124	.0016695	-0.006	-0.001
Respondents				
income	$ 50,606	33,533	5,000	150,000
age	51.60	15.11	25	93

Table 2

Distribution of Program Characteristics within Illness Types

Variable	Breast Cancer	Prostate Cancer	Lung Cancer	Colon Cancer	Skin Cancer	Heart Attack	Heart Disease	Stroke	Respiratory Disease	Diabetes	Alzheimer's Disease
N=	599	548	1111	1107	1122	1144	1150	1154	1108	1097	1103
Cost	**31.649**	**29.095**	**31.611**	**30.866**	**31.162**	**30.677**	**30.148**	**30.724**	**30.888**	**30.290**	**30.480**
baseline_risk	0.0167	0.0155	0.0166	0.0159	0.0169	0.0166	0.0167	0.0165	0.0162	0.0156	0.0161
risk_change	-0.0033	-0.0035	-0.0034	-0.0035	-0.0035	-0.0035	-0.0034	-0.0034	-0.0034	-0.0033	-0.0034
mod_pain_duration	41.68	38.79	64.55	69.78	75.35	29.62	84.81	31.61	56.76	54.76	55.53
sev_pain_duration	18.32	18.84	34.15	30.35	13.89	10.70	37.19	10.76	31.73	23.59	25.09
hospital_duration	2.190	2.287	2.184	2.167	2.054	1.012	2.129	0.839	1.950	2.157	27.177
hosp_open_end	0.000	0.000	0.026	0.034	0.031	0.014	0.047	0.095	0.037	0.013	0.073
minor_surgery	0.329	0.336	0.320	0.476	0.543	0.441	0.344	0.432	0.337	0.000	0.000
major_surgery	0.331	0.314	0.357	0.524	0.457	0.159	0.312	0.167	0.292	0.000	0.000
latency	16.66	18.13	18.69	18.19	17.33	20.15	18.97	21.25	20.95	17.83	21.96
life-years lost	**11.072**	**11.535**	**10.175**	**8.388**	**9.725**	**13.191**	**7.070**	**11.920**	**7.492**	**13.235**	**8.840**
die_suddenly	0.000	0.000	0.000	0.000	0.000	0.523	0.000	0.510	0.000	0.000	0.000
die_sick	0.404	0.339	0.354	0.224	0.291	0.073	0.106	0.063	0.204	0.861	0.842
die_after_chronic	0.000	0.000	0.395	0.380	0.298	0.210	0.624	0.231	0.410	0.139	0.158
recover	0.596	0.661	0.251	0.396	0.412	0.194	0.270	0.196	0.386	0.000	0.000

Table 4

Sensitivity of Parameter Estimates to Alternative Discount Rate Assumptions

Parameter and description of variable(s)	3% discount rate			**5% discount rate**			7% discount rate		
	No Age Effects	Linear Age Effects	Quadratic Age Effects	**No Age Effects**	**Linear Age Effects**	**Quadratic Age Effects**	No Age Effects	Linear Age Effects	Quadratic Age Effects
β_{00} (linear net income term)	3.83E-05 (8.60)***	6.11E-05 (4.20)***	0.0000726 (4.54)***	**4.62E-05 (8.31)*** **	**8.29E-05 (4.37)*** **	**0.0001009 (4.81)*** **	5.336E-05 (7.97)***	9.658E-05 (4.14)***	0.0001293 (4.94)***
β_{01} (age_{i0} interaction)		-3.65E-07 (-1.64)	-5.44E-07 (2.15)**		**-5.61E-07 (1.98)** **	**-8.34E-07 (2.58)*** **		-6.296E-07 (1.84)*	-1.119E-06 (2.83)***
β_3 *E-9 (DMU(Y) term)	-0.1350 (4.40)***	-0.1514 (4.08)***	-0.1468 (3.95)***	**-0.2130 (4.62)*** **	**-0.195 (4.17)*** **	**-0.1917 (4.09)*** **	-0.2670 (4.78)***	-0.2398 (4.22)***	-0.2378 (4.17)***
Sick years									
$\delta_{100}\Delta\Pi_i^{AS} pdvi_i$	-7.4602 (6.01)***	0.0323 (0.00)	-69.0238 (-1.40)	**-9.6248 (5.41)*** **	**2.0959 (-0.17)**	**-85.1591 (-1.35)**	-11.582 (4.79)***	3.6529 (-0.23)	-105.5609 (-1.33)
$\delta_{101}\Delta\Pi_i^{AS} pdvi_i \times age_{i0}$		0.6526 (4.22)***	-2.1009 (-1.52)		**1.3143 (5.04)*** **	**-3.6357 (1.68)***		2.2562 (5.43)***	-6.0954 (1.86)*
$\delta_{102}\Delta\Pi_i^{AS} pdvi_i \times age_{i0}^2$			0.0018 (-0.13)			**-0.0243 (-1.01)**			-0.0931 (2.22)**
$\delta_{110}\Delta\Pi_i^{AS} agepdvi_i$		-0.5568 (2.76)***	3.5999 (1.72)*		**-1.1362 (3.55)*** **	**5.3522 (1.77)***		-1.9604 (4.04)***	8.0433 (1.88)*
$\delta_{111}\Delta\Pi_i^{AS} agepdvi_i \times age_{i0}$			0.0352 (-1.13)			**0.1025 (1.86)***			0.2536 (2.66)***
$\delta_{12}\Delta\Pi_i^{AS} age2\,pdvi_i$			-0.0428 (1.86)*			**-0.0842 (2.23)** **			-0.167 (2.73)***

Recovered years

$\delta_{200}\Delta\Pi_i^{AS}\, pdvr_i$	-6.4233 (2.86)***	47.7764 (2.59)***	-41.111 (-0.47)	**-9.3288** **(2.70)***	**65.9143** **(2.49)****	**-82.4354** **(-0.69)**	-12.691 (2.51)**	86.569 (2.37)**	-143.7686 -0.92
$\delta_{201}\Delta\Pi_i^{AS}\, pdvr_i \times age_{i0}$		0.2011 (-0.67)	-3.5696 (-1.16)		**0.5672** **(-1.11)**	**-7.3201** **(-1.47)**		1.1393 (-1.36)	-13.751 (1.76)*
$\delta_{202}\Delta\Pi_i^{AS}\, pdvr_i \times age_{i0}^2$			-0.0048 (-0.16)			**-0.0238** **(-0.45)**			-0.0807 (-0.87)
$\delta_{210}\Delta\Pi_i^{AS}\, agepdvr_i$		-0.9283 (2.31)**	4.6351 (-1.12)		**-1.5232** **(2.34)****	**9.1315** **(-1.43)**		-2.3448 (2.32)**	16.5341 (1.74)*
$\delta_{211}\Delta\Pi_i^{AS}\, agepdvr_i \times age_{i0}$			0.0592 (-0.85)			**0.1453** **(-1.17)**			0.3319 (-1.55)
$\delta_{22}\Delta\Pi_i^{AS}\, age2\, pdvr_i$			-0.062 (-1.28)			**-0.1318** **(-1.59)**			-0.2643 (1.92)*

Lost life-years

$\delta_{300}\Delta\Pi_i^{AS}\, pdvl_i$	-6.9292 (7.70)***	11.0571 (-1.29)	16.3833 (-0.34)	**-9.4543** **(6.70)****	**17.6609** **(-1.45)**	**44.1991** **(-0.68)**	-11.9302 (5.75)***	24.7046 (-1.5)	81.9856 (-0.97)
$\delta_{301}\Delta\Pi_i^{AS}\, pdvl_i \times age_{i0}$		0.6312 (5.13)***	-1.7962 (-1.25)		**1.2888** **(5.80)****	**-2.3208** **(-1.02)**		2.2547 (5.96)***	-2.6087 (-0.75)
$\delta_{302}\Delta\Pi_i^{AS}\, pdvl_i \times age_{i0}^2$			-0.0177 (-1.49)			**-0.0525** **(2.41)****			-0.1224 (3.13)***
$\delta_{310}\Delta\Pi_i^{AS}\, agepdvl_i$		-0.6921 (3.88)***	1.0102 (-0.47)		**-1.3365** **(4.56)****	**0.7263** **(-0.22)**		-2.2651 (4.89)***	0.0092 0
$\delta_{311}\Delta\Pi_i^{AS}\, agepdvl_i \times age_{i0}$			0.0563 (1.87)*			**0.1225** **(2.31)****			0.2461 (2.68)***
$\delta_{32}\Delta\Pi_i^{AS}\, age2\, pdvl_i$			-0.0315 (-1.35)			**-0.0579** **(-1.51)**			-0.1064 (1.71)*
Alternatives	19788	19788	19788	**19788**	**19788**	**19788**	19788	19788	19788
Log L	-7175.195	-7146.39	-7141.535	**-7186.375**	**-7149.029**	**-7142.45**	-7196.076	-7154.093	-7143.988

Table 5

Sensitivity of Fitted VSIs in Estimating Sample to Alternative Discount Rate Assumptions

Descriptive Statistic	3% discount rate			**5% discount rate**			7% discount rate		
	No Age Effects	Linear Age Effects	Quadratic Age Effects	**No Age Effects**	**Linear Age Effects**	**Quadratic Age Effects**	No Age Effects	Linear Age Effects	Quadratic Age Effects
Sample mean VSI ($ million)	4.17	4.09	4.65	**2.2**	**3.65**	**8.92**	1.96	2.69	2.11
Sample 5th %	0.13	0.03	0	**0**	**0**	**0**	0	0	0
Sample 25th %	1.21	1.26	1.45	**0.61**	**0.96**	**1.09**	0.36	0.71	0.82
Sample 50th %	2.4	2.62	2.78	**1.54**	**2.01**	**2.11**	1.07	1.59	1.65
Sample 75th %	4.16	4.28	4.13	**2.88**	**3.29**	**3.11**	2.29	2.68	2.46
Sample 95th %	11.74	8.51	8.25	**6.76**	**6.65**	**6.16**	6.4	5.46	4.72

In the choice scenarios presented to respondents, there was no opportunity for any individual to express a negative willingness to pay for a program. At most, they could choose the other alternative, or "Neither Program." As a consequence, for these descriptive statistics, we interpret negative fitted point values of the VSI for a particular program as zero values, both in computing the marginal mean and in describing the percentiles of the marginal distribution.

Table 6

VSI for Four Classes of Sudden Death Scenarios (US $ million)

				No Age Effects	Linear Age Effects	Quadratic Age Effects
	Age Now	Age at Death	Latency	50% (5%,95%)	50% (5%,95%)	50% (5%,95%)
1. Simulation:	25	25	0	7.40 (5.79,9.58)	2.94 (0.08,6.34)	1.32 (-4.03,7.55)
Sudden death	35	35	0	7.19 (5.62,9.31)	2.74 (0.35,5.53)	2.90 (-0.87,7.20)
this year	**45**	**45**	**0**	**6.82 (5.34,8.83)**	**2.08 (0.05,4.42)**	**3.59 (0.69,6.89)**
	55	55	0	6.36 (4.97,8.24)	1.35 (-0.58,3.34)	3.98 (1.19,7.33)
	65	65	0	5.68 (4.44,7.36)	0.15 (-2.24,2.42)	3.70 (0.12,7.50)
2. Simulation:	25	30	5	5.71 (4.47,7.40)	4.00 (2.21,6.57)	2.11 (-0.39,5.42)
Sudden death	35	40	5	5.50 (4.31,7.13)	3.86 (2.41,5.86)	3.07 (1.63,5.03)
in 5 years	45	50	5	5.13 (4.02,6.65)	3.34 (2.25,4.77)	3.27 (2.17,4.65)
	55	60	5	5.67 (3.66,6.06)	2.72 (1.70,3.86)	3.19 (1.99,4.65)
	65	70	5	4.00 (3.12,5.18)	1.75 (0.41,3.04)	2.49 (0.96,4.10)
3. Simulation:	25	70	45	0.49 (0.38,0.63)	1.36 (1.00,1.96)	2.08 (1.45,3.01)
Sudden death	35	70	35	0.82 (0.64,1.06)	1.99 (1.53,2.64)	2.51 (1.90,3.36)
@ fixed age (70)	45	70	25	1.34 (1.04,1.73)	2.53 (2.02,3.22)	2.57 (2.05,3.19)
	55	70	15	2.32 (1.81,3.01)	2.98 (2.46,3.66)	2.54 (1.84,3.28)
	65	70	5	4.00 (3.12,5.18)	1.75 (0.41,3.04)	2.49 (0.96,4.10)
4. Simulation:	25	30	5	5.71 (4.47,7.40)	4.00 (2.21,6.57)	2.11 (-0.39,5.41)
Sudden death	25	40	15	3.36 (2.63,4.36)	4.32 (3.22,6.07)	3.32 (2.09,5.19)
varying latency	25	50	25	1.92 (1.50,2.48)	3.52 (2.65,4.90)	3.63 (2.61,5.26)
	25	60	35	1.03 (0.80,1.33)	2.41 (1.81,3.34)	3.11 (2.25,4.46)
	25	70	45	0.49 (0.38,0.63)	1.36 (1.00,1.92)	2.08 (1.45,3.01)

NOTE: Based on 1000 random draws from joint distribution of estimated parameters. Models do not restrict the signs of parameters and do not restrict the sign of fitted VSI to be non-negative; no negative or zero values drawn for marginal utility of income

Examples of Illness Profiles

Figure 1: A nonfatal illness (with recovery) that reduces life expectancy

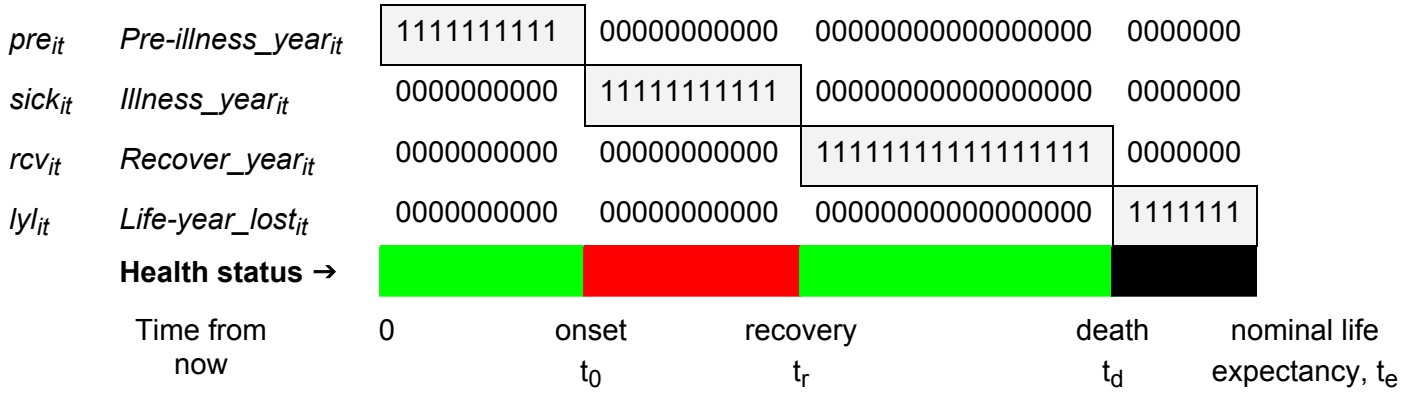
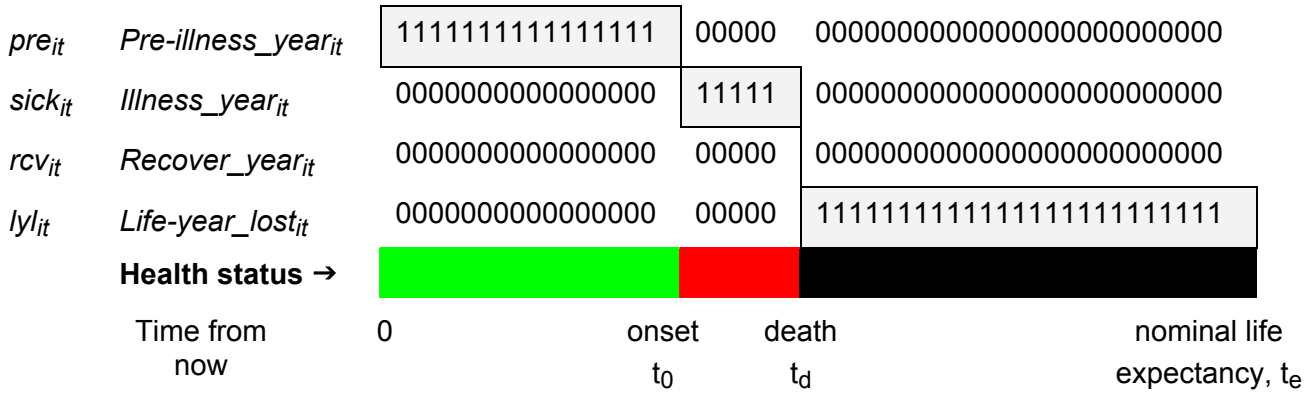


Figure 2: A fatal illness



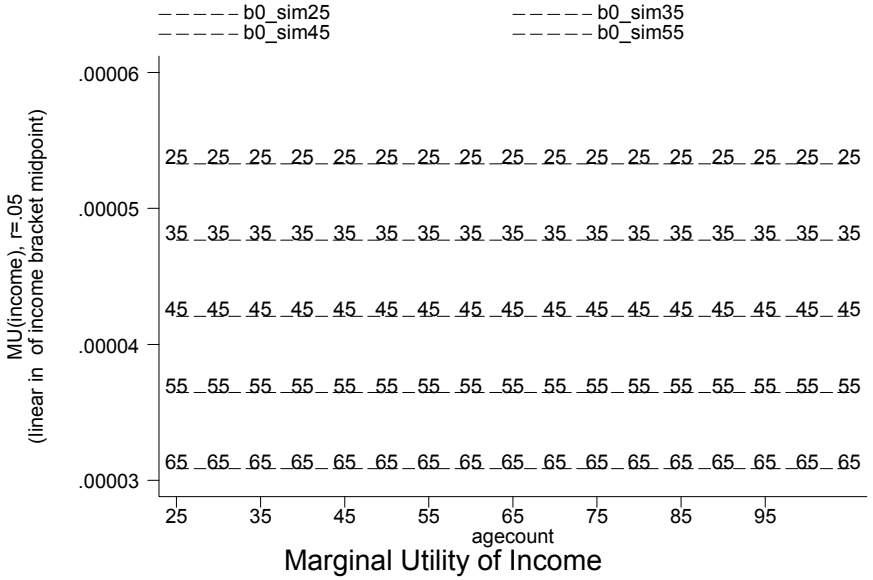


Figure 3A

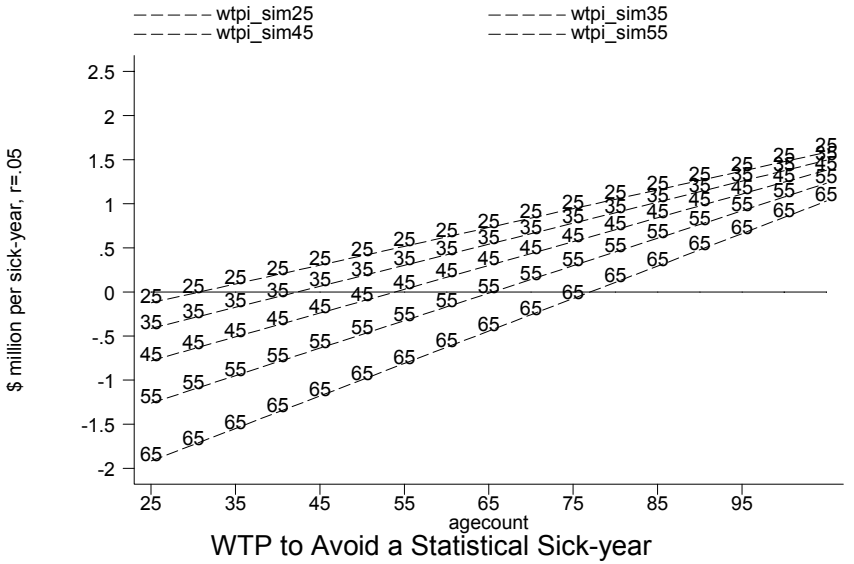


Figure 3B

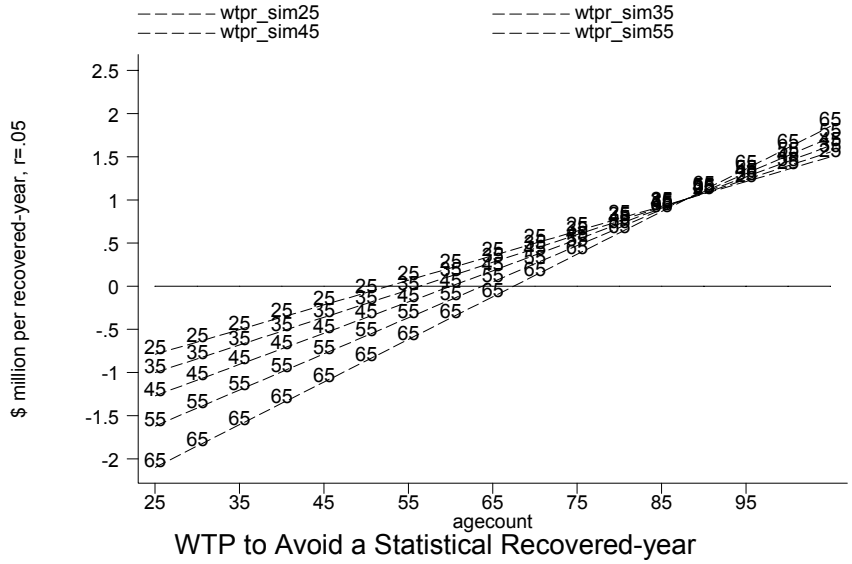


Figure 3C

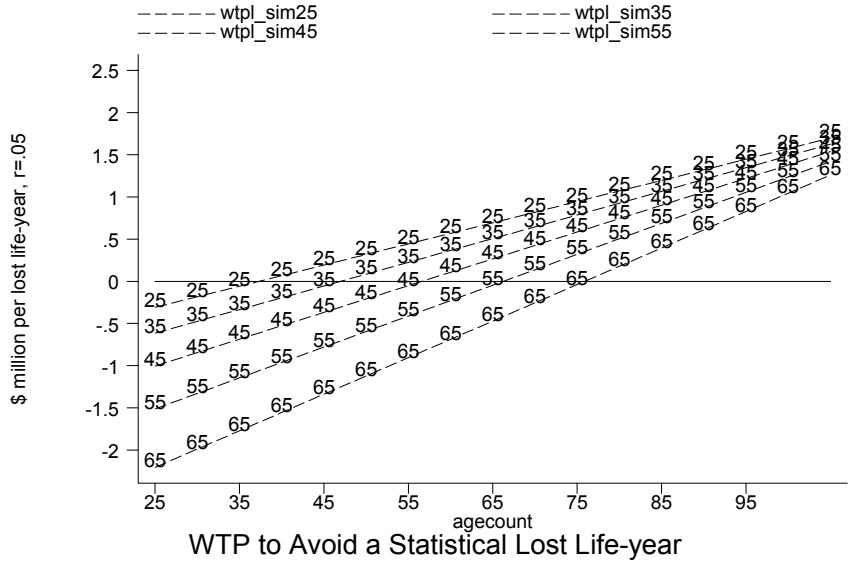


Figure 3D

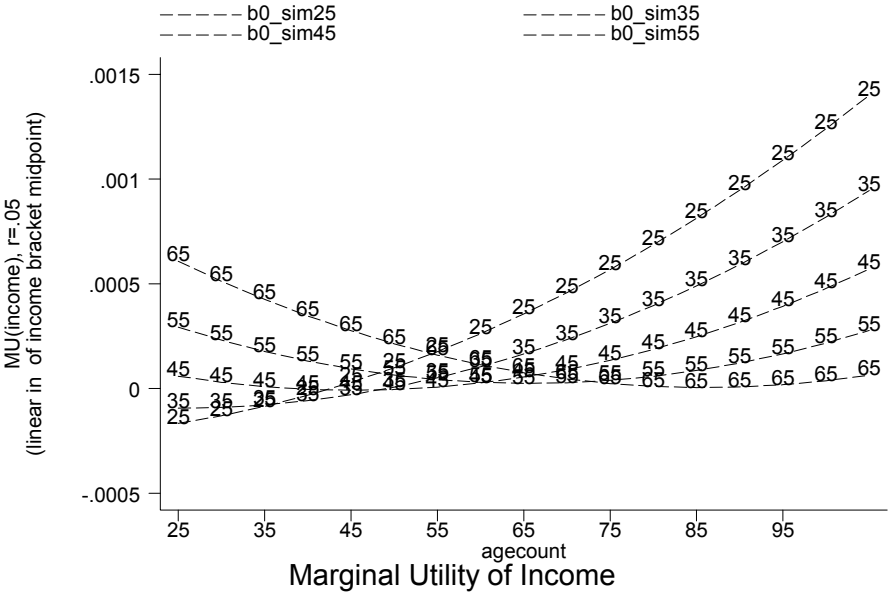


Figure 4A

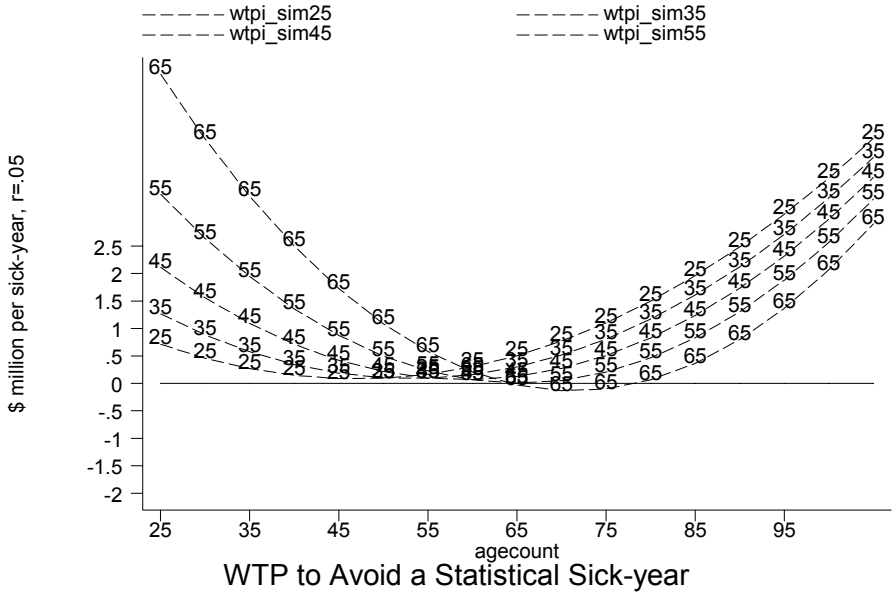


Figure 4B

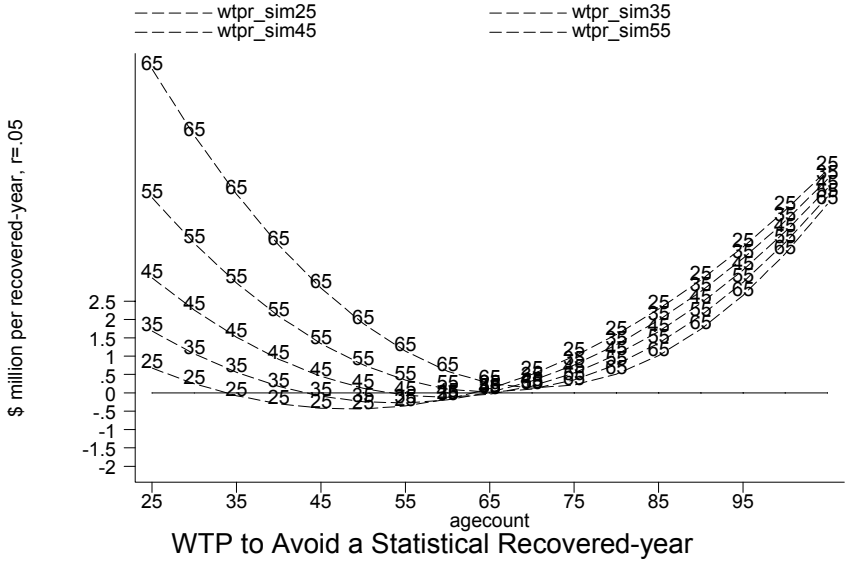


Figure 4C

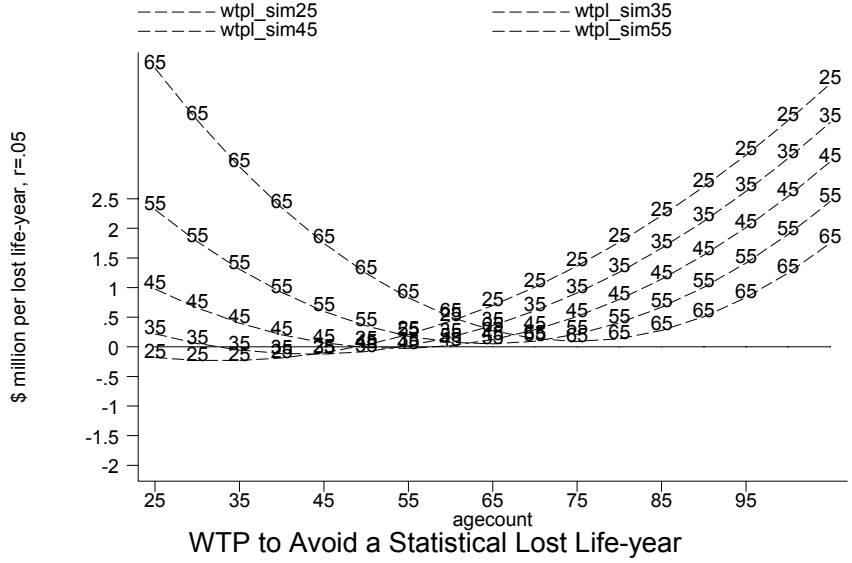


Figure 4D

Valuation of Environmental Risks to Children's Health[*]

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1. Introduction

Do parents value improvements in their children's health more than improvements in their own health? This question bears directly on central issues in research on family behavior including resource allocation between family members and the extent of parental altruism toward their children. It also has important implications for public policy in light of the growing worldwide emphasis on protecting children's health from environmental hazards (Scapecchi 2003). Nevertheless, little is known about how parents allocate health-related resources between themselves and their children despite the fact that public policy measures for protecting children operate at least partly through parents or other adult caregivers. Also, the few studies that do examine how parents value their own health relative to their children's health focus more heavily on morbidity (Liu *et al.* 2000 and Dickie and Messman 2003), base estimates on crude health measures (Agee and Crocker 2001), and reach widely differing conclusions. For example, Jenkins, Owens, and Wiggins (2001) find that the value of a statistical life (VSL) of a child (about $3 million year 2000 dollars) is about two-thirds of that for a parent, while Mount *et al.* (2001) find that the VSL for parent and child are about equal ($7.3 million in year 2000 dollars). Additionally, Liu *et al.* (2000), Dickie and Messman (2003), and Agee and Crocker (2001) find that parents are willing to pay about twice as much to reduce morbidity risk for their children than for themselves.

This paper uses unique field data on skin cancer to estimate parents' marginal rates of substitution between morbidity and mortality risks to themselves and to their children. Skin cancer risk, previously considered in related context by Dickie and Gerking (1996, 1997), is a common affliction that can but usually does not result in death. Also, solar radiation exposure during childhood is an important determinant of lifetime skin cancer risk (e.g., Reynolds, et al.

1996, Robinson, Rigel and Amonette 1997, American Academy of Dermatology 1997 and Creech and Mayer 1998) and people accumulate as much as 80% of lifetime exposure before the age of 18.

From a conceptual standpoint, a key advantage of this study is that morbidity and mortality risks are treated together in a consistent theoretical framework. Prior studies of health risks treat either morbidity or mortality, but not both, yet these two health outcomes are obviously related (i.e., death is a possible outcome of illness). Also, the expected utility model developed shows how to make econometric estimates of the desired marginal rates of substitution as risk-risk tradeoffs from an indifference map. Whereas Viscusi, Magat and Huber (1991) used risk-risk tradeoffs to see how people evaluate different sources of risk, this study looks at how parents make interpersonal risk trade offs between themselves and their children, as well as how they make trade offs between morbidity and mortality risks from the same disease.

An important methodological advantage of the study is that data are collected using an experimental design that randomizes health risk changes presented to parents. This feature sidesteps a number of econometric problems because risk changes are exogenous treatments that are orthogonal to individual characteristics. Additionally, although marginal rates of substitution are obtained from parents' stated preference bids, the desired estimates are ratios of bids. Thus, the problem identified by Diamond and Hausman (1994) and Cummings et al. (1997) that stated preference bids overestimate what people actually would pay may be at least partially ameliorated. Additionally, use of stated preference bids may in any case be more appropriate than revealed preference value estimates because tastes do not have to be disentangled from a household production technology (Hanemann 2003).

The paper is divided into four additional sections. Section 2 develops an expected utility model with compound probabilities for a parent-child "family" in which either person might get skin cancer and then might die from this disease. Section 3 describes field data on perceived risk of skin cancer and willingness to pay to avoid the disease collected from 610 parents in Hattiesburg, MS during the summer of 2002. Section 4 presents results indicating that for the full sample, parents' estimated marginal rate of substitution between health risk reductions for their children and health risk reductions for themselves is about 2. This estimate, however, exhibits considerable variation across sub-samples of parents. It is larger for white parents than for black parents, larger for sons than daughters, and larger for younger children than older children. Section 5 concludes.

2. Model

This section presents a one-period expected utility model with state dependent utility functions to guide the experimental design, data collection and empirical analysis. The model consistently treats both morbidity and mortality risk from skin cancer in a "family" composed of one parent and one child. This approach abstracts from several issues considered elsewhere to make application tractable in the field study. For example, the model does not consider divergent interests between family members (see Mount et al. 1991 and Smith and van Houtven 2002) because expenditures to reduce risks of skin cancer represent a small fraction of family budgets. The child is assigned no role in household decision-making; in consequence, the parent is assumed to allocate family resources to maximize his or her own expected utility. Only one child is included in the model to focus on how parents make tradeoffs between their own health and the health of their children, rather than on how parents allocate resources among different children. A one-period model is presented so as to emphasize parent-child tradeoffs and

consistent treatment of morbidity and mortality while abstracting from latency periods and time preferences. Extensions of the model to introduce latency periods and two or more children are briefly described at the end of this section.

The parent's expected utility is a probability-weighted sum of utilities in 3^2=9 possible states of the world that depend on whether the parent and child are healthy, sick, or dead. Four probabilities determine which of the nine states of the world actually emerges: (1) the probability that the parent will get skin cancer (S_p), (2) the conditional probability that the parent will die from skin cancer given that the disease is contracted (D_p), (3) the probability that the child will get skin cancer (S_c), and (4) the conditional probability that the child will die from skin cancer given that the disease is contracted (D_c). This approach has at least broad similarities to models previously applied in the literature on environmental risks to health. In their model of health consequences of exposure to hazardous wastes, Smith and Desvousges (1986, 1987) split the unconditional risk of death from exposure into the probability of exposure and the conditional probability of premature death given exposure. Eeckhoudt and Hammitt (2001) examine how a specific risk to an individual's health should be valued when the individual faces independent life-threatening background risks. Both of these models, however, envision only two health states (alive and dead) and thus do not explicitly treat morbidity, and neither model considers the allocation of health resources in a family.

In the model applied in this paper, the four probabilities are determined as shown in equation (1).

$$S_j = S_j(Z_j, \Omega_j, l_j) \qquad D_j = D_j(Z_j, \Omega_j, d_j), \qquad j = p, c, \tag{1}$$

In this equation, probabilities of getting skin cancer and of dying from the disease if it is contracted are influenced by predetermined factors (Ω_j, $j = p,c$) such as genetic characteristics like complexion and sensitivity of skin to sunlight. Still, the probabilities are endogenously determined because parents may purchase goods (e.g., hats, sun lotions, medical care) for themselves and their children (Z_j, $j = p,c$) to reduce the chances of getting skin cancer and to reduce conditional death risk if the disease is contracted. Because the experimental design applied in the field study manipulates the four probabilities, S_j and D_j also are specified as functions of treatments l_j and d_j.

As described in Section 3, the treatments are hypothetical sun lotions that resemble currently marketed products but offer greater skin cancer protection. If purchased, the hypothetical sun lotion would replace any currently used sunscreens, resulting in a savings in expenditure on existing products but no attenuation of the risk reduction offered by the hypothetical sun lotion. Any changes in other protective actions Z_j (e.g., seeking less evaluation of skin damage during medical checkups) are assumed to be negligible. (See Dickie and Gerking 1996 for a model incorporating adjustments in protective behavior.) Also, for ease of exposition, treatment parameters have the property $\partial S_j / \partial l_j = \partial D_j / \partial d_j = -1$.

Perceived skin cancer risks are incorporated into the expected utility model as shown in equation (2).

$$\begin{aligned} E(U) &= (1-S_p)(1-S_c)U_0(Y) \\ &+ (1-S_c)S_p[(1-D_p)U_p(Y) + D_pV_p(Y)] + (1-S_p)S_c[(1-D_c)U_c(Y) + D_cV_c(Y)] \\ &+ S_pS_c[(1-D_p)(1-D_c)U_{pc}(Y) + (1-D_c)D_pW_p(Y) + (1-D_p)D_cW_c(Y) + D_pD_cW_{pc}(Y)], \end{aligned} \tag{2}$$

where U_0 denotes utility in the state where both parent and child are healthy, U_j denotes utility in a state in which either the parent or child ($j = p,c$) contracts skin cancer but the other does

not and neither dies, V_j denotes utility in a state in which either the parent or child ($j = p,c$) dies from skin cancer but the other does not get it, U_{pc} denotes utility in the state where both parent and child get skin cancer but neither dies, W_j denotes utility in the state in which both parent and child contract skin cancer and one of the two dies ($j = p,c$) but the other does not, and W_{pc} denotes utility in the state in which both parent and child die from skin cancer. In states in which the parent and/or child die, parental utility is not restricted to zero; for example, if the child dies, the parent's life may still go on and if the parent dies utility may be obtained from a bequest. Also, Y denotes the parent's wealth net of: (1) expenditures for self- and child-protection goods (Z_j) and (2) bids for treatments presented in the experimental design (l_j and d_j). The parent's gross wealth is denoted as y and for simplicity here is assumed to be the same in all health states. (See Shogren and Crocker (1991) for a model incorporating differences in wealth between health states.)

The model can be manipulated to obtain parents' willingness to pay for reduced morbidity and mortality risks to themselves and their children. Ratios of marginal willingness to pay values provide measures of parents' marginal rates of substitution between: (1) morbidity risk to themselves and to their children, (2) mortality risk to themselves and to their children, (3) morbidity and mortality risk themselves, and (4) morbidity and mortality risk to their children. Assume that the parent already has chosen expected utility maximizing values of self- and child-protection expenditures in each health state, and l_j and d_j are initially zero. Then, willingness to pay for reduced risk of skin cancer to the child is obtained by setting $dE(U) = 0$ $= d\,l_p = d\,d_p = d\,d_c$ and computing

$$-\partial y/\partial l_c = \{(1-S_p)[(U_0-U_c)+D_c(U_c-V_c)] + S_p(1-D_p)[(U_p-U_{pc})+D_c(U_{pc}-W_c)]+S_pD_p[(V_p-W_p)+D_c(W_p-W_{pc})]\}/\Delta. \quad (3)$$

In equation (3), Δ denotes the expected marginal utility of wealth and is positive if the marginal utility of wealth is positive in each state. Also, the numerator of the right hand side of equation (3) is positive if the utility difference in each term of the sum is positive (i.e., healthy is preferred to sick, sick is preferred to dead, one person sick is preferred to two people sick, etc.). Then, $\partial y/\partial l_c < 0$ and gross wealth must fall to hold expected utility constant if the child's morbidity risk is reduced.

Similarly, willingness to pay for a small reduction in perceived conditional death risk faced by the child, holding all other perceived health risks constant, is

$$-\partial y/\partial d_c = S_c\{(1-S_p)(U_c-V_c)+S_p[(1-D_p)(U_{pc}-W_c)+D_p(W_p-W_{pc})]\}/\Delta. \quad (4)$$

Thus $\partial y/\partial d_c < 0$ if $\partial y/\partial l_c < 0$. Because perceived unconditional risk of death from skin cancer is $R_c = S_cD_c$, equations (3) and (4) can be combined to obtain the parent's willingness to pay to reduce the child's unconditional death risk:

$$-\partial y/\partial R_c = \left(\frac{1-S_c}{1-R_c}\right)(-\partial y/\partial l_c)+\left(\frac{1-D_c}{1-R_c}\right)(1/S_c)(-\partial y/\partial d_c). \quad (5)$$

Thus $\partial y/\partial R_c < 0$ if $\partial y/\partial l_c < 0$. The parent's marginal rate of substitution, or risk-risk tradeoff, between the child's unconditional risk getting skin cancer and unconditional risk of dying from the disease equals $(\partial y/\partial R_c)/(\partial y/\partial S_c)$. This ratio measures the parent's relative valuation of reducing mortality and morbidity risks for the child. However, if skin cancer is an event that may occur in the future, the absolute magnitudes of $\partial y/\partial R_c$ and $\partial y/\partial S_c$ cannot be used to estimate the value of a statistical life or of a statistical case of skin cancer (i.e., the willingness to pay today to save a life or to avoid a case today).

Key comparative static properties of willingness to pay expressions in equations (3) – (5) are similar those found in the more familiar setting of one individual facing mortality risk only (Jones-Lee 1974). For example, parental willingness to pay to reduce the child's morbidity or mortality risk increases with gross wealth and with the initial levels of risk faced by the child, if the expected marginal utility of wealth is decreasing in wealth and in initial risk levels. Also, for marginal reductions in small risks of morbidity or mortality, willingness to pay is approximately proportional to the size of the risk change.

Similar properties apply to parents' willingness to pay for reduced risks to themselves. These values, which can be obtained by parallel calculations corresponding to equations (3) – (5), are useful in their own right and as benchmarks for assessing the magnitudes of parents' valuations of their children's risks. It will be of interest to test whether parents' marginal rates of substitution between unconditional risks to their children and unconditional risks to themselves equal unity, i.e., whether $(\partial y / \partial l_c)/(\partial y / \partial l_p) = 1$ and whether $(\partial y / \partial R_c)/(\partial y / \partial R_p) = 1.$

The model may be extended to a temporal setting incorporating a latency period before the possible onset of skin cancer and including an arbitrary number of children in the family. The specific extension envisioned features identical children who face a longer latency period than do their parents. In this broader model, willingness to pay for reduced risk for the parent or a child falls as the number of children rises, if the marginal utility of aggregate family consumption is higher when more children are present. Willingness-to-pay values and parent-child marginal rates of substitution depend on weighted sums of utility differences similar to those appearing in the one-period setting, as well as on discount factors determined by latency periods and parents' subjective discount rates. Like the individual utility differences appearing

in equations (3)-(5), the discount factors are components of parents' valuations that need not be separately identified to estimate willingness to pay or marginal rates of substitution. While measures of parents' discount factors for latent health risks would be of interest, these measures might be better estimated in a study that focused on latency of one risk to one person, rather than on morbidity and mortality risk for two people.

3. Data Collection

Data on risk beliefs about skin cancer and willingness to pay to avoid this disease were collected during summer of 2002 using a self-paced, interactive, computerized instrument. All respondents were residents of the Hattiesburg, MS metropolitan statistical area. Hattiesburg is located in the southern part of Mississippi, has a mean annual high temperature reading of 77.5 degrees Fahrenheit, a subtropical climate, and a large number of sunshine days each year. Thus, residents have experience with consequences of exposure to ultraviolet radiation from sunlight. The sample was drawn by random digit dialing after removing business, government, and cellular telephone numbers. When the calls reached adults, interviewers described the general purpose of the survey (federally funded research on health risks to parents and their children), asked whether they had at least one biological child between the ages of 3-12 living at home, and asked whether they were willing come to the University of Southern Mississippi to participate in the survey. Biological children were singled out for inclusion in the study because skin cancer risk is partly determined by genetic characteristics inherited from parents (e.g., fairness of skin and sensitivity of skin to sunlight). The age range was chosen to have children old enough to regularly spend time outdoors, but young enough for parents to exert substantial control over their activities. Respondents were paid $25 for completing the 30-minute questionnaire.

The final sample consisted of 610 parents; children did not participate in the survey. The survey obtained information about the parent/respondent and one sample child (chosen at random from among biological children living at home if more than one in the 3-12 year age range was present. Information was obtained about the number of children in the household, but other questions about children pertained only to the sample child in order to limit the length of the interview, to avoid repetitive questioning, and because the model presented in Section 3 assumes that parents treat each child equally. Of sample parents, 75.4% were white, 20.0% were African-American, 4.6% were members of other races, 23.4% were male, 76.9% were under the age of 40, mean household income was $53,000 per year, 75.9% were married, and 59.0% worked full time. Because of random selection, about half (50.5%) of the sample children were male. The average age of sample children was 7.07 years. Also, parents were generally familiar with skin cancer: (1) 95.4% had heard of skin cancer, (2) 83.8% knew of someone (public figures, friends, or relatives) who had been diagnosed with this disease, (3) 22.1% knew of someone who had died from skin cancer, (4) 80.3% had thought about the possibility of getting skin cancer, (5) 3.4% had been diagnosed with this disease themselves, and (6) 71.1% had considered the possibility that one of their children might get skin cancer.

Chances of getting skin cancer were assessed using an interactive risk scale that closely resembled the grid squares used by Krupnick et al. (2002). This approach was used because risk information appears to be better understood using this type of visual aid (Corso, Hammitt, and Graham 2001). As shown in Figure 1, the scale depicted a large square divided into 20 rows and 20 columns showing 400 equal-sized smaller squares. Initially, all 400 of these squares were green. Parents changed green squares to red ones to represent the amounts of risk. By pressing a button at the bottom of each column of squares, they could recolor a column of 20 squares from

green to red (or from red back to green) and the color of any individual square could be changed by clicking on it with a mouse. A box beneath the scale showed the percentage of red squares out of 400. This calculation was updated each time one or more squares was re-colored. Before using the scale to estimate skin cancer risk, parents practiced using the risk scale for an unrelated event (a possible auto accident) and were told about the meaning of "chances in 400". Also, they were told to consider only the chances of getting this disease (or of getting it again if they had already had it), rather than how serious the case might be. Parents then used the risk scale to estimate lifetime chances of getting skin cancer, first for themselves and then for their sample children. In making these estimates, they could take as much time as they desired and could make as many changes in the risk scale as desired. Table 1, discussed momentarily, presents the frequency distribution of these risk estimates.

After providing lifetime skin cancer risk estimates for themselves and their children, parents were: (1) provided with information about skin cancer, (2) asked a series of questions about skin cancer risk factors, and (3) given an opportunity to revise these estimates. The idea behind asking respondents to estimate lifetime skin cancer risk a second time was to help them pin down their estimate as well as they could before moving on to the remaining portions of the survey. In particular, they were told that according to the National Cancer Institute, the average person in the United States has a lifetime risk of getting skin cancer of 18% and were questioned about skin color and sensitivity to sunlight, family history of skin cancer, time spent outdoors in direct sunlight, past sunburns, and use of sun protection products and protective clothing. Brief narratives provided information about how these aspects have been related to skin cancer risks in epidemiological studies. To elicit the revised lifetime skin cancer risk perception estimates,

parents again were shown the previously described risk scales for themselves and their sample child as they originally were marked, and were given an opportunity to make changes.

After this task was completed, parents were asked about their perceived severity of skin cancer: "Suppose that a doctor tells you that you have skin cancer and you begin treatment. What do you think is the chance that you would die within five years of this diagnosis?" Parents answered for themselves and their sample child using a risk scale like the one shown in Figure 1. Responses are interpreted as estimates of the conditional risk of death from skin cancer given that the disease is contracted.

Table 1 presents frequency distributions of parents' perceived lifetime risk of skin cancer and conditional risk of death from skin cancer both for themselves and for their children. For perceived lifetime risk, the frequency distribution shown pertains to the initial risk estimates. As it turned out, parents made only small revisions in their initial lifetime risk estimates for themselves (the two estimates of mean risk are virtually the same, 23.9%), but revised risk estimates for children were on average about 1.5 percentage points lower than initial risk estimates (19.0 vs. 20.5), a significant difference at the 1% level. Table 1 indicates considerable variation in perceptions about lifetime skin cancer risk, with some parents believing that skin cancer is highly unlikely and a smaller number of other parents believing that skin cancer is virtually inevitable. Regarding the possibility of death from skin cancer, about two-thirds of parents believed that their conditional risk of death given a diagnosis of skin cancer is 10% or less and about three-fourths of parents believed that if similarly diagnosed, their sample child's conditional risk of death is 10% or less. This outcome suggests that parents were aware that skin cancer is seldom fatal.

Table 2 shows estimates of mean lifetime of getting skin cancer and mean conditional risk of dying from this disease for various sub-samples of parents. These sub-samples are further analyzed in Section 4. As shown, white parents estimated that their own lifetime risk of getting skin cancer exceeded that of their sample child (27.6% vs. 22.8%, a statistically significant difference at the 1% level), whereas among blacks, the corresponding difference was not significant at conventional levels (11.8% vs. 12.9%). Parents in both racial groups appear to have overestimated this risk. Ries et al. (1999) found that whites have a lifetime chance of 21% of getting either melanoma or non-melanoma skin cancer and African-Americans have a corresponding risk of less than a 1%. The fact that the survey introduced the possibility of getting skin cancer again if the parent had already had it does not appear to be an important complicating factor in this regard. Sample members are relatively young and few reported having been previously diagnosed with this disease.

Table 2 also shows that parents reported higher mean conditional death risk estimates for themselves (12.2%) than for their sample children (9.4%), a statistically significant difference at 1%. Differences in these estimates between white and black parents are quite small. Thus, it appears that parents generally believe that skin cancer risks for their children are lower than their own. This outcome may reflect parents' beliefs that they take greater precautions to protect their children from skin cancer risk with their own children than their parents did in an earlier period when less was known about the hazards of solar radiation exposure. Also, it may reflect a belief that skin cancer will take longer to develop in children than in parents together with the idea that delayed risks are perceived as smaller. Finally, Table 2 indicates that among whites, who comprise 67% of the sample: (1) mothers believed that their own risks of skin cancer exceeded

those for fathers, (2) parents thought that their sons' and daughters' risk was about the same, (3) parents believed that risks faced by younger children exceeded those for older children.

The final section of the survey assessed willingness to pay for a hypothetical sun protection product that would reduce skin cancer risk for both the parent and the child when used as directed. The approach of using a single product to get willingness to pay means that parents do not make separate bids to protect themselves and their children as in Liu *et al.* (2000) and Dickie and Messman (2003). This procedure is aimed at reducing the potential problem that parents might feel that they "should" bid more for child protection than for protection for themselves. Parents became familiar with this product by reading a label that was designed to look like those used on bottles of over-the-counter sun lotions (see Figure 2). The label indicated that the hypothetical sunscreen would be similar in most respects to currently marketed products (available in a variety of SPFs, offer protection against premature aging of skin, non-comedogenic, oil-free, and unscented), but that it would offer greater levels of skin cancer protection.

Eight labels were used in the study. Except for differences in the amount of skin cancer reduction offered, labels were identical in every respect to control for other possible motivations driving the purchase decision such as to prevent or get a suntan and guard against aging or wrinkling of skin (see Dickie and Gerking 1996 who more fully discuss these possibilities). Four labels varied reductions in risk of getting skin cancer, while four other labels varied reductions in conditional death risk of this disease. Table 3 shows the reductions in risk stated on each of label. Labels A, D, E, and H offered equal percentage reductions in skin cancer risk (either 10% or 50%) for both adults and children. Labels B and F offered relatively greater skin cancer protection for children, while Labels C and G offered protection for adults. Each respondent was

shown two randomly assigned labels. One of these offered reduced risk of getting skin cancer and the other offered reduced conditional death risk from skin cancer. The order in which these labels were presented was randomized.

After respondents were given time to read the label as if buying a product for the first time, the risk scale was used to show the amount by which the hypothetical sunscreen would reduce skin cancer risks for themselves and their children. Then, parents were asked, "Now please think about whether you would buy the new sun protection lotion for yourself or your child. Please do not consider buying it for anyone else. Suppose that buying enough of the lotion to last you and your child for one year would cost $X. Of course, if you did buy it, you would have less money for all of the other things that your family needs. Would you be willing to pay $X for enough of the sunscreen to last you and your child for one year?" The value of X was varied between $20 and $125. When responses were affirmative, parents were asked if they would pay a higher price; when responses were negative, they were asked whether a lower price would be paid. This procedure was repeated for the second label assigned to the parent.

4. Empirical Estimates

Data described in Section 3 are used to obtain estimates of the marginal rates of substitution described in Section 2. Marginal rates of substitution are inferred from estimates of an equation describing parents' willingness to pay for the hypothetical sunscreen. This equation was obtained from the model presented in Section 2 by totally differentiating equation (2), setting $dE(U) = 0,$ and interpreting the bid for the sunscreen as the change in wealth, dy. The equation estimated is

$$\ln(w_{it}) = d_{it}'\beta + x_i'\gamma + u_i + v_{it}, \qquad (6)$$

where i indexes parents and $t = 1, 2$ indexes the two experimental treatments (labels) assigned to parent i. In equation (6), w_{it} denotes willingness to pay for one year's supply of the sun lotion, d_{it} denotes a vector of attributes of the sun lotion including the risk changes for the parent and child as described on the label, and b represents the corresponding vector of coefficients. The b coefficients measure effects of risk changes on (the log of) willingness-to-pay and must be estimated to infer marginal rates of substitution. Also, x_i represents a vector of measured characteristics of the parent, child or family, g represents the corresponding vector of coefficients, and u_i and v_{it} are uncorrelated mean zero normal random variables with variances s_u and s_v, respectively. Thus, v_{it} reflects uncontrolled factors varying over parents and over treatments, while u_i captures the impact of uncontrolled factors specific to the parent (or her child or family) and constant over treatments. Among the many factors that might be reflected in the individual-specific error component are unobserved genetic endowments, current spending on sunscreen lotion, concern for skin cancer risks to herself and her child, and propensity to misstate willingness to pay in response to hypothetical questions. Willingness-to-pay is assumed log-normally distributed in view of its non-negativity and the positive skewness typically characterizing its distribution.

Random assignment of labels to parents implies that risk changes are exogenous experimental treatments that are independent of all measured and unmeasured individual and family characteristics. As a consequence, randomization avoids two potential problems that would otherwise complicate estimation of willingness to pay for reduced risks and marginal rates of substitution. First, variables measuring risk change are orthogonal to characteristics such as initial perceived risks, income, number of children in the household, and race and gender of

parent and child, so that the d_{it} is orthogonal to x_i. Thus, the specification of the variables in x_i has no effect on the estimate of b.

Second, random assignment implies that d_{it} is uncorrelated with u_i, so that b may be estimated consistently in a random-effects framework. Without random assignment (e.g., with non-experimental data), the risk changes to be valued are likely to be correlated with unobserved individual characteristics. Previous research indicates that inferences about intra-family allocations may be seriously misleading when heterogeneity of this sort is uncontrolled (Pitt and Rosenzweig 1990, Pitt, Rosenzweig, and Hassan 1990). Fixed-effects methods would remove family-specific heterogeneity but are less efficient that random-effects when heterogeneity is absent, as it is under randomization of experimental treatments. Instrumental-variable methods represent an alternative approach to the heterogeneity problem that are frequently used when repeated observations on individuals are not available. But randomization allows consistent and efficient estimation of b without resorting to use of instrumental variables.

Estimates of equation (6) are obtained by maximum likelihood. Respondents did not directly report their bids for the sunscreen, but the interval in which willingness-to-pay lies may be inferred from responses to the initial and follow-up questions asked about each sun lotion (Hanemann, Loomis and Kanninen 1991). Let w_{it}^u and w_{it}^l respectively denote the natural logarithms of the upper and lower bounds of willingness-to-pay for parent i, label t. Thus w_{it}^u equals the log of the lowest price at which the respondent declined to purchase the sunscreen (or $+\infty$ if she responded "yes" to both initial and follow-up questions), while w_{it}^l equals the log of the highest price at which the respondent agreed to purchase the sunscreen (or $-\infty$ if she responded "no" to both initial and follow-up questions). Then the probability that the natural

logarithm of willingness-to-pay lies between the upper and lower bounds, conditional on u_i, equals

$$L_{it} = \Phi\left(\frac{w_{it}^{u} - d_{it}'b - x_i'g - u_i}{s_v}\right) - \Phi\left(\frac{w_{it}^{l} - d_{it}'b - x_i'g - u_i}{s_v}\right), \tag{7}$$

where Φ denotes the standard normal cumulative distribution function. The sample log-likelihood function is

$$\sum_{i=1}^{N} \ln\left[\int_{-\infty}^{+\infty} \prod_{t=1}^{2} L_{it} f(u) du\right], \tag{8}$$

where N equals the number of parents in the sample and f denotes the normal density function. The automated routine included in the econometric package LIMDEP and used to maximize the log-likelihood function computes the integral in equation (8) using Monte Carlo simulation.

Estimates of equation (6) are presented in Table 4. Covariate definitions are in column 1, their sample means are presented in column 2, and results from two regressions using the full sample of 610 parents are in columns 3 and 4. Five covariates are dummy variables that reflect the reductions in skin cancer risk shown on the eight labels (see Table 3). *GET* shows whether the label presented a reduction in the chance of getting skin cancer or a reduction in the conditional risk of dying from it. Thus, *GET=1* for Labels A-D and *GET=0* for Labels E-H. Also, *PARENTCHG=1* if the label offered parents a 50% reduction in risk for themselves and *KIDCHG=1* if the label offered a 50% risk reduction for their children. Interactions of *GET* and (*1-GET)* with *PARENTCHG* and *KIDCHG* show whether the risk reduction pertained to getting skin cancer or the conditional risk of dying from it. Label E, offering a 10% reduction in the conditional risk of dying from skin cancer for both parents and children, is represented by setting all five dummies equal to zero.

The column 3 regression uses only the five label dummies as covariates and column 4 shows the outcome when covariates measuring household income and number of children in the family are added. In both of these regressions, likelihood ratio tests at the 1% level reject the null hypotheses that: (1) the variance of the parent-specific error is zero and (2) all slope parameters are jointly zero. Asymptotic t-statistics, presented in Table 4, show that each coefficient estimated differs significantly from zero at the 5% level or lower under a two-tail test. As expected, coefficients of the label dummies change little when controls for family characteristics are added.

In columns 3 and 4, the positive coefficients of *GET*PARENTCHG*, *GET*KIDCHG*, *(1-GET)*PARENTCHG*, and *(1-GET)*KIDCHG* indicate that parents are willing to pay more for larger risk reductions than for smaller risk reductions. Although this outcome is broadly consistent with the conceptual model presented in Section 2, larger risk reductions bring about less than proportional increases in willingness to pay (see Hammitt and Graham 1999 for further discussion of this issue). For example, as shown by the coefficient of *GET*KIDCHG*, a five-fold reduction in risk to children of getting skin cancer (from 10% to 50%) increases willingness to pay by a little more than 40%. Also, likelihood ratio tests at the 1% level reject the null hypothesis that coefficients of *GET*PARENTCHG* and *GET*KIDCHG* are equal as well as the null hypothesis that coefficients of *(1-GET)*PARENTCHG*, and *(1-GET)*KIDCHG* are equal. In fact, the numerically larger coefficients of the risk change treatments for children suggest that parents are willing to pay more for skin cancer risk reduction for their children than they are for risk reduction for themselves. This point is developed more fully below in the context of estimating parents' marginal rates of substitution between skin cancer risk to their children and skin cancer risk to themselves.

In column 4, the positive coefficient of household income indicates that, all else constant, an increase in income by $10,000 increases willingness to pay for the hypothetical sunscreen by 3%. At sample mean household income of $53,000, the estimated income elasticity of willingness to pay for the hypothetical sunscreen is about 0.16. Also, the negative coefficient of the number of children in the household suggests that an additional child (of any age) in the household reduces willingness to pay for the hypothetical sunscreen by about 8%. This outcome is consistent with the discussion in Section 2 that fewer resources are invested in risk reduction per child when more children are present.

Estimates of marginal rates of substitution are computed as ratios of marginal willingness to pay from the column 4 regression. For example, the marginal rate of substitution between unconditional morbidity risk for the parent and child is estimated as the ratio of the coefficient of (*GET*KIDCHG)* to the coefficient of (*GET*PARENTCHG)*, multiplied by the ratio of the sample mean change in the level of unconditional morbidity risk for parents to the sample mean change in the level of unconditional morbidity risk for children. A parallel procedure is used to estimate the marginal rate of substitution between conditional death risks for the parent and child. The marginal rate of substitution between *unconditional* death risks for the parent and child then is estimated by combining the marginal valuations of morbidity and conditional mortality risk using equation (5), and taking the ratio of the resulting child valuation to the parent valuation.

The outcomes of these calculations, based on the column 3 in Table 4, are shown in column 2 of Table 5. These results indicate parents are willing to pay about twice as much to reduce the risk of getting skin cancer for their children as they are to reduce it for themselves. Similarly, the child vs. parent unconditional mortality marginal rate of substitution estimate is

2.33 (again see column 2 of Table 5). Standard errors of these estimates, reported in Table 5, indicate rejection of the null hypotheses that these marginal rates of substitution are equal to unity. That parents are willing to pay more to reduce risks to their children's health than they are willing to pay to reduce risks to their own health is of particular interest because age at onset of skin cancer is in the more distant future for children than for parents. Based on the discussion of latency in Section 2, if the time to onset of illness were the same both for parents and children, the marginal rate of substitution values may well be larger.

Column 2 of Table 5 also reports calculations of parents' marginal rates of substitution between the unconditional risk of dying from skin cancer and the unconditional risk of getting skin cancer for themselves and for their children. Whereas the marginal rates of substitution discussed above reflect tradeoffs between the same risk faced by different people, these calculations reflect tradeoffs between different types of risk faced by the same person. As shown in Table 5, parents' marginal rate of substitution between unconditional death risk and unconditional morbidity risk for themselves is 19.16 and the corresponding value for their children is 21.78. These estimates indicate that parents are willing to pay approximately 20 times more to reduce unconditional death risk by one unit than to reduce unconditional morbidity by one unit. Although, this outcome supports the idea that public policies aimed at reducing death risk are much more important to people than policies aimed at reducing morbidity, it may not generalize to related situations. Skin cancer is frequently not life threatening and while treatment may be disfiguring, patients generally expect to resume normal activities. Other illnesses and injuries may exact a greater toll on health if death does not occur and in these cases the marginal rate of substitution between mortality and morbidity may well be lower.

In addition to obtaining point estimates of marginal rates of substitution for a representative parent, it is of interest to examine how health risk tradeoffs may vary with the characteristics of parents or children. To obtain this information, the Table 4, column 4 regression was re-estimated for sub-samples defined by (exogenous) genetic characteristics that may be associated with differences in perceived risks and other initial endowments. A useful starting point in this regard is to compare marginal rates of substitution for whites and blacks. As discussed in Section 3, average perceived risks of skin cancer by white parents are roughly twice as large as those for black parents. Estimates shown in Table 5 indicate that the four marginal rates of substitution for whites are roughly similar to those obtained for the full sample (notice that the 460 white parents represent 67% of 610 parents in the full sample). These estimates, however, differ substantially from those for blacks; in fact, a likelihood ratio test at 1% rejects the null hypothesis that marginal rates of substitution for the two groups are equal. For blacks, two of the marginal rates of substitution could not be computed because the coefficient of *GET*PARENTCHG* was negative and did not differ significantly from zero at conventional levels. Also, the marginal rate of substitution for child vs. parent unconditional mortality is significantly less than unity at the 1% level, suggesting that black parents may be less altruistic toward their children than are white parents. This interpretation, however, should be treated quite cautiously because of the relatively small number of black parents in the sample.

The significant racial differences in valuation estimates suggest that pooling sub-samples of black and white parents to estimate marginal rates of substitution is inappropriate. Thus, in light of the relatively small sample size for blacks, outcomes from additional demographic breakdowns shown in Table 5 are computed only for parents in the white sub-sample. The first of these compares marginal rate of substitution estimates for 351 white mothers and 109 white

fathers. Whereas both mothers and fathers similarly evaluate the child vs. parent unconditional mortality tradeoff, the child vs. parent unconditional morbidity tradeoff for fathers is about unity and about half the magnitude of that found for mothers. Thus, in comparison to mothers, fathers appear to be relatively less concerned with morbidity than mortality. This outcome leads fathers' marginal rate of substitution between mortality and morbidity for their child to be larger than that for mothers (50.05 vs. 19.06).

Also, parents appear to place significantly greater weight on reducing both morbidity and mortality risk for sons than for daughters. Estimates of child vs. parent marginal rate of substitution for unconditional morbidity is 2.60 for sons and 1.14 (not significantly different from unity) for daughters. Corresponding estimates of the marginal rate of substitution for unconditional mortality are 5.40 for sons and 2.01 for daughters. The null hypothesis that marginal rates of substitution for sons and daughters are equal is rejected at 1% level. Thus, relative to their own health, parents appear to be willing to invest more in health risk protection for sons than daughters.

Finally, parents are more protective of younger children than older children. The child vs. parent marginal rate of substitution estimates for unconditional morbidity are 1.42 for children aged 3-7 years and 2.22 for children aged 8-12 years; however, these estimates do not differ significantly from zero at the 1% level. On the other hand, corresponding estimates of the marginal rate of substitution for unconditional mortality are significantly larger for young children than for older children (4.38 for children aged 3-7 years vs. 1.73 for children aged 8-12 years). This finding is consistent with recent evidence that health risk protection for young children is valued more highly than that for older children. Nastis and Crocker (2003), find that

mothers-to-be value the expected postnatal health of their unborn child as much as six times more than the expected post-partum state of their own health.

5. Conclusions

This paper has presented new empirical estimates aimed at valuing environmental risks affecting parents and children. The application focused on skin cancer, the most common form of cancer in the U.S. Links between environmental exposure to ultraviolet radiation and skin cancer are well established, and chances of getting skin cancer, for a given amount of exposure to solar radiation, depend partly on observable genetic characteristics such as skin type and complexion. The theoretical model is developed from the viewpoint of parents and supports empirical valuation of morbidity and mortality risks faced by both parents and children in a consistent framework. Risk is treated as endogenous and is measured as the risk perceived by survey respondents. The method for estimating willingness to pay rests on directly estimating an indifference relation showing utility-constant trade-offs between morbidity risks, mortality risks, and consumption goods.

The model provides a basis for computing parents' marginal rates of substitution between risk of death from skin cancer faced by both themselves and their children. This calculation shows how parents value children's health relative to their own and may be useful benefits transfer in situations where willingness to pay for reduced risk to adults have been established but corresponding values for children are not available. The model is estimated using data collected by an interactive computerized questionnaire administered on the University of Southern Mississippi campus during summer of 2002. Key aspects of the experimental design were to: (1) determine parents' perceptions of skin cancer risk to themselves and their children, and (2) obtain willingness to pay for skin cancer risk reductions. Risk reductions were presented

to parents using randomly assigned labels of a hypothetical sun lotion that offered different amounts of protection to adults and children. Random assignments of risk reductions facilitate estimation of marginal rates of substitution between parent's health and children's health. For example, parents' marginal rate of substitution between their children's unconditional lifetime risk of dying from skin cancer and the corresponding risk for themselves is 2.33. Thus, parents view their children's health as more than twice as valuable than their own. Also, parents see the reductions in mortality risk to be about 20 times more valuable than reductions in morbidity risk both for themselves and their children. This outcome suggests that the morbidity component of benefits for environmental risk reduction may be quite small.

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Table 1. Frequency Distribution of Parents' Perceived Risks.
N=610.

	Risk of Getting Skin Cancer[a]		Conditional Risk of Dying from Skin Cancer	
Risk Range (%)	**Parents**	**Children**	**Parents**	**Children**
0 - 4.75	85	75	103	142
5 - 9.75	57	79	163	194
10 - 14.75	70	94	122	111
15 - 19.75	65	69	67	44
20 - 24.75	65	74	42	31
25 - 29.75	66	73	26	23
30 - 34.75	45	35	13	8
35 - 39.75	23	19	8	8
40 - 44.75	36	25	7	7
45 - 49.75	6	5	5	2
50 - 54.75	53	32	19	11
55 - 59.75	4	2	2	1
60 - 64.75	5	7	3	0
65 - 69.75	0	1	0	0
70 - 74.75	5	2	2	0
75 - 79.75	6	5	0	0
80 - 84.75	2	3	0	0
85 - 89.75	3	2	0	0
90 - 94.75	8	5	0	0
95 – 100	6	3	0	0

[a]Initial risk assessment.

Table 2. Parents' Mean Risk Perceptions (%).

Sample	Risk of Getting Skin Cancer[a]	Conditional Risk of Dying from Skin Cancer	Sample Size
All Parents	23.90	12.24	610
All Children	20.54	9.44	610
Black Parents	11.79	12.98	122
Black Children	12.88	9.77	122
Whites:			
All Parents	27.61	12.15	460
All Children	22.76	9.44	460
Mothers	29.79	12.54	351
Fathers	20.59	10.90	109
Daughters	22.76	9.39	230
Sons	22.76	9.49	230
Children aged 3 to 7 years	24.47	10.35	258
Children aged 8 to 12 years	20.57	8.28	202

[a]Initial risk assessment.

Table 3

Hypothetical Sun Protection Product Labels

	Percent Change in Morbidity Risk		Percent Change in Mortality Risk	
Label	Parent	Child	Parent	Child
A	10	10	0	0
B	10	50	0	0
C	50	10	0	0
D	50	50	0	0
E	0	0	10	10
F	0	0	10	50
G	0	0	50	10
H	0	0	50	50

Table 4
Willingness to Pay for Reduced Risk of Skin Cancer

Variable	Full Sample		
	Mean	**Estimate (t-ratio)**	**Estimate (t-ratio)**
Constant	---	4.028 (130.32)	4.023 (86.63)
GET=1 if label changes risk of getting skin cancer; *=0* if label changes conditional risk of dying from skin cancer	0.500	-0.089 (-1.992)	-0.093 (-2.079)
PARENTCHG=1 if parent risk change = 50%; *=0* if risk change = 10%	0.498	---[a]	---[a]
KIDCHG=1 if child risk change = 50%; *=0* if parent risk change = 10%.	0.496	---[a]	---[a]
*GET*PARENTCHG*	0.249	0.251 (6.82)	0.252 (6.86)
*GET*KIDCHG*	0.251	0.436 (11.84)	0.437 (11.85)
*(1-GET)*PARENTCHG*	0.248	0.309 (8.38)	0.306 (8.30)
*(1-GET)*KIDCHG*	0.245	0.340 (9.23)	0.339 (9.22)
FAMILY INCOME ($10,000 per year)	5.325	---	0.031 (7.66)
NUMBER OF CHILDREN IN HOUSEHOLD	2.075	---	-0.076 (-5.23)
s_u	---	1.029 (53.79)	1.023 (53.65)
s_v	---	0.548 (57.78)	0.548 (57.80)
Number of Parents	610	610	610

[a] Denotes omitted dummy variable.

Table 5

Estimated Marginal Rates of Substitution
(Asymptotic Standard Errors in Parentheses)

			White Parents						
Marginal Rate of Substitution	**Full Sample**	**Black Parents**	**All**	**Mothers**	**Fathers**	**Child is Daughter**	**Child is Son**	**Child Age 3-7 yrs**	**Child Age 8-12 yrs**
Child vs. Parent Unconditional Morbidity	2.05 (0.35)	---[a]	1.61 (0.27)	1.83 (0.35)	0.96 (0.38)	1.14 (0.24)	2.60 (0.88)	1.42 (0.29)	2.22 (0.74)
Child vs. Parent Unconditional Mortality	2.33 (0.32)	0.52 (0.20)	3.28 (0.51)	3.24 (0.58)	3.35 (1.02)	2.01 (0.40)	5.40 (1.46)	4.38 (0.90)	1.73 (0.46)
Unconditional Mortality vs. Unconditional Morbidity (Parent)	19.16 (3.15)	---[a]	11.35 (1.83)	10.76 (2.08)	14.36 (4.09)	10.42 (1.78)	14.17 (4.93)	7.86 (1.55)	24.60 (7.73)
Unconditional Mortality vs. Unconditional Morbidity (Child)	21.78 (2.59)	22.48 (8.98)	23.19 (2.84)	19.06 (2.57)	50.05 (15.74)	18.42 (3.55)	29.38 (4.84)	24.25 (3.58)	19.18 (4.71)
Number of Parents	610	122	460	351	109	230	230	258	202

[a] Estimate is negative but not significantly different from zero at the ten percent level.

Figure 1. Risk Scale.

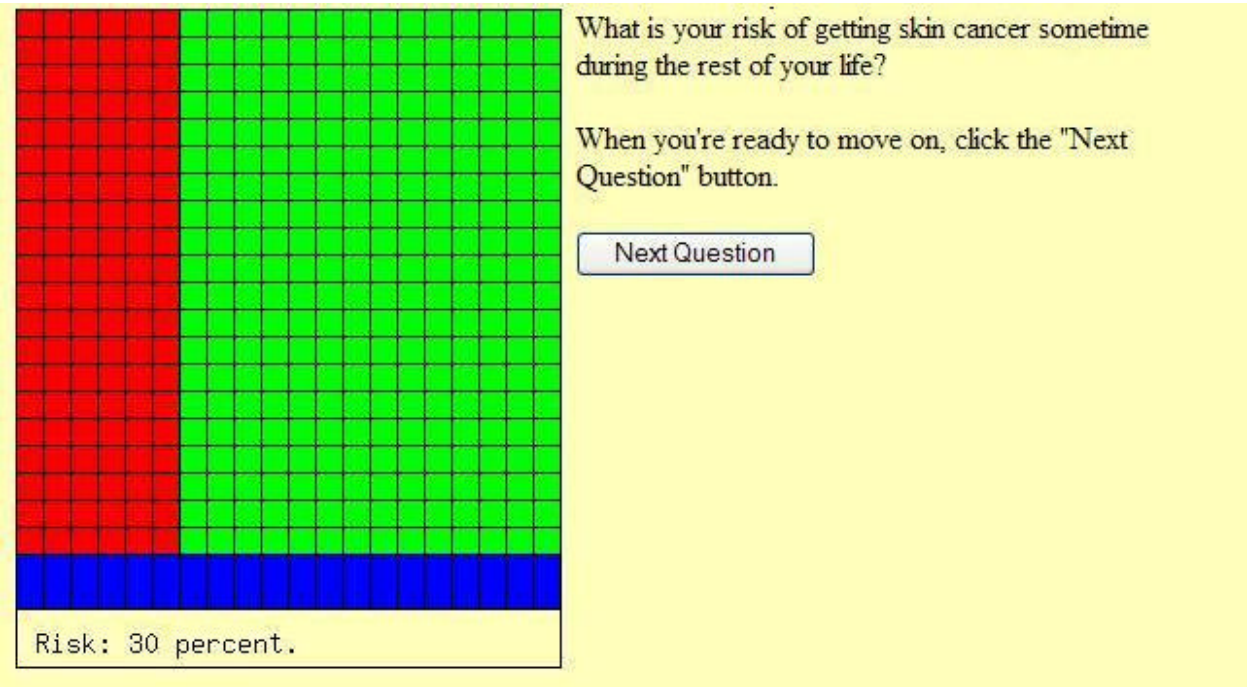
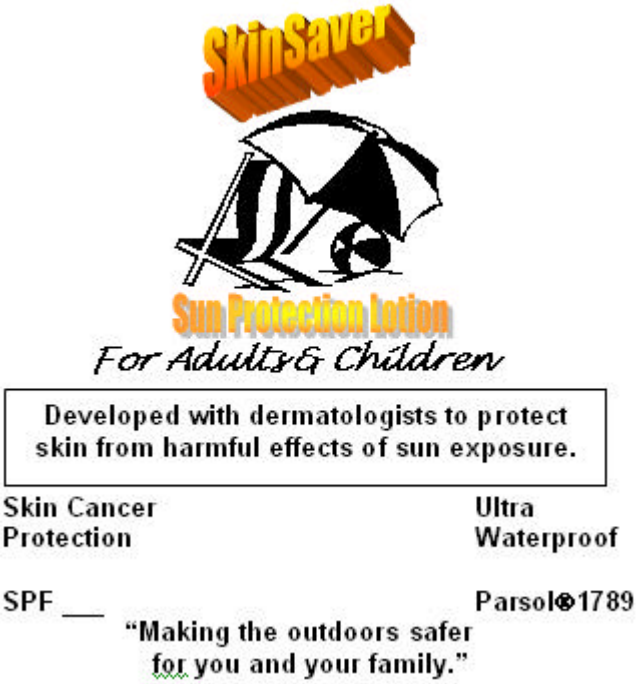


Figure 2. One of Eight Sun Lotion Labels.



(Back of bottle)

New SkinSaver® sun protection lotion.

Skin Cancer Protection		
✓ Used as directed in clinical trials, SkinSaver reduced risk of skin cancer by:		
10% for Adults		10% for Children
✓ Used as directed in clinical trials, SkinSaver had no effect on the risk of dying if skin cancer occurred.		
More Skin Protection		
Parsol®1789		SPF_____
Protects against premature skin aging		Protects against sunburn

More Added Features

* Ultra long-lasting waterproof formula – One application lasts all day *

* Non-comedogenic–Won't block pores * Oil-free–Won't feel greasy *

* Hypoallergenic * PABA-free * Unscented *

DIRECTIONS: Apply generously and evenly to all exposed areas of skin at least 15 minutes before sun or water exposure.

ACTIVE INGREDIENTS: Oxybenzone, octocrylene, 2-ethylhexyl salicate, homosalate, avobenzone.

Comments on "Not All Deaths Are Created Equally"

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November 2003

Cameron and DeShazo undertake an ambitious survey to elicit valuations of health episodes that respect the timing of the episode. They incorporate latency of onset, as well as latency of the experience, for a wide range of possible health episodes. Mortality and morbidity are treated in the same conceptual framework, which is a major attraction. In short, their attempt to undertake valuation of the "health life cycle" is novel and important. The strengths of the study are well presented by the authors.

They claim that one novelty of their work is that they calculate the value of a statistical illness (VSI) rather than the value of a statistical life (VSL). Since many of the hedonic wage-risk regressions also included non-fatal risks, this would seem to be a trivial innovation. Important to do, but nothing to claim as novel.

Similarly, they claim to show that individual differences matter for the VSI and VSL. Again, this is worth saying as loudly as possible, but isn't this already in older data, even if has tended to be ignored in analysis? That is, many of the earlier studies included a rich array of individual characteristics that could have been used to predict VSL estimates that would have varied over those characteristics. So I am not sure what is conceptually novel here.

With respect to heterogeneity of VSI or VSL estimates, I worry a lot about the treatment of negative predicted values. These appear to have been set to $0, but that causes obvious biases in the aggregate estimates. One of the grubby secrets of VSL analysis, particularly in some recent meta-analyses, is that negative or statistically insignificant estimates are dropped or set to zero. One understands the desire of the Environmental Protection Agency to "see big VSL numbers," but such mis-handling of the data is not acceptable. I am not sure that such things are going on here, but the results appear to be very sensitive to how certain observations are dropped, and this deserves more careful discussion.

Related to this, the practice of deleting "outliers" should be completely reconsidered. If my data set includes a Bill Gates, who is an outlier in terms of income and wealth, and he responds in a numerically extreme manner, then in what sense is that an outlier? There are answers to this question that make sense, but they should not be enshrined in mechanical rules for dropping subjects. The present analysis has some questionable bases for dropping observations, and that needs further exploration.

The massive cognitive burden on respondents is an obvious concern, but we need to start somewhere if we are to examine health life-cycles. My concern here is tempered by the desire to see someone spell out a complete framework for valuation, such as one has here. But one cannot take the responses too seriously for policy work, given the uncontrolled context in which subjects were responding and the unfamiliarity of the task.

Related to this concern, I believe it was a major error to start such a complex survey with elaborate field survey procedures. While the *Knowledge Networks* technology is fascinating, it makes much more sense to pilot surveys of this kind in a less constrained and more controlled setting. My understanding is that such data points cost roughly $50 per subject, which seems a lot for such a pilot study. I appreciate that the authors undertook a large number of focus groups, and consulted some smart people in the field about design issues, but that is no substitute for controlled comparisons of different ways of presenting tasks and evaluation of cognitive burden.

The authors implicitly take the view that there is only one way to generate a social VSL – to estimate the individual VSL for different segments of the population and then take some appropriately weighted average. Of course, there are other ways to arrive at the same concept. One could elicit a household VSL rather than an individual VSL, and then weight those. Or one could directly elicit a social VSL from individuals or households. There is no *a priori* reason for the directly elicited social VSL to equal the weighted averages of individual or household VSLs. Indeed, it would be interesting to see how they are related. In the same vein, estimates of individual VSLs could be used in various social welfare functions to arrive at a social VSL. So there are many paths to the social VSL, not just the one implicit here.

The statistical analysis is heavy on math that could be relegated to appendices, and light on some of the nuts and bolts that likely drive the results. I should add that some of the "present value math" is really very interesting, and notationally delicate, so I would not want to see that lost; but it detracts from the general comprehension since it is better read off-line. My concern is more with the way the data is handled. I have already discussed the handling of negative valuations and outliers. But I missed the use of control for characteristics other than income, own-age and age-of-onset of the disease. Since this is, after all, a conference on children's health valuation, one is entitled to a "where is the beef?" question: why no controls for whether the respondent has children, or how many? I suspect that there may be some dark computational reason why more covariates are not thrown in, akin to why one sees so few covariates in the "stated choice" literature. But this needs a simple explanation and evidence, rather than assertions that it would not change results.

There are some hidden assumptions about risk aversion and individual discount rates that need to be made explicit. These are not minor matters. Once we recognize individual heterogeneity with respect to the valuation of uncertain future heath states, we have to confront the fact that these estimated values will necessarily confound the certainty-equivalent valuation of the health state, individual risk attitudes, individual discount rates, and possibly preferences individuals might have over the temporal resolution of uncertainty. Is it possible that the first component is constant with respect to the things it is claimed to vary over, but that the others

vary? We simply do not know, and teasing these apart is a formidable enterprise. We do now have relatively good estimates of risk attitudes and discount rates for individuals from controlled laboratory experiments, in some cases conducted in the field with samples representative of larger populations than college students, and one would hope that one could marry such estimates to the valuations of health life-cycles to see what is really driving the VSI estimates. The evidence so far suggests considerable heterogeneity of risk attitudes and individual discount rates with respect to the standard observables, so we cannot ignore the issue by assuming homogeneity (as is done here).

The authors loudly trumpet the claim that a "senior VSL discount exists!" This claim is far too premature. The issue is an important one, but I am sensitive to a rush to judgment on such an important issue from such a pilot study. My enthusiasm for the scope of this pilot study would be nearly unbounded if I were not concerned that such claims would be ripped out of their academic context. In terms of the old Latin motto, *festine lente* (hasten slowly).

Comments on "Valuation of Environmental Risks to Children's Health"

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Dickie and Gerking get at risks to children through parental decisions. This is a sensible way to get at children's valuation, and deserves to be explored further. Their elicitation scope is also modest, which makes for a well-focused study. The study looks at morbidity and mortality in the same framework, which is attractive. Related to this, one again sees the nice idea of a "health life-cycle" as the conceptual setting for valuation.

Asking parents for valuation of risks to the health of children makes obvious sense, but raises some questions. Which parent? The one that makes the decisions, or the one that was picked at random? How would this differ from the situation in which both parents made the decision, allowing them to endogenously resolve their internal household decision-making as they do naturally?

One major concern, however, was whether subjects would or could keep morbidity and mortality separate. It seems incoherent *a priori* that some product could reduce the risk of contracting skin cancer but not reduce the risk of dying from it. At the very least, one would surmise that they are highly, positively correlated. Given this, how do we know that the responses that subjects make to the morbidity question are in fact just that, and do not include concerns with mortality?

The data for blacks should e discarded. Given the low propensity of blacks to get skin cancer, and the wide understanding of this by blacks, why should they ever rationally invest in knowledge about the risks? At the very least, these data should be analyzed separately.

Related to this concern, why compare an individual's own perception of risk to the population risk? It is quite possible that individuals know more about their own circumstances than they do about the population as a whole. In particular, occupation may influence the amount of time spent outside, which could be an important factor influencing individual risk.

Why rely solely on hypothetical responses? This is a setting in which it would have been easy to use real incentives for risk elicitation, and possibly even elicit a real willingness to pay (WTP) for sunscreen. Hypothetical bias is not obviously avoided by taking ratios for a marginal rate of substitution, although that is an intriguing speculation worth investigation. We simply have too much data on the unreliability and higher variance of hypothetical responses to ignore when we are able to elicit responses for which subjects have real consequences.

What effect might the existence of field substitutes for sunscreen have on responses? Such field substitutes might be expected to play an important role, by censoring the WTP for a new product. Simple statistical methods exist for handling this.

The elicitation format was double-bounded dichotomous-choice. That method is not incentive compatible when responses are real, since the subjects have an incentive to reduce their payment for the good by misrepresenting. Hence the assumption under which it generates more information, that the underlying population of valuations is invariant to the repeated sampling sequence, is invalid. One could conjure up heavily-parametric ways to correct for this, but that seems like a costly thing to do when one could avoid the problem by design. In a hypothetical setting, subjects have no incentives for any response, but one hardly wants to rely on that premiss to defend the double-bounded procedure! In the future this procedure should be dropped. For now, at the very least the analysis should just use the first response, and then see if there are large differences when the second response is included.

The authors note that the WTP for risk reduction of a child exceeds the WTP for risk reduction for the parent. This need not be a puzzle, since these are not the same good. If 80% of exposure causing skin cancer occurs up to age of 18, which is apparently the case, then one is simply buying more health benefit for children. There should be a simple way to normalize these estimates to account for this.

Summary of Q&A Discussion Following Session IV-PM

Bryan Hubbell (U.S. EPA) addressed J.R. DeShazo and Trudy Cameron saying that he, too, finds it interesting that they "rushed to the conclusion that we have this big age difference," and adding that he "tried to look quickly at the confidence intervals and . . . as far as I could tell, *all* of them overlap, so there's no statistical difference between any of those numbers." He also suggested that it might be worthwhile to look at the possibility of controlling the variance with respect to age, because "it certainly looked like there might have been higher variance in the responses from the older individuals."

Trudy Cameron responded that "the first and last confidence intervals, for the youngest group and the oldest group, don't overlap. . . . Linking together, all the intervening ones do have some overlap, but, fortunately, the first and last ones don't.

Addressing the other comment, Dr. Cameron stated, "We have been estimating models that employ systematic differences in the errors, and one thing that does show up, not surprisingly, is education level. If we include, specifically, a dummy for less than high school education—those folks are way noisier in the information they're giving us—but as I recall, there wasn't a lot of other action on the dimension."

Laurie Chestnut (Stratus Consulting, Inc.) addressed what she termed a "primarily empirical question" to Trudy Cameron and J.R. DeShazo. She said that in the survey she and her colleagues conducted, they asked about *physical* health, which declined with age, although a simple question regarding enjoyment of life showed no decline with *current* age. On the other hand, she said, peoples' expectations regarding quality of life 10 to 20 years in the future *did* show a decline. In considering the list of all the terrible things that happen as we get older, she urges "some qualification of, maybe while some things deteriorate, some heart-felt appreciation for what we have left might be moving in the other direction." She clarified that this possibility interests her partly because she is facing a "big birthday" soon.

She went on to ask another question regarding what appears to her to be some "counter-intuitive results" (admittedly preliminary) from the study. This concern regards the finding that the value of a current risk reduction was found to be less for someone who is 65 than for someone who is 70, going from half a million to two million over this 5-year span. Reiterating that this seems counter-intuitive, she questioned whether this might be an artifact of the way the researchers "chopped the things up."

Trudy Cameron responded, "There's this one little anomaly in those sloping graphs of the portion that hangs down below zero: People, in considering risk profiles that involved something dreadful happening to them in the near term, the next five years, weren't interested in that program, quite typically. So, there's this sort of bias against near-term risks. So, the near-term negative willingness to pay is there for all the age groups."

Glenn Harrison interjected, ". . . you didn't want to tell people that "your life expectancy is one year," –you've jacked it up by 8 years."

J.R. DeShazo answered that peoples' "nominal assessment of their life expectancy and what we told them that the doctor would assess their life expectancy at were both inflated compared to what their actual life expectancy was." He then explained a couple of issues relevant to Laurie Chestnut's question, saying, "One is that people's information set contains a focus on their immediate perceived risk, and then people seem to have confidence intervals around that as they look further into the future—they're more willing to accept that 5 or 10 years from now they may face a threat of a heart attack or a stroke, whereas they really feel healthy today and so anything in the next 2 or 3 years they disbelieve."

Speaking to Ms. Chestnut's initial point, Dr. DeShazo clarified that nothing in their analysis suggests that older people value a year of their life less. However, he said, the evidence does suggest that people begin to look at the gains from avoiding illness differently as they get older. He cited the fact that after the age of sixty-five 50 to 60 percent of people have some chronic condition—"they're in some state of morbidity, and their assessment of avoiding other kinds of morbidity in the future changes. Their information set upon which they base their willingness to avoid a worsening of the health state changes." He clarified that what he and his colleagues have found is that "how much you're willing to pay to avoid a loss in the future changes because that loss looks smaller the more morbid your current health state becomes."

Alan Krupnick (Resources for the Future) said that he also was interested in the question about the latency result. He said that he and his colleagues had found a strong latency effect in their study, which looked at the whole population aged 40 to 60 and their willingness to pay for a reduction in the risk of death beginning at age 70 and going up to 80. They found a "strong lower willingness to pay for that contemporaneous risk reduction." He asked the researchers to consider the question: "If you looked at it *that* way, would you find that same effect?"

He then addressed two questions to Shelby Gerking: Stating that he and his colleagues found that blacks are willing to pay more than whites for an equivalent risk reduction, he asked whether Dr. Gerking and his colleagues had found that to be true also. In addition, he commented that a lot of researchers have struggled with trying to get people to understand conditional probability, and this seems so implausible to him. He asked for their views on, for example, a person saying "When I apply this sunscreen, it doesn't reduce my risk of getting cancer, but it reduces my risk of dying from cancer," which he related to their latter cases.

In regard to Dr. Krupnick's first question, Trudy Cameron replied that she didn't know off the top of her head but they could surely run a simulation that captures the same type of information he had gathered and find an answer.

Shelby Gerking conjectured that blacks aren't willing to pay a lot for sunscreen probably because their risk of getting skin cancer is much lower than it is for whites "so the result here is specific to the context in which it's estimated." He continued by saying, "Regarding the plausibility of dying from skin cancer," it's an issue that he and Mark Dickie "worried about quite a lot and then went ahead with on the basis of the results they got initially." He closed by saying that it didn't seem to be as big a problem as he initially thought it might have been and he was pleasantly surprised.

J.R. DeShazo stated, "We found that when you look at individuals' subjective assessment of their risks for specific illnesses and then their ability to mitigate and defend against or control those risks that there was a lot of variability in socio-economic and ethnic characteristics."

Don Kenkel (Cornell University) said he was struck by the fact that "there is an active market to *get* skin cancer—in the tanning booths—where people spend time and money to do this." He commented that he wondered about the implications of the fact that there is "a very real sense that skin cancer prevention is jointly produced with being pale." Are there whites who aren't going to pay for sunscreen because of this? Furthermore, Dr. Kenkel posited that some people's attitude that "I'm willing to make my kids have disutility to keep *them* safe, but *I* want to look good" might explain some of the differences observed.

Shelby Gerking responded that these questions and the ones brought by Alan Krupnick are really important. He said that he was involved in a prior skin cancer study that looked at the issue of the joint products associated with tanning beds and being out in the sun—"some people want *some* tanning; others don't want premature aging and wrinkling—and we tried to sort all of that out in an earlier paper and discovered that the joint production effects . . . really weren't that important to consider. So, even though we do consider them a little bit in this study, it's not to the same extent as in the earlier study, and I didn't talk about that at all."