Two Types of Age Effects in the Demand for Reductions in Mortality Risks with Differing Latencies

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We develop and test an empirical model of individuals' intertemporal demands for programs to mitigate health risks over the remaining years of their lives. We estimate this model using data from an innovative national survey of demand for preventative health care. We find qualified support for the Erhlich (2000) life-cycle model, which predicts that individuals expect to derive increasing marginal utility from reducing health risks that come to bear later in their lives. However, we also find that as individuals age, there appears to be a systematic downward shift in their anticipated schedule of marginal utility for risk reduction at future ages. Our model improves upon earlier work by differentiating between the respondent's current age and the future ages at which they would experience adverse health states. Using estimated demand schedules specific to an individual's current age, we demonstrate the calculation of values for risk mitigation programs that reduce the probabilities of specified time profiles of adverse future health states involving various latency periods. JEL Classifications: I12, J17, J28, J78

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1 Introduction

Policymakers need to know much more than they currently do about life-cycle differences in individual demand for risk-mitigation programs that enhance health and extend life. The efficient design of a wide range of environmental, safety and health programs, as well as preventative and remedial health care interventions, has been hampered by gaps in this knowledge. Examples of this problem have been evidenced recently--in the U.S., Canada, and Europe--when policymakers proposed modifying the benefit estimates used in benefit-cost analysis of regulations to reflect a lower value for reducing the risk of death for senior citizens as compared to adults. Furthermore, there is an important theoretical debate between competing life-cycle models of health-risk mitigation that can only be resolved through empirical hypotheses testing (Erhlich, 2000; Sheppard and Zeckhauser, 1984). A better understanding of life-cycle patterns in willingness to pay for health-risk mitigation may help explain not only trends in life-cycle savings and consumption, but also the timing of individuals' transitions to retirement, Social Security, Medicare, and Medicaid (Hamermesh, 1995; Hurd et al., 1995, Gan et al., 2003).

Existing empirical analyses have tended to emphasize only one of several important age-varying variables. For risk reductions that occur in the current period, researchers have explored how demand varies with the individual's current age (Jones-Lee et al., 1985; Johannesson et al., 1997; Persson et al., 2001; Krupnick et al., 2002; Smith and Evans, 2003; Aldy and Viscusi, 2004). However, the vast majority of public and private programs yield reductions in the risk of adverse health states not in the current period, but in future periods of life. For these programs, several other factors may vary systematically with age, such as the individual's income, their discount rate, and their age when the future adverse health state would occur (i.e. the delayed onset or "latency" of the risk). Researchers have explored a few of these factors in isolation from the others, such as how income varies with age (Kniesner, et al., 2004) or the effects of latency (Cropper and Sussman,1998; Hammitt and Lui, 2003). Until now, however, no empirical analyses have simultaneously and explicitly accommodated all of these factors that may vary with age.

We develop an empirical model of individuals' allocations of health-risk-mitigation expenditures to address health risks that differ in their likely time profiles. Our model defines the consumer's multi-period planning problem, into which we incorporate utility parameters that may vary with their age now and with the age at which each future health state is experienced. The model accounts for income, the latency of program benefits and each individual's remaining years of life. We estimate this model using data from an innovative national survey of demand for preventative health care. By eliciting information on individuals' program preferences, we are able to estimate their willingness to pay to reduce their risk of a future sick-year and a future lost life year at any time during their remaining lifespan.

The development and empirical testing of our model contributes to the literature in several ways:

(a.) We provide the first evidence in the literature that individuals derive increasing marginal utility from reducing risks that come to bear later in life, when both their shadow value of health and their risk of mortality are likely to be greatest. However, we also find support for the hypothesis that as individuals age, there is a systematic downward shift in willingness to pay for statistical risk reductions at future ages. As individuals age, they appear to revise downward their assessment of the value of consumption at very advanced ages; this, in turn, reduces the shadow value of risk mitigation at those ages.

(b.) This evidence about the age dependence of the willingness to pay for risk mitigation enables us to assess which of two competing theoretical regimes is most pertinent. The first modeling tradition examines life-cycle demand for mortality risk mitigation, predicting that the value of risk mitigation should be flat or fall with age (Arthur, 1981; Sheppard and Zeckhauser, 1984; Rosen, 1984). The second modeling tradition examines the risk of both morbidity and mortality and, in contrast to the first, predicts that the value of health risk mitigation whould rise with age, with or without complete markets (Ehrlich and Chuma, 1990; Ehrlich, 2000). Our empirical analysis finds qualified support for the prediction of the second modeling tradition -- that the value individuals place on health risk mitigation rises with the age at which the adverse health states would occur.

(c.) Our model is an attempt to bridge the gap between the dynamic life-cycle models in the theoretical literature and current empirical methods, which are based predominantly upon a static theoretical model in which the individual considers a single risk that is reduced in the current period (Dreze, 1962; Jones Lee, 1974).[1] Although our model is not formally dynamic, it incorporates elements of these dynamic models. For example, demand in any period depends not only on consumption in that period, but also on the time path of future consumption and health states as well as the individual's discount rate and life expectancy. Instead of the single planning period in most state-of-the-art valuation methods, our model permits individuals to allocate risk-mitigating expenditures across programs with different time-profiles of risk. These improvements not only expand the purview of risk valuation methods, but also reduce some sources of unobserved heterogeneity in current demand estimates.

[1] These single-risk, single-period models have motivated hundreds of empirical demand analyses, including those currently used to evaluate the social benefits of life-saving public policies (Viscusi, 1993).

(d.) Finally, our model provides a more general and theoretically consistent framework within which to evaluate a wide variety of life-saving and health-extending policies. Most public policies yield reductions in the risk of both future morbidity and premature mortality for distinct age cohorts (Cropper and Sussman, 1990). Our model recovers the present value of policies dealing with health risks that have varying latency periods and benefit diverse age cohorts. (In our models, each age cohort has a specific schedule of marginal utility for future risk reductions.) We believe this to be the most comprehensive empirical assessment, currently available in the literature, of health policies addressing risks with variable latencies.

Ideally, we would estimate our model of demand for risk mitigating programs using market data. However, revealed-preference data that would readily identify the types of ex ante tradeoffs that we wish to quantify do not exist. Thus, we choose to administer a representative national survey that elicits individuals' stated choices over alternative risk-mitigation programs in a stated-preference experiment. Each health risk in our study is presented as an illness profile that describes a probabilistic time pattern of health states that the individual could experience. Each health profile consists of randomly assigned values for the individual's future age at the time of onset, the severity and duration of treatments and morbidity, the age at recovery (if recovery occurs), and the number of lost life-years (if death is premature).

We present respondents with an illness-specific health-risk reduction program that involves diagnostic screening, remedial medications and life-style changes that would reduce their probability of experiencing that illness profile. Individuals must pay an annual fee to participate in each risk-reducing program. They are asked to choose between one of two risk reducing programs (each associated with a different illness profile) or to reject both programs. An advantage of this choice setting is that the individual faces a portfolio of health risks that resemble those they actually face. Through their choices, individuals reveal trade-offs across different illnesses involving a wide array of health states of different durations.

To analyze individuals' program choices, we estimate a simple indirect utility function using data from a representative national survey of more than 1,600 U.S. citizens. Our estimated model recovers an individual's marginal utility of avoiding a year spent in each of three health states: morbidity (sickness), post-morbidity (a "recovered" state), and mortality (death). Controlling for the individual's current age, we find that the marginal utility of avoiding a future lost life-year rises with the age at which that lost life-year would be experienced. In contrast, controlling for the ages at which the undesirable future health states would potentially be experienced, we find that the choices made by older individuals imply that their values of risk reductions at each future age are lower. We then evaluate the net effect of these two types of age dynamics by simulating the fitted distributions of demand for policies with different risk latencies and different illness and mortality profiles.

In section 2, we compare the two dominant modeling traditions and explain their pertinence to the specification of the indirect utility function that we estimate and the hypotheses that we test. We describe the survey and the data that we use to estimate our model in Section 3. In Section 4 we develop our model and in Section 5 we present our results before concluding in Section 6..

2 Predicting Life-cycle Patterns of Risk Mitigation

There are two distinct theoretical traditions that predict different life-cycle patterns of health risk mitigation. The first of these approaches we characterize as models of "disembodied health risk." In these models, health risks do not directly enter the utility function. Risk is portrayed as affecting only the probabilty of current and future consumption. Early versions of these models characterized demand in a static framework (Dreze, 1962; Schelling, 1968; Jones-Lee, 1974; Arthur, 1981) followed later by inter-temporal life-cycle models (Sheppard and Zeckhauser, 1984; Cropper and Sussman, 1990; and Johansson, 2002; Alberini, et al., 2004). In the case of a discrete life-cycle model, an individual at age j derives expected utility, V_j , from consumption over the remainder of his lifetime:

(1) $$V_j = \sum_{t=j}^{T} q_{j,t} \left(1+r\right)^{j-t} u_t\left(C_t\right)$$

where $u_t\left(c_t\right)$ is the utility of consumption in year *t* of life, multiplied by the probability $\left(q_{j,t}\right)$ that the individual at age *j* survives to age *t*, discounted to the present at a discount rate *r*. *T* is the maximum length of life used in the planning period. The individual makes choices that affect $q_{j,t}$ and C_t to maximize the present value of V_j, subject to wealth constraints that reflect opportunities for lending and borrowing.

From the first order conditions for this utility-maximization problem, several researchers have shown that an individual's willingness to pay at age *j* for a risk reduction at age *j* depends upon two components: 1) the probability of survival in each period and 2) the present value of the expected utility from their remaining life span (Sheppard and Zeckhauser, 1984; Alberini, et. al., 2003). The prediction for the first component is unambiguous: the decrease in the probability of survival as age increases will cause a corresponding increase in willingness to pay. However, the prediction for the second component is ambiguous. It is not theoretically clear how, at more advanced ages, the present value the expected utility of consumption across one's remaining lifespan will change. In many of the older simulation exercises, researchers have assumed that $u_t\left(C_t\right)$ is constant across time. In that case, the present value of expected consumption would be proportional to the discounted remaining lifespan (Sheppard and Zeckhauser, 1984). Thus, increases in age unambiguously decrease willingness to pay. In the absence of perfect markets, simulations reveal per-year consumption first rising, and then falling, as individuals advance in age. This pattern of consumption leads to predictions that the demand for mortality risk mitigation will follow an inverted U-shaped time path.[2]

While the structure of these models accommodates mortality risks, it precludes consideration of the enormous set of morbidity states that individuals may face over their remaining lifetimes. Yet nearly all types of risks simultaneously influence the individual's probability of experiencing morbidity, as well as pre-mature mortality The omission of morbidity states from the indivdual's choice set limits these models' abilities to characterize individuals' marginal rates of substitution across programs that alter the individual's probability of experiencing future healthy, morbid and premature mortality states.

A second modeling tradition involves health-embodied risk. It has arisen from scholars modeling life-cycle demand for health (Grossman, 1972; Ehrlich and Chuma, 1990). Most recently, Ehrlich (2000) portrays health risks (*q*) in year t as affecting the flow of health $\left(h\left(q_t\right)\right)$ in year *t*.[3] In contrast to the mortality-risk-only models discussed above, here *q* may represent any risk that diminishes the individual's level of health. Let hmin represent the minimum flow of health needed to survive. A health risk that results in $\left(h_t\right) < hmin$ causes mortality. The range of $h(t)$ greater than *hmin* represents the continuum of health states ranging from perfect health to acute morbidity. Increases in health risks move $h(t)$ towards *hmin* leading to greater morbidity.

[2] More recently, researchers have emphasized that, theoretically, u_{t}(C_{t}) may be not constant (Johansson, 2000; Alberini, et al., 2004). Empirically, Kneisner et al. (2004) have shown that consumption tends follow an asymmetric inverted U-shaped over the typical lifespan.
[3] Also see the erratum in Ehrlich (2001).

Importantly, the effect of the time path of risk on the time path of health $\left(h\left(q_t\right)\right)$ directly enters the individual's utility function alongside a consumption activitiy $\left(C_t\right)$. "Healthy time," h_t h_{t}, is also an input into the production of the $\left(C_t\right)$ so there may be strong complementarities between an individuals' health state and the utility they are able to derive from market goods. For the purposes of our cursory review, we present the objective function in a discrete and additively separable form (with respect to time):

(2) $$V_j = \sum_{t=j}^{T} \left(1+r\right)^{j-t} u_t\left(C_t, h\left(q_t\right)\right)$$

The individual chooses C_t, q_t (and, by implication, $h_t\left(\cdot\right)$ to maximize the present value of utility, V_j, subject to wealth constraints.. Risk is therefore "embodied." It directly influences utility through its impact on individuals' health states, which may also influence the utility they derive from other goods.

The first-order conditions describe how an individual's willingness to pay at age *j* for a risk reduction at age *t* depends upon three general components (Ehrlich, 2000, p. 346-48). The first component again depends upon the magnitude of the risk and rises unambiguously with age. First, just as before, increasing health risks decrease the probability of surviving to future periods which increases individuals' incentives to allocate greater resources to risk mitgation. The second component is the marginal utility of preventing a further diminution in the level of one's health state. Within increasing age, the marginal utility of health increases as individuals enjoy less health which increases incentives to allocate additional mitigation to more advanced ages (Ehrlich, 2000, p. 348). The value of this forgone health (e.g., its shadow value) is determined by (a) the disutility from an increase in morbidity, (b) a diminished value of consumption if health is a strong complement to consumption and (c) foregone labor earnings. The second component is absent from the disembodied risk model. The third component equals the loss in the expected utility of consumption across time over the individual's remaining life span. As before, it varies with age in a theoretically indeterminate fashion. As indivduals age, Ehrlich's analyses suggest that the first two components will rise, probably offsetting the decreases in the third.

At progressively older ages, the value of a marginal risk reduction rises with increases in health risk levels and with increases in the shadow value health, which tends to offset the effect of a shrinking expected value of future consumption. For the case without annuities (i.e. where there are no savings opportunities), Ehrlich concludes that "the value of life and health protection is seen to be rising over a good part of the life-cycle because aging raises the benefits of protection except in the late phases of the planning horizon" (2000, p. 348). With annuities, the time path of self-protection is expected to rise more steeply with age (p. 352). Only a strong bequest value (expressed via life insurance markets) would temper this upward trend in the value of health and life protection with age.

Ehrlich's health-embodied model treats risk more generally by allowing for a wide range of health states.[4] Important is the weight it gives the disutility associated with declining health status, thus allowing for substitution between morbidity and mortality and, in particular, for the possibility of "fates worse than death." Our model also permits individuals to substitute among a wide range of future health states. Ehrlich's model of risk predicts that the marginal value of health risk mitigation will rise with the future age at which adverse health states will be experienced. Empirically, we find that individuals allocate progressively increasing amounts of risk-mitigation to more-distant future years of their lives. Individuals expect their shadow value

[4] Alternative health states range from perfect health to short periods of mild morbidity to extended and severe morbidity that results in mortality to immediate mortality without morbidity. This stands in contrast to the model of disembodied mortality risk in which the individual demand for risk mitigation results in only two health states: perfect health and death.

of health to rise in future years as their health state declines, so the expected marginal utility of risk mitigation in future years rises.

However, our analysis does not offer unqualified support for this model. We find support for the hypothesis that as individuals grow older (e.g. age t to age t+1), there is a systematic downward shift in their schedule of marginal utility for health risk mitigation over future ages. Individuals appear to revise downward the expected utility that they will derive from risk mitigation as they approach age t. There may be several reasons for this. First, as they age, individuals may revise their expectations downward about their future time path of health, their life expectancy or their expected lifetime income. Second, if perceived complementarities between health and all other consumption increase with age, then declining health will, in turn, diminish the marginal utility of all other consumption goods. It is reasonable to assume that individuals learn about the extent of this complementarity as they age. If so, rational individuals will respond to this new knowledge by reallocating income to earlier years of their lives, where its marginal value in consumption is higher than it will be in later years. (For example, as we start to realize that we may not actually be healthy enough to globe-trot in our seventies, we decide to see the world now, while we can still enjoy the trip.) This, in turn, will decrease the value of mitigating health risks that come to bear in later years.[5]

[5] There is also a third possible explanation for this downward shift. Some individuals may not believe that actuarial illness risks apply to them personally, and others may not believe that a specified risk-reduction program would be as effective as it is advertised to be.

3 Survey Methods and Data

Adequate market data are not available to illustrate how individuals allocate risk mitigation expenditures across competing risks and across their remaining years of life.[6] Therefore, we have conducted a survey of 1,619 randomly chosen adults in the United States. The centerpiece of the survey is a conjoint choice experiment that presents individuals with hypothetical specific illness profiles and programs designed to mitigate these risks. Here, we briefly describe the five modules of this survey.[7]

The first module evaluates the individual's subjective risk assessment for each of the major illnesses considered in the study, their familiarity with each illness, and behaviors they may currently undertake to mitigate or avert these health risks.[8]

The second module of the survey consists of a tutorial that introduces individuals to the idea of an illness profile and programs that may manage these illness-specific risks. Each illness profile is a description of a time sequence of health states associated with a major illness that the individual is described as facing with some probability over the course of his or her lifetime. The attributes of the illness profiles are randomly varied, subject to some plausibility constraints for each illness type.[9]

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

[7] An the annotated survey is available at http://www.uoregon.edu/~cameron/*VSL*/Annotated_survey_DeShazo_Cameron.pdf.

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

[9] We took great care to try to ensure individuals did not reject the scenario because it was implausible (e.g., one does not recover from Alzheimer's or die suddenly from diabetes). We summarize the key attribute levels employed in the choice sets in Appendix Table A-1.

Twelve specific illnesses are used in our study, and up to eleven attributes characterize each illness profile and program. These illness profiles include an illness name, age of onset, treatments, duration and level of pain and disability, and a description of the outcome of the illness.[10] We next explain to individuals that they could purchase a new program that would be coming on the market that would reduce their risk of experiencing a specific illness over current and future periods of their lives. These programs are described as involving annual diagnostic testing and, if needed, associated drug therapies and recommended life-style changes.[11] The effectiveness of these programs at reducing risk is described using four means: 1) graphically, with a risk grid, 2) as risk probabilities, 3) as measures of relative risk reduction across the two illness profiles and 4) using a qualitative textual description of the risk reductions (Corso et al., 1999; Krupnick et al., 2002). The payment vehicle for each program is described as a co-payment, expressed in both monthly and annual terms, that would be necessary for the remainder of their life unless they actually experienced that illness.[12]

In the preamble to the five choice sets that form the core of the survey, we implement several measures to avoid potential biases.[13] We include an explicit "cheap talk" reminder to ensure that respondents carefully consider their budget constraint and to discourage them from

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[10] Our selection of these attributes was guided by a focus on those attributes that 1) most affected the utility of individuals and 2) spanned all the illnesses that the individuals evaluated (Moxey et al. 2003). In terms of the number and type of attributes, our design is comparable to existing state-of-the-art health valuation studies (Viscusi et al., 1991; O'Connor and Blomquist, 1997; Sloan et al., 1998; Johnson et al., 2000). We sought to estimate demand conditional on the individual's ex ante information set. Therefore, we chose not to give individuals extensive background information on illnesses, which might make one illness risk appear more salient than others.

[11] We selected this class of interventions because pretesting showed that individuals viewed this combination of programs (diagnostic tests, followed by drug therapies) as feasible, potentially effective and familiar for a wide range of illnesses. Depending upon their gender and age, individuals were familiar with comparable diagnostic tests such as mammograms, pap smears and prostrate exams, or the new C-reactive protein tests for heart disease.

[12] Most respondents' experience with co-payments and differing insurance premiums for different levels of service made this annual cost assumption entirely plausible.

[13] Targeted biases include hypothetical and incentive compatibility biases as well as yea-saying behavior. Other biases that we address include order and sequencing effects, Weber's law in risk perception and various framing and anchoring concerns.

overstating their willingness to pay (Cummings and Taylor, 1999; List, 2001).[14] We also carefully explain to individuals that they can choose Neither Program and offer several reasons why a reasonable person might do so.[15]

The third module of the survey contains the five key choice sets that respondents are asked to consider independently. Each choice set offers two programs to reduce the risk of two distinct illness profiles.[16] In a preliminary ad hoc analysis to assess the construct validity of our study, we also explore whether individual choices are sensitive to the scope of the illness profile and risk-mitigating program (Hammitt and Graham, 1999; Yeung et al., 2003).[17]

The fourth module contains various debriefing questions that can be used to document the individual's status quo health state profile and to cross check the validity of their subjective responses in the first module (Baron and Ubel, 2002).

Module five was administered separately from the choice experiment. It collects a detailed medical history of the individual and household socio-economic information.[18]

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[14] This screen began "In surveys like this one, people sometimes do not fully consider their future expenses. Please think about what you would have to give up to purchase one of these programs. If you choose a program with too high a price, you may not be able to afford the program when it is offered…" An appendix available from the authors provides the complete context.

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

[16] Presenting individuals with a large array of illness risks had advantages and disadvantages. The greatest advantage was that individuals considered a more complete choice set, allowing us to observe how they substitute across programs associated with these competing illness risks. Second, presenting a range of major illnesses increases the representativeness of our estimates and makes the motivation of a fuller range of illness profiles plausible, and thus possible. One disadvantage is that it limits the background information that we could provide about each illness. A second potential disadvantage is the cognitive complexity associated with the choice task, which we sought to minimize, through the survey design, and to evaluate ex post.

[17] Additional appendix tables, available from the authors, report estimates for a standard atheoretic linear additively separable conjoint analysis. Individuals are highly sensitive to changes in the scope of our central attributes: the number of years spent in a morbid condition, the number of premature lost life years, the costs of the program, and the size of the risk reduction.

[18] We have a great deal of health and sociodemographic profile information on each individual that helps us to characterize his or her future health state expectations. A detailed assessment of the effects of comorbidity on willingness to pay for health risk reductions is the subject of a separate paper.

The development of this survey instrument involved 36 cognitive interviews, three pretests (n=100 each) and large pilot study (n=1,109).[19] Knowledge Networks Inc. (KNI) administered the final version of the demand survey and the health-profile survey to a sample of 2,439.[20] In addition to the benefits of regular KNI panel membership, respondents were paid an additional $10 incentive for completing the survey. Our response rate for those panelists contacted was 79 percent. Our observable sample characteristics are generally representative of the US population.[21] However, we have elsewhere explored for any problems in terms of sample selection on unobservables, relative to the entire pool of random-digit dialed original recruiting contacts for the KNI panel. Minimal sample selection distortions are present, so the results we present here do not include these further minor corrections.

Basic descriptive statistics for our randomized risk reduction programs and our survey respondents are provided in Table 1.

4 A Utility-Theoretic Choice Model

We expand upon most earlier empirical treatments by considering four distinct health states: 1) a pre-illness healthy state, 2) an illness (sick) state, 3) a post-illness recovered state and 4) a dead state.[22] 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. Let i index individuals and let t index time periods. To capture an illness profile, we use sets of dummy

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

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

[21] Appendix Table A-2 compares the marginal distributions for our sample against those for the 2000 Census for age, income and gender.

[22] Within our data, the illness states are further differentiated into specific named illnesses, each of which can exhibit a wide variety of different symptom-treatment profiles that may last for widely differing periods of time.

variables that collectively exhaust the period of time between the individual's present age and the end of his nominal life expectancy. We focus on single spells of illness. The dummy variable $1(\textit{pre-illness}_{it})$ take a value of 1 in years when the individual enjoys a healthy state. When the healthy state ends, the value of $1(\textit{pre-illness}_{it})$ 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, whereupon $1(\textit{illness}_{it})$ takes on a value of 1 in each period of illness. The individual may then recover, although perhaps not to the exact state of health he experienced prior to the illness. We define $1(\textit{recovered}_{it})=1$ for the periods between the conclusion of the illness and the individual's time of death. Finally, we $1(\textit{lost life-year}_{it})$ for the time periods between death and what would otherwise would have been the end of the individual's nominal lifespan.

For each health-state period, we assume initially that the indirect utility derived per unit of time from that particular health state is constant within that period. In our simplest model, the individual's future undiscounted indirect utility is linear and additively separable in the utility from an arbitrary function of income and the utility derived from each distinct health state:

$$
\begin{aligned}
V_{it} &= f(Y_{it}) + \alpha_0 1(\textit{pre-illness}_{it}) + \alpha_1 1(\textit{illness}_{it}) \\
&\quad + \alpha_1 1(\textit{recovered}_{it}) + \alpha_1 1(\textit{life-year lost}_{it}) + \eta_{it}
\end{aligned} \tag{3}
$$

where $f(Y_{it})$ is the indirect utility from income. Utility from health status in the pre-illness state, α_0, will be normalized to zero. Let α_1 be the undiscounted (dis)utility from a future year of illness, α_2 be the (dis)utility from a year of the post-illness recovered state, and α_3 be the (dis)utility from a year of being, prospectively, prematurely dead.

The simplest ways to accommodate heterogeneous preferences involve allowing these marginal (dis)utilities to depend upon characteristics of the individual *at the time they are asked to make program choices*. The individual's current age, age_{i0}, is one of a wide variety of personal characteristics that we might allow to shift the marginal (dis)utility of each adverse health state. In this paper, however, we wish to allow the indirect utility in each future period also to depend upon the future age of the individual while they are experiencing the health state corresponding to that future period, age_{it}. During the development of this specification, we will abstract temporarily from any systematic effects on preferences of differences in the individual's current age, age_{i0}. These "age now" effects will be re-introduced later as factors which shift the baseline utility parameters. Initially, we concentrate upon the more complicated manner in which future age_{it} enters the model--by shifting the marginal undiscounted utility from each distinct future health state. For example, $\alpha_1 = \alpha_{10} + \alpha_{11} age_{it} + \alpha_{12} age_{it}^2$. Throughout our analysis, the disutility of each adverse health state will be interpreted as being the same as the utility associated with avoiding it. The role of the time-indexed dummy variables, $1(illness_{it})$, $1(recovered_{it})$, and $1(\mathit{life\text{-}year\ lost}_{it})$ will be simply to adjust the limits of the summations used for the present value of future intervals of new illness, recovered time, and life-years lost. We will assume that the individual uses the same discount rate, *r*, to discount both future money costs and the future disutility from either illness or premature mortality.[23]

[23] 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)^{λ}. Other than this, the formulas will be the same.

With this framework, 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. Here, we use the terminology of "option price" in the sense of Graham (1981). Define the present discounted value of indirect utility V_i^{jk} for the i^{th} individual when j=A if the program is chosen and j=N if the program is not chosen. The superscript k will be S if the individual gets sick and H if the individual remains healthy.

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 individual's nominal life expectancy, and δ^{t}=(1+r)^{-t}.

(4) $$PDV\left(V_i^{AS}\right)=\sum \delta^t f\left(Y_{it}^*-c_{it}^{*A}\right)+pterm_i^A+\varepsilon_i^{AS}$$

where the terms capturing the details of the illness profile are:

(5)

$$\begin{aligned} pterms_i^A &= \alpha_{10}\sum \delta^t 1\left(illness_{it}^A\right)+\alpha_{11}\sum \delta^t age_{it}1\left(illness_{it}^A\right)+\alpha_{12}\sum \delta^t age_{it}^2 1\left(illness_{it}^A\right) \\ &+\alpha_{20}\sum \delta^t 1\left(recovered_{it}^A\right)+\alpha_{21}\sum \delta^t age_{it}1\left(recovered_{it}^A\right)+\alpha_{22}\sum \delta^t age_{it}^2 1\left(recovered_{it}^A\right) \\ &+\alpha_{30}\sum \delta^t 1\left(life\text{-}year\ lost_{it}^A\right)+\alpha_{31}\sum \delta^t age_{it}1\left(life\text{-}year\ lost_{it}^A\right)+\alpha_{32}\sum \delta^t age_{it}^2 1\left(life\text{-}year\ lost_{it}^A\right) \end{aligned}$$

Note that the respondent's imputed pattern of income and program costs under the four different health states will be relevant to their indirect utility in each state. We define

(6) $$\begin{aligned} Y_{it}^* &= Y_i\left[1\left(pre\text{-}illness_{it}^A\right)+\gamma_1 1\left(illness_{it}^A\right)+1\left(recovered_{it}^A\right)+\gamma_2 1\left(life\text{-}year\ lost_{it}^A\right)\right] \\ c_{it}^{*A} &= c_i^A\left[1\left(pre\text{-}illness_{it}^A\right)+\gamma_3 1\left(illness_{it}^A\right)+1\left(recovered_{it}^A\right)+\gamma_4 1\left(life\text{-}year\ lost_{it}^A\right)\right] \end{aligned}$$

We assume that $(\gamma_1,\gamma_2,\gamma_3,\gamma_4)=(1,0,0,0)$. In words, usual income is expected to be sustained through periods of illness via health and disability insurance, but not after death (there is no life insurance and there are no bequests). Program costs are expected to be paid only while the individual is alive and healthy.

If the individual does choose the program but does not suffer the illness, there will be no period of illness, no recovery, and no reduced lifespan. Both income and the annual costs of program will continue until the end of the individual's nominal life expectancy, so that the present value indirect utility is:

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

If the individual does *not* choose the program but *does* suffer the illness, his or her lifespan is potentially reduced, so future income continues only until the time of death, and $pterms_i^A$, capturing the avoided disutility of the illness, any recovery period, and any life-years lost, will again be relevant. Present value indirect utility is given by:

(8) $$PDV\left(V_i^{NS}\right) = \sum \delta^t f\left(Y_{it}^*\right) + pterms_i^A + \varepsilon_i^{NS}$$

If the individual does not choose the program and does not suffer the illness, we assume the individual anticipates that his current income level will be sustained until the end of his lifespan in the absence of premature mortality. Present value indirect utility is simply:

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

In deriving the individual's option price for Program A, 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 utilities are taken over the uncertainty about whether the individual will suffer the illness. The present value of expected utility $PDV\left(E\left[V_i^A\right]\right)$, if the individual buys program A, and $PDV\left(E\left[V_i^N\right]\right)$, if the program is not purchased (i.e. "Neither Program", N, is chosen) will be denoted as:

$$
\begin{aligned}
PDV\left(E\left[V_i^A\right]\right) &= \Pi_i^{AS} \times PDV\left(V_i^{AS}\right) + \left(1-\Pi_i^{AS}\right) \times PDV\left(V_i^{AH}\right) \\
PDV\left(E\left[V_i^N\right]\right) &= \Pi_i^{NS} \times PDV\left(V_i^{NS}\right) + \left(1-\Pi_i^{NS}\right) \times PDV\left(V_i^{NH}\right)
\end{aligned}
\tag{10}
$$

We assume that the expected discounted utility difference, $PDV\left(E\left[V_i^A\right]\right) - PDV\left(E\left[V_i^N\right]\right)$ drives the individual's decision to participate in program A. Details of the derivation of this expected discounted utility difference are provided in Appendix __.

In this paper, we assume that the function of income, $f\left(Y_{it}\right)$ is given by $\left(\beta_0 + \beta_1 Y_{it}\right) Y_{it}$, so the marginal utility of income is not constant simply at β_0, but free to vary with the level of income according to the magnitude of the parameter β_1. We make use of a number of notational abbreviations in getting to our empirical expected utility difference formula. First, let $\Delta\Pi_i^A = \Pi_i^{AS} - \Pi_i^{NS}$. In addition, there are many distinct present discounted value terms, each signalled by the prefix pdv. Let $pdvc_i = \sum \delta^t$, the present discounted number of years in the individual's nominal remaining lifespan. Let

$pdvp_i^A = \sum \delta^t \left[1\left(pre\text{-}illness_{it}\right) + 1\left(pre\text{-}illness_{it}\right) + 1\left(pre\text{-}illness_{it}\right)\right]$

the smaller present discounted number of years in the individual's remaining lifespan if the individual suffers the illness profile associated with the health threat addressed by Program A. Let $pdvl_i^A = \sum \delta^t 1\left(life\text{-}year\ lost_{it}^A\right)$, the present discounted number of life-years lost if the individual suffers the illness profile associated with Program A. Simplify further by using $PDV\left(E\left[lifespan_i^A\right]\right)$ to represent $\left(1-\Pi_i^{AS}\right) pdvc_i + \Pi_i^{AS} pdvp_i^A$, interpreted as the individual's expected present discounted lifespan remaining if they participate in program A (with the expectation taken with respect to whether the individual actually suffers the illness profile).

Key to our specifications are variables that consist of the present discounted interaction terms between health states and the individual's future age at the time each health state is experienced. Our abbreviations for these terms are prefixed by *agepdv* for linear age interactions and *age²pdv* for squared age interactions.[24]

A mathematical appendix available from the authors shows that the expected utility difference driving the individual's choice between Program A and the Neither Program alternative can then be written as a quadratic in c_i^A (there will be an analogous utility-difference for Program B versus the Neither Program alternative):

$$\begin{aligned} PDV\left(E\left[V_i^A\right]\right) - PDV\left(E\left[V_i^N\right]\right) &= A\left[c_i^A\right]^2 + B\left[c_i^A\right] + C \\ \text{where } A &= \beta_1 \cdot PDV\left(E\left[lifespan_i^A\right]\right) \\ B &= -\left(\beta_0 + 2\beta_1 Y_i\right) \cdot PDV\left(E\left[lifespan_i^A\right]\right) \\ C &= -\Delta\Pi_i^{AS}\left(\beta_0 + \beta_1 Y_i\right) Y_i pdvl_i^A + \Delta\Pi_i^{AS}\left[pterms_i^A\right] + \varepsilon_i^A \end{aligned} \tag{11}$$

[24] The complete definitions of these abbreviations are given in Appendix I.

and where the $pterms_i^A$ expression used in equation (5) can be expressed more succinctly using our new abbreviations, *agepdv* and *age²pdv,* as:

$$\begin{aligned} pterms_i^A &= \alpha_{10} pdvi_i^A + \alpha_{11} agepdvi_i^A + \alpha_{12} age^2 pdvi_i^A \\ &\quad + \alpha_{20} pdvr_i^A + \alpha_{21} agepdvr_i^A + \alpha_{22} age^2 pdvr_i^A \\ &\quad + \alpha_{30} pdvl_i^A + \alpha_{31} agepdvl_i^A + \alpha_{32} age^2 pdvl_i^A \end{aligned} \tag{12}$$

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, which requires that a number of variables be constructed. Each of the variables in the $pterms_i^A$ expression must be multiplied by the risk change (which is negative). Also, all terms involving each of the β_0 and β_1 parameters must be combined. These two constructed variables are calculated as:

$$\begin{aligned} \beta 0term_i^A &= -\left[c_i^A\right] PDV\left(E\left[lifespan_i^A\right]\right) - Y_i \Delta\Pi_i^{AS} pdvl_i^A \\ \beta 1term_i^A &= \left(\left[c_i^A\right]^2 - 2\left[c_i^A\right] Y_i\right) PDV\left(E\left[lifespan_i^A\right]\right) - Y_i^2 \Delta\Pi_i^{AS} pdvl_i^A \end{aligned} \tag{13}$$

Once the parameters have been estimated, we can revert to the expression for the utility difference as a quadratic function in the payment, c_i^A, that would make the utility-difference exactly zero.[25]

It is now straightforward to re-introduce the "age now" variable, age_{i0}. The baseline marginal utility parameters β_0, α_{10}, α_{20} and α_{30} can be allowed to shift with age_{i0} and age_{i0}^2. The coefficients on the linear age-at-health-state terms, α_{11}, α_{11} and α_{31}, can also be allowed to

[25] Of course, the squared term in c_i^A will be activated only if $\beta_1 \neq 0$. If the error term takes on its expected value of zero, the systematic portion of the difference in expected utilities can be solved to yield point estimates of the option price.

shift with age_{i0}, to permit interactions between current age and the age at which a particular health status is to be experienced.

Equation (11) demonstrates that the difference in expected present value indirect utilities associated with choosing a risk-reduction program is a function of income, program costs, the illness profile (as captured by the $pdvi_i^A$, $pdvr_i^A$ and $pdvl_i^A$ terms), and implicitly the individual discount rate r_i assumed for each respondent.[26] All choices posed to respondents are three-way choices (Program A, Program B, or Neither Program), so the models will be estimated using McFadden's conditional logit estimator (actually the fixed-effects variant of this model, to control for any unobserved heterogeneity across individuals that may be correlated with age).

The option price for the program that accomplishes this decrease in health risks is the common certain annual payment, c_i^{A*}, regardless of which way the uncertainty about contracting the illness is resolved, that will make $PDV\left(E\left[V_i^A\right]\right) - PDV\left(E\left[V_i^N\right]\right) = 0$. However, these annual payments $\hat{c}_i^{A*}$ are necessary for the rest of the individual's life, so their present value must be calculated.[27] We will use the present discounted expected value of this time profile of costs, $PDV\left(E\left[\hat{c}_i^{A*}\right]\right) = \left(\hat{c}_i^{A*}\right) PDV\left(E\left[lifespan_i^A\right]\right)$. To sketch the necessary calculations, we can revert to the case where the marginal utility of income is constant, so that $\beta_1 = 0$ β1=0, where the formula reduces to:

(14) $$PDV\left(E\left[\hat{c}_i^{*A}\right]\right) = \Delta\Pi_i^{AS} \beta_0^{-1}\left[-\beta_0 Y_i pdvl_i^A + pterms_i^A + \varepsilon_i^A\right]$$

---

[26] 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.

[27] 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.

If the marginal utility of income is constant across the population, as it is this special case, 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, as captured by the present discounted health state variables and their age-at-health-state interaction terms).

If one were to further assume that there was no heterogeneity in *VSL*s across illness profiles (captured by $pdvl_i^A$ and $pterms_i^A$ or the age of the individual, the $-\beta_0 Y_i pdvl_i^A + pterms_i^A$ terms in equation (14) would collapse into a single scalar parameter, α, multiplying a dummy variable, say D_i^A, that indicates whether this generic adverse health state affects the generic individual under alternative A. In many existing empirical studies, a parameter α describes the marginal utility of avoiding "sudden death this year":

$$(15)\qquad \begin{aligned} PDV\left(E\left[\hat{c}_i^{*A}\right]\right) &= \Delta\Pi_i^{AS}\beta_0^{-1}\left[\alpha D_i^A + \varepsilon_i\right] \\ &= \left(\alpha / \beta_0\right)\Delta\Pi_i^{AS} \text{ if } D_i^A = 1 \text{ and } \varepsilon_i = 0 \\ &= 0 \qquad\qquad\quad \text{if } D_i^A = 0 \text{ and } \varepsilon_i = 0 \end{aligned}$$

However, with the diverse sources of heterogeneity entertained in the present paper, these simplifications are not possible. Here, the process of calculating the expected present value of program costs in equation (??) does not produce a term that cancels 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 in equation (11).

The expected present discounted value in equation (14) pertains to the maximum annual willingness to pay for a small risk reduction, $\Delta\Pi_i^{AS}$. The proportionality assumption leads to a tradition in the mortality valuation literature of standardizing on a 100% risk difference to produce an estimate of the so-called "Value of a Statistical Life" (*VSL*). In the very special case of the variant in equation (15), division by the absolute risk change produces a *VSL* equal to -$\left(\alpha / \beta_0\right)$. To convert our more-general expected present value option price to something that might be termed the "value of a statistical illness profile" (*VSIP*), we could also divide our richer formula by the absolute size of the risk reduction. Using the same abbreviations B and C for the detailed expressions defined for equation (11), but again for the expositionally simpler case where $\beta_1 = 0$, the formula reduces to:

$$\text{(16)} \qquad \frac{PDV\left(E\left[c_i^{A*}\right]\right)}{\left|\Delta\Pi_i^{AS}\right|} = \beta_0^{-1}\left[\beta_0 Y_i pdvl_i^A - pterms_i^A + \frac{\varepsilon_i}{\left|\Delta\Pi_i^{AS}\right|}\right]$$

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 (16).[28] The *VSIP* 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 to be experienced. It will also depend upon the time profiles for each of these states as embedded in the terms $pdvi_i^A$, $pdvr_i^A$, $pdvl_i^A$, as well as $agepdvi_i^A$, $agepdvr_i^A$, $agepdvl_i^A$ and potentially $age^2 pdvi_i^A$, $age^2 pdvr_i^A$, $age^2 pdvl_i^A$, and (implicit in this model) upon the individual's own discount rate.[29]

In this simple model with a constant marginal utility of income, increases in income Y_i will increase the predicted point estimate of the *VSIP*. The effect of income on $VSIP_i^A$ is given by $\partial VSIP_i^A / \partial Y_i = pdvl_i^A$ which is non-negative. Thus the effect of an increase in income on the predicted *VSIP* will be larger (i.) as more life-years are lost, (ii.) as the individual is older, so that

[28] This ignores, for now, the asymptotic joint normality of the estimated marginal utility parameters obtained by maximum likelihood methods.
[29] 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.

life-years lost come sooner in time. The effect of income on *VSIP* can be estimated more generally if the marginal utility of income is not constant.[30]

The existing literature, especially the hedonic wage-risk literature, focuses most intently on society's willingness to pay for incremental reductions in the chance of a sudden accidental death in the current period. Thus there are no age-at-health-status differences that are not captured by age_{i0}. In the framework of our illness profiles, such an event would be captured by (1) zero years of morbidity and (2) 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 (assuming $\varepsilon_i = 0$ will be simply:

$$E\left[VSL\right] = \frac{PDV\left(E\left[c_i^{A*}\right]\right)}{\left|\Delta\Pi_i^{AS}\right|} = \left(\frac{-\alpha_{30}}{\beta_0} + Y_i\right) pdvl_i^A \tag{17}$$

where $pdvl_i^A = \sum \delta^t 1\left(\textit{life-year lost}_{it}^A\right)$. 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 the version of our model with homogeneous preferences, the *VSIP* will vary with age. Our *VSIP* estimates also depend upon the individual's income and discount rate. (See Cameron and DeShazo, 2004 for additional details.)

5 Results and Discussion

Our estimating sample is reduced in size from the 2439 respondents to 1801 by two main exclusion criteria. First, we exclude choice sets with outright scenario rejection. This is defined

[30] Nothing in this specification precludes negative point estimates of the *VSIP*. A positive *VSIP* estimate will result, however, if the estimated value of the marginal utility of income is positive and there are negative values for the marginal utilities of each adverse health state.

as a case where the individual selected the Neither Program alternative and indicated that their sole reason for doing so was that they did not believe the programs would work as described. Second, after the risk tutorial, respondents were asked to answer a question to verify their comprehension of the notion of risk used in the survey scenarios. If an individual answered this question incorrectly, we do not use any of their choices.[31] Furthermore, the estimates reported here are based upon an assumption of a 5% individual discount rate.[32] For any given discount rate, we must calculate in advance the various present discounted value terms (capturing the time profiles of morbidity and mortality) employed in construction of the eventual estimating variables.[33]

Our baseline Model 1, reported in Table 2, allows for the level of income to affect the marginal utility of additional income, but excludes any age effects on either the marginal utility of income or the marginal (dis)utilities of health states:

$$\begin{aligned} &PDV\left(E\left[V_i^A\right]\right) - PDV\left(E\left[V_i^N\right]\right) = \\ (18)\qquad &\beta_0\left\{\beta 0term_i^A\right\} + \beta_1\left\{\beta 1term_i^A\right\} \\ &+\alpha_{10}\left\{\Delta\Pi_i^{AS}pdvi_i^A\right\} + \alpha_{20}\left\{\Delta\Pi_i^{AS}pdvr_i^A\right\} + \alpha_{30}\left\{\Delta\Pi_i^{AS}pdvl_i^A\right\} + \varepsilon_i \end{aligned}$$

This model without age effects exhibits robust significance and the expected signs on all five basic marginal indirect utility parameters. The marginal utility of income is positive, but declines as expected with the level of income. The marginal utilities of sick-years, recovered years, and lost life-years are all negative. Post-illness ("recovered") years are not interpreted by

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[31] Additionally, about 1% of choice sets were excluded because a programming error in the randomized design algorithm created some illness profiles where the illness was reported to slightly extend, rather than reduce, the individual's life expectancy. While this outcome may be possible, we make a conservative choice and exclude these choice sets.
[32] Additional appendices, available from the authors, detail the results of sensitivity analyses with respect to the discounting assumptions used by considering both a 3% discount rate and a 7% discount rate. These rates were chosen based on the range of values recommended for benefit-cost analysis by the Science Advisory Board of the US EPA.
[33] In the models presented in this paper, we lean heavily on linearities that allow us to estimate our marginal utility parameters using packaged software algorithms for McFadden's conditional logit models.

respondents to be equivalent to pre-illness years. Respondents seem to impute 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 may be due to the fact that the illnesses are described as major life-threatening illnesses, including cancers, respiratory disease, and stroke, for example.[34]

Model 2, reported in Table 3, allows the marginal utility of income to be shifted by the respondent's current age (age_{i0}), and the marginal (dis)utility of each health state to vary linearly with both the respondent's current age (age_{i0}) and and future "age-at-health-state X" (age_{it} , embodied in the $agepdvX_i^A$ terms, where $X = i, r, l$):

$$
\begin{aligned}
(19)\qquad & PDV\left(E\left[V_i^A\right]\right) - PDV\left(E\left[V_i^N\right]\right) = \left(\beta_{00} + \beta_{01} age_{i0}\right)\left\{\beta 0 term_i^A\right\} + \beta_1\left\{\beta 1 term_i^A\right\} \\
& + \left[\alpha_{100} + \alpha_{101} age_{i0}\right]\left\{\Delta\Pi_i^{AS} pdvi_i^A\right\} + \alpha_{11}\left\{\Delta\Pi_i^{AS} agepdvi_i^A\right\} \\
& + \left[\alpha_{200} + \alpha_{201} age_{i0}\right]\left\{\Delta\Pi_i^{AS} pdvr_i^A\right\} + \alpha_{21}\left\{\Delta\Pi_i^{AS} agepdvr_i^A\right\} \\
& + \left[\alpha_{300} + \alpha_{301} age_{i0}\right]\left\{\Delta\Pi_i^{AS} pdvl_i^A\right\} + \alpha_{31}\left\{\Delta\Pi_i^{AS} agepdvl_i^A\right\} + \varepsilon_i
\end{aligned}
$$

This model succinctly makes the main point of this paper. The limited number of previous empirical studies of the effects of age on WTP for risk reductions have typically allowed *VSL* estimates to depend systematically only upon the respondent's current age. They have not considered the respondent's future age at the time the respondent would be experiencing different adverse health states. In most cases, this limitation is an artifact of the strategy of considering only current-period risk reductions, and only mortality risks.

In some of these earlier studies (e.g. Chestnut et al., 19__), there has been some evidence that WTP for risk reductions first increases, then decreases, with the individual's current age. Model 3 represents a distinct departure from any model that has been estimated in the prior

[34] In other work, we have shown that a better fit to the data can be obtained if we model choices as being determined by present discounted time in each future health state, and if utility is modeled as nonlinear in these present discounted time periods. The linear specification used in this paper is a convenient approximation.

literature. This model allows the marginal utility of a year in each type of adverse health state to vary linearly with both the respondent's age at the time of the survey and their future age when they would be experiencing each probabilistic adverse health state. The respondents age now does dictate the range of future ages at which these health states can possibly be experienced, so these two age variables will be correlated in our data. The estimates for Model 3 reveal that failure to control for age-at-health-state produces a substantial bias in the apparent effects of age now on the marginal disutility of each type of health state. In these linear specifications, age now decreases the disutility from a year in each health state (although not significantly so for the post-illness state), whereas age-at-health-state significantly increases the disutility from each type of adverse health state.

Model 3, with linear effects for both types of age variables, succinctly makes the main empirical point in this paper. WTP to avoid each adverse health state is greater, the more advanced the future age at which that health state would be experienced. However, the older the respondent is now, the less they are willing to pay to avoid adverse health states at any future age. These tendencies are very clear for avoided sick-years and avoided lost life-years, although they are less pronounced for avoided post-illness years. These findings are fully consistent with the two main hypotheses discussed in the theoretical section of this paper.[35]

However, one troubling feature of the Model 3 (with its linear age effects) is that it implies negative undiscounted fitted WTP estimates in early future years. This feature will tend to bias downward the present value employed as an estimate of the Value of a Statistical Illness Profile (*VSIP*) for near-term health threats. We suspect that many respondents, feeling currently

[35] We rely on the very strong statistical significant of the relevant individual parameter estimates in Model 3 to support the inference that these slopes are definitely not zero and that the lines for each current age group are indeed distinct.

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.[36]

In our survey, however, 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-health-state. This strategy maintains the hypothesis that survey subjects are responding to exactly the illness profile information provided in the survey, but assesses whether these intervals of age-at-health-status displaying negative fitted undiscounted WTP may be simply an artifact of functional form.

Finally, Model 3 allows each of the (dis)utilities of the different health states to be fully quadratic in the respondent's age now (age_{i0}) and age-at-event (age_{it}, via the $agepdvX_i^A$ and $age^2 pdvX_i^A$ terms).

$$
\begin{aligned}
PDV\left(E\left[V_i^A\right]\right) - PDV\left(E\left[V_i^N\right]\right) &= \left(\beta_{00} + \beta_{01} age_{i0}\right)\left\{\beta 0term_i^A\right\} + \beta_1\left\{\beta 1term_i^A\right\} \\
&+\left[\alpha_{100} + \alpha_{101} age_{i0} + \alpha_{102} age_{i0}^2\right]\left\{\Delta\Pi_i^{AS} pdvi_i^A\right\} \\
&\quad +\left[\alpha_{110} + \alpha_{111} age_{i0}\right]\left\{\Delta\Pi_i^{AS} agepdvi_i^A\right\} + \alpha_{13}\left\{\Delta\Pi_i^{AS} age^2 pdvi_i^A\right\} \\
&+\left[\alpha_{200} + \alpha_{201} age_{i0} + \alpha_{202} age_{i0}^2\right]\left\{\Delta\Pi_i^{AS} pdvr_i^A\right\} \qquad (20) \\
&\quad +\left[\alpha_{210} + \alpha_{211} age_{i0}\right]\left\{\Delta\Pi_i^{AS} agepdvr_i^A\right\} + \alpha_{23}\left\{\Delta\Pi_i^{AS} age^2 pdvr_i^A\right\} \\
&+\left[\alpha_{300} + \alpha_{301} age_{i0} + \alpha_{302} age_{i0}^2\right]\left\{\Delta\Pi_i^{AS} pdvl_i^A\right\} \\
&\quad +\left[\alpha_{310} + \alpha_{311} age_{i0}\right]\left\{\Delta\Pi_i^{AS} agepdvl_i^A\right\} + \alpha_{33}\left\{\Delta\Pi_i^{AS} age^2 pdvl_i^A\right\} + \varepsilon_i
\end{aligned}
$$

[36] It is not clear whether this should be interpreted as a form of partial scenario rejection (or scenario revision) in response to our stated preference choice scenarios, or whether this is a legitimate property of people's preferences. We explore this possibility further in a separate study.

In contrast to these other studies, if we allow our marginal utilities to be quadratic in current age, there are no individually statistically significant coefficients at all in the expressions for the marginal utilities of health states. The marginal utility of income should be positive, but is not constrained to be positive in these models. Our different competing specifications also involve sets of parameters that describe the marginal (dis)utility of a sick year, a recovered year, and a lost life-year. The marginal utilities of adverse health states should also be negative, at least on average, but for tractability in estimation we do not enforce this restriction.[37]

In Model 3, we allow all marginal utilities from adverse health states to be fully quadratic functions of both age now and age-at-event. In terms of statistical significance of the individual parameters in each health-state marginal utility expression, the results can only be described as underwhelming. However, we entertain this model to consider its beneficial effects on the fitted near-term undiscounted WTP estimates. Figures 1 and 2 display the profiles of undiscounted WTP to avoid statistical years in each adverse health state, according to the fully quadratic model. It seems clear that the negative near-term estimates of undiscounted WTP from Model 2 are merely an artifact of the too-strong linearity assumption. Overall, figures 1 and 2 suggest that most respondents place little value on avoiding a sick-year that will occur prior to their 50s.[38] Respondents who are currently younger place higher value on avoiding future sick-years at specified ages than do currently older respondents (for adverse health states at those same

[37] One would typically expect that the marginal utility of a lost-life-year would be negative, but there may be specific exceptions. A positive marginal utility associated with a lost life-year might be expected when the illness is question constitutes a "fate worse than death." For certain illnesses, perhaps some cancers, 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.

[38] The downward-sloping and/or slightly negative portions of the curves in these figures are most likely just an artifact of fitting the best quadratic form to the mass of the data, which will tend to lie higher up in the age-at-health-state distribution.

specified ages). Similar patterns, to a greater or lesser degree, are apparent for recovered-years (not graphed) and for lost life-years, as displayed in Figure 2.[39]

We could use Model 3 as the basis for our simulations in the next section, since the results appear to be the least contaminated by negative undiscounted WTP to avoid very near-term portions of any risk profile. However, the least statistically significant coefficients in this specification contribute to some unnecessarily wide (5%, 95%) intervals in our simulated *VSIP* distributions. To minimize this problem, Model 4 in Table 3 backs off from the fully quadratic specification to consider a more parsimonious version of the quadratic specification. An interaction term between age now and age-at-health-state is strongly statistically significant for the marginal disutility of a sick-year. This same interaction term, plus the quadratic term in age now, are significant shifters of the marginal disutility of a lost life-year. These results suggest that the most statistically defensible model is richer than the simple linear specification in Model 2, but perhaps not as elaborate as the fully quadratic specification in Model 3.[40]

Fitted *VSIP*s for the estimating sample of illness profiles described in Table 1 can be readily computed. However, these *VSIP* 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 many short-term and non-fatal illnesses among the programs we presented to respondents. Thus,

[39] Model 5 creates a strong impression that it will be desirable in future work to break away from linear-in-parameters models, in spite of their extremely attractive properties for ease of estimation. 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, may be promising.

[40] It is very likely that the statistical insignificance of individual quadratic and interaction terms in age now and age-at-health-state is, to some extent, a result of the degree of collinearity between these two age variables that is created because we ask individuals to consider only future health states. In any event, the medians for simulations we explore are not qualitatively different for Models 4 and 5, and the confidence intervals are only slightly narrower.

we would not expect to see anything akin to the usual $6.1 million *VSL* estimate in these distributions.[41]

How do the WTP implications from our statistical illness model comport with those of earlier *VSL* studies? 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 will focus on the predicted *VSIP* for an illness profile consisting of sudden death for a 45-year-old. However, in order to highlight the greater generality of our WTP models across different patterns of age and disease latency, 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 the same individuals value a reduction in the chance of sudden death starting 10 years from now?
Simulation 3: How would they 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 4 summarizes the results of these four classes of simulations for Models 1 and 4.[42] 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 *VSIP*. We report the median of this distribution, as well as the 5th and 95th percentiles.[43]

[41] Descriptive statistics of fitted *VSIP*s for the estimating sample are provided in an appendix, Table A-6, available from the authors.

[42] Results for other specifications are relegated to an appendix, available from the authors. Of particular note is the fact that the simulations for the complete and parsimonious quadratic models are very similar in their median values, but the (5%,95%) interval for the parsimonious model is smaller because the specification is limited to fewer, more precisely estimated parameters.

[43] Technically, the mean of this distribution is undefined, since it the mean of a ratio of normally distributed random variables. We report these selected percentiles of the sampling distribution of these different point estimates to convey the implications of the degree of precision in the parameter estimates.

Since it concerns sudden death in the current year for a 45-year-old, the middle row for Simulation 1 is the closest thing we have to a conventional wage-risk *VSL*, so it is highlighted in boldface type. With no age effects, Model 1 conforms as closely as possible to the implicit risk assumptions underlying many previous studies. The median predicted *VSIP* is nevertheless still expected to differ with the respondent's current age because our model emphasizes life-years and involves discounting. Remarkably, despite these fundamental differences from previous models, our median *VSIP* for sudden death for a 45-year-old is $5.86 million, with simulated 90% confidence bounds of $4.44 million to $7.45 million. This range of estimates subsumes the roughly $6 million estimate used routinely by the US EPA in their major benefit-cost analyses.

However, our data emphatically reject Model 1 in favor of models that acknowledge the systematic variation of WTP for risk reductions with respect to age variables. Controlling for our two types of age effects, Model 4 suggests somewhat lower median values (around $3.25 million) for the *VSIP* in Simulation 1, for sudden death now for a 45-year-old. This estimate more closely matches the roughly $3 million estimate used by the US Department of Transportation for highway risks. This *VSIP* is also closer to the $3.7 million proposed by the U.S. Office of Management and Budget (OMB) as a revision to “the” Value of a Statistical Life.

The main insight from our research, however, is that seems inappropriate to use one single *VSL* value for all types of health risks and all types of populations. For bevity's sake in this paper, we limit our simulations only to the “sudden death” case, but vary both the latency of this threat and the individual's current age. For example, in Simulation 2 (sudden death in 10 years), the *VSIP* appears to decline by 50% between age 45 and age 65.[44] In contrast, the two competing types of age effects seems to more-or-less offset each other as we consider Simulation 3 (sudden

[44] Note that we need to be somewhat cautious due to the negative near-future predicted WTP for avoided lost life-years in the case of 25-year-olds and 35-year-olds.

death at age 70) for individuals of increasing current age. Finally, for individuals of the same current age (25 years) considering sudden death with increasingly greater latency (Simulation 4), note that we need to view the *VSIP*s for death at age 30 and death at age 40 with some skepticism because of the remaining negative range in the fitted undiscounted WTP for future lost life-years. However, where the fitted values are most plausible, the *VSIP* appears to decline with the age at which death would occur.

Across just these two dimensions of heterogeneity in risks (i.e. latency) and affected populations (i.e. age now), the simulation results for Model 4 suggest the possibility of considerable variability. When varying durations of pre-mortality morbidity are added to the mix, the variability in *VSIP*s can likely be expected to be much greater.

What about the evidence for a systematic senior death discount? The greater willingness to pay among younger people for reduction of health risks at any given future age is offset by the fact that this willingness to pay is more heavily discounted. For the more reliable simulated scenarios in Table 3, however, there is some evidence of a senior discount in Simulation 2 and Simulation 4, but little evidence of a senior discount for the other two cases. Based on the evidence in our estimated models, our conclusion is that the heterogeneity in *VSIP*s is likely to be far more complex than anything that could be captured by a simple pair of differentiated *VSL*s for adults and seniors.

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 may be important to preserve information about the nature of the risk reduction involved (its size, and perhaps the baseline risk), we show in this paper that our option price WTP formulas lead naturally to what we have labeled as the "value of a statistical illness profile" (*VSIP*). The *VSIP* 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, 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, older individuals seem willing to pay less to reduce risks to their health.

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Table 1
Descriptive statistics for Risk Reduction Programs (5% discount rate) and Respondents;
(7520 choice sets; 22560 alternatives; 15040 profiles; 1619 individuals)

Variable	Mean	Std. Dev.	Min	Max
Risk Reduction Programs				
Present discounted sick-years	2.21	2.51	0	16.3
Present discounted recovered-years	0.474	1.36	0	15.9
Present discounted lost life-years	2.57	2.93	0	17.8
Monthly cost	$ 29.87	28.71	2	140
Risk change	-.00341	.00167	-0.006	-0.001
Respondents				
income	$ 50,771	33,966	5,000	150,000
age (years)	50.30	15.21	25	93
female (1=female, 0=male)	0.513			

Table 2 - Parameter Estimates with Homogeneous Preferences

Parameter and description of variable(s)	**Model 1** No Age Effects
β_{00} *10^{-5} (linear net Y term)	4.875 (8.60)***
β_3 *10^{-9} (DMU(Y) term)	-0.2199 (-4.71)***
$\alpha_{100}\Delta\Pi_i^{AS}\, pdvi_i$	-8.390 (-5.00)***
$\alpha_{200}\Delta\Pi_i^{AS}\, pdvr_i$	-8.0219 (-2.48)**
$\alpha_{300}\Delta\Pi_i^{AS}\, pdvl_i$	-8.083 (-6.04)***
Alternatives	22560
Log L	-11733.469

Table 3 - Parameter Estimates for Quadratic-in-Age Specifications

Parameter and description of variable(s)	**Model 2** Both Age Effects (linear)			**Model 3** Both Age Effects (quadratic)			**Model 4** Parsimonious Variant (quadratic)		
β_{00} *10^-5 ($\beta 0term_i^j$)		6.987 (3.92)***			8.079 (4.24)***			7.542 (4.13)***	
β_{01} *10^-7 ($age_{i0} \times \beta 0term_i^j$)		-3.345 (-1.25)			-5.259 (-1.78)*			-4.656 (-1.66)*	
β_3 *10^-9 ($\beta 1term_i^j$)		-0.2015 (-4.25)***			-0.2017 (-4.25)***			-.2031 (-4.29)***	
X=	***Sick years***	***Recovered years***	***Lost life-years***	***Sick years***	***Recovered years***	***Lost life-years***	***Sick years***	***Recovered years***	***Lost life-years***
$\alpha_{j00} \Delta\Pi_i^{jS} pdvX_i^j$	1.316 (0.11)	53.26 (2.27)**	8.288 (0.73)	-10.79 (-0.19)	-49.15 (-0.51)	79.36 (1.29)	47.80 (2.65)***	42.38 (2.13)**	95.08 (2.25)**
$\alpha_{j01} age_{i0} \times \Delta\Pi_i^{jS} pdvX_i^j$	1.1783 (4.95)***	0.3965 (0.85)	1.047 (5.07)***	-1.170 (-0.59)	-4.449 (-1.04)	-0.3568 (-0.17)	-	-	0.5216[a] (0.73)
$\alpha_{j02} age_{i0}^2 \times \Delta\Pi_i^{jS} pdvX_i^j$	-	-	-	-0.0133 (-0.59)	-0.0132 (-0.27)	-0.0402 (-1.95)*	-	-	-0.0381 (2.27)**
$\alpha_{j10} \Delta\Pi_i^{jS} agepdvX_i^j$	-1.0029 (-3.43)***	-1.2055 (-2.08)**	-1.0032 (-3.69)***	1.154 (0.42)	5.692 (1.10)	-2.109 (-0.70)	-1.561 (-3.82)***	-0.7653 (-2.67)***	-3.364 (3.28)***
$\alpha_{j11} age_{i0} \times \Delta\Pi_i^{jS} agepdvX_i^j$	-	-	-	0.0504 (1.00)	0.0881 (0.81)	0.0737 (1.50)	0.0142 (4.58)***	-	0.0573 (2.41)**
$\alpha_{j2} \Delta\Pi_i^{jS} age^2 pdvX_i^j$	-	-	-	-0.0333 (-0.97)	-0.0835 (-1.21)	-0.0163 (-0.46)	-	-	-
Choices Maximized Log L		22560 -11700.9			22560 -11697.01			22560 -11699.009	

[a] We retain the insignificant linear term when the higher-order (quadratic) term is statistically significant.

Table 4
VSI for Four Classes of Sudden Death Scenarios (US $ million), based on 22560 alternatives

	Age Now	Age at Death	Latency	**Model 1** No Age Effects 50% (5%,95%)	**Model 4** Parsimonious (quadratic) 50% (5%,95%)
1. Simulation: Sudden death this year	25	25	0	6.36 (4.82, 8.09)	-0.46 (-5.84, 5.49)[a]
	35	35	0	6.18 (4.68, 7.86)	1.89 (-0.84, 5.34)[a]
	45	**45**	**0**	**5.86 (4.44, 7.45)**	**3.25 (0.95, 6.12)**
	55	55	0	5.46 (4.14, 6.95)	3.88 (1.02, 7.28)[b]
	65	65	0	4.88 (3.70, 6.21)	3.47 (0.21, 7.61)[b]
2. Simulation: Sudden death in 10 years	25	35	10	4.91 (3.72, 6.25)	2.47 (-0.79, 6.43)[a]
	35	45	10	4.73 (3.59, 6.02)	3.50 (1.80, 5.99)[a]
	45	55	10	4.41 (3.34, 5.61)	3.63 (2.29, 5.41)
	55	65	10	4.01 (3.04, 5.11)	3.20 (1.72, 4.87)
	65	75	10	3.43 (2.60, 4.37)	2.02 (0.54, 3.63)
3. Simulation: Sudden death @ fixed age (70)	25	70	45	0.42 (0.32, 0.53)	1.86 (1.24, 3.00)
	35	70	35	0.70 (0.53, 0.90)	2.14 (1.56, 3.04)
	45	70	25	1.15 (0.87, 1.46)	2.05 (1.51, 2.72)
	55	70	15	1.99 (1.51, 2.54)	1.87 (1.13, 2.71)
	65	70	5	3.43 (2.60, 4.37)	2.02 (0.54, 3.63)
4. Simulation: Sudden death varying latency	25	30	5	4.91 (3.72, 6.25)	2.47 (-0.79, 6.43)[a]
	25	40	15	2.89 (2.19, 3.67)	4.61 (2.94, 7.52)[a]
	25	50	25	1.65 (1.25, 2.09)	4.33 (3.03, 6.88)
	25	60	35	0.88 (0.67, 1.13)	3.18 (2.17, 5.09)
	25	70	45	0.42 (0.32, 0.53)	1.86 (1.24, 3.00)

[a] Likely to be slightly underestimated because of negative near future values in fitted undiscounted WTP (see Figure 2).
[b] Likely to be slightly overestimated due to upward-bending portion of quadratic form in near-future fitted undiscounted WTP (see figure 2).

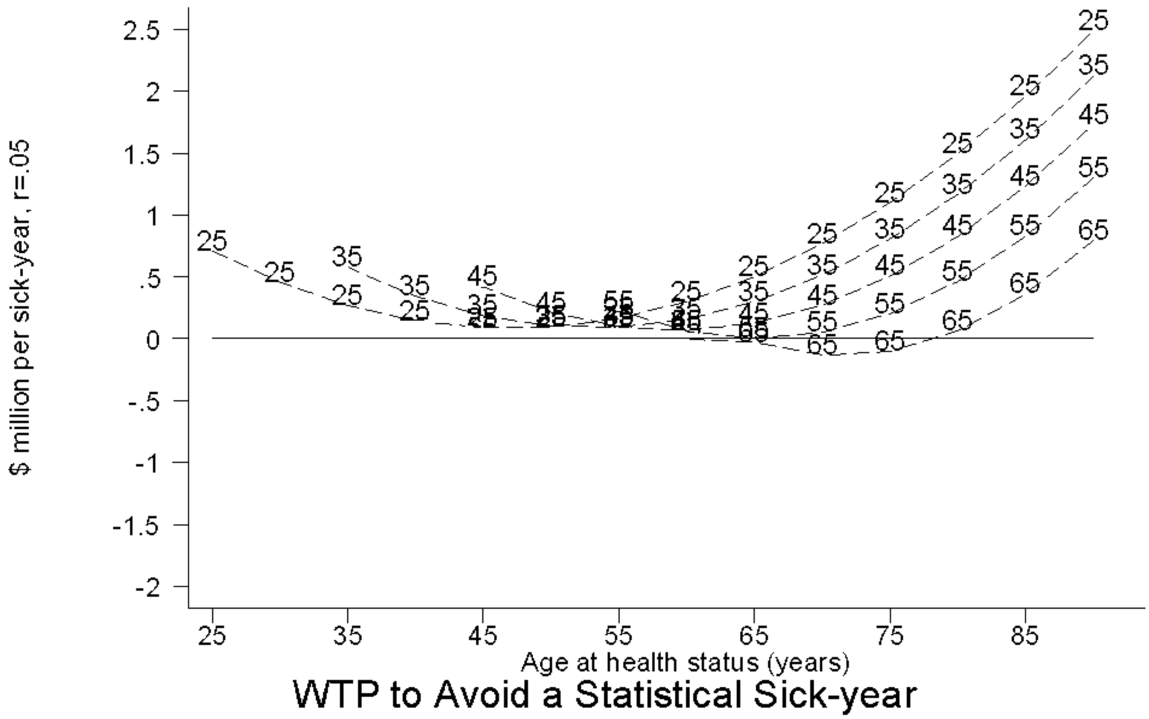

Figure 1 – Quadratic Model: Fitted future current values for Statistical Sick-years, for individual now 25, 35, 45, 55 and 65.

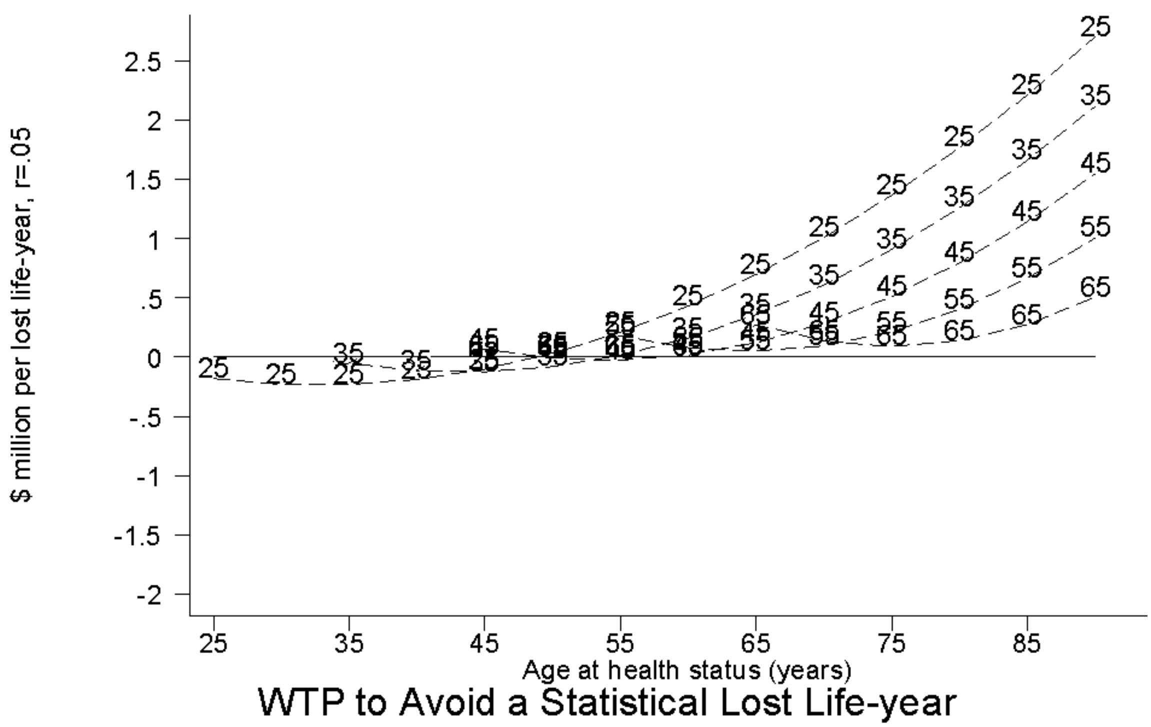

Figure 2 – Quadratic Model: Fitted future current values for Statistical Lost Life-years, for individual now 25, 35, 45, 55 and 65.

APPENDIX TABLES

Table A-1 – Sample versus Population Characteristics (percent)

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

Table A-2
Distribution of Program Characteristics within Illness Types
(1619 individuals, 7520 choice sets, 15040 illness profiles, 22560 alternatives)

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

------------------------- END OF TABLES FOR PUBLICATION --------------------------------

Reviewers Only Table A-3 – Sample versus Population Characteristics (percent)

Including "minimum time-on-task subsample"

	Sample n=1619 individuals	Sample n=1407 individuals (Min time on task)	2000 U.S. Census
Age			% of 25+ pop
25 to 34	18	16	22
35 to 44	23	22	25
45 to 54	21	21	21
55 to 64	17	19	7
65 to 74	14	15	6
75 and older	7	8	10
Income			% of hhlds
Less than $10,000	5.7	5.3	9.5
$10,000 to $15,000	6.1	6.1	6.3
$15,000 to $20,000	4.9	5.0	6.3
$20,000 to $25,000	6.1	6.3	6.6
$25,000 to $30,000	6.6	6.5	6.4
$30,000 to $40,000	7.4	16.2	6.4
$40,000 to $50,000	8.6	13.3	5.9
$50,000 to $60,000	13.3	11.0	10.7
$60,000 to $75,000	11.1	11.3	9.0
$75,000 to $100,000	11.1	10.5	10.4
$100,000 to $125,000	10.4	4.1	10.2
More than $125,000	4.2	4.3	5.2
Female	0.51	0.53	0.51

Reviewers Only Table A-4

Model 2' (limited to subsample satisfying minimum time-on-task requirement)

Parameter and description of variable(s)		**Model 2'** Age Now Effects Only (quadratic)	
β_{00} *10^{-5} ($\beta 0term_i^j$)		4.020	
		(2.34)**	
β_{01} *10^{-7} ($age_{i0} \times \beta 0term_i^j$)		0.292	
		(0.11)	
β_3 *10^{-9} ($\beta 1term_i^j$)		-0.2033	
		(4.30)***	
	Sick years	***Recovered years***	***Lost life-years***
	X=i	*X=r*	*X=l*
$\delta_{100} \Delta\Pi_i^{jS} pdvX_i^j$	-33.05	19.97	-26.12
	(1.62)	(0.54)	(-1.62)
$\delta_{101} age_{i0} \times \Delta\Pi_i^{jS} pdvX_i^j$	0.513	-0.6913	0.3965
	(0.64)	(-0.45)	(0.61)
$\delta_{102} age_{i0}^2 \times \Delta\Pi_i^{jS} pdvX_i^j$	-0.0002	0.0023	-0.0004
	(-0.03)	(0.15)	(-0.06)
Alternatives		22560	
Log L		-11714.527	

Time on Task:

We wondered whether our empirical results from our fully quadratic specification in Model 4 were being somewhat confounded by a minority of individuals who rushed through the survey without devoting much careful consideration to their choices. As a check on this possibility, we limited the sample to only those individuals who spent an average of at least 20 seconds on each choice set page of the survey. We term this restriction a "minimum time-on-task" requirement. This limitation reduces the number of choice sets in the estimation from 7520 to 6627. However, Model 4 estimated on this limited sample produces a number of statistically significant coefficients among the terms associated with the marginal disutility of a sick-year and the marginal disutility of a lost life-year, and the signs of the statistically significant coefficients match those produced with the full sample.

Reviewers Only Table A-5

Model 4' (limited to subsample satisfying minimum time-on-task requirement)

Parameter and description of variable(s)		**Model 4'** Both Age Effects (Min. time on task)	
β_{00} *10^{-5} ($\beta 0 term_i^j$)		8.186	
		(4.01)***	
β_{01} *10^{-7} ($age_{i0} \times \beta 0 term_i^j$)		-5.034	
		(-1.61)	
β_3 *10^{-9} ($\beta 1 term_i^j$)		-.233	
		(-4.59)***	
	Sick years	***Recovered years***	***Lost life-years***
	X=i	*X=r*	*X=l*
$\delta_{100} \Delta \Pi_i^{jS} pdvX_i^j$	-79.87	-31.26	45.01
	(-1.27)	(-0.30)	(0.70)
$\delta_{101} age_{i0} \times \Delta \Pi_i^{jS} pdvX_i^j$	-3.547	-5.869	-2.346
	(-1.65)*	(-1.26)	(-1.04)
$\delta_{102} age_{i0}^2 \times \Delta \Pi_i^{jS} pdvX_i^j$	-0.0292	-0.0218	-0.0550
	(-1.21)	(-0.42)	(-2.51)**
$\delta_{110} \Delta \Pi_i^{jS} agepdvX_i^j$	5.106	6.523	0.6322
	(1.70)*	(1.15)	(0.20)
$\delta_{111} age_{i0} \times \Delta \Pi_i^{jS} agepdvX_i^j$	0.1083	0.1235	0.1263
	(1.98)**	(1.03)	(2.40)**
$\delta_{12} \Delta \Pi_i^{jS} age^2 pdvX_i^j$	-0.0842	-0.1055	-0.0579
	(-2.25)**	(-1.38)	(-1.53)
Alternatives		*19881*	
Log L		-10295.367	

Reviewers Only Table A-6
Fitted VSIs for Illness Profiles used in Estimating Sample
($ million)

Descriptive Statistic	**Model 1** No Age Effects	**Model 2** Age Now Effects (linear)	**Model 2'** Age Now Effects (quadratic)	**Model 3** Both Age Effects (linear)	**Model 4** Both Age Effects (quadratic)	**Model 4'** Both Age Effects (Min time on task)	**Model** 5 Parsimonious Variant (quadratic)
Sample mean VSI	1.63	0.69	2.75	7.09	2.54	2.62	4.85
Sample 5th %	0 [a]	0	0	0 [a]	0 [a]	0 [a]	0
Sample 25th %	0.41	0	0.2	0.81	0.17	0.13	0.61
Sample 50th %	1.08	0	1.22	2.04	1.25	1.60	1.97
Sample 75th %	2.16	0	3.26	3.77	2.59	3.29	3.63
Sample 95th %	5.09	3.03	10.44	10.45	5.46	7.46	9.78
Alternatives used	22560	22560	22560	22560	22560	*19881*	22560

[a] 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. Means are sensitive to large positive outliers.

Reviewers Only Table A-7 (simulations for other models, analogous to Table 3)

VSI for Four Classes of Sudden Death Scenarios (US $ million), based on 22560 alternatives

	Age Now	Age at Death	Latency	**Model 2** Age Now Effects Only (linear) 50% (5%,95%)	**Model 2'** Age Now Effects Only (quadratic) 50% (5%,95%)
1. Simulation: Sudden death this year	25	25	0	2.03 (-1.69, 7.50)	15.10 (7.58, 38.64)
	35	35	0	-3.33 (-11.26, 2.75)	11.29 (7.48, 21.35)
	45	**45**	**0**	**-7.94 (-18.51, -0.30)**	**7.85 (5.52, 11.33)**
	55	55	0	-11.79 (-24.23, -2.51)	4.68 (2.68, 7.18)
	65	65	0	-14.47 (-28.93, -3.94)	1.97 (-0.15, 4.16)
2. Simulation: Sudden death in 10 years	25	35	10	0.64 (-3.35, 4.72)	11.66 (5.86, 29.85)
	35	45	10	-3.48 (-10.5, 1.53)	8.65 (5.73, 16.35)
	45	55	10	-6.80 (-15.36, -0.67)	5.91 (4.15, 8.53)
	55	65	10	-9.33 (-18.95, -2.19)	3.44 (1.97, 5.28)
	65	75	10	-10.75 (-21.37, -3.04)	1.38 (-0.11, 2.93)
3. Simulation: Sudden death @ fixed age (70)	25	70	45	-0.54 (-1.86, -0.01)	0.99 (0.50, 2.54)
	35	70	35	-1.25 (-3.06, -0.19)	1.29 (0.85, 2.44)
	45	70	25	-2.51 (-5.39, -0.55)	1.54 (1.08, 2.22)
	55	70	15	-5.29 (-10.47, -1.41)	1.71 (0.97, 2.62)
	65	70	5	-10.75 (-21.37, -3.04)	1.38 (-0.11, 2.93)
4. Simulation: Sudden death varying latency	25	30	5	0.64 (-3.35, 4.72)	11.66 (5.86, 29.85)
	25	40	15	-0.79 (-4.44, 1.84)	6.86 (3.45, 17.56)
	25	50	25	-1.07 (-4.16, 0.60)	3.91 (1.96, 10.02)
	25	60	35	-0.88 (-3.14, 0.14)	2.10 (1.06, 5.39)
	25	70	45	-0.54 (-1.86, -0.01)	0.99 (0.50, 2.54)

Reviewers Only Table A-7 (simulations for other models, analogous to Table 3)

VSI for Four Classes of Sudden Death Scenarios (US $ million), based on 22560 alternatives

	Age Now	Age at Death	Latency	**Model 3** Both Age Effects (linear) 50% (5%,95%)	**Model 4** Both Age Effects (quadratic) 50% (5%,95%)
1. Simulation: Sudden death this year	25	25	0	4.30 (1.31, 8.80)	0.35 (-7.53, 8.06)
	35	35	0	3.68 (1.20, 7.02)	2.48 (-2.53, 7.53)
	45	**45**	**0**	**2.69 (0.56, 5.17)**	**3.54 (-0.01, 7.36)**
	55	55	0	1.61 (-0.43, 3.69)	3.98 (0.66, 7.48)
	65	65	0	0.24 (-2.10, 2.46)	3.38 (-0.14, 7.38)
2. Simulation: Sudden death in 10 years	25	35	10	4.78 (2.79, 8.16)	2.33 (-1.39, 6.38)
	35	45	10	4.31 (2.78, 6.67)	3.39 (1.37, 5.86)
	45	55	10	3.47 (2.32, 5.10)	3.56 (2.14, 5.21)
	55	65	10	2.56 (1.51, 3.80)	3.20 (1.94, 4.69)
	65	75	10	1.40 (0.01, 2.70)	2.12 (0.60, 3.70)
3. Simulation: Sudden death @ fixed age (70)	25	70	45	1.31 (0.93, 1.97)	1.93 (1.20, 3.04)
	35	70	35	1.86 (1.37, 2.56)	2.26 (1.61, 3.17)
	45	70	25	2.28 (1.78, 2.95)	2.21 (1.69, 2.94)
	55	70	15	2.54 (1.97, 3.17)	2.12 (1.31, 2.92)
	65	70	5	1.40 (0.01, 2.70)	2.12 (0.60, 3.70)
4. Simulation: Sudden death varying latency	25	30	5	4.78 (2.79, 8.16)	2.33 (-1.39, 6.38)
	25	40	15	4.58 (3.31, 7.11)	4.08 (2.52, 6.34)
	25	50	25	3.55 (2.61, 5.34)	4.04 (2.73, 6.12)
	25	60	35	2.37 (1.70, 3.54)	3.13 (2.13, 4.78)
	25	70	45	1.31 (0.93, 1.97)	1.93 (1.20, 3.04)

Reviewers Only Table A-8

Sensitivity of Parameter Estimates to Alternative Discount Rate Assumptions: Models 1, 3, and 4

(Sensitivity Analysis uses 19788 alternative sample)

	3% discount rate			**5% discount rate**			7% discount rate		
Parameter and description of variable(s)	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} *10^{-5} ($\beta 0term_i^j$)	3.83 (8.60)***	6.11 (4.20)***	7.26 (4.54)***	**4.62** **(8.31)*****	**8.29** **(4.37)*****	**10.09** **(4.81)*****	5.336 (7.97)***	9.658 (4.14)***	12.93 (4.94)***
β_{01} *10^{-7} ($age_{i0} \times \beta 0term_i^j$)		-3.65 (-1.64)	-5.44 (2.15)**		**-5.61** **(1.98)****	**-8.34** **(2.58)*****		-6.296 (1.84)*	-11.19 (2.83)***
β_3 *10^{-9} ($\beta 1term_i^j$)	-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									
$\delta_{100} \Delta\Pi_i^{jS} pdvi_i^j$	-7.460 (6.01)***	0.0323 (0.00)	-69.03 (-1.40)	**-9.6248** **(5.41)*****	**2.096** **(-0.17)**	**-85.16** **(-1.35)**	-11.582 (4.79)***	3.653 (-0.23)	-105.6 (-1.33)
$\delta_{101} age_{i0} \times \Delta\Pi_i^{jS} pdvi_i^j$		0.6526 (4.22)***	-2.101 (-1.52)		**1.314** **(5.04)*****	**-3.6357** **(1.68)***		2.2562 (5.43)***	-6.095 (1.86)*
$\delta_{102} age_{i0}^2 \times \Delta\Pi_i^{jS} pdvi_i^j$			0.0018 (-0.13)			**-0.0243** **(-1.01)**			-0.0931 (2.22)**
$\delta_{110} \Delta\Pi_i^{jS} agepdvi_i^j$		-0.5568 (2.76)***	3.600 (1.72)*		**-1.136** **(3.55)*****	**5.352** **(1.77)***		-1.9604 (4.04)***	8.043 (1.88)*
$\delta_{111} age_{i0} \times \Delta\Pi_i^{jS} agepdvi_i^j$			0.0352 (-1.13)			**0.1025** **(1.86)***			0.2536 (2.66)***
$\delta_{12} \Delta\Pi_i^{jS} age^2 pdvi_i^j$			-0.0428 (1.86)*			**-0.0842** **(2.23)****			-0.167 (2.73)***

Table A-8, continued:

Recovered years									
$\delta_{200}\Delta\Pi_i^{jS}\,pdvr_i$	-6.423	47.78	-41.11	-9.329	65.91	-82.44	-12.69	86.57	-143.8
	(2.86)***	(2.59)***	(-0.47)	(2.70)***	(2.49)**	(-0.69)	(2.51)**	(2.37)**	-0.92
$\delta_{201}age_{i0}\times\Delta\Pi_i^{jS}\,pdvr_i$		0.2011	-3.570		0.5672	-7.320		1.139	-13.75
		(-0.67)	(-1.16)		(-1.11)	(-1.47)		(-1.36)	(1.76)*
$\delta_{202}age_{i0}^2\times\Delta\Pi_i^{jS}\,pdvr_i$			-0.0048			-0.0238			-0.0807
			(-0.16)			(-0.45)			(-0.87)
$\delta_{210}\Delta\Pi_i^{jS}\,agepdvr_i$		-0.9283	4.635		-1.523	9.132		-2.345	16.53
		(2.31)**	(-1.12)		(2.34)**	(-1.43)		(2.32)**	(1.74)*
$\delta_{211}age_{i0}\times\Delta\Pi_i^{jS}\,agepdvr_i$			0.0592			0.1453			0.3319
			(-0.85)			(-1.17)			(-1.55)
$\delta_{22}\Delta\Pi_i^{jS}\,age^2\,pdvr_i$			-0.062			-0.1318			-0.2643
			(-1.28)			(-1.59)			(1.92)*
Lost life-years									
$\delta_{300}\Delta\Pi_i^{jS}\,pdvl_i$	-6.929	11.06	16.38	-9.454	17.66	44.20	-11.93	24.70	81.99
	(7.70)***	(-1.29)	(-0.34)	(6.70)***	(-1.45)	(-0.68)	(5.75)***	(-1.5)	(-0.97)
$\delta_{301}age_{i0}\times\Delta\Pi_i^{jS}\,pdvl_i$		0.6312	-1.796		1.289	-2.321		2.255	-2.609
		(5.13)***	(-1.25)		(5.80)***	(-1.02)		(5.96)***	(-0.75)
$\delta_{302}age_{i0}^2\times\Delta\Pi_i^{jS}\,pdvl_i$			-0.0177			-0.0525			-0.1224
			(-1.49)			(2.41)**			(3.13)***
$\delta_{310}\Delta\Pi_i^{jS}\,agepdvl_i$		-0.6921	1.010		-1.337	0.7263		-2.265	0.0092
		(3.88)***	(-0.47)		(4.56)***	(-0.22)		(4.89)***	0
$\delta_{311}age_{i0}\times\Delta\Pi_i^{jS}\,agepdvl_i$			0.0563			0.1225			0.2461
			(1.87)*			(2.31)**			(2.68)***
$\delta_{32}\Delta\Pi_i^{jS}\,age^2\,pdvl_i$			-0.0315			-0.0579			-0.1064
			(-1.35)			(-1.51)			(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

Reviewers Only Table A-9

Sensitivity of Fitted VSIs in Estimating Sample to Alternative Discount Rate Assumptions: Models 1, 3 and 4

	3% discount rate			**5% discount rate**			7% discount rate		
Descriptive Statistic	Model 1 No Age Effects	Model 3 Linear Age Effects	Model 4 Quadratic Age Effects	**Model 1 No Age Effects**	**Model 3 Linear Age Effects**	**Model 4 Quadratic Age Effects**	Model 1 No Age Effects	Model 3 Linear Age Effects	Model 4 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[a]	**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

[a] 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.