Willingness to Pay for Health Risk Reductions: Differences by Type of Illness

Trudy Ann Cameron
Department of Economics
University of Oregon
cameron@oregon.edu

J.R. DeShazo*
School of Public Affairs
3250 Public Policy Building, UCLA,
Los Angeles, CA 90095-1656
deshazo@ucla.edu

Erica H. Johnson
School of Business Administration
Gonzaga University
johnsone@jepson.gonzaga.edu

December 4, 2010

Keywords: willingness to pay for a microrisk reduction, value of a statistical life (VSL), value of a statistical illness profile, stated preference, value of health risk reductions

JEL Classifications: Q51, I18

Acknowledgements: We would like to thank Vic Adamowicz, attendees of the Association of Environmental and Resource Economists Workshop in 2008, the Western Economic Association Annual Meetings in 2009, and the American Society of Health Economists Annual Meetings in 2010. This research has been supported by a grant from the National Science Foundation (SES-0551009) to the University of Oregon (PI: Trudy Ann Cameron). It employs original survey data from an earlier project supported by the US Environmental Protection Agency (R829485) and Health Canada (Contract H5431-010041/001/SS). Additional support has been provided by the Raymond F. Mikesell Foundation at the University of Oregon. Office of Human Subjects Compliance approval filed as Protocol #C4-380-07F at the University of Oregon. This work has not been formally reviewed by any of the sponsoring agencies. Any remaining errors are our own.

**Corresponding Author*

Willingness to Pay for Health Risk Reductions: Differences by Type of Illness

Our research identifies large systematic differences, by type of illness, in individual willingness to pay (WTP) to reduce the risk of the major health threats. These include five types of cancers (breast cancer, prostate cancer, colon cancer, lung cancer, and skin cancer), chronic heart disease (as well as sudden heart attacks), respiratory disease, strokes, diabetes, Alzheimer's disease and traffic accidents. Our estimates take the form of individuals' WTP to reduce the risk of experiencing specific illness profiles (i.e. the different patterns of sick-years, recovered/remission-years and/or lost life-years associated with each illness). Our results suggest that analyses which constrain the marginal utility parameters for different health states to be the same across all illnesses are too restrictive, causing the loss of valuable information for benefit-cost analyses of health, environmental and safety policies. We also find that the rank ordering of private willingness to pay for illness-specific risk reductions is highly correlated with public spending patterns by government agencies. (*JEL* Q51, I1)

When conducting a benefit-cost analysis for a policy that protects human health or human lives, government agencies have typically monetized the benefits from health risk reductions using a measure known as the Value of a Statistical Life (*VSL*). The *VSL* is based on an ex ante measure of individuals' willingness to pay (*WTP*) to achieve a small change in the risk of premature death.[1] Like many agencies, the US Environmental Protection Agency (EPA) uses a single *VSL* estimate ($6-7 million) that is based largely on a group of hedonic wage studies that estimate the wage premium that workers accept for the risk of a sudden fatal accident on the job (W. Kip Viscusi and Joseph E. Aldy (2003)). EPA then transfers this one-size-fits-all estimate to value its policies which reduce the general population's mortality risk from a range of cancers and

[1] All the empirical evidence concerning these *WTP* measures is based on very tiny risk changes. It is conventional practice to scale these *WTP* estimates to an aggregate risk reduction of 1.0. It is tempting to interpret this scaled *WTP* amount (called the *VSL*) as "*WTP* to avoid certain death," but this is inappropriate. A *VSL* reflects the average marginal rate of substitution between income (or wealth) and risk, and it is never used to place a dollar value on the prevention of one particular person's death with certainty. Instead, the *VSL* is implicitly scaled back down to its implied *WTP* for some tiny risk change that would be produced by a given policy, and the corresponding small *WTP* amount is summed across the affected population. This strategy is not without problems, however. See Trudy Ann Cameron (2010).

respiratory illnesses as well strokes, diabetes, Alzheimer's, and other health threats. (Lisa A. Robinson (2007)) .

The contribution of this paper is to demonstrate, within the context of a single demand estimation framework, that willingness to pay for health risk reductions varies systematically and significantly by type of illness. Other researchers have provided single-illness estimates and a few have even valued two or more illnesses within a single study (Ian Savage (1993); James K. Hammitt and Jin-Tan Liu (2004); Sujitra Vassanadumrongdee and Shunji Matsuoka (2005); George Van Houtven et al. (2008)). However, this is the first study to provide estimates of the differing marginal disutilities associated with the prospect of dying from each of eleven major illnesses, plus traffic accidents, using a representative sample of the US population and a common methodological framework.

It should not be surprising that individuals value different illness risk reductions differently. These estimates of *WTP* are simply measures of individuals' inverse demands for different "goods." Each illness represents a different prospective illness profile that involves a sequence of future health states including pre-illness years, sick-years, potential recovered years, and potential lost life-years. Massive strokes or heart attacks and major accidents may involve no morbidity and sudden mortality. In contrast, the vast majority of cancers, heart diseases, respiratory illnesses and other threats, as targeted by health and environmental policies, involve systematically differing health states: the individual's status quo health state before illness onset, some number of partial or whole sick-years, potential recovered/remission years, and lost life-years if the illness or injury leads to premature mortality.[2]

[2] Inverse demand for a given disease risk will also differ with the individual's ability to mitigate that particular risk as well as perceptions of the timing and size of competing health risks that might strike first.

We use a large general-population stated preference survey to examine how individual *WTP* for health risk reductions varies systematically across different types of major health problems, including five types of cancers (breast cancer, prostate cancer, colon cancer, lung cancer and skin cancer), chronic heart disease and sudden heart attacks, respiratory disease, strokes, diabetes, Alzheimer's disease and traffic accidents. Respondents make choices that reveal their willingness to pay to reduce the risk of suffering a specified illness profile, and we collect other data that allow us to control for respondent age, smoking status, and a selection of attitudinal variables. We recover estimates of the implicit values of discounted sick-years and lost life-years, determined as in a hedonic model, via the derivatives of the overall willingness to pay with respect to discounted time periods spent in each type of adverse health state for each illness. These illness-specific marginal utilities permit us to simulate estimates of the *WTP* for "microrisk" reductions (that is, a risk reduction of one in one million). This $WTP(\mu r)$ measure is more general than the conventional *VSL*, but when estimated for an illness profile that consists of sudden death in the current period, can be directly scaled to a *VSL* as explained in [Blinded for review] (2010).

Like most researchers, we would have preferred to use revealed preference (RP) data but instead choose stated preference (SP) data for two reasons. First, wage-risk studies tend to focus narrowly on only one type of health risk outcome—the risk of sudden death on the job. Thus they are ill-suited to capturing individuals' preferences for reducing illness risks that involve long latency periods, extended periods of morbidity, possible recovery or remission, and future lost life-years, if any. Second, the sample data available for hedonic wage studies tend to be unrepresentative of those populations that will benefit significantly from the types of health and environmental programs that are often being valued. The typical participant in wage-risk studies

is a male who is approximately 36 years old, while those who benefit from environmental programs are likely to be children, the elderly, and the infirm. A state-of-the-art and peer-reviewed stated preference survey permits us to circumvent these limitations of wage-risk tradeoffs, which are especially problematic for the valuation of environmental benefits for policy assessment.

Our utility-theoretic estimates of differences in demand for risk reductions, by illness, are especially relevant because public policies usually target *specific* illnesses or injuries. Normatively, our findings may guide the design of regulations in the health, environmental and safety arenas. When combined with measures of program effectiveness, these findings might also inform the allocation of health care resources by the Independent Payment Advisory Board under the recently passed Patient Protection and Affordable Care Act. Used in positive analyses, our findings offer an economic explanation for the observed patterns of regulation and investment by public agencies that result in risk reductions for particular illnesses and injuries. For example, our findings may justify why the Department of Transportation has historically used a *VSL* that is about half the size of that used by the Environmental Protection Agency. Similarly, this preference information may explain differences in funding by the National Institutes of Health for different health care and health research investments, as we discuss in this paper.

A set of consistent illness-specific estimates of the marginal disutility of sick-years and lost life-years, such as the ones estimated here, also advances several research agendas. One example involves the "cancer premium" debate in which some researchers have argued that the social benefits of a cancer risk reduction are larger than a comparable risk reduction of other major illnesses (Ian Savage (1993), George Van Houtven, Melonie B. Sullivan and Chris Dockins (2008)). We provide a structured and systematic framework for distinguishing specific

types of cancer: individuals are willing to pay significantly more to reduce some types of cancers but significantly much less to reduce other types of cancer. Another example involves recent efforts to quantify the social benefits associated with illness-specific risk reductions as expressed through increases in average longevity (David M. Cutler and Elizabeth Richardson (1997); Kevin M. Murphy and Robert H. Topel (2006)). In the absence of illness-specific estimates, researchers have imputed a one-size-fits-all per-year estimate of the value of a lost life-year, by arbitrarily dividing the standard *VSL* by the population average of the number of expected remaining discounted life-years.[3] This approach implies that the marginal utility of a discounted lost life-year is the same across all illnesses and omits the marginal disutility associated with the sick-years caused by these illnesses. Our approach provides illness- and age-specific estimates of the marginal utility of both a sick-year and lost life-year, which would enable these important analyses to be done with greater resolution.

The paper is structured as follows. In Section I, we briefly discuss the available survey data. In Section II, we describe our random utility choice model and in Section III describe the empirical implementation. Section IV reviews our estimation results and Section V covers the implications of our estimated models for estimates of *WTP* which generalize conventional *VSL* estimates. Section VI concludes.

I. Available Data

We use data from a stated preference survey that elicits *WTP* for health risk reductions described more fully in a related paper [Blinded for review] (2010). Beyond our use of these data in other work, they data provide sufficient information to permit an analysis of differences in *WTP* by type of illness. The survey was administered by Knowledge Networks, Inc. to a random general-population sample of respondents in the United States. Respondents are members of

[3] For an improved approach to calculating the *VSLY* see Michael J. Moore and W. K. Viscusi (1988).

households selected by random-digit dialing techniques from the population of the United States. They are offered free internet access, and WebTV technology if necessary, in return for completing a few surveys every month. Since these respondents are part of a standing consumer panel, a large quantity of demographic and background information, such as health status and health history, is available for every member of the panel.[4]

The survey has five parts. The first part asks respondents to think about some of their own health habits and their subjective risks of suffering from the different classes of illness which will be the subject of the survey. The second part is a risk tutorial for the survey, where risks are displayed in three different ways and respondents are required to answer successfully a risk comprehension question. After 24 screens of preparation and training material, the third part of the survey asks the respondent to consider five different three-alternative conjoint choice sets.[5] In each choice scenario, respondents choose between Program A, Program B, and the status quo ("Neither Program") as seen in the example of a choice summary table in Figure 1. Each program reduces the risk that the individual will suffer a particular illness profile. The health risk reduction programs, as described to respondents, consist of a diagnostic pin-prick blood test given by the individual's doctor once per year that indicates whether the individual is at risk for the illness. If the blood test indicates the individual is at risk, then the doctor would prescribe medication and life-style changes (such as diet and exercise) and continue to monitor the individual.[6] Each illness profile consists of a brief description which includes the

[4] For a thorough description of the development of the survey and a single instance of the randomized survey instrument, see the compilation of Supplementary Materials that supports all papers in this series.
[5] The "conjoint choice" terminology emerged from the marketing literature to describe choice tasks involving multiple alternatives each with multiple attributes.
[6] For traffic accidents, the program is described as "new airbag, braking, and impact reduction technologies that are becoming available. These will reduce your chance of injury or death due to auto accidents. These technologies can be built into new vehicles, or added to existing vehicles. You will probably pay the cost of these technologies all at once when you buy a new car or have the equipment installed in an older one. When we describe costs, we will convert them to monthly costs and also annual costs to make them easier to compare across programs."

approximate age of the individual when the illness starts, the duration of the illness, the symptoms and treatments, and its anticipated effects on life expectancy. The risk reduction programs are characterized in terms of the expected risk reduction achieved by the program, and the cost of the program (expressed in both monthly and annual terms). All of the attributes are independently randomized, including the name of the illness, subject only to some basic plausibility constraints. Any more-efficient blocked design for the mixes of attributes in these experiments is precluded by the fact that eligible illness profiles are dictated by the gender and current age of the individual respondent (because illness profiles must be expressed relative to the individual's status quo life expectancy).[7]

The fourth part of the survey consists of debriefing questions which follow up on each conjoint choice task. The fifth part of the survey was taken separately by all panelists and gathers socio-demographic information that can be readily merged with the data collected expressly for this study.

The survey was administered to 2,439 respondents with a 79% response rate among invited panelists. In certain cases, a respondent or a specific choice set was dropped from the estimating sample. Respondents were excluded from the estimating sample if they failed to pass a skill-testing question about risk comprehension, if they rejected outright the types of choice scenarios the survey posed, or because of an unintended design feature that cropped up in a small fraction of the choice sets used in the survey.[8] The remaining respondents considered 6,848 choice sets involving 13,696 risk reduction programs (and a total of 20,544 alternatives when the

[7] For a thorough description of the attributes used in the choice sets in this survey, see Section 3 of the Supplementary Materials (Details of the Choice Set Design).

[8] Due to a lack of risk comprehension 1,236 choices were dropped; due to scenario rejection (where the respondent only chose scenario rejection as the reason for choosing the "neither program" alternative) 2,236 choices were dropped; and due to an error in the randomization of the survey 332 choices were dropped. A few more respondents were dropped for the models used in this paper, due to incomplete survey responses to key attitudinal questions. Complete details for the basic exclusion criteria for the main study are contained in Section 4 of the Supplementary Materials (The Knowledge Networks Panel and Sample Selection Corrections).

status quo is included). Descriptive statistics for the variables used in this paper are shown in Tables 1A and 1B.

II. Utility-Theoretic Choice Model

As mentioned above, survey respondents choose from three alternatives in each choice set. They choose between two risk reduction programs (Program A and Program B) and the status quo (Neither Program), which are denoted *A*, *B* and *N*. Each program reduces the risk of facing an illness profile attributed to one of eleven different illnesses, but each program has an associated monetary cost. An illness profile is a sequence of future health states that includes a specified combination of pre-illness years, sick-years, post-illness (recovered/remission) years and lost life-years. The program cost is assumed to apply only during pre-illness years and recovered years, so the individual would not pay for the program if he or she were to fall ill as described in the illness profile. Respondents are assumed to choose the alternative with the combination of attributes that gives them the highest level of utility.

This utility-theoretic choice model is described in detail in [Blinded for review] (2010), but we offer a brief explanation of the model in this paper. For simplicity, consider just the pair-wise choice between Program A and Neither Program.[9] We assume that utility for individual *i* at time *t* depends upon net income in that period (Y_{it} minus the cost of any selected program) and the health state experienced in that period. The survey considers only single spells of the illness in question. In any given period, the individual will occupy one of four possible health states. An illness profile is denoted by the sequence of values for a set of four (0,1) indicator variables: $1(pre_{it})$ for pre-illness years, $1(ill_{it})$ for illness-years, $1(rcv_{it})$ for recovered or post-illness years, and $1(lyl_{it})$ for lost life-years. The health states are mutually exclusive and exhaustive, meaning

[9] The three-way choice between two programs and neither program is analogous.

that the individual experiences one, and only one, of these four health states in any future time period. We can write the individual's indirect utility function in each time period, *t*, as:

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

where (net) income, Y_{it}, enters in a square root form (i.e. $f(Y_{it}) = \beta\sqrt{Y_{it}}$) and η_{it} is the error term.[10]

There is uncertainty about whether the individual will actually fall victim to any of these illnesses or injuries, so we model each program choice as depending upon expected indirect utility, with the expectation taken across the sick (S) and healthy (H) outcomes. Participation in Program A, instead of the status quo, is described as altering the probability of getting sick from π_i^{NS} to π_i^{AS} (a *negative* change that we denote as $\Delta\pi_i^{AS}$). Furthermore, each illness profile extends through the remainder of the individual's life expectancy, so we discount future time periods using discount rate *r* and a standard discount factor $\delta^t = (1+r)^{-t}$ to convert indirect utility into present value terms, which we denote as PDV.[11] The individual is assumed to choose Program A over the status quo alternative (N) if his or her discounted expected utility is greater under Program A. That is, the individual chooses Program A if:

(2) $$PDV\left(\pi_i^{AS}V_i^{AS} + (1-\pi_i^{AS})V_i^{AH}\right) - PDV\left(\pi_i^{NS}V_i^{NS} + (1-\pi_i^{NS})V_i^{NH}\right) > 0$$

[10] In [Blinded for review] (2010), the net income variable is subjected to a Box-Cox transformation with a fixed coefficient of 0.42 for the transformation, although in that paper, the model does not allow for heterogeneity with respect to the type of illness or injury. Given that income is measured in dollars, the square root transformation used in this paper is a close approximation to a Box-Cox transformation with parameter 0.5. We use the square root transformation because it simplifies somewhat the calculation of willingness to pay.

[11] In this paper, we assume a common discount rate of 5%. [Blinded for review] (2010) explore the consequences of assuming either a 3% discount rate or a 7% discount rate. Work in progress also involves the estimation of individual-specific discount rates simultaneously with these stated choices concerning health risk reduction programs, using additional data on intertemporal choices by a separate sample of respondents from the same population. Preliminary results, however, suggest that the 5% across-the-board discount rate assumption produces a maximized value of the log-likelihood function that is almost 80 points higher than the individual-specific fitted discount rates which are a function of socio-demographic characteristics of each individual.

The present discounted number of years making up the remainder of the individual's nominal life expectancy, T_i, is given by $pdvc_i = \sum_{t=1}^{T_i} \delta^t$. Under Program A, the discounted health states are summed from $t=1$ to $t=T_i$ and are denoted $pdve_i^A = \sum \delta^t 1\left(pre_{it}^A\right)$, $pdvi_i^A = \sum \delta^t 1\left(ill_{it}^A\right)$, $pdvr_i^A = \sum \delta^t 1\left(rcv_{it}^A\right)$, and $pdvl_i^A = \sum \delta^t 1\left(lyl_{it}^A\right)$. Since the different health states exhaust the individual's complete nominal life expectancy, it will be the case that $pdvc_i = pdve_i^A + pdvi_i^A + pdvr_i^A + pdvl_i^A$. Finally, to accommodate the assumption that each individual expects to pay for Program A only during the pre-illness or recovered post-illness periods, we let $pdvp_i^A = pdve_i^A + pdvr_i^A$, so that $pdvp_i^A$ is defined as the present discounted time over which payments must be made.

To simplify the notation, let $cterm_i^A = \left(1 - \pi_i^{AS}\right) pdvc_i + \pi_i^{AS} pdvp_i^A$ and $yterm_i^A = pdvc_i - \pi_i^{AS} pdvi_i^A - \pi_i^{NS} pdvl_i^A$. These terms pertain to the intervals when the individual will pay program costs and/or earn income. Then the expected utility-difference over the individual's remaining life span that drives his or her choice between Program A and the status quo (based on equation (2)) can be specified as follows:

$$\Delta PDV\left(E_{S,H}\left[V_i\right]\right) = \left\{f(Y_i - c_i^A) cterm_i^A + f(Y_i) yterm_i^A\right\} + \\ + \alpha_1\left\{\Delta\pi_i^{AS} pdvi_i^A\right\} + \alpha_2\left\{\Delta\pi_i^{AS} pdvr_i^A\right\} + \alpha_3\left\{\Delta\pi_i^{AS} pdvl_i^A\right\} + \varepsilon_i^A \tag{3}$$

It is necessary to construct the present discounted expected net income separately under each of the risk-reduction programs and under the status quo since the time profile of income and program costs will depend on the sequence of health states and whether the individual suffers from the illness or injury in question. See [Blinded for review] (2010) for complete details and note that there will be an analogous term for the utility difference between Program B and the status quo in our three-alternative estimating specification. This notation allows us to focus on

the four main coefficients: β (the coefficient on the square-root-of-net-income term implicit in the function $f(\cdot)$), and α_1, α_2 and α_3 (the coefficients on the three health-state terms).

The option price for the risk reduction, in the sense of Daniel A. Graham (1981), rather than in the sense it is used in the finance literature, is the common certain maximum payment that makes an individual indifferent between paying for the program and getting the risk reduction, or not paying for the program and doing without the risk reduction. As described in [Blinded for review] (2010), we can solve the discounted expected indirect utility-difference equation (3) for the value of this common certain payment, $\hat{c}_i^A$:

$$(4) \qquad \hat{c}_i^A = Y_i - f^{-1}\left(\frac{-1}{cterm_i^A}\left\{f(Y_i)\, yterm_i^A + [\alpha_1 pdvi_i^A + \alpha_2 pdvr_i^A + \alpha_3 pdvl_i^A]\Delta\pi_i^{AS} + \varepsilon_i^A\right\}\right)$$

The present discounted expected value of this annual certain payment over the individual's remaining lifetime can be written as:

$$(5) \qquad PDV\left[E_{S,H}\left(\hat{c}_i^A\right)\right] = cterm_i^A\left[\hat{c}_i^A\right]$$

Next, we standardize this expected present value of the certain payment on a risk change of one in one million (a microrisk reduction) to allow comparison between different risk changes. Mechanically, we divide $PDV\left[E_{S,H}\left(\hat{c}_i^A\right)\right]$ by the absolute size of the risk reduction and scale the results as follows:

$$(6) \qquad WTP(\mu r) = \frac{PDV\left[E_{S,H}\left(\hat{c}_i^A\right)\right]}{\Delta\pi_i^A}(.000001)$$

This $WTP(\mu r)$ reflects the marginal rate of substitution (MRS) between a microrisk reduction and net income. This MRS involves the marginal utility of a change in the risk of suffering given sequence of health states in the numerator, and the marginal utility of income in

the denominator. Since the marginal utility of an adverse illness profile is in the numerator of the formula for $WTP(\mu r)$, any increase in the marginal disutility of any component of an illness/injury profile of health states (illness years, recovered years, and lost life-years) will increase the *WTP*. In contrast, the marginal utility of income is in the denominator, so any increase in the marginal utility of income will decrease the $WTP(\mu r)$.

To calculate a simulated $WTP(\mu r)$ using our choice data, for any real health threat, we would need an approximate joint distribution for the possible time profiles for the illness in question. This information could come from epidemiological studies. We would also need a joint distribution for age, gender, and income level for the affected sub-population. Then, we could make a large number of draws from these two joint distributions and simulate a distribution for the resulting $WTP(\mu r)$ values. The mean of the distribution of *WTP* estimates could then be interpreted as the model's prediction of the average *WTP* in the case of this particular illness and for this particular sub-population. However, since we do not have a particular real-life health risk reduction that we seek to analyze at this point, we will use our fitted model to simulate *WTP* amounts for a particular type of individual and a selection of illnesses and illness profiles.

As described in [Blinded for review] (2010), the data suggest that the basic, homogeneous-preferences model given in equation (3) is dominated by one with a more complex specification for the health state terms that allows for shifted logarithms of the three terms for the discounted adverse health states (plus some additional higher-order terms in these functions), a sample selection control term, and age heterogeneity in the estimated effects of all of the terms in lost life-years. However, the final specification is otherwise analogous to the model in equation (3).

III. Empirical Specification

We build on the basic specification outlined in the previous section by generalizing the marginal utilities of time in the different future health states so that they vary systematically by the type of illness or injury. There is no theory to recommend specific functional forms whereby these individual parameters should be expected to vary, so we introduce a set of indicator variables for illness types and interact these with illness profile attributes and with relevant individual attitudes and characteristics. This allows us to build an understanding of how the illnesses in question (or, more specifically, the implicit *information* these illness descriptors contain) can influence respondents' stated preferences over the alternative health-risk reduction programs proposed in our survey.

A. *Net Income Term*

The "marginal utility of net income" parameter β corresponds to the square-root-in-net-income term in the underlying assumed indirect utility function. In all models, the estimated coefficient on the income term has the expected positive sign (the square root form is utilized to allow for diminishing marginal utility of net income). As described in Section II, the marginal utility of income enters into the denominator of the $WTP(\mu r)$ formula for health risk reductions. A smaller marginal utility of income can thus be expected to correspond to a higher *WTP* for a microrisk reduction.[12,13]

[12] In the analyses in this paper, we assume that the individual's marginal utility of net income is unaffected by any characteristics conveyed by the illness label used for each program. In some simple alternative models which allow for utility to be a quadratic function of income, there is some suggestion that the coefficient on the linear term in net income may be lower when the illness addressed by the program is described as being respiratory disease. In richer models, however, the effect disappears and a different effect, for diabetes, materializes. There is no evidence of any heterogeneity by disease type in the coefficient on the quadratic-in-net-income term.

[13] As usual, it is difficult to allow every parameter in both the numerator and denominator in the $WTP(\mu r)$ formula to vary systematically with the *same* long list of shifters. Letting each utility parameter differ by the type of illness expands the parameter space by a factor of twelve. Thus we introduce illness-label heterogeneity only where it seems to produce the most robust results, remaining mindful of the risks of over-fitting a model.

B. *Health State Terms*

Our focus in this paper is the effect of different health threats on *WTP* for risk reductions. It seems plausible that the effects of illnesses could enter the empirical model by shifting the marginal ex ante (dis)utility of sick-years from that particular health threat. The illnesses could even shift the marginal ex ante (dis)utility of lost life-years, but there is also the possibility that "dead is dead," and that the marginal (dis)utility of the affliction has much more to do with the sick-years leading up to death than with the prospect of being prematurely dead due to any particular illness. Alternatively, illness effects could enter simply as a "lump" of additional indirect utility affecting preferences for each alternative in the choice set, independent of the duration of time in any particular future health state described for that illness.

The broader nature of each health threat is likely conveyed to the respondent by the name of the illness. The illness name suggests the unspecified implicit attributes of each illness that are not captured solely by the time periods in different health states (latency, sick-years, recovered/remission-years and/or lost life-years). It is crucial that the illness names used in our survey were assigned *randomly* to different illness profiles. It would therefore be possible for two identical illness profiles to appear in the study, but with different names. Thus we can be confident that the effects we find for the impacts of illness labels are distinct from the effects of the time patterns of the illness profiles. Some of the randomized combinations were of course implausible (such as sudden death from diabetes or Alzheimer's disease), so these combinations were removed from the inventory of choice set designs.

In all specifications, we use heart disease as the base case. For the simple indicator variables that we add to the specification in (3), heart disease is the omitted category. It is important to appreciate that the pairs of illnesses appearing in each choice set are randomized so

that the illness variables are not simply alternative-specific dummy variables. A positive coefficient on one of these "intercept-shifter" types of variables implies that $WTP(\mu r)$ is larger for the illness in question than it is for heart disease.

For the α parameters in (3), the baseline coefficient applies to heart disease and the indicators for each other illness or injury serve to shift this "slope" type coefficient. The marginal utility of time in each of these adverse future health states is expected to be negative, so if it were not for the higher-order terms in our estimating specification that generalize equation (3), a positive coefficient differential would imply a reduction in the (dis)utility of the adverse health state, and hence a lower $WTP(\mu r)$.

C. *Other Controls*

We also allow for additional types of control variables that we suspect might influence a respondent's perceptions of an illness. The six additional types of control variables involve attitudes and characteristics (as well as some interaction terms). These variables include age, whether the individual is a smoker (in the cases of lung cancer and respiratory disease), subjective vulnerability to any of these health threats over the next twenty years, confidence that any treatment would be timely and effective, controllability of the illness, and the individual's subjective risk for the illness. While many of these individual attitudes or behaviors could be jointly endogenous with preferences for health risk reductions, these variables serve as important indicators of the "theoretical construct validity" of our findings. In subsequent simulations of fitted $WTP(\mu r)$, we set these controls to their median levels (normalized to zero) or to their omitted categories when they are not featured in the simulations.

Age.—We find that age plays an important role in determining *WTP* for health risk reductions, probably because age has so much to do with people's perceptions of their health

risks. In the basic specification from [Blinded for review] (2010), we find that the baseline coefficient on the lost life-years term, the coefficient on the squared term in lost life-years and the coefficient on the interaction term between life-years and sick-years all vary with age. In this paper, we allow additional interactions between illness indicators and age, and we find additional age effects.

Smoking Status.—If respondents are current smokers, they may feel more vulnerable to respiratory disease and lung cancer. Thus, we control for whether individuals reveal that there is room for them to reduce their health risks by improving their lifestyle or habits if they were to quit smoking. We use this response to identify each individual as a likely current smoker or likely non-smoker (although we acknowledge that it may pick up some smokers who merely do not believe that their health could be improved by smoking cessation).

Vulnerability.—We allow the coefficients on the health state terms to vary by perceived health "vulnerability," which is the respondent's answer to the question (regarding the next twenty years): "What is the chance that you will experience, either for the first time or as a recurrence, one of the major illnesses we discussed?" The four response options are coded as -2="very unlikely," -1="somewhat unlikely," 0="somewhat likely," and +1= "very likely."[14] If some respondents feel that they have a higher chance of suffering from a major illness over this time horizon, we expect that their prospective (dis)utility will be greater and they will have a higher *WTP* for health risk reduction programs. The perception of health vulnerability is likely to be correlated with age, however, so we also allow the effects of perceived vulnerability to vary with the respondent's current age. The relationship between age and subjective future health

[14] While we could allow for greater generality by capturing factors like this with a set of dummy variables, we treat them as approximately cardinal variables to conserve on parameters. We normalize these variables to zero on their median values in the sample, and our simulations will assume that these variables are set to their medians.

vulnerability is shown in Figure 2. Older respondents are more likely to face at least one of these named illnesses in the next twenty years, so if "vulnerability" were to be used alone in the model, it might merely be picking up this age effect.

Confidence.—"Confidence" is the respondent's answer to the general question "Imagine you experience one of the major illnesses described in this survey. How confident are you that your diagnosis and treatment by your current health care provider would be both timely and of high quality?" The three possible responses include -1= "not at all confident," 0= "somewhat confident," and "+1=highly confident." If a respondent does not have a high level of confidence in access to, or the quality of, their current health care, they may be more willing to pay for a preventative program.

Controllability.—We also allow for heterogeneity in the marginal (dis)utility of sick-year terms with respect to the extent to which the individual feels the illness is controllable. "Controllability" is the respondent's answer to a survey question worded as follows: "How much do you think that improving your lifestyle or habits would reduce your risk of [each class of health risk]." The five response options range from -2= "very little," to +2= "a lot."

The anticipated effect of this attitude on demand for health-risk reduction programs cannot be signed unambiguously in advance. If respondents feel that an illness is more controllable, they might express a greater demand for a program to prevent it, since the program would be more likely to work.[15] On the other hand, if they feel the illness is controllable, perhaps they do not feel the need for a special prevention program since they anticipate that they

[15] The health-risk reduction programs described in the survey involve a simple diagnostic test. Respondents are told: "If a test says that you have a problem, your doctor could prescribe medication and life-style changes that reduce your risk of getting the illness. You would continue to be monitored."

will be able to control the risk of the illness on their own, making demand for the program smaller.

Subjective Risk.—Finally, we expect that individuals who feel more at risk for getting a *particular* illness would have a higher *WTP* for a risk reduction program for that illness. Our survey asked respondents to "Think about your health, your family history, and hazards to which you are exposed. Which illnesses or injuries do you feel most at risk of experiencing over your lifetime?" The five response options ranged from -2= "low risk," to +2= "high risk." We expect that for illnesses corresponding to specific health threats for which the respondent feels particularly at risk, the (dis)utilities will be greater (i.e. the α coefficients will be more negative, if we were relying on the simpler model in equation (3)).

As discussed above, we consider the possibilities that heterogeneity in demand, by illness, may affect the indirect utility associated with each program *regardless* of the time profile of the illness, the baseline marginal (dis)utility of discounted sick-years, and the baseline marginal (dis)utility of discounted lost life-years. There are overwhelming numbers of coefficients in the most extensive fully parameterized model, however, which suggests that it is helpful to reduce the size of the parameter space where this is warranted by the data. We thus prune away persistently insignificant variables. The additional variables we use to control for respondent attitudes and characteristics are likely to be correlated with each other to a certain extent, but we will normalize our *WTP* estimates on the central tendencies for these variables in our representative sample. These are merely control variables, included where necessary to help us better discern the tendencies in the data which can be identified for a respondent with "typical" attitudes on all dimensions, for selected specific age levels.

Next we focus on the results from our preferred parsimonious model. In Table 2, we show the estimated parameter values for the special case of an individual whose attitudinal control variables coincide with the modal values in the sample.

IV. Main Estimation Results

Table 2 shows the basic framework of our estimating specification, but indicates where we use separate tables to expand upon those particular coefficients which are permitted to vary with the specific illness or injury associated with each offered risk-reduction program. Sub-tables 2A, 2B, and 2C show selected parameters for a parsimonious specification that retains the persistently significant coefficients on (a) the indicator variables for each illness, (b) the sick-years interaction terms with each illness indicator, and (c) the lost-life-years interaction terms with each illness indicator. These sub-tables also show significant differentials in these effects according to age (for all illnesses, where significant) and smoking status (only for lung cancer and respiratory disease). The complete set of coefficients for this parsimonious model is provided in the Appendix. The Appendix includes coefficients on the attitudinal control variables whose terms in the indirect utility-difference function drop out when these attitudinal variables are all set to zero (as they have been, implicitly, in Table 2). We assume that these attitudes are predetermined, rather than contemporaneously jointly endogenous with the demands for health risk reductions which are the focus of this study.

A. Differences in Autonomous Utility

In Table 2A, our empirical results suggest that the autonomous utility associated with a risk-reduction program differs considerably across illnesses. Positive coefficient differentials in Table 2A, relative to the base case for heart disease, imply a greater *WTP* for a risk reduction

program for the illness in question. The utility associated with programs to reduce the risk of heart attacks, breast cancer (for female respondents), prostate cancer (for male respondents), colon cancer, and strokes appears to be greater than the utility associated with programs to reduce the risk of heart disease, regardless of the time profile of health states for the illness question.

For diabetes and Alzheimer's disease, however, this autonomous utility starts out being greater than that for heart disease (if age were to be zero, i.e. out-of-sample). But this utility premium for risk reductions decreases with age. Beyond about age 56 for both diabetes and Alzheimer's disease, the autonomous utility premium for these programs becomes less than that for programs to deal with heart disease (which is normalized to zero).

On average, the autonomous component of utility for programs to reduce skin cancer risk is less than that for heart disease since they start out about equal but the premium for skin cancer falls with age. Interest in skin cancer programs will tend to decline with age, based on this control variable.

Being a smoker leads to a strongly significantly larger amount of autonomous utility associated with programs to reduce lung cancer and respiratory disease, relative to the baseline for heart disease, but for respiratory disease, this premium declines with age. In fact, by about age 32, smokers' autonomous utility associated with programs to reduce the risk of respiratory disease drops to the level of that for heart disease in general. This effect implies that smokers will appear to be more interested in programs to reduce the risk from respiratory disease than non-smokers, independent of the prospective illness profile involved, but only up until their early thirties.

B. *Differences in the Marginal (Dis)utility of a Sick-Year*

In Table 2B, the estimated coefficients suggest that the baseline term in the marginal (dis)utility of a sick-year for many illnesses is statistically different from that associated with heart disease.[17] Disutility from sick-years due to heart disease decreases with age, as does that for sick-years due to heart attack, breast cancer, prostate cancer, lung cancer, stroke and traffic accidents, since the differential in the age effect, relative to that for heart disease, is statistically zero. In contrast, the disutility from sick-years due to colon cancer and skin cancer appear to decrease with age at a slower rate because the differential age effect bears a negative sign but is not large enough to overcome the base age effect. For respiratory disease, diabetes, and Alzheimer's disease, however, the disutility from prospective future sick-years may actually increase with age, implying a greater interest in diagnostic programs for these illnesses among older people.

C. *Differences in the Marginal (Dis)utility of a Lost Life-Year*

In Table 2C, there appears to be very little statistically significant heterogeneity by type of illness in the baseline term for the ex ante disutility from prospective future lost life-years. Life-years lost due to any cause seem to have a statistically significant effect that is comparable to that for heart disease. The only statistically significant differences concern breast cancer, traffic accidents, and diabetes. Baseline disutility from lost life-years due to breast cancer starts out being greater than that for heart disease, but decreases with age. By about age 54, female respondents begin to derive less disutility from the prospect of lost life-years from breast cancer than from other causes. Younger respondents derive greater disutility from prospective life-years lost due to breast cancer than from other illnesses. For traffic accidents and diabetes, the

[17] Recall, however, that there is an additional interaction term involving both sick-years and lost life-years.

disutility from lost life-years seems to decline steadily with age, and at a slightly faster rate for diabetes.

D. *Effects of Other Control Variables*

In addition to the variables appearing in Table 2 and its sub-tables, we noted in Section III.C that we also control for the respondent's self-assessed vulnerability to at least one of the major health threats described in our survey, along with his or her degree of confidence in the quality and timeliness of health care, perceived controllability of different types of health threats, and subjective risks for each type of health threat. Additional discussion of these additional variables and their estimated effects is included along with the full set of parameter estimates in the Appendix.

V. Implications for Differences in $WTP(\mu r)$ by Illness

While utility parameter estimates are interesting, it is more informative for policy purposes to demonstrate the effects of the utility parameter differences described in the last section upon the resulting estimates of $WTP(\mu r)$. We use the parsimonious model reported in Table 2 to simulate estimates of $WTP(\mu r)$. We focus mainly on variation by illness, but also by age and smoking status, and we show estimates for two different types of illness profiles. We simulate $WTP(\mu r)$ for a "standard" individual with an income of $42,000 who is assumed to have median levels (i.e. zero values) for the other control variables we employ—namely, the variables for subjective vulnerability to major health problems in the future, confidence in the quality of future health care, the subjective controllability of each type of illness and the subjective risk of suffering each type of illness.

In estimating the parameters of the indirect utility-difference function for Table 2, it is important to acknowledge that respondents probably expect, if they currently have an illness, that

they would *not* have to continue to pay for a private testing program to reduce the probability of suffering from that illness. Likewise, respondents would find it implausible that they (or their estate) would have to continue paying the annual costs of these diagnostic tests if they are dead. The implication of the probabilistic illness profile for the individual's discounted expected net income is thus an important consideration during the estimation phase.

However, if these estimated private preferences are to be used to infer preferences for public policies such as environmental regulations, it is unlikely that an individual would expect to be excused from paying the social cost of the policy if they developed the illness. In formulating their public policy preferences, individuals are also probably less likely to work out the future net income implications of a possible premature death from one of these illnesses. Consequently, when we simulate *WTP* for a particular illness profile, we preserve the pattern of probabilistic future health states in the simulation scenario, but we suppress any variation in future net income. This strategy has the advantage of making $cterm_i^j = yterm_i^j = pdvc_i$ in equation (4), which means that our fitted *WTP* estimates depend upon the size of the risk reduction involved, $\Delta\pi_i^{jS}$, but no longer depend upon the absolute levels of these health risks without and with the program: π_i^{NS} and π_i^{jS}.

The means of our simulated *WTP* amounts reported in Table 3 can be interpreted as the fitted willingness to pay for a one-in-one-million reduction in the risk of the specified illness profile (including latency, sick-years, and lost life-years from a particular named illness, as relevant).[18] However, to reflect the degree of precision in these estimates, which stems from the

[18] These *WTP* values are generated by drawing 1000 values from the asymptotically normal joint distribution of the maximum likelihood parameter estimates and using each draw of these parameters to calculate the *WTP* from the basic formula in terms of a specific set of values for the explanatory variables. We suppress the additional noise due to the mean-zero standard logistic error term in our *WTP* calculations since we seek to understand the dispersion in a measure of central tendency, rather than the dispersion in individual predictions. We acknowledge that the nonlinear

precision of the estimated utility parameters, we also report the 5th and 95th percentiles of each distribution.[19]

Table 3 displays results for six benchmark cases. We use three different ages: a 30-year-old, a 45-year-old, and a 60-year-old. Two different illness profiles are considered. The first illness profile is "sudden death now."[20] This scenario is used because it is most similar to the actuarial mortality risk data used in conventional wage-risk studies to produce an estimate of the *VSL*. To illustrate the versatility of our model, however, we also offer an arbitrarily selected example of an alternative illness profile. This second illness profile has ten years of latency before the individual gets sick, five years of illness, and then death. This versatility is important because this sort of simulation scenario is beyond the reach of other research where investigators have relied upon models using only wage-risk revealed preference data.

A. *Disease-specific Discussion*

For our six types of benchmark individuals with standard attitudes, some of our highest estimates of willingness to pay for microrisk reductions in illness appear to be for young women to reduce the risk of breast cancer, where $WTP(\mu r)$ is above \$10. Clearly, the salience of breast cancer is high for this group, as is the salience of *future* lung cancer for young smokers, for which $WTP(\mu r)$ is similarly large. Non-smokers, on the other hand, seem to have relatively low

---

transformation f^{-1} in equation (4) implies that the resulting point estimates of *WTP* represent medians, rather than means, of the implied conditional distribution of individual *WTP*.

[19] In reporting the distribution of these simulated medians across 1000 replications, we acknowledge that respondents were given no opportunity to express a negative willingness to pay. All they could do was to "not choose" a less desirable program. Thus we convert all negative calculated values of *WTP* to zero and report the mean of the resulting distribution. However, we do not censor the 5th or 95th percentiles at zero, although one could easily do so.

[20] For some of these health threats, of course, sudden death may be unlikely. In fact, in the choice scenarios used in the survey we found that many respondents felt sudden death was implausible. Therefore, in most of the illness profiles shown to respondents, a latency period of at least two years was used. The "sudden death" *WTP* estimates thus represent an out-of-sample extrapolation to an illness profile consisting solely of lost life-years, with no latency, no sick-years, and no recovered/remission time.

willingness to pay to reduce their risks of lung cancer. Their $WTP(\mu r)$ is not more than $3.50 under the sudden death scenario. Under the more realistic latent illness scenario, $WTP(\mu r)$ for non-smokers is higher, at $4.80 for the 30-year-old, but it falls dramatically with age, amounting to only about $0.58 for the 60-year-old.

For smokers versus non-smokers, there is also a substantial difference in willingness to pay for microrisk reductions for respiratory disease. $WTP(\mu r)$ in the sudden death scenario for respiratory disease is on the order of $5 to $6 for smokers of different ages. For non-smokers, it ranges between about $1.20 and $2.00. The latent illness scenario, which is again more realistic, produces much higher *WTP* estimates for smokers than for non-smokers. The *WTP* to reduce the risk of *future* respiratory illness appears to be near zero for a non-smoker who is already 60 years old.

Concerning measurement of the potential benefits from reducing environmental threats to health, one might think first of respiratory disease and lung cancer from "criteria" pollutants and toxic air pollutants. (Some portion of the population may also be aware of the role of air pollution in heart disease.) Our results suggest that there may be a huge difference between the smoking and non-smoking populations in demands for health risk reductions via reductions in air pollution through environmental policies. Improved ambient air quality, for example, may be viewed as a substitute for quitting smoking.

Among other cancers, both breast cancer and prostate cancer are of considerable concern to all age groups, whether or not there is a latency period. With no latency period, these *WTP* values, when scaled up by a factor of one million to be compared with a conventional *VSL*, can be argued to be in roughly the same ballpark as the *VSL* numbers used by the U.S. EPA and the Department of Transportation. Willingness to pay to reduce colon cancer risk is typically lower

than for breast or prostate cancer, except *future* breast cancer risks for 60-year-old women seem to be a lesser concern.

Measures to reduce the risk of skin cancer attract less interest, with *WTP* between about $0.40 and $1 in the sudden death scenario. The *WTP* estimates in the scenario with latency for 45- and 60-year-olds are lower, but the estimates for 30-year-olds are slightly higher, at roughly $2. Sixty-year-olds have negligible willingness to pay to reduce their risks of *future* skin cancer. Thus, we do not find strong evidence of a universal "cancer premium" where an individual has a high *WTP* to avoid risk across *all* types of cancer. We do find that some cancers are of much greater concern than others. However, we are not able to control separately for perceived risks of different types of cancers since our subjective risk question elicited information only about "cancers in general." It is entirely possible that most people perceive relatively little risk from skin cancer, and this accounts for their lack of interest in paying any money for diagnostic testing. Perhaps they believe that these cancers would be readily detectable and treatable, and that an extra risk reduction program would not be particularly helpful.

Among non-cancer illnesses, the largest *WTP* amounts are those associated with heart disease and heart attacks. *WTP* for a microrisk reduction in the case of sudden death is around $5 to $8 for both heart disease and heart attacks. From middle age onwards—especially in the case with latency—the *WTP* numbers for these two related types of illnesses appear to be very similar, which is reassuring. There is absolutely no requirement that the data yield identical values for these two different risk reduction programs, but logically we might expect them to be similar. We see, for the scenario of sudden death now, that *WTP* to reduce heart disease risks continues to increase with age, even for the 60-year-olds. This pattern is different from many other illnesses that have the 45 year-olds with the highest estimates.

Cerebrovascular illness (stroke) is also of considerable concern to our respondents, with *WTP* amounts on the order of $6 for 30-year-olds and numbers more in the vicinity of $7 for 45-year-olds and 60-year-olds in the case of the risk of sudden death in the current period. However, the *WTP* to reduce the risk of a *future* stroke appears to decline with age, and drops to less than $2 for 60-year-olds.

Despite the actual incidence of diabetes increasing with age, as shown in Figure 3, the *WTP* for a risk reduction for diabetes (in the unrealistic sudden death case) drops from about $5 for the 30-year-old to only $0.22 for the 60-year-old. For the more-plausible prospective scenario with latency and five years of future illness, the *WTP* is a little higher for the 30-year-old (at $5.04), but it drops to essentially zero for the 60-year-old. Diabetes appears to be more of a concern among the young than among older people. There is of course some possibility that this is a cohort effect rather than an age effect, with younger respondents simply being more attuned to the prospect of diabetes given greater awareness in recent years.[21]

Willingness to incur costs to reduce the risk of injuries or death from traffic accidents is surprisingly low. However, we suspect that our choice scenarios may have left something to be desired. Respondents were told that they could buy additional equipment with their new car, or retrofit an older vehicle, at a specified annualized cost. For most of the illness profiles, however, the injury was described as occurring more than seven years into the future. It is possible that many people, assuming that they would not own their current car for more than a few additional years, might have been reluctant to pay for these measures. It was difficult to get this illness scenario to conform to the others. In fact, most people perceive themselves to be at relatively little risk of a motor vehicle accident (i.e. we are all better-than-average drivers).

[21] We cannot explore cohort effects since we have just a one-time cross-sectional survey, not longitudinal data or repeated cross-sectional data.

Despite the potential for "scenario rejection" with the traffic accident risk reduction programs, the implied *WTP* for a microrisk reduction in the chance of sudden death from a traffic accident in the current year is still $1.11 for the 30-year-old and $1.53 for the 45-year-old, although it drops to $0.75 for the 60-year-old. For the case with latency, the 30-year-old has a *WTP* of $1.71. *WTP* decreases to essentially zero for the 60-year-olds in the scenario with latency. Our data appear to support the notion that willingness to pay to reduce traffic accident risks may be lower than that for all of the specific health threats covered in our study, with the exception of skin cancer (and perhaps diabetes amongst the oldest age group).

Traffic accidents are of surprisingly little concern among older people, perhaps because they see themselves to be less at risk because they spend less time on the road, or because they believe themselves to be safer drivers than younger people are. Figure 4 reveals that older respondents report less experience with traffic accidents, either for themselves or among their family and friends. Only for the youngest group does there appear to be an interval estimate for willingness to pay to reduce serious traffic accidents that, when scaled, could capture the *VSL* used by the Department of Transportation in 2003.[22]

The *WTP* to avoid Alzheimer's disease is highest for 45-year-olds, at $4.27. For the 60-year-old case, *WTP* to reduce death from Alzheimer's disease in the current period is about $2.74. In the more-plausible latent case for the 60-year-old, where Alzheimer's will not begin until they are 70 and they will not die until they are 75, the *WTP* is lower, at $1.40.

B. *Comparisons with Public Spending*

What is the correlation between our estimates of the private demand to reduce specific illnesses and observed public spending patterns? In Table 4, we provide a side-by-side

[22] We use 90% intervals. A 95% interval would of course be somewhat wider.

comparison of our estimates of *WTP* for a microrisk reduction in the chance of sudden death now, for 45-year-olds, and actual 2006 public expenditures on specific illnesses and accidents as reported by the National Institutes of Health and the National Highway Traffic Safety Administration.[23] There appears to be a close correlation in the rank-ordering of individuals' willingness to pay to reduce their risks of specific illnesses and the ranking-ordering of public sector expenditures on these specific illness and accident risks. We cannot claim that the private preferences we have identified in this research directly account for this pattern of public spending. However, the correlation is notable.

Among the patterns in Table 4, prostate cancer and stroke have similar *WTP* and attract similar magnitudes of public expenditure. Colon cancer and lung cancer are similar in terms of both *WTP* and public expenditures, and both amounts are lower than they are for prostate cancer and stroke. Traffic accidents and respiratory disease involve distinctly lower *WTP* and attract less public expenditure (although we have data only for chronic obstructive pulmonary disease, COPD). Skin cancer has the lowest *WTP* on the list, and a distinct category of public spending is not even reported for this illness.

VI. Conclusions

Overall, there are substantial differences in willingness to pay for health risk reductions by type of illness or injury. These differences go beyond just what can be accounted for by the future pattern of health states represented by the health risk in question (i.e. latency, sick-years, recovered/remission years and lost life years). This suggests that models which constrain the estimated marginal utility parameters for different health states to be the same across all illnesses

[23] Since we focus in Table 4 on demand for programs to reduce near-term mortality risks, we exclude those illnesses associated primarily with extended periods of morbidity (such as diabetes and Alzheimer's disease).

may be too restrictive. These restrictions may cause the loss of information that could actually be very valuable from a policy perspective.

Our estimated differences in *WTP* suggest that respondents have different *WTP* values for avoiding different illnesses. This implies that the types of health threats to be targeted by a specific health-related policy (as well as the age and income groups the policy will affect) may need to be taken into consideration in any thorough benefit-cost analysis, especially when the possible distributional consequences of policy are important.

References

[Blinded for review]. 2010. "Demand for Health Risk Reductions." *under review*.

Cameron, Trudy Ann. 2010. "Euthanizing the Value of a Statistical Life." *Review of Environmental Economics and Policy*.

Cutler, David M. and Elizabeth Richardson. 1997. "Measuring the Health of the United States Population." *Brookings Papers on Economic Activity: Microeconomics*, pp. 217–71.

Graham, Daniel A. 1981. "Cost-Benefit-Analysis under Uncertainty." *American Economic Review*, 71(4), pp. 715-25.

Hammitt, James K. and Jin-Tan Liu. 2004. "Effects of Disease Type and Latency on the Value of Mortality Risk." *Journal of Risk and Uncertainty*, 28(1), pp. 73-95.

Moore, Michael J. and W. K. Viscusi. 1988. "The Quantity-Adjusted Value of Life." *Economic Inquiry*, 26(3).

Murphy, Kevin M. and Robert H. Topel. 2006. "The Value of Health and Longevity." *Journal of Political Economy*, 114(5).

Robinson, Lisa A. 2007. "How US Government Agencies Value Mortality Risk Reductions." *Review of Environmental Economics and Policy*, 1(2), pp. 283-99.

Savage, Ian. 1993. "An Empirical Investigation into the Effect of Psychological Perceptions on the Willingness-to-Pay to Reduce Risk." *Journal of Risk and Uncertainty*, 6(1), pp. 75-90.

Van Houtven, George; Melonie B. Sullivan and Chris Dockins. 2008. "Cancer Premiums and Latency Effects: A Risk Tradeoff Approach for Valuing Reductions in Fatal Cancer Risks." *Journal of Risk and Uncertainty*, 36(2), pp. 179-99.

Vassanadumrongdee, Sujitra and Shunji Matsuoka. 2005. "Risk Perceptions and Value of a Statistical Life for Air Pollution and Traffic Accidents: Evidence from Bangkok, Thailand." *Journal of Risk and Uncertainty*, 30(3), pp. 261-87.

Viscusi, W. Kip and Joseph E. Aldy. 2003. "The Value of a Statistical Life: A Critical Review of Market Estimates Throughout the World." *Journal of Risk and Uncertainty*, 27(1), pp. 5-76.

Figure 1: One example of a randomized choice scenario

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

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

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

Figure 2: Mean perceived health vulnerability by age
(with moving averages of mean and +/- 2 std.dev.)

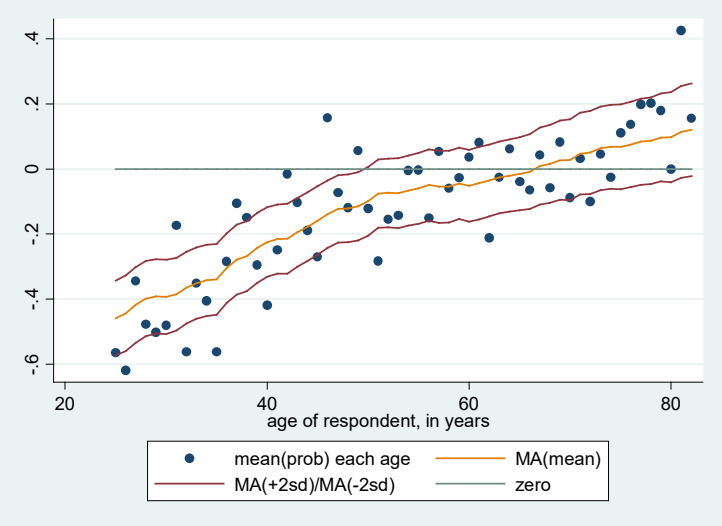

Figure 3: Own experience with diabetes by age
(with moving averages of mean and +/- 2 std.dev.)

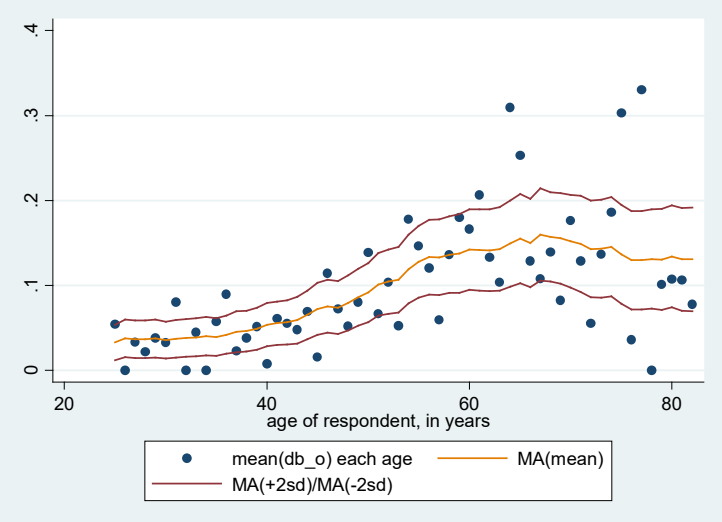

Figure 4: Own or family/friends experience with traffic accidents by age (with moving averages of mean and +/- 2 std.dev.)

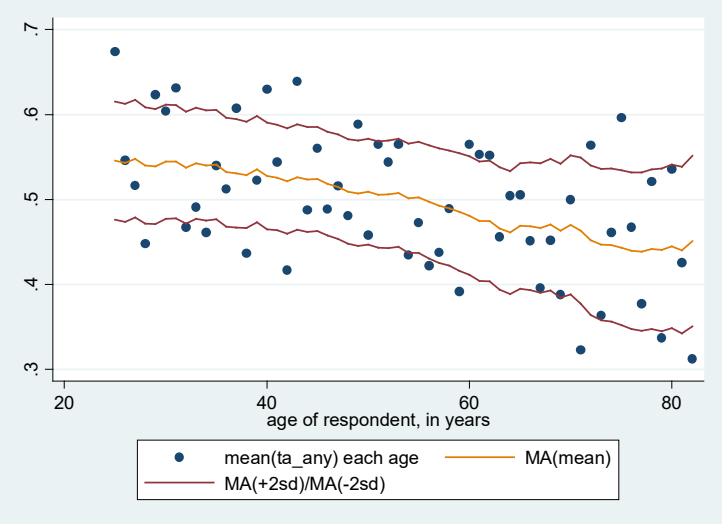

TABLE 1A—DESCRIPTIVE STATISTICS FOR HETEROGENEITY (N = 13,972 ILLNESS PROFILES)[a]

Illness	Share of profiles	# resp.	Controllability [b]					# resp.	Subjective Risk [b]				
			-2 very little	-1	0	+1	+2 a lot		-2 low risk	-1	0	+1	+2 high risk
Breast Cancer	0.047	1661	0.233	0.214	0.302	0.137	0.113	1661	0.16	0.195	0.322	0.213	0.112
Prostate Cancer	0.045	”	”	”	”	”	”	”	”	”	”	”	”
Lung Cancer	0.091	”	”	”	”	”	”	”	”	”	”	”	”
Colon Cancer	0.090	”	”	”	”	”	”	”	”	”	”	”	”
Skin Cancer	0.091	”	”	”	”	”	”	”	”	”	”	”	”
Heart Disease	0.094	1658	0.130	0.153	0.280	0.248	0.189	1655	0.151	0.194	0.297	0.227	0.131
Heart Attack	0.094	”	”	”	”	”	”	”	”	”	”	”	”
Respiratory Disease	0.089	1661	0.316	0.200	0.220	0.114	0.151	1661	0.337	0.207	0.227	0.135	0.095
Stroke	0.094	1661	0.195	0.173	0.291	0.199	0.142	1661	0.225	0.231	0.325	0.141	0.080
Traffic Accident	0.086	1661	0.543	0.199	0.163	0.043	0.052	1647	0.202	0.234	0.39	0.125	0.05
Diabetes	0.090	1661	0.293	0.169	0.223	0.159	0.156	1650	0.312	0.208	0.226	0.128	0.127
Alzheimer's Disease	0.090	1661	0.526	0.192	0.188	0.039	0.055	1641	0.427	0.252	0.236	0.067	0.018

[a] Descriptive statistics for basic variables in the choice model (income, program costs, and the stated durations in each health state in the illness profile in question) are provided in [Blinded for review] (2010) and its supporting appendices.

[b] While it may be generally preferable to use sets of dummies to capture these variables in our empirical specification, we assume that the measured relationships are roughly linear in the ratings for each variable, to conserve on the size of the parameter space (which would become huge).

TABLE 1B—DESCRIPTIVE STATISTICS FOR HETEROGENEITY (N = 1,661 RESPONDENTS)

Variable	Distribution of values				
Age (at time of survey, continuous)			mean (std dev) 50.4 (15.1)		
Room to improve by quitting smoking[a,b]	-2 no room	-1	0	+1	+2 much room
	0.718	0.014	0.034	0.04	0.194
Implied smoker?			0	1	
	-	-	0.722	0.278	-
Vulnerability (next 20 years) [b]	-2 very unlikely	-1 somewhat unlikely	0 somewhat likely	+1 very likely	
	0.058	0.217	0.504	0.222	-
Confidence (in health care) [b]		-1 not at all confident	0 somewhat confident	+1 highly confident	
	-	0.155	0.526	0.319	-

[a] Sample size is 1,637 respondents for this variable

[b] Again, it will be assumed that the marginal utilities in question are approximately linear in these ratings, to conserve on parameters.

TABLE 2—ESTIMATED PARAMETERS FOR PARSIMONIOUS MODEL
WHEN ATTITUDINAL VARIABLES ARE SET TO THEIR NEUTRAL (MODAL) VALUES[A]

Basic Model Terms	
(β)[square-root-term in net income]	0.02144 (10.55)***
(δ_j)[illness-specific indicators]	(expanded in Table 2a)
$(\alpha_{20})\Delta\pi_i^{jS}\log(pdvr_i^j+1)$	-65.44 (5.67)***
$(\alpha_{10})\Delta\pi_i^{jS}\left[\log(pdvi_i^j+1)\right]$	(expanded in Table 2b)
$(\alpha_{13})\left[P(sel_i)-\overline{P}\right]\Delta\pi_i^{jS}\left[\log(pdvi_i^j+1)\right]$	4.086 (2.50)**
$(\alpha_{30})\Delta\pi_i^{jS}\log(pdvl_i^j+1)$	(expanded in Table 2c)
$(\alpha_{31})age_{i0}\cdot\Delta\pi_i^{jS}\log(pdvl_i^j+1)$	44.33 (5.69)***
$(\alpha_{32})age_{i0}^2\cdot\Delta\pi_i^{jS}\log(pdvl_i^j+1)$	-0.3791 (5.02)***
$(\alpha_{40})\Delta\pi_i^{jS}\left[\log(pdvl_i^j+1)\right]^2$	302.9 (3.17)***
$(\alpha_{41})age_{i0}\cdot\Delta\pi_i^{jS}\left[\log(pdvl_i^j+1)\right]^2$	-16.18 (4.16)***
$(\alpha_{42})age_{i0}^2\cdot\Delta\pi_i^{jS}\left[\log(pdvl_i^j+1)\right]^2$	0.1363 (3.59)***
$(\alpha_{52})age_{i0}\cdot\Delta\pi_i^{jS}\left[\log(pdvi_i^j+1)\right]\cdot\left[\log(pdvl_i^j+1)\right]$	-2.869 (3.75)***
$(\alpha_{52})age_{i0}^2\cdot\Delta\pi_i^{jS}\left[\log(pdvi_i^j+1)\right]\cdot\left[\log(pdvl_i^j+1)\right]$	0.02798 (2.37)**
Total number of: choice sets (alternatives)	6,986 (20,958)
LogL	-9894.76

[a] Appendix 1 to this paper contains the complete set of parameters for this model, including the coefficients on the attitudinal variables: *Vulnerability* (to one of this list of illnesses over the next 20 years) and an interaction between *age* and this variable, *Confidence* (that treatment would be timely and effective), *Controllability* (of the named class of illness), and *At Risk* (the individual's own subjective risk of suffering from this class of illness).

TABLE 2A—AUTONOMOUS EFFECT OF ILLNESSES ON UTILITY IN PARSIMONIOUS MODEL [a]

		Shifters	
Autonomous utility term	Basic Terms	* Age	* Smoker
(base case = heart disease) [b]	0	0.01244 (6.24)***	-
heart attack	0.757 (9.15)***	-	-
breast cancer	0.5671 (3.75)***	-	-
prostate cancer	0.7155 (5.11)***	-	-
lung cancer	-	-	0.2209 (6.33)***
colon cancer	0.2455 (2.36)**	-	-
skin cancer	-	-0.00841 (3.67)***	-
respiratory disease	-	-0.00507 (2.22)**	0.1603 (4.12)***
stroke	0.6003 (7.10)***	-	-
traffic accident	-	-	-
diabetes	1.59 (4.15)***	-0.02824 (3.58)***	-
Alzheimer's disease	0.6305 (1.73)*	-0.01109 (-1.54)	-

[a] TABLE 2 and its sub-tables emphasize the main variables we examine in this paper. Statistically significant coefficients on other control variables for Vulnerability, Confidence, Subjective Risk (of the illness), and Control(lability) are not reported in the body of this paper. See the Appendix 1 for the complete set of coefficient estimates.

[b] Utility is normalized on the level for heart disease, so the coefficient for heart disease is set to zero.

TABLE 2B—EFFECTS OF ILLNESS ON SICK-YEARS TERMS IN PARSIMONIOUS MODEL

		Shifters[a]	
Sick Year Terms	Basic Terms	* Age	* Smoker
$(\alpha_{10})\Delta\pi_i^{jS}\log(pdvi_i^j+1)$ (base case = heart disease)	-181.7	3.18	-
	(3.72)***	(3.32)***	
*heart attack	198	-	-
	(3.73)***		
*breast cancer	199.9	-	-
	(3.26)***		
*prostate cancer	209.9	-	-
	(3.53)***		
*lung cancer	116.4	-	-
	(2.35)**		
*colon cancer	192.3	-1.634	-
	(2.93)***	(1.72)*	
*skin cancer	204.7	-2.206	-
	(3.13)***	(2.07)**	
*respiratory disease	291.4	-3.214	-
	(3.74)***	(2.58)***	
*stroke	216.5	-	-
	(4.02)***		
*traffic accident	202.7	-	-
	(3.92)***		
*diabetes	393.2	-5.193	-
	(3.82)***	(2.98)***	
*Alzheimer's disease	280.8	-3.471	-
	(2.45)**	(1.83)*	

[a] See footnote to TABLE 2A.

TABLE 2C—EFFECTS OF ILLNESS ON LOST LIFE-YEARS TERMS IN PARSIMONIOUS MODEL

		Shifters[a]	
Lost life-year Terms	Basic Terms	* Age	* Smoker
$(\alpha_{30})\Delta\pi_i^{jS}\log(pdvl_i^j+1)$ (base case = heart disease)	-846.8 (4.43)***	-	-
*breast cancer	-191.3 (2.35)**	3.512 (2.21)**	-
*traffic accident	-	0.7696 (2.33)**	-
*diabetes	-	1.14 (2.27)**	-

[a] See footnote to TABLE 2A.

TABLE 3—WILLINGNESS TO PAY FOR A 1 IN 1,000,000 RISK REDUCTION, BY HEALTH THREAT (TWO SCENARIOS, INCOME = $42,000) [a]

Profile	Sudden Death Now			10 year latency; sick 5 years, then death		
Health Threat / Age now	30	45	60	30	45	60
Heart Disease	4.61 [2.23, 7.14]	7.02 [5.10, 9.09]	7.73 [5.67, 10.16]	7.69 [5.98, 9.67]	5.79 [4.57, 7.14]	3.45 [2.42, 4.59]
Heart Attack	7.07 [4.55, 9.61]	8.28 [6.50, 10.29]	7.82 [5.94, 9.93]	7.60 [5.78, 9.52]	5.69 [4.35, 7.25]	3.34 [2.24, 4.60]
Breast Cancer	10.75 [6.40, 15.7]	8.91 [5.79, 12.45]	5.55 [2.05, 9.23]	10.02 [7.22, 13.2]	5.76 [4.07, 7.52]	1.43 [-0.32, 3.09]
Prostate Cancer	6.79 [3.86, 9.80]	8.01 [5.82, 10.48]	7.54 [5.23, 10.11]	7.05 [5.38, 8.84]	5.13 [3.87, 6.56]	2.78 [1.54, 4.01]
Colon Cancer	3.81 [1.20, 6.45]	5.03 [3.29, 6.84]	4.56 [2.70, 6.62]	5.74 [4.06, 7.44]	4.41 [3.32, 5.68]	2.65 [1.66, 3.73]
Lung Cancer	2.27 [-0.12, 4.59]	3.46 [1.94, 5.04]	3.00 [1.28, 4.77]	4.80 [3.46, 6.36]	2.88 [1.90, 3.96]	0.58 [-0.44, 1.46]
…* smoker	7.86 [4.87, 10.94]	9.07 [6.77, 11.57]	8.61 [6.32, 11.05]	10.40 [8.19, 12.86]	8.50 [6.61, 10.56]	6.16 [4.51, 7.88]
Skin Cancer	0.94 [-1.82, 2.98]	1.12 [-0.87, 2.95]	0.41 [-2.49, 2.08]	2.63 [1.19, 4.17]	0.78 [-0.39, 1.83]	0 [-2.82, -0.37]
Stroke	6.08 [3.57, 8.71]	7.30 [5.45, 9.25]	6.83 [4.97, 8.87]	6.15 [4.48, 8.02]	4.23 [2.94, 5.64]	1.88 [0.68, 3.14]
Respiratory Disease	1.41 [-1.2, 3.64]	2.00 [0.21, 3.76]	1.20 [-1.16, 3.07]	1.94 [0.04, 3.74]	0.77 [-0.59, 1.95]	0.03 [-2.29, 0.24]
…* smoker	5.33 [2.61, 8.20]	6.06 [3.85, 8.38]	5.11 [2.62, 7.60]	6.00 [3.94, 8.18]	4.78 [3.22, 6.50]	3.12 [1.59, 4.71]
Traffic Accident	1.11 [-1.4, 3.22]	1.53 [-0.14, 3.24]	0.75 [-1.43, 2.37]	1.71 [0.24, 3.24]	0.10 [-2.03, 0.62]	0 [-4.75, -1.68]
Diabetes	4.98 [1.83, 8.16]	2.60 [0.02, 5.13]	0.22 [-4.5, 1.62]	5.04 [3.34, 6.82]	1.77 [0.58, 2.98]	0 [-3.04, -0.37]
Alzheimer's Disease	4.12 [1.12, 7.18]	4.27 [2.38, 6.21]	2.74 [0.63, 5.06]	5.17 [3.22, 7.18]	3.51 [2.27, 4.82]	1.40 [0.35, 2.46]

Note: Based on 1000 random draws from the asymptotically joint normal distribution of the estimated parameters. Simulations assume that for health risk reductions provided by public policies, respondents do not assume that they will be excused from paying for the policy if they get sick. Furthermore, if they die early from this illness, they do not factor into their implicit willingness to pay calculations the fact that if they die, they will earn no income but will not have to pay for the program or other consumption. In this case, $cterm_i^j = yterm_i^j = pdvc_i^j$. The absolute levels of the separate probabilities of getting sick, either with or without the risk reduction program, do not figure into the $WTP(\mu r)$ formula.

TABLE 4—COMPARISON OF WTP WITH PUBLIC SPENDING

Disease	*WTP* by 45-year olds	Weighted average [a]	2006 Public spending[a]	Public spending rank[b]
Heart Disease/ Heart Attack	$7.02/$8.28		$2,485 m	1
Breast Cancer	8.91		718 m	2
Prostate Cancer	8.01		348 m	3
Stroke	7.30		342 m	4
Colon Cancer	5.03		269 m	5
Lung Cancer	3.46	} $5.02	$266 m	6
- Smokers	9.07			
Traffic Accidents	1.53		$155 m[c]	7
Skin Cancer	1.12		-	-
Respiratory Disease	2.00	} 3.13	$67 m (COPD only)	8
- Smokers	6.06			

[a] Assuming 27.8% of population smokes.
[b] Center for Disease Control, Estimates of Funding for Various Research, Condition, and Disease Categories (RCDC), http://report.nih.gov/rcdc/categories/
[c] NHTSA Budget Overview FY2006, National Highway Traffic Safety Administration, http://www.nhtsa.gov/ ; Spending on Vehicle Safety.

APPENDIX—COMPLETE SET OF PARAMETER ESTIMATES FOR THE MODEL IN TABLE 2 (OPTIONAL OR ON-LINE APPENDIX)

The discussion in the body of this paper focuses on just the key results, with all of the attitudinal control variables in the model set to their median (zero) values in the estimating sample. This Appendix provides the entire parsimonious model in Table A and some further discussion of the additional coefficients not displayed in Table 2 or 2A, 2B, and 2C in the text.

We control for a set of attitudinal variables because we do not wish to confound our estimated age effects with attitudes that are correlated with the respondent's age. Note that controls for age are essential, since eligible illness profiles for each offered program in our choice sets are conditioned on each individual respondent's gender and current age (for which there are 135 unique combinations among our respondents). Programs associated with very long illnesses and large numbers of prospective lost life-years are only offered to individuals who are currently young, for example.

Vulnerability.—Perhaps the most notable finding with respect to these additional control variables is that greater perceived vulnerability to at least one of the major health threats covered in the survey increases the size of the estimated autonomous utility from programs for every type of health threat other than traffic accidents. There is further evidence that the size of this vulnerability effect on autonomous utility may decline with the age of the respondent in a way that does not differ across illness types. Greater perceived vulnerability also seems to amplify the disutility associated with sick-years from heart attacks and traffic accidents, where there are no apparent age effects. However, the disutility from lost life-years does not seem to be affected by perceived vulnerability to any of these health threats. When we calculate our willingness to pay estimates, however, we set these vulnerability ratings and the other attitudinal variables to their

central tendencies in the sample (which has been normalized to zero). Thus these terms will drop out.

Confidence.—Compared to the coefficients on the interactions between illness indicators and the "vulnerability" perception variable mentioned in the text of the paper, the estimated effects of "confidence" about the prospects for timely and effective health care are less robust. Several statistically significant coefficient estimates merit comment, however. Greater confidence in health care means that the autonomous utility associated with breast cancer and stroke-related programs is reduced, but the baseline disutility per discounted lost life-year due to breast cancer or stroke is increased. For colon cancer, the effects are different. Greater confidence means there is more autonomous utility associated with programs for colon cancer, and that the baseline disutility per discounted sick-year with colon cancer is reduced. For respiratory disease, greater confidence in health care lessens the baseline disutility associated with discounted sick-years, while for diabetes, it increases the autonomous utility associated with programs to reduce risk. The results for Alzheimer's disease are particularly interesting. The more confident the respondent is in the timeliness and effectiveness of their health care, the less disutility they express for discounted sick-years from Alzheimer's and the more disutility they express for discounted lost life-years due to this illness. Thus they are less concerned about being sick from Alzheimer's and relatively more concerned about dying early from this affliction if they are confident about their health care. This makes sense.

Controllability.—Perceived controllability of each health threat does not appear to have a statistically significant effect on the autonomous utility associated with any of the risk reduction programs. However, the more controllability the respondent ascribes to cancers, traffic accidents, and diabetes, there appears to be greater disutility associated with sick-years from those illnesses

(although the effect is not quite significant for cancers or traffic accidents). In contrast, a greater perceived controllability of Alzheimer's disease reduces the ex ante disutility from sick-years due to that ailment. Greater controllability appears to lessen the anticipated disutility from life-years lost due to respiratory disease, but it increases the anticipated disutility from life-years lost due to stroke. As noted in the paper, however, the perceived controllability may capture two competing effects. Greater controllability may mean that the individual perceives less of a need for a special intervention in the form of the health tests described in the choice scenarios, decreasing demand for these tests. Alternatively, greater controllability may mean that the prescribed medication and life-style changes as a result of positive test results may be more effective, increasing the demand for the diagnostic tests. The controllability effects should thus be interpreted as net effects across these two competing tendencies.

Subjective risks.—The individual's "subjective risks" of experiencing the type of health threat associated with each illness profile appear to have no impact upon the autonomous utility associated with each disease. The ex ante disutility from sick-years due to respiratory disease appears to be lessened for those with greater perceived risk of this disease, but this likely reflects the fact that we also control for smoking status. Non-smokers may feel an unwarranted immunity from respiratory disease. As one might expect, a greater perceived risk of cancers in general increases the disutility from lost life-years due to cancers. In contrast, greater perceived risk seems to reduce the disutility associated with prospective lost life-years due to stroke. This may reflect an assumption that strokes lead to sudden death, rather than long-term pre-mortality morbidity.

Again, we note that the systematic effects of these attitudes (independent of the respondent's age and the time profiles of each illness) are netted out of the model before it is used to produce the WTP estimates featured in this paper.

TABLE A - ENTIRE PARSIMONIOUS MODEL: TABLE 2 EXPANDED TO SHOW ADDITIONAL CONTROLS
(COEFFICIENTS NOT ROBUSTLY SIGNIFICANTLY DIFFERENT FROM ZERO HAVE BEEN SET EQUAL TO ZERO)

		Shifters (0=non-smoker or neutral, except for age)						
	Basic Terms	* Age	* Smoker	*Vulnerability	*Age *Vulnerability	*Confidence	*Control	*Subjective Risk
Illnesses								
heart disease	-	0.01244 (6.24)***	-	1.081 (4.04)***	-0.01465 (2.79)***	-0.221 (-1.53)	-	-
heart attack	0.757 (9.15)***	-	-	0.3845 (4.14)***	-	-	-	-
breast cancer	0.5671 (3.75)***	-	-	0.3459 (3.23)***	-	-0.3555 (1.90)*	-	-
prostate cancer	0.7155 (5.11)***	-	-	0.4317 (3.89)***	-	-	-	-
lung cancer	-	-	0.2209 (6.33)***	0.3603 (4.28)***	-	-	-	-
colon cancer	0.2455 (2.36)**	-	-	0.2934 (3.55)***	-	0.2859 (1.92)*	-	-
skin cancer	-	-0.00841 (3.67)***	-	0.2852 (3.08)***	-	-	-	-
respiratory disease	-	-0.00507 (2.22)**	0.1603 (4.12)***	0.4043 (4.43)***	-	-	-	-
stroke	0.6003 (7.10)***	-	-	0.4679 (5.71)***	-	-0.2787 (2.08)**	-	-
traffic accident	-	-	-	-	-	-	-	-
diabetes	1.59 (4.15)***	-0.02824 (3.58)***	-	0.4518 (5.03)***	-	0.2112 (2.13)**	-	-
Alzheimer's disease	0.6305 (1.73)*	-0.01109 (-1.54)	-	0.2439 (2.79)***	-	-	-	-

Continued on next page…

Appendix 1, continued

		Shifters (0=non-smoker or neutral, except for age)						
Sick Year Terms:	**Basic Terms**	* Age	* Smoker	*Vulnerability	*Age *Vulnerability	*Confidence	*Control	*Subjective Risk
$(\alpha_{10})\Delta\pi_i^{jS}\log\left(pdvi_i^j+1\right)$	-181.7 (3.72)***	-	-	-	-	-	-	-
*heart disease	-	3.18 (3.32)***	-	-	-	-45.77 (-1.62)	-	-
*heart attack	198 (3.73)***	-	-	-55.51 (1.76)*	-	-	-	-
*general cancer	-	-		-	-	-	-9.189 (-1.61)	
*breast cancer	199.9 (3.26)***	-	-	-	-	-	-	-
*prostate cancer	209.9 (3.53)***	-	-	-	-	-	-	-
*lung cancer	116.4 (2.35)**	-	-	-	-	-	-	-
*colon cancer	192.3 (2.93)***	-1.634 (1.72)*	-	-	-	91.47 (3.00)***	-	-
*skin cancer	204.7 (3.13)***	-2.206 (2.07)**	-	-	-	-	-	-
*respiratory disease	291.4 (3.74)***	-3.214 (2.58)***	-	-	-	42.59 (1.84)*	-	16.45 (3.64)***
*stroke	216.5 (4.02)***	-	-	-	-	-	-	-
*traffic accident	202.7 (3.92)***	-	-	-84.91 (3.04)***	-	-	-8.435 (-1.49)	-
*diabetes	393.2 (3.82)***	-5.193 (2.98)***	-	-	-	-	-8.018 (1.65)*	-
*Alzheimer's disease	280.8 (2.45)**	-3.471 (1.83)*	-	-	-	106.1 (2.83)***	12.67 (2.03)**	-

Continued on next page…

Appendix 1, continued

		Shifters (0=non-smoker or neutral, except for age)						
Lost life-year Terms:	**Basic Terms**	* Age	* Smoker	*Vulnerability	*Age *Vulnerability	*Confidence	*Control	*Subjective Risk
$(\alpha_{30})\Delta\pi_i^{jS}\log\left(pdvl_i^j+1\right)$	-846.8 (4.43)***	-	-	-	-	-	-	-
*any cancer	-	-	-	-	-	-	-	-9.837 (2.02)**
*breast cancer	-191.3 (2.35)**	3.512 (2.21)**	-	-	-	-86.45 (1.93)*	-	-
*respiratory disease	-	-	-	-	-	-	16.44 (3.56)***	-
*stroke	-	-	-	-	-	-84.65 (3.18)***	-12.6 (2.39)**	16.32 (3.14)***
*traffic accident	-	0.7696 (2.33)**	-	-	-	-	-	-
*diabetes	-	1.14 (2.27)**	-	-	-	-	-	-
*Alzheimer's disease	-	-	-	-	-	-93.64 (2.41)**	-	-

Continued on next page…

Appendix 1, continued

Basic Model Terms and Scenario Adjustment Variables:	**Basic Terms**	$\times 1(never_i^j)$	$\times$ *overest. latency*$_i^j$	$\times$ *overest. life expect*
(β)[square-root-of-income term]	0.02144 (10.55)***	-	0.000467 (3.33)***	-
$(\alpha_{20})\Delta\pi_i^{jS}\log(pdvr_i^j+1)$	-65.44 (5.67)***	-	-	-
$(\alpha_{13})\left[P(sel_i)-\overline{P}\right]\Delta\pi_i^{jS}\left[\log(pdvi_i^j+1)\right]$	4.248 (2.59)***	-	-	-
$\alpha_{10}\Delta\pi_i^{jS}\left[\log(pdvi_i^j+1)\right]$	See Table 2b	282.4 (5.37)***	8.738 (8.46)***	-1.581 (1.66)*
$(\alpha_{31})age_{i0}\cdot\Delta\pi_i^{jS}\log(pdvl_i^j+1)$	44.33 (5.69)***	-	-	-
$(\alpha_{32})age_{i0}^2\cdot\Delta\pi_i^{jS}\log(pdvl_i^j+1)$	-0.3791 (5.02)***	-	0.008492 (10.39)***	-0.00217 (2.73)***
$(\alpha_{40})\Delta\pi_i^{jS}\left[\log(pdvl_i^j+1)\right]^2$	302.9 (3.17)***	400.3 (4.28)***	-	-
$(\alpha_{41})age_{i0}\cdot\Delta\pi_i^{jS}\left[\log(pdvl_i^j+1)\right]^2$	-16.18 (4.16)***	-5.298 (3.52)***	0.1561 (4.35)***	-
$(\alpha_{42})age_{i0}^2\cdot\Delta\pi_i^{jS}\left[\log(pdvl_i^j+1)\right]^2$	0.1363 (3.59)***	-	-0.00422 (5.23)***	0.00079 (2.13)**
$(\alpha_{51})\cdot\Delta\pi_i^{jS}\left[\log(pdvi_i^j+1)\right]\cdot\left[\log(pdvl_i^j+1)\right]$	0	-381.8 (4.03)***	-5.617 (4.73)***	1.17 (-1.38)
$(\alpha_{52})age_{i0}\cdot\Delta\pi_i^{jS}\left[\log(pdvi_i^j+1)\right]\cdot\left[\log(pdvl_i^j+1)\right]$	-2.869 (3.75)***	-	-	-
$(\alpha_{52})age_{i0}^2\cdot\Delta\pi_i^{jS}\left[\log(pdvi_i^j+1)\right]\cdot\left[\log(pdvl_i^j+1)\right]$	0.02798 (2.37)**	0.0788 (3.38)***	-	-
Choice sets (alternatives)	6,986 (20,958)			
LogL	-9894.76			