Advances in Evaluating the Demand for Risk Prevention Policies

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Advances in Evaluating the Demand for Risk Prevention Policies

Abstract

We evaluate several concerns related to measuring the demand for public risk prevention policies, using an innovative national survey and new modeling strategies. We find that the omission of avoided morbidity leads to an upward bias in estimates of the marginal utility of avoided deaths. Individuals experience diminishing marginal utility in the scope of mortality- and morbidity-reducing policies. Individual attitudes towards government involvement and, particularly, perceptions of the personal benefits of different policies, appear to be important determinants of demand. Finally, we uncover little evidence of heterogeneity in demand for public health policies according to the proximate health threat (e.g. cancer, stroke, respiratory disease, injury) or the underlying cause (e.g. exposure to contaminants in air, water, food; highway hazards).

Keywords: morbidity, mortality, public health, VSL, environmental health, risk prevention

1 Introduction

Economists strive to design efficient—or at least cost-effective—health, environmental and safety programs that reduce individuals' risks of illness and death. However, relative to the number of studies of demand for private risk reductions,[2] researchers have undertaken few demand analyses for public risk prevention programs. Furthermore, several concerns about the benefits of public risk prevention policies have impeded the confident application of both benefit-cost and cost-effectiveness analyses. We address some of these concerns by empirically exploring sources of preference heterogeneity, using new national survey of demand. This survey employs an unusually comprehensive description of policy attributes and evaluates, in one set of experiments, what seems to be the widest array of public risk prevention policies to date.

In general, existing empirical models have not adequately controlled for the effects of morbidity when risk prevention policies reduce both illnesses and deaths. As a result, estimates of the value of an avoided death may be biased because of the omission of a substitute health state, especially when mortality and typical morbidity profiles are correlated. We improve upon past specifications by explicitly estimating individuals' marginal utilities of preventing both illnesses and deaths.

In addition, neither private nor public risk demand analyses have adequately explored how marginal utilities change with the size of the risk reduction in question for either illnesses or deaths. Instead, researchers have maintained the ad hoc assumption of constant marginal utility, which is reflected in the proportionality assumption typically used when calculating the Value of Statistical Life (VSL). Even if utility is approximately linear with respect to small changes in the

[2] See Viscusi and Aldy [25] for a review. [1] and [10] represent two recent papers on the topic of mortality risk valuation in the environmental economics literature.

size of a private risk, we may still expect to see diminishing marginal utility with respect to the number of lives saved by public health policies. This is because individuals may be willing to pay for the policy for reasons other than just their own private risk reductions. We allow the marginal utilities of both avoided illnesses and avoided deaths to vary with the size of the risk reduction, thereby revealing the extent to which public preferences tend to exhibit diminishing marginal utility.

Beyond these basic modeling concerns, individuals' demands for public risk prevention policies may also exhibit complicated preference structures not found in the demand for private programs. For example, individuals may hold preferences over the private benefits to themselves or their families as well as the public benefits to others from a particular policy. This raises a potential concern about the current practice wherein researchers rely upon demand estimates only for private risk reductions when they conduct benefit-cost analyses of public programs. Do individuals hold strong enough other-regarding preferences to invalidate the practice of estimating benefits based only on self-regarding preferences? Surprisingly little empirical evidence exists with which to answer this question. We document how the perceived direct personal benefits of public programs vary across individuals, and how the levels of these personal benefits, in turn, affect individual demands for a public program.

In addition, individuals may hold preferences not only over the final risk reduction, but also *how* that risk reduction is achieved. In particular, some may find risk prevention programs that require extensive government invention to be welfare diminishing. Including these preferences is essential if the researcher seeks to develop a highly predictive behavioral model that explains the systematic variation in individuals' observed support for alternative programs. More often, however, researchers seek to estimate the benefits of the risk reduction outcome independent of individuals' preferences over *how* that outcome is achieved. Given that public policies may be particularly vulnerable to the confounding of preferences over outcomes and provision mechanisms, we explicitly accommodate and control for both of these during data collection and model estimation. In doing so, our specification retains some relevant behavioral determinants, while at the same time, it permits researchers to isolate the benefits of the program's mortality and morbidity risk reductions (as distinct from the provision mechanism) for use in benefit-cost analyses.

The policies that individuals consider in our survey are pure public goods in that they are non-rival and non-excludable. In part, an individual may be willing to pay for a policy because it reduces the risk that he, himself, may get sick or die—the purely private benefits. However, willingness-to-pay for these policies may not be motivated exclusively by a desire for private safety improvements [22].[3] Individuals may also have other motives, such as altruism, for expressing positive willingness-to-pay. We focus on estimating willingness-to-pay for reductions in the number of community illnesses and deaths, rather than on willingness-to-pay for a risk reduction that only benefits one individual. This approach is similar to that of Subramanian and Cropper [22]. Hammitt and Liu [14], in contrast, focus on willingness to pay for a single private risk reduction provided by a public good.

Certainly, individuals' motivations for expressing positive willingness-to-pay are important for public policy. Bergstrom [4] showed that the component of willingness-to-pay that is motivated by altruism needs to be excluded from benefit-cost analysis if the purpose of the analysis is to identify potential Pareto improvements. A clear exception to this rule is the case of "safety-focused" or "paternalistic" altruism [19, 20]. Other authors have argued that even when

[3] Rodriguez and Leon [21] find that altruism is a significant portion of willingness to pay.

altruism is non-paternalistic, it is not clear that this source of WTP should be completely disregarded. For example, Harbaugh [15] argues that the Bergstrom result does not hold if it is cheaper to transfer a good like safety to others than it is to transfer cash. Moreover, Flores [12] shows that when there is preference interdependence between public goods and the distribution of income, the Bergstrom result likewise no longer holds.

When undertaking cost-effectiveness analysis, researchers have expressed concern that representing the benefits in terms of "lives saved" per policy may be too unidimensional, obscuring individuals' preferences over other aspects of policies and their outcomes. Individuals may hold preferences over types of health risk outcomes avoided by the policy, perhaps preferring reductions in deaths from one type of illness (e.g., heart attack) relative to another (e.g., breast cancer) [6, 14, 22]. Individuals' demands for particular programs may vary with the type of risk exposure avoided. For example, research suggests that individuals' preferences for risk reductions vary depending upon whether exposures are perceived as controllable and voluntary [7, 22]. To address the question of benefit heterogeneity in cost-effectiveness studies, we directly evaluate shifts in demand for categorically different types of risk exposures as well as programs targeting a wide range of illnesses.

Our analysis is based on data from a conjoint stated preference survey of demand for preventative risk-reducing policies that was administered to a nationally representative sample of over 1,500 individuals. Within choice sets, we vary the number of illnesses prevented, the number of deaths avoided, the length of time the policy is in effect, the source of the health threat, the type of disease avoided, the size of the affected population, and several other attributes. We also elicit individual-specific measures of the perceived incidence of the private benefits of each program as well as a measure of attitudes toward government intervention. As a matter of course, we also submit our estimated models to numerous robustness and validity checks: we assess scope effects, order effects, sample selection biases and (through survey design) we attempt to mitigate hypothetical bias associated with incentive incompatibility.

We find that failing to measure and control for the avoided illnesses associated with a policy may produce an upward bias in estimates of the marginal utility of an avoided death. We show that individuals view avoided morbidity and avoided mortality as substitute goods, so omitting one of these goods from the individual's choice set may artificially increase apparent demand for the other. Failing to acknowledge changes in the number of illnesses inflates estimates of the marginal utility of an avoided death by a dramatic amount. We also find clear evidence of diminishing marginal utility for risk reductions in the case of both illnesses and deaths. For example, individuals are willing to forego an extra \$60 to avoid an additional death when the policy avoids only 10 deaths, but when the policy avoids 200 deaths, the model indicates that individuals are willing to forego only \$3 to avoid an additional death.

An innovative feature of our empirical model is the construction of a variable that measures individuals' general propensities to choose public risk prevention programs over a status quo alternative. Interestingly, we find a general disinclination to pay to support public prevention programs. The size of this disinclination (e.g., the attractiveness of the status quo alternative) is largest when individuals prefer minimal government intervention and also anticipate receiving very little personal benefit from the program. Relatively speaking, however, an individual's perception of significant personal benefits from a policy appears to be far more important in explaining their demand than is their attitude toward government intervention. Individuals' general preferences against government involvement in risk prevention programs matter most when these programs benefit only others. It is telling, however, that this antiintervention preference does not decrease their demand nearly as much when they anticipate that a program will benefit them personally. In our data, many individuals anticipate no personal risk reduction, while others anticipate very large risk reductions for themselves. These discrepancies contribute to wide variability in estimated WTP.

Overall, we find that yearly WTP for an average program in our sample, conditional on average reported personal benefits and average attitudes about government intervention, is about \$519. We hasten to add, however, that our WTP estimates can also vary widely depending on the characteristics of the particular policy or respondent.[4]

Finally, we directly evaluate differences in demand across different categories of risk exposures including air, water and food contaminants as well as highway risks. We also evaluate differences in individuals' demands for programs according to whether the program targets cancers (in general), leukemia, colon/bladder cancer, asthma, lung cancer, heart disease, heart attack, stroke, respiratory disease, and traffic accidents. We assess whether these two types of risk attributes shift individuals' estimated marginal utilities from 1) avoided deaths, 2) avoided illnesses, and 3) the duration of the program. We find no evidence of statistically significant effects of these dimensions of risk heterogeneity on the willingness to pay of individuals for the range of programs in our study.

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[4] A VSL \$6.1 million would imply a WTP of \$517 per person per year if it was applied (for example) to a program that saves 10 lives per year in a population of 118,000 people (\$517 = (10*\$6,100,000)/118,000), because WTP implied by a VSL depends on the size of the affected population. In our survey, the population size is framed randomly (median 50,000, mean of 245,000). Effects of this experiment are described in a separate paper.

Section 2 of this paper describes our data and the survey used to collect them. Section 3 lays out our demand model. Our basic empirical estimates are detailed in Section 4, while Section 5 explores some dimensions of the systematic variability in our demand data. Section 6 concludes.

2 Data and Survey Design

The data used for this analysis were gathered using a survey instrument designed specifically to elicit individuals' willingness to pay for publicly provided preventative health policies, rather than strictly private interventions. The survey was administered by Knowledge Networks Inc., an internet-based market research firm offering a representative panel of households in the US who complete surveys via a web TV or personal computer interface. A nationally representative sample of 1,511 respondents completed this survey. In Appendix A, we outline the array of measures taken to ensure the quality of our data and to assess the robustness and validity of our empirical results.[5]

The first module of our survey evaluates the individual's subjective risk assessment for the major types of risks and illnesses they face, their familiarity with each illness, and any mitigating and averting behavior they may undertake. The survey is introduced to respondents as a way "to better understand how you view threats to your health and the health of others."

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[5] Marginal distributions of various socio-demographic variables for both our estimating sample and the U.S Census are provided for comparison in the online appendix in Table A1. Our response rate was 79% among invited participants from this consumer panel with excellent sampling properties. Models that allow the marginal utilities to shift with the individual's fitted selection probability (from a model that predicts participation in this survey from an RDD panel sample of over half a million households) reveal little sensitivity.

Respondents are informed that “your answers may help public officials provide you and your community with better ways of managing health threats.”[6]

The second module consists of an extended tutorial that introduces individuals to the idea of policies that may manage these illness-specific risks. The survey explains that new governmental policies could keep environmental problems from getting worse, that new clean technologies could prevent air, water, and food contamination from getting worse, and that other technologies could reduce traffic hazards. The attributes of the first pair of policies to be considered (costs and benefits) are introduced in a careful step-by-step process. Each health risk presented to respondents has an (asserted) underlying cause. Each cause is coupled only with a plausible type of illness or injury. For example, a policy may be presented to the respondent as one that “reduces air pollutants that cause respiratory disease.”[7] The eligible causes include: air pollutants, drinking water contaminants, pesticides in foods, and road and car hazards. The associated proximate health threats are described in terms of illnesses or injuries attributed to the specified cause, and consist of cancer, leukemia, leukemia in children, colon/bladder cancer,

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[6] Carson, et al. [5] suggest that for a survey question to yield useful answers it needs to be consequential and incentive-compatible. Our survey design is consequential in the sense that individuals are notified that their answers to the survey questions will be made available to policy makers to help them make better decisions.

[7] Obviously, some combinations of risk sources and diseases or injuries are not plausible, and these are eliminated from the randomized design. Efforts to avoid implausible combinations come at the cost of some correlation among the design variables, although there should be no correlations with observed or unobserved respondent characteristics.

asthma, asthma in children, lung cancer, heart disease, heart attack, stroke, respiratory disease, or car accident.

The third module contains the five main choice sets, each offering the individual two prevention policies, Policy A and Policy B, that reduce both future deaths and illnesses, as well as a “neither policy” alternative (denoted N). Respondents are asked to consider each choice separately, are reminded that the policies are not free, are asked to consider their budget constraint, and are reminded of people’s propensities in survey settings not take these constraints adequately into account.[8]

An example of the types of three-alternative choice scenarios presented to respondents in our study is shown in Figure 1. The yearly policy cost to the respondent is randomly varied from $60 to $1200. Both this annual cost and the corresponding monthly cost of each policy are explicitly shown to respondents. The length of time the policy would be in effect is randomly varied. Policies run for 2, 4, 5, 10, 15, 20, 25, or 30 years. The means and standard deviations of the randomized choice-set design variables are presented in Table 1.[9]

In each of the five choice sets presented to each respondent, the individual could choose between the two explicit policies offered (A or B) or she could choose neither policy (N, the status quo). We carefully explain to individuals that they may find it appropriate to choose neither policy by pointing out several possible explanations why reasonable people might choose

[8] Individuals were given a “cheap talk” script, as recommended by Cummings and Taylor [9].

[9] Online Appendix Table A2 shows the utilized design matrix for death and illness reductions.

neither policy in some cases.[10] If individuals choose "neither policy," we assume that they prefer the status quo to either of the two costly policies in each choice set.

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

3 Demand Model

The empirical models we use in this paper fall into the class of random utility models for conjoint choice data (see [24]). Each choice set presented to respondents consists of three policy alternatives (A, B, and N), where each alternative can be characterized by different levels of a common set of attributes. There is now a long tradition of using such models to infer utility-theoretic estimates of demand for different types of goods.

In the body of this paper, we present and discuss our “ad hoc” specification.[11] $\textit{Illness Reductions}_{ji}$ is the total number of illness reductions provided by policy j offered to respondent i. Likewise, $\textit{Death Reductions}_{ji}$ is the total number of deaths avoided by policy j, and $\textit{Duration}_{ij}$ is the number of years for which the policy is described to be in effect. We hypothesize that

[10] These reasons include that they 1) cannot afford either policy, 2) did not believe the policies would reduce health risks 3) would rather spend the money on other things, 4) did not believe the specified environmental problems cause illness, 5) did not believe their community faced these risks. If the individual chose “neither policy” (N) we asked them why (in a follow-up question). Although reasons 2, 4, and 5 may be considered “non-economic” reasons for choosing “neither Policy”, we find that excluding these choices has no qualitative impact on the estimation results.

[11] The online appendix develops an alternative “structural” model that attends specifically to the issue of discounting [14] and attempts to incorporate time preferences more rigorously than in much of the existing literature (e.g. [3, 7, 8, 18, 22]).

individual i's indirect utility is linear in income (a very common assumption). Relative to the status quo, we also assume that indirect utility is linear in particular functions of avoided illnesses, avoided deaths, and the length of time the policy lasts. For any policy j, the individual's deterministic indirect utility is thus:

$$\begin{aligned} V_{ji} = \beta\left(Y_{ji}\right) + \delta_1 f\left(Illness\ Reductions_{ji}\right) \\ + \delta_2 g\left(Death\ Reductions_{ji}\right) \\ + \delta_3 h\left(Duration_{ji}\right) \end{aligned} \tag{1}$$

where Y_{ji} is income, β is the marginal utility of income, δ_1 is the marginal utility of an increase in f, δ_2 is the marginal utility of an increase in g, and δ_3 is the marginal utility of an increase in h.[12]

We also introduce a dummy variable, POL_j, that is equal to 1 if the alternative is either of the two explicit public policy options (A or B) and 0 if the alternative is "neither policy" (i.e., the status quo). The coefficient on this dummy variable, θ, serves a function similar to that of an intercept shifter in an ordinary regression model. It will capture the average effect on utility of all other unspecified factors associated with either of the two policy alternatives for which we do not explicitly control in our random-utility model [24, pp. 21-27]. Allowing θ to vary systematically with individual- or policy-specific attributes, as we will do, increases flexibility in estimation without sacrificing the utility-theoretic foundations of the model.

To allow for flexible estimation options, we assume here only that $f(0)=0$, $g(0)=0$, $h(0)=0$ and that f, g, and h are increasing in their arguments. By explicitly recognizing policy costs c_{ji}

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[12] δ_3 conveys the marginal disutility experienced when the benefits of the policy are spread more thinly across time. One objection to (1) is the assumption that utility is additively separable in avoided illnesses and deaths. In the empirical section, we relax this assumption by including an interaction term. It is omitted here, to simplify the exposition.

(and rendering the model stochastic with an extreme-value distributed error term η_{ji}), the utility level provided by policy *j* to individual *i* can be written:

$$\begin{aligned} V_{ji} = \beta(Y_i - c_{ji}) &+ \delta_1 f(\textit{Illness Reductions}_{ji}) \\ &+ \delta_2 g(\textit{Death Reductions}_{ji}) \\ &+ \delta_3 h(\textit{Duration}_{ji}) \\ &+ \theta POL_j + \eta_{ji} \ , \qquad j = A, B \end{aligned} \tag{2}$$

In contrast, if the status quo option is chosen instead, total utility is given simply by:

$$V_{Ni} = \beta Y_i + \eta_{Ni} \tag{3}$$

We normalize the utility from each policy on the level of utility under the status quo alternative (N), and assume that these perceived indirect utility differences drive the stated choices of our respondents:

$$\begin{aligned} \left(\Delta V_{ji}\right) = \beta\left(-c_{ji}\right) &+ \delta_1 f(\textit{Illness Reductions}_{ji}) \\ &+ \delta_2 g(\textit{Death Reductions}_{ji}) \\ &+ \delta_3 h(\textit{Duration}_{ji}) \\ &+ \theta POL_j + \varepsilon_{ji} \ , \qquad j = A, B \end{aligned} \tag{4}$$

where $\varepsilon_{ji} = \eta_{ji} - \eta_{Ni}$. Equation (4) represents our basic estimating specification.

The preference parameters β, δ_1, δ_2, δ_3 and θ implied by our three-way choices can be estimated using McFadden's conditional logit model. The probabilities that individual *i* will choose policy A, policy B, or neither policy (N) are:

$$\Pr(\mathrm{A})_i = \frac{\exp(\Delta V_{Ai})}{\exp(\Delta V_{Ai}) + \exp(\Delta V_{Bi}) + 1} \tag{5}$$

$$\Pr(\mathrm{B})_i = \frac{\exp(\Delta V_{Bi})}{\exp(\Delta V_{Ai}) + \exp(\Delta V_{Bi}) + 1} \tag{6}$$

$$\Pr(\mathrm{N})_i = \frac{1}{\exp(\Delta V_{Ai}) + \exp(\Delta V_{Bi}) + 1} \tag{7}$$

For each policy choice, the indicators A_i, B_i, and N_i take on a value of 1 if respondent *i* selects, "Policy A," "Policy B," or "Neither". Each indicator is zero otherwise. Using these abbreviations, the log-likelihood function can be written compactly as:

$$\text{LogL} = \sum_{i=1}^{n} \left[A_i \log(\Pr(\text{A})_i) + B_i \log(\Pr(\text{B})_i) + N_i \log(\Pr(\text{N})_i) \right] \qquad (8)$$

We next derive formulas for total WTP, marginal WTP, and pair-wise marginal rates of substitution. Crude point estimates of WTP can be calculated by solving for the annual payment that would make the individual just indifferent between (a) paying for the policy and receiving the benefits, and (b) not paying for the policy and not receiving the benefits. We set the utility difference in equation (4) equal to zero and solve for c_{ji}^* :

$$WTP_{ji} = c_{ji}^* = \beta^{-1} \begin{bmatrix} \delta_1 f(Illness\ Reductions_{ji}) \\ +\delta_2 g(Death\ Reductions_{ji}) \\ +\delta_3 h(Duration_{ji}) \\ +\theta POL_j + \varepsilon_{ji} \end{bmatrix}, \qquad j = A, B \qquad (9)$$

Treating the utility parameters as deterministic and taking expectations over the symmetrically distributed error term yields a rough point estimate of maximum willingness to pay (*WTP*) for a policy with specified levels of each of the three main policy characteristics (and, of course, $POL_j = 1$). Allowing the parameters β, δ_1, δ_2, and δ_3 to vary systematically with individual- or policy-specific attributes allows us to predict willingness-to-pay for different types of individuals or policies. [13]

[13] The ratio of two asymptotically normally distributed variables has an undefined mean, although a sample mean can be calculated for any finite number of simulated draws from the joint distribution of the parameters. Estimates of, say, the 5th and 95th percentiles of the sampling

Estimates of *marginal WTP* (*MWTP*) for a particular policy attribute can be obtained by taking the derivative of expected *WTP* with respect to that attribute. *MWTP* typically involves the ratio of the coefficient on that attribute to the estimated marginal utility of income. For example, the estimated MRS between policy cost and illness reductions is given by:

$$MRS_{IllnessReductions,\,Cost} = \left(\frac{-\delta_1}{\beta}\right) f'(Illness\ Reductions_{ji}) \tag{10}$$

While WTP estimates derived from our model are not directly comparable to conventional estimates of the Value of a Statistical Life (*VSL*), the marginal rates of substitutions reported in the estimation section below reveal that the overall WTP estimates derived from our model are broadly consistent with empirical VSL estimates.

4 Estimation Results

We employ ordinary three-alternative conditional logit models[14] to estimate the unknown utility parameters and investigate several different functional forms for the utility-difference "index" that is linear in the negative of $Yearly\ Cost_{ji}$: a simple all-linear functional form, as well

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distribution of the ratio can be approximated via bootstrapping techniques. Here, we rely on the ample statistical significance of the estimated parameters to imply respectably narrow confidence intervals for these WTP estimates. Before applying these estimates for policy purposes, it would of course be advisable to simulate the sampling distributions for estimated *WTP* for the particular policy in question.

[14] We have also conducted the analysis using a fixed-effects multinomial logit algorithm. The results are qualitatively unchanged (as expected, given the randomized design of the policy attributes.). Thus, we report results for the simpler econometric specification only.

as specifications that are quadratic and logarithmic in the other variables. Our most parsimonious specification is presented in Table 2. [15,16]

As a model allowing for some curvature, the superior fit of the logarithmic specification relative to the linear model is corroborated by the individual statistical significance of the squared terms in the quadratic models. The logarithmic specification also displays the highest maximized value of the log-likelihood function. For the logarithmic functional form, of course, the estimated parameter δ_1 can be roughly interpreted as the marginal utility of a 1% increase in the number of avoided illnesses.

Overall, the results obtained from the simple specification that is logarithmic in health effects seem plausible and intuitive. The estimated marginal utility of avoiding deaths is larger than the marginal utility of avoiding illnesses in all specifications. The logarithmic specification indicates that MWTP for a 1% increase in avoided illnesses is about \$70 per year, while MWTP for a 1% increase in avoided deaths is about \$250 per year.[17] The coefficient on Log($Duration_{ji}$)

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[15] We use a shifted log specification to maintain the assumption that $f(0)=0$ and $g(0)=0$. For example, we use log(Illness Reductions+1) rather than log(Illness Reductions).

[16] For policies with death and/or illness reductions that differ dramatically from the means of the design matrix, the linear models tend to give implausible fitted values for willingness-to-pay. A linear approximation may fit well near the means of the data, but predict poorly at the fringes of the sample if the true model is non-linear.

[17] The fact that the estimated derivatives of indirect utility are declining in the size or scope of a policy has several possible explanations. Natural to economists is the idea of diminishing marginal utility in health policy attributes, but other explanations are possible. Part of the motivation for expressing positive WTP for these policies may be “warm glow” [2] that is not

can be interpreted as the disutility from spreading the policy benefits over a longer period of time (e.g. 10 deaths avoided over 10 years instead over 9 years). The coefficient θ on POL_j is statistically significantly negative, suggesting a negative average effect on utility of the common unspecified attributes of any of the hypothetical public risk prevention policies. We return to examine variability in θ more closely in Section 5.

4.1 The Effect of Morbidity When Valuing Reduced Mortality

In Table 3, we evaluate an experiment concerning the role of morbidity information in these demand analyses. Information about the illness reductions achieved by each policy was included for a randomly selected subsample of respondents ($Seeill_i$=1) while for others, it was omitted ($Seeill_i$=0). The dummy variable capturing these different experimental treatments does not appear in any of the models reported so far because this treatment is constant across alternatives for each individual, and therefore drops out of the indirect utility differences. The marginal utility of avoided illnesses is conditional on illness information being available. Within these models, we first assess whether individuals perceive morbidity and mortality to be complements or substitutes. Next we explore the extent of the bias in the estimated marginal utility of avoided mortality when information on illnesses is not made explicit in the survey.

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systematically related to the scope of the policy. Another explanation is a "psychophysical numbing" or "Weber's law" phenomena. Psychologists have long documented that our ability to discern a difference in a physical stimulus diminishes as the base level increases [11]. Regardless of the explanation, these data suggest that sharply diminishing estimated marginal utilities are a basic feature of demand for preventative public health policies.

Finally, we characterize how the marginal rate of substitution between avoided deaths and avoided illnesses varies with different levels of avoided illnesses.

In Table 3, observe the negative and statistically significant coefficient on the interaction between the *Illness Reduction*$_{ji}$ term and the *Death Reduction*$_{ji}$ term (δ_{22}), which suggests that the estimated marginal utility of a 1% reduction in deaths is smaller when the number of illness reductions is larger. Information about the number of avoided illnesses thus affects the apparent marginal utility of avoided deaths. Respondents appear to view illness reductions and death reductions as substitutes.

Most empirical analyses focus solely on mortality risks, ignoring any associated morbidity. This implies a presumption that the marginal utility of reducing deaths should be unaffected by the presence or absence of information about the number of illnesses. However, we find that the inclusion of illness information in a choice scenario changes the resulting estimates of the marginal utility of avoided deaths. Estimated MWTP for a 1% increase in avoided deaths is about $480 when avoided illnesses are not mentioned to the respondent (*Seeill*$_i$=0) but this drops to about $192 when the number of illnesses are presented (*Seeill*$_i$=1) and the number of avoided illnesses is set equal to the sample median of 100.

These results suggest that typical estimates of the marginal utility attributed exclusively to avoided deaths may be subject to considerable (upward) distortion when a study fails to describe the avoided illnesses achieved by different policies. At a minimum, the estimated marginal utilities should be viewed as pertaining to a package of mortality effects and their associated morbidity effects, rather than to mortality effects alone. Moreover, the size of this bias appears to vary systematically with the number of deaths avoided. This bias is likely to be largest for studies of policies that value reductions in hazards that present high risks of morbidity but low probabilities of death, relative to high probability mortality hazards, since relatively fewer deaths can be avoided and thus valued within the study's context. This apparent bias holds implications for both cost-effectiveness and benefit-cost analyses that focus only upon "lives saved," ignoring morbidity.

Furthermore, we find that even when avoided illnesses are explicitly presented, the imputed MRS between avoided illnesses and deaths varies in a nonlinear way. The *Seeill*=1 columns of Table 4 shows the estimated MRS between avoided illnesses and avoided deaths. The results suggest that, for a policy that prevents 50 deaths and 50 illnesses, individuals would require about 3 more avoided illnesses to compensate for one more death. However, for a policy that prevents the same number of deaths but allows 600 illnesses, the individual would require almost 25 avoided illnesses to compensate for one more death.

4.2 Diminishing Marginal Utility of Additional Prevented Deaths

Researchers who employ the Value of Statistical Life often make the strong assumption of a constant marginal utility for risk reductions. This assumption, equivalent to the proportionality assumption implicit in the standard VSL calculation, precludes the possibility of diminishing marginal utility. Within our models, we do not need to make such an assumption since individuals may reveal how the marginal utility of risk reductions varies as the magnitude of the reduced risk increases. We observe diminishing marginal utility in the magnitude of the public risk reduction. To illustrate the potential magnitude of this effect, Table 4 presents point estimates of the marginal rates of substitution between policy attributes and dollars implied by the indirect utility parameter estimates in Table 3. We find that the estimated marginal utilities decline quickly as the number of prevented deaths or illnesses increases. For example, when $Seeill_i$=0, individuals are willing to forgo an extra $48 to avoid an additional death when the policy only avoids 10 deaths. However, when the policy avoids 200 deaths, the model indicates that individuals are willing to forgo only an additional \$2.40.

The fact that the estimated marginal utility of an avoided death declines rapidly has important implications for how benefits estimates are transferred from a study setting to a benefit-cost policy setting. Great care must be taken to ensure that the studies upon which a benefits transfer exercise relies involve risk magnitudes that are comparable to those relevant in the policy setting of interest.

5. Systematic Variability in Demand for Public Prevention Policies

We now return to interpret and explore the implications of using the alternative-specific dummy variable, denoted POL_j. Across alternatives, this variable is equal to 1 if the alternative is either of the two public risk prevention policy options and equal to 0 for the status quo option. The coefficient θ on this dummy variable captures the average effect on person *i*'s utility, *relative* to the status quo option, of all other factors associated with policy options A or B for which we do not explicitly control in the random-utility model [23, 24].

In Tables 2 and 3, we see that θ, the estimated coefficient on POL_j, is statistically significant and negative. The average effect on utility of all unspecified policy attributes is large relative to the collective effect of those attributes of policies explicitly described to the respondents. The negative sign on the coefficient implies that respondents do not, on average, view the unspecified attributes of the hypothetical policies as desirable. They require, on average, that the "specified" benefits (illness and death reductions) more than outweigh the specified costs in order for them to choose one of the two public policies.

5.1. Sources of Systematic Variability in Demand for Public Policies

We now explore two variables that may help explain why some individuals have a tendency to perceive both of the two offered risk prevention programs as categorically less desirable than the status quo alternative. First, researchers have long suspected that individuals hold preferences over not only (a) the *level* of risk reduction achieved, but also (b) the *manner* in which risk reductions are achieved [16, 17, 22]. Individuals might strongly oppose government intervention because of its reliance upon public financing of risk prevention (i.e., taxes) or the imposition of new regulations. Instead they may prefer to rely solely upon market-provided programs and the defensive or mitigating behavior of individuals to reduce risks. Such preferences might systematically shift the utility the associated with public risk prevention programs. To measure these preferences, we presented individuals with the following question: "People have different ideas about what their government should be doing. How involved do you feel the government should be in regulating environmental, health and safety hazards?" Individuals were invited to rate their preferred level of government involvement along a continuum ranging from minimally involved (0) to heavily involved (7). We call this variable *Government Preference*$_i$.[18]

We next explore a second variable that may also explain systematic shifts the utility individuals derive from public risk prevention programs. We asked individuals to rate the extent to which they perceived each public program to yield private benefits in the form risk reductions to themselves or their families, as do Subramanian and Cropper [22]. Demand studies vary in

[18] This variable is ordinal but we limit the complexity of our estimating specification by treating it as an approximately cardinal variable. We have explored treating it as a categorical variable and found no qualitative change in the implications of the model.

how they present the benefits of public risk programs. Some present only the private benefits of a public program to individuals [14], which individuals might assume apply to all members of the public including themselves. Others simply describe the consequences of the program in terms of the illness and risk-exposure context that is targeted by the program as well as the number of illnesses avoided and lives saved over a period of time [6, 22]. Importantly, these studies do not attempt to assert the particular private benefits to each respondent.

We follow in this later tradition, believing that individuals will invariably infer different levels of private benefits from particular programs (depending upon their individual and family characteristics). To obtain a program- and individual-specific measure of anticipated private benefits, we posed the following question after each choice set: "To what extent would each policy directly benefit you or your family?" Individuals could respond along a five-level ordinal scale ranging from "very little" to "greatly." We call this variable *Personal Benefit*$_{ji}$. Again, to keep our models simple, we treat this variable as approximately cardinal.

Next we allow θ, representing the magnitude of the common disutility shared by both active policy alternatives in each choice set, to vary systematically with both *Government Preference*$_i$ and *Personal Benefits*$_{ji}$. Results for the "Full Model" in Table 5 show that both variables have statistically significant positive coefficients while the coefficient on their interaction is negative and significant. To see the impact of this heterogeneity on estimated *WTP*, we note from equation (9) that the portion of *WTP* contributed by the POL_j variable and its systematically varying θ coefficient is

$$\beta^{-1}\begin{bmatrix} \theta_0 + \theta_1 Government\ Preference_i \\ + \theta_2 Personal\ Benefits_{ji} \\ + \theta_3 Government\ Preference_i \cdot \\ Personal\ Benefits_{ji} \end{bmatrix} POL_j \tag{11}$$

In Figure 2, we illustrate the potential magnitude of the influence of these factors on the *WTP* estimates implied by our model. The plotted lines show how this component of fitted *WTP* varies with the rating of *Personal Benefits*$_{ji}$, for three selected levels of *Government Preference*$_i$. The relative bias against the policy options is largest when individuals prefer "minimal" government intervention (*Government Preference*$_i$ =0) and simultaneously anticipate receiving "very little" personal benefit from either program (*Personal Benefits*$_{ji}$=0). Under these conditions, the policy alternatives are handicapped by more than \$3,700 against the status quo. However, the status quo alternative becomes dramatically less appealing to individuals who prefer heavy government provision (*Government Preference*$_i$ =6) and who simultaneously expect to benefit directly from the public program under consideration (*Personal Benefits*$_{ji}$=4). For policies with this combination of conditions, willingness to pay is higher by about \$2,400. The robust statistical significance of the relevant parameters suggests that these estimated differences are important.

Overall, differences in *Personal Benefit*$_{ji}$ appear to explain relatively more of the variation in individuals' demands for the public program than variation in *Government Preference*$_i$, although this difference may be due to the fact that *Personal Benefit*$_{ji}$ is an individual- and alternative-specific variable, whereas *Government Preference*$_i$ is merely individual-specific. It appears that individual demand for public programs varies substantially according to whether one anticipates private benefits from the programs. The average rating of benefits in our sample was 1.8 (on a scale of zero to four, with four being highest). This average rating may explain why the status quo alternative, on average, is valued relatively more than the offered policies. Interestingly, any rating of *Personal Benefit*$_{ji}$ exceeding 2 would shift upward the value of the average public policy to the point where it would be valued, on average, more than the individual's status quo alternative.

5.2. Heterogeneity in Risk Exposure Contexts and Risk of Illnesses

Finally we explore the extent to which marginal utilities shift with different risk contexts and types of illnesses. As part of our research design, we randomly assigned individuals the opportunity to reduce risk in different risk contexts and for different types of illnesses. Recall that each policy option presented to respondents improves community health by reducing one of four underlying sources of risk: pesticides in food, air pollution, drinking water contaminants, and road hazards. Each policy also targets the reduction of a particular illness (or group of illnesses): cancer (generic), colon/bladder cancer, leukemia in general, asthma in general, lung cancer, heart disease, heart attack, stroke, respiratory disease, leukemia in children, asthma in children, and traffic injuries.[19]

5.2.1. Heterogeneity by Source of Risk

Table 6 shows results from an analysis that explores heterogeneity by underlying cause: air pollution, chemicals in drinking water, pesticides in food, and traffic accidents. For

[19] Policies that reduce air pollution are paired with leukemia, asthma, lung cancer, heart disease, heart attack, respiratory disease, leukemia in children, and asthma in children. Policies that reduce contaminants in drinking water are paired with cancer, colon/bladder cancer, leukemia, stroke, and leukemia in children. The same diseases that are paired with contaminants in drinking water are also paired with pesticides in food. Road hazards are paired only with injuries from traffic accidents.

completeness, we allow these sources of risk to shift the marginal utilities of (1) illnesses reduced, (2) deaths avoided, (3) the duration of the programs, and (4) the individual's propensity to choose any public program (rather than the status quo). Many components of these now systematically varying marginal utility parameters remain individually significantly different from zero, but the relevant issue here is whether there are significant differences within each set of coefficients. Wald tests reported at the foot of each column are used to assess whether all the disease-specific coefficients in that column are jointly equal. We find that we cannot reject the hypotheses that the marginal utilities are identical within each column. We thus conclude that different risk exposure contexts do not significantly affect the estimated marginal utility of avoided illnesses, avoided deaths, or the duration of the policy. Our results are consistent with those of Subramanian and Cropper [22], but differ from those of Hammitt and Liu [14] and Chestnut et al. [6]. However, these latter two studies acknowledge that the apparent differences they detect may be due to differences in payment vehicles, mitigation strategies, or the fact that their illnesses are correlated with different risk exposure contexts.

5.2.2. Heterogeneity by Type of Illness/Injury

Table 7 shows selected coefficients for a generalization that allows each marginal utility and the coefficient on the POL_j dummy variable to differ by type of illness. The overall message of this analysis is similar to that for risk exposure contexts--individuals appear to value a life saved by preventing one type of illness the same as a life saved by preventing another type of illness, *ceteris paribus*. We cannot reject the hypotheses that the estimated marginal utilities are each identical across the different illness types. Again, our results differ from those of Hammitt and Liu [14] and Chestnut et al. [6], but this outcome could be explained by the greater conformability of our choice scenarios across different risk contexts.

6. Conclusion

Using a nationally representative survey, we have addressed several issues relevant to measurement of the demand for preventative public health policies. This is but the first paper in a series of papers that will further analyze the wealth of data concerning such public health policies that has been collected in a comprehensive stated preference survey.[20]

In addition to preventing premature deaths, public health policies also prevent the onset of illnesses. A major contribution of our work is to examine expressed preferences for avoided illnesses as well as avoided premature deaths, rather than just for deaths alone. We find that the estimated magnitude of the marginal utility of an avoided community death depends on whether the number of illnesses avoided is also acknowledged. Furthermore, we find that individuals view avoided illnesses and avoided deaths as substitutes. There is also considerable evidence of diminishing marginal utility from avoided deaths and illnesses. This result suggests that the common assumption of "proportionality" embodied in the standard VSL calculation may be incorrect.

A basic concern about preferences for public goods is that individuals may have complicated other-regarding preferences that make the estimation of private benefits (and specification of optimal provision rules) difficult. We find surprisingly little evidence of other-regarding preferences. Simulations suggest that demand is weak for policies that do not yield anticipated personal or family benefits. Individuals appear extremely reluctant to pay for policies

[20] An example of the complete survey may be accessed at http://darkwing.uoregon.edu/~cameron/vsl/public_prevention_framed.pdf . A description of the randomizations is contained at http://darkwing.uoregon.edu/~cameron/vsl/prevention_randomization.pdf .

that do not directly benefit them. Finally, we allow estimated utility parameters to vary based upon the type of illness that a policy prevents (e.g. respiratory disease) and based upon the underlying cause of the health threat (e.g. air pollution). We find no significant evidence of heterogeneity in preferences by these policy attributes.

In an online appendix to this paper, we introduce an alternative more-structural model for the estimation of preferences with respect to these types of public health policies. Our survey did not incorporate much detail (or heterogeneity) in the time profiles of benefits and costs to be expected from the public health policies it describes. In future surveys, if researchers can find an effective way to convey differing time profiles for benefits and costs, a structural model like this one will enable researchers to more accurately measure intertemporal preferences for public risk prevention policies. In addition to the value of avoided illnesses and deaths, heterogeneous time preferences are key concern in any effort to understand demand for policies with varying patterns of costs and benefits over time. This will be an important direction for future research.

Figure 1: Sample Choice Set

These two policies would be implemented for the 100,000 people living around you. Would you be most willing to pay for Policy A, Policy B, or neither of them?

	Policy A	**Policy B**
	reduces pesticides in foods that cause colon and bladder cancer	reduces air pollutants that cause heart attacks
Policy in effect	over 5 years	over 10 years
Cases prevented	100 fewer cases	200 fewer cases
Deaths prevented	10 fewer deaths over 5 years	5 fewer deaths over 10 years
Cost to you	$70 per month (= $840 per year for 5 years)	$6 per month (= $72 per year for 10 years)
Your choice	Policy A reduces pesticides in foods that cause colon and bladder cancer	Policy B reduces air pollutants that cause heart attacks

Neither Policy

Next Question

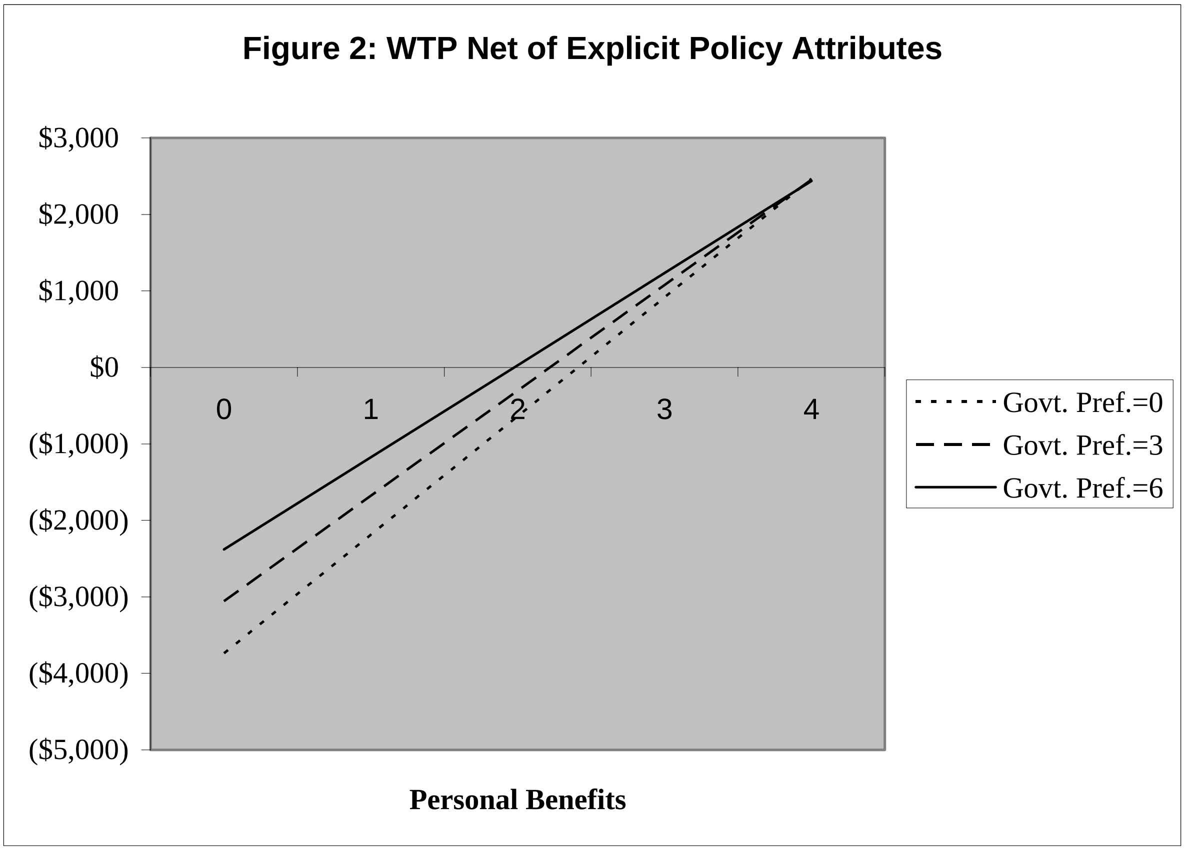
Figure 2: WTP Net of Explicit Policy Attributes
$3,000
$2,000
$1,000
$0
($1,000)
($2,000)
($3,000)
($4,000)
($5,000)
0
1
2
3
4
Govt. Pref.=0
Govt. Pref.=3
Govt. Pref.=6
Personal Benefits

Table 1: Policy-Specific Variables[a] (randomized)[b]

Variable	Mean	St. Dev.	Min	Max	Description
Yearly Cost	498.28	351.74	60	1200	Yearly cost of policy
Illness Reductions	862	1584	0	5000	Illness reductions provided by policy
Death Reductions	101	464	0	5000	Death reductions provided by policy
Duration	13.99	9.72	2	30	Length of policy (years)
See Illness Data (Seeill)	0.709	0.454	0	1	= 1 if survey provides illness reduction information, = 0 otherwise

[a] n=15122 non-status-quo policy options
[b] Except for exclusions based on implausible combinations

Table 2: Alternative Specifications (7556 choices)

Parameter	Variable	Linear	Quadratic	Log
β	*Yearly Cost*/1000[a]	0.3325 (5.95)*** [b]	0.3873 (7.12)***	0.5680 (9.72)***
δ_{10}	*Illness Reductions*/1000	0.0766 (5.99)***	0.2568 (3.87)***	-
δ_{11}	(*Illness Reductions*/1000)^2	-	-0.03812 (2.88)***	-
δ_{12}	Log(*Illness Reductions*)	-	-	0.04046 (5.77)***
δ_{20}	*Death Reductions*/1000	0.1860 (5.08)***	0.8245 (6.00)***	-
δ_{21}	(*Death Reductions*/1000)^2	-	-0.1367 (4.84)***	-
δ_{22}	Log(*Death Reductions*)	-	-	0.1394 (11.16)***
δ_{30}	*Duration*	-0.01289 (6.85)***	-0.02346 (2.98)***	-
δ_{31}	*Duration*^{2}	-	0.00035 (1.36)	-
δ_{32}	Log(*Duration*)	-	-	-0.1612 (7.05)***
θ	Policy Dummy (*POL*)	-0.1339 (2.98)***	-0.1011 (1.75)*	-0.2371 (3.30)***
Maximized Log-likelihood		-8092.00	-8073.73	-8035.20

[a]All specifications reported in this paper use the negative of the cost variable, allowing its coefficient to be interpreted as the marginal utility of income.

[b]All specifications are reported with absolute asymptotic t-ratios.

Table 3: Effects of Explicit Illness Information (7556 choices)

Parameter	Variable	Basic	Marginal Utility Shifters	Status Quo Dummy Shifter	Full Model
β_0	*Yearly Cost*/1000	0.5620	0.4282	0.5808	0.4328
		(9.72)***	(4.07)***	(9.90)***	(4.05)***
β_1	… · **1**(*See Illness Data*)	-	0.2157	-	0.2094
			(1.72)*		(1.64)
δ_{10}	Log(*Illness Reductions*)	0.0405	0.1113	0.1149	0.1136
		(5.77)***	(6.84)***	(8.30)***	(6.16)***
δ_{20}	Log(*Death Reductions*)	0.1395	0.2096	0.2195	0.2081
		(11.16)***	(8.18)***	(10.52)***	(8.27)***
δ_{21}	… · **1**(*See Illness Data*)	-	-0.00262	-	-0.00381
			(0.06)		(0.08)
δ_{22}	… · **1**(*See Illness Data*) · Log(*Illness Reduct.*)	-	-0.01677	-0.01941	-0.01752
			(2.94)***	(5.50)***	(2.69)***
δ_{30}	Log(*Duration*)	-0.1688	-0.1408	-0.1686	-0.1491
		(7.39)***	(4.00)***	(7.37)***	(3.52)***
δ_{31}	… · **1**(*See Illness Data*)	-	-0.02782	-	-0.02670
			(0.73)		(0.53)
θ_0	Policy Dummy (*POL*)	-0.2372	-0.4975	-0.3874	-0.4738
		(3.30)***	(5.39)***	(4.11)***	(3.51)***
θ_1	… · **1**(*See Illness Data*)	-	-	-0.1919	-0.0444
				(2.67)***	(0.24)
Maximized Log-likelihood		-8035.20	-8012.84	-8014.28	-8012.81

Table 4: Selected Estimated Marginal Rates of Substitution[a]

MRS between:	*Seeill*$_i$=0			*Seeill*$_i$=1		
	Avoided: *Deaths*=10	*Avoided:* *Deaths* =50	*Avoided:* *Deaths* =200	*Avoided:* *Deaths* =50 *Illnesses*=50	*Avoided:* *Deaths* =50 *Illnesses*=200	*Avoided:* *Deaths* =50 *Illnesses*=600
Policy Cost, Avoided Deaths	$48.08	$9.62	$2.40	$4.23	$3.47	$2.87
Policy Cost, Avoided Illnesses	--	--	--	$1.40	$0.35	$0.12
Avoided Illnesses, Avoided Deaths	--	--	--	-3.013	-9.894	-24.557

[a] Estimates derived from "full model" specification in Table 3.

Table 5: Personal Benefits and Government Preference Effects (7556 choices)

		Government Only	Personal Benefits Only	Full Model
β	*Yearly Cost*/1000	0.60024 (10.08)***	0.63459 (9.90)***	0.64204 (10.01)***
δ_1	Log(*Illness Reductions*)	0.04249 (5.95)***	0.04497 (5.82)***	0.04480 (5.78)***
δ_2	Log(*Death Reductions*)	0.14572 (11.46)***	0.1378 (10.06)***	0.13984 (10.19)***
δ_3	Log(*Duration*)	-0.17121 (7.37)***	-0.17550 (7.02)***	-0.17600 (7.04)***
θ_0	Policy Dummy (*POL*)	-1.3082 (12.35)***	-1.6770 (19.45)***	-2.3999 (14.88)***
θ_1	… · *Government Preference*	0.20983 (14.18)***		0.14549 (5.47)***
θ_2	… · *Personal Benefits*		0.81276 (42.46)***	0.99595 (14.63)***
θ_3	… · *Government Preference* · *Personal Benefits*			-0.03712 (3.10)***
Maximized Log-likelihood		-7752.92	-6742.31	-6725.25

Table 6: Heterogeneity by Risk Source in Utility Parameters and Implied MRS[a]

(7556 choices)

Marginal utility of income (assumed constant):

	β (*Yearly Cost*/1000)
	0.56805 (11.16)***

Other utility parameters (systematically varying):

Risk source	Log(*Illness Red.*) δ_1 (t-ratio)	Log(*Illness Red.*) MRS[b]	Log(*Death Red.*) δ_2 (t-ratio)	Log(*Death Red.*) MRS	Log(*Duration*) δ_3 (t-ratio)	Log(*Duration*) MRS	*POL*[c] θ (t-ratio)
Pesticides in Food	0.04283 (2.94)***	$0.75	0.1462 (5.46)***	$25.74	-0.1785 (3.35)***	-$31.42	-0.12391 (0.78)
Water Contaminants	0.03611 (2.44)**	$0.64	0.15314 (5.55)***	$26.96	-0.06994 (1.31)	-$12.31	-0.4954 (3.00)***
Air Pollution	0.03864 (4.14)***	$0.68	0.1260 (7.69)***	$22.18	-0.1917 (5.96)***	-$33.74	-0.1529 (1.57)
Road Hazards	0.05203 (2.96)***	$0.92	0.1685 (5.30)***	$29.66	-0.2104 (3.29)***	-$37.05	-0.3765 (1.98)**
Wald Test: δ_j identical	p=0.892		p=0.582		p=0.219		p=0.228
Log-likelihood:	-8024.94						

[a] All of the estimates in this table pertain to a single model; marginal utilities are arrayed to highlight systematic variations by cause of illness/injury.

[b] Point estimate of MRS computed at median numbers of illnesses, deaths, and durations.

[c] Coefficient on dummy variable (= 1 if policy reduces given cause, e.g. pesticides in foods.)

Table 7: Heterogeneity by Disease in Utility Parameters and Implied MRS[a]
(7556 choices)

Marginal utility of income (assumed constant):

	β (*Yearly Cost*/1000)
	0.56786 (9.61)***

Other utility parameters (systematically varying):

Disease Name	Log(*Illness Red.*) δ_1 (t-ratio)	MRS[b]	Log(*Death Red.*) δ_2 (t-ratio)	MRS	Log(*Duration*) δ_3 (t-ratio)	MRS	*POL*[c] θ (t-ratio)
Cancer (General)	0.01974 (0.95)	$0.35	0.11354 (2.78)***	$19.99	-0.09108 (1.16)	-$16.04	0.05118 (0.21)
Colon/Bladder Cancer	0.01508 (0.68)	$0.27	0.16679 (4.10)***	$29.37	-0.14055 (1.68)*	-$24.75	-0.14025 (0.56)
Leukemia	0.09223 (3.77)***	$1.62	0.1806 (4.25)***	$31.80	-0.22489 (2.62)***	-$39.60	-0.8094 (3.16)***
Asthma	0.02827 (1.17)	$0.50	0.12674 (2.97)***	$22.32	-0.22631 (2.55)**	-$39.85	-0.48274 (1.83)*
Lung Cancer	0.06566 (2.87)***	$1.16	0.15781 (3.73)***	$27.79	-0.10748 (1.26)	-$18.93	-0.52184 (1.99)**
Heart Disease	0.03871 (1.73)*	$0.68	0.14046 (3.53)***	$24.73	-0.19787 (2.46)**	-$34.84	-0.09119 (0.39)
Heart Attack	0.0164 (0.71)	$0.29	0.14916 (3.70)***	$26.27	-0.20109 (2.38)**	-$35.41	-0.13975 (0.57)
Stroke	0.06716 (2.78)***	$1.18	0.12193 (2.76)***	$21.47	-0.12541 (1.40)	-$22.08	-0.64914 (2.38)**
Respiratory Disease	0.03537 (1.57)	$0.62	0.10921 (2.63)***	$19.23	-0.33171 (3.91)***	-$58.41	0.27132 (1.11)
Leukemia in Children	0.02399 (1.21)	$0.42	0.1899 (4.97)***	$33.44	-0.18664 (2.54)**	-$32.87	0.01973 (0.09)
Asthma in Children	0.03725 (1.87)*	$0.66	0.09428 (2.77)***	$16.60	-0.09536 (1.30)	-$16.79	-0.03925 (0.18)
Traffic Accidents	0.05073 (2.88)***	$0.89	0.16875 (5.30)***	$29.72	-0.20741 (3.24)***	-$36.52	-0.37773 (1.99)**
Wald Test: δ_j identical	p=0.334		p=0.786		p=0.719		p=0.069
Log-likelihood:	-7916.28						

[a] All of the estimates in this table pertain to a single model; marginal utilities are arrayed to highlight systematic variations by cause of illness/injury.
[b] Point estimate of MRS computed at sample median numbers of illnesses, deaths, and durations.
[c] Coefficient on dummy variable that is equal to 1 if policy reduces given illness (e.g. stroke)

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ONLINE APPENDIX

In this appendix, we collect information about robustness, validation, and bias mitigation, as well as additional supporting tables. We also outline an alternative structural utility-theoretic model that more rigorously incorporates time preferences than do most existing models in the related literature. References unique to this appendix, and not appearing in the main paper, are cited with the prefix "A" (e.g. [A1]). References appearing in the main paper are cited by number from the references associated with the main paper (e.g. [1]).

I. Robustness, Validation Checks and Bias Mitigation

Mitigating Bracketing Biases Associated with Omitted Substitutes. In contrast with many valuation studies that focus on just one risk and just one risk-mitigating program, we endeavored to reduce biases associated with bracketing [A4] by ensuring that relevant substitute risks and policies were included in individuals' choice sets. Presenting a full set of major illnesses and underlying causes also increases the representativeness of our estimates and makes the motivation of a fuller range of illness profiles plausible and possible. A potential disadvantage of this approach is the cognitive complexity associated with the choice task, which we empirically evaluate and seek to minimize through the survey design and evaluate ex post.

Mitigating Hypothetical Bias. At the beginning of the valuation module, we include a "cheap talk" reminder to ensure that respondents carefully consider their budget constraint and to discourage them from overstating their willingness to pay [9, A3]. Individuals are instructed, "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…."

Mitigating Bias from Provision Rules and Order effects. In order to clarify provision rules for each choice set [A5] and to avoid potential choice set order effects [A1, A6], we instructed individuals to assume that every choice is binding and to evaluate each choice set independently of the other choice sets. Our empirical analyses showed an absence of order effects.

Testing for the Effects of Scope on Willingness to Pay. We explore whether individual choices are sensitive to scope [A2, A7]. We show using a simple ad hoc conjoint choice analysis that individuals were highly sensitive to changes in the scope or level of our central attributes (Table 2, in the main text). These models evaluate the most crucial attributes of the program, its cost and the public health benefits.

Other Validity Checks on Willingness to Pay. We also show that individuals' willingness to pay for these programs varies with several factors as economic theory would predict. Groups that can be expected to benefit most from public risk mitigations, such as racial minorities and low-income individuals expressed greater WTP. Similarly, willingness-to-pay rises with education, the level of personal benefits, and the degree to which individuals believe that government regulation of health risks is appropriate.

Validating the Representativeness of Our Estimating Sample. Our estimating sample is representative of the U.S. population in terms of standard demographic characteristics. Table A1 in this appendix illustrates this by comparing the individuals in our estimating sample with corresponding population characteristics (e.g., age, income, and gender) from the 2000 Decennial Census. Our sample consists of 7,556 choices involving 22,668 alternatives. The estimating sample, at least on these dimensions, is comparable to the population as a whole.

II. Other Information

Table A2 shows the utilized design matrix for death and illness reductions for the stated preference module of the survey. It also reveals that we have eliminated from the design a number of policies that have high death reductions but low illness reductions. This strategy helps keep the randomized design free of implausible combinations that may lead to scenario rejection by respondents.

III. An Alternative "Structural" Model

When conducting benefit-cost analyses, several concerns arise about the proper estimation of demand. For example, researchers recognize that the benefits and costs of these programs extend over several time periods. Furthermore, these benefits and costs may differ in their time profiles. Despite these concerns, existing empirical models tend to include the temporal dimension of the program's benefits and costs in an ad hoc manner, generally letting the duration of the program enter the utility function only as a separate argument [3, 7, 8, 18, 22]. By failing to temporally denominate the flows of benefits and costs, researchers limit their ability to incorporate individuals' time preferences structurally. To overcome this limitation, we explicitly incorporate time preferences in one of our estimated models, thereby directly modeling program choices in terms of the present discounted values of alternative programs.

Our comparison of the conventional ad hoc model, employed in the body of this paper, with a more-structural model suggests that the latter offers the potential for significant improvements. However, in order to take full advantage of this new type of model, the way in which researchers present the consequences of these public policies must change. Currently, most survey designs (including ours) fail to describe in any detail the intertemporal variability in the flow of costs and benefits over the project period. Over precisely which periods the various costs and benefits of the programs occur is typically left unspecified. Therefore, the added specificity of our new model, achieved through explicit incorporation of time preferences, cannot be fully realized using such abbreviated representations of benefits and costs.

When modeling consumer choices between rival prevention policies, most economists would prefer to consider the present discounted values of the two policies, especially in light of the inter-temporal consequences of time-inconsistent choices [13]. However, most surveys under-specify the per-period flows of policy costs and benefits, making the incorporation of time preferences into the demand model an ad hoc process (e.g. [3, 7, 8, 18, 22]). Most researchers thus tend to specify the utility function in terms of the total costs of a policy, the total deaths avoided, perhaps the total illness avoided, and then the duration of the policy.

In this section, we develop an alternative more structural model of demand that directly incorporates time into the estimated model and can therefore be argued to recover the present discounted value of the policy in question. Let $\textit{Illness Reductions/Year}_{jit}$ be the average number of illness reductions per year provided by policy j proposed to person i over the duration of the policy. Likewise, $\textit{Death Reductions/Year}_{jit}$ represents the average number of deaths avoided due to policy j in year t. Again as a starting point, we hypothesize linearity in income, but this time we assume that utility depends not upon the total number of illnesses and/or deaths avoided over the life of the policy, as in equation (2), but on the annual numbers of illnesses and deaths avoided in year t.

$$\begin{aligned} V_{jit} = \beta\left(Y_i - c_{jit}\right) + \delta_1 f\left(\textit{Illness Reductions/Year}_{jit}\right) \\ + \delta_2 g\left(\textit{Death Reductions/Year}_{jit}\right) + \nu_{jit} \end{aligned} \tag{12}$$

Again, β represents the common marginal utility of income, δ_1 represents the marginal utility of an increase in f and δ_2 represents the marginal utility of an increase in g. As before, we assume that $f(0) = 0$ and $g(0)=0$ and that both f and g are increasing in their arguments. To adapt this model to the way in which most researchers have presented policy costs and benefits in their survey designs, we further assume that individuals interpret the avoided illnesses and deaths as being uniformly distributed across the years of the policy. However, a major advantage of this model is that it can potentially accommodate the use of more realistic intertemporal presentations of costs and benefits to individuals, if these have been described in the choice scenarios. Again, if the person chooses "neither policy" then utility is just $V_{Nit} = \beta Y_{it} + \nu_{Nit}$. (We further simplify by assuming that individuals discount future costs and benefits at the same rate.[21])

Let T_j represent the duration in years of policy j. Over the length of time that policy j is in effect, and for each of the two policy alternatives, we can express the present discounted value (PDV) version of equation (12) as: [22]

[21] Note that discounting would be irrelevant for individual decision-making if these were simple pair-wise choices between a single policy and the status quo in these particular data, because the choice scenarios used here provide nothing to suggest that costs and benefits would be incurred with different time profiles. Discounting may be relevant to the choices expressed in our survey, however, because they involve three-way choices where time profiles explicitly differ between the two policies.

[22] We include an individual subscript on r to allow for the possibility of individual-specific discount rates in subsequent generalizations of the model since we also collected discounting choices that will allow us to distinguish between individuals with smaller and larger apparent discount rates. Here, we will assume a uniform discount rate. We also assume that POL_j just has a lump-sum effect, although more sophisticated models could be entertained.

$$PDV(V_{jit}) = \beta\left(Y_i \sum_{t=1}^{T_j} \frac{1}{(1+r_i)^t} - c_{jit} \sum_{t=1}^{T_j} \frac{1}{(1+r_i)^t} \right)$$
$$+ \delta_1 \left(f(Illness\ Reductions / Year_{jit}) \sum_{t=1}^{T_j} \frac{1}{(1+r_i)^t} \right) \quad (13)$$
$$+ \delta_2 \left(g(Death\ Reductions / Year_{jit}) \sum_{t=1}^{T_j} \frac{1}{(1+r_i)^t} \right) + \theta POL_j + \eta_{jit}$$

while for the status quo, present discounted utility will be merely

$$PDV(V_{nit}) = \beta\left(Y_i \sum_{t=1}^{T_j} \frac{1}{(1+r_i)^t} \right) + \eta_{nit} = \beta Y_i d_{nit} + \eta_{nit} \quad (14)$$

where $d_{jit} = \sum_{t=1}^{T_j} \frac{1}{(1+r_i)^t}$ can be defined for simplicity and $\eta_{jit} = d_{jit} v_{jit}$ is distributed extreme value.

If we again normalize on the utility level provided by the status quo and include a policy dummy, we can express the utility difference for policy *j* as:

$$PDV(\Delta V_{jit}) = \beta\big(-(c_{jit}) d_{jit}\big) + \delta_1 \big(f(Illness\ Reductions / Year_{jit}) d_{jit} \big)$$
$$+ \delta_2 \big(g(Death\ Reductions / Year_{jit}) d_{jit} \big) + \theta POL_j + \varepsilon_{jit} \quad (15)$$

The choice probabilities for are analogous to those for the ad hoc model in the main text.

A word is in order about comparisons of the structural model and the ad hoc model. β represents the same marginal utility of income in both models. However, the illness and death variables are defined differently in the two models. Thus the coefficient δ_1 (for example) has a slightly different interpretation in each. In the ad hoc model, δ_1 represents the marginal utility of an increase in $f(Illness\ Reductions_{ji})$ .This is the utility derived from a marginal increase in the total number of illnesses avoided by a policy, regardless of how long the policy lasts. In the structural model, δ_1 represents marginal utility of an increase in $f\,(Illnesses\ Reductions/Year_{jit})$, the utility derived from a marginal increase in the number of avoided illnesses per year.

Formulas for total WTP, marginal WTP, and pair-wise marginal rates of substitution for the structural model are derived analogously to those for the ad hoc model.

Estimation Results

For the estimates we report, all time-indexed variables are discounted at a constant 5% annual rate.[23] For the logarithmic functional form of the structural model, the estimated parameter δ_1 can be roughly interpreted as the marginal utility of a 1% increase in the number of avoided illnesses-per-year.[24] Table A3 provides results for the structural model that are analogous to those presented for the ad hoc model in Table 2 in the main paper. Table A4 corresponds to Table 3 in the main paper, and Table A5 corresponds to Table 4. We do not

[23] Models using 3% and 7% discount rates were also investigated. These models change the qualitative results of the model only modestly. Future work will employ additional survey information to estimate individual-specific discount rates simultaneously with policy preferences.

[24] Since a 1% increase in avoided illnesses per year corresponds to a 1% increase in total undiscounted avoided illnesses, the estimates of δ_1 derived from the two models have the same interpretation. Even though the parameters have the same interpretation, they are not directly comparable. This is because the scale of utility is irrelevant for individual choices, and exact levels of utility cannot be identified. Estimated marginal utilities actually reflect the "true" marginal utility divided by a scale parameter. Estimates of marginal rates of substitution are unaffected by this normalization, however, since the scale parameter drops out when any ratio of coefficients from the same model is considered [24, p.45].

duplicate for the structural model the types of results displayed in Tables 5, 6 and 7 in the main paper, since the flavor of the estimates is very similar.

Comparing the Ad Hoc and Structural Models

Compared to the results for the ad hoc model employed in the body of the paper, the relative magnitudes of the marginal utility parameters are very similar for the structural model. The ad hoc model fits better than the structural (in terms of the maximized value of the log-likelihood function), although both models yield similar results and perform comparably along most evaluative dimensions. In principle, however, the theoretical rigor of the structural model should enable it to outperform the ad hoc model *if* individual preferences over the time-denominated flows of costs and benefits are time-consistent and well-defined, and each individual uses the same discount rate.[25] However, like the researchers preceding us, we characterized the benefits in our survey in total terms, such as "10 fewer deaths over 5 years", while the costs are presented as being constant in annual (and monthly) terms. Individuals are invited to form preferences over the policies as described to them, so it is perhaps unsurprising that the best-fitting model is the model that assumes utility to depend directly on yearly cost and total health benefits.

The added rigor of the structural model may therefore be wasted if individuals do not hold time-consistent preferences, or if there is heterogeneity in the individual discount rates used by respondents. This structural model will be emphasized in other research, currently in progress,

[25] We use the term "time-consistent" to refer to preferences that are consistent with a standard exponential discounting framework.

where we employ auxiliary choices elicited at the end of the survey to directly estimate individual discount rates at the same time as we estimate the other utility parameters.

The advent of survey designs that offer higher-resolution descriptions of the time-varying costs and benefits of policies may enable analogous structural models in future surveys to outperform ad hoc models. In the next generation of research, we expect this model to be especially useful in evaluating policies when certain types of benefits occur earlier than others. For example, one policy may reduce the onset of an illness in early periods and then reduce mortality in later periods, whereas another may simply reduce the incidence of sudden accidental death. Alternatively, individuals may perceive a policy to yield mostly public benefits in early periods and then to begin to additionally yield private benefit as he or she ages.

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Table A1: Marginal Distributions for Sample and Population

	Percentage of Total		
	Census 2000: All Households	Census 2000: Households Age 25+	Estimating Sample (age 24+)
Gender			
Male	49		48.2
Female	51		51.8
Age			
Under 5 years	6.8	0	0.0
5 to 9 years	7.3	0	0.0
10 to 14 years	7.3	0	0.0
15 to 19 years	7.1	0	0.0
20 to 24 years	6.8	0	1.4*
25 to 34 years	14.1	21.7	16.8
35 to 44 years	16.3	25.1	23.3
45 to 54 years	13.4	20.6	21.3
55 to 59 years	4.8	7.4	9.2
60 to 64 years	3.8	5.9	8.3
65 to 74 years	6.6	10.2	13.1
75 to 84 years	4.4	6.8	5.7
85 years and over	1.5	2.3	1.0
			*all 24 years old
Household Size			
1-person household	25.8		18.7
2-person household	32.6		41.1
3-person household	16.5		18.6
4-person household	14.2		12.9
5-person household	6.6		5.8
6-person household	2.5		2.1
7-or-more-person household	1.8		0.9
Educational Attainment			
Less than high school		19.6	12.7
High school graduate		28.6	32.6
Some college		27.3	27.2
College graduate or more		24.4	27.5
Race			
White, Non-Hispanic	69.1		77.9
Black, Non-Hispanic	12.0		9.5
Other, Non-Hispanic	6.4		5.0
Hispanic	12.5		7.7
Household Income			
Less than $10,000	9.5		7.3
$10,000 to $14,999	6.3		5.8
$15,000 to $24,999	12.8		12.5
$25,000 to $34,999	12.8		13.8
$35,000 to $49,999	16.5		21.1
$50,000 to $74,999	19.5		21.2
$75,000 to $99,999	10.2		9.9
$100,000 or more	12.3		8.3

Table A2: Design Matrix for Illness and Death Reductions

		Cross-Tabulation (*Seeill$_i$*=1)										*Seeill$_i$* =1	*Seeill$_i$* =0
		Illnesses											
		0	5	25	50	100	200	500	1000	2,500	5,000	Total	Total
Deaths	0	134	84	136	102	90	163	165	80	45	134	1133	1,133
	5	307	920	625	635	337	255	305	193	48	214	3,839	5,547
	10	201	130	192	158	221	263	208	86	47	136	1,642	2,470
	25	126	66	118	120	269	198	209	120	50	163	1,439	2,104
	50	46	0	56	78	130	109	192	101	47	134	893	1,265
	100	0	0	35	43	60	104	129	63	48	116	598	882
	200	0	0	0	41	25	66	174	63	39	144	552	831
	500	0	0	0	0	21	52	92	69	38	80	352	499
	1,000	0	0	0	0	0	13	51	18	23	70	175	262
	5,000	0	0	0	0	0	0	24	0	10	53	87	119
	Total	814	1,200	1,162	1,177	1,153	1,223	1,549	793	395	1,244	10,710	15,112

Table A3: Alternative Specifications (*Structural*; 7556 choices)[a]

Param.	Variable	Linear	Quadratic	Log
β	PDV *Cost*/1000	0.03023 (6.86)***	0.0379 (8.27)***	0.0573 (11.16)***
δ_{10}	PDV((*Avoided Illnesses/Year*)/1000)	0.09667 (5.93)***	0.2826 (4.35)***	-
δ_{11}	PDV((*Avoided Illnesses/Year*)/1000)^2	-	-0.04728 (3.10)***	-
δ_{12}	PDV(Log(*Avoided Illnesses/Year*))	-	-	0.00397 (3.88)***
δ_{20}	PDV((*Avoided Deaths/Year*)/1000)	0.2107 (4.44)***	0.9456 (6.38)***	-
δ_{21}	PDV((*Avoided Deaths/Year*)/1000)^2	-	-0.1902 (4.74)***	-
δ_{22}	PDV(Log(*Avoided Deaths/Year*))	-	-	0.01856 (9.83)***
θ	Policy Dummy (*POL*)	-0.3243 (10.47)***	-0.3489 (11.10)***	-0.3779 (11.74)***
Maximized Log-likelihood		-8101.43	-8081.01	-8067.85

[a]5% discount rate

Table A4: Alternative Specification: Effects of Explicit Illness Information (*Structural*; 7556 choices)[a]

Parameter	Variable	Basic	Marginal Utility Shifters	Status Quo Dummy Shifter	Full Model
β_0	PDV of *Cost*/1000	0.00573	0.04340	0.05944	0.04310
		(11.16)***	(4.96)***	(11.50)***	(4.66)***
β_1	… · **1**(*See Illness Data*)	-	0.02301	-	0.02331
			(2.21)**		(2.09)**
δ_{10}	PDV(Log(*Avoided Illnesses/Year*))	0.00397	0.00820	0.00779	0.008155
		(3.88)***	(6.24)***	(5.74)***	(5.77)***
δ_{20}	PDV(Log(*Avoided Deaths/Year*))	0.01856	0.02374	0.02686	0.02380
		(9.82)***	(7.11)***	(9.96)***	(7.00)***
δ_{21}	… · **1**(*See Illness Data*)	-	0.00498	-	0.004789
			(0.89)		(0.80)
δ_{22}	… · **1**(*See Ill. Data*) · PDV(Log(*Avoided Ill./Year*))	-	-0.00028	-0.00027	-0.00028
			(3.33)***	(4.49)***	(3.10)***
θ_0	Policy Dummy (*POL*)	-0.3779	-0.4536	-0.4171	-0.4574
		(11.74)***	(12.38)***	(8.09)***	(7.95)***
θ_1	… · **1**(*See Illness Data*)	-	-	-0.0446	0.00653
				(0.76)	(0.09)
Maximized Log-likelihood		-8067.85	-8054.92	-8057.09	-8054.91

[a] 5% discount rate

Table A5: Alternative Specification: Selected Estimated Marginal Rates of Substitution (*Structural*)[a]

MRS between:	*Seeill$_i$* =0			*Seeill$_i$* =1		
	Avoided Deaths/Yr =5	*Avoided Deaths/Yr* =10	*Avoided Deaths/Yr* =50	*Avoided:* *Deaths/Yr*=10 *Illness/Yr*=10	*Avoided:* *Deaths/Yr*=10 *Illness/Yr*=20	*Avoided:* *Deaths/Yr*=10 *Illness/Yr*=100
Policy Cost, Avoided Deaths/Year	\$110.44	\$55.22	\$11.04	\$42.08	\$41.79	\$41.11
Policy Cost, Avoided Illnesses/Year	--	--	--	\$11.31	\$5.65	\$1.13
Avoided Ill./Year, Avoided Deaths/Year	--	--	--	-3.721	-7.390	-36.350

[a] Estimates derived from "full model" specification in Table 7. Discount rate=5%