Is An Ounce of Prevention Worth a Pound of Cure?
Comparing Demand for Public Prevention and Treatment Policies

Ryan Bosworth[1]
Assistant Professor
School of Public and International Affairs
North Carolina State University
NCSU Box 8102
Raleigh, NC 27695-8102

Trudy Ann Cameron
R.F. Mikesell Professor of Environmental and Resource Economics
Department of Economics, 435 PLC
1285 University of Oregon
Eugene, OR 97403-1285
Email: cameron@uoregon.edu
Phone: (541) 346-1242; Fax: (541) 346-1243

and

J.R. DeShazo
Associate Professor
Department of Public Policy
School of Public Affairs
3250 Public Policy Building, Box 951656
Los Angeles, CA 90095-1656

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Abstract

Using a national survey designed to assess preferences for publicly funded health policies and a discrete choice experiment format, we find estimated marginal utility associated with avoided deaths to be about twice as high for policies designed to prevent serious illnesses as for policies designed to treat those who are already sick or injured. Our survey design allows respondents to make tradeoffs between policies designed to prevent, or treat those affected by, a wide variety of illnesses or injuries, including most major health threats: heart disease, heart attack, stroke, leukemia, asthma, various cancers, and traffic injuries. Our research design permits us to explain these preference differences in terms of attributes common across both prevention policies and treatment policies, including the number of avoided deaths, avoided cases of illness, and type of illness avoided. We also explore several sources of systematic heterogeneity in preferences for prevention versus treatment policies. We find statistically significant heterogeneity with respect to the specific types of diseases (for all major diseases), the identity of the group being targeted by the policy, and the individual's socio-economic characteristics.

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1 Introduction

Some public risk-reducing policies can prevent illnesses or injuries by providing a cleaner environment or safer roads. Other public policies can reduce the risk of death or sustained illness by treating those who are already sick or injured. In this paper, we report the results of a study designed to examine how public preferences differ systematically across policies intended to prevent adverse health outcomes and policies that provide resources to treat those who are already sick or injured. These results can help policy makers more effectively allocate public health resources among alternative uses.

Our approach to evaluating individual preferences for public risk-reduction policies differs from that taken elsewhere in the literature in that we permit individuals to express both self-regarding and other-regarding preferences when revealing their demand for public risk prevention and treatment policies. Many studies evaluate individuals' preferences for *private* risk reduction. (Aldy and Viscusi 2008, Viscusi and Aldy 2007 and 2003, Viscusi 2004, Mrozek and Taylor 2002, Alberini 2005) Other studies of public policies evaluate only the private benefits of the risk reduction policies (Hammitt and Liu 2004, Hammitt and Zhou 2006, Johannesson et al. 1996, Alberini et al. 1997, Tsuge et al. 2005). Although the current design does not allow us to break preferences cleanly into self- and other-regarding components, we allow preferences to vary systematically depending on whether the individual is a member of the demographic group directly affected by the policy. This distinction provides a more complete measure of public demand for these policies. This distinction also permits to us to more thoroughly explore whether systematic heterogeneity in each of these preference components might differentially shift individuals' demands for prevention versus treatment policies.[2]

To measure demand, we estimate a random utility model using data from two surveys designed for direct comparison of preferences for treatment and prevention policies. Each survey evaluates just one of these two classes of policies, but the descriptions in each survey use comparable measures of policy cost, effectiveness, and scope, and the two surveys address a similar array of targeted diseases and injuries. The conjoint and randomized design of the public health risk reduction policies proposed within each choice set allows us to investigate heterogeneity in preferences along several dimensions. This analysis is enriched further by a wide variety of individual-level sociodemographic variables. The survey was administered in 2003 to a nationally representative sample of over 3,000 respondents drawn from the consumer panel maintained by Knowledge Networks, Inc.

Researchers have compared the cost-effectiveness of prevention versus treatment policies but, in general, they have not focused on how individuals perceive the relative benefits of prevention and treatment policies.[3] Several researchers have estimated demands for specific prevention or treatment policies taken individually, but most earlier studies have not employed research designs that permit direct comparison of the marginal benefits of two types of policies.[4] One exception is Corso et al. (2002). These authors undertake a head-to-head comparison, based

[2] Additional arguments for this approach come from researchers such as Gyrd-Hansen (2004) who finds that the extent to which individuals value health increments depends on whether the question is framed as an individual or a social choice. Richardson and Nord (1997) find evidence that individuals feel that the distributional consequences of health programs are important and should be included in the evaluation of any health policy. Ubel et al. (1996) illuminates the need to include other-regarding preferences by presenting experimental evidence that individuals may actually reject the public policy implications of their self-regarding preferences.
[3] For example, see Morral (2003), Ramsberg and Sjoberg (1997), and Graham et al. (1997).
[4] For prevention programs, see Jones-Lee, et al. (1995), Birch et al. (1999), Lindholm et al. (1997), O'Reilly et al. (1994) and Bos et al. (2004). For treatment programs, see, for example, Morey et al. (2003), Kartman et al. 1996, O'Conor and Blomquist (1997), Zethraeus (1998) and Bulte et al. (2005).

on survey data, of willingness to pay for treatment versus prevention policies that reduce the risk of food-borne illnesses. For food-borne illnesses, they find that estimated WTP for prevention policies is only about one-third of that for treatment policies.

In contrast to the Corso et al. (2002) results, and across a wide range of illnesses and injuries, we find that individuals perceive the benefits of risk prevention policies of comparable scope to be larger than those for treatment policies by a factor of almost two to one. The external validity of this result is enhanced by our evaluation of preferences across almost all major life-threatening illnesses. It is also enhanced by our use of a nationally representative sample.[5] Another refinement offered by our approach is that it permits a direct comparison of the marginal benefits of common attributes. These include the number of cases of illnesses avoided (morbidity reductions), the number of lives saved (mortality reductions), and policy costs.

Preferences for prevention versus treatment may depend upon disease type (as in Subramanian and Cropper, 2000; Hammitt and Liu, 2004). The logic for this conjecture is that individuals may have different perceptions about the extent to which it is medically feasible to prevent or treat specific diseases.

Researchers have also hypothesized that individuals' perceptions of the controllability of exposure to hazards that cause diseases or injuries may vary (Subramanain and Cropper, 2000; Vassanadumrongdee and Matsuoka, 2005; Carlsson et al. 2004; Chilton et al. 2002). As a result, individuals may feel more justified in allocating public funds to reduce exposures for hazards that individuals themselves cannot otherwise control.[6] To evaluate this hypothesis, we present

[5] The sample selection issues associated with our sample have been carefully evaluated (Cameron and DeShazo 2006).

[6] Jacobsson et al. (2005) find that the altruistic component within willingness to pay is greater for more severe diseases. Wittenberg et al. (2003) find that respondents "were 10 to 17 times more likely to allocate liver transplants or asthma treatment to patients they deemed not responsible for their illnesses than to patients they deemed responsible for their conditions."

individuals in our prevention survey with one of several possible proximate causes of the disease such as air pollution, water contaminants, and pesticides in food, for the major disease types, and traffic accidents for injuries.

Both self-regarding and other-regarding preferences may shift systematically with different individual-specific factors. In the case of preferences for private risk reductions, researchers have shown that self-regarding preferences for private risk reductions vary systematically with the individual's age, income, education, etc. In many studies, the relationship between age and demand for private risk reductions is U-shaped: willingness to pay rising until around age 55 before declining with advancing age (Alberini et al. 2004; DeShazo and Cameron, 2005; Aldy and Viscusi 2008; Viscusi and Aldy 2007).

2 Survey Design

In 2003, we conducted two distinct national stated preference surveys. For each, the sample size is approximately 1,500.[7] The two surveys that provide the data used for this paper were designed to elicit demands for policies which are publicly financed and benefit many individuals (i.e., public goods), rather than privately paid programs with just individual benefits; The surveys were administered by Knowledge Networks Inc., an internet-based survey firm offering a representative panel of households in the U.S. who complete surveys via either a personal computer or WebTV® interface. [8] For full details of each survey see Cameron and DeShazo (2005a) and (2005b).

[7] A third survey was also conducted, concerning demands for priced programs that benefit only the purchaser (i.e., private goods). A large pre-test for this third survey, involving over 1000 respondents, was conducted for Canadian consumers.

[8] Marginal distributions of various socio-demographic variables for our estimating sample for this "public prevention" survey and the U.S Census are available from the authors. Our response rate was 79% among invited participants from this consumer panel which has generally been shown to have excellent sampling properties. Models that allow the marginal utilities to shift with the individual's fitted selection probability (from a model that

(a) The public "prevention" survey concerns policies that reduce contaminants that cause illness (i.e., air pollution, water pollution, food safety problems; see Cameron and DeShazo, 2005a). In terms of broader impacts, we intend these prevention policies to be analogous to the real public policies that lie within the purview of the Environmental Protection Agency and the Department of Agriculture.

(b) The public "treatment" survey concerns public provision of remedial medical interventions for individuals who are ill or injured and which increase their chances of recovery (i.e. devices, therapies, and procedures; see Cameron and DeShazo, 2005b). In terms of broader impacts, these treatment policies are intended to mirror the kinds of real public policies achieved, for example, through the drug approval decisions of the Food and Drug Administration or the medical research funding decisions of the National Institutes of Health.

For conformability, the survey instruments for the prevention and treatment studies have initial and concluding modules that are very similar. Where they differ is in their key policy choice scenarios. Each policy is described as preventing or treating a named illness or injury. The illnesses in the prevention survey are attributed to a particular exposure pathway (i.e., air, water, food). The effectiveness of these policies is described in terms of the numbers of illnesses prevented (or successfully treated) and the number of deaths prevented. For the individual's community to enjoy the policy, he or she must pay costs in the form of higher taxes (expressed both per month and per year). Each respondent is shown 5 choice sets consisting of two explicit policies plus the option to choose neither. We planned these two surveys so that it would be

predicts participation in this survey from a random digit dialing panel recruitment sample of over half a million households) reveal little sensitivity. See Cameron and DeShazo (2006) straightforward to pool their data, to test whether the subsets of corresponding utility parameters are identical, and to impose common preference parameters as warranted.

2.1 Survey Details

Module 1 (Introduction) – The first module of our survey elicits the individual's subjective own-risk assessment for a variety of major health threats, respondent familiarity with each health threat, and any mitigating and averting behaviors he or she 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." Respondents are informed that "your answers may help public officials provide you and your community with better ways of managing health threats."

Module 2 (Tutorial) - The second module of each survey introduces the idea of public prevention policies (or public treatment policies, according to the topic of the survey), and begins to train the respondent concerning how to interpret the summaries of policy attributes that will eventually be incorporated into compact choice tables. Eight pages of the prevention survey (and eleven pages of the treatment survey) are devoted to the tutorial process, where the information to be summarized in each row of the five upcoming choice sets is unfolded one row at a time, with careful and clear explanations. These tutorial pages also include comprehension-testing questions to confirm that the respondent understands key attributes of the choices.

Module 3 - The third module of each survey contains the five stated choice exercises. Each choice, with its preamble and debriefing questions, occupies a set of four survey pages.[9,10]

[9] In both the prevention and treatment surveys, choice sets are "pruned" of combinations that may be impossible or implausible to the respondent. For example, random combinations of attributes are rejected if the number of avoided deaths exceeds the number of avoided illnesses. We also reject implausible combinations of diseases and underlying causes in the prevention survey. For example, water pollution is not a plausible cause of traffic injuries.

[10] The arrays of targeted illnesses and injuries are designed to be as similar as possible between the prevention and treatment surveys. However, the lists of targeted illnesses diverge slightly. The main area of divergence is that we

Module 3: Prevention - The choice set is preceded by a page that first describes each policy in words, such as: “Policy B reduces types of pesticides in foods that cause adult leukemia. New growing techniques and standards would reduce food contaminants that cause leukemia in adults.” On the next page, the respondent studies the complete set of attributes of the two alternatives and makes a choice (which can include selection of “Neither policy”). See Figure 1 for an example of a prevention policy choice set.

The key attributes of the hypothetical prevention policies presented to respondents in our prevention survey include the number of cases (illnesses) prevented, the number of deaths avoided, the duration of the policy, and the cost of the policy to the respondent. These prevention policies also vary in terms of the underlying cause to which the health effects are attributed: (e.g. an environmental cause (water contaminants, air pollution, pesticides in food); or a non-environmental cause (traffic accidents)). Prevention policies also vary by the specific type of illness or injury that is addressed. These include very common illnesses and injuries such as heart disease, heart attack, stroke, and traffic injuries as well as leukemia and asthma. A sub-set of the policies designed to reduce leukemia or asthma are targeted specifically towards children. We also include policies that avoid cases of general (unspecified) cancer, colon/bladder cancer, and lung cancer.

Module 3: Treatment - Each of the five choice exercises also involves a set of four survey pages. The first page again describes the two policies in more detail. For example, “Policy A treats children, adults, and seniors who have leukemia. Those helped will be 25% children, 25%

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allow treatment policies to be targeted toward different socio-demographic groups. As a pure public good, prevention policies cannot easily be targeted towards different groups.

adults, and 50% seniors (i.e. 25/25/50 mix). Then the choice table is presented, containing its summaries of each program. See Figure 2 for an example of this type of choice set.

The key attributes of the policies described in the treatment survey are analogous to those described in the prevention survey. However, rather than the number of avoided illnesses or deaths, the treatment policies include the number of increased recoveries as well as the number of avoided deaths. Treatment policies vary in terms of the demographic group that would most benefit from the policy (men, women, children, adults, seniors, or some combination of these groups) as well as the specific health threat addressed. For the treatment policies the list includes: heart disease, heart attack, stroke, leukemia in children, leukemia in general, respiratory disease in children, respiratory disease in general, asthma in children, asthma in general, injuries in children, injuries in general, colon/bladder cancer, lung cancer, prostate cancer, breast cancer, and skin cancer.

Module 4 (Follow-up) – This module of each survey asks a number of auxiliary questions. Among these, the relevant one for this paper is the question that invites respondents to both the prevention and treatment surveys to rate how involved they feel their government should be in regulation of environmental, health, and safety hazards.[11]

Key Variables – In Table 1, we summarize the key variables presented to respondents in both the prevention and treatment policy surveys. These variables include the yearly cost of the policy, the number of illness reductions, the number of deaths avoided, and the duration of the policy. Table 2 presents the percentage of policy options represented in the choice sets by each type of Risk Source (prevention policies), Illness or Injury, and Affected Group (treatment policies)[12]

[11] See Cameron and DeShazo (2005a) and (2005b) for more about Module 4.
[12] Although the survey variables were designed to be as comparable as possible, the algorithm used for "pruning" implausible combinations of scenario attributes resulted in distributions of avoided deaths that are different for

3 Theoretical Framework

This section explains a simple framework that will allow us to analyze, simultaneously, preferences for prevention policies and treatment policies. Prevention policies work by avoiding illnesses and deaths while treatment policies work by increasing recoveries and avoiding deaths. As part of our analysis, we test for systematic differences, across both respondents and health threats, in individuals' implied preferences over how these health improvements are achieved. We also provide estimates of the relative values of changes in these health improvements.

For our most basic specifications, we let the utility of a policy (treatment or prevention) depend on the number of avoided illnesses (prevention policies) or increased recoveries(treatment policies), and the number of avoided deaths. The individual's income can also be expected to influence utility. Thus, individual *i*'s indirect utility from policy *j* can be represented as:

$$V_{ji} = \beta(Y_i) + \delta_1 f(Avoided\ Illnesses_{ji}) + \delta_2 g(Avoided\ Deaths_{ji}) \qquad (1)$$

where Y_i is income, β is the marginal utility of income, δ_1 is the marginal utility of an increase in *f*, and δ_2 is the marginal utility of an increase in *g*.[13]

We also employ the indicator variable $Policy_j$ --equal to 0 if the alternative is "neither policy" (i.e., the status quo) and equal to 1 if it is one of the policy options. The coefficient on this dummy variable, θ, serves a function similar to that of an intercept shifter in a regression

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treatment and prevention policies. The key difference is that more scenarios involving large numbers of avoided deaths were shown to treatment policy respondents than to prevention policy respondents, although the distributions do span the same range. The means and medians reported the Table 1 reflect this difference. As described in the Results section below, sensitivity analysis suggests that this asymmetry does not meaningfully affect our results. A full description of the distributions of avoided deaths (and other variables) is available from the authors.

[13] An obvious objection to this simple linear-in-attributes specification is the implicit assumption that utility is additively separable in these generic functions of avoided illnesses and deaths. In empirical work documented in Bosworth et al. (2005), we relax this assumption by including an interaction term between our functions of avoided illnesses and avoided deaths. To minimize the complexity of our combined prevention and treatment specification, we omit the interaction term in this paper. Of course, more elaborate specifications can be entertained.

model. It captures the average effect on person *i*'s utility of all other unobserved factors, associated with any affirmative policy in the choice set, for which we do not explicitly control in the random-utility model. θ merely shifts the entire utility level and is interpreted as the average effect of unspecified factors on utility of *any* policy *j* relative to the status quo (Train 1986, 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.

Each choice set consists of two possible policies and a status quo alternative. We employ a random-utility model that permits analysis with a multiple-conditional logit specification for econometric estimation.[14] To allow for a range of flexible estimation options, we assume at this point only that *f*(0) =0 and *g*(0)=0 and that *f* and *g* are increasing in their arguments. The utility level provided by policy *j* to individual *i* is thus:

$$\begin{aligned} V_{ji} = \beta(Y_i - c_{ij}) &+ \delta_1 f(Avoided\ Illnesses_{ji}) \\ &+ \delta_2 g(Avoided\ Deaths_{ji}) \\ &+ \theta Policy_j + \eta_{ji} \end{aligned} \tag{2}$$

where c_{ji} is the total cost of the policy (yearly cost*duration) and η_{ji} is the unobserved random component of total utility. [15] Total indirect utility over the time period of the policy, if the status quo option (neither policy) is chosen, is given by:

$$V_{ni} = \beta(Y_i) + \eta_{ni} \tag{3}$$

[14] Because of the possibility of violating the Independence of Irrelevant Alternatives (IIA) property inherent in conditional logit, we have also used nested logit models to estimate all models that do not pool the two data sets. All inferences drawn using the models reported here can also be drawn from the nested logit models. Full results available from the authors upon request.

[15] Respondents may care about the time profile of benefits and costs. We abstract here from the intertemporal nature of preferences by defining utility over the total costs and total benefits of the policy. This important issue is directly addressed in a separate paper by the same authors where we develop a structural utility-theoretic model with preferences defined over the present discounted utility of policies that employs a variety of alternative discounting schemes. However, these models provide no substantial additional insight on the issues addressed in this paper, namely, heterogeneity in preferences.

Since we assume that *f(0)=0* and *g(0)=0*, it is convenient to normalize on the level of indirect utility derived under the status quo. The perceived indirect utility difference that we assume drives the stated choices of our respondents is:

$$\begin{aligned}\Delta V_{ji} = \beta(-c_{ij}) + \delta_1 f(Avoided\ Illnesses_{ji}) \\ + \delta_2 g(Avoided\ Deaths_{ji}) \\ + \theta Policy_j + \varepsilon^*_{ji}\end{aligned} \tag{4}$$

where the η_{ji} are distributed extreme value and $\varepsilon^*_{ji} = \eta_{ji} - \eta_{ni}$.

If we wish to test the equivalence of parameters across the two samples, it will be necessary to allow for the possibility of distinct error variances. (See Cameron et al. 2002). We scale the level of indirect utility for the prevention policies and treatment policies by κ_p and κ_t, respectively. Let 1(*Treatment*) be an indicator variable equal to 1 for treatment policy choices and equal to 0 for prevention policy choices. Thus, the indirect utility differences for the prevention policies and treatment policies are:

$$\begin{aligned}\Delta V_{ji}\big|_{1(Treatment)=0} = \frac{\beta_p}{\kappa_p}(-c_{ij}) + \frac{\delta_{1p}}{\kappa_p} f(Avoided\ Illnesses_{ji}) \\ + \frac{\delta_{2p}}{\kappa_p} g(Avoided\ Deaths_{ji}) \\ + \frac{\theta_p}{\kappa_p} Policy_j + \frac{\varepsilon_{ji}}{\kappa_p}\end{aligned} \tag{5}$$

$$\begin{aligned}\Delta V_{ji}\big|_{1(Treatment)=1} = \frac{\beta_t}{\kappa_t}(-c_{ij}) + \frac{\delta_{1t}}{\kappa_t} f(Avoided\ Illnesses_{ji}) \\ + \frac{\delta_{2t}}{\kappa_t} g(Avoided\ Deaths_{ji}) \\ + \frac{\theta_t}{\kappa_t} Policy_j + \frac{\varepsilon_{ji}}{\kappa_t}\end{aligned} \tag{6}$$

Given that the scale of utility is arbitrary, we normalize by assuming $\kappa_p = 1$ for the prevention data set. The parameter κ_t is then freely estimated and is interpreted as the ratio of dispersion of the unobserved portion of utility in the treatment sample to the dispersion of the unobserved portion of utility in the prevention sample.

We wish to investigate whether the utility parameters are systematically different for prevention policies and treatment policies, based on inferences from respondents' choices. By introducing the indicator variable **1**(Treatment) as a shifter we can permit parameters to vary systematically. With the pooled sample, we can test for statistically significant differences in preferences.

4 Results

We model the utility of avoided illness (or increased recoveries) and avoided deaths via a shifted log specification (e.g. log(Avoided Illnesses+1) rather than log(Avoided Illnesses)) for three reasons. First, we wish to maintain our theoretical assumption that *f(0)=0* and *g(0)=0*. Second, exploratory models suggest that this specification fits better than linear-in-attributes models. Third, a shifted log specification indicates that preferences are defined approximately over percentage changes and minimizes the chance that any asymmetry in the randomized design would affect our empirical results by naturally accommodating a "diminishing marginal utility" property in our estimation of preferences.[17,18]

[17] For estimation purposes, we constrain κ to be positive by estimating the logarithm of this parameter. The estimates of κ in the tables below need to be exponentiated to conform to the model presented in section 2.
[18] Models that pool the prevention and treatment samples (or allow for heteroscedasticity in other contexts) are estimated via a heteroscedastic conditional logit optimization routine programmed by the authors using the software package Matlab. Models that do not involve heteroscedasticity are estimated using the packaged conditional logit routine in Stata software. The Matlab code is validated for special cases where either type of software can be used.

For our most basic specifications, Models 1 and 2 reported in Table 3, we follow the standard practice in the choice literature and specify a utility function that is linear and additively separable in some function of each of the fundamental attributes of the policy. [19] In Models 3 and 4, where we pool the data from the two samples, we test whether or not the marginal utilities associated with illnesses and deaths can be constrained to be the same across treatment and prevention policies by allowing the coefficients on these fundamental attributes (as well as that on the generic policy indicator) to vary systematically with an indicator for whether the policy is a treatment policy. We also allow the error variance to differ across policy type.

For Models 3 and 4 in Table 3, the negative and statistically significant coefficient on the interaction term between the Log(*Death Reductions+1*) variable and the treatment indicator suggests that respondents place a higher value on deaths avoided via prevention policies than treatment policies. However, the other utility parameters (including the marginal utility of avoided illnesses) are not statistically different for treatment and prevention policies. As a check that this finding is not simply a result of the relatively greater number of scenarios involving large numbers of avoided deaths shown to treatment policy respondents (see footnote 10), we have also investigated models that discard information obtained via choice sets involving more than 1000 avoided deaths. This result holds even when these "outlier" cases are omitted.

Loosely speaking, the question posed in the title of this paper may be answered as follows: In terms of the estimated marginal utility of avoided deaths, an "ounce" of prevention appears to be worth only about two "ounces" of cure in the sense that individual marginal utility from avoided deaths appears to be about twice as much for an incremental (1%) improvement in the number of deaths avoided via a prevention policy than via a treatment policy. This result stands

[19] In a separate paper using only the "prevention" survey (Bosworth et al. 2009), we submit our inferences to numerous robustness and validity checks. We also assess scope effects, order effects, sample selection biases and, through our survey design, attempt to mitigate hypothetical bias associated with incentive incompatibility.

in contrast to that of Corso et al. (2002) who find that respondents are willing to pay more to treat than to prevent foodborne illness for themselves. We find that, for large scale public polices, respondents are willing to pay more for prevention than treatment in a wide variety of contexts. This result suggests that individual preferences in the context of publicly-provided goods may be sharply different than preferences for private goods. We also note that this result persists even in models that allow autonomous utility to vary with the specific disease or underlying cause (as will be reported in Sections 4.3 and 4.4. See Tables 7, 8, and 9.)

It should be noted that this difference in estimated utility applies only to avoided deaths. Perhaps counter-intuitively, given typical results with respect to "loss aversion", estimated marginal utility associated with an avoided illness is not statistically different from estimated marginal utility associated with an increased recovery. Although in both instances the person is enjoying a healthy state as a result of the program, we might expect the ex ante utility from others of avoidance of an illness to be higher than that associated with others recovering an illness. This is because the prevention policy would allow people to avoid the period of illness preceding the recovery.

While we do not have strong *a priori* reasons to expect substantial differences in utility for treatment and prevention programs, we do note some possible explanations for our results. First, individuals may simply feel that prevention policies are more likely to be effective at preventing deaths than treatment policies are at helping individuals recover from serious illnesses. It is also important to note that prevention and treatment policies are fundamentally different in nature. Prevention policies work by providing cleaner air, water, food, or traffic safety. These goods are pure public goods, non-excludable and non-rival. Treatment policies provide publicly-funded private goods. As a result of these differences, individuals may have very different motivations for choosing to support a particular policy. For example, individuals may choose to support prevention policies because of the subsequent risk reductions or because prevention policies are primarily environmental policies and respondents may also interpret these policies as providing ancillary environmental benefits. Individuals may choose to support treatment policies because of the benefits to disadvantaged groups who could not otherwise pay for the treatment options themselves.

Another difference between treatment and prevention policies may be relevant for explaining apparent differences in utility: treatment options will be beneficial only as long as the technology provided by the policy is relevant. If an individual believes that treatment technology may improve before he or she is likely to need treatment, then the treatment policy may be subsequently viewed as less valuable. In contrast, the individual may view a policy that helps prevent an adverse health outcome as useful even if treatment technology improves.

4.2 Sociodemographic Effects

We now investigate how preferences for prevention policies appear to differ from preferences for treatment policies according to the sociodemographic characteristics of the respondent. Tables 4, 5, and 6 present these results. To keep the dimensionality of the parameter space manageable, we allow only the coefficient on the policy indicator to vary with the sociodemographic variables.[20] Recall that the coefficient on the policy indicator captures how individuals feel about any policy, relative to the no-policy status quo. Coefficients on the interaction terms in Table 4 can be roughly interpreted as capturing the effect of change in a

[20] More complex specifications that allow the other parameters to vary with respondent characteristics or policy attributes can also be estimated. Future research may explore this heterogeneity in greater detail.

given variable on the latent propensity to choose either of the two offered policy options over the status quo.

In Table 4 the treatment sample indicates females receive lower relative utility from these policies than men. This result may be driven not by lower utility of the policy itself, but may instead reflect the lower average incomes of women (and the attendant higher marginal utility of income). Alternatively, it may reflect a different propensity to avail themselves of private health care services and diagnostic procedures. However, there is no indication that females are less likely than males to choose either prevention policy over the status quo in the prevention sample.

Table 4 also indicates that willingness to pay for publicly-funded health policies has a U-shaped profile with respect to the age of the respondent. This profile reaches an estimated minimum at about age 61 in the prevention sample and at about age 49 in the treatment sample. This result contrasts sharply with the inverted U-shaped age profile found by many researchers in the context of WTP for private risk reductions. (Alberini et al. 2004; DeShazo and Cameron, 2005; Aldy and Viscusi 2008; Viscusi and Aldy 2007) Moreover, WTP for private risk reductions appears to peak when WTP for public risk reductions approaches a minimum.[21]

The estimates in Table 4 also suggest that the income of the respondent, (a continuous variable constructed from income bracket midpoints), has *opposite* effects on utility in the two samples. In particular, higher income individuals receive *lower* utility from prevention policies, while we estimate *higher* utility from treatment policies for higher income individuals. One plausible explanation for this difference may be the availability of substitutes. Recall that the

[21] The contrast between the u-shaped age profile for public policies that we find and the inverted u-shaped profile other researchers have found for private risk reductions is striking. While we cannot conclusively determine the reason(s) for the difference, we suggest two possible explanations: 1) As respondents begin to reach their peak earning potential, they begin to worry about the taxation costs of public goods relatively more and this worry begins to erode as they retire. 2) As individuals age, they gain information about what their own health risks are and begin to invest in private means of reducing those risks. When still older, respondents may perceive that little can be done (through public or private means) about their own risks and they are relatively more concerned about public risks again.

prevention policies work in one of four ways: cleaner air, cleaner water, fewer pesticides in food, and safer roads. A high income individual can more easily move to a cleaner location, drink bottled or filtered water, eat organic produce, and purchase safer automobiles. However, there are relatively fewer substitutes for prevention policies that lower-income people can exploit. We also find that more highly educated people are more likely to support prevention policies, but not treatment policies. Non-white individuals are generally more likely to support both prevention and treatment public policies over the status quo, and more likely to support treatment than prevention policies.

We find that respondent attitudes toward government intervention influence receptivity to publicly supported health policies. Tables 5 and 6 demonstrate the impact of the additional variable *Government Preference* on preferences in our two samples. After the choice scenarios, 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 indicate their preferred level of government involvement along a continuum ranging from minimally involved (0) to heavily involved (7). While this variable is merely ordinal, we limit the complexity of our estimating specification by treating it as an approximately continuous variable.[22]

The results in both Tables 5 and 6 make clear the statistical importance of this (endogenous) variable. The maximized value of the log-likelihood function is higher (in both the treatment and prevention samples) when the variable *Government Preference* is included as a single shifter on the θ parameter (Model 2) than when the entire suite of other sociodemographic variables is included (Model 1). Moreover, Model 3 in each of Tables 5 and 6

[22] Models that treat this variable as ordinal provide similar qualitative results.

demonstrates that there is almost no impact on the statistical significance of the other sociodemographic variables when the *Government Preference* variable is included.

We conclude from this analysis that although the basic sociodemographic characteristics of the respondent are important in determining policy choices, an individual's perception of the proper role of government is relatively more predictive of their stated preferences across proposed public policies.

4.3 Cancer vs. Non-Cancer Policies

Previous research (e.g. Hammitt and Liu 2004, Van Houtven et al. 2008) has suggested that individuals may be willing to pay more to reduce cancer risks than non-cancer risks, independent of the severity of the symptoms of either type of disease.[23] Cancers may simply instill greater fear than other diseases. We address this interesting question by assessing whether individuals are (broadly speaking) more likely to support policies that address cancer risks than other non-cancer risks. Our prevention policies survey asks about several different diseases, including cancers (in general) lung cancer, colon/bladder cancer, and leukemia. The treatment policy sample is asked about colon/bladder cancer, leukemia, lung cancer, prostate cancer, breast cancer and skin cancer. We define an indicator variable, "Cancer," to be equal to 1 if the policy provides prevention or treatment with respect to a major cancer.[24] Table 7 presents results that utilize this variable to differentiate between preferences for cancer versus non-cancer policies.

The results in Table 7 suggest that individuals are *more* likely to support a cancer *prevention* policy than other types of policies, but *less* likely to support cancer *treatment* policies. Since many types of cancers are still viewed as incurable, these findings seem plausible,

[23] Other researchers, including Tsuge et al. (2005), and Magat et al. (1996) find that it may not be necessary to adjust estimates of the value of a statistical life (VSL) for cancer.
[24] We exclude skin cancer from the list of "major" cancers because skin cancer is generally perceived as a less serious health threat than the other cancers considered in our survey, despite the prevalence of melanoma.

especially given that even successful treatments can impose large monetary and other costs on cancer victims.

4.4 Heterogeneity by Policy Attributes

We also exploit variation in terms of the source of the risk, the disease or health threat that is addressed, and the population sub-group that is affected by our policies. In Tables 8 and 9, we report selected results for models that allow the coefficient on the policy indicator to vary with a variety of additional policy attributes. We find evidence that individuals have statistically distinguishable preferences for some types of policies.

The models in Table 8 allow the coefficient on the policy indicator to vary by the targeted disease. The model in column 1 uses the entire prevention sample to estimate differences in the *Policy* variable for each disease type. Similarly, the model in column 2 uses the entire treatment sample. We have chosen heart disease as the baseline disease (the omitted category) because it is one of the most common causes of death and there are effective methods for both the prevention and treatment of heart disease. The estimated coefficients on the policy-indicator interaction terms in Table 8 can be interpreted as utility differences for the given type of policies, relative to the base case of heart disease. We have also grouped the coefficients in these comprehensive models by categories: coefficients that represent preference differences for policies that address illnesses affecting children, preference differences for policies that address illnesses that can affect anyone, and preference differences for policies designed to address cancer threats.

In both the prevention and treatment samples, respondents are more likely to support public policies designed to treat or prevent adverse outcomes in children. Policies that are (at least partially) targeted at avoiding leukemia, respiratory disease, asthma, and injuries in children are all statistically more likely to be chosen than policies targeting the same illness or injury in adults. Also common to both the prevention and treatment samples is the lower estimated utility (relative to heart disease) for policies that target leukemia, asthma, and stroke.

The only type of policy with a statistically significant estimated increment to utility (other than policies targeted at children) is prevention policies designed to reduce the incidence of cancer (general). Respondents are less likely to support prevention policies designed to reduce traffic injuries. Respondents are also less likely to support policies designed to treat victims of colon/bladder cancer, respiratory disease, lung cancer, injuries, prostate cancer, breast cancer, and skin cancer.

Finally, Table 9 shows results for models that utilize additional sources of heterogeneity in the types of health risks that are unique to either the prevention or the treatment surveys. As in the choice set example in Figure 1, the scenarios concerning the public prevention policies vary in terms of the underlying cause of the particular illness or injury. These causes include: air pollution, drinking water contaminants, pesticides in foods, and traffic accidents. The "Prevention" model in Table 9 suggests that individuals prefer prevention policies that reduce air pollution, drinking water contaminants and pesticides in foods, (relative to policies that reduce the likelihood of injuries via traffic accidents). Traffic accidents may simply be viewed as more controllable.

The "Treatment" model in Table 9 presents results for a specification which reflects the fact that our treatment policies are often targeted at specific socio-demographic groups. For example, breast cancer treatment policies primarily benefit women and prostate cancer treatment policies only benefit men. The results in the "Treatment" model of Table 9 suggest, perhaps unsurprisingly, that females are statistically significantly more likely than males to support breast cancer treatment policies, while they are less likely than males to support prostate cancer policies.

Other types of treatment policies may be targeted primarily at children, adults, or seniors or some mix. When policies are designed to benefit more than one group, the percentages of the benefits accruing to each group are included explicitly in the description of the choice (see "Policy A" in Figure 2 for an example[25].) We construct the continuous variables *Percent Children* and *Percent Senior* and allow the coefficient on the policy indicator to vary systematically with these variables. We also utilize indicator variables for "*Female*", "*Age65+*", and "*HasKids*" to distinguish how preferences differ for treatment policies that affect particular groups. 1(*Age65+*) is equal to 1 if the respondent is age 65 or older, and 1(*HasKids*) denotes a respondent who lives in a household with at least one child under the age of eighteen.

In Table 9, the positive coefficient on the interaction term labeled *Percent Children* indicates that respondents prefer policies that benefit children, all else equal. However, this term is statistically insignificantly different from zero. The statistically insignificant interaction between this term and the term "*Age65+*" suggests that respondents aged 65 or more do not have preferences for policies that affect children that are substantially different from the baseline. However, when *Percent Children* is interacted with a dummy variable indicating that the respondent has children at home (*HasKids*=1) the estimated coefficient indicates that respondents with children support policies that affect children more than seniors or adults without children at home.

The results in Table 9 also suggest that policies that benefit seniors are less likely to be supported by adults, as indicated by the negative coefficient on the interaction term labeled "*Percent Seniors*". However, we also allow this coefficient to vary for respondents who are seniors themselves, using the interaction term between "*Percent Seniors*" and "*Age65+*". The

[25] The tutorial portion of the treatment survey, which precedes these choice scenarios, explains the interpretation of these proportions.

coefficient on this interaction term is not statistically significantly different from zero—in other words, seniors' preferences for policies that affect seniors are not statistically distinguishable from the preferences of other adults. This result suggests that the apparent lack of support for policies that benefit seniors is also shared by seniors themselves.

5 Conclusion

Policymakers must make tradeoffs when allocating funds for public risk reductions and health-improvement policies. Some policies can help prevent adverse health states, while other policies can allocate resources to help treat those who are already sick or injured. These tradeoffs should certainly recognize the relative effectiveness of different policies (i.e. the marginal rate of transformation in production of health improvements). However, they should also recognize the public's *preferences* for these different policies (i.e. the marginal rate of substitution in consumption of health improvements). We find that preferences for prevention and treatment policies differ in several important ways.

Individuals appear to have a preference for prevention policies over treatment policies. This preference appears to be driven by a higher marginal utility from lives saved via prevention policies. Although an ounce of prevention may be worth a pound of cure in a production context, we estimate that individuals value marginal lives saved via prevention only about twice as much as marginal lives saved via treatment options. Moreover, we find no statistical evidence that marginal illnesses prevented are valued differently than marginal increased recoveries.

This paper focuses on the estimation of *preferences* for different types (and scopes) of public health policies. Marginal utilities for different policy attributes, including policy cost, are the basis for calculations of marginal willingness-to-pay (WTP) for different features of a policy, or for estimates of the overall WTP for a policy with particular features. When there is statistically significant heterogeneity in preferences for public health policies, there will almost certainly be corresponding heterogeneity in the inverse demand function that yields WTP.

Our research demonstrates that utility does not appear to be linear in the numbers of avoided deaths, or in prevented or treated illnesses. Instead, there is diminishing marginal utility along these quantity dimensions. This is not surprising, given the phenomenon known to psychologists as "psychophysical numbing" (Fetherstonhaugh et al. 1997).

We also find evidence of significant heterogeneity in utility for prevention and treatment policies according to differences in socio-demographic characteristics. We find that utility has a U-shaped age profile that reaches a minimum at about age fifty or sixty. Individuals with higher income are *more* likely to support treatment policies, while they are *less* likely to support prevention policies. This seemingly strange result may stem from the wider array of preventative/risk-mitigating options available to wealthier individuals.

We also note that more highly educated people are more likely to support prevention policies but there is no apparent systematic heterogeneity in preferences for treatment policies by education level. Females are less likely to support treatment policies, while individuals who self-identify as non-white are more likely to support both prevention and treatment policies.

We identify several areas of heterogeneity in preferences by individual and policy attributes. We find that individuals with children are more likely to support policies that benefit children, females are more likely than males to support policies that treat breast cancer, and males are more likely to support policies that treat prostate cancer. However, seniors are not more likely to support policies that benefit seniors. We also find that individual perceptions of the proper role of government are especially significant in explaining whether individuals support public health policy measures over the status quo.

Respondents in our sample are *more* likely to support prevention policies for major cancer risks than for other risks, but are *less* likely to support treatment policies for major cancers than those for other major illnesses or injuries. We find that females are more likely to support breast cancer treatment policies and less likely to support prostate cancer treatment policies.

Many other studies have sought to estimate a population average (one-size-fits-all) marginal rate of substitution between income and the risk of one's own death (where this willingness to pay is often scaled to a risk change of 1.00 and reported as the value of a "statistical" life, VSL). In contrast, we focus upon the estimation of individual preferences for a wide variety of public policies designed to improve life and health in the broader community. The main take-home point is that we find significant variation in preferences for public health policies. These preferences vary markedly with policy attributes and with individual characteristics. Our findings suggest that benefits measurements for welfare assessments of public health policies may need to be tailored to the type of health threat in question, and the characteristics of the affected population. A single number as a universal measure of the value of a saved life or avoided illness is unlikely to be adequate to fully and accurately assess the benefits of any given public health policy.

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Figure 1 - Sample Prevention 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 - Sample Treatment Choice Set

Recall that these two policies will be implemented for the 100,000 people living around you. Below we describe how many of these people get sick and die, with and without these policies.

Would you be most willing to pay for Policy A, Policy B, or neither of them?

	Policy A	**Policy B**
	treats children, adults, and seniors (25/25/50 mix) who have leukemia	treats seniors who have heart disease
How many Policy will affect, and when	700 will get sick over 30 years	10,000 will get sick over 4 years
Increased Recoveries	25 more full recoveries	50 more full recoveries
Deaths prevented	5 fewer deaths over 30 years	5,000 fewer deaths over 4 years
Cost to you	$6 per month (= $72 per year for 30 years)	$35 per month (= $420 per year for 4 years)
Your choice	○ Policy A treats children, adults, and seniors (25/25/50 mix) who have leukemia	○ Policy B treats seniors who have heart disease

○ Neither Policy

Next Question

Table 1: Basic Policy-Specific Variables (orthogonal)[a]

Variable	Median	Mean	St. Dev.	Min	Max	Description
Yearly Cost						
Prevention	480	498	351	60	1200	Yearly cost of policy
Treatment	480	498	346	60	1200	Yearly cost of policy
Illness Reductions						
Prevention	100	862	1584	0	5000	Cases avoided
Treatment	100	841	1550	0	5000	Increased recoveries
Death Reductions						
Prevention	10	101	464	0	5000	Deaths avoided
Treatment	50	539	1240	0	5000	Deaths avoided

[a]Except for exclusions based on implausible combinations

Table 2: Risk Sources and Illness/Injury Types

Variable	% of Policy Options Presented to Respondents	
	Prevention	Treatment
Risk Sources		
Air Pollution	50.79	--
Water Contaminants	18.03	--
Pesticides in Foods	18.05	--
Traffic Accidents	13.12	--
Illness/Injury		
Heart Disease	7.49	8.27
Heart Attack	7.60	8.32
Stroke	7.46	8.52
Traffic Injuries	13.12	--
Leukemia in Children	8.68	--
Asthma in Children	8.69	--
Leukemia in general	8.74	8.44
Resp. Dis. in general	7.44	8.35
Asthma in general	8.63	8.31
Injuries in general	--	7.98
Cancer, General	7.52	--
Colon/Bladder Cancer	7.29	8.35
Lung Cancer	7.31	8.38
Prostate Cancer (Male only)	--	8.23
Breast Cancer (Female only)	--	8.43
Skin Cancer		8.42
Affected Group		
Children only	--	5.73
Children, Adults, and Seniors	--	4.64
Seniors only	--	27.1
Seniors and Adults	--	27.7
Adults only	--	26.0
Children and Adults	--	4.52
Children and Seniors	--	4.28

Table 3: Basic Specifications[b]

Parameter	Variable	Separate Samples		Pooled Sample	
		(1) Prevention Sample	(2) Treatment Sample	(3) Less Restricted	(4) More Restricted
β	-(Total Cost[c]/10,000)	0.2730	0.1979	0.2730	0.2623
		(9.87)***	(5.66)***	(9.86)***	(11.27)***
δ_1	Log(Illness Reductions)	0.0402	0.03497	0.04017	0.04128
		(5.74)***	(4.93)***	(5.74)***	(7.47)***
	… · **1**(Treatment)	--	--	.007805	--
				(0.54)	
δ_2	Log(Death Reductions)	0.1225	0.05238	0.1225	0.1221
		(10.38)***	(5.71)***	(10.37)***	(10.73)***
	… · **1**(Treatment)	--	--	-0.05046	-0.05759
				(-2.84)***	(-5.09)***
θ	**1**(Policy)	-0.7017	-0.5914	-0.7017	-0.7135
		(16.10)***	(-7.01)***	(-16.10)***	(-17.77)***
	… · **1**(Treatment)			-0.1106	--
				(-0.67)	
$ln(\kappa)$	Heteroscedasticity Parameter	0	--	0	0
	… · **1**(Treatment)	--	0	0.3162	0.2137
				(1.85)*	(2.54)***
Maximized log-likelihood		-8051.61	-7556.73	-15608.33	-15608.60
Maximized log-likelihood overall		-15608.34		-15608.33	-15608.60
Total sample size (choices)		7556	7033	14589	14589
Total sample size (respondents)		1531	1423	2954	2954

[b]All specifications use shifted log format for Log(*X*) variable. For example, Log(Death Reductions) is actually Log(Death Reductions +1)

[c]Total Cost=Yearly Cost*Duration

Test stat for restrictions in Model 3: 0.02 Critical value: 3.84: Fail to reject restriction

Test stat for restrictions in Model 4: 0.56 Critical value: 7.81: Fail to reject restrictions

Table 4: Sociodemographic Effects

Parameter	Variable	(1) Prevention	(2) Treatment
β	**-**(Total Cost/10,000)	0.2745	0.2016
		(9.90)***	(7.36)***
δ_1	Log(Illness Reductions)	0.0417	0.0347
		(5.93)***	(4.88)***
δ_2	Log(Death Reductions)	0.1225	0.0536
		(10.35)***	(6.01)***
θ	**1**(Policy)	-0.9402	-0.3498
		(3.23)***	(-1.23)
	…· **1**(Female)	0.0202	-0.1264
		(0.43)	(2.58)***
	…· (Age)	-0.0243	-0.0194
		(2.34)**	(1.93)*
	…· (Age^2)	0.0002	0.0002
		(2.04)**	(1.75)*
	…· Income/10,000	-1.985	2.201
		(2.62)***	(2.88)***
	…·Educ.Years/10	0.7084	0.1096
		(6.92)***	(1.03)
	…·**1**(Non-White)	0.1708	0.3768
		(2.94)***	(6.00)***
	Note: Age effect minimized at	60.75	48.5
Maximized log-likelihood		-8015.06	-7526.49

Table 5: Sociodemographic Effects (Prevention Sample)				
Parameter	Variable	(1) Demographics Only	(2) Govt. Only	(3) Demographics and Govt.
β	-(Total Cost/10,000)	0.2745	0.2812	0.2821
		(9.90)***	(10.07)***	(10.08)***
δ_1	Log(Illness Reductions)	0.0417	0.0418	0.0429
		(5.93)***	(5.90)***	(6.04)***
δ_{2p}	Log(Death Reductions)	0.1225	0.1257	0.1256
		(10.35)***	(10.56)***	(10.53)***
θ	**1**(Policy)	-0.9402	-1.7777	-1.9508
		(3.23)***	(20.04)***	(6.38)***
	…· Government Preference	--	0.2057	0.2007
			(14.01)***	(13.60)***
	…· **1**(Female)	0.0202	--	0.0102
		(0.43)		(0.21)
	…· (Age)	-0.0243	--	-0.0200
		(2.34)**		(1.90)*
	…· (Age^2)	0.0002	--	0.0002
		(2.04)**		(1.54)
	…· Income/10,000	-1.985	--	-1.848
		(2.62)***		(2.40)**
	…·Educ.Years/10	0.7083	--	0.6217
		(6.92)***		(5.98)***
	…·**1**(Non-White)	0.1708	--	0.1327
		(2.94)***		(2.23)**
Maximized log-likelihood		-8015.07	-7892.84	-7864.54

Table 6: Sociodemographic Effects (Treatment Sample)

Parameter	Variable	(1) Demographics Only	(2) Govt. Only	(3) Demographics and Govt.
β	-(Total Cost/10,000)	0.2016	0.1998	0.2021
		(7.36)***	(7.26)***	(7.33)***
δ_1	Log(Illness Reductions)	0.0347	0.0372	0.0369
		(4.88)***	(5.20)***	(5.15)***
δ_{2p}	Log(Death Reductions)	0.0536	0.0528	0.0537
		(6.01)***	(5.89)***	(5.99)***
θ	**1**(Policy)	-0.3498	-1.3644	-1.0108
		(1.23)	(15.06)***	(3.44)***
	…· Government Preference	--	0.1510	0.1448
			(10.28)***	(9.78)***
	…· **1**(Female)	-0.1264	--	-0.1253
		(2.58)***		(2.53)**
	…· (Age)	-0.0194	--	-0.0205
		(1.93)*		(2.02)**
	…· (Age^2)	0.0002	--	0.0002
		(1.75)*		(1.85)*
	…· Income/10,000	2.201	--	2.254
		(2.88)***		(2.91)***
	…·Educ.Years/10	0.1098	--	0.0762
		(1.03)		(0.71)
	…·**1**(Non-White)	0.3768	--	0.3317
		(6.00)***		(5.20)***
Maximized log-likelihood		-7526.50	-7449.58	-7424.48

Table 7: Cancer v. Non-Cancer Policies				
Parameter	Variable	(1) Prevention Sample	(2) Treatment Sample	(3) Pooled Sample
β	-(Total Cost/10,000)	0.2734	0.1989	0.2686
		(9.87)***	(7.27)***	(10.14)***
δ_1	Log(Illness Reductions)	0.0402	0.0349	0.0422
		(5.75)***	(4.92)***	(7.11)***
δ_{2p}	Log(Death Reductions)	0.1224	--	0.1211
		(10.36)***		(10.44)***
δ_{2t}	Log(Death Reductions)	--	0.0525	0.0694
			(5.90)***	(5.07)***
θ	**1**(Policy)	-0.7721	-0.5667	-0.7784
		(16.66)***	(10.66)***	(-17.33)***
	… · **1**(Treatment)	--	--	0.0503
				(0.42)***
	… · **1**(MajorCancer)	0.1754	-0.0663	0.1754
		(4.59)***	(1.78)*	(4.59)***
	…· **1**(MajorCancer)·**1**(Treatment)	--	--	-0.2624
				(-4.14)***
ln(κ)	Heteroscedasticity Parameter	0	--	0
	… · **1**(Treatment)	--	0	0.2699
				(1.86)*
Maximized log-likelihood		-8041.10	-7555.15	-15596.40
Sample size (choices)		7556	7033	14589
Maximized log-likelihood overall		-15596.25		-15596.37
Total sample size (choices)		7556	7033	14589

LR-test of restrictions in pooled model: $\chi^2_{0.05}(4) \approx 9.48$, $\chi^2 = 0.24$, fail to reject restricted model.

Table 8: Heterogeneity by Disease Type

Parameter	Variable	(1) Prevention Sample	(2) Treatment Sample
β	**-**(Total Cost/10,000)	0.2809	0.2072
		(10.05)***	(7.52)***
δ_1	Log(Illness Reductions)	0.0397	0.0340
		(5.64)***	(4.75)***
δ_2	Log(Death Reductions)	0.1281	0.0533
		(10.75)***	(5.93)***
θ	**1**(Policy)	-0.6356	-0.2890
		(8.42)***	(3.73)***
	… × **1**(Heart Disease)[d]	--	--
	… × **1**(Heart Attack)	-0.1037	-0.0045
		(1.14)	(0.05)
	… × **1**(Stroke)	-0.3448	-0.3734
		(3.66)***	(4.25)***
	… × **1**(Traffic Injuries)	-0.1883	--
		(2.33)**	
In children	… × **1**(Leukemia in children)	0.2247	0.7825
		(2.57)**	(5.60)***
In children	… × **1**(Resp. Dis. in children)	--	0.4505
			(3.50)***
In children	… × **1**(Asthma in children)	0.1729	0.6283
		(1.98)**	(4.35)***
In children	… × **1**(Injuries to children)	--	0.7917
			(5.61)***
In anyone	… × **1**(Leukemia in general)	-0.4640	-0.8774
		(4.86)***	(6.91)***
In anyone	… × **1**(Respiratory Disease in general)	-0.0626	-0.4160
		(0.68)	(3.61)***
In anyone	… × **1**(Asthma in general)	-0.5400	-0.7853
		(5.59)***	(5.85)***
In anyone	… × **1**(Injuries in general)	--	-0.7456
			(5.77)***
Cancers	… × **1**(Cancer, General))	0.2589	--
		(2.92)***	
Cancers	… × **1**(Colon/Bladder Cancer)	0.0752	-0.2864
		(0.83)	(3.26)***
Cancers	… × **1**(Lung Cancer)	-0.0630	-0.5220
		(0.69)	(5.77)***
Cancers	… × **1**(Prostate Cancer)	--	-0.4652
			(5.18)***
Cancers	… × **1**(Breast Cancer)	--	-0.0613
			(0.72)
Cancers	… × **1**(Skin Cancer)	--	-0.8496
			(8.91)***
Maximized Log-likelihood		-7946.50	-7431.36
Sample Size (Choices)		7556	7033

[d] Omitted category

Table 9: Heterogeneity by Other Policy Attributes

Parameter	Variable	(1) Prevention	(2) Treatment
β	-(Total Cost/10,000)	0.2727	0.2002
		(9.85)***	(7.28)***
δ_{1p}	Log(Illness Reductions)	0.0403	0.0350
		(5.75)***	(4.92)***
δ_2	Log(Death Reductions)	0.1220	0.0535
		(10.33)***	(5.99)***
θ	**1**(Policy)[e]	-0.8149	-0.5422
		(12.75)***	(9.38)***
Cause of ailment			
	…× **1**(Air Pollution)	0.0996	--
		(1.78)*	
	…× **1**(Water Contaminants)	0.1171	--
		(1.78)*	
	…× **1**(Pesticides in Foods)	0.2291	--
		(3.51)***	
Gender-specific illnesses; respondent gender			
	…× **1**(Breast Cancer)	--	0.0831
			(0.88)
	…× **1**(Breast Cancer) × **1**(Female)	--	0.3585
			(2.88)***
	…× **1**(Prostate Cancer)	--	0.1599
			(1.70)*
	…× **1**(Prostate Cancer) × **1**(Female)	--	-0.5488
			(4.00)***
"Affected group" choices			
	…× Percent Children	--	0.0013
			(1.32)
	…× Percent Children × **1**(Age65+)	--	-0.0026
			(1.52)
	…× Percent Children × **1**(HasKids)	--	0.0059
			(4.14)***
	…× Percent Seniors	--	-0.0023
			(4.48)***
	…× Percent Seniors × **1**(Age65+)	--	0.0000
			(0.02)
Maximized Log-likelihood		-8045.14	-7494.63
Sample Size (Choices)		7556	7033

[e] Prevention: omitted category= traffic accidents;
Treatment: omitted category=all other illnesses or injuries