Morbidity and Mortality: How Do We Value the Risk of Illness and Death?

PROCEEDINGS OF SESSION II: ISSUES WITH MORBIDITY VALUATION AND KEYNOTE ADDRESS BY BRIAN MANNIX

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U.S. EPA NCER/NCEE Workshop
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Keynote Address
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He [Al McGartland] told you I'm not a lawyer, but he didn't say what my background is—I'm actually a chemist, although you couldn't tell by my career. . . . What I want to do is step back and take a look at the metrics that we use to describe the benefits of mortality reductions that we attribute to environmental regulations. In particular, I want to raise questions about the statistical robustness of the "lives saved" metric that is now commonplace. I should say that years ago I was an advocate for VSL analysis at the beginning of my career, and I encouraged EPA to focus on lives saved. Now that I'm back at EPA (and I did start here at EPA in 1977), I'm surprised at how much progress has been made in incorporating VSL into Agency analyses and decisions. I'm surprised, too, that I'm not very comfortable with where that progress has left us, and I'm *most* surprised to find that the most serious difficulty in my mind turns out not to be with the "V" but with the "SL." That is, economic valuation of mortality benefits is a tractable problem analytically and politically, but figuring out the right metric for mortality benefits is much more problematic. I'll illustrate this with a contrived example:

Suppose on Monday a hospital in a small town publishes a press release announcing that over the busy weekend it had managed to save a dozen lives. The local TV station sends down a camera crew and asks if it can interview a few of the lucky survivors. The ER nurse tells them, "I'm sorry, that won't be possible—he died." "What do you mean—who died?" the reporter asks. "The man who was having the heart attacks," the nurse replies. "We managed to save him 12 times in 13 attempts."

The point of this story is that while we can easily count "lives" or "deaths," we cannot easily count "lives saved." It is not well defined, and it is inherently unbounded. The airbag may save your life in the event that your brakes fail, but how many times has your life been saved when the brakes didn't fail? The number of lives saved during my commute this morning is already beyond my ability to reckon. In some narrow context, we might be able to come up with a workable definition of a "life saved." As a lifeguard, Ronald Reagan would put a notch in a log every time he saved a life, and I don't doubt that it was accurate and meaningful. If he had kept the notched log during his presidency, however, I can't imagine how we would come up with an accurate count—or interpret it if we had one.

I don't believe it is possible to come up with a definition of "lives saved" that is robust, that can be applied to a wide variety of situations, and that can be aggregated in a

statistically meaningful way. The underlying difficulty is that "lives saved" lacks a time dimension. We know that all lives are temporary, and while the valuation problem is quite complex, we are generally in agreement that a longer life is better than a shorter one. If we don't capture the time dimension, we are unlikely to come up with a metric for mortality that is versatile and that behaves well in statistical usage.

There is a standard statistic for measuring longevity that everyone is familiar with—the expected value of the length of life, or life expectancy. It has several advantages in communicating with the public. Everyone has a pretty good idea of what it measures. People also have a good sense of what the units mean. They may have a great deal of difficulty picturing what a "ten to the minus six" risk of death is, but they know how long a minute is and how long 10 years is, and that covers more than six orders of magnitude. This also solves the problem of divisibility—some find it difficult to think about a fraction of a life saved or about the same life being saved multiple times, but they have no trouble dividing time into units of arbitrary size. The public will also have less difficulty attaching a monetary value to changes in life expectancy, even those who cannot imagine attaching a finite value to a life saved.

I should mention here that just yesterday I saw a new Ford commercial in which Bill Ford says, "Every life saved is worth it." I couldn't agree more. The real advantage of using life expectancy, though, is that it is a well-defined and well-behaved summary statistic that reflects mortality risks across an entire population, including risks of all kinds and at all ages without discriminating against any particular subgroup. Let's suppose we're evaluating a range of policy options, all of which have a small marginal effect on mortality risks. If we take as our mandate to maximize life expectancy using limited resources, we can easily solve the problem. We know that the solution will give us a cost-effectiveness criterion, a fixed dollar amount per incremental year of life expectancy. The decision rule would be to adopt those measures that met the cost-effectiveness criterion and to avoid committing resources to those that didn't.

Note that if we use another decision criterion in place of this one, we will get a shorter life expectancy for the same expenditure of resources. If we use a VSL rule, for example, we might save more lives, whatever that might mean, but on average, people will live shorter lives. In most cases I think the two criteria would likely lead to similar outcomes. When they don't, however, we have to ask whether policies that cause a shorter life expectancy can really be said to be improving public health. Similarly, if we adopt maximum life expectancy as the goal, but make adjustments to the metric for age, quality, or willingness to pay, the result will be that people live shorter lives—better, maybe, in some sense, but shorter. I believe this creates a strong presumption for using life expectancy as a standard metric in evaluating regulatory decisions, using a flat VSLY (value of a saved life year) as the cost-effectiveness criterion. As the first-order approximation of mortality benefits, I think this is vastly superior to the VSL approach, and I think anyone advancing some other decision rule needs to explain how we can justify adopting policies that will lead to a shorter life expectancy. I don't rule out that such justifications may exist, but I think we should be cautious in entertaining them.

Al McGartland has pointed out to me that there's a contradiction here. I embrace the use of willingness-to-pay data in figuring out what our cost-effectiveness criterion should be, but I shrink from looking any deeper into the data to find out how it might vary from group to group or person to person. I think this is a contradiction I can live with. An individual, perhaps because he is wealthy, who is willing to pay and does pay much more than average to reduce his own mortality risks, should certainly be able to do so. However, I am not ready to concede that that same individual is entitled to tilt public health measures in his favor simply because he is willing to pay—but does not pay—for them. When writing rules or spending public funds, there is an egalitarian consideration that does not apply when individuals are spending their own money. As analysts we may feel that we can improve the analysis by making adjustments for age or quality or to incorporate the latest willingness-to-pay data, but as a government official I'm reluctant to go very far down that road. In part, that's because I question whether government has any legitimate business making such adjustments, and in part it's because if the government did get into that business, the adjustments would likely be made according to the rules of politics, not necessarily those of economic analysis. So, perhaps a flat VSLY is desirable for the same reason that a flat tax is appealing to some—it minimizes the opportunities for making mischief.

I'll stop there and look for reactions.

(A question and answer session followed.)

IoM Committee Recommendations and Cost Effectiveness Analysis at EPA

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Presentation Prepared for "Morbidity and Mortality: How do We Value the Risk of Illness and Death
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The views expressed in this presentation are entirely those of the presenter and do not necessarily represent those of the USEPA. No endorsement by the Agency should be inferred.

A Very Brief History

- In 2003, OMB released Circular A-4
  - Requiring Agencies to perform health-based cost effectiveness analyses of economically significant rules where health is the primary benefit
  - Prior to this, EPA seldom performed CEAs using health-related quality of life measures.
- Later that year, the Institute of Medicine (IoM) convened a committee, at the request of John Graham and with funding from several Agencies, to address a number of questions on how best to perform CEAs in a regulatory context.
- Specifically, the Committee was asked to:
  - Describe current agency practices in estimating benefits and costs of regulatory actions
  - Review measures currently used in CEAs to aggregate health improvements
  - Develop criteria for choosing among available measures
  - Assess the various measures for data requirements, feasibility, theoretical validity and ethical implications
  - Recommend measures appropriate for federal agency use
- IoM released its long anticipated report in January 2006

Recommendation 1: Regulatory CEAs that integrate morbidity and mortality impacts in a single effectiveness measure should use the quality-adjusted life year to represent net health effects.

Recommendation 2: Regulatory analyses should report four measures of cost- effectiveness:

- *Compliance cost per death averted*
- *Compliance cost per life year gained*
- *A health-benefits-only ratio* using the net change in QALYs as the outcome measure.
- *A comprehensive ratio* using QALYs as the outcome measure and incorporating the value of other benefits as offsets to compliance costs.

Recommendation 3: The life year and QALY estimates used in regulatory analyses should reflect actual population health as closely as possible

Recommendation 4: Incremental cost-effectiveness ratios are generally the most useful summary measure for comparing different regulatory interventions.

Recommendation 5: In addition to reporting effects in the aggregate, regulatory analyses should report QALY impacts separately for each health endpoint.

Recommendation 6: The reporting of all CEA results should be accompanied by information on related uncertainties and non-quantified effects.

Recommendation 7: Regulatory analyses should not assign monetary values to estimates of health-adjusted life years as a method for valuing health states.

Recommendation 8: The regulatory decision-making process should explicitly address and incorporate the distributional, ethical, and other implications of a proposed intervention along with the quantified results of BCA and CEA.

Recommendation 9: Policy makers and program administrators should work to ensure the substantive involvement of a broad range of individuals and groups at all stages of policy development for regulating risks.

Recommendation 10: A high research priority should be improving the data used to assess the health risks (effects on incidence of particular types of illness, injuries, and deaths, and the duration and latency of effects) addressed by regulatory actions.

Recommendation 11: The Department of Health and Human Services (DHHS) and other federal agencies should collect HRQL information through routinely administered population health surveys and other major studies and data collection efforts related to risk assessment and monitoring.

Recommendation 12: DHHS should coordinate, with the involvement of federal regulatory offices and agencies, the development of an integrated research agenda to improve the quality, applicability, and breadth of HRQL measures for use in regulatory CEA. The Committee identifies the following areas as priorities for research:

- Current elicitation methods such as the standard gamble and time trade-off, while theoretically well founded, may be difficult for respondents to understand and prone to generate inconsistent responses. Research to facilitate improved methods is needed. In addition, methods for eliciting societal values for investments in health (in contrast to individual preferences for health states), such as person trade-off techniques, should also be investigated.
- Methods for measuring children's health-related quality of life, including characterization of the impact of illness and injury and the valuation of these impacts, need continued development and refinement.
- Methods to correlate QALY estimates based on different generic HRQL indexes should be developed so that estimates from different underlying valuation studies are consistent and can be used in the same analysis.

Some Key Issues for EPA

- What do we do if BCA and CEA produce different rankings of policies/programs…or if the four CEA ratios produce different rankings?
- We sometimes have policies that reduce morbidity in one population and prevent deaths in another. How do we combine these effects using a single HRQL index?
- Are QALYs biased since they undervalue health gains to the disabled, elderly and chronically ill?
- How should we report uncertainty? Do we somehow develop ranges of QALYs as we've been asked to do with benefits estimates?
- What do we do when we are unable to quantify the impacts but we know what they are?
- How will the CEA results be used? Will they be used to construct league tables? These may lead to systematic bias away from environmental policies to direct health policies simply because we are unable to quantify some of the environmental effects.

Next Steps for EPA

- The Agency is in the process of updating its *Guidelines for Preparing Economic Analysis*
- A cross-office workgroup was recently convened to write a chapter on CEA for the Guidelines
  - Working through IoM recommendations
  - A public review draft is anticipated by end of calendar year.

For those of you interested in learning more about the IoM report:

see "recent reports" at www.iom.edu

Altruism and Environmental Risks to Health of Parents and their Children[*]

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Altruism and Environmental Risks to Health of Parents and their Children

ABSTRACT

This paper tests an equilibrium condition from a model that incorporates: (1) altruism of parents toward their young children and (2) household production of latent health risks. The model demonstrates that an altruistic parent's marginal rate of substitution between an environmental health risk to herself and to her child is equal to the ratio of marginal risk reduction costs. Econometric estimates support this prediction based on data from a stated preference study involving 488 parents of children aged 3-12 years. This outcome implies that parents reallocate family resources to at least partly offset the effectiveness of public programs that aim to reduce their children's environmental risks.

Key words: Altruism, household production, environmental risk, child health.

Altruism and Environmental Risks to Health of Parents and their Children

1. Introduction

Special protection of young children from environmental hazards has become a worldwide priority in government policies to improve human health.[1] Effectiveness of these measures depends on what steps parents voluntarily take to keep children out of harm's way. If parents are naive about hazards, do not care about their children, or lack the resources to protect their health, implementation of well-designed public policies to increase protection of children may have the intended effect. On the other hand, if parents are informed, altruistic, and sufficiently well off financially, measures aimed at increasing protection of their children from particular hazards will be offset to some extent as parents redistribute family resources. In any case, the fundamental tension between altruism and self-interest in family exchange looms as a crucial behavioral factor determining the effectiveness of government policies to protect children's health.

What is known about altruism in families? Several prominent empirical studies (e.g., Cox and Rank 1992, Altonji, Hayashi, and Kotlikoff 1992, 1997, Laitner and Juster 1996) do not support the implication of altruism for transfer-income derivatives in examining inter-household financial transfers between parents and adult children. Other papers (e.g., Liu *et al*. 2000, Jenkins, Owens, and Wiggins 2001, Nastis and Crocker 2003, Agee and Crocker 2004, Dickie and Messman 2004) look at how parents protect themselves and their pre-teenage children from

[1] For example, Executive Order 13045 (Federal Register, 1997) directs U.S. federal executive branch agencies to assign a high priority to addressing health and safety risks to children, coordinate research priorities on children's health, and ensure that their standards take into account special risks to children. The U.S. Environmental Protection Agency has formulated a seven-step strategy to protect children's health (U.S. EPA 1996). Some of the more visible federal decisions in which protection of children's health figured prominently include tightening of air quality standards for ozone and particulate matter and implementation of the 1996 Safe Drinking Water Act Amendments and the 1996 Food Quality Protection Act. Scapecchi (2006) summarizes similar efforts undertaken in other countries.

environmental and other hazards. In this branch of the literature, altruism is sometimes mentioned as a possible parental motivation, but equilibrium conditions implied by altruism are not tested.

This paper tests a model of altruistic family behavior (Becker 1974, 1981 and Barro 1974) that incorporates household production of latent health risks. The model demonstrates that the parent's marginal rate of substitution between risks faced by herself and her child is equal to the ratio of marginal risk reduction costs. This prediction is tested using survey data on skin cancer risks faced by 488 parents in Hattiesburg, MS and their biological children between the ages of 3 and 12 years. Marginal rates of substitution are obtained from stated preference values for a hypothetical sun lotion. While stated preference valuation remains a controversial method of obtaining willingness to pay for reduced environmental risk, its application here supports consistent estimation of the desired marginal rates of substitution because of the way the survey (described more fully later on) is designed. Test outcomes support the model and imply that parents are altruistic toward their young children.

2. Conceptual Framework

2.1 Model

This subsection presents an extension of Becker's (1981) model of altruism that incorporates household production of latent health risks. The model envisions a "family" composed of one altruistic parent and one child. Because only one child is included in the model, the analysis focuses on how parents allocate resources between themselves and their children, rather than on how parents make tradeoffs among different children. By including only one parent in the model, a unitary perspective is adopted in which possible divergent interests between parents in a family are not considered. Although the unitary model has been rejected in

several empirical tests (e.g., Lundberg et al. 1997), tests presented in Section 4 reveal no significant differences in valuation of latent health risks between fathers and mothers.

To facilitate treatment of latent health risks, assume that the parent has two periods of life remaining while the child has three. During the present period ($t = 0$), the parent receives all family income, purchases market goods for her family, and behaves as a paternalistic altruist in that she derives utility from her own consumption as well as from the combination of goods that she provides to her child.[2] Thus, the parent allocates goods to the child according to her own views as to what is best and disregards the child's preferences (if any) except in situations in which they are congruent with her own. In period $t = 1$, the child will be an adult with his own income, which the parent may supplement with transfers, and will make his own consumption decisions. In this period, the parent will derive utility from her own consumption and may also derive satisfaction from the level of utility achieved by the child. The model therefore envisions that the parent's altruism may switch from paternalistic altruism to the more all-encompassing concern for the child's well-being considered by Altonji, Hayashi, and Kotlikoff (1997) after the child is mature enough to exhibit well-defined preferences and the parent can no longer dictate the combination of goods that the child will consume.[3] In the third and final period ($t = 2$), the child continues to receive income and purchase market goods while the parent is deceased.

The survey, described more fully in Section 3, elicits willingness to pay to reduce two latent environmental health risks facing both the parent and the child. In the model, these two risks are denoted a and b. To consider a latency period that is longer for the child than for the parent, assume that the events at risk may occur in the last period of either individual's life.

[2] Paternalistic altruism is more fully discussed by Jones-Lee (1991, 1992)

[3] Both types of altruism are incorporated into the model to assist in clarifying the interpretation of statistical tests presented in Section 4. All-encompassing concern for another's well-being has also been termed "benevolence" (Bergstrom 2006) or "pure" altruism (Jones-Lee 1991, 1992).

Constraining the lifetime risk to lie in a single period simplifies the task of communicating changes in risk to survey respondents (see Section 3). Perceptions of the *j*th latent risk to the *i*th person are denoted R_i^j, where superscript *j* distinguishes between the two risks (*a* and *b*) while subscript *i* distinguishes the parent (*p*) from the child (*k*). Perceived lifetime risks are influenced by the use of market goods that otherwise have no utility:

$$\begin{aligned} R_p^j &= R_p^j(G_{p0}^j, G_{p1}^j), \\ R_k^j &= R_k^j(G_{k0}^j, G_{k1}^j, G_{k2}^j), \qquad j = a, b. \end{aligned} \tag{1}$$

where G_{it}^j denotes individual *i*'s use in period *t* of a market good affecting the *j*th risk. Simplifying assumptions here are that: (1) the risk production functions do not shift over time, (2) the child when grown is assumed to share his parent's assessment of both risks, and (3) marginal products of the G_{it}^j are strictly negative in both production functions.

When the child begins to make his own consumption decisions as an adult in period *t=1*, he will maximize his lifetime utility given by $U_k(C_{k0}, C_{k1}, C_{k2}, R_k^a, R_k^b)$ subject to his perceived risk production functions given in equation (1), the choice of $(C_{k0}, G_{k0}^a, G_{k0}^b)$ that already will have been made by the parent, and his lifetime budget constraint,

$T + y_{k1} + (1+r)^{-1} y_{k2} = C_{k1} + P^a G_{k1}^a + P^b G_{k1}^b + (1+r)^{-1}[C_{k2} + P^a G_{k2}^a + P^b G_{k2}^b]$. Here and in equations (2) and (3), variables y_{it} and C_{it} respectively denote individual i's income and consumption of an aggregate market good in period *t*, *T* denotes the income transfer from parent to child in period *t*=1 ($T \geq 0$), *r* denotes the market interest rate and P^j denotes the market price of the protective good affecting the *j*th risk.

In period *t* = 0 the parent maximizes the utility function

$$U_p(C_{p0}, C_{p1}, C_{k0}, R_p^a, R_p^b, R_k^a, R_k^b) + \eta U_k^*(C_{k0}, G_{k0}^a, G_{k0}^b, T, y_{k1}, y_{k2}, r, P^a, P^b) \tag{2}$$

subject to the four perceived risk production functions in equation (1), the restriction $T \geq 0$ and her lifetime budget constraint

$$\begin{aligned} y_{p0} + (1+r)^{-1} y_{p1} = C_{p0} + C_{k0} + P^a(G^a_{p0} + G^a_{k0}) + P^b(G^b_{p0} + G^b_{k0}) \\ + (1+r)^{-1}[C_{p1} + T + P^a G^a_{p1} + P^b G^b_{p1}], \end{aligned} \tag{3}$$

where $\eta \geq 0$ is the weight the parent places on the child's lifetime utility and $U^*_k(\bullet)$ denotes the indirect utility function from the child's maximization problem. When *t = 0*, the parent chooses quantities of all market goods that she and her young child use and when *t = 1*, the parent makes these choices only for herself while deciding how much income to transfer to her child.

The parent's paternalistic altruism in period $t = 0$ is reflected in her concern for her child's present consumption and his risk . If $\eta = 0$, the parent has no further concern for the child in future periods and will not care how his future choices may affect the lifetime risk he ultimately faces. If $\eta > 0$, the parent continues to care about the child in the future, but she exhibits benevolence or all-encompassing altruism in that she respects the child's adult preferences and cares about his overall level of well-being rather than the specific bundle of goods he consumes.

First order conditions[4] for period *t = 0* quantities imply that for *j = a, b*

$$\begin{aligned} &\partial U_p / \partial C_{p0} = \partial U_p / \partial C_{k0} + \eta \partial U_k / \partial C_{k0} \\ &(\partial U_p / \partial R^j_p)(\partial R^j_p / \partial G^j_{p0}) = (\partial U_p / \partial R^j_k)(\partial R^j_k / \partial G^j_{k0}) + \eta(\partial U_k / \partial R^j_k)(\partial R^j_k / \partial G^j_{k0}). \end{aligned} \tag{4}$$

[4] These equations make use of the relationships $\partial U^*_k / \partial G^j_{k0} = (\partial U_k / \partial R^j_k)(\partial R^j_k / \partial G^j_{k0})$. Equations (4) and (5) also make use of the assumption that the parent exhibits paternalistic altruism only in period *t=0*. Thus her paternalistic altruissm encompasses concern for how her present choices affect her child's risk but does not extend to concern for how his future choices may alter his risk. Any concern for the child in future periods is reflected by $\eta > 0$, not by $\partial U_p / \partial R^j_k$. This assumption means that the parent does not have to consider the dependence of her child's future choices on her decisions today. A more formal analysis of this point is available on request.

Thus, in period *t = 0*, the model predicts the familiar result that if both individuals consume *C* and *G* in positive quantities, the parent's marginal rate of substitution between the child's consumption of *C* (*G*) and her own consumption of *C* (*G*) is equal to unity.[5] This outcome holds independently of the magnitude of η, the weight that the child's utility receives in the parent's utility function, and also holds if the parent exhibits either type of altruism. If instead the parent exhibits neither type of altruism (i.e., is not an altruist toward the child), then these marginal rates of substitution equal zero. If the parent exhibits either or both types of altruism toward the child but does not care about her own consumption or about the level of risks that she faces, then these marginal rates of substitution are arbitrarily large.

In periods *t = 1* and *t = 2*, first order conditions imply that

$$\begin{aligned}
&\partial U_p / \partial C_{p1} = \lambda_p (1+r)^{-1} \\
&\partial U_k / \partial C_{kt} = \lambda_k (1+r)^{1-t} && t = 1,2 \\
&(\partial U_p / \partial R_p^j)(\partial R_p^j / \partial G_{p1}^j) = \lambda_p P^j (1+r)^{-1} && j = a,b \\
&(\partial U_k / \partial R_k^j)(\partial R_k^j / \partial G_{kt}^j) = \lambda_k P^j (1+r)^{1-t} && j = a,b \quad t = 1,2 \\
&\eta \lambda_k = \lambda_p (1+r)^{-1} && \text{if } T > 0.
\end{aligned} \tag{5}$$

Equation (5) shows that if $\eta > 0$ and if $T > 0$, then in period *t = 1* the parent's marginal rate of substitution between the child's consumption of *C* (*G*) and her own consumption of *C* (*G*) also is equal to unity. In the case in which $\eta > 0$, therefore, transfers from the parent to child ensure that the parent's marginal rate of substitution between the child's consumption of market goods and her own consumption of market goods is equal to unity in all periods in which both individuals are alive. If $\eta > 0$, but $T = 0$ (as may occur in period *t = 1* if the child is rich and the parent is poor) then the parent's marginal rates of substitution between her child's consumption

[5] Throughout the paper, the convention adopted for calculating marginal rates of substitution is that the parent's marginal utility of the child's consumption is in the numerator and the parent's marginal utility of her own consumption is in the denominator.

and her own consumption are positive, but in general are not equal to unity because $\eta\lambda_k \neq \lambda_p(1+r)$. On the other hand, if the parent is a paternalistic altruist only and has no concern for the child's well-being after period *t = 0* has ended ($\eta = 0$), then in period *t = 1* the parent's marginal rates of substitution between her child's consumption and her own consumption are equal to zero. Finally, just as in period *t = 0*, if the parent cares about her child's well-being but not about her own consumption of market goods, then her marginal rates of substitution between the child's consumption and her own consumption become arbitrarily large.[6]

The empirical analysis presented in Section 4 looks at risk reduction, not consumption of G^j. So, in period *t = 0*, the first order equation for G^j in (4) is rewritten as equation (6) to show that when corner solutions are set aside, the parent's marginal rate of substitution between risk to her child and risk to herself is equal to the ratio of marginal products of a risk-reducing market good that both individuals consume.

$$\frac{(\partial U_p / \partial R_k^j) + \eta(\partial U_k / \partial R_k^j)}{(\partial U_p / \partial R_p^j)} = \frac{(\partial R_p^j / \partial G_{p0}^j)}{(\partial R_k^j / \partial G_{k0}^j)} = \frac{MC_{k0}^j}{MC_{p0}^j} \qquad j = a, b. \tag{6}$$

The ratio of marginal products, in turn, equates to the ratio of present value marginal costs because the price per unit of G^j is the same no matter who uses it.

Equation (5) also implies that each individual equates the present-value marginal costs of risk reduction over time, provided that risk production functions are constant over time. Thus, in

[6] Equation (5) also implies that when the parent and child consume positive quantities of all goods in all periods, the inter-temporal marginal rate of substitution between consumption of *C* (*G*) in period *t + 1* and consumption of *C* (*G*) in period *t* equals the discount factor $(1+r)^{-1}$ for both the parent and the child. The inter-temporal marginal rate of technical substitution between risk-reducing goods in different periods likewise equals the discount factor for both individuals. If $\eta > 0$ and if $T > 0$, then the parent's marginal rate of substitution between her child's consumption of *C* (*G*) in period *t + 1* and her own consumption of *C* (*G*) in period *t* is equal to the discount factor as well.

period $t = 1$, the present-value marginal cost of risk reduction for the parent will be the same as in period $t = 0$, and the present-value marginal cost of risk reduction will be the same for the child in periods $t = 1$ and $t = 2$. In addition, if $\eta > 0$ and $T > 0$, then the marginal costs of risk reduction for the child are the same in all three periods.[7] Evidently, the parent's all-encompassing concern for the child's well-being together with her monetary transfers enables her to choose marginal cost of risk reduction values that the child will use for the rest of his life. In consequence, if $\eta > 0$ and $T > 0$

$$\frac{\eta(\partial U_k / \partial R_k^j)}{(\partial U_p / \partial R_p^j)} = \frac{(\partial R_p^j / \partial G_{p1}^j)}{(\partial R_k^j / \partial G_{kt}^j)} = \frac{MC_k^j}{MC_p^j} \qquad j = a, b \qquad t = 1, 2. \tag{7}$$

On the other hand, this marginal rate of substitution equates to zero if $\eta = 0$ and will not equate to the marginal cost ratio if either $T = 0$ or if the parent does not care about risk to herself.

Together, equations (6) and (7) imply that if $\eta > 0$ and $T > 0$, and both the child and parent consume positive quantities of all market goods in all periods when they are alive, then the parent's marginal rate of substitution between her child's and her own latent risk equals the ratio of present-value marginal costs of reducing risk in any period. Three further implications of equations (6) and (7) are that even if the parent is a paternalistic altruist in period t=0 and if $\eta > 0$ and $T > 0$: (1) the ratio of marginal risk reduction costs for the child and the parent is not expected to equal unity because the technologies used to produce perceived risk reduction may differ and, even if the technologies are the same, levels of perceived risk faced by the two people may not be the same, (2) for either individual, the ratio of marginal costs for reducing the first risk need not equal the ratio of marginal costs for reducing the second risk, and thus (3) for either

[7] $MC_p^j = (1+r)^{-t} P^j / (\partial R_p^j / \partial G_{pt}^j), t = 0, 1,$ and $MC_k^j = (1+r)^{-t} P^j / (\partial R_k^j / \partial G_{kt}^j), t = 0, 1, 2.$

individual, the marginal rate of substitution between the two types of risks equals the corresponding ratio of marginal costs in reducing the two risks.

Empirical estimates described in Section 4 test the null hypothesis that the equilibrium conditions stated in equations (6) and (7) hold. This test is facilitated by considering percentage risk changes rather than changes in risk by absolute amounts. For instance, when the parent and child experience the same percentage reduction in a risk, the ratio of marginal products in equation (6) equals the ratio of initial risk levels, as illustrated below for period $t = 0$.[8]

$$\frac{(\partial R_p^j / \partial G_{p0}^j)}{(\partial R_k^j / \partial G_{k0}^j)} = \frac{R_p^j}{R_k^j} \qquad j = a, b$$

Thus, in this case, as shown in equation (8), the parent's marginal rate of substitution between equal percentage risk changes for herself and for the child equates to unity.

$$\frac{[(\partial U_p / \partial R_k^j) + \eta(\partial U_k / \partial R_k^j)]R_k^j}{(\partial U_p / \partial R_p^j)R_p^j} = \frac{(\partial R_p^j / \partial G_{p0}^j) / R_p^j}{(\partial R_k^j / \partial G_{k0}^j) / R_k^j} = 1 \qquad j = a, b \qquad (8)$$

If $\eta > 0$ and $T > 0$, then the corresponding condition will hold for periods $t = 1$ and $t = 2$, as shown in equation (9).

$$\frac{\eta(\partial U_k / \partial R_k^j)R_k^j}{(\partial U_p / \partial R_p^j)R_p^j} = \frac{(\partial R_p^j / \partial G_{p1}^j) / R_p^j}{(\partial R_k^j / \partial G_{kt}^j) / R_k^j} = 1 \qquad j = a, b \quad t = 1,2 \qquad (9)$$

Evidence that equation (8) holds supports the notion that parents are altruistic toward their children, but does not indicate whether parents are paternalistic altruists only, whether parents only exhibit the broader type of altruism associated with $\eta > 0$ and $T > 0$, or whether

[8]This outcome also yields a useful corollary for transferring adult morbidity estimates to children when equal proportionate changes in risk to both groups are considered. If the parent and child experience the same percentage reduction in risk, the ratio of marginal products in equation (4) equals the ratio of initial risk levels. This means that the ratio of the parent's willingness to pay to reduce risk to the child to the parent's willingness to pay to protect herself equates to this ratio of risks. The ratio of actual risks faced might be estimated in some cases using existing health science and biomedical information. The ratio of perceived risks might be established by studies of parents' perceived risks to children and to themselves.

parents exhibit both types of altruism. Evidence that equation (9) holds, on the other hand, says nothing about paternalistic altruism, but supports the notion that $\eta > 0$ and $T > 0$. Evidence supporting equations (8) and/or (9) does not indicate whether η or the provisions the parent makes for the child (C_{k0}, G_{k0}^{j}, T) are large or small. As discussed more fully in Section 4, tests applied do not distinguish between paternal and all-encompassing altruism and do not identify the value of η if $\eta > 0$.[9]

2.2 Policy implications

The model developed in the previous subsection suggests that effectiveness of government programs aimed at reducing risk through behavior modification will be compromised to some extent because they motivate parents to reallocate family resources, as illustrated by the following three examples.[10] First, suppose that in a country composed of M identical families[11], the government initiates an administratively costless program in time period $t = 0$ to provide special protection of children from risk, as envisioned by Executive Order #13045 (Federal Register 1997) in the United States and by similar policies pursued by other countries (Scapecchi 2006). Assume that: (1) the government has access only to the "family technology" for risk reduction described by equation (1), (2) the program provides the parent

[9] The model presented can be modified or extended in a variety of ways without altering the basic result that the altruistic parent's marginal rate of substitution between her child's and her own risk equals the ratio of marginal costs of risk reduction. For example, a discounted expected utility model in which individuals produce risk but probabilities condition expectations rather than utility itself also implies equality between the parent's marginal rate of substitution and the ratio of risk-reduction costs.

[10] Although the model does not address issues related to government risk information provision or how parents might respond to such information, it is at least plausible that such programs might be more effective than behavior modification programs. Also, along these lines, note that if in addition to paternalistic altruism, $\eta > 0$ and $T > 0$, parental learning about risks will be retained by the child through adulthood in the sense that his marginal costs of avoiding a risk are equated through all periods of his life. In this situation, parental learning may be passed to future generations as well, but a formal investigation of this matter would require reformulating the model to allow the child to have children of his own as, for example, in Becker (1974).

[11] Further examples based on heterogeneity of parent incomes, two-parent families, and families with multiple children easily can be constructed based on those presented below. Similar examples also can be developed for models where government policy operates by determining the level of an environmental hazard that affects child and/or parent risk rather than by providing G, although in that case the rate of substitution between G and the environmental hazard in the risk production functions must be considered.

with an extra unit of G earmarked for the child's use, (3) the program is financed by levying a tax on each parent in the amount of $\$P$, the price per unit of G,[12] and (4) and parents exhibit one or both types of altruism. As long as prices of market goods and the parent's income remain unchanged, parents and children in each family end up consuming the same quantities of all goods as before. In consequence, the program does not alter behavior and has no effect on the level of risk faced by either person.

Second, suppose instead that the government program sets out to protect everyone (i.e., both adults and children) from risk by giving each family one unit of G for either person to use, rather than earmarking it for the child's use. In this situation, each family simply "purchases" one unit of G for $\$P$ from the government rather than from the private market. Again, if incomes and market prices remain unchanged and parents behave altruistically, each family member consumes the same quantities of C and G as before so that the program has no effect on behavior or on risk levels faced by either parents or children.

Third, suppose that the government is more efficient than families in lowering risk, perhaps because of economies of scale in providing risk reduction. In this case, each family might receive more than one unit of G in return for the tax payment of $\$P$, thereby experiencing the equivalent of an increase in income. Pure paternalistic altruists would then divide the income increase between their own consumption of C and G in periods $t = 0$ and $t = 1$ and their child's consumption of these goods in period $t = 0$, with the increment in G allocated between the parent and the child so that the parent's marginal rate of substitution between risk to the child and risk to herself remained equal to the ratio of marginal costs of risk reduction. If in addition to or instead of paternalistic altruism, parents also exhibit all-encompassing altruism

[12] Becker (1981, Chapter 8) presents a closely related example with extended discussion in the context of an income transfer between an altruistic person and his/her spouse.

with $\eta > 0$ and $T > 0$, more substitution possibilities arise because a portion of the income increase could be transferred to the child for use later in his life. Thus, while the program could succeed in lowering risk, the efficiency gain is diffused because both family members now consume more of all goods in the present period and possibly in future periods.

3. Data and Experimental Design

3.1 Background

Field data were collected from parents of pre-teenage children during summer of 2002 using a self-paced, interactive, computerized instrument.[13] An early version of this instrument was used in a pilot study of parents' willingness to pay to reduce perceived skin cancer risks (Dickie and Gerking 2003). Two subsequent versions of the instrument were pre-tested and de-briefing sessions with pre-test participants guided development of the final version. Parents who participated in this study were residents of the Hattiesburg, MS metropolitan statistical area and were initially identified by random digit dialing. When calls reached adults, interviewers asked whether they had at least one biological child between the ages of 3-12 living at home, and whether they were willing come to the University of Southern Mississippi to participate in a federally funded study of health risks to parents and their children. Biological children were singled out for inclusion in the study because skin cancer risk is partly determined by genetic characteristics inherited from parents (e.g., fairness of skin and sensitivity of skin to sunlight). Parents were offered a $25 payment for participating in the study.[14]

[13] A more complete description of these data is provided in Dickie and Gerking (2006).

[14] Approximately 30% of calls to presumed working residential numbers yielded no contact with an adult after three attempts at different times of day and days of the week. In 64% of cases in which a call reached an adult, the adult declared that the household did not meet eligibility requirements (had no biological children aged 3-12 living at home). Parents agreeing to participate in the study constituted 3.5% of working residential numbers, 5% of contacts with adults, and 14.3% of contacts with adults who did not declare the household ineligible. Finally, 68% of persons agreeing to participate completed the instrument.

The sample consisted of 610 parents; children did not participate.[15] Of the parents, 75% were white, 20% were African-American, and 5% were members of other races. Data from the 122 African-American parents are not considered further in this paper (but are analyzed in Dickie and Gerking 2006) because blacks face low levels of risk and therefore have fewer incentives than whites to think about precautions against solar radiation exposure and how their own risk might differ from that of their children. Of the 488 non-black parents, 25% were male, 75% were under the age of 40, mean household income was $60,000 per year, 83% were married, and 60% worked full time. Parents generally were aware of skin cancer: 83% knew someone personally who had been diagnosed with this disease, 18% knew of someone (public figures, friends, or relatives) who had died from skin cancer, and 82% had considered the possibility that one of their children might get skin cancer. At an early stage in the interview, one biological child aged 3-12 of each parent was randomly selected (if there was more than one in this age range) and designated as the sample child. Questions asked mainly focused on the parent and the sample child. Half (50.4%) of the sample children were male and the average age of sample children was 7 years.

3.2. Elicitation of Risk Beliefs

Two types of risk to both parents and children were elicited: (1) the unconditional risk of getting skin cancer during one's lifetime and (2) the conditional risk of dying from this disease given that it occurs.[16] Parents Slovic, Paul, Baruch Fischhoff, and Sarah Lichtenstein made

[15] Responses from 25 parents were disregarded either because they did not answer all questions (21 parents) or because they did not follow instructions given by the experiment administrator (4 parents).

[16] The ability of respondents to understand the risk concepts presented and to clearly distinguish between these two types of risk was a concern from the beginning of the study because of difficulties people have thinking about probabilities (Slovic, Fischhoff and Lichtenstein 1985). This concern was amplified for the present study because few previous surveys have dealt with compound risks. In de-briefing sessions conducted after the pre-tests, the meaning of the morbidity risk and conditional death risk questions were extensively discussed with participants. Participants suggested a number of wording changes in the questions, but through this discussion and through their direct statements, they demonstrated facility with the risk concepts involved.

preliminary assessments of lifetime skin cancer risk using an interactive scale similar to that used by Krupnick *et al.* (2002) and Corso, Hammitt, and Graham (2001). The scale, which underwent a number of design changes based on the pre-tests, depicted 400 squares in 20 rows and 20 columns and all 400 squares were initially colored green. Parents changed green squares to red ones to represent amounts of risk. Before using the scale to estimate skin cancer risk, parents practiced using the risk scale for an unrelated event (a possible auto accident) and were told about the meaning of "chances in 400". Also, they were told to consider only the chances of getting skin cancer (or of getting it again if they had already had it), rather than how serious the case might be. Parents then used the risk scale to estimate lifetime chances of getting skin cancer, for themselves and then for their sample child. Frequency distributions of these responses presented in Table 1 indicate considerable variation in risk estimates with some parents believing that skin cancer is highly unlikely and a smaller number of parents believing that skin cancer is inevitable. Risk estimates tended to pile up at the 5, 10, 15, etc. percent marks.

As shown in Table 2, parents estimated that their own lifetime risk of getting skin cancer exceeded that of their sample child (26.9% vs. 22.5%). The null hypothesis that mean perceived skin cancer risks are equal for parents and children is rejected at the 1% level in a matched-samples test. This outcome may reflect a number of factors possibly including parents' beliefs that they take greater precautions to protect their children from skin cancer risk than their parents did in an earlier period when less was known about the hazards of solar radiation exposure. Parents also appear to have overestimated skin cancer risk. Ries *et al.* (1999) found that whites have a lifetime chance of 21% of getting either melanoma or non-melanoma skin cancer. The fact that the survey introduced the possibility of getting skin cancer again if the parent had

already had it does not appear to be an important complicating factor in this regard. Sample parents are relatively young and 4.3% reported having been previously diagnosed with this disease.

Parents were given an opportunity to revise their beliefs about the chances of getting skin cancer after receiving information about this disease. They were told that: (1) according to the National Cancer Institute, the average person in the United States has a lifetime risk of getting skin cancer of 18% and (2) a person's risk may differ from this average because of skin color and sensitivity to sunlight, family history of skin cancer, amount of time spent in direct sunlight, experience with sunburns, and use of sun protection products. Parents were questioned about observable skin characteristics, sun exposure history, and use of sun protection products both for themselves and their sample children. Over 90% of parents and 97% of children use sun protection products such as sun lotion. Children use sun protection products a greater fraction of the time that they are outside and use products with a higher sun protection factor than do their parents (Table 3). About 40% of parents revised their own lifetime risk estimates, but upward and downward revisions balanced to yield zero mean revision. Revised risk estimates for children were on average 2 percentage points lower than initial risk estimates.

To obtain a rough indication of beliefs about latency of skin cancer risks, parents were asked, “Suppose you do get skin cancer sometime in the future. At what age do you think you would get it for the first time (or for the next time if you have already had it)?” Responses to this and a parallel question about the children are summarized in Table 4. About 65% of parents saw skin cancer as a disease that would strike them or their children at age 50 or later. Based on the midpoints of the age intervals listed in Table 4, parents on average expected that skin cancer, if it occurs, would strike them at age 53 or their children at age 55. Comparing expected age at onset

to current age, the average implied latency period is 18 years for parents and 48 years for children, a difference that is significant at the 1% level. These rough measures of perceived latency suggest that parents see skin cancer as a disease that occurs later in life and see their children's risk as lying farther in the future than their own.

Parents also provided estimates of mortality risk from skin cancer both for themselves and for their sample children assuming a doctor had diagnosed this disease. Parents were unaware that they would be asked about the likelihood of dying from skin cancer when they answered the previously described questions about getting this disease.[17] Parents provided their perceptions of conditional mortality risk of skin cancer given a diagnosis of this disease using the previously described risk scale. Table 1 presents the frequency distribution of responses. About two-thirds of parents believed that their conditional risk of death given a diagnosis of skin cancer is 10% or less and about three-fourths of parents believed that if similarly diagnosed, their sample child's conditional risk of death is 10% or less. Many parents felt that the conditional risk of death is less than 5% both for themselves and for their children. This outcome suggests that parents were aware that skin cancer is seldom fatal. Parents reported higher mean conditional death risk estimates for themselves (12.1%) than for their sample children (9.4%), a significant difference at the 1% level.

3.3 Experimental Design and the Choice Experiment

Parents valued risk reductions by expressing willingness to pay for a hypothetical sun lotion.[18] The product was described using labels (see Figure 1 for an example) designed to look like those on bottles of over-the-counter sun lotions. Except for differences in the type and

[17] Respondents were instructed not to look ahead or to go back to previous questions but rather to see the experiment administrator if they needed to correct a mistaken answer. Data from 4 respondents who did not comply with this instruction were among the previously mentioned observations that were deleted.

[18] This approach also was used in a recent cross-country study of skin cancer risks (see Brouwer and Bateman 2005).

amount of skin cancer protection offered, the labels were identical in all respects to control for other possible motivations for purchasing sun lotion, such as to prevent sunburn or to get a suntan and to guard against aging or wrinkling of skin (see Dickie and Gerking 1996). Eight labels were used in the study: Four labels varied reductions in risk of getting skin cancer (10%/50% for parent/child) and four labels varied reductions in conditional death risk (10%/50% for parent/child).[19] As demonstrated in Section 2, use of percentage changes simplifies the econometric tests. Use of percentage changes in risk also has an advantage over presenting absolute risk reductions in that the post-treatment risk levels always are non-negative.[20]

Each parent was randomly assigned two of the eight labels and asked for willingness to pay for each.[21] One of the assigned labels offered reduced risk of getting skin cancer and the other offered reduced conditional death risk from skin cancer. Labels were presented one at a time in randomized order. After parents were given time to read a label as if considering buying the product for the first time, they were shown their previously marked risk scales both for themselves and their children showing the level of perceived risk the parent originally indicated,

[19]The survey presents exogenous changes in risk to avoid issues that arose in a previous study (Dickie and Gerking 1996) in which risk changes were treated as endogenous. In the earlier work, labels were presented without the stated risk changes and respondents indicated the amount by which risk would be reduced if the product were used as directed. Survey participants, however, expressed little confidence in their response to this question and responses obtained were unavoidably correlated with unobserved participant characteristics. In the present context, telling parents what to believe about the magnitude of risk change is at least arguably better than asking a difficult question. Also, random assignment of labels means that risk changes are orthogonal to respondent characteristics. Nonetheless, because changes in risk actually are endogenous, interpretation of the econometric estimates presented in the next section must necessarily be guarded.

[20] Data on actual purchases of currently marketed sunscreen lotions would not support valuation of the two risks separately from other motivations for using sunscreen (Dickie and Gerking 1991, 1996) and would not reflect random assignment of exogenous risk changes. These two features of the field study are critical for estimating the marginal rate of substitution.

[21] Means of the four perceived risks, family income, number of children in the family, and age and gender of parent and children were compared across labels, separately for the four morbidity labels and four conditional mortality labels. Statistical tests fail to reject the null of a constant mean across labels at 10% for all characteristics except gender of parent across the four morbidity labels. With that one exception, the randomly assigned labels are orthogonal to important parent and child characteristics.

and the risk reduction the sun lotion would offer. In this way the magnitude of the risk change for the parent and the child was described in absolute as well as in percentage terms.

For the first of the two labels, parents were asked, "Now please think about whether you would buy the new sun protection lotion for yourself or your child. Please do not consider buying it for anyone else. Suppose that buying enough of the lotion to last you and your child for one year would cost $X. Of course, if you did buy it, you would have less money for all of the other things that your family needs. Would you be willing to pay $X for enough of the sunscreen to last you and your child for one year?" The value of X was randomly selected from among nine values ranging between $20 and $125. The narrative also reminded parents that lifetime use of the sun lotion is necessary to obtain the stated skin cancer protection benefits. For the second label, parents were told, “Suppose that instead of the previous label, we showed you the following label.” Willingness to pay then was elicited as before.

4. Empirical Estimates

4.1. Methods and Interpretation

Following Cameron (1988), the null hypothesis that parents’ stated purchase intentions for the hypothetical sun lotion are consistent with equations (8) and (9) is tested based on a specification of the willingness-to-pay function rather than on an explicit specification of a difference in random utility functions. The approach taken uses the model developed in Section 2 to derive present period ($t = 0$) willingness to pay (WTP^j) for the hypothetical sun lotions to reduce the unconditional risk of getting skin cancer ($j = a$) and the conditional risk of dying from this disease if it is contracted ($j = b$).

Each new sun lotion is treated as a newly available private good that if purchased would provide an increment, S_{it}^j, in the planned amount of protective goods that was optimal in the

absence of the new sun lotion. If individual *i* uses sunscreen *j* during period *t* then $dG_{it}^{j} = S_{it}^{j} = 1$; otherwise $dG_{it}^{j} = S_{it}^{j} = 0$. The resulting changes in lifetime risk are $dR_i^j = \sum_t (\partial R_i^j / \partial G_{it}^j) S_{it}^j$.[22]

Parents participating in the field study were told the lifetime risk reductions that would result from use of the new sun lotion and that achieving these risk reductions would require lifetime use of the product. Therefore assume that the parent would prefer not to purchase the sun lotion for herself now, unless she envisioned continuing to use it in the future. Likewise, she would prefer not to purchase the sun lotion for her child now, unless she believed that he would find it in his interest to use it in the future. Also, the first period's supply of the sun lotion is offered as a single purchase decision for the parent and child together, rather than as a separate purchase decision for each. In consequence, the parent decides that neither she nor her child will use the sun lotion at all ($S_{it}^{j} = S = 0$), or that both will use it now and in the future ($S_{it}^{j} = S = 1$). The possibility that only one of the two individuals would use the sun lotion is addressed below.

Suppose that the required expenditure for the lotion for the parent and child together during $t = 0$ is denoted X^j, and that in subsequent periods, when the child makes his own allocation decisions, each individual may purchase the sun lotion in an amount for one person at half of this expenditure, $X^j / 2$. Then the parent's maximal lifetime utility assuming continuing use of the sun lotion is $U_p^*(y_{p0} - X^j, y_{p1} - X^j/2, y_{k1} - X^j/2, y_{k2} - X^j/2, r, P^a, P^b; S = 1)$, where

[22] This specification assumes that users of the new sun lotions would not neutralize the risk reductions by making other substitutions, for example by spending more time outdoors in sunlight. In two previous skin cancer surveys, attempts were made to account for possible substitutions that might influence endogenously perceived risk changes associated with hypothetical sun lotions. In Dickie and Gerking (1996), an indicator for whether respondents used current sunscreen in order to stay outdoors longer was not significantly related to the perceived risk reduction associated with a hypothetical sun lotion. In Dickie and Gerking (2003), respondents were asked whether using a hypothetical sun lotion would lead them or their children to spend more time outdoors in sunlight. Fewer than 10% of parents responded affirmatively, and indicators for this type of substitution were not significantly related to perceived risk changes associated with the hypothetical sun lotion, or with willingness to pay for it. These results suggested that the possibility of offsetting substitutions would not be a major factor considered by parents when they initially evaluated the new sun lotions and consequently no questions concerning this type of behavior were included in the present study.

$U_p^*(\bullet)$ denotes the indirect utility function and where $\partial U_p^* / \partial y_{kt} = 0$ if $\eta = 0$. Derivatives of this function include

$$\begin{aligned}(\partial U_p^* / \partial S) &= (\partial U_p / \partial R_p^j) dR_p^j + (\partial U_p / \partial R_k^j) dR_k^j + \eta(\partial U_k / \partial R_k^j) dR_k^j \\ (\partial U_p^* / \partial X^j) &= -\left[\lambda_p + (1/2)(1+r)^{-1}(\lambda_p + \eta\lambda_k) + (1/2)(1+r)^{-2}\eta\lambda_k\right] \\ &= -\lambda_p \sum_{t=0}^{2} \left(n_t / 2\right)(1+r)^{-t}\end{aligned} \tag{10}$$

where the dR_i^j denote the lifetime risk changes resulting from use of the sun lotion in all periods and n_t denotes the number of users of the sun lotion in period *t* whom the parent cares about (if $\eta > 0,\ n_0 = 2 = n_1,\ n_2 = 1$ because the parent cares about the child in all periods, while if $\eta = 0,\ n_0 = 2,\ n_1 = 1,\ n_2 = 0$ because the parent cares about the child only in $t = 0$). As shown in equation (10), the child's decision to purchase the sun lotion in periods $t = 1$ and $t = 2$ affects the parent's welfare if $\eta > 0$.

The parent's willingness to pay for the sun lotion per period, WTP^j, is the value of X^j that equates $U^*(\bullet) \equiv \bar{U}$, where $\bar{U}$ denotes the parent's maximal lifetime utility if neither she nor her child uses the sun lotion. Applying the implicit function theorem to this identity and using equation (10) implies that marginal willingness to pay for the first period of sun lotion use is

$$\begin{aligned}d(WTP^j) &= (1/\lambda_p)\left[\sum_{t=0}^{2}(n_t/2)(1+r)^{-t}\right]^{-1}\left[\begin{array}{l}(\partial U_p / \partial R_p^j)(dR_p^j) \\ +[(\partial U_p / \partial R_k^j) + \eta(\partial U_k / \partial R_k^j)](dR_k^j)\end{array}\right] \\ &= \beta\left(\delta_p^j(-dR_p^j / R_p^j) + \delta_k^j(-dR_k^j / R_k^j)\right). \qquad j = a, b,\end{aligned} \tag{11}$$

In this equation $\delta_p^j = -(\partial U_p / \partial R_p^j) R_p^j / \lambda_p$ and $\delta_k^j = -[(\partial U_p / \partial R_k^j) + \eta(\partial U_k / \partial R_k^j)] R_k^j / \lambda_p$ denote the parent's marginal willingness to pay for proportionate reductions in her own and her child's

lifetime risk, and $\beta = \left[\sum_{t=0}^{2}(n_t/2)(1+r)^{-t}\right]^{-1}$ denotes the fraction of the present value of total planned expenditures on the sun lotion that occur in the first period. Because $\beta < 1$, coefficients of lifetime risk reductions understate the parent's marginal willingness to pay for risk reduction; i.e., first-period expenditures on sun lotion do not reveal the full willingness to pay for lifetime risk reduction. Nonetheless, the ratio of coefficients of lifetime risk changes $\beta\delta_k^j / \beta\delta_p^j = [(\partial U_p / \partial R_k^j) + \eta(\partial U_k / \partial R_k^j)R_k^j] / ((\partial U_p / \partial R_p^j)R_p^j)$ equals the parent's marginal rate of substitution between equal percentage risk changes for herself and for the child. If the parent is altruistic, this marginal rate of substitution equals unity.[23]

For econometric estimation, equation (11) is specified for parent *h* as

$$WTP_h^j = \gamma_0^j + \gamma_p^j\left[\Delta_p^j / R_p^j\right]_h + \gamma_k^j\left[\Delta_k^j / R_k^j\right]_h + controls_h + \varepsilon_h^j. \qquad (12)$$

In equation (12), Δ_p^j and Δ_k^j are interpreted as the discrete reduction in the *j*th risk for the parent and the child that would occur if the sun lotion was used, the R_i^j denote the last estimate the *j*th perceived risk elicited for individual *i* in the field study, and $\gamma_i^j = \beta\delta_i^j$, *i=p,k*. Thus the variables in square brackets denote the percentage risk reductions (divided by 100) shown on the sun lotion labels for the *j*th type of risk and take the value 0.1 or 0.5. Treating the γ_i^j as constants implies that willingness-to-pay per unit of risk reduction $\partial WTP^j / \partial\Delta_i^j = \gamma_i^j / R_i^j$ decreases with

[23] Nonmonetary costs of using the sun lotion such as time costs of ensuring proper application and disutility from odor or other product attributes are assumed equal for parent and child. The description of the sun lotion attempted to minimize time requirements by indicating that one application would last all day and to control for potential sources of disutility such as odor, allergic reactions and blocking of pores. The description was constant across all labels. To the extent that nonmonetary costs differ between parent and child, however, the costs would be confounded in the δ_i^j coefficients.

the magnitude of perceived risk initially faced.[24] Also: (1) *controls* refers effects on willingness to pay of measured parental characteristics such as income and family size, and (2) ε_h^j denotes a random disturbance term with standard properties included to capture unobserved characteristics of parent *h*. These characteristics might include willingness to try new products, the ability to process the information presented on the sun lotion label, evaluation of joint outputs such as sunburn protection and skin aging, as well as other factors that influence whether the product would be purchased.

Five aspects of equation (12) warrant further discussion before turning to the results of estimation. First, altruism implies that $\gamma_k^j / \gamma_p^j = 1$. But a test of this hypothesis does not distinguish between types of altruism that may motivate parents' stated intentions to purchase the sun lotion, because $\partial U_p / \partial R_k^j$ and η are not separately identified; both are components of γ_k^j. Distinguishing between the types of altruistic motivations considered in Section 2 must await further research that contrasts parental behavior toward both young and adult children. In any case, the test does not rest on directly estimating WTP for risk reduction, but instead on estimating the ratio of estimated contributions of risk reduction to willingness to pay. This means that γ_k^j and γ_p^j must be consistently estimated, but it is not necessary to obtain a consistent estimate of γ_0^j.

Second, the percentage risk reduction variables are randomly assigned experimental design points. Thus, they are orthogonal to other experimental design points as well as to parent

[24] In other words, the marginal value of risk reduction $\partial U_i / \partial R_i^j$ diminishes as R_i^j rises so that γ_i^j remains constant. To test the adequacy of this specification, which treats willingness to pay as a linear function of percentage risk changes, separate regressions were run for low-risk and high-risk groups. The null hypothesis that slope coefficients in both the morbidity and conditional mortality equations are equal in the high and low risk groups was not rejected at conventional levels. This result occurred whether morbidity risk or conditional mortality risk of the parent or the child was used to distinguish between low and high risk groups. The test was based on the first specification reported in Table 5 below.

characteristics included in *controls* and to parent characteristics captured by ε_h^j. This means that if the functional form of equation (12) is correct: (1) endogeneity problems in estimating the γ_i^j are avoided and (2) estimates of the γ_i^j are unaffected by the choice of variables to include in *controls*.

Third, willingness to pay for the sun lotion is treated in an errors-in-variables framework in which stated willingness to pay (W_h^j) by parent *h* to reduce the *j*th risk differs from true willingness to pay (WTP_h^j) by both systematic and random factors according to

$$W_h^j = WTP_h^j + \alpha_h^j = WTP_h^j + \alpha^j + \nu_h^j, \qquad j = a, b. \tag{13}$$

In equation (13), α^j is the nonzero mean of α_h^j and ν_h^j is a random disturbance. α^j is assumed to represent systematic misstatement of true willingness to pay. For example, parents may misstate willingness to pay because the choice of whether to buy the sun lotion was presented as a hypothetical question and/or may not have been adequately considered in light of preferences, and financial constraints.[25] Also, ν_h^j captures unobserved parent-specific heterogeneity as well as purely random factors that may affect a parent's stated willingness to pay for the label presented. The ν_h^j are assumed to be normally distributed with mean zero and constant variance and the possibility that $E(\nu_h^a \nu_h^b) \neq 0$ motivates joint estimation of willingness-to-pay equations for the two types of risk.

The marginal rate of substitution (γ_k^j / γ_p^j) is estimated by substituting equation (13) into equation (12) to obtain

[25] As discussed by Carson, Groves, and Machina (2000) the overstatement of purchase intentions arising from incentive incompatibility of hypothetical, binary discrete-choice questions for private goods is unrelated to the scope of the good and its costs. Also, joint benefits of the sun lotion are held constant across labels but the parent's evaluation of any perceived difference between joint outputs of the lotion and existing products would be reflected in the constant term.

$$W_h^j = (\gamma_0^j + \alpha^j) + \gamma_p^j \left[\Delta_p^j / R_p^j\right]_h + \gamma_k^j \left[\Delta_k^j / R_k^j\right]_h + controls_h + \varepsilon_h^j + \nu_h^j, \qquad j = a, b. \quad (14)$$

Notice that estimators of the constant term (γ_0^j) will be inconsistent if, as expected, $\alpha^j \neq 0$. Also, estimators of coefficients of parent characteristics included in *controls* will be inconsistent if the controls are correlated with the composite error ($\omega_h^j = \varepsilon_h^j + \nu_h^j$). Nevertheless, consistent estimators of γ_k^j and γ_p^j still can be obtained as long as equation (14) is correctly specified, because the two risk reduction variables are experimental design points that were assigned independently of parent characteristics.

Fourth, the dependent variable W_h^j (stated willingness to pay for a one year's supply of sun lotion) is latent: Parents only were asked to state whether they would be willing to make a randomly assigned expenditure. Parents are assumed to answer in the affirmative if $W_h^j > P_h^j$, where P_h^j denotes the expenditure for a one year supply of sun lotion *j* that was randomly assigned to parent *h*. Thus a parents states that she will purchase the sun lotion if

$$\omega_h^j / \sigma^j < (\gamma_0^j + \alpha^j)/\sigma^j + (\gamma_p^j / \sigma^j)\left[\Delta_p^j / R_p^j\right] + (\gamma_k^j / \sigma^j)\left[\Delta_k^j / R_k^j\right] - (1/\sigma^j)P_h^j,$$

where the *controls* are suppressed for notational simplicity, $E(\omega_h^j) = 0$ and $\text{var}(\omega_h^j) = (\sigma^j)^2$, and ω_h^j is symmetrically distributed. These features together with an assumption of normally distributed composite errors that have an expected non-zero covariance across equations $E(\omega_h^a \omega_h^b) = \sigma_{ab} \neq 0$ motivates estimation by bivariate probit, where $\rho = \sigma_{ab} / \sigma^a \sigma^b$.[26] Following Cameron and James (1987), the coefficient of the randomly assigned sun lotion price is interpreted as an estimate of $-1/\sigma^j$ that can be used to recover unnormalized coefficients of risk reductions (γ_i^j) from the normalized estimates of ${\gamma_i}^j / \sigma^j$.

[26] Of course, the assumption of normally distributed errors will not be exactly satisfied when non-normally distributed parent characteristics (e.g., income) are not included as covariates.

Fifth, a concern is that use of stated preference data to estimate the willingness to pay function will result in a comparatively large variance of the composite error ($\omega_h^j = \varepsilon_h^j + \nu_h^j$). Stated preference data are often "noisy" and this feature could lead to wide confidence intervals around the estimated values of marginal rates of substitution, thus making it more likely that the null hypothesis being tested will not be rejected.

4.2 Results

Full information maximum likelihood bivariate probit estimates are shown in Table 5.[27] Sample means of covariates are presented along with the regression estimates. Two pairs of estimates are reported. The first uses only design points as covariates and the second shows the outcome when two controls for parent characteristics (family income and number of children in the family) are added. Two design points measure skin cancer risk changes for the parent and the child (see equation (14)) and a third measures the randomly assigned sun lotion price. A fourth design point variable is added to control for the order in which the morbidity and conditional mortality labels were shown.

Consider first the pair of estimated regressions that use only design points as covariates. The estimated value of ρ (=0.778) is positive, as expected, and significantly different from zero, indicating an efficiency gain from joint estimation of the two equations. The coefficients of the required annual expenditure are negative and differ significantly from zero at 1%, suggesting that parents were more reluctant to purchase the sun lotion at higher costs than at lower costs. Additionally, coefficients of variables measuring percentage reductions in the two types of risk to both parent and child are positive and significantly different from zero at the 1% level in each

[27] Ordinary least squares estimates were used as initial values in computing the binomial probit estimates used as starting values for the bivariate probit routine. Coefficient estimates and estimates of the marginal rate of substitution between child and parent risks from the binomial probit estimates are broadly consistent with those reported in Tables 4 and 5, but are less precisely estimated.

of the two equations. This outcome suggests that parents are willing to pay more for larger than for smaller reductions in the two types of risk and is consistent with the conceptual model presented in Section 2. Comparing these coefficients to the estimated intercept, however, appears to suggest that increases in risk reduction do not bring about proportionate increases in willingness to pay. Many previous studies have found that stated willingness to pay does not increase proportionately with increases in risk reductions (see Hammitt and Graham 1999 for further discussion of this issue). Nevertheless, this conclusion may not apply because the (unnormalized) intercepts actually are estimates of $(\gamma_0^j + \alpha^j)$ rather than γ_0^j, and $\alpha^j > 0$ if parents tend to overstate purchase intentions. Also, as mentioned previously, coefficients understate willingness to pay for reduced risk because $\beta < 1$. Estimates show that the order in which the morbidity and conditional mortality labels were presented is unimportant.

When controls for income and family size are introduced, estimates again indicate positive correlation between the errors in the two equations (0.788). Coefficients of family income are positive while coefficients of the total number of children in the family are negative as expected. These coefficients, however, are not consistently estimated if income and family size are correlated with unobserved family characteristics influencing the sun lotion purchase decision. Income coefficients are significantly different from zero only at the 10% level under a two-tail test, suggesting a weak tendency for parents' willingness to pay to increase with income. The small effect of income may simply reflect the relatively low costs of the sun lotion, with the highest cost reaching only about $10/month. Coefficients of the number of children are significant at the 1% level, providing evidence that parents reduce protective expenditures per family member when more children are present. Because the risk change variables are orthogonal to these parent characteristics, coefficients and standard errors of risk changes are

little altered from their corresponding values discussed previously. Supplementary regressions (Appendix) specified like those in the last pair of columns but also including covariates for marital status, education, age and gender of parent, age and gender of child, and whether a close relative had been diagnosed with skin cancer also demonstrated this same result. Only two of the additional 14 coefficients differed significantly from zero at 10%.[28] Also, in this expanded regression, coefficients of the risk change variables were almost unchanged as compared with those presented in Table 5.

Table 6 reports tests of whether the equilibrium condition implied by altruism holds ($\gamma_k^j / \gamma_p^j - 1 = 0,\ j = a,b$). Column (2), Table 6, labeled "full sample," reports results based on Table 5 estimates that control only for design points. Standard errors are computed using the delta method. As shown, the null hypothesis that this equilibrium condition holds is not rejected at conventional significance levels in either the unconditional morbidity or conditional mortality equations. This null hypothesis also is not rejected using a Wald test of the restriction $\gamma_k^j / \gamma_p^j - 1 = 0$ in both equations jointly.

Remaining columns of Table 6 summarize outcomes of parallel tests in six subsamples defined according to the gender of parent, gender of child, and age of child. Results for subsamples were obtained by re-estimating the willingness-to-pay equations separately by subsample using only the four experimental design points as covariates. Parent gender is considered because the unitary model assumes that families act as if maximizing a single utility function, so that decisions made by mothers should be consistent with those made by fathers. Gender and age of child are considered because parental marginal rates of substitution should not

[28] The two variables with significant coefficients were parent gender in the morbidity equation and child age in the conditional mortality equation. Also, in regressions including only experimental design points and the constructed measures of perceived latency for parents and children, three of the four latency coefficients were negative as expected, but none was significant.

differ between children as long as marginal costs of risk reduction are the same, as in this field study. As shown in Table 6, results are consistent with the hypothesis $\gamma_k^j / \gamma_p^j = 1$ in all six subsamples. Furthermore, likelihood ratio tests detect no significant differences in willingness to pay functions by gender of parent, or by age or gender of child.[29]

Although not reported in Table 6, a comparable analysis was undertaken based on subsamples defined by family income, by age and education of parent, and by presence of one versus more than one child in the family. This analysis is motivated by the assumed constancy of coefficients of the willingness to pay functions, relative to the possibility that the marginal utility of income, the β term, or other parameters may vary with characteristics of the parent.[30] Also, the model in Section 2 includes only one child in the family and the survey asked parents to consider using the sun lotion for only one of their children, even though most parents in the sample reported having more than one child. However, the null hypothesis that parameters of willingness to pay functions are equal between families with high or low income, or between parents with and without college educations, or between older and younger parents, or between single or multi-child families, is not rejected. Also, the hypothesis $\gamma_k^j / \gamma_p^j = 1$ is not rejected in any of these additional subsamples.

[29] The null hypotheses that slope coefficients of the equations do not differ by gender of parent, or by gender or age of child, after allowing for different intercepts, were each separately tested using likelihood ratio tests. Results indicated that the null hypothesis would not be rejected at conventional significance levels in any comparison. Further analysis of the role of parent gender was conducted by re-estimating the model in the last two columns of Table 5 while including a dummy variable for parent gender and interactions of this variable and all covariates. The only statistically significant difference between male and female parents was found in the coefficient of the number of children in the morbidity equation, where female willingness to pay for the sun lotion declined less than male willingness to pay with increases in the number of children. Coefficients of risk changes, annual cost and income appear to be the same for mothers and fathers. Also, outcomes of all of these tests by parent gender are the same if the comparison is restricted to married parents.

[30] A related issue involves whether parents differed in their perceptions of available substitutes for the hypothetical sun lotion. The survey would have been improved had parents been asked how skin cancer risks could have been reduced by the amounts shown on the labels if the product were not available or if they chose not to buy it. In the absence of this information, we assume that either substitution opportunities are negligible or are the same for all parents.

The analysis presented assumes that the parent would use the sun lotion for herself and her sample child but not for anyone else. The apparent decline in willingness to pay for the sun lotion with increases in the number of children in the family (Table 5) along with the lack of significant differences in slope coefficients of willingness to pay functions between single- and multiple-child families suggests that parents did not envision using the sun lotion to protect additional children when stating their purchase intentions. Also, parents who indicated that they would buy the sun lotion were asked about the intended users. The majority of parents indicated that the lotion would be used for the parent and the sample child (85% for the morbidity labels and 90% for the conditional mortality labels), with almost all of the remaining purchasers intending to use the lotion for the child only.[31] Excluding parents who envisioned purchasing the sunscreen but using it for only one individual does not change the outcome of any of these statistical tests. Additionally, because parents were told that achieving the stated risk reductions required use of the lotion as directed, the above tests were performed again after adjusting the risk change measures of Table 5 so that the risk change would be zero for the parent or child if the parent did not envision that person using the sun lotion. The null hypothesis is not rejected using these adjusted measures of risk changes.

Finally, empirical results obtained can be used to test another aspect of the model presented in Section 2. Wald tests are carried out to determine whether the marginal rate of substitution between the two types of risk for both parent and child are equal to the corresponding ratio of marginal costs in reducing these risks. This amounts to testing whether the cross-equation coefficient restrictions $\gamma_i^a / \gamma_i^b = 1,\ i = p, k,$ are valid. To control for different values of σ^j in the two equations, the tests were conducted using the unnormalized coefficient

[31] Four parents who indicated that they would purchase one of the sun lotions envisioned using it for themselves only (three for the morbidity labels and one for the conditional mortality labels).

estimates. Standard errors of ratios of these coefficients were computed using the delta method. In separate tests involving the coefficients of risk reduction for parents and children, the null hypothesis is not rejected at conventional significance levels. Additionally, a joint test of the null hypothesis for parents and children together yields the same result. These results are consistent with altruism and suggest that parents responded to the assigned changes in the two types of risk consistently with the theoretical model of Section 2.[32]

5. Summary and Conclusions

Special protection of young children from environmental hazards has become a worldwide priority of government policies to improve human health. The fundamental tension between altruism and self-interest in families looms as the crucial behavioral factor determining the effectiveness of these policies. This paper estimates parents' marginal rates of substitution between skin cancer risks faced by 488 parents and their children between the ages of 3 and 12 years. A model of altruistic family behavior that incorporates household production of latent health risk guides the estimates. The model demonstrates that the marginal rate of substitution between risks faced by the parent and child is equal to the ratio of marginal risk reduction costs. Resulting empirical estimates then focus on whether this equality holds.

Tests rest on an examination of stated preference values for a hypothetical sun lotion. Although stated preference valuation is a controversial method of obtaining willingness to pay to reduce environmental risks, it supports consistent estimation of parents' marginal rates of substitution between health risks to themselves and corresponding health risks to their children in the field study described here. Consistent estimation of marginal rates of substitution is made possible by: (1) allowing for both systematic and random errors in parents' stated willingness to

[32] The outcome of this test reinforces the conclusion that respondents sensibly considered the compound probabilities involved in the study.

pay for the sun lotion and (2) randomly assigning skin cancer risk reductions offered by sun lotion to the sample of parents. Together, these innovations imply that the skin cancer risk reductions assigned are orthogonal both to parent characteristics and to errors parents may make in assessing their willingness to pay for the sun lotion.

In the theoretical model, an altruistic parent's marginal rate of substitution between risk to her child and risk to herself equates with the corresponding ratios of marginal skin cancer risk reduction costs. This prediction is the basis of the null hypothesis for econometric tests using data from the field study. The null hypothesis is not rejected, so test results support the notion that parents are altruistic toward their young children. This outcome stands in contrast to findings in related studies that present evidence against altruism of parents toward their children. This study, however, looks at behavior of parents toward pre-teenage children living at home, rather than behavior of parents toward their adult children who have formed households of their own. An important implication is of findings from this study is that effectiveness of public intervention programs to reduce environmental risks faced by children may be compromised to some extent because parents will respond by redistributing family resources.

References

Agee, Mark D. and Thomas D. Crocker. 2004. "Transferring Measures of Adult Health Benefits to Children: A Review of Issues and Results," *Contemporary Economic Policy* 22: 468-482.

Altonji, Joseph, Fumio Hayashi, and Laurence Kotlikoff. 1992. "Is the Extended Family Altruistically Linked? Direct Tests Using Micro Data," *American Economic Review* 82, 1177-98.

Altonji, Joseph, Fumio Hayashi, and Laurence Kotlikoff. 1997. "Paternalistic Altruism and Inter- vivos Transfers: Theory and Evidence," *Journal of Political Economy* 105: 1121-1166.

Barro, Robert J. 1974. "Are Government Bonds Net Wealth?" *Journal of Political Economy*, 82: 1095-1117.

Becker, Gary S. 1974. "A Theory of Social Interactions," *Journal of Political Economy*, 82: 1063-1094.

Becker, Gary S. 1981. *A Treatise on the Family*. Cambridge, MA: Harvard University Press.

Bergstrom, Theodore C. 2003. "Benefit-Cost Analysis and the Entanglements of Love," University of California, Santa Barbara manuscript.

Bergstrom, Theodore C. 2006. "Benefit-Cost in a Benevolent Society," *American Economic Review* 96: 339-351.

Brouwer, Roy and Ian J. Bateman. 2005. "Benefits Transfer of Willingness to Pay Estimates and Functions for Health Risk Reductions: A Cross-Country Study," *Journal of Health Economics* 24: 591-611.

Cameron, Trudy A. and Michelle D. James. 1987. "Efficicient Estimation Methods for 'Closed-Ended' Contingent Valuation Surveys," *Review of Economics and Statistics* 69: 269-276.

Cameron, Trudy A. 1988. "A New Paradigm for Valuing Non-market Goods Using Referendum

Data: Maximum Likelihood Estimation by Censored Logistic Regression," *Journal of Environmental Economics and Management* 15: 355-379.

Carson, Richard T, Theodore Groves and Mark J. Machina. 2000. "Incentive and Informational Properties of Preference Questions." University of California, San Diego, Department of Economics working paper.

Corso, Phaedra S., James K. Hammit and John D. Graham. 2001. "Valuing Mortality-Risk Reduction: Using Visual Aids To Improve The Validity Of Contingent Valuation," *Journal of Risk and Uncertainty* 23: 165-84.

Cox, Donald and M. Rank. 1992. "Inter-vivos Transfers and Intergenerational Exchange," *Review of Economics and Statistics* 74: 305-314.

Dickie, Mark and Shelby Gerking. 1991. "Valuing Reduced Morbidity: A Household Production Approach," *Southern Economic Journal* 57: 690-702.

Dickie, Mark and Shelby Gerking. 1996. "Formation of Risk Beliefs, Joint Production and Willingness to Pay to Avoid Skin Cancer. *The Review of Economics and Statistics* 78: 451-464.

Dickie, Mark and Shelby Gerking. (2003). "Parents' Valuation of Latent Health Risks to their Children," in *Risk and Uncertainty in Natural Resource and Environmental Economics*, (eds.) Justus Wesseler, Hans-Peter Weikard, and Robert D. Weaver, Edward Elgar: Cheltenham, UK.

Dickie, Mark and Shelby Gerking. (2006). "Valuing Children's Health: Paternalistic Perspectives," in *Economic Valuation of Environmental Health Risks to Children*, OECD: Paris.

Dickie, Mark and Victoria L. Messman. 2004. "Paternalistic Altruism and the Value of Avoiding Acute Illness: Are Kids Worth More than Parents," *Journal of Environmental Economics and Management* 48: 1146-1174.

Federal Register. 1997. Executive Order 13045 of April 21, 1997—Protection of Children from Environmental Health Risks and Safety Risks, 62, FR Doc. 97-10695 (April 23).

Hamilton, William D. 1964. "The Genetical Evolution of Social Behavior, i and ii," *Journal of Theoretical Biology* 7: 1-52

Hammitt, James K. and John D. Graham. 1999. "Willingness to Pay for Health Protection: Inadequate Sensitivity to Probability?" *Journal of Risk and Uncertainty* 18: 33-62.

Jenkins, Robin R., Nicole Owens, and Lanelle B. Wiggins. 2001. "Valuing Reduced Risks To Children: The Case Of Bicycle Safety Helmets," *Contemporary Economic Policy* 19: 397-408.

Jones-Lee, Michael. 1991. "Altruism and the Value of Other People's Safety," *Journal of Risk and Uncertainty* 4: 213-219.

Jones-Lee, Michael. 1992. "Paternalisticistic Altruism and the Value of Statistical Life," *The Economic Journal* 102: 80-90.

Krupnick, Alan, Anna Alberini, Maureen Cropper, Nathalie Simon, Bernie O'Brien, Ron Goeree, and Martin Heintzelman. 2002. Age, Health, and the Willingness to Pay for Mortality Risk Reductions: A Contingent Valuation Study of Ontario Residents. *Journal of Risk and Uncertainty* 24: 161–86.

Laitner, John and F. Thomas Juster. 1996. "New Evidence on Altruism: A Study of TIAA-CREF Retirees," *American Economic Review* 86: 893-908.

Liu, Jin-Tan, James K. Hammitt, Jung-Der Wang and Jin-Long Liu. 2000. "Mother's Willingness to Pay for Own and Her Child's Health: A Contingent Valuation Study in Taiwan," *Health Economics* 9: 319-26.

Lundberg, Shelly J., Robert A. Pollak, and Terence J. Wales. 1997. "Do Households and Wives Pool Their Resources? Evidence from the United Kingdom Child Benefit", *Journal of Human Resources*, 32, 463-480.

Nastis, Stefanos A. and Thomas D. Crocker. 2003. "Pregnant Mother's Valuation of Own and of Child Health," presented at USEPA/University of Central Florida conference, "Valuing Environmental Health Risk Reductions to Children," Oct 20-21, http://yosemite.epa.gov/EE/epa/eerm.nsf/vwRepNumLookup/EE-0475?OpenDocument.

Ries, L.A.G., M.P. Eisner, C.L. Kosary, B.F. Hankey, B.A. Miller, L. Clegg, A. Mariotto, M.P. Fay, E.J. Feuer, B.K. Edwards (eds). 2003. *SEER Cancer Statistics Review, 1975-2000*, National Cancer Institute. Bethesda, MD, http://seer.cancer.gov/csr/1975_2000.

Scapecchi, Pascale. 2006. "Valuation Differences between Adults and Children," in *Economic Valuation of Environmental Health Risks to Children*, OECD: Paris.

Slovic, Paul, Baruch Fischhoff, and Sarah Lichtenstein, "Regulation of risk: A psychological perspective," in Roger Noll (ed.), *Regulatory Policy and the Social Sciences* (Berkeley: University of California Press, 1985).

U.S. Environmental Protection Agency. 1996. *A National Agenda to Protect Children's Health from Environmental Threats*, Washington, D.C.: U.S. Government Printing Office.

Table 1. Frequency Distribution of Parents' Perceived Risks.

N=488.

	Risk of Getting Skin Cancer[a]		Conditional Risk of Dying from Skin Cancer	
Risk Range (%)	**Parents**	**Children**	**Parents**	**Children**
0 - 4.75	53	46	78	111
5 - 9.75	24	48	140	169
10 - 14.75	53	78	112	97
15 - 19.75	55	62	59	40
20 - 24.75	55	59	33	28
25 - 29.75	61	63	22	17
30 - 34.75	39	32	9	5
35 - 39.75	22	16	7	5
40 - 44.75	33	23	4	5
45 - 49.75	6	4	5	1
50 - 54.75	49	29	16	9
55 - 59.75	4	2	1	1
60 - 64.75	5	5	0	0
65 - 69.75	0	1	0	0
70 - 74.75	4	2	2	0
75 - 79.75	6	5	0	0
80 - 84.75	2	3	0	0
85 - 89.75	2	2	0	0
90 - 94.75	9	5	0	0
95 – 100	6	3	0	0

[a]Initial risk assessment.

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

Sample	Risk of Getting Skin Cancer[a]	Conditional Risk of Dying from Skin Cancer	Sample Size
All Parents	26.93	12.05	488
All Children	22.46	9.36	488
Mothers	29.17	12.46	368
Fathers	20.08	10.82	120
Daughters	22.31	9.38	242
Sons	22.61	9.33	246
Children aged 3 to 7 years	23.84	10.10	275
Children aged 8 to 12 years	20.68	8.39	213

[a]Initial risk assessment.

Table 3. Use of Sun Protection Products.

Fraction of Time Outdoors that Sun Protection Products Used	Parents	Children
Never	44	15
Less than half	115	80
About half	109	106
More than half	91	106
Always/almost always	129	181

Sun Protection Factor Normally Used	Parents	Children
Less than 15	67	15
15 to less than 30	185	103
30 or higher	192	355

Table 4. Frequency Distribution of Expected Age at Onset.

N=488

Age Range (years)	Parents	Children
Before age 40	45	68
40 - 44	63	42
45 - 49	64	52
50 - 54	111	84
55 - 59	61	66
60 - 64	84	55
65 - 69	41	46
70 - 74	13	49
75 - 79	1	12
Age 80 or later	5	14
Mean age at onset (years)	53	55
Mean age (years)	35	7
Implied mean expected latency period (years)	18	48

Table 5. Willingness to Pay to Reduce Skin Cancer Risks: Bivariate Probit Estimates (N=488).

	Sample Mean (Std. Dev.) or Proportion		Coefficients (Standard Errors)			
Covariate (Parameter Notation)	Morbidity Risk	Conditional Mortality Risk	Morbidity Risk	Conditional Mortality Risk	Morbidity Risk	Conditional Mortality Risk
Parent's Percentage Risk Reduction	0.289	0.302	0.912	0.717	0.901	0.739
(γ_p^j / σ^j)	(0.200)	(0.200)	(0.272)	(0.267)	(0.274)	(0.267)
Child's Percentage Risk Reduction	0.300	0.299	0.854	1.426	0.843	1.487
(γ_k^j / σ^j)	(0.200)	(0.200)	(0.270)	(0.267)	(0.275)	(0.272)
Cost of Sun Lotion ($/year)	64.518	64.150	-0.011	-0.011	-0.011	-0.011
$(-1/\sigma^j)$	(34.520)	(34.897)	(0.002)	(0.002)	(0.002)	(0.002)
Order (=1 if risk change in column presented last, 0 if first)	0.488	0.512	-0.149	-0.087	-0.151	-0.105
			(0.122)	(0.122)	(0.126)	(0.125)
Family Income ($10,000/year)	5.957				0.028	0.029
	(3.569)				(0.018)	(0.017)
Number of Children in Family	2.078				-0.190	-0.004
	(0.952)				(0.069)	(0.068)
Constant			0.733	0.520	0.981	0.347
$((\gamma_0^j + \alpha^j)/\sigma^j)$			(0.171)	(0.170)	(0.251)	(0.229)
Error Correlation			0.778		0.788	
(ρ)			(0.044)		(0.044)	
Log-Likelihood			-512.553		-505.391	

Table 6. Estimates of γ_k^j / γ_p^j and Altruism Tests.

Estimates of γ_k^j / γ_p^j (Standard Errors) and Tests of Altruism							
	Full Sample	Mothers	Fathers	Daughters	Sons	Child Age 3-7	Child Age 8-12
Morbidity ratio $(\gamma_k^a / \gamma_p^a)$	0.936	0.927	0.88	0.902	0.96	1.438	0.441
	(0.415)	(0.456)	(0.678)	(0.777)	(0.503)	(0.766)	(0.462)
z-test ratio=1 (*p*)	0.878	0.873	0.860	0.900	0.937	0.568	0.226
Conditional Mortality ratio $(\gamma_k^b / \gamma_p^b)$	2.005	1.816	3.746	1.512	3.003	5.018	0.661
	(0.853)	(0.837)	(6.133)	(0.702)	(2.688)	(4.962)	(0.417)
z-test ratio=1 (*p*)	0.240	0.329	0.654	0.465	0.456	0.418	0.416
Wald test, both ratios=1 (*p*)	0.493	0.608	0.883	0.761	0.750	0.601	0.398
Sample Size	488	368	120	242	246	275	213
LR test, equal parameters between groups (*p*)		0.975		0.958		0.214	

For Adults & Children

Developed with dermatologists to protect skin from harmful effects of sun exposure.

Skin Cancer Protection

Ultra Waterproof

SPF ___

Parsol®1789

"Making the outdoors safer for you and your family."

(Back of bottle)

New SkinSaver® sun protection lotion.

Skin Cancer Protection	
✓ **Used as directed in clinical trials, SkinSaver reduced risk of skin cancer by:**	
10% for Adults	**10% for Children**
✓ **Used as directed in clinical trials, SkinSaver had no effect on the risk of dying if skin cancer occurred.**	

More Skin Protection		
Parsol®1789		SPF_____
Protects against premature skin aging		Protects against sunburn

More Added Features

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

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

*** Hypoallergenic * PABA-free * Unscented ***

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

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

APPENDIX: Supplemental Data and Empirical Results

Table A-1

Hypothetical Sun Protection Product Labels

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

Table A-2. Sample Means by Experimental Design Point.

	Morbidity Risk				Conditional Mortality Risk			
Label	A	B	C	D	E	F	G	H
Percentage risk change for parent	10	10	50	50	10	10	50	50
Percentage risk change for child	10	50	10	50	10	50	10	50
Perceived risk of getting skin cancer for parent	30.26	25.58	26.19	25.44	27.40	25.08	27.59	27.63
Perceived risk of getting skin cancer for child	23.37	22.88	22.18	21.27	23.13	18.90	23.47	24.27
Perceived conditional risk of dying from skin cancer for parent	11.89	11.89	12.05	12.41	11.83	10.66	13.21	12.47
Perceived conditional risk of dying from skin cancer for child	9.30	8.76	9.85	9.59	8.58	8.73	10.43	9.66
Family Income ($10,000/year)	5.67	6.49	5.99	5.66	6.03	6.00	6.14	5.67
Number of Children in Family	2.10	2.10	2.04	2.07	2.23	1.97	2.05	2.07
Parent is female	0.85	0.78	0.68	0.70	0.78	0.78	0.73	0.74
Child is female	0.45	0.53	0.46	0.55	0.46	0.56	0.52	0.45
Child age	7.18	7.12	7.25	6.72	6.95	7.40	6.86	7.07
Sample Size	130	127	114	117	121	120	124	123

Table A-3. Willingness to Pay to Reduce Skin Cancer Risks: Bivariate Probit Estimates (N=488).

	Mean (s.d.) or Proportion		Coefficients (Standard Errors)			
	Morb. Risk	Cond. Mort. Risk	Morb. Risk	Cond. Mort. Risk	Morb. Risk	Cond. Mort. Risk
Parent's Percentage Risk Reduction	0.289	0.302	0.990	0.711	0.918	0.749
	(0.200)	(0.200)	(0.300)	(0.277)	(0.278)	(0.271)
Child's Percentage Risk Reduction	0.300	0.299	0.849	1.412	0.850	1.384
	(0.200)	(0.200)	(0.279)	(0.288)	(0.271)	(0.272)
Cost of Sun Lotion ($/year)	64.518	64.150	-0.011	-0.011	-0.011	-0.011
	(34.520)	(34.897)	(0.002)	(0.002)	(0.002)	(0.002)
Order (=1 if risk change in column presented last, 0 if first)	0.488	0.512	0.026	0.024	-0.146	-0.104
			(0.022)	(0.021)	(0.123)	(0.123)
Parent Perceived Latency Period	18.092				-0.045	-0.077
	(9.811)				(0.072)	(0.073)
Child Perceived Latency Period	48.148				0.012	-0.028
	(12.239)				(0.060)	(0.059)
Family Income ($10,000/year)	5.957		0.026	0.024		
	(3.569)		(0.022)	(0.021)		
Number of Children in Family	2.078		-0.194	-0.022		
	(0.952)		(0.073)	(0.073)		
Parent is Married	0.830		0.104	-0.019		
			(0.182)	(0.188)		
Parent is College Graduate	0.576		0.081	0.072		
			(0.138)	(0.137)		
Parent Age	35.117		-0.004	-0.004		
	(6.63)		(0.012)	(0.011)		
Parent is Female	0.754		0.271	0.161		
			(0.154)	(0.149)		
Child Age	7.070		0.011	0.051		
	(2.937)		(0.025)	(0.025)		
Child is Female	0.496		0.156	0.061		
			(0.128)	(0.127)		
Close Relative of Parent Diagnosed with Skin Cancer	0.252		0.036	-0.177		
			(0.150)	(0.158)		
Constant			0.063	0.520	0.751	0.815
			(0.144)	(0.170)	(0.303)	(0.296)
Error Correlation			0.791		0.777	
			(0.0443)		(0.0445)	
Log-Likelihood			-500.121		-511.018	

Is An Ounce of Prevention Worth a Pound of Cure?

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Is An Ounce of Prevention Worth a Pound of Cure?

Abstract

We examine how preferences for prevention and treatment policies vary with individual characteristics and policy attributes, which include costs to the individual, the prevalence of the public health problem (numbers of illnesses and deaths), the extent to which each policy reduces illnesses and deaths, the type of health risk (disease) and, for prevention policies, the underlying cause and the time horizon for the policy. Individuals do prefer prevention policies to treatment policies, although at a rate considerably less than the 16 to 1 ratio implied by the "ounce of prevention…" adage. Preferences also differ substantially by the characteristics of the respondent or policy.

JEL Classifications: I12, J17, J28, Q51

Keywords: Prevention, Treatment, Morbidity, Mortality, Public Health

1 Introduction

Is an ounce of prevention really worth a pound of cure? Some polices can prevent illnesses by providing a cleaner environment or safer roads. Other policies can allocate resources to help treat those who are already sick or injured. Should we allocate additional resources to help those who are already sick, or should we spend more on measures that will help people avoid illnesses in the first place? Policy makers, at one level or another, must often make these types of tradeoffs when allocating resources for community health improvements.

Previous economic research that directly examines differences in preferences for treatment and prevention policies in a utility-theoretic or willingness-to-pay (WTP) framework is sparse. The existing literature most closely related to our own includes Corso et al. (2002), Hammit and Liu (2004), and Subramanian and Cropper (2000).

Corso et al. (2002) use survey data to assess preferences for treatment policies and prevention policies that provide equivalent mortality risk reductions and find that WTP for treatment policies is much higher. The research reported herein uses a more detailed survey instrument and can exploit a richer set of data on responded characteristics to better understand the systematic differences that tend to make prevention policies preferable to treatment policies.

Hammit and Liu (2004) do not address the difference in prevention and treatment policies. However rather, their research is related to the present study because they investigate in the impact of latency and disease type on WTP. By considering two different latencies and two disease types, Hammit and Liu find that WTP for risk prevention declines with latency and that WTP to avoid a specific cancer risks is moderately larger than WTP to avoid a non-cancer chronic disease with similarly severe symptoms. We also find evidence that WTP declines with

latency and that WTP is relatively higher for policies that prevent cancer risks. However, we find that WTP is relatively lower for policies that provide treatment to cancer victims.

Subramanian and Cropper (2000) investigate the relationship between WTP for public risk reduction policies and the qualitative factors (such as funding fairness or blame for the health risks) associated with those policies. Relative to their study, we provide a more extensive analysis of how WTP for both treatment and prevention policies is related to a broader variety of both quantitative and qualitative factors.

The question of how to value various prevention or treatment policies has been discussed extensively in the Quality Adjusted Life Years (QALY) literature. For example, Gyrd-Hansen (2004) finds that how individuals value health increments depends on whether the question is framed as an individual or 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. The difficulty of using private choices to make public policy is clearly illustrated in Ubel et al. 1996). These authors find that subjects in an experimental setting strongly rejected the health rationing choices derived from their own utility responses. Finally, Nord (1994) argues that for the QALY to be a generally empirically meaningful concept, it needs to be interpreted as a measure of social value, rather than of private value.[1]

The findings of this paper, related papers, and the QALY literature have important policy implications. When policy makers allocate resources devoted to public health policies, several strategies are possible. One strategy is to observe individual preferences about tradeoffs between

[1] QALYs are most useful for cost-effectiveness analysis of alterative medical therapies. They focus on physical measures of health status and involve the standardization of health decrements relative to a year of perfect health (where death is 0 and perfect health is normalized as 1.) For a brief overview, see Appendix A, available from the authors.

private risk and private income and then use these preferences to make public policy. A policy maker who relies on estimates of the value of a statistical life (VSL) to make public policy would be following this strategy. Another strategy would be to directly estimate the demand (or WTP) for the public health program in question and compare aggregate WTP to the cost of the policy. Similarly, the policy maker may simply hold a referendum on a proposed project. Researchers have noted that using private preferences to make public policy may be problematic. For example, Ubel et al. (1996) provide experimental evidence that in individuals may soundly reject the public policy implications of their own preferences.

The research reported in this paper focuses on directly estimating the demand for public health policies. We feel that this strategy has several important advantages. First, individual preferences for public policies that reduce risk may be very different from the preferences that individuals have for private risk reductions. For example, individuals may be willing to pay for a policy that reduces drinking water contaminants because in reduces risk, provides ecosystem benefits, or because individuals feel that clean drinking water is a "right" that should be enforced by government. Individuals may also have altruistic motives or different notions of fairness that influence WTP for public polices. This issue is especially important when considering polices that affect children, the elderly, or economically disadvantaged groups. Assessing the demand for public health policies directly also allows us to see how heterogeneity in preferences for private risk-reducing polices compares with the heterogeneity in preferences for public polices.

Another advantage of our research strategy is that it allows us to assess what attributes of public health policies individuals view as desirable, as well as how different sociodemographic groups value different kinds of public health policies.

In this study, we use data collected from two analogous surveys of demand for health-related public policies. These surveys were designed to allow us to compare preferences for treatment policies with preferences for prevention policies. The surveys were designed by Trudy Ann Cameron at the University of Oregon Economics Department and J.R. DeShazo at UCLA. The data were collected, either via computer or Web-TV interface, by Knowledge Networks, Inc. The hypothetical treatment and prevention policies presented to respondents follow a randomized design that allows for the investigation of heterogeneity in preferences along several dimensions. The analysis is also enriched by the availability of a wide variety of individual-level sociodemographic variables.

Our analysis uses data from two conjoint stated preference surveys of demand for risk reducing policies that were administered to a nationally representative sample of over 1,500 individuals each. In addition to respondent's answers to the policy questions, we elicited individual-specific measures of the incidence of the perceived private benefits of each policy as well as a measure of attitudes toward government intervention.

The basic empirical framework used for analyzing respondents' stated survey choices is developed in the context of the prevention policy survey in Bosworth, Cameron, and DeShazo (2005) (hereafter BCD). In the present paper, we develop complementary analyses for the analogous treatment policy survey and compare the two types of demands.

While both prevention policies and treatment policies can lead to improved community health outcomes, the presence of systematic differences in consumer preferences for treatment and prevention policies would indicate that resources could perhaps be allocated more efficiently. We seek to establish key differences and similarities across policy types and to provide policy

makers with improved information about the potential welfare effects of different types of policy options.

Both the prevention and treatment scenarios presented to respondents vary in elicitation format, as well as in the specific type of illness threat that is addressed, the number of individuals who would benefit from the policies, and the size of the affected community. Basic respondent-level variables include the age, gender, income, education level, and ethnicity of the respondent. We describe the survey design in detail below.

2 Survey Design

In 2003, we conducted two distinct national stated preference surveys. For each, the sample size is approximately 1,500.[2] The two surveys that provide the data used for this paper were designed to elicit demands for policies which are publicly financed and which benefit many individuals (i.e., public goods), rather than privately paid programs with just individual benefits:

(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 to 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

[2] 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.

achieved, for example, through the regulatory decisions of the Food and Drug Administration or the medical research funding decisions of the National Institutes of Health.[3]

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 the 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 of the five choice sets consists of two explicit policies plus the option to choose neither. We planned these two surveys so that it would be straightforward to pool their data, to test whether the subsets of corresponding utility parameters are identical, and to impose common preference parameters as warranted.

Details about the two surveys:

Module 1 (Introduction) - In the first modules of both the prevention and the treatment surveys, respondents are asked:

(a) whether they have themselves suffered from each of a range of health threats, or whether family members or friends have experienced these problems.

(b) to think about their family health histories, and to assess their own degree of risk from each of seven major classes of health threats.

[3] Of course, much research and development for medicines is also undertaken privately by pharmaceuticals firms, but these products must still be approved by the FDA.

(c) whether there is room to reduce their health risks by improving their lifestyle or habits,

(d) whether such improvements would reduce their risks of each of a range of health threats

The treatment survey asks the respondent to rate the likelihood that they would recover from each of a list of illnesses if they experienced it, given the quality of their current health care plan.

Both surveys then ask respondents to put aside their personal health concerns and to rate the prevalence of each class of illness and injury in their community (with "community" defined for them explicitly as a randomly assigned number of people living around them).

Module 2 (Tutorial) - The second module of each survey introduces the ideas of public prevention policies and public treatment policies, according to the topic of the survey, and begins to train the respondent 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 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 (Choice Scenarios) - The third module of both surveys contains the five-different stated choice exercises. Each choice, with its preamble and debriefing questions, occupies a set of four survey pages.

In the prevention survey: The complex choice table 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 2 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: cancer (general), colon/bladder cancer, leukemia, asthma, heart disease, heart attack, lung cancer, stroke, respiratory disease, and traffic accident injuries.

In the treatment survey: Each choice exercise 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% adults, and 50% seniors (i.e. 25/25/50 mix). Then the choice table is presented, containing its summaries of each program. See Figure 3 for an example of this type of choice set.

The duration of the policy and the policy cost are also key attributes of the policies described in the treatment 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: prostate cancer, breast cancer, colon/bladder cancer, leukemia, lung cancer, asthma, heart attack, heart disease, stroke, respiratory disease, traffic injuries, and skin cancer.

In both surveys, to follow up on the choice exercise, the respondent is then asked how difficult it was for them to make up their mind on the previous screen with the choice table, and is then asked to reply directly to the question "To what extent would each policy directly benefit you or your family?" This question was asked about each of the two policies in the choice set just considered. Finally, any respondent who selected the "Neither policy" alternative was given an opportunity to check which reasons explain their choice. Some of the available answers constitute reasons that reveal choice-scenario rejection on the part of the respondent (e.g. disbelief that the policy would achieve what was advertised).[4]

Module 4 (Follow-up) – This module of each survey asks a number of auxiliary questions. Among these, the most 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 environmental, health, and safety hazards.[5]

The final three pages of each survey instrument are devoted to a hypothetical choice about how to take some lottery winnings, either as a lump sum now, or as a series of payments

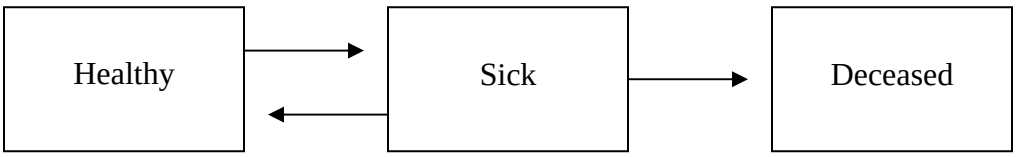
[4] These answers can be used to limit the estimating sample, if no other economically admissible reason for choosing "Neither Policy" is selected.
[5] See Cameron and DeShazo (2005a) and (2005b) for more about Module 4.

spread out over several years. These choices are used to estimate individual-specific discount rates. An understanding of these individual discount rates is important to our analysis of the policy choices in both the prevention and the treatment studies, since the prevention and treatment policies under consideration in the choice sets in each survey are described as having different durations.

3 Theoretical Framework

This section explains a simple framework that will allow us to analyze, simultaneously, preferences for prevention policies and treatment policies. As summarized in Figure 1, individuals can be in one of three "health" states: healthy, sick, or deceased. Prevention and treatment policies can both help to decrease the rate of flow from the "sick" to the "deceased" state. Prevention policies work by decreasing the flow from the "healthy" state to the "sick" state, while treatment policies work by increasing the flow from the "sick" state to the "healthy" state. As part of our analysis, we test for systematic differences, across both respondents and health threats, in individuals' implied preferences over how these flow changes are achieved. We also provide estimates of the relative values of changes in various flows.

Figure 1



For our most basic specifications, we let the utility of a policy (treatment or prevention) depend on the number of avoided illnesses (or increased recoveries), the number of avoided deaths, and the duration of the policy (the length of time the policy is in effect). The individual's

income can also be expected to influence utility. Thus, individual *i*'s indirect utility from policy *j* can be represented as:

$$V_{ji} = \beta(Y_i) + \delta_1 f(Avoided\ Illnesses_{ji}) + \delta_2 g(Avoided\ Deaths_{ji}) + \delta_3 h(Duration_{ji}) \quad (1)$$

Where Y_i 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 (dis)utility of an increase in *h*.[6] δ_3 captures preferences over the length of time the policy lasts, where δ_3 can be interpreted as the marginal disutility experienced when the benefits of the policy are spread more thinly across time.[7]

We also employ the dummy variable POL_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 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.

[6] 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 BCD (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.

[7] BCD (2005) develops a structural utility-theoretic model with constant exponential discounting employed explicitly. Since the ad-hoc model presented here provides a better fit, and is more comparable to previous research, we use it in the empirical portions of this paper.

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. To allow for a range of flexible estimation options, we assume at this point only that $f(0) = 0$, $g(0)=0$, $h(0)=0$ and that f, g, and h are increasing in their arguments. The utility level provided by policy j to individual i is thus:

$$\begin{aligned} V_{ji} = \beta(Y_i - c_{ij}) &+ \delta_1 f(Avoided\ Illnesses_{ji}) \\ &+ \delta_2 g(Avoided\ Deaths_{ji}) \\ &+ \delta_3 h(Duration_{ji}) + \theta POL_j + \eta_{ji} \end{aligned} \quad (2)$$

Where c_{ji} is the annual cost of the policy and η_{ji} is the unobserved random component of total utility. Total indirect utility over the time period of the policy, if the status quo option (neither policy) is chosen, is given by:

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

Since we assume that $f(0)=0$, $g(0)=0$, and $h(0)=0$, 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:

$$\begin{aligned} \Delta V_{ji} = \beta(-c_{ij}) &+ \delta_1 f(Avoided\ Illnesses_{ji}) \\ &+ \delta_2 g(Avoided\ Deaths_{ji}) \\ &+ \delta_3 h(Duration_{ji}) + \theta POL_j + \varepsilon^*_{ji} \end{aligned} \quad (4)$$

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

For this homogeneous-preferences case, it should be noted that the parameters β, δ_1, δ_2, and δ_3 represent the marginal indirect utilities that individuals associate with the attributes of the policy while the parameter θ represents overall increment to utility provided by any policy, regardless of the other attributes. We can allow each of these marginal utility

parameters to vary depending on whether the policy is a treatment or prevention policy and can identify whether differences in preferences are attributable to different characteristics of the policies or to a general difference in the value placed on any type of policy, independent of its particular attributes.

There is no *a priori* expectation that the error dispersion in the choice model for prevention policies will be identical to the error dispersion in the choice model for treatment policies, although this is a testable hypothesis. If we wish to test the equivalence of the marginal utility parameters across the two samples, it will be necessary to allow for 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 a dummy 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:

$$\Delta V_{ji}\Big|_{1(Treatment)=0} = \frac{\beta_p}{\kappa_p}(-c_{ij}) + \frac{\delta_{1p}}{\kappa_p} f(Avoided\ Illnesses_{ji}) + \frac{\delta_{2p}}{\kappa_p} g(Avoided\ Deaths_{ji}) + \frac{\delta_{3p}}{\kappa_p} h(Duration_{ji}) + \frac{\theta_p}{\kappa_p} POL_j + \frac{\varepsilon_{ji}}{\kappa_p} \quad (5)$$

$$\Delta V_{ji}\Big|_{1(Treatment)=1} = \frac{\beta_t}{\kappa_t}(-c_{ij}) + \frac{\delta_{1t}}{\kappa_t} f(Avoided\ Illnesses_{ji}) + \frac{\delta_{2t}}{\kappa_t} g(Avoided\ Deaths_{ji}) + \frac{\delta_{3t}}{\kappa_t} h(Duration_{ji}) + \frac{\theta_t}{\kappa_t} POL_j + \frac{\varepsilon_{ji}}{\kappa_t} \quad (6)$$

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 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 parameters β_p, δ_{1p}, δ_{2p}, δ_{3p}, and θ_p are systematically different from β_t, δ_{1t}, δ_{2t}, δ_{3t}, and θ_t, based on inferences from respondents' choices among prevention policies and among treatment policies (from separate samples). By introducing the dummy variable **1**(Treatment) as a shifter we can permit the marginal utilities of avoided illness, avoided deaths, and policy duration vary systematically. With the pooled sample, we can test for statistically significant differences in preferences. Of course, we can (and do) allow all parameters (including κ) to vary with other individual- or policy-specific characteristics as well.

3.1 Willingness to Pay

In the deterministic case, formulas for total WTP and marginal WTP are straightforward. Point estimates of total 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. Suppose we ignore the symmetric and mean zero error term and the variance-covariance matrix for the maximum likelihood estimates of the unknown preference parameters. We can set the utility difference in equation (4) equal to zero and solve for c_{ij}^* in terms of the parameter point estimates and the data. Total WTP for policy *j* is thus:

$$c_{ji}^{*} = \frac{\delta_1 f(Avoided\ \ Illnesses_{ji}) + \delta_2 g(Avoided\ \ Deaths_{ji}) + \delta_3 h(Duration_{ji}) + \theta POL_j}{\beta} \quad (7)$$

Marginal WTP (MWTP)--WTP for incremental changes in one of the attributes of the policy--is calculated by taking the derivative of total WTP with respect to that attribute. For example, MWTP for one-unit increase in $g(Avoided\ \ Deaths_{ji})$ is simply:

$$\frac{\partial c_{ji}}{\partial g(Avoided\ \ Deaths_{ji})} = \frac{\delta_2}{\beta} \quad (8)$$

In our empirical work, we use a shifted log specification for the functions *f*, *g*, and *h*. The MWTP in equation (8) above is therefore roughly interpreted as marginal willingness to pay for a 1% increase in avoided deaths.[8]

4 Results

There are five different threads to our empirical results. Section 3.1 discusses our most basic specifications; Section 3.2 describes effects related to the size of the affected population. Section 3.3 details results relating to the socio-economic status of the respondent. Section 3.4 discusses differences in preferences for cancer and non-cancer policies. Finally, section 3.5 reports the results of models designed to investigate preference heterogeneity according to policy attributes.[9]

4.1 Basic Specifications

For our most basic specifications, reported in Table 2, we follow the standard practice in the choice literature and specify a utility function that is linear and additively separable in some

[8] Crude confidence bounds of fitted WTP and MWTP, reflecting estimation precision, can always be calculated by sampling from the joint (asymptotically normal) distribution of the maximum likelihood parameters and building up a sampling distribution for each calculated quantity. Of course, since total WTP is a function of policy attributes (see equation (7)), this sampling distribution will differ across policies.

[9] In a separate paper using only the "prevention" survey (BCD 2005), 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.

function of the fundamental attributes of the policy. These fundamental attributes include the number of avoided illnesses or increased recoveries, the number of avoided deaths and the duration of the policy. In models where we pool the data from the two samples, we test whether or not the marginal utilities associated with illnesses, deaths, and the duration of the policy can be constrained to be the same across treatment and prevention policies by allowing the coefficients on these fundamental attributes (as well as the generic policy dummy) to vary systematically with a dummy variable that is equal to one if the policy is a treatment policy. We also allow the error variance to differ across policy type. [10,11,12]

In Table 2, the negative and statistically significant coefficient on the interaction term between the Log(*Death Reductions*) variable and the treatment dummy, in models 3 and 4, 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.

The estimates for our parsimonious model 4 in Table 2 imply that (yearly) marginal WTP for a 1% increase in avoided deaths via a prevention policy is about $238, compared to about $142 for the same 1% increase in avoided deaths via a treatment policy. These estimates are, unsurprisingly, almost identical to the estimates obtained for models 1 and 2 for the two separate samples. The estimates in model 1 (the prevention sample) indicate MWTP of $245 for a 1% increase in avoided deaths, while model 2 (the treatment sample) indicates MWTP of $138.

[10] 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.
[11] 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.
[12] We use a shifted log specification to maintain the assumption that *f(0)=0* and *g(0)=0.* For example, we use log(Avoided Illnesses+1) rather than log(Avoided Illnesses)

MWTP estimates for a 1% increase in avoided illnesses, in all models in Table 2, are about $70. We also note that the variance of the errors associated with choices concerning treatment policies appears to be larger by a factor of about $e^{0.3639}=1.439$.

Loosely speaking, the question posed in the title of this paper may be answered as follows: In terms of the estimated marginal utility avoided deaths, an "ounce" of prevention appears to be worth only about two "ounces" of cure in the sense that individuals appear to be willing to pay about twice as much for an incremental (1%) improvement in the number of deaths avoided via a prevention policy than they are for the same incremental improvement via a treatment policy. However, it should be noted that this difference applies only to avoided deaths. This result stands in contrast to that of Corso et al. (2002) who find that respondents to general allocation questions are willing to pay much more for treatment programs than for prevention programs.

There appears to be no statistical difference between the marginal amount individuals are willing to pay to avoid illnesses and the amount they are willing to pay to increase the number of recoveries. In terms of the diagram in Figure 1, individuals are willing to pay about twice as much to decrease the flow from the "Sick" state to the "Deceased" state via prevention policies as they are willing to pay to achieve the same net result via treatment policies. However, they are willing to pay about the same amount to increase the flow from the "Sick" state to the "Healthy" state as they are to decrease the flow from the "Healthy" state to the "Sick" state.

We also note that in all models in Table 2, the estimated marginal utility associated the duration of the policy is statistically significantly negative, indicating that individuals generally prefer policy of shorter duration (holding the total number of avoided illnesses and deaths constant). This result is consistent with positive discounting and is similar to that found by Alberini et al. (2004) who find that WTP to reduce mortality risk declines with latency. Ariely

and Lowenstien (2000) show that in most cases individuals underweight the importance policy latency, but that models (such as the research reported herein) that carefully and explicitly describe policy attributes can increase the likelihood that respondents discount future benefits. Cropper, et al. (1994) also finds that individuals generally values lives saved in the future less than lives saved in the present.

4.2 Population Size Effects

While Table 2 provides an initial answer to the question that headlines this paper, there are a number of additional insights that can be gleaned from more-general models built upon the same framework. For example, most previous studies that ask respondents to value policies that save a given number of lives do not ask respondents to consider the population size of the affected community. The policies presented to respondents in our study offer potential reductions in the number of illnesses and/or deaths in the community where the respondent lives. All policies considered by a given respondent are described as affecting "their community", where the community is described as a specified number of people living around the respondent. This asserted community size is varied randomly across respondents. The results related to population size heterogeneity reported in Table 3 do not exhibit the strong statistical significance characteristic of the other results reported herein. This is unsurprising, however, given the fact that population size is not a line-item attribute in the survey and that variation in asserted population size occurs only across respondents, rather than policies or choice sets.

We endeavor in this study to evaluate willingness-to-pay for health improvements from a public-goods perspective, so we must consider the size of the affected population. Note that this issue does not arise in studies that attempt to estimate only private trade-offs between health and

income. To make this issue clear, consider a simple example: Suppose that the leaders of a community of 100,000 people are considering two policies (policy A and policy B) that are each expected to reduce the number of deaths in the community. Policy A is expected to save the lives of 100 individuals in the community by reducing the risk level of each individual in the community. Policy B is also expected to save 100 lives, but the risk reductions from Policy B will accrue only to the inhabitants of the western side of the community. (i.e. only 50,000 people will see their risk level reduced.)

Even if the two policies cost the same, there is no *a priori* reason why a person (or a community) should be indifferent between the two programs. The decision maker would be choosing between providing a relatively large risk reduction to a smaller number of people, or providing a relatively small risk reduction to a larger group of people. In our example, we would expect that the 50,000 people on the west side of the community would prefer policy B to policy A (if they are selfish), while the rest of a selfish population would presumably prefer policy A to policy B. However, individual notions of fairness or altruistic preferences may lead to valuations that differ from the purely selfish outcome. If individuals are concerned only about their own health and income, we might expect that they would be willing to pay more for a program that affects a smaller population, *ceteris paribus*.

Table 3 thus presents the results of more-general models that allow the estimated utility parameters in our model to vary with the size of the population that will be affected by the policy. Models 1 and 2 again show results for analogous models estimated on our separate samples. In the less-restrictive pooled specification of model 3, we constrain the basic utility parameters (the ones that Table 2 suggests can be constrained) to be the same across treatment and prevention policies, but allow them to vary systematically with the size of the affected population. In the

prevention sample, the marginal utility of avoiding illnesses appears to be lower when the population size is larger. We also note that the coefficient on the interaction with population size and the policy dummy appears to be statistically significantly negative in models 1 and 4, indicating that individuals are less likely to choose either offered policy over the status quo option when the affected population size is larger. Both of these effects suggest selfish behavior. This result is consistent with the idea that social discount rates may be smaller than private discount rates: a larger population size probably causes the specified health improvements to be viewed as less of a private good and more of a public good. In other words, if it is not your life that is saved, it doesn't matter as much *when* that life is saved. However, this tendency is not apparent in the treatment sample.

4.3 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 dummy to vary with the sociodemographic variables. Recall that the coefficient on the policy dummy 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 given variable on the latent propensity to choose either of the two offered policy options over the status quo.

Previous work that investigates how WTP for health benefits varies with the sociodemographic characteristics of the individual includes Alberini et al. (2002), and DeShazo

and Cameron (2005), Alberini et al. (2002) find that WTP declines with age, but only after age 70. DeShazo and Cameron (2005), however, find that WTP follows an inverted U-shaped profile. Kartman et al. (1996) find that income is positively related to WTP to reduce the risk of angina pectoris attacks. It should be noted, however, that these authors investigate WTP for private risk reductions rather than the public choices considered here.

The treatment sample indicates lower WTP for females. This may reflect lower incomes and higher marginal utility of income for women (not estimated here) or may reflect different propensities to avail themselves of private health care services and diagnostic procedures. In fact, the magnitude of this effect is relatively large in terms of estimated WTP. The estimates in model 2 in Table 4 indicate that females are willing to pay about $248 less per year for a typical treatment policy than males. 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.

In contrast to the inverted U-shaped age profile found by DeShazo and Cameron (2005), the separate prevention and treatment samples (as well as the pooled model) indicate that willingness to pay has a U-shaped age profile. This profile reaches an estimated minimum at about age 60 in the prevention sample and at about age 71 in the treatment sample. The curvature of the age profile is also significantly less for the treatment sample.

The models in models 1 and 2 indicate that the income of the respondent, as a proxy for general socioeconomic status, has *opposite* effects on the estimated WTP of the respondent in the two samples. In particular, higher income individuals are *less* willing to pay for prevention policies, while they are *more* willing to pay for treatment policies. These effects, while statistically significant, are relatively small in magnitude: the estimates in model 1 indicate that a $10,000 increase in annual income is associated with an estimated decrease of $0.34 in annual

WTP for a typical prevention policy. Similarly, the estimates in model 2 indicate that a $10,000 increase in annual income is associated with an estimated increase of $0.44 in annual WTP for a typical treatment policy. One plausible explanation for this difference may be the availability of substitutes. Recall that the 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.

The results for years of education suggest that more highly educated people are more likely to support prevention policies, but not treatment policies. The estimates in model 1 suggest that, for prevention policies, one additional year of education is associated with an estimated increase of $128 in annual WTP for a typical prevention policy.

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. The estimates from models 1 and 2 suggest that non-white individuals are willing to pay an estimated $299 per-year more than non-white individuals for prevention policies and $660 more for treatment policies.

Attitudes toward government intervention have a lot to do with individuals' receptivity to publicly supported health policies. Tables 5 and 6 present separate results for the prevention and treatment samples, and demonstrate the impact of the additional variable *Government Preference*. 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.

The results in Tables 5 and 6 make the statistical importance of this (endogenous) variable clear. 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, the third models of Tables 5 and 6 demonstrate 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 choices, an individual's perception of the proper role of government is relatively more predictive of their stated choices across proposed public policies.

4.4 Cancer vs. Non-Cancer Policies

Previous research (e.g. Hammitt and Liu (2004)) 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.[13] Cancers may simply instill greater fear than other diseases. We address this interesting question by assessing whether or not individuals are (broadly speaking) more likely to support policies that address cancer risks than other non-cancer

[13] Other researchers, including Tsuge et al. (2005), and Magat et al. (1996) find that it may not be necessary to adjust VSL estimates for 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.[14] 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.

WTP calculations based on the estimates in Table 7 suggest that, in the prevention sample, individuals are willing to pay about $310 more (annually) for a policy that avoids deaths and illnesses from a major cancer than from other (non-cancer) illnesses or injuries. In the treatment sample, however, estimates suggest that individuals are willing to pay about $130 less per year for policies that address major cancer risks than for other types of policies. The pooled sample provides similar estimates: increase WTP of about $280 for prevention of cancer, but about $160 less for the treatment of cancer.

4.5 Heterogeneity by Policy Attributes

Tables 8 and 9 present parameter estimates for models that allow the coefficient on the policy dummy to vary systematically with additional attributes of each policy. We find evidence that individuals have statistically distinguishable preferences for some types of policies.

[14] 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.

Previous Research: Authors that investigate how WTP for public health benefits varies with the source of the risk include Vassanadumrongdee and Matsuoka (2005), Carlsson et al. (2004), and Chilton et al. (2002). Vassanadumrongdee and Matsuoka (2005) find that WTP for reductions in the risk of disease from air pollution and the risk of traffic accident are comparable while Chilton et al. (2002) find that the perception of risk influences WTP values for reducing the risk of rail accidents. Carlsson et al. (2004) find that individuals in their sample are willing to pay more to improve air travel safety than taxi travel safety. Subramanian and Cropper (2000) find that the number of lives saved, as well as psychological risk characteristics are important determinants of allocation decisions, and Krupnick and Cropper (1992) find that individuals who have had friends or family with chronic lung disease are willing to pay more to reduce the risk of chronic lung disease. Jacobsson et al. (2005) find that the altruistic component of WTP is greater for more severe diseases. Wittenberg et al. (2003) find that their 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".

This study appears to represent the most comprehensive comparative analysis of systematic variation in WTP for public health policies to date. The policies in our survey vary, as reported above, in terms of basic attributes such as the number of lives saved of the cost of the policy. The policies presented to respondents also vary in terms of the source of the risk, the disease or health threat that is addressed, and the population sub-group that is affected, allowing respondents to consider a wide range of substitute policies when making allocation decisions. In Tables 8 and 9, we report the results of models that allow key utility parameters to vary with a variety of additional policy attributes.

Table 8 allows the coefficient on the policy dummy to vary by the type of disease. 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-dummy interaction terms in Table 6 are interpreted relative to the base case of heart disease.[15]

In the prevention sample, we see that individuals are more likely to support public policies that prevent cancer (general), leukemia in children, and asthma in children than they are to support heart disease policies. However, individuals are less likely to support prevention policies that address leukemia in general, stroke, asthma in general, and traffic injuries.

In the treatment sample, there are no public policies that are statistically significantly more likely to be supported than those for heart disease. However, public policies to reduce colon/bladder cancer, leukemia, stroke, respiratory disease, asthma, asthma in children, lung cancer, injuries, prostate cancer, and skin cancer are all less likely to be chosen relative to public heart disease treatment policies.

Finally, Table 9 shows results for models that utilize additional sources of heterogeneity in the type of health risk that are unique to either the prevention or the treatment surveys. As in the choice set example in Figure 2, 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).

[15] We report in Tables 8 just the prevention policy and treatment policy results, separately. The pooled model has a very large parameter space and offers few additional insights.

The "treatment" model in Table 9 presents results for a specification which reflects the fact that some treatment policies are targeted at specific socio-demographic groups. For example, breast cancer treatment policies primarily benefit women and prostate cancer treatment policies primarily 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 policies may be targeted primarily at children, adults, or seniors. Notice in the choice set example in `Figure 3 that the choice scenarios presented to respondents make the targeted beneficiary group explicit. 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. For example, policy A in the Figure 3 (the treatment choice set example) treats children, adults, and seniors who have leukemia. The percentage mix is given as 25/25/50, indicating that 25% of the benefits would accrue to children, 25% to adults, and 50% to seniors.[16] We construct the continuous variables *Percent Children* and *Percent Senior* and allow the coefficient on the policy dummy to vary systematically with these variables. We also utilize the variables "*Female*", "*Age65+*", and "*Kids*" to distinguish how preferences differ for treatment policies that affect particular groups. "*Female*" is equal to 1 if the respondent is female (and 0 otherwise), Likewise, "*Age65+*" is equal to 1 if the respondent is age 65 or older, and "*Kids*" is equal to 1 if the respondent lives in a household with any children under the age of 18.

The results in Table 9 suggest that respondents with children in the household are statistically significantly more likely to support policies that benefit children while policies that

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

benefit seniors are less likely to be supported. Interestingly, this apparent lack of support for policies that benefit seniors is also shared by seniors themselves.

5 Conclusion

Policymakers face many tradeoffs when allocating funds for public risk reduction 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. 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 value placed on lives saved via prevention policies. We find that individuals are willing to pay about twice as much to avoid deaths via prevention than they are to avoid deaths via treatment.

We also find that the size of the affected population affects preferences for both treatment and prevention policies in ways that are generally consistent with selfish behavior. In particular, individuals are less likely to support prevention policies when the affected population size is larger. The size of the affected population has a much less pronounced effect on preferences for treatment policies.

We find evidence of significant heterogeneity in WTP for prevention and treatment policies according to differences in socio-demographic characteristics. We find that WTP has a U-shaped age profile that reaches a minimum at about age 60 for both types of policies. High income individuals are *more* likely to support treatment policies, while they are *less* likely to support prevention policies. This seemingly strange result may be the result of a 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 than less educated people, while there is no systematic heterogeneity in preferences for treatment policies by education level. Females are less likely to support treatment policies, while non-white (non-Caucasian) individuals are more likely to support both prevention and treatment policies.

Respondents in our sample are *more* likely to support prevention policies that address cancer risks than non-cancer risks, but are *less* likely to support major cancer treatment policies than policies that treat other major illnesses or injuries. Respondents in both samples are less likely to support policies that address stroke, leukemia, and asthma than policies that address heart disease. We also find that females are more likely to support breast cancer treatment policies and less likely to support prostate cancer treatment policies. Individuals with children are more likely to support policies that benefit children, but seniors are not more likely to support policies that benefit seniors.

We identify several areas of heterogeneity in preferences by individual and policy attributes and find that respondents are more likely to choose policies that directly affect themselves and/or their family members. We also find that individual perceptions of the proper role of government are significant in explaining whether or not individuals support policy changes over the status quo.

References

Alberini, A., Cropper, M., Krupnick, A., Simon, N. (2002). Does the value of a statistical life vary with age and health status? Evidence from the United States and Canada. Resources for the future discussion paper 02-19. Washington, D.C.

Alberini, A., Cropper, M., Krupnick, A., Simon, N. (2004). Willingness to pay for mortality risk reductions: Does latency matter? Resources for the future discussion paper 04-13. Washington, D.C.

Andreoni, J. (1990). "Impure altruism and donations to public-goods - a theory of warm-glow giving", *Economic Journal* 100, 464-477.

Arana, J.E., Leon, C.J. (2002). "Willingness to pay for health risk reduction in the context of altruism", *Health Economics* 11, 623-635.

Ariely, D., Loewenstein, G. (2000). "When does duration matter in judgment and decision making?" *Journal of Experimental Psychology-General* 129, 508-523.

Bosworth, R.C., Cameron, T.A., DeShazo, J.R. (2005). Advances in evaluating the demand for risk prevention policies. University of Oregon, Department of Economics Working Paper. Eugene, OR.

Cameron, Trudy Ann, and J.R. DeShazo (2005a) "Demand for Public Health-Risk Reduction Policies: The Prevention Survey" http://darkwing.uoregon.edu/~cameron/vsl/public_prevention_framed.pdf

Cameron, Trudy Ann, and J.R. DeShazo (2005b) "Demand for Public Health-Risk Reduction Policies: The Treatment Survey" http://darkwing.uoregon.edu/~cameron/vsl/public_treatment_framed.pdf

Cameron, T.A., Poe, G.L., Ethier, R.G., Schulze, W.D. (2002). "Alternative non-market value-elicitation methods: Are the underlying preferences the same?" *Journal of Environmental Economics and Management* 44, 391-425.

Carlsson, F., Johansson-Stenman, O., Martinsson, P. (2004). "Is transport safety more valuable in the air?" *Journal of Risk and Uncertainty* 28, 147-163.

Chilton, S., Covey, J., Hopkins, L., Jones-Lee, M., Loomes, G., Pidgeon, N., Spencer, A. (2002). "Public perceptions of risk and preference-based values of safety", *Journal of Risk and Uncertainty* 25, 211-232.

Corso, P.S., Hammitt, J.K., Graham, J.D., Dicker, R.C., Goldie, S.J. (2002). "Assessing preferences for prevention versus treatment using willingness to pay", *Medical Decision Making* 22, S92-S101.

Cropper, M.L., Aydede, S.K., Portney, P.R. (1994). "Preferences for life saving programs - how the public discounts time and age", *Journal of Risk and Uncertainty* 8, 243-265.

Cummings, R.G., Taylor, L.O. (1998). "Does realism matter in contingent valuation studies?" *Land Economics* 74, 203-215.

DeShazo, J.R., Cameron, T.A. (2005). Two types of age effects in the demand for reductions in mortality risks with differing latencies. University of Oregon, Department of Economics Working Paper. Eugene, OR.

Fetherstonhaugh, D., P. Slovic, S. M. Johnson, and J. Friedrich. (1997). "Insensitivity to the value of human life: A study of psychophysical numbing", *Journal of Risk and Uncertainty* 14, 283-300.

Frederick, S., G. Loewenstein, and T. O'Donoghue. (2002). "Time discounting and time preference: A critical review", *Journal of Economic Literature* XL, 351-401.

Hammitt, J.K., Liu, J.T. (2004). "Effects of disease type and latency on the value of mortality

risk", *Journal of Risk and Uncertainty* 28, 73-95.
Horowitz, J.K., Carson, R.T. (1991). "A classification tree for predicting consumer preferences for risk reduction", *American Journal of Agricultural Economics* 73, 1416-1421.
Horowitz, J.K., Carson, R.T. (1993). "Base-line risk and preference for reductions in risk-to-life", *Risk Analysis* 13, 457-462.
Jacobsson, F., Carstensen, J., Borgquist, L. (2005). "Caring externalities in health economic evaluation: How are they related to severity of illness?" *Health Policy* 73, 172-182.
Johannesson, M., Johansson, P.O., Oconnor, R.M. (1996). "The value of private safety versus the value of public safety", *Journal of Risk and Uncertainty* 13, 263-275.
Kartman, B., Andersson, F., Johannesson, M. (1996). "Willingness to pay for reductions in angina pectoris attacks." *Medical Decision Making* 16, 248-253.
Krupnick, A.J., Cropper, M.L. (1992). "The effect of information on health risk valuations", *Journal of Risk and Uncertainty* 5, 29-48.
Magat, W.A., Viscusi, W.K., Huber, J. (1996). "A reference lottery metric for valuing health", *Management Science* 42, 1118-1130.
Nord, E. (1994). "The QALY - a measure of social value rather than individual utility", *Health Economics* 3, 89-93.
Richardson, J., Nord, E. (1997). "The importance of perspective in the measurement of quality-adjusted life years", *Medical Decision Making* 17, 33-41.
Subramanian, U., Cropper, M. (2000). "Public choices between life saving programs: The tradeoff between qualitative factors and lives saved", *Journal of Risk and Uncertainty* 21, 117-149.
Train, K. (1986). *Qualitative choice analysis*. Cambridge: The MIT Press.
Tsuge, T., Kishimoto, A., Takeuchi, K. (2005). "A choice experiment approach to the valuation of mortality", *Journal of Risk and Uncertainty* 31, 73-95.
Ubel, P.A., Loewenstein, G., Scanlon, D., Kamlet, M. (1996). "Individual utilities are inconsistent with rationing choices: A partial explanation of why Oregon's cost-effectiveness list failed", *Medical Decision Making* 16, 108-116.
Ubel, P.A., Loewenstein, G., Scanlon, D., Kamlet, M. (1998). "Value measurement in cost-utility analysis: Explaining the discrepancy between rating scale and person trade-off elicitations", *Health Policy* 43, 33-44.
Vassanadumrongdee, S., Matsuoka, S. (2005). "Risk perceptions and value of a statistical life for air pollution and traffic accidents: Evidence from Bangkok, Thailand", *Journal of Risk and Uncertainty* 30, 261-287.
Viscusi, W.K., Aldy, J.E. (2003). "The value of a statistical life: A critical review of market estimates throughout the world", *Journal of Risk and Uncertainty* 27, 5-76.
Wittenberg, E., Goldie, S.J., Fischhoff, B., Graham, J.D. (2003). "Rationing decisions and individual responsibility for illness: Are all lives equal?" *Medical Decision Making* 23, 194-211.

Figure 2 - 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 3 - 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	Mean	St. Dev.	Min	Max	Description
Yearly Cost					
Prevention	498	351	60	1200	Yearly cost of policy
Treatment	498	346	60	1200	Yearly cost of policy
Illness Reductions					
Prevention	862	1584	0	5000	Cases avoided
Treatment	841	1550	0	5000	Increased recoveries
Death Reductions					
Prevention	101	464	0	5000	Deaths avoided
Treatment	539	1240	0	5000	Deaths avoided
Duration					
Prevention	13.8	9.7	2	30	Length of policy (years)
Treatment	13.9	9.7	2	30	Length of policy (years)
Population Size					
Prevention	0.246	0.359	0.001	1	Size of affected population (millions)
Treatment	0.758	0.358	0.001	1	Size of affected population (millions)

[a]Except for exclusions based on implausible combinations

Table 2: Basic Specifications[b]

Parameter	Variable	Separate Samples		Pooled Sample	
		(1) Prevention Sample	(2) Treatment Sample	(3) Less Restricted	(4) More Restricted
β	-(Yearly Cost/10,000)	5.680	4.9854	6.1162	6.1091
		(9.72)***	(8.13)***	(10.90)***	(12.09)***
δ_1	Log(Illness Reductions)	0.04046	0.0358	0.04156	0.04305
		(5.77)***	(5.05)***	(5.92)***	(7.42)***
	… · **1**(Treatment)	--	--	.001797	--
				(0.48)	
δ_2	Log(Death Reductions)	0.1394	0.0692	0.1455	0.15206
		(11.16)***	(7.20)***	(11.72)***	(12.76)***
	… · **1**(Treatment)	--	--	-.05804	-0.07738
				(-3.26)***	(-6.15)***
δ_3	Log(Duration)	-0.1688	-0.1198	-0.1586	-0.17048
		(-7.39)***	(-5.14)***	(-6.92)***	(-8.72)***
	… · **1**(Treatment)	--	--	-.03868	--
				(-0.70)	
θ	Policy Dummy	-0.2371	-0.2657	-0.2649	-0.27051
		(-3.30)***	(-3.48)***	(-3.67)***	(-4.51)***
	… · **1**(Treatment)			-.04018	--
				(-0.27)	
$ln(\kappa)$	Heteroscedasticity Parameter	0	--	0	0
	… · **1**(Treatment)	--	0	.3659	0.35857
				(2.04)**	(4.01)***
Maximized log-likelihood		-8035.19	-7539.49	-15576.35	-15577.87
Maximized log-likelihood overall		-15574.68		-15576.35	-15577.87
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)

Test stat for restrictions in Model 3: 3.34 Critical value: 3.84: Fail to reject restriction

Test stat for restrictions in Model 4: 3.04 Critical value: 7.81: Fail to reject restrictions

Table 3: Population Size Effects

Parameter	Variable	Separate Samples		Pooled Sample	
		(1) Prevention Sample	(2) Treatment Sample	(3) Less Restricted	(4) More Restricted
β	-(Yearly Cost/10,000)	6.2373	3.5863	5.7920	6.7188
		(8.51)***	(1.57)	(8.14)***	(10.13)***
	… · Population Size[a]	0.0008	2.0745	3.5046	--
		(0.00)	(0.27)	(0.70)	
δ_1	Log(Illness Reductions)	0.0545	-0.0277	0.0452	0.0486
		(5.99)***	(-0.51)	(5.05)***	(6.92)***
	… · Population Size	-0.0527	0.0885	0.0147	--
		(-1.95)*	(0.74)	(0.50)	
δ_{2p}	Log(Death Reductions)	0.1324		0.1407	0.1414
		(8.40)***		(8.85)***	(9.62)***
	… · Population Size	0.1067		0.0668	0.0648
		(0.11)		(0.55)	(1.27)
δ_{2t}	Log(Death Reductions)	--	0.0919	0.0415	0.0352
			(2.66)***	(1.47)	(1.37)
	… · Population Size	--	-0.0271	0.1111	0.1055
			(-0.41)	(1.13)	(2.32)**
δ_3	Log(Duration)	-0.2107	-0.1083	-0.2011	-0.1901
		(-7.37)***	(-1.37)	(-7.24)***	(-7.56)***
	… · Population Size	0.1381	-0.0268	-0.0199	--
		(1.39)	(-0.14)	(-0.17)	
θ	Policy Dummy	-0.0967	-0.4665	-0.1444	-0.1396
		(-1.06)	(-1.56)	(-1.61)	(-1.65)*
	… · Population Size	-0.5216	0.2623	-0.5030	-0.4708
		(-2.45)**	(0.82)	(-1.25)	(-1.83)*
$ln(\kappa)$	Heteroscedasticity Parameter	--	--	--	--
	… · Population Size	0.4114	0.0597	0.5356	0.4407
		(0.67)	(0.05)	(0.98)	(2.07)**
	… · **1**(Treatment)	--	--	0.1315	0.1320
				(1.27)	(1.30)
Maximized log-likelihood		-8025.39	-7529.39	-15569.80	-15573.09
Maximized log-likelihood overall		15554.78		15569.80	-15573.09
Total sample size (choices)		7556	7033	14589	14589
Total sample size (respondents)		1531	1423	2954	2954

[a] Affected population size measured in millions.

Table 4: Sociodemographic Effects

Parameter	Variable	(1) Prevention	(2) Treatment	(3) Pooled
β	-(Yearly Cost/10,000)	5.7124	5.0104	5.8665
		(9.75)***	(8.16)***	(11.03)***
δ_1	Log(Illness Reductions)	0.0419	0.0355	0.0424
		(5.95)***	(4.99)***	(7.32)***
δ_{2p}	Log(Death Reductions)	0.1396	--	0.1406
		(11.14)***		(11.59)***
δ_{2t}	Log(Death Reductions)	--	0.0702	0.0840
			(7.29)***	(6.64)***
δ_3	Log(Duration)	-0.1688	-0.1204	-0.1601
		(-7.38)***	(-5.16)***	(-8.11)***
θ	Policy Dummy	-0.4793	-0.0264	-0.2737
		(-1.62)	(-0.09)	(-1.19)
	…· **1**(Female)	0.0203	-0.1244	0.0198
		(0.43)	(-2.53)**	(0.42)
	…· **1**(Female) ·**1**(Treatment)	--	--	-0.1705
				(-2.18)**
	…· (Age/100)	-2.4105	-1.8901	-3.2836
		(-2.32)**	(-1.89)*	(-3.72)***
	…· (Age/100) ·**1**(Treatment)	--	--	2.0492
				(2.20)**
	…· (Age^2/10,000)	2.0078	1.6335	2.8272
		(2.02)**	(1.71)*	(3.29)***
	…·(Age^2/10,000)·**1**(Treatment)	--	--	-1.8463
				(-1.90)*
	…· Income/10,000	-1.9524	2.2224	-1.8301
		(-2.57)**	(2.90)***	(-2.42)**
	…·Income/10,000·**1**(Treatment)	--	--	4.4788
				(3.62)***
	…·Educ.Years/10	0.7071	0.1046	0.6941
		(6.90)***	(0.98)	(7.06)***
	…·Educ.Years/10·**1**(Treatment)	--	--	-0.5557
				(-3.78)***
	…·**1**(Non-White)	0.17135	0.3770	0.1696
		(2.94)***	(6.00)***	(2.92)***
	…·**1**(Non-White)·**1**(Treatment)	--	--	0.2867
				(2.66)***
$ln(\kappa)$	Heteroscedasticity Parameter	0	--	--
	… · **1**(Treatment)	--	0	0.1931
				(1.62)
	Age effect minimized at	60.7	70.8	41.1(Prev) 128.3 (Treat)
Maximized log-likelihood		-7998.81	-7509.59	-15509.46

Table 5: Sociodemographic Effects (Prevention Sample)

Parameter	Variable	(1) SES Only	(2) Govt. Only	(3) SES and Govt.
β	-(Yearly Cost/10,000)	5.7175	5.9084	5.9274
		(9.75)***	(10.00)***	(10.01)***
δ_1	Log(Illness Reductions)	0.0419	0.0420	0.0432
		(5.95)***	(5.92)***	(6.06)***
δ_{2p}	Log(Death Reductions)	0.1396	0.1438	0.1438
		(11.14)***	(11.40)***	(11.37)***
δ_3	Log(Duration)	-0.1688	-0.1730	-0.1728
		(-7.38)***	(-7.51)***	(-7.50)***
θ	Policy Dummy	-0.4793	-1.3082	-1.4867
		(-1.62)	(-12.42)***	(-4.77)***
	…· Government Preference	--	0.2073	0.2022
			(14.09)***	(13.67)***
	…· **1**(Female)	0.0204	--	0.0103
		(0.43)		(0.21)
	…· (Age/100)	-2.4154	--	-1.9811
		(-2.32)**		(-1.87)*
	…· (Age^2/10,000)	2.0071	--	1.5260
		(2.02)**		(1.51)
	…· Income/10,000	-1.9524	--	-1.8089
		(-2.57)**		(2.34)**
	…·Educ.Years/10	0.7071	--	0.0619
		(6.90)***		(5.95)***
	…·**1**(Non-White)	0.1714	--	0.1329
		(2.94)***		(2.23)***
Maximized log-likelihood		-7998.81	-7875.33	-7847.22

Table 6: Sociodemographic Effects (Treatment Sample)

Parameter	Variable	(1) SES Only	(2) Govt. Only	(3) SES and Govt.
β	-(Yearly Cost/10,000)	5.0104	4.9810	4.9977
		(8.16)***	(8.07)***	(8.08)***
δ_1	Log(Illness Reductions)	0.0356	0.0381	0.0378
		(4.99)***	(5.32)***	(5.26)***
δ_{2p}	Log(Death Reductions)	0.0703	0.0695	0.0703
		(7.29)***	(7.17)***	(7.24)***
δ_3	Log(Duration)	-0.1204	-0.1208	-0.1215
		(-5.06)***	(-5.15)***	(-5.18)***
θ	Policy Dummy	-0.0264	-1.0415	-0.6918
		(-0.09)	(-9.76)***	(-2.31)***
	…· Government Preference	--	0.1524	0.1463
			(10.36)***	(9.86)***
	…· **1**(Female)	-0.1244	--	-0.1235
		(-2.53)**		(-2.49)***
	…· (Age/100)	-1.8962	--	-2.0106
		(-1.89)*		(-1.98)**
	…· (Age^2/10,000)	1.6330	--	1.7432
		(1.71)*		(1.81)*
	…· Income/10,000	2.222	--	2.2750
		(2.90)***		(2.94)***
	…·Educ.Years/10	0.1046	--	0.0710
		(0.98)		(0.66)
	…·**1**(Non-White)	0.3770	--	0.3312
		(6.00)***		(5.18)***
Maximized log-likelihood		-7509.60	-7432.74	-7407.98

Table 7: Cancer v. Non-Cancer Policies

Parameter	Variable	(1) Prevention Sample	(2) Treatment Sample	(3) Pooled Sample
β	-(Yearly Cost/10,000)	5.6529	4.9757	5.6253
		(9.67)***	(8.12)***	(10.46)***
δ_1	Log(Illness Reductions)	0.0404	0.0357	0.04067
		(5.77)***	(5.03)***	(7.13)***
δ_{2p}	Log(Death Reductions)	0.1391	--	0.1363
		(11.11)***		(11.27)***
δ_{2t}	Log(Death Reductions)	---	0.0691	0.0808
			(7.19)***	(6.45)***
δ_3	Log(Duration)	-0.1707	-0.1201	-0.1557
		(-7.46)***	(-5.15)***	(-7.86)***
θ	Policy Dummy	-0.3035	-0.2377	-0.3325
		(-4.13)***	(-3.05)***	(-5.01)***
	… · **1**(Treatment)	--	--	0.0984
				(0.98)
	… · MajorCancer	0.1748	-0.0652	0.1805
		(4.57)***	(-1.75)*	(4.73)***
	…· MajorCancer·(Treatment)	--	--	-0.2619
				(-4.50)***
$ln(\kappa)$	Heteroscedasticity Parameter	0	--	0
	… · **1**(Treatment)	--	0	0.1207
				(0.97)
Maximized log-likelihood		-8024.78	-7537.96	-15563.38
Sample size (choices)		7556	7033	14589
Maximized log-likelihood overall		-15562.74		-15563.38
Total sample size (choices)		7556	7033	14589

LR-test of restrictions in pooled model: $\chi^2_{0.05}(4) \approx 9.48$, $\chi^2 = 1.28$, fail to reject restricted model.

Table 8: Heterogeneity by Disease Type

Parameter	Variable	(1) Prevention	(2) Treatment
β	-(Yearly Cost/10,000)	5.6739	5.1971
		(9.62)***	(8.42)***
δ_1	Log(Illness Reductions)	0.0398	0.0350
		(5.65)***	(4.90)***
δ_2	Log(Death Reductions)	0.1439	0.0705
		(11.41)***	(7.28)***
δ_3	Log(Duration)	-0.1781	-0.1180
		(-7.71)***	(-5.02)***
θ	Policy Dummy	-0.1508	0.0388
		(-1.59)	(0.40)
	… · Heart Disease	--	--
	… · Heart Attack	-1.59	-0.0093
		(-1.16)	(-0.11)
	… · Cancer (General)	0.2582	--
		(2.91)***	
	… · Colon/Bladder Cancer	0.0833	-0.2862
		(0.92)	(-3.26)***
	… · Leukemia	-0.4663	-0.4785
		(-4.88)***	(-5.16)***
	… · Leukemia in Children	0.2250	0.0197
		(2.57)**	(0.11)
	… · Stroke	-0.3380	-0.3764
		(-3.59)***	(-4.28)***
	… · Respiratory Disease	-0.0612	-0.1531
		(-0.67)	(-1.70)*
	… · Resp. Dis. in Children	--	-0.1774
			(-1.03)
	… ·Asthma	-0.5373	-0.3942
		(-5.55)***	(-4.03)***
	… ·Asthma in Children	0.1691	-0.3036
		(1.93)*	(-2.19)**
	… ·Lung Cancer	-0.0674	-0.5230
		(-0.74)	(-5.78)***
	… ·Traffic Injuries	-0.1877	--
		(-2.32)**	
	… ·Injuries	--	-0.3486
			(-3.73)***
	… ·Injuries to Children	--	0.2580
			(1.50)
	… ·Prostate Cancer	--	-0.4677
			(-5.20)***
	… ·Breast Cancer	--	-0.0578
			(-0.68)
	… ·Skin Cancer	--	-0.8526
			(-8.94)***
Maximized Log-likelihood		-7930.80	-7453.51
Sample Size (Choices)		7556	7033

Table 9: Heterogeneity by Other Policy Attributes

Parameter	Variable	(1) Prevention	(2) Treatment
β	-(Yearly Cost/10,000)	5.6777	5.1482
		(9.72)***	(8.35)***
δ_{1p}	Log(Illness Reductions)	0.0405	--
		(5.78)***	
δ_{1t}	Log(Illness Reductions)	--	0.0359
			(5.04)***
δ_2	Log(Death Reductions)	0.1390	0.0714
		(11.11)***	(7.38)***
δ_3	Log(Duration)	-0.1693	-0.11896
		(-7.40)***	(-5.07)***
θ	Policy Dummy[a]	-0.3491	-0.2135
		(-4.08)***	(-2.63)***
Cause of ailment			
	…· Air Pollution	0.0981	--
		(1.75)*	
	…· Water Contaminants	0.1181	--
		(1.80)*	
	…· Pesticides in Foods	0.2317	--
		(3.55)***	
Gender-specific illnesses; respondent gender			
	…· Breast Cancer	--	0.0865
			(0.92)
	…· Breast Cancer·**1**(Female)	--	0.3655
			(2.94)***
	…· Prostate Cancer	--	0.1620
			(1.72)*
	…· Prostate Cancer·**1**(Female)	--	-0.5533
			(-4.03)***
"Affected group" choices			
	…· Percent Children	--	0.1220
			(1.29)
	…· Percent Children·**1**(Age65+)	--	-0.2553
			(-1.50)
	…· Percent Children·**1**(Kids)	--	0.6027
			(4.24)***
	…· Percent Seniors	--	-0.2295
			(-4.50)***
	…· Percent Seniors·**1**(Age65+)	--	0.0042
			(0.05)
Maximized Log-likelihood		-8028.5356	-7475.99
Sample Size (Choices)		7556	7033

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

Discussant Comments
Kelly Maguire
EPA Workshop
Morbidity and Mortality: How Do We Value the Risk of Illness and Death?
April 11, 2006

Session II: Issues With Morbidity Valuation

Altruism and Environmental Risks to Health of Parents and Children by Mark Dickie and Shelby Gerking

Is An Ounce of Prevention Worth a Pound of Cure? By Ryan Bosworth, Trudy Ann Cameron, and J.R. DeShazo

Mark Dickie and Shelby Gerking's paper, Altruism and Environmental Risks, is very interesting and well written. It is thorough and was a pleasure to read. The authors test a model of altruistic family behavior using a sun screen that will protect against both the risk of getting skin cancer, as well as dying from the cancer conditional on a positive diagnosis. They employ a stated preference survey using adults in Mississippi. Adults are asked their perceived risks of contracting and dying from skin cancer for both themselves and their child, and then they are asked the willingness to pay (WTP) for a sun screen that will reduce these risks by 10 percent or 50 percent, which are randomly assigned. The results are used to test the existence of altruism in the family.

Altruism is an important concept to consider in economic analysis. Primarily our concerns rest with the impact of altruism on valuation. In its simplest form, if parents, or any individual for that matter, behave in an altruistic manner, then individual values for a risk reduction will be compromised to the extent that they incorporate more than just the individual's WTP. By summing individual values we would then risk double-counting or over-estimating the total value for a risk reduction.

The paper could be more informative in this regard by including some discussion of the different types of altruism. Paternalistic altruism exists when an individual has concern for another's welfare, but is not necessarily concerned about the costs imposed on that individual. In other words, the paternalistic altruist does not incorporate the other's utility function into their own decision-making. Non-paternalistic altruism exists when an individual cares about both the benefits and costs imposed on another. That is, the non-paternalistic altruist fully accounts for the other's utility when making decisions. It would be useful to have a discussion of the different types of altruism and how they relate to this study, as well as valuation results.

Some additional questions that arose when reading the paper that could have implications for the application of these results to policy include:

How do the results change when there are multiple children in the household? Do parents adjust their WTP to account for the additional children?

How do you account for two-parent versus single-parent households? If each parent in a two-parent household is altruistic how does this affect the values for the child?

How do you account for other individuals who are altruistic towards children, such as grandparents?

Overall, this is a well-written and interesting paper that sheds light on an important issue for benefits analysis.

Ryan Bosworth, Trudy Cameron, and J.R. DeShazo also have an interesting and well-written paper, "Is An Ounce of Prevention Worth a Pound of Cure?" They investigate preference for treatment versus prevention policies over a wide variety of policy attributes, types of illnesses and accidents, and respondent characteristics. There is a substantial amount of information in a short paper. Their results show that individuals are willing to pay almost double for prevention of death than for treatment of an illness that can cause death. For example, WTP for prevention of a death is $245, whereas WTP to treat an illness that causes death is $138. This is not surprising. There is disutility associated with entering the diseased state and therefore individuals are willing to pay to avoid entering that state. The authors also find that people are willing to pay equivalent amounts to treat and prevent illnesses, at about $70 for both.

The largest contribution of this paper to policy is in terms of determining how a policy maker may allocate resources. These results suggest that people would rather prevent than treat outcomes. Again, this is not surprising and it would be useful for the paper to explore more of why this might be the case. My sense is that it is related to either the uncertainty associated with outcomes, or the stigma, or both.

In terms of uncertainty, people are WTP to avoid uncertain outcomes, particularly those that result in death. Individuals would rather prevent cancer, than be in the state of having cancer and facing the possibility of death and having to back out from that state.

These results are consistent with the approach we have found to be the case in the manufacturing sector. Twenty years ago the Pollution Abatement Costs and Expenditures (PACE) survey primarily addressed costs associated with treating pollution, say installing scrubbers on a stack to treat emissions, or filters at water discharge areas to treat water before release. Today, we are in a pollution prevention paradigm. The treatment options have been addressed and we now focus on preventing emissions before they are created. Much of the expenditures at manufacturing facilities that we see through the PACE results support this notion.

It is also possible that stigma is driving these results. People would rather not enter a disease or illness state that may have a stigma associated with it. Hence, they are willing to pay more to avoid the stigma of being a survivor. It would be useful to explore these ideas further in the paper.

Other questions that would be useful to address include:

What are the implied VSL or morbidity values that result from this study?

What is the impact of the complex question design on results?

Overall, the paper is interesting and provides a useful discussion of how individuals value treatment versus prevention programs.

No documents are available regarding Kevin Boyle's discussion comments.

Summary of the Q&A Discussion Following Session II

Perry Beider, (Congressional Budget Office)
Commenting on the presentation of the Bosworth/Cameron/DeShazo paper and referring specifically to the finding that "someone ideologically opposed to government intervention would support a certain program once there was enough personal direct benefit perceived from it," Mr. Beider asked if the researchers observed that it went the other way also. In other words, was it observed that people who were generally in favor of government intervention *did not* support policies if there was too little perceived personal benefit?

Trudy Cameron, (University of Oregon)
Dr. Cameron responded that "it is sort of treated symmetrically—if it works in one direction, then it works in the opposite direction also, just by the structure of the model."

J.R. DeShazo, (UCLA)
Dr. DeShazo continued the response, adding: "But the effect isn't quite as large—the ideology effect dominates. It's true that people strongly ideologically in favor of government intervention are responsive to the size of the private benefits, but much less so than at the other end of the continuum."

Bryan Hubbell, (U.S. EPA, OAQPS)
Also addressing the Bosworth/Cameron/DeShazo paper, Dr. Hubbell commented on the finding presented toward the end of the paper that when people were asked whether they prefer policies that help seniors or not, all of them said "no," including the seniors. He commented that "we just throw out the term *seniors* as if that's a well-defined term," and he added that he is curious to know whether the researchers worked to uncover an age breakpoint for this phenomenon. He clarified by asking, "What age does a policy have to affect before people will say that they'd rather not have that policy?—Is it 50? 55? 60? 65?—and is there any kind of declining support ratio at that point?"

Trudy Cameron
Dr. Cameron responded that the issue raised is an item of discussion on the Wednesday agenda. She added, "For private preferences we have some very detailed and elaborate analysis of age effects that are much richer than the simple quadratic thing that tends to dominate most of the prior literature. In the public choices study, which was discussed today, the distinction among beneficiaries is just defined in three groups—seniors, adults, or children. It's left to the individuals to interpret whether they are a senior or not."

J.R. DeShazo
Picking up on the response, Dr. DeShazo added, "Actually, I think for the respondents we did define the age intervals—60 or 65 was the cutoff."

Trudy Cameron
Dr. Cameron clarified, "But that's the beneficiaries—we have very detailed information about the respondent's age, of course, so that can be much richer."

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Douglass Shaw, (Texas A&M University)
Addressing the authors of both papers, Dr. Shaw asked, "What's the welfare measure?—what is it *really*?" He said that in Dr. Cameron's journal paper it is a "pretty careful derivation of an option price, which is kind of what we *think* it should be."

Dr. Shaw also asked, "When you do the subjective risk estimates, are you going after just the baseline risks, or are you also getting the subjectives on the risk changes?—and in either one of the designs, did you look to see if things are adding up?" He expounded that particularly in the Dickie/Gerking study there should be an obvious implication when doing a conditional probability. Acknowledging that the authors said they can do compound probabilities, which Dr. Shaw classified as "a very unusual result in the literature," he asked whether they did anything simple also.

J.R. DeShazo
Seeking clarification of the question, Dr. DeShazo asked, "Do you mean data analysis-wise or with the respondents or . . . ?"

Shaw
Dr. Shaw stated, "On the latter one, you're sort of saying that the results support that you can do compound probabilities, so obviously there's a law of probability between a conditional and an unconditional probability, so did you kind of just ask them to do a little experiment in the survey where you could verify that in fact they got that?"

DeShazo
Dr. DeShazo responded, "When I said you could do compound probabilities, I'm not sure I meant that if you asked them the unconditional probability and then did the multiplication on their conditional and their unconditional morbidity risk, would you actually get exactly the same number. I think they were making tradeoffs between those two risks that were consistent with the model, and I think they could distinguish between the two risks and not be confused between them. But we didn't ask them "what do you think the unconditional mortality risk is?" which you could use then to test whether they were really doing the math right. So, I don't know that."

Dr. DeShazo continued, "The perceived risk is all baseline; we asked them "what do you think the risk is?" The risk changes are exogenously assigned in the experimental design—they just come packaged in the sunscreen." He added that for the welfare measure they were looking at anti-willingness to pay for risk changes that would occur later in life.

Unidentified Participant

The response to Dr. Shaw was clarified by explaining that the probabilities were presented one at a time. For an example, "first the respondents were asked about the probability of getting skin cancer, and after they wrestled their way through that question, then they were asked about the chance they would die, given that they had it. So, we don't really have any results that say people can juggle two probabilities at the same time—and I'll bet they can't do it, just as you alluded."

New Questioner
"How do you go about measuring violations of rationality when people are answering your survey questions?—is it a violation of transitivity assumption? If you do those measures, what do you do with the results? Do you throw out people who are clearly violating rationality?

J.R. DeShazo
Commenting that it was a very good question, Dr. DeShazo replied, "You can and we have looked at violations of rationality. We've also looked at how much attention people spend absorbing the information that we've given them, and we have altered our sample based on some minimum level of attentiveness that we felt they needed." He went on to say that there is always the sticky issue of how much information is enough and how much is too much. He added that he is "deeply concerned about the declining cognitive efficiency of individuals when they're given too much information." Saying that "we are all always given too much information—and we sort through it," he identified one of the tasks for researchers presenting information to individuals is to ask, "Have we left out something that is important?" Dr. DeShazo said he believes that if you give individuals enough familiarity with the attributes that make up a program, they'll decide for themselves which attributes are most and least important, and the proof (or disproof) of that will show up in your statistical analysis.

Dr. DeShazo added that in addition to looking at time on task his research team asks respondents, "How difficult was that choice?" In closing, he said that "in the context of evaluating their risk judgments, we can actually look at whether or not they make consistent decisions—we give them quizzes, basically, in the private version of the survey."

Trudy Cameron
Continuing the response to the questioner, Dr. Cameron stated, "J.R. mentioned this notion of how much attention people give to different aspects of a particular survey design. J.R. with Herman Fermo has some pretty rigorous work that came out in 2002 looking at how the structure of the randomized design affects the amount of noise, the choice inconsistencies that people make." She added that work that they're doing now, in conjunction with another student at Oregon University, Dan Burkhart, "has to do with an

actual sort of optimal allocation of attention problem." Dr. Cameron asserted that this deepens the model a bit by "acknowledging that what you think you're estimating as a marginal utility in a choice model as a consequence of standard multiple-choice specification is actually the product of some fractional attention, which may be very small or very large, times the true underlying marginal utility that you would be estimating if they were paying full attention—and that's producing some very interesting results. That's just some fundamental broader research that will have some bearing on these data as well."

Lauraine Chestnut, (Stratus Consulting, Inc.)
Saying that this might be getting back to Douglass Shaw's question about welfare measure, Ms. Chestnut addressed this question to Drs. DeShazo and Cameron: "When you're asking questions about public policies that affect the person and everybody else in the community, how do you interpret that relative to the private valuation numbers that we tend to want for benefit/cost analysis. So, the example of the responses for seniors—and we've seen this in some other studies that ask these questions about public policy—what does that mean for valuation purposes?"

Trudy Cameron
Dr. Cameron responded, "Going back to respond to Douglass's question, which I didn't get a chance to: In the private choices survey, the model is highly structural and has to do with discounted expected utility maximization getting to an option price. But, for individual choices with respect to their own budgets and their own preferences for stuff that happens to them, it's a little easier to do that. This may account for why we haven't directly addressed much of the public choice stuff before—it's harder to come up with a solid, theoretical model about how people should think about these public goods. So, by its nature the public choices study with its two different surveys is very much more exploratory. Perhaps the term *descriptive* would be better—we're sort of identifying the stylized facts that need to be addressed in any further theorizing rather than starting with a rigid model. Bosworth has a more structural specification with respect to discounting—that's stuff he's working on now and finishing up for his third essay—but we figured we'd start with just the high points of the actual description of people's choices."

J.R. DeShazo
Acknowledging that he is relatively young to this field, having been actively involved in VSL literature only for 3 or 4 years, Dr. DeShazo said he finds it "a hard sell that we should be using these private good estimates for public policies because preferences over aspects of the public policy are *so different*. We could try to explain two different things—their actual support, their behavior—and it seems to me that if you're interested in their actual behavior with respect to these policies, you have to give them these attributes of public policies that don't hold or don't exist for private programs. Also, that behavior presumably reveals something about their perceived welfare from the public policy. I think the challenge is really on those that want to use the private estimates,

because, to me, they seem like very different utility functions with very different arguments in them."

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Reed Johnson, (RTI)
Mr. Johnson said that he had actually "looked forward to a lively discussion on the IOM Report, but I guess neither of the discussants were asked to comment on that. I'm afraid that we have on our hands another NOAA Blue Ribbon Panel Report that's going to be cited for the next 15 or 20 years, long after the evidence base that was used to make the recommendations has become obsolete. I'm a little concerned that the panel was constituted in a way that sort of biased it in favor of conventional ways of thinking about health utility that don't really line up very well with the way most people in this room think about utility—and I'd like to thank Alan Krupnick for his valiant efforts to try to keep the process a little bit more honest in that respect."

He continued, "There are a couple of aspects of the recommendations that I find troubling, in addition to Nathalie's points. For example, the quality recommendation is that the quality should be elicited for a general population sample. I work a lot with patient surveys and patient preferences and with some general population surveys. For many of the particular outcomes of interest, it is difficult for people who have never experienced that outcome to give meaningful values. . . . The general result is that patients experience much less of a utility loss than the general population assumes that they experience, partly because of adaptation and partly because people just imagine that something is going to be a lot worse than the experience actually turns out to be."

Mr. Johnson added that the report includes a recommendation for more research, but he said he thinks "the recommendation on gathering more data is stronger than the recommendation for improving methods," and he said he would have liked to have seen a much stronger advocacy for providing "measures of health utility that are both theoretically correct and empirically robust."

In conclusion, Mr. Johnson stated that he feels the publication of the report is an opportunity for groups like this to become engaged in trying to understand not only what obligation EPA is going to have in terms of doing their analysis but also what we can do to help encourage "more nuance of interpretation and more flexibility in use of methods."

Someone
"I thank Reed for that compliment. There were a lot of people on the committee that worked hard to do what we did. What we were trying to do is to create separation between measures of utility that we use in this literature, the economic valuation literature, and the measures of quality-adjusted life years and so on that are used in this other literature. . . . Hopefully that will serve the policy process and also serve our profession."

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END OF SESSION II Q&A