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

PROCEEDINGS OF SESSION V: EMPIRICAL ISSUES ASSOCIATED WITH MORTALITY RISK VALUATION

A WORKSHOP SPONSORED BY THE U.S. ENVIRONMENTAL PROTECTION AGENCY'S NATIONAL CENTER FOR ENVIRONMENTAL ECONOMICS AND NATIONAL CENTER FOR ENVIRONMENTAL RESEARCH

April 10 – 12, 2006

National Transportation Safety Board
Washington, DC 20594

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ACKNOWLEDGEMENTS

This report has been prepared by Alpha-Gamma Technologies, Inc. with funding from the National Center for Environmental Economics (NCEE). Alpha-Gamma wishes to thank NCEE's Maggie Miller and the Project Officer, Cheryl R. Brown, for their guidance and assistance throughout this project.

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Valuing Mortality Risk Reductions at EPA

Presentation at EPA Workshop
Morbidity and Mortality:
How Do We Value the Risk of Illness and Death?
April 11, 2006

Kelly Maguire
US EPA
National Center for Environmental Economics

Background

- Value of statistical life (VSL) estimate used in monetizing mortality risk reductions
- Same central estimate used since 1999
- Currently revising Economic Guidelines and revisiting VSL guidance
  – Literature grown considerably since default estimate was derived
  – EPA commissioned reports have raised issues with underlying literature
  – Recently published meta-analyses provide new means of combining estimates

EPA's current VSL Guidance

- EPA relies on benefits transfer:
  - Point estimate of $6.2 million ($1999) as an estimate of the value of statistical life
  - $6.9 million ($2004)
- Derived from 26 studies:
  - 5 stated preference studies
  - 21 hedonic wage studies
  - Studies date from 1974-1991
  - Values range from $0.7 million to $16.9 million ($1999); $0.8 million to $18.6 million ($2004)
- One value from each study was used to fit a Weibull distribution

Alternative Estimates

- $5.5 million ($1999) has been applied recently in air rules
- Central value from the range of values suggested in recent meta-analyses
- Distribution has a confidence interval from $1 to $10 million
  - $1 million is lower end of interquartile range from Mrozek and Taylor (2000)
  - $10 million is upper end of interquartile range from Viscusi and Aldy (2003)

Further Guidance

- EPA applies the same estimate to all populations
- EPA applies same estimate to all types of risk
- VSL is adjusted for timing
  - Discounted for risk reductions in future years
  - Inflated to account for growth in real income over time

Revisiting the VSL

- Number of new mortality risk valuation studies
- EPA funded three studies to examine various segments of the literature
  - Black, et al. (2002): HW literature
  - Alberini (2004): CV literature
  - Blomquist (2004): AB literature

Revisiting the VSL (cont.)

- New meta-analyses of mortality risk valuation literature
  - Mrozek and Taylor (2000): HW only
  - Viscusi and Aldy (2003): HW only
  - Kochi, et al. (forthcoming): SP and HW

Process for Revising VSL: Meta-analysis Panel

- SAB-EEAC expressed an interest in learning more about meta-analysis
- Panel of experts met in December 2005
- Goals
  - Discuss the issues and challenges in conducting meta-analysis for mortality risk literature
  - Prepare summary report

Process for Revising VSL: Consultation with SAB-EEAC

- Presentation of meta-analysis report by SGEs
- Other issues to raise
  - Population issues
  - Types of studies
  - Relevant measures
  - Covariates
- Guidance on revising VSL estimate

Some Options

- Continue to use current estimate
- Adopt results from existing meta-analysis
- Derive new estimate
  - Fit a distribution
  - Conduct a new meta-analysis
  - Other?

Next Steps

- Finalize meta-analysis report for delivery to SAB-EEAC
- Prepare White Paper for presentation to SAB-EEAC on study selection criteria and methodology to combine estimates
- SAB-EEAC meeting in July 2006
- Final guidance to be completed in 2007

Eliciting Risk Tradeoffs for Valuing Fatal Cancer Risks

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May 2006**

Paper prepared for presentation at

U.S. EPA NCER/NCEE Workshop:
"Morbidity and Mortality: How Do We Value the Risk of Illness and Death"
Washington, DC
April 10-12 2006

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** We dedicate this paper to the memory of our courageous and passionate colleague Elizabeth McClelland, formerly of the National Center for Environmental Economics, U.S. EPA, whose efforts were integral to the genesis and early design of this project. Financial support for this research was provided by the U.S. Environmental Protection Agency under Cooperative Agreement C R 824861-01-0. Thanks are due to John Bennett, Rebecca Allen, Mark Dickie, James Hammitt, and Alan Krupnick, Clark Nardinelli, Maureen Cropper, and Mary Evans for their helpful comments and suggestions. We also acknowledge research assistance provided by Catherine Corey and Jui-Chen Yang. Any opinions, findings, conclusions, or recommendations expressed in this paper are those of the authors and do not necessarily reflect the views of the U.S. EPA.

Abstract:

Reductions in cancer risks are among the most important and tangible benefits resulting from a variety of environmental, food safety and other public health initiatives; however, relatively little is known about how individuals value reducing cancer risks compared to other types of risks. Most of the existing empirical research on the valuation of mortality risks has focused on accidental (occupational and/or automobile) fatalities. It is often argued, however, that differences between the characteristics of cancer risks and accidental risks may lead to significant differences in how they are valued. In particular, the time lag between exposure to carcinogens and its physical manifestation (i.e., the latency period), as well factors such as the fear, dread, pain and suffering may affect individuals preferences for avoiding cancer risks. To address this issue, we conducted a national survey of adults that elicits their relative preferences for avoiding automobile fatality and fatal cancer risks. We specifically examine how strongly individuals prefer avoiding one type of risk over the other, how this strength of preference is affected by the length of the morbidity and latency periods, and how preferences differ across different types of cancer. Our results indicate that individuals generally have a strong preference for avoiding fatal cancer risks relative to automobile fatality risks; however, as expected, this preference is inversely related to the length of the cancer latency period.

Introduction

Reductions in cancer risks are among the most important and tangible benefits resulting from a variety of environmental, food safety, and other public health initiatives. Nevertheless, little is known about how individuals value reducing cancer risks relative to other types of risks. Although a large empirical literature exists that has generated estimates of willingness to pay (WTP) to reduce mortality risk, this literature has focused almost exclusively on accidental (occupational and/or automobile) fatalities. It is often argued, however, that differences between the characteristics of cancer risks and accidental risks may lead to significant differences in how they are valued (as measured by WTP). Specifically, the time lag between exposure to the cancer risk and its physical manifestation (i.e., the latency period) may lower WTP for cancer risk reductions relative to accidental risk reductions. In contrast, the pain and suffering associated with the morbidity period that precedes a cancer death may increase WTP for reducing cancer risks. If a fatal cancer engenders more fear and dread than an accidental fatality, then WTP to reduce cancer risks may be higher.

Although a few studies have examined the empirical effects of risk characteristics on preferences for risk reductions, there has been little attempt to specifically and systematically test for how variation in latency and morbidity associated with cancer affects preferences.[1] To address this research gap, we have designed and implemented a national survey of adults that elicits their relative preferences for avoiding two types of potentially very different mortality risks—risk of automobile fatality and risk of contracting a fatal cancer.

The objective of this study is to use stated preference methods to assess individuals' tradeoffs between the two types of risks. In particular, we estimate how strongly individuals prefer avoiding one type of risk over the other, how this strength of preference is affected by the length of the morbidity and latency periods, and how preferences differ across different types of cancer. In addition to informing the debate on how individuals perceive different types of risks, and how these perceptions may affect preferences to reduce different risks, the results will indicate that additional research on valuing different types of fatal risks is warranted.

The analysis finds that individuals have a strong preference for avoiding cancer risks relative to automobile fatality risks of the same magnitude; however, as expected, this preference decreases as the cancer latency period increases. Individuals' preferences for avoiding future cancer risks are also, as expected, positively related to their chances of surviving until the age of onset of illness. The details of these results are discussed below.

[1] The only exception appears to be recent work by Trudy Cameron and J.R. DeShazo described in section 1, below.

1. Background

Although some anecdotal evidence exists that preferences for reducing fatal cancer risks may depend on characteristics of the risk, the U.S. Environmental Protection Agency's (EPA's) Science Advisory Board Environmental Economics Advisory Committee (SAB-EEAC) (EPA, 2000) concluded that "there is not sufficient theoretical and empirical basis for … accounting for these differences [in characteristics]." On the specific question of how cancer risk valuation differs from risks of accidents, the SAB-EEAC noted that "the value of reductions in cancer risks should include both the value of the reduced risk of death and the value of reduced risk of the morbidity, fear, and dread that precedes the death incident" but added that "existing studies provide little reliable information as to the magnitude of this premium." The purpose of this study is to begin to provide a basis for this empirical research by exploring specific aspects of cancer risk valuation in a limited sample setting.

The existing empirical literature on mortality valuation focuses largely on safety rather than on cancer-related mortality risks.[2] There are a few exceptions, but even these studies provide relatively little evidence on how specific risk characteristics may affect preferences for reducing fatal cancer risks. For example, Smith and Desvousges (1987), Hammitt (1990), and duVair and Loomis (1993) use contingent valuation (CV) to estimate individuals' WTP to reduce environmental/food safety risks of death; however, in none of these cases were deaths described or necessarily interpreted as cancer risks. In contrast, Carson and Mitchell (2000) used a CV survey, conducted in 1985, to elicit WTP to reduce carcinogenic risks from trihalomethanes in drinking water. The survey did not specify the type of cancer or related health outcomes, nor did it discuss latency effects; therefore, it is difficult to establish whether and how these factors affected respondents' stated preferences. The Carson and Mitchell results were based on a relatively small (n = 237) and very localized sample (Herrin, IL).

Two recent surveys from Asia have begun to examine cancer risks relative to other mortality risks. Hammitt and Liu (2004) employ CV in Taiwan to estimate WTP to reduce risks of cancer and non-cancer illness (liver disease). The design characterizes risks as either acute (beginning within a few months with death to follow 2 or 3 years later) or latent, where symptoms begin about 20 years in the future. Results suggest that WTP for cancer is about one-third larger than WTP to reduce the risk of a comparable chronic disease, but the estimate is not statistically significant at the 10% level. Individuals appear to discount for latency at about 1.5% per year, but the survey does not vary latency periods, morbidity times, or consider accidental fatalities.

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[2] Some of these studies address risk dimensions associated with cancer, such as latency (see, for example, Krupnick, et al. 2005). There is also a body of literature on how public preferences for risk reduction programs vary by type of illness and other risk attributes (e.g., Subramanian and Cropper, 2000).

Tsuge, Kishimoto, and Takeuchi (2005) use a choice experiment to estimate marginal WTP for reduced mortality risks from cancer, heart disease, and accidents. Results from a Tokyo-area sample (n=400) show a small, but significant preference for reducing a generalized cancer risks relative to heart disease and accidents. This difference is not sensitive to risk magnitude. Results also suggest that respondents exhibited a strong preference for earlier risk reductions, with implicit discount rates estimated at approximately 20%. The survey does not vary morbidity periods or examine specific cancer types.

Cameron and DeShazo (2004) use a choice experiment to evaluate several aspects of health and risk valuation, including cancer, morbidity, and latency effects. Draft results suggest WTP generally diminishes over latency periods, with the specific effect contingent upon age, wealth, and the "illness profile," including length of morbidity and whether or not the effect is ultimately fatal.

Magat, Viscusi, and Huber (MVH) (1996)) used a computer-based survey to explore individuals' tradeoffs between automobile fatality and specific cancer risks. Using a mall intercept recruitment in Greensboro, NC, MVH administered the survey to 727 adults. The survey asked individuals to choose between two hypothetical residential locations that differed only in terms of the risks of automobile death and risk of lymph cancer. By varying the risks in the two locations, MVH estimated the lymph cancer "risk equivalents" for auto death—the risk ratio at which respondents were indifferent between the two locations. They found that for *terminal* lymph cancer the median respondent viewed the two risks as equivalent (risk equivalent = 1), and on average, nonfatal lymph cancer risks were "valued" at roughly two-thirds the rate of auto death risks. Although respondents were provided with information about the consequences of the disease, it is not clear which attributes of the disease or its risk primarily affected individuals' relative preferences for avoiding the two types of risks. In particular, the role of latency periods for cancer risks was not addressed in this study.

This study builds on the work by MVH, using a similar preference elicitation method. However, our survey is specifically designed to examine how individuals' risk equivalence rates between auto death and fatal cancer risks are affected by latency periods, morbidity outcomes, and types of cancer. This type of information is not available from existing research.

3. Conceptual Model

To model risk preferences we use an approach similar to MVH (1996). We assume that respondents make choices to maximize expected lifetime utility, E(U), which is defined in the following way:

$$E(U) = P_D U(D,Y) + P_C U(C,Y) + (1 - P_D - P_C) U(H,Y). \qquad (1)$$

According to this expression, lifetime utility is determined by health outcomes (D, C, or H) and wealth (Y). Individuals are assumed to face probabilities of three mutually exclusive lifetime health profiles. The first is dying in the very short term (e.g., within a year) in an auto accident (D) with probability P_D, the second is contracting an eventually fatal cancer (C) with probability P_C, and the third "normal health" or all other health outcomes (H), with probability $1 - P_C - P_D$[3].

Totally differentiating Eq.(1) and setting $dE(U) = 0$ and $dP_C = 0$ results in the following expression for the marginal rate of substitution between income and risk of automobile death, which is also commonly referred to as the value of a statistical life (VSL) (see, for example, Hammitt [2000]).

:

$$VSL = \frac{dY}{dP_D} = \frac{U(H,Y) - U(D,Y)}{\frac{\partial E(U)}{\partial Y}} \qquad (2)$$

Alternatively, setting $dP_D = 0$ results in the following expression for the marginal rate of substitution between income and risk of cancer, which can be interpreted as the value of a statistical cancer case avoided (VSC):

$$VSC = \frac{dY}{dP_C} = \frac{U(H,Y) - U(C,Y)}{\frac{\partial E(U)}{\partial Y}} \qquad (3)$$

Combining Eqs. (2) and (3), and assuming that *U(D,Y)* = 0, the relationship between VSL and VSC can be rewritten as

$$MER = \frac{VSC}{VSL} = \left(1 - \frac{U(C,Y)}{U(H,Y)}\right). \qquad (4)$$

We refer to the term in brackets as the "mortality equivalence ratio" (MER) for avoided fatal cancer risks, which translates avoided fatal cancers into equivalent avoided accidental deaths. In other words MER = VSC/VSL. Therefore, if MER is less (greater) than 1 this implies that avoided fatal cancer risks are valued less (more) than avoided immediate mortality risks from car accidents. If, for example, MER equals 2, this implies that an avoided fatal cancer is "equivalent" to 2 avoided car fatalities.

[3] Since latent risks of cancer are only relevant if one does not die from immediate automobile fatality risks, P_C in this model should more accurately be replaced by $P_C(1-P_D)$ in Eq.(1); however the second order interaction of the two risks is small enough relative to P_c that excluding the interaction has little effect on the analysis.

The conceptual framework outlined above defines the general relationship between VSL and VSC; however, it does not specifically address how VSC is expected to vary with respect to characteristics of the cancer risks. In particular, it does not address the effects that latency, *t*, may have on the expected utility of the fatal cancer profile, U(C, Y) and therefore on VSC and MER. Including latency in equation (4) we express MER as:

$$MER(t) = \left(1 - \frac{U(C(t),Y)}{U(H,Y)}\right) \qquad (5)$$

In this expression, the lifetime utility of the cancer health profile can be expressed as the discounted sum of utilities in future periods.

$$U(C(t),Y) = \left(\sum_{j=0}^{t-1}(s_j)(d_j)u^h(y_j)\right) + (s_t)(d_t)u^c(y_t) \qquad (6)$$

where:

s_j = probability of surviving *j* periods into the future from the present (*j*=0)

d_j = time preference factor, discounting utility in period j to the present

y_j = consumption in period *j*

$u^k(y_j)$ = state dependent utility in period *j*, with k=c referring to cancer state and k=h referring to healthy state.

Similarly the lifetime profile for H, which is independent of the latency factor t, can be expressed as:

$$U(H,Y) = \sum_{j=0}^{\infty}(s_j)(d_j)u^h(y_j) \qquad (7)$$

Based on this framework it is possible to formulate and examine specific hypotheses regarding the effects of latency period and perceived survival probabilities on preferences for avoiding cancer risks. In particular, as demonstrated in Appendix A,

- an increase in the cancer latency is expected under most circumstances to have a negative effect on MER, so the relative preference for avoiding cancer risks declines[4], and
- for any specified cancer latency t, an increase in the perceived survival probability to that period (s_t) is expected to have a positive effect on MER.

4. Empirical Methods

In our survey, which is described in more detail below, respondents are faced with a choice between two locations, A and B, where the only difference between the locations is the rate (i.e., risk) of fatal cancers (P_C^A vs. P_C^B) and auto deaths (P_D^A vs. P_D^B). Location A has fewer auto deaths and Location B has fewer cancers than the respondent's current location. In effect, they are presented with a pair of lotteries and asked to choose the one they prefer.

This choice is also illustrated in Figure 1, where Location A has fewer auto deaths and Location B has fewer stomach cancers than the respondent's current location. To compare the two options, we define the risk difference ratio (RDR) between A and B as:

$$RDR = \frac{P_D^B - P_D^A}{P_C^A - P_C^B} \qquad (8)$$

The RDR therefore represents the slope (in absolute value) of the line between the A and B risk combinations. The respondent is assumed to choose the location that lies on the indifference line that is closer to the origin (i.e. the risk combination that provides the highest expected utility).

In Figure 1, both locations A and B are shown on the same indifference line. Indifference between the two areas (lotteries) implies that these areas offer the same expected utility:

$$\begin{aligned} &P_D^A U(D,Y) + P_C^A U(C,Y) + (1 - P_D^A - P_C^A) U(H,Y) = \\ &P_D^B U(D,Y) + P_C^B U(C,Y) + (1 - P_D^B - P_C^B) U(H,Y) \end{aligned} \qquad (9)$$

Assuming again that U(D,Y) = 0, and rearranging terms

[4] Using a somewhat different framework, Hammit and Liu (2004) also conclude that under most conditions, individuals' willingness to pay for reducing latent risks will be lower than for reducing current risks by the same amount.

$$MER = 1 - \frac{U(C,Y)}{U(H,Y)} = \left[\frac{P_D^B - P_D^A}{P_C^A - P_C^B} \right]^* = RDR^* . \qquad (10)$$

This equation show that the value of RDR that equates E(U) between two location -- RDR* -- is also equal to MER. In other words, MER represents the negative slope of the indifference curves in Figure 1; therefore, it defines the RDR that is consistent with indifference between the two locations.

By varying the values of P_C^B and P_D^A across respondents, the survey presents location choices that entail different RDRs. By observing how choices vary with respect to this variation in RDR, the survey responses can be used to estimate the average/expected value of MER. Equally important, they can be used to estimate how MER varies according to the characteristics of the cancer risks and the characteristics of respondents.

To model and interpret results using the discrete choice approach, we assume that MER varies in both systematic and stochastic ways across respondents. This assumption is formally expressed as

$$MER_i = \alpha + \beta X_i + \varepsilon_i . \qquad (11)$$

The systematic component of this expression describes MER as a function of *X*, which is a vector that includes both survey variables and characteristics, as well individual characteristics. The random component (ε_i) captures factors that are unobservable to the analyst and are assumed to vary randomly, identically, and independently across respondents.

In the discrete choice context, one does not observe MER_i for each respondent but rather a latent variable m_i^*, which can be characterized as

$$m_i^* = 0 \text{ if } RDR_i \geq MER_i \qquad (12a)$$

$$m_i^* = 1 \text{ if } RDR_i < MER_i . \qquad (12b)$$

In this case, m_i^* can be represented by a dummy variable, which is equal to 1 if the respondent prefers Location B (the location with fewer cancers) and 0 otherwise. In other words, the lower (higher) the value of RDR_i, the larger (smaller) is the reduction in cancers relative to auto deaths and the more likely that respondent i chooses Location B.

Assuming that ε_i is normally distributed $N(0, F^2)$, a probit model can be used to analyze the discrete choice responses and to estimate coefficients of the MER function (Eq. [4.9]) and ***F***. The results of the probit analysis are discussed in Section 7 below.

A stated preference by individual *i* for Location B ($PREFERB_i$=1) indicates that she prefers the location offering a reduction in cancer risk over the location offering a reduction in auto death risk. It also implies that $MER_i > RDR_i$. Given the probability distribution of ε_i, the probability of preferring Location B can be expressed as:

$$\begin{aligned}&\Pr(PREFERB_i = 1)\\&= \Pr(MER_i > RDR_i)\\&= \Pr(\beta X_i - RDR_i > \varepsilon_i)\end{aligned} \tag{13}$$

The last equality holds due to the symmetry of the distribution. By defining $\theta = \varepsilon / \sigma$, we define a standard normal random variable, $\theta \approx N(0,1)$, which implies that

$$\begin{aligned}&\Pr(PREFERB_i = 1)\\&= \Pr(\left(\frac{\beta}{\sigma}\right)X_i - \left(\frac{1}{\sigma}\right)RDR_i > \theta_i)\\&= \Phi(\left(\frac{\beta}{\sigma}\right)X_i - \left(\frac{1}{\sigma}\right)RDR_i)\end{aligned} \tag{14}$$

By varying RDR randomly across individuals in the survey and controlling for factors included in X_i, a probit model can be used to estimate the vector β / σ and the scalar $1/\sigma$. We refer to the corresponding probit coefficient estimates as the vector $\hat{\alpha}$ and the scalar $\hat{\gamma}$ respectively

Given the assumptions in Eq. (11) and the assumed distribution of the random term, *expected* MER for individual *i* can be expressed as:

$$E(MER_i \mid X_i) = \left(\frac{\beta / \sigma}{-1/\sigma}\right)X_i = \beta X_i \tag{15}$$

Therefore, using the probit results, expected MER_i can be estimated by $(-\hat{\alpha} / \hat{\gamma})X_i$.

5. Survey Design

The survey questionnaire was designed to be administered via WebTV to households in the U.S.. It was developed, pretested, and revised in several stages, using input from focus groups and multiple in-person cognitive interviews.

The sample for the survey was drawn from a panel of respondents prerecruited by Knowledge Networks, Inc. (KN). The only specific inclusion criterion was that respondents needed to be at least 18 years of age. The KN panel is based on a nationally representative, list-assisted, random-digit-dial (RDD) sample drawn from all 10-digit telephone numbers in the United States.

The survey instrument presented respondents with information on two hazards: death from a car accident and death from cancer. Respondents were randomly assigned one of three different types of cancer: stomach, liver, or brain cancer. The survey provided information on national averages and ranges of risk of each hazard, as well as information on cancer symptoms, treatment, and side effects. Importantly, the survey further explained that, although death from an automobile accident usually occurs almost immediately, cancers take years to develop before they are diagnosed (the latency period) and that the individual is typically sick for some time before death occurs (the morbidity period). Respondents were asked to assume for the purposes of the survey that the latency period has a length of t years (where respondents are randomly assigned values of t equal to 5, 15, or 25 years) and the morbidity period has a length of m years (with randomly assigned values of 2 or 5 years). Time lines, which are individualized to the respondent's reported age, were used to illustrate the differences in timing of exposure and death from the two hazards. Specifically, the time lines show that auto accidents and death are typically simultaneous occurrences, while demonstrating that exposure to the carcinogen occurs in year 1, diagnosis occurs in year $t + 1$, and death occurs in year $t + m+1$.

Respondents were then presented with a sequence of similar choice scenarios. They were asked to imagine that they have a job that requires them to move to one of two areas (A or B) for a period of 1 year. They must choose between the two areas, which differ only with respect to their exposure to the two hazards. They were asked to assume that their annual baseline risks from the two hazards-- the risk of dying in auto accident and the risk of dying of a specific cancer in their current area of residence – were both represented by 100 deaths per million people. They were then asked to choose between moving to Area A which has fewer auto accident deaths per million than their current location or Area B which has fewer fatal cancer deaths per million than their current location. Respondents were first introduced to the choice task with a few simplified practice questions. They were then presented with a choice scenario where they faced a tradeoff between avoiding risks of fatal auto accidents or avoiding risks of fatal cancers. An example choice scenario is shown in Figure 2.

Several aspects of the questionnaire design were randomly varied across respondents to test for their effects on a respondent's choices regarding risk reductions. These treatments were selected to test for scope effects and question-framing effects. They include the following:

- three different types of fatal cancers (stomach, liver, or brain cancer, each compared to fatal auto death risks);
- three different assumed latency periods for the cancer (5, 15, or 25 years);
- two different assumed morbidity periods for the cancer (2 or 5 years);

- two different formats for "introductory" choice questions, one in which Location A was clearly superior in the introductory scenarios and the other in which Location B was superior (included to test for framing effects in choice responses); and
- five different choice scenarios, each corresponding to a different RDR –

Thus, all together, there are 180 (3x3x2x2x5) different versions of the survey that are randomized across respondents.

Several other design characteristics are noteworthy. First, restricting the time frame to 1 year allows us to focus on risks from 1 year of exposure to the carcinogen and avoids the confounding issue of cumulative exposure to the carcinogen. This implicitly assumes an underlying dose-response model in which a single exposure can cause the cancer, as opposed to a model in which there is no risk of cancer until some threshold of cumulative exposures is reached. Second, emphasizing that the two new areas are exactly the same in every way but the risk exposure controls for the effects of other perceived location characteristics on reported preferences. Third, providing a baseline and maintaining new risk levels at or below the baseline controls for scenario rejection. Finally, after the practice questions and before the choice task, respondents were reminded of their individual time line for cancer exposure, diagnosis, and death.

6. Survey Data

The on-line WebTV survey was sent to a total of 1,351 households participating in the KN panel. To ensure proper functioning of the instrument, a subset of this sample—125 households—was initially contacted via email, and responses were acquired from about half this sample. After reviewing these responses and making minor adjustments to the instrument, email invitations were sent to the remainder of the sample.

By the end of March, 1,010 individuals (each from a different household) had submitted completed surveys to KN—a 73.7 percent invitation response rate. To achieve this rate of response, several of the 1,351 households were sent email and telephone reminders throughout the survey administration period.

To analyze responses to the main choice question, we excluded 136 respondents who "failed" the practice choice question. That is, if respondents did not indicate a preference for the "dominant" location (with fewer auto deaths *and* fewer fatal cancers), even after being given a chance to revise their response, it was assumed that they did not understand or were not willing to accept the choice scenario. An additional 17 respondents were dropped because, when presented with an automated follow-up description of their response to the first (nonpractice) choice question, they did not agree with the description but also were not willing to revise their answer. We also excluded 69 respondents who did not have a preference for either location. Consequently, the size of the analysis sample is 788 respondents.

To investigate whether there were systematic differences between the analysis sample and (N=788) initial recruitment sample (N=1351), we conducted a probit analysis with respect to demographic characteristics. This analysis revealed that age, race, education, and household size were all significant determinants of whether respondents were included in the analysis sample. However, when this process was included as the first stage of a Heckman sample selection model, with the probit analyses described in Section 7 as the second stage, there was no evidence that the selection process led to biased estimates of the coefficients in the second stage model.

Descriptions and summary statistics for all the variables used in the analysis are provided in Tables 1 and 2 respectively. Overall, over half of the respondent (65 percent) preferred to location with lower cancer risks. The average age of the sample was 45.4 years, ranging from 18 to 93, average income was $50,600, and the average number of years of education was 12.5. Nineteen percent of the sample classified themselves as from a minority group.

The analysis also includes variables describing respondents' experience with and perceptions of cancer and automobile fatality risks. A relatively small percentage of the sample had experienced cancer themselves (CANCYOU, 8 percent) or had a close friend or relative who had experienced the cancer described to them in the survey (CANCFRIEND, 12 percent). A somewhat larger percentage had experienced a serious autoaccident (CARYOU, 18 percent) or had lost a close friend or relative to a car accident (CARFRIEND, 17 percent). On average, respondents believed that they had lower risk of dying of cancer or a car accident than others in their area; however, a large majority indicated that, for the purposes of the survey, they were able to assume that their risks were the same. Twenty five percent of respondents indicated that, in choosing between Locations A and B, they considered the possibility that a cure for cancer might be found.

Finally, to account for how differences in perceived survival probabilities affect preferences for avoiding cancer risks, we included data from the survey where respondents were asked: "How likely do you think it is, in percentage terms, that you will live for another X years or more?" The value for X corresponded to the cancer latency period that was presented to the respondent later in the survey. As expected, the average perceived survival rate was higher for X=5 (87 percent) than for X=15 (75 percent), which was also higher than for X=25 (68 percent). However, contrary to expectations and evidence from life tables, the perceived survival rate declined more rapidly from 5 to 15 years than from 15 to 25 years.

A main objective of the analysis is to evaluate how preferences for avoiding fatal cancer risks relative to auto death risks vary with respect to the relative size of the risk reductions and the length of the cancer latency period. Figure 3 provides a first look at this issue, by graphing the percent of respondents who preferred the location with lower cancer risks in relation to RDR and latency period. As expected, this percent generally declines with the RDR (i.e., larger relative reductions in auto death risks reduce the preference for the lower cancer risk location) and it declines with latency. The statistical significance of these results and their implications for calculating MERs are examined in the next section.

7. Model Results

Based on this framework, we estimated several probit specifications, all using PREFB as the dependent variable. In the simplest model specification, we assumed only random (no systematic) heterogeneity across respondents:

$$MER_i = \beta_0 + \varepsilon_i \qquad (16)$$

This model was estimated using probit specification (1) in Table 3. X_i in this case is simply the constant term, and, using Eq. (15), expected MER is estimated to be 2.3. In other words, without accounting for systematic heterogeneity across respondent characteristics or across survey versions, individuals were estimated to value avoided fatal cancer risks at somewhat more than twice the rate of fatal auto risks.

More complex models, which allow and control for heterogeneity in various ways are reported in specifications (2) through (5) in Table 3. All of these additional specifications control for and measure the effects of latency period on MER. These models consistently find that respondents' choices are significantly affected by differences in the latency period. As expected, individuals' preferences for avoiding fatal cancer risks (relative to automobile risks) decrease as the length of the cancer latency period increases. These specific results are described and discussed in more detail below.

Specifications (2) through (5) also control for the type of cancer (STOMACHC and BRAINC), the duration of cancer morbidity (MORB5), and the framing of introductory "practice" questions (INTROFORMAT), all of which were varied randomly across respondents. The brain cancer coefficient is consistently negative and statistically significant, whereas the coefficient for stomach cancer is never statistically significant. These results suggest that individuals have a significant preference for avoiding stomach and liver cancer risks compared to brain cancer risks.

Differences in the duration of cancer morbidity (MORB5) never have a significant effect on stated preferences in any of the model specifiations. The lack of an observed morbidity duration effect on preferences may be because any negative effect of increasing the length of illness prior to death is offset by a corresponding delay in the time of death (for a given latency period, which in the survey is defined from the current period to the time of diagnosis). Alternatively, the difference between two and five years of morbidity may not have been large enough to influence respondents' choices.

In contrast, the framing of the introductory questions does have a significant effect on respondent choices in all of the model specifications. Respondents who received the format in which Location A (Location B) was clearly superior in the introductory scenarios were also less (more) likely to prefer Location B in the choice question involving a tradeoff between cancer and automobile risk reductions. Therefore, although these questions were included to help respondents understand the choice framework, they also appear to have created somewhat of a starting point bias for respondents..

Specification (3) also includes several demographic characteristics such as age, health status, education, and race, as well as the variables characterizing respondents' experience with and perceptions of cancer and automobile fatality risks. Of these variables, the only ones that have consistently significant (at a 10% level or less) effect on stated preferences are household income and whether they live in an MSA. Individuals in higher income households are less likely to prefer reducing cancer risks, whereas urban residents are more likely to do so. The effect of age on the relative preferences for avoiding cancers is negative, but it is not statistically significant in any specifications. To the extent that age affects preferences through perceived survival probabilities, these effects are explored in specification (4) and are discussed in more detail below.

Individuals' experience with and perceptions of cancer and automobile risks are also explored in specifications (2) to (4). Although individuals were asked to assume, in answering the choice questions, that their own risks were the same as others in their area, perceptions of higher than average cancer risks for themselves made them more likely to prefer the area with lower cancer risks. Similarly, perceptions of higher than average automobile risks for themselves made them more likely to prefer the area with lower automobile risks. These results suggest the respondents may have implicitly adjusted the risk reductions presented to them to fit their own circumstances. Individuals who had experienced cancer themselves were less likely to prefer reducing future cancer risks. This effect is not statistically significant, but it may reflect some adaptation to the illness. Also, respondents who had close friends or relatives die from cancer or automobile accidents were more and less likely, respectively, to prefer avoiding these risks. These effects are not statistically significant either, but they may be a sign of individuals' heightened fear or dread of these outcomes through indirect personal experience. Finally, individuals who had considered the possibility of a cancer cure were significantly less likely to prefer avoiding latent cancer risks. This finding is consistent with individuals expecting to derive higher utility from a future cancer health state, if the cancer has a lower chance of being fatal.

To evaluate the effects of latency on preferences, specifications (2) and (3) estimate separate coefficients for the 15 year and 25 year latency period dummies ($\hat{\alpha}_1$ for LAT15 and $\hat{\alpha}_2$ for LAT25), with the 5 year latency period as the reference condition. Both coefficients are negative, significantly different from zero, and significantly different from one another. Therefore, as expected, longer latency periods reduce the relative preference for avoiding cancer risks. To specifically explore the effect of latency on MER, we define latency-specific MER as MER(t), such that.

$$MER(t)_i = \beta X(t)_i + \varepsilon_i \qquad (17)$$

Using this definition and equation (15) and setting all variables in X set at their sample means (except for LAT 15 and LAT 25), we estimate separate expected MERs for the 5, 15, and 25 year latency periods[5]. The predicted values range from 3.23 for the 5 year latency to 1.54 for the 25 year latency.

If MER declines linearly with respect to latency, adapting equation (17) we then have:

$$MER(t)_i = MER(0)_i - \phi t + \varepsilon_i \qquad (18)$$

Testing the linearity restriction in specifications (2) and (3) is therefore equivalent to testing whether $\hat{\alpha}_2 - \hat{\alpha}_1 = \hat{\alpha}_1$. Applying a Wald test to the estimated coefficients, we found that in both cases the linearity restriction cannot be rejected (at a 5% level of significance).

In specification (4), we impose the linearity assumption by replacing the latency dummy variables with a continuous variable (LATENCY = t). With this model and equation (18), it is also possible to extrapolate the results and estimate:

- E[MER(0)]—the implied expected MER if latency were zero and the onset of cancers, like auto deaths, were immediate[6] and
- t^*—the length of the latency period that would be required to make expected MER equal 1 (i.e., to make individuals indifferent between reducing fatal cancer and auto death risks).

To estimate E[MER(0)] we set LATENCY=0 and the other explanatory variables in X at the sample mean. The results, which are reported Table 3 indicate that on average, avoided fatal cancer risks *without* latency would be valued at over three times avoided automobile death risks.

To estimate t*, we define the following condition

[5] For the MER calculations, the values of CANCERRISK and CARRISK were set at 3 – equal to the same risk as the average individual in their area – rather than at the sample means, which were somewhat smaller.

[6] In the case of cancer, death would still be delayed by the duration of morbidity.

$$E[MER(t^*)_i] = \beta X(0)_i - \phi t^* = 1 \qquad (19)$$

and solve for t*. Using specification (4) and the mean sample characteristics, we estimated t* to be roughly 32 years. In other words, latency periods for cancer risks would need to be on average over 30 years to make individuals indifferent between reducing fatal cancer and auto death risks.

The final specification in Table 3 was included to specifically examine how individuals' perceived survival probabilities (SURVIVERATE) modified the effect of latency period on their choices. Because these survival probabilities are specific to the latency period presented to each respondent, they are interacted with their corresponding latency dummy variables in specification (4). As expected, the coefficients on the survival probabilities are all positive and significant. These results suggest that individuals prefer to avoid cancer risks in X years if they are more likely to be alive in X years. The size of these three coefficients are also ordered as expected, decreasing in magnitude as the latency period increases from 5 to 15 to 25 years. The difference between 5 and 15 years is not statistically significant, but the difference between 25 years and the two shorter latency periods is significant (at a 0.05 level) in both regressions. Therefore, even after controlling for differences in perceived survival probabilities, latency still has a significant effect on individuals' preferences for avoiding future risks.

8. Summary and Conclusions

Environmental protection programs, as well as food safety and many other public health programs, often benefit society by reducing cancer risks. Because many avoided cancers are expected to be fatal, these health benefits are often measured in terms of "statistical lives saved," and they are typically valued using available estimates of VSL. One of the drawbacks of this benefits assessment approach is that few of these VSL estimates, which reflect individuals' WTP to reduce mortality risks, have been specifically designed to capture preferences for avoided cancer fatalities. In most cases, these estimates have been derived in the context of immediate and or accidental deaths.

There are at least two reasons why VSL estimates based on risks of immediate accidental deaths may not be appropriate for valuing avoided fatal cancer risks. The first is that individuals may view cancer deaths as being qualitatively different from accidental deaths, perhaps associating particular dread or fear with cancers. The second reason is that cancer risks are often likely to involve extended latency periods between the time of exposure and the observable effects of illness.

The purpose of this study has therefore been to directly explore differences in individuals' preferences regarding fatal accidental and fatal cancer risks. First, when directly comparing risk reductions of the same magnitude, is there evidence of a "cancer premium"? That is, do individuals systematically prefer avoiding cancer risks and, if so, by how much? Second, to what extent does cancer latency modify differences in preferences for the two types of risks?

To address these issues we administered a web-based preference elicitation survey to a general population sample of adults in the US. The focal point of the survey was a choice task that asked respondents to choose locations that offered either lower automobile fatality or cancer risks. The relative risk reductions, as well as the characteristics of the cancers, were varied randomly across respondents.

The main findings of the survey are that individuals made choices that revealed (1) a significant cancer premium and (2) a cancer premium that declined with the length of the cancer latency period. On average, to make individuals indifferent between avoiding the two types of risks, they required risk reductions for fatal cancers that were two to three times larger than for fatal automobile risks. Preferences for avoiding cancer risks were also significantly reduced by longer latency periods; however, the survey results indicate that latency periods greater than 30 years were generally required to offset the effects of a cancer premium.

Our analysis also finds that the effect of latency periods on preferences is itself affected by individuals' perceived survival probabilities. The lower the chance of survival for a given latency period, the less individuals preferred avoiding cancers with that latency. Our results indicate that perceived survival probabilities (less than 100 percent) are one reason that individuals discount future cancer risks; however, this discounting persists to some extent even after accounting for survival.

Our results suggest that using current estimates of VSL based mainly on data from accidental death risks may not be appropriate when evaluating the benefits of avoided cancer risks. Unless cancer latency periods exceed 30 years, these VSL estimates are likely to understate the true benefits of reduced cancer risks. Further research using different preference elicitation and measurement approaches is needed to confirm these findings; however, they provide more evidence that policy analyses would benefit from VSL estimates that are better tailored to the risk reductions contexts in which they are applied.

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Figure 1. Preference Map for Two Categories of Risk

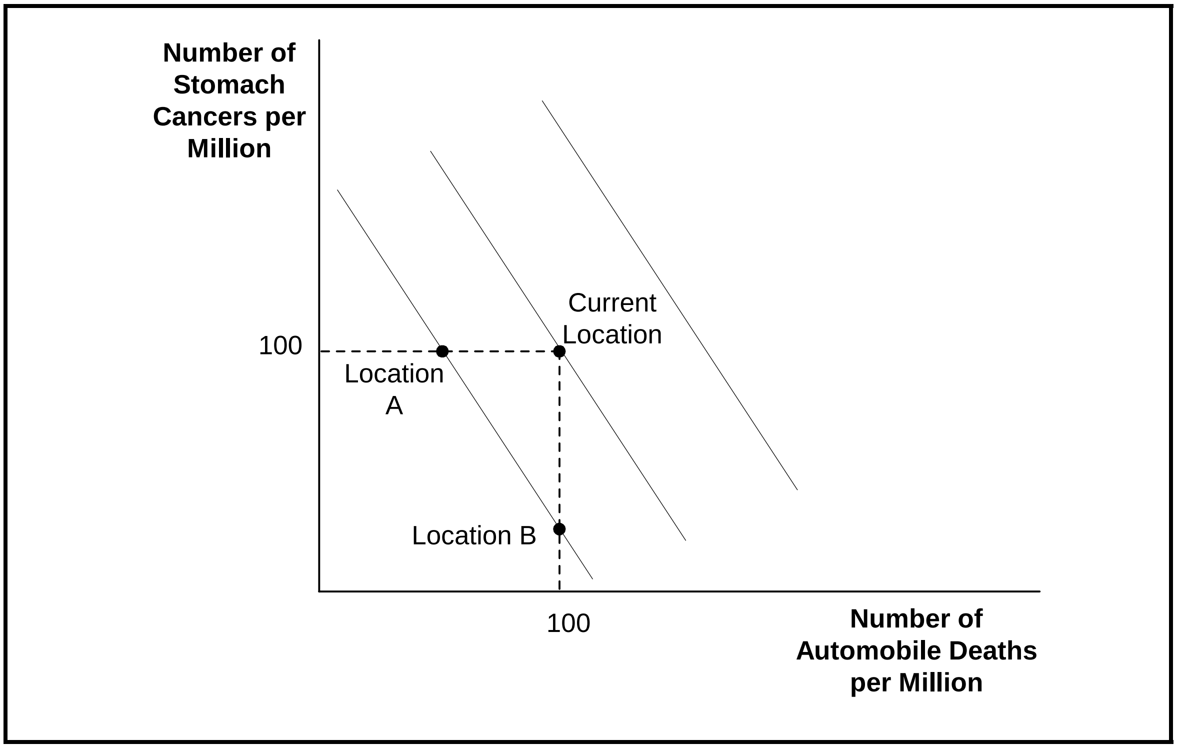

Figure 2. Example Choice Task in the Risk Tradeoff Survey

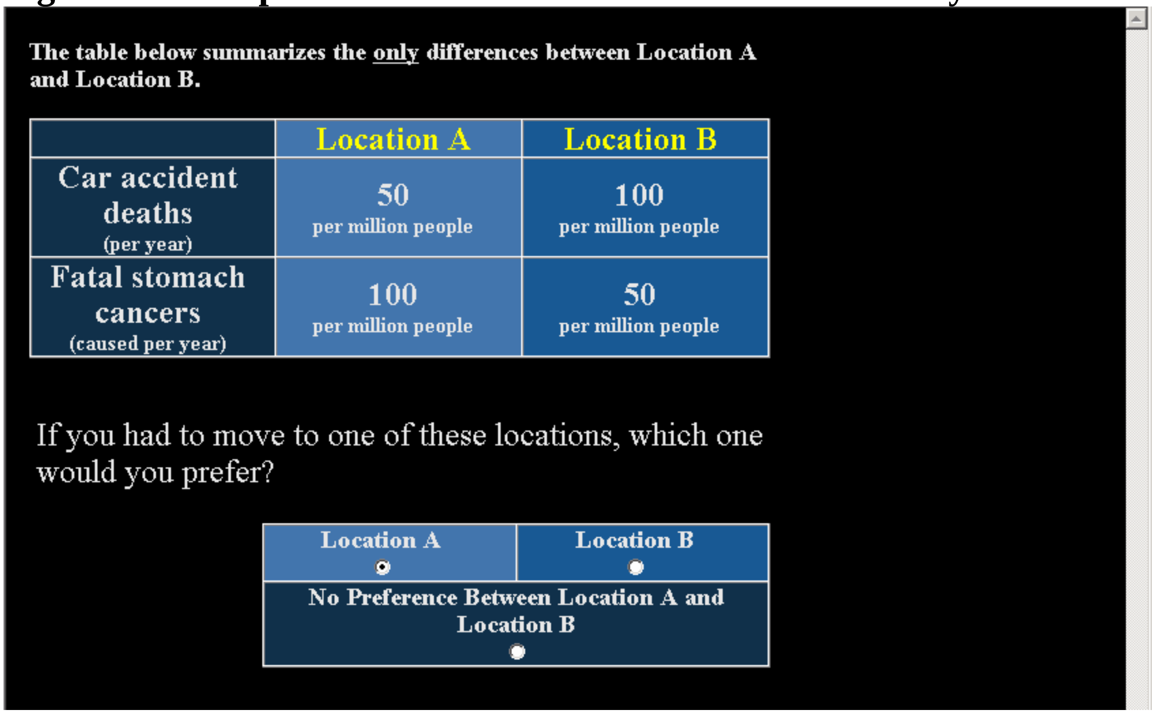

Figure 3. Preferences for Avoiding Fatal Cancer Risks Relative to Auto Death Risks

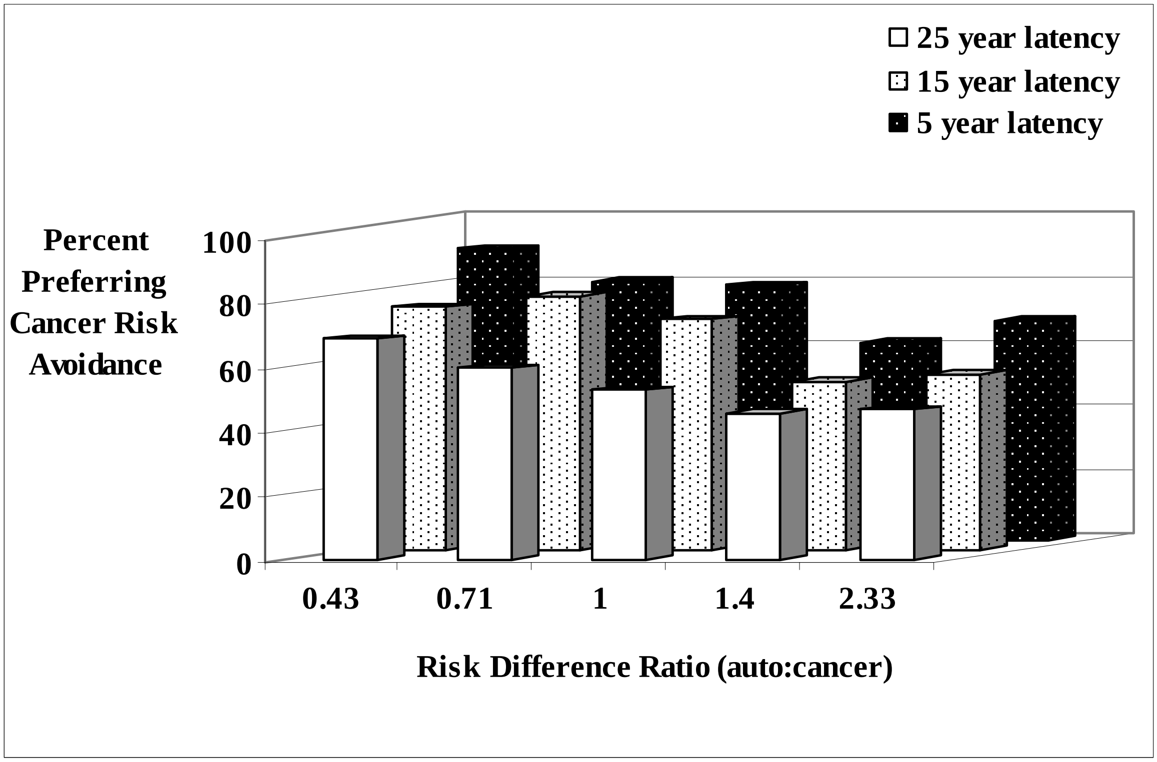

Table 1. Descriptions of Analysis Variables

Variable Name	Description
PREFERB	= 1 if choose "Prefer Location B"
RDR	= Risk difference ratio presented in choice table
LAT15	= 1 if 15-year latency period
LAT25	= 1 if 25 year latency period
LATENCY	= Latency period (5, 15 or 25)
SURVIVERATE	Self-reported (perceived) probability of surviving for duration of latency period
LAT5SURV	= Interaction between 5-year latency period and perceived chance of survival during latency period (LAT5*SURVRATE)
LAT15SURV	= Interaction between 15-year latency period and perceived chance of survival during latency period (LAT15*SURVRATE)
LAT25SURV	= Interaction between 25-year latency period and perceived chance of survival during latency period (LAT25*SURVRATE)
MORB5	= 1 if 5-year morbidity period (= 0 if 2-year morbidity period)
INTROFORMAT	= 1 if Location A dominates Location B in introductory choice questions
STOMACHC	= 1 if stomach cancer version
BRAINC	= 1 if brain cancer version
AGE	= respondent's age
HEALTHNOW	= Self assessment of respondent's current health status
GENDER	= 1 if male
MINORITY	= 1 if race non-white
EDUC	Number of years of education
HHINCOME	Household income ($'000)
HHSIZE	Household size
MSA	= 1 if respondent lives in an MSA
CANCERYOU	= 1 if respondent ever had cancer
CANCFRIEND	= 1 if friend or relative had experienced the cancer described in the survey
CANCERCURE	= 1 if considered possibility of cure for cancer during latency period
CANCERRISK	Self-rated fatal cancer risk compared to average (1= much lower, 5 = much higher)
CARYOU	= 1 if hospitalized because of a car accident
CARFRIEND	= 1 if friend or relative died in car accident in last 10 years
CARRISK	Self-rated fatal car risk compared to average (1= much lower, 5 = much higher)

Table 2. Summary Statistics for Analysis Variables

Variable	N	Mean	SD	Min	p25	p50	p75	Max
PREFERB	788	0.65	0.48	0	0	1	1	1
RDR	788	1.16	0.65	0.43	0.71	1	1.4	2.33
LAT15	788	0.32	0.47	0	0	0	1	1
LAT25	788	0.36	0.48	0	0	0	1	1
LATENCY	788	15.36	8.21	5	5	15	25	25
SURVIVERATE	788	0.77	0.27	0	0.6	0.9	1	1
MORB5	788	0.50	0.50	0	0	1	1	1
INTROFORMAT	788	0.49	0.50	0	0	0	1	1
STOMACHC	788	0.34	0.47	0	0	0	1	1
BRAINC	788	0.33	0.47	0	0	0	1	1
AGE	788	45.39	16.97	18	31	44	58	93
HEALTHNOW	787	2.54	0.92	1	2	3	3	5
GENDER	788	0.48	0.50	0	0	0	1	1
MINORITY	788	0.19	0.40	0	0	0	0	1
EDUC	788	12.45	3.22	6	12	14	14	16
HHINCOME	788	50.56	36.49	2.5	22.5	45	67.5	187.5
HHSIZE	788	2.61	1.24	1	2	2	3	8
MSA	788	0.84	0.37	0	1	1	1	1
CANCERYOU	788	0.08	0.27	0	0	0	0	1
CANCFRIEND	782	0.12	0.33	0	0	0	0	1
CANCERCURE	783	0.25	0.43	0	0	0	0	1
CANCERRISK	782	2.56	0.84	1	2	3	3	5
CARYOU	788	0.18	0.38	0	0	0	0	1
CARFRIEND	785	0.17	0.38	0	0	0	0	1
CARRISK	783	2.47	0.95	1	2	3	3	5

Table 3. Analysis of Risk Tradeoffs: Probit Results for Location Choice

	Dependent Variable = PREFERB									
	(1)		(2)		(3)		(4)		(5)	
Variable	**Coef.**	**z-statistics**	**Coef.**	**z-statistics**	**Coef.**	**z-statistics**	**Coef.**	**z-statistics**	**Coef.**	**z-statistics**
CONSTANT	0.816	8.56	1.262	8.28	1.788	4.01	1.947	4.31	0.302	0.57
RDR	-0.355	-5.03	-0.350	-4.89	-0.374	-4.92	-0.373	-4.91	-0.382	-4.98
LAT15			-0.316	-2.60	-0.300	-2.34				
LAT25			-0.634	-5.39	-0.632	-5.06				
LATENCY							-0.032	-5.10		
LAT5SURV									1.239	4.99
LAT15SURV									1.061	4.09
LAT25SURV									0.710	2.57
MORB5			0.031	0.33	-0.042	-0.43	-0.042	-0.42	-0.039	-0.39
INTROFORMAT			-0.173	-1.83	-0.207	-2.10	-0.208	-2.11	-0.234	-2.36
STOMACHC			0.111	0.95	0.096	0.78	0.097	0.80	0.071	0.57
BRAINC			-0.215	-1.86	-0.235	-1.97	-0.235	-1.96	-0.253	-2.10
AGE					-0.005	-1.57	-0.005	-1.56	0.002	0.53
HEALTHNOW					-0.046	-0.82	-0.046	-0.80	0.004	0.07
GENDER					-0.053	-0.54	-0.053	-0.54	-0.022	-0.22
MINORITY					-0.100	-0.79	-0.101	-0.79	-0.106	-0.82
EDUC					-0.008	-0.47	-0.008	-0.47	-0.013	-0.83
HHINCOME					-0.002	-1.79	-0.002	-1.79	-0.003	-2.15
HHSIZE					0.006	0.14	0.006	0.14	0.008	0.20
MSA					0.251	1.89	0.250	1.89	0.238	1.83
CANCERYOU					-0.296	-1.49	-0.296	-1.48	-0.192	-0.94
CANCFRIEND					0.249	1.53	0.250	1.55	0.268	1.67
CANCERCURE					-0.401	-3.60	-0.400	-3.58	-0.409	-3.63
CANCERRISK					0.239	3.73	0.240	3.75	0.240	3.71
CARYOU					-0.027	-0.21	-0.027	-0.21	-0.033	-0.26
CARFRIEND					-0.170	-1.27	-0.170	-1.28	-0.152	-1.15
CARRRISK					-0.207	-3.69	-0.206	-3.69	-0.189	-3.33
Number of obs	788		788		775		775		775	
Calculated Values										
E[MER]	2.30									
E[MER(0)]							3.67			
E[MER(5)]			3.31		3.23		3.24			
E[MER(15)]			2.41		2.43		2.39			
E[MER(25)]			1.50		1.54		1.54			
t*							31.40			

Appendix: Proofs of latency and survival probability effects on MER

A.1 The effect of cancer latency on MER

As shown in equation (5), the effect on MER of increasing latency (t) depends on how it affects the lifetime utility of the cancer profile. Expanding on equation (6), the effect on U(C(t), Y) of increasing latency by one period, from t to t+1, can be written as

$$\begin{aligned}
&U(C(t+1),Y) - U(C(t),Y) \\
&= \left(\sum_{i=1}^{t-1} (s_i)(d_i)u^h(y_i) \right) + (s_t)(d_t)u^h(y_t) + (s_{t+1})(d_{t+1})u^c(y_{t+1}) \\
&- \left(\sum_{i=1}^{t-1} (s_i)(d_i)u^h(y_i) \right) - (s_t)(d_t)u^c(y_t) \\
&= (s_t)(d_t)\left[u^h(y_i) - u^c(y_t)\right] + (s_{t+1})(d_{t+1})u^c(y_{t+1})
\end{aligned} \qquad \text{(A.1)}$$

For simplicity, the duration of each time period, as indexed by i, is the same as the duration of cancer morbidity (i.e., between diagnosis and death). The first term in equation A.1 will be positive as long as the utility of a period in normal health, $u^h(y)$, is greater than with cancer, $u^c(y)$. Even if the utility of a period (t or t+1) with cancer is negative, the second term in this expression will also be less in absolute value terms than the first, as long as $u^h(y)$ is positive (and y_{t+1} is not substantially less than y_t). Consequently, an increase in latency should increase U(C(t),Y) and decrease MER. This result is consistent with the intuition that extending cancer latency will reduce aversion to cancer risks.

A.2 The effect of survival probability on MER

In contrast to a change in cancer latency, an increase in survival probability, s_t, will affect MER through both the cancer and the normal health utility profiles. To examine the effect of increasing s_t on the MER, we must examine its effect on the ratio U(C.Y)/U(H.Y). To do this we first define the following expressions:

$$\begin{aligned}
A &= \sum_{i=0}^{t-1} (s_i)(d_i)u^h(y_i) \\
B &= (d_t)u^c(y_t) \\
C &= \sum_{j=t}^{\infty} (s_{jt})(d_j)u^h(y_j)
\end{aligned} \qquad \text{(A.2)}$$

Where

$$R = \frac{U(C(t),Y)}{U(H,Y)} = \frac{A + s_t B}{A + s_t C}$$

s_{ij} = probability of surviving to period j conditional on surviving to period t

Differentiating the lifetime utility ratio R with respect to s_t, we get:

$$\frac{\partial R}{\partial s_t} = \frac{A(B-C)}{(A+s_t C)^2} < 0 \qquad \text{if } A>0 \text{ and } B<C \qquad \text{(A.3)}$$

These results imply that as long as the healthy state provides positive utility, and this utility is greater than the utility in the cancer state, then, *for a given latency t*, increasing the probability of survival to t, will decrease U(C(t),Y) and increase MER. In other words, for a given cancer latency, increasing the probability of survival for that period will increase aversion to cancer risks.

DISCUSSION PAPER

April 2006 ■ RFF DP 06-19

Adjusting the Value of a Statistical Life for Age and Cohort Effects

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Adjusting the Value of a Statistical Life for Age and Cohort Effects

Joseph E. Aldy and W. Kip Viscusi

Abstract

To resolve the theoretical ambiguity in the effect of age on the value of statistical life (VSL), this article uses a novel, age-dependent fatal risk measure to estimate age-specific hedonic wage regressions. VSL exhibits an inverted-U shaped relationship with age. In the year 2000 cross-section, workers' VSL rises from \$3.2 million (ages 18–24), to \$9.9 million (35–44), and declines to \$3.8 million (55–62). Controlling for birth-year cohort effects in a minimum distance estimator yields a peak VSL of \$7.8 million at age 46 and flattens the VSL-age relationship. The value of statistical life-year also follows an inverted-U shape with age.

Key Words: value of statistical life, job risks, hedonic wage regression, VSLY

JEL Classification Numbers: J17, I12

Contents

Adjusting the Value of a Statistical Life for Age and Cohort Effects

Joseph E. Aldy and W. Kip Viscusi*

A strident controversy with respect to the value of life has been whether the benefit of reducing risks to the old are less than for younger age groups. In particular, should there be a so-called "senior discount" when assessing the value of reduced risks to life? This question has drawn the attention of policymakers in a number of countries. In 2000, Canada employed a value of statistical life (VSL) for the over-65 population that is 25 percent lower than the VSL for the under-65 population (Hara and Associates 2000). In 2001, the European Commission recommended that member countries use a VSL that declines with age (European Commission 2001). In 2003, the U.S. Environmental Protection Agency (EPA), which has traditionally employed a constant value of a statistical life to monetize mortality risk reductions irrespective of the age of the affected population, conducted analyses of the Clear Skies initiative that included a "senior discount."[1] This effort to apply such a discount in its Clear Skies initiative analyses generated a political firestorm and ultimately led to abandonment of any age adjustments in benefit values assigned by the Agency.[2]

Intuitively one might expect that older individuals may value reducing risks to their lives less because they have shorter remaining life expectancy. The commodity they are buying through risk reduction efforts is less than for younger people. Carrying this logic to its extreme,

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[1] In the "senior discount" analyses, the EPA provided two alternatives to account for age. One approach was based on a standard value of a statistical life-year approach that explicitly accounts for life expectancy. The second approach assumed that individuals over age 70 had a value of statistical life equal to 63 percent of the value for those under 70.

[2] For a sense of the political reaction and EPA's decision to discontinue the use of an age-based value of statistical life, refer to "EPA Drops Age-Based Cost Studies," *New York Times*, May 8, 2003; "EPA to Stop 'Death Discount' to Value New Regulations," *Wall Street Journal*, May 8, 2003; and "Under Fire, EPA Drops the 'Senior Death Discount,'" *Washington Post*, May 13, 2003.

the VSL would peak at birth and decline steadily thereafter. For models in which consumption is constant over the life cycle, Jones-Lee (1989) showed that the VSL should decrease with age. Whether consumption will in fact be constant over time depends critically on the presence of perfect capital and insurance markets.

Numerous theoretical studies have shown that the age variation in VSL becomes more complex once changes in consumption over time are introduced into the analysis. Changes in consumption levels and wealth over the life cycle influence risk-money tradeoffs in a complex manner. Johansson (2002) concluded that the theoretical relationship between the VSL and age is ambiguous and could be positive, negative, or zero. Often theoretical studies, however, have imposed additional structure on the analysis, implying that there is either an inverted U-shaped relationship between the value of statistical life and age or that VSL decreases with age. The simulations by Shepard and Zeckhauser (1984) show a steadily declining value of life if there are perfect annuity and insurance markets, and an inverted-U VSL-age relationship in an economy with no borrowing or insurance, as do Johansson (1996) and Ehrlich and Yin (2004). Rosen (1988), Arthur (1981), and Cropper and Sussman (1988) also present simulation results with VSL decreasing with age.

Empirical evidence based on labor market data may be instructive in resolving the theoretical ambiguity in the VSL-age relationship. Viscusi and Aldy (2003) review eight studies of labor markets in Canada, India, Switzerland, and the United States that included an age-mortality risk interaction term in their hedonic wage analysis. Five studies estimated statistically significant coefficient estimates on the age-risk interaction and all find a negative effect indicating that older workers value risks to their lives less.[3] These results imply implausibly low VSL levels with negative VSL amounts beginning at ages ranging from 42 to 60. The failure of labor market evidence to resolve the age variation issue may stem in part from data limitations. All these labor market studies use fatality risk data that are based on industry averages rather than age-specific values, causing potential biases, where the magnitude of the bias varies with age. If, for example, average industry fatality risks for workers of all ages overstate the risks faced by older workers, the estimated implied VSL amounts for older workers will understate the wage-risk tradeoffs that are actually being made.

[3] These studies are reviewed in Section 8 of Viscusi and Aldy (2003). In contrast, a recent study by Smith et al. (2004) has found that the value of statistical life is increasing with age and risk aversion for workers 51–65 years of age.

All previous papers assessing how the compensating differential for job mortality risk varies with age have employed cross-sectional survey data. By using a single cross-section, such approaches confound the cohort-specific influence and age-specific effects on the estimated compensating differential. The cohort influence based on the year of birth should have an unambiguous effect on VSL. Lifetime incomes are rising over time, and the VSL has a positive income elasticity of 0.5 to 0.6.[4] Because older workers belong to an earlier cohort with lower lifetime incomes, they will tend to be willing to pay less for a given risk reduction, implying a lower VSL. The pure age effect is less clear-cut. As a worker ages, there are fewer years of remaining life expectancy, implying lower benefits for a given risk reduction, which should reduce the worker's willingness to pay to reduce risk. This effect is unambiguous if capital markets are perfect. In a world with imperfect capital markets, however, lower income younger workers will not be able to borrow against higher future expected earnings. This will depress their VSLs at young ages until borrowing constraints become less stringent, resulting in an age-related VSL trajectory similar to the inverted-U shape of life-cycle consumption patterns. Extending the traditional analysis to a pooled series of cross-sections will enable us to distinguish age effects from cohort effects. Two separate, but both policy-relevant, questions can then be considered: (1) How does the value of life vary with age across the population? and (2) How do differences in cohorts influence this relationship?

This article extends the previous literature in several respects. Because our focus is on risky labor market decisions, we make job risk decisions a choice variable in a life-cycle consumption model in Section I, deriving an expression for VSL in this context. In Section II, we present empirical estimates how the VSL varies over the life cycle through conventional hedonic wage equations and a minimum distance estimator. These results reflect two innovations to this literature: (1) we employ age-specific job mortality and nonfatal injury risks in our hedonic wage analyses; and, (2) we estimate how the VSL changes over the life cycle by pooling eight years of cross-sectional data and by using a minimum distance estimator that controls for cohort effects based on year of birth. In these empirical approaches, the VSL rises and then falls across the population and over the life cycle. In the cross-sectional analysis, the VSL peaks at age 39 and subsequently declines so that the VSL for workers in their early 60s have values of about $2 million. In the cohort-adjusted analysis, the VSL peaks at age 46, and experiences a more modest

[4] See Viscusi and Aldy (2003) for a meta-analysis of the VSL income elasticity value.

decline to about $5 million by age 62.[5] In Section III, we calculate age-specific values of statistical life-years (VSLY) from our age-VSL profiles and find that VSLYs also take an inverted-U shape with a peak at an older age than the VSLs. In the cross-sectional analysis, the VSLY peaks at $375,000 at age 45 and subsequently declines to about $150,000 in workers' early 60s. In the cohort-adjusted analysis, the VSLY peaks at $401,000 at age 54, and experiences a more modest decline to about $350,000 by age 62. Section IV concludes the paper.

I. Wage-Risk Tradeoffs over the Life Cycle

The standard approach in the life-cycle VSL literature employs a time-separable utility function in one consumption good, integrated over the life-cycle subject to a discount function and a survival function, as in Shepard and Zeckhauser (1984), Rosen (1988), Johansson (1996, 2002), and Johannesson et al. (1997). The only choice variable is the level of consumption over time. In these analyses, the value of statistical life is given by a representative agent's expected present value of consumer surplus conditional on having achieved a given age. For example, Shepard and Zeckhauser represent this as the ratio of expected remaining lifetime utility to the marginal utility of consumption.

To motivate our empirical work, we provide a model of wage-risk tradeoffs in a life-cycle setting. We modify and extend the standard life-cycle approach to explicitly account for the choice of job fatality risk on the survival function and the worker's wage. Since a change in job fatality risk affects both the worker's wage and life expectancy, our approach provides an alternative illustration of the VSL varies over the life cycle by characterizing the wage-risk tradeoff given the impacts of both on future consumption. By incorporating a compensating differential framework in our model, we can demonstrate how the wage-risk trade-off varies over the life cycle, which is what we will estimate in our empirical work presented below.

Our simple model indicates variations in VSL, but the linkage is ambiguous. This life-cycle model can illustrate the influences – especially the life-cycle variation in consumption – that can generate an inverted U-shaped relationship between VSL and age. The worker's problem can be characterized by maximizing discounted expected remaining lifetime utility:

$$\max_{p,c} EU(\tau) = \int_{\tau}^{\infty} u[c(t)]\sigma[t;\tau, p(t)]e^{-rt}dt \,, \tag{1}$$

[5] All VSL estimates are presented in year 2000 dollars in this paper.

subject to

(2a) $\dot{k}(t) = rk(t) + w[t, p(t)] - c(t) + f(t)$,

(2b) $k(t) \geq 0$,

and

(2c) $\lim_{t \to \infty} k(t)e^{-rt} = 0$,

where

p represents the probability of dying on the job,

$u(c)$ represents the utility of consumption, c, and $u'(c) \geq 0$, $u''(c) \leq 0$,

k represents assets,

w represents labor income,

e^{-rt} represents the discount function,

$\sigma[t; \tau, p(t)]$ represents the survival function, i.e., the probability of surviving to age t, given that the individual has reached age τ,[6]

r represents the return on assets, and

$f(t)$ represents the net amount received through an actuarially fair annuity represented by the condition:

$$\int_0^\infty e^{-rt}\sigma[t;0, p(t)]f(t)dt = 0 .$$ [7]

The worker's expected utility is represented in (1) as the sum of period utilities weighted by a discount factor and the probability that the worker will survive to that period conditional on the worker's current age. The worker maximizes this expected utility expression subject to the constraints: (2a) represents the dynamic budget constraint, and it allows for the worker's assets

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[6] This expression of the survival function follows Johansson (1996): $\sigma[t; \tau, p(t)] = \sigma[t; p(t)] / \sigma(\tau)$.

[7] To simplify notation, we have followed Shepard and Zeckhauser and assumed that the rate of time preference in the discount function is equal to the rate of return on assets, and that this rate is time-invariant. Allowing for the rate of time preference to differ from the return on assets would not substantively influence the primary conclusion of this analysis that the age-VSL relationship is ambiguous.

to change over time based on capital income $rk(t)$, labor income $w[t, p(t)]$, consumption $c(t)$, and net annuity receipts $f(t)$; (2b) provides a no debt condition; and (2c) is the standard no Ponzi game condition. The actuarially fair annuity envisioned here is similar to that in Shepard and Zeckhauser's (1984) perfect markets case, and the annuity allows for the worker to borrow against human capital during early years of life to provide for consumption smoothing.

The present value Hamiltonian, conditional on having lived to age τ, is given by:

(3) $$H(t) = u[c(t)]\sigma[t;\tau, p(t)]e^{-rt} + \lambda(t)\left[rk(t) + w[t, p(t)] - c(t) + f(t)\right]$$

where $\lambda(t)$ represents the present value costate variable. The first-order conditions for the Hamiltonian are:

(4) $$\frac{\partial H}{\partial c} = u_c \sigma e^{-rt} - \lambda = 0,$$ [8]

(5) $$\frac{\partial H}{\partial p} = u\sigma_p e^{-rt} + \lambda w_p = 0,$$

and

(6) $$-\frac{\partial H}{\partial k} = \dot{\lambda} \rightarrow \dot{\lambda} = -r\lambda .$$

To see more generally how the value of a statistical life varies with age, we rearrange (5), differentiate with respect to time, where time derivatives are denoted by a dot over the variables in question, and substitute into (6), yielding:

(7) $$\frac{\dot{w}_p}{w_p} = \frac{\dot{u}}{u} + \frac{\dot{\sigma}_p}{\sigma_p}$$

The percentage change over time in the compensating differential for job fatality risk is equal to the percentage change over time in utility and the percentage change over time in the change in the survival function with respect to job fatality risk.[9] This expression holds irrespective of the assumption of actuarially fair annuity markets, although the assumption regarding these markets clearly influences the change in utility over the life cycle. The sign on

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[8] This is essentially identical to equation 12 of Shepard and Zeckhauser (1984).

[9] Note that the survival function, $\sigma[t;\tau, p(t)]$, and the discount function, e^{-rt}, implicitly enter equation (7) through their influence on the optimal consumption and job fatality risk paths.

equation (7) is ambiguous without imposing restrictions on the survival function and specifying the assumptions regarding annuity markets. This ambiguity is consistent with the life-cycle model provided by Johansson (2002) and the simulation results based on the life-cycle model in Shepard and Zeckhauser (1984). This theoretical ambiguity motivates our interest in resolving empirically how the value of a statistical life varies over the life cycle.

II. Hedonic Wage Methods and Results

To assess empirically the age-VSL relationship, we have expanded the standard hedonic wage framework in two ways. First, using our new and more refined age-specific job-related mortality and injury data, we estimated hedonic wage regressions that allow for the compensating differential for these risks to vary among five age groups. These results indicate how the VSL varies with age across the population. Second, we develop a minimum distance estimator that incorporates age-specific hedonic wage regressions in the first stage and controls for cohort effects in the second stage. This analysis, based on eight years of pooled cross-sections, indicates how the value of life varies with an individual's age.

A. Data

To characterize the fatality risks faced by workers of different ages more precisely than is possible using average risk values by industry, we constructed a novel risk measure conditional upon age and the worker's industry rather than using an industry basis alone, which is the norm for all previous studies of age variations in workers' VSL. The source of the fatality measures is the Bureau of Labor Statistics (BLS) Census of Fatal Occupational Injuries (CFOI), for the 1992-2000 period. We structured the mortality risk cells by 2-digit SIC industries and these six age groups specified in the CFOI data: 16–19, 20–24, 25–34, 35–44, 45–54, and 55–64. To construct the denominator for the mortality risk variable, we used the 1992–2000 Current Population Survey Merged Outgoing Rotation Group files to estimate worker populations for each cell in the mortality data. The annual mortality risk measures are averaged to minimize any potential distortions associated with catastrophic mortality incidents in any one year and to have a better measure of the underlying risks for industry-age groups with infrequent deaths. Our injury risk measure, the probability of a lost-workday injury, also varies by age, and we constructed it in an identical manner for each 2-digit industry and for each of the age groups listed above. While injury risk decreases with age across most industries, mortality risk increases monotonically with age in all industries, except for in mining.[10]

We have matched these constructed mortality risk and injury risk measures by age and industry with data on adult workers in the Current Population Survey Merged Outgoing Rotation Group data files for 1993–2000. We employed a number of screens in constructing our sample for analysis. The sample excludes agricultural workers and members of the armed forces. We have excluded workers younger than 18 and older than 62, those with less than a 9th grade education, workers with an effective hourly labor income less than the minimum wage, and less than full-time workers, which we defined as those working at least 35 hours per week.

B. Hedonic Wage Regression Framework

The standard hedonic wage model estimates the locus of tangencies between the market offer curve and workers' highest constant expected utility loci. The age variation in the wage-mortality risk tradeoff simultaneously reflects age-related differences in preferences as well as age-related differences in the market offer curve. If older workers are more likely to be seriously injured than are younger workers because of age-related differences in safety-related productivity, then the market offer curve will reflect that, given that age is a readily monitorable attribute. Because workers' constant expected utility loci and firms' offer curves each may vary with age, there is no single hedonic market equilibrium. Rather, workers of different ages will settle into distinct market equilibria as workers of different ages select points along the market opportunities locus that is pertinent to their age group.[11]

Conventional hedonic wage analyses of job risks specify the natural logarithm of the hourly wage or some comparable income measure as a function of worker and job characteristics, mortality risk, and, in more comprehensive specifications, injury risk and a measure of workers' compensation. Our base specification takes the following form:

$$\ln(w_i) = \alpha + H_i'\beta + \gamma_1 p_i + \gamma_2 q_i + \gamma_3 q_i WC_i + \varepsilon_i\,, \tag{8}$$

where

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[10] Refer to Aldy and Viscusi (2004) for more details about the construction of this age-specific job mortality risk measure.

[11] This analysis generalizes the hedonic model analysis for heterogeneous worker groups using the model developed for an evaluation of smokers and nonsmokers by Viscusi and Hersch (2001). Their worker groups differ in their safety-related productivity and in their attitudes toward risk.

w_i is the worker i's hourly after-tax wage rate,

H is a vector of personal characteristic variables for worker i,

p_i is the fatality risk associated with worker i's job,

q_i is the nonfatal injury risk associated with worker i's job,

WC_i is worker i's compensation replacement rate for a job injury, and

ε_i is the random error reflecting unmeasured factors influencing worker i's wage rate.

We calculated the workers' compensation replacement rate on an individual worker basis taking into account state differences in benefits and the favorable tax status of these benefits. We use the benefit formulas for temporary total disability, which comprise about three-fourths of all claims, and have formulas similar to those for permanent partial disability.[12] The terms α, β, γ_1, γ_2, and γ_3 represent parameters to be estimated.

All wage regression specifications used in this paper include the following controls: demographic indicator variables (race and ethnicity, gender of head of household, marital status, union membership, public sector employment, and resident of urban area); educational attainment; indicator variables for one-digit occupation and region of residence; and job mortality risk, job nonfatal injury risk, and expected workers' compensation replacement rate.[13]

The estimated regression then yields a measure of the average value of a statistical life for the sample:

$$VSL = \hat{\gamma}_1 * \overline{w} * 2{,}000 * 100{,}000 . \tag{9}$$

This equation normalizes the VSL to an annual basis by the assumption of a 2,000-hour work-year and by accounting for the units of the mortality risk variable. As a preliminary check on our age-industry risk variables, we estimated equation (8) with the 1997 CPS MORG and compared this with the results for industry risk variables merged with the 1997 CPS MORG

[12] The procedures for calculating the workers' compensation benefit variable are discussed in more detail in Viscusi (2004), which also provides supporting references.

[13] The workers' compensation expected replacement rate represents the interaction of a worker's injury rate and that worker's estimated workers' compensation wage replacement rate based on the worker's wage, state of residence, state benefit formulas, and estimated state and federal tax rates. Given the endogeneity of the wage, we have also estimated instrumental variables regressions. IV estimation does not qualitatively influence determinations of coefficient magnitudes or statistical significance for the mortality risk variable of interest in this study. Refer to Aldy and Viscusi (2004) for additional details.

dataset presented in Viscusi (2004). We estimated a mean VSL of $4.5 million (1997$), which is virtually indistinguishable from the Viscusi (2004) estimate of $4.7 million, and both studies fall within the range of VSLs from hedonic wage regression studies of the U.S. labor market reported in Viscusi and Aldy (2003).[14]

C. Estimated Age Group VSLs

As an initial assessment of how the value of life varies with age across the population, we modified (8) so that the estimated compensating differentials can vary by age. We interacted five age group indicator variables – for age groups 18–24, 25–34, 35–44, 45–54, and 55–62 – with the various risk measures, and included the first four age group indicator variables in the specification:

$$\text{(8a)}\quad \ln(w_i) = \alpha + H_i'\beta + \sum_{j=1}^{4}\delta_j age_j + \sum_{j=1}^{5}\gamma_{1j} age_j p_i + \sum_{j=1}^{5}\gamma_{2j} age_j q_i + \sum_{j=1}^{5}\gamma_{3j} age_j q_i WC_i + \varepsilon_i,$$

where age_j are the indicator variables for the five age groups and δ_j are parameters to be estimated.

We estimated this modified specification with eight annual CPS MORG samples from 1993–2000 and our industry by age job mortality risk and nonfatal injury risk data.[15] As distinct cross-section regressions, these specifications cannot discern age effects from cohort effects. They do, however, reveal how much an individual currently in one age group at a point in time is willing to pay for a given risk reduction vis-à-vis how much a different individual currently in another age group is willing to pay for such a risk reduction.

Table 1 presents the age-group specific results for this specification. We report two sets of standard errors: White heteroskedasticity-adjusted standard errors and robust and clustered standard errors that account for within-group correlations due to the assignment of the same job risk level to workers in an age-industry cell in each year.[16] The eight annual cross-section

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[14] In our analysis with the 1997 CPS MORG, the mortality risk coefficient estimate is 0.0019 with a robust standard error of 0.00021.

[15] Note that we used averages of the lagged risk measures in these analyses. For example, the 1995 regression included risk measures averaged over 1992-1994 while the 2000 regression included risk measures averaged over 1992–1999.

[16] Refer to Hersch (1998) and Viscusi and Hersch (2001) as examples of papers in this literature that account for this type of correlation.

regressions reveal similar patterns of the VSL with respect to age: an inverted-U shape with the VSL peaking for the 35–44 age group in six of the eight years. As an illustration, consider the results for the year 2000 cross-section. The coefficient estimate on the 18–24 age group mortality risk variable is 0.0021, and it increases substantially to 0.0039 for the 25–34 age group. The mortality risk coefficient then declines with age: 0.0036 for the 35–44 age group, 0.0028 for the 45–54 age group, and 0.0014 for the 55–62 age group. The five age-group-specific job mortality risk coefficient estimates are individually statistically significant at the 1 percent or 5 percent level. The estimated VSLs for each age group depend on these coefficient estimates as well as age-group-specific average wages, which follow an inverted-U shape over the life cycle. The 35–44 age group has the largest VSL of $9.85 million, more than triple the 18–24 VSL of $3.16 million and nearly triple that of the 55–62 VSL of $3.77 million.[17]

To show how these differences in magnitudes are often statistically significant, we focus on the results for the year 2000 cross-section, which we report again at the top of Table 2. We conducted a series of pairwise Wald tests on the estimated VSLs, and the table presents the F-statistics associated with these tests. The first row of these tests shows that the 18–24 VSL of $3.16 million is statistically different from the VSL estimates for the next three age groups, but does not differ significantly from the 55–62 VSL of $3.77 million. The last column, corresponding to the 55–62 age group, shows that the estimated 55–62 VSL differs significantly from the VSL estimates for the 25–34 age group, the 35–44 age group, and the 45–54 age group. These results indicate that the VSL takes an inverted-U with respect to age across a population. The VSL pattern is relatively flat in the middle age groups as there is no statistically significant difference among the age 25–34, 35–44, and 45–54 categories for the 2000 cross-section.

D. Minimum Distance Estimator and Cohort Effects

We have extended this age-specific regression analysis in subsection C through a two-stage minimum distance estimator using VSL estimates for each year rather than age bands. This approach allows us to infer information about the VSL with respect to age based on a larger number of regressions based on more narrowly defined age bands for each year. While these individual regressions will provide less precise estimates of the compensating differential for risk

[17] Refer to Jones-Lee et al. (1985) for an example of a stated willingness to pay for safety study that also finds an inverted-U shaped VSL-age relationship.

than broader age groups, it will then be possible to estimate VSLs as a function of age if age-specific VSLs follow a systematic pattern over the life cycle.

In the first stage, we estimate age-specific hedonic wage regressions of the form expressed in equation 8 and use the mortality risk coefficient estimates to construct age-specific VSL. We estimated age-specific compensating differentials for 45 age levels from age 18 to 62 and eight cross-sections from 1993–2000, yielding 360 separate regressions. With the exception of the youngest and oldest birth-year cohorts, every cohort has eight observations in our constructed panel.[18] We estimated the VSL using the mean real wage for that respective age and year. Based on these first stage regressions, we construct a panel of cohort-specific and age-specific VSL estimates. Each VSL estimate is assigned to a birth-year cohort. For example, the estimated VSL for a 40-year old in 1993 is assigned to the 1953 birth-year cohort; the estimated VSL for a 41-year old in 1994 is also assigned to the 1953 birth-year cohort, and so on. We followed this procedure for all 360 VSL estimates.

In the second stage, we specify these VSLs by age. To characterize how the VSL estimates from the first stage, $V\hat{S}L$, vary with age across a population, the second stage includes a polynomial in age, $a(\theta)$. To characterize how the VSL varies over the life cycle, we account for the differences across cohorts by including a vector of birth-year indicator variables, c, in addition to the age polynomial. We also employ $\hat{V}$, the inverse of a diagonal matrix of the variance estimates of these VSLs, as a weight matrix based on Chamberlain's (1984) analysis of the minimum distance estimator and the choice of the inverse of the variance-covariance matrix as the optimal weight matrix.[19, 20]

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[18] Refer to Deaton (1985) and Deaton and Paxson (1994) for the advantages of such a constructed panel based on birth-year cohorts.

[19] Because of the potential small sample bias in the optimal minimum distance estimator, we also evaluated the equally weighted minimum distance estimator (Altonji and Segal 1996). To address concerns about the small sample bias, we have presented the results for the equally weighted minimum distance estimator in Figures 1 and 2. The choice of weight matrix has no qualitative impact on our conclusions.

[20] We have employed a test of overidentifying restrictions to assess the appropriate order of the polynomial in age. If we assume that θ is a Kx1 vector, then a restricted parameter vector, α, which is Rx1 where R<K, can be estimated by some function, $b(\alpha)$. The following test statistic can then be used to evaluate the restrictions on the parameter vector:

$$N[V\hat{S}L - b(\hat{\alpha})]'\hat{V}^{-1}[V\hat{S}L - b(\hat{\alpha})] - N[V\hat{S}L - a(\hat{\theta})]'\hat{V}^{-1}[V\hat{S}L - a(\hat{\theta})] \sim \chi^2_{K-R}.$$

An analogous statistic was employed to evaluate the order of the age function in the cohort-based minimum distance estimator.

For the cross-sectional analysis, the minimum distance estimator solves:

$$\min_{\theta\in\Theta}[V\hat{S}L - a(\theta)]'[\hat{V}]^{-1}[V\hat{S}L - a(\theta)]. \tag{10}$$

For the life-cycle (cohort-adjusted) analysis, the minimum distance estimator solves:

$$\min_{\theta\in\Theta,\delta\in\Delta}[V\hat{S}L - a(\theta) - c'\delta]'[\hat{V}]^{-1}[V\hat{S}L - a(\theta) - c'\delta]. \tag{11}$$

where θ and δ represent parameters to be estimated. We specified $a(\theta)$ in a variety of analyses as a polynomial in age of order one to order eight.

The solid curve in Figure 1 presents the fitted age-VSL functions based on a third-order polynomial in age specification (cross-section VSL), while the dashed line presents the relationship based on a third-order polynomial in age with birth-year cohort indicator variables (cohort-adjusted VSL).[21] In the pooled cross-sections, the value of statistical life increases with age from age 18 with a VSL of $4.87 million through age 39, at which the VSL peaks at $8.27 million. The value of a statistical life then declines with age to a minimum of $1.67 million at the highest age in the sample, which is 62. The cohort-adjusted function, also yields a VSL that follows an inverted-U shape over the life cycle. It starts at $3.39 million at age 18, peaks at $7.79 million at age 46, and then declines to $5.09 million at age 62. Across the population and along the life cycle, the value of statistical life increases, peaks, and then decreases with age. While not presented, the birth-year indicator variables follow a general trend of increasing values with year of birth, consistent with the proposition that the value of life has increased with temporal increase in lifetime income.

The cohort adjustment affects the age-related pattern of VSLs in several ways. The peak of the age-VSL curve is seven years later when accounting for date of birth. The high VSLs for younger age groups is due in part to their higher lifetime wealth, as their cross-section VSLs lie above those in the cohort-adjusted values. For older age groups the pattern is reversed. While there is a steep drop in VSL levels with age in the cross-section results, this decline is due in part to cohort effects. Accounting for cohort differences attributable to changes in lifetime income more than doubles the estimated VSLs for the older age groups and flattens their VSL trajectory. Finally, the counter-clockwise pivoting of the VSL function from the cross-sectional analysis to

[21] Based on the specification test presented in footnote 17, we could not reject the hypothesis that a third-order age polynomial fit the data as well as higher-ordered polynomials. We could, however, reject the hypothesis that lower-ordered polynomials fit the data as well as a third-order polynomial.

the cohort-adjusted analysis also illustrates the importance of accounting for lifetime income, implicitly through the birth-year indicator variables, in estimating the age-VSL relationship over the life cycle.

We also tested two economic propositions that are prominent in current policy applications of the value of life. First, many analyses assume that the VSL remains constant, irrespective of age.[22] To assess this proposition, we employed our cohort-based minimum distance estimator and specified the age polynomial function as a constant. We then tested this restriction versus the more flexible, higher-ordered polynomials and we reject the hypothesis that the VSL is constant over the workers' life cycle at the 1 percent level in comparison with all age polynomials of order two or higher. Second, other analyses have assumed that the value of a statistical life is always decreasing with age.[23] To test this proposition, we specified the age polynomial function as linear, but such an approach yielded a negative coefficient estimate that clearly could not be distinguished from zero. The test of overidentifying restrictions rejected the linear specification in comparison to all higher-ordered polynomials. It should also be noted that all order two through order eight polynomials resulted in similar inverted U-shaped relationships between the value of a statistical life and age.[24]

IV. Implications for the Value of a Statistical Life-Year

The preceding section illustrates the estimated age-VSL profile consistent with the theory model presented in Section I and with previous simulations published in the literature. The implicit assumptions underlying the value of a statistical life-year (VSLY) approach, which requires the value of life to be decreasing with age at all ages, are rejected by our data. In light of the common application of VSLYs in evaluations of medical interventions and government regulations, such as those promulgated by the U.S. Food and Drug Administration and the U.S. Environmental Protection Agency in their sensitivity analyses, we have estimated age-specific VSLYs based on our age-specific VSLs.

[22] For example, most U.S. Environmental Protection Agency benefit-cost analyses, including September 2003 revisions to its assessment of the Clear Skies initiative, make this assumption.

[23] For example, this is consistent with the European Commission's proposed position and the life-year approach used by the U.S. Food and Drug Administration.

[24] We also evaluated whether the higher VSLs for individuals in the 25-44 age range reflect major life-cycle events such as marriage or having children, and not variations in age, but find no evidence to support this notion. Refer to Aldy and Viscusi (2004) for more details.

To construct values of statistical life-years, we have annuitized age-specific VSLs based on age-specific years of life expectancy L and an assumed discount rate r of 3 percent:[25]

$$VSLY = \frac{rVSL}{1-(1+r)^{-L}} . \tag{12}$$

Figure 2 presents these calculations for the cross-section and cohort-adjusted VSLs derived from the minimum distance estimator. The average VSLY is $296,000 for the cross-section and $302,000 for the cohort-adjusted estimates. VSLYs follow a similar inverted U-shaped relationship over the life cycle as depicted for VSL. The increase in VSLY is clearly expected for young workers because VSL is increasing and life expectancy is decreasing. The monotonic decrease in VSLY after its peak indicates that age-specific VSLs are decreasing at a faster rate than life expectancy. The peak in the VSLY occurs at a higher value and at a much higher age for the cohort-adjusted measure. It peaks at a value of $401,000 at age 54 for the cohort-adjusted measure, as compared to a peak of $375,000 at age 45 for the cross-section measure. The cohort-adjusted VSLY declines at a much slower rate than the VSLY after the peak for the cross-section measure. The influence of cohort adjustments has an even greater relative effect on the VSLY levels for the older workers in the sample than they did on VSL. Interestingly, the VSLY for those age 62 is higher than for all age 39 or younger.

V. Conclusion

The implications of wage-risk tradeoffs for the dependency of VSL on age is consistent based on both age group-specific estimated VSLs and a minimum distance estimator derived from age-specific VSLs. We find that the VSL rises and then falls with age across the population and over the life cycle, displaying an inverted U-shaped relationship. The minimum distance estimator results are perhaps most instructive, as they can more flexibly represent the age relationship while controlling for cohort effects. Failing to account for the secular increase in incomes with birth-year indicator variables yields much lower VSLs for older individuals and higher VSLs for younger individuals in cross-section analysis. Including cohort effects results in a much flatter age-VSL function over the life cycle, and older individuals have a higher value of a statistical life.

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[25] We have also calculated VSLYs based on a 7 percent discount rate (the current preferred rate by the U.S. Office of Management and Budget for evaluating government regulations). The higher discount rate yields larger VSLYs and a more pronounced inverted U-shaped age-VSLY relationship.

The result that the VSL rises and falls with age is of both theoretical and policy interest. Theoretical analysis of VSL over the life cycle suggests such a relationship may exist, particularly in situations in which there are insurance and capital market imperfections. The results are supportive of these models rather than those that generate steadily declining VSL with age, such as some models with perfect annuity and insurance markets. VSL is not steadily declining with age even though the amount of expected lifetime at stake steadily declines with age. As the life-cycle models indicate, this result is not surprising since the age-VSL linkage depends on factors such as the life-cycle consumption pattern, which also displays a similar age structure.

These estimates may help inform policymakers as they consider policies that would simultaneously reduce mortality risk for individuals of various ages. In terms of the appropriate "senior discount," in the cross-section analysis workers in their early 60s have a VSL of about $1.7–$2.0 million, which is between one-fifth and one-fourth the size of the VSLs for prime-aged workers. Understanding how the value of statistical life varies over the life cycle can inform policymakers as they consider government interventions that would reduce mortality risks posed to individuals over multiple stages of their life. The cohort-adjusted VSL levels for older workers are much higher than in the cross-section analysis, with a VSL of about $5 million for workers in their early 60s. While below the peak VSL over the life cycle, these older workers' VSLs are above the VSLs for very young workers. This analysis does not provide support for approaches that focus only on the remaining quantity of life as the valued attribute. Both the value per life-year approach and the quality-adjusted life year methodology yield a steadily decreasing VSL with age, whereas the revealed preferences of workers' risk decisions indicate a quite different relationship that rises and then declines with age. Explicit construction of age-specific values of statistical life-years from our age-VSL profiles show that the value of a statistical life-year varies with age. Likewise, there is no support for the standard practice of transferring VSLs from studies based on the average of the labor market to risk contexts specific to the elderly population. Individuals make decisions over risk and income that clearly indicates that the value of their life varies with age, but the relationship is not a simple one.

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Tables and Figures

Table 1. Age Group-Specific Values of a Statistical Life, Annual Cross-Sections, 1993-2000[a]

Year		18-24 Age Group	25-34 Age Group	35-44 Age Group	45-54 Age Group	55-62 Age Group
1993	Mortality Risk	0.00040 (0.00045) [0.00046]	0.00434 (0.00040)*** [0.00077]***	0.00308 (0.00041)*** [0.00084]***	0.000728 (0.00041)* [0.00068]	0.00089 (0.00066) [0.00087]
	Mean VSL	$0.64	$9.92	$8.36	$2.04	$2.36
1994	Mortality Risk	0.00238 (0.00047)*** [0.00064]***	0.00329 (0.00038)*** [0.00064]***	0.00277 (0.00038)*** [0.00078]***	0.00132 (0.00043)*** [0.00078]*	0.00176 (0.00065)*** [0.00083]**
	Mean VSL	$3.97	$7.73	$7.75	$3.86	$4.87
1995	Mortality Risk	0.00298 (0.00051)*** [0.00064]***	0.00313 (0.00039)*** [0.00063]***	0.00223 (0.00039)*** [0.00079]***	0.00174 (0.00042)*** [0.00078]**	0.00162 (0.00059)*** [0.00080]**
	Mean VSL	$4.87	$7.31	$6.16	$5.02	$4.46
1996	Mortality Risk	0.00319 (0.00077)*** [0.00089]***	0.00350 (0.00043)*** [0.00069]***	0.00310 (0.00044)*** [0.00084]***	0.00163 (0.00043)*** [0.00070]**	0.00124 (0.00056)** [0.00069]*
	Mean VSL	$5.13	$8.08	$8.45	$4.67	$3.39
1997	Mortality Risk	0.00288 (0.00058)*** [0.00075]***	0.00348 (0.00043)*** [0.00071]***	0.00329 (0.00043)*** [0.00076]***	0.00196 (0.00043)*** [0.00073]***	0.00162 (0.00061)*** [0.00080]**
	Mean VSL	$4.60	$8.08	$8.98	$5.64	$4.47
1998	Mortality Risk	0.00346 (0.00064)*** [0.00086]***	0.00283 (0.00045)*** [0.00068]***	0.00305 (0.00044)*** [0.00076]***	0.00159 (0.00045)*** [0.00072]**	0.00158 (0.00058)*** [0.00078]***
	Mean VSL	$5.65	$6.76	$8.61	$4.69	$4.55
1999	Mortality Risk	0.00154 (0.00052)*** [0.00059]***	0.00359 (0.00050)*** [0.00071]***	0.00355 (0.00050)*** [0.00089]***	0.00337 (0.00048)*** [0.00082]***	0.00162 (0.00063)*** [0.00086]*
	Mean VSL	$2.18	$7.18	$8.41	$8.35	$3.95
2000	Mortality Risk	0.00211 (0.00060)*** [0.00073]***	0.00391 (0.00049)*** [0.00074]***	0.00356 (0.00047)*** [0.00088]***	0.00277 (0.00046)*** [0.00074]***	0.00135 (0.00059)** [0.00086]
	Mean VSL	$3.16	$9.03	$9.85	$7.97	$3.77

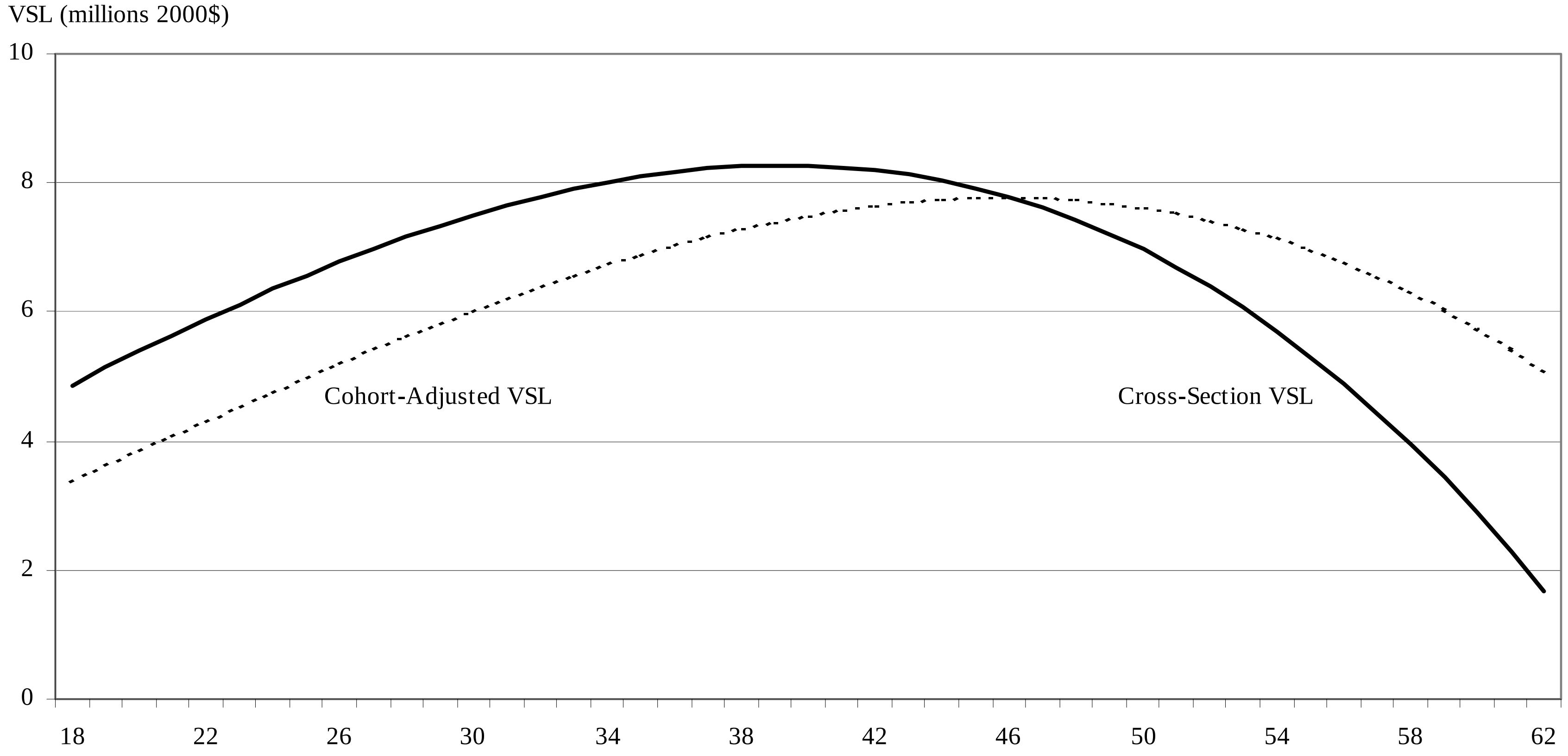
[a] VSLs are expressed in millions of year 2000 dollars based on age-specific wages. Dependent Variable: natural logarithm of hourly labor income. Each specification includes 9 1-digit occupation indicator variables, 8 regional indicator variables, demographic variables, nonfatal injury risk, and expected workers' compensation replacement rate. Robust (White) standard errors are presented in parentheses, and standard errors accounting for within-group correlation are presented in brackets. ***, **, * Indicates statistical significance at 1 percent, 5 percent, and 10 percent levels, two-tailed test.

Table 2. Age Group-Specific Values of a Statistical Life, 2000[a]

	18-24 Age Group	25-34 Age Group	35-44 Age Group	45-54 Age Group	55-62 Age Group
Mortality Risk	0.00211 (0.00060)*** [0.00073]***	0.00391 (0.00049)*** [0.00074]***	0.00356 (0.00047)*** [0.00088]***	0.00277 (0.00046)*** [0.00074]***	0.00135 (0.00059)** [0.00086]
Mean Age Group VSL (millions 2000$)	$3.16	$9.03	$9.85	$7.97	$3.77
<u>Age Group</u>	H_0: Pairwise Tests of Equality of VSL Estimates, F-Statistics, F(1, 118,639)				
18-24	-	16.16	17.52	8.89	0.10
25-34	-	-	0.22	0.36	6.94
35-44	-	-	-	1.01	8.39
45-54	-	-	-	-	3.97

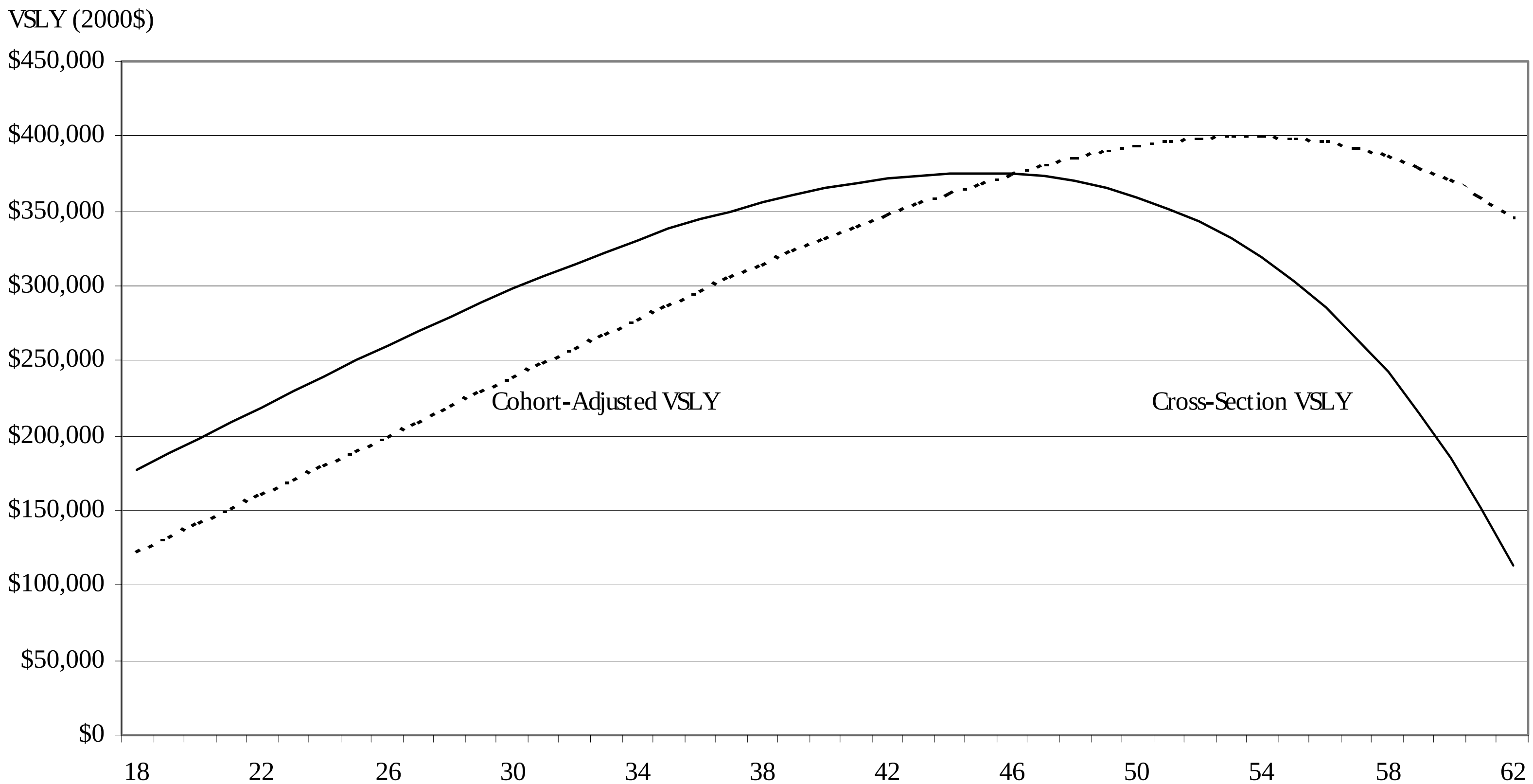
[a] N = 118,762. R^2 = 0.56. Dependent Variable: natural logarithm of hourly labor income. Specification includes 9 1-digit occupation indicator variables, 8 regional indicator variables, demographic variables, nonfatal injury risk, and workers' compensation expected replacement rate. Robust (White) standard errors are presented in parentheses and standard errors accounting for within-group correlation are presented in brackets. ***, ** Indicates statistical significance at 1 percent, and 5 percent levels, two-tailed test.

Figure 1. Cohort-Adjusted and Cross-Section Value of Statistical Life, 1993–2000



NOTES: Both series are based on equally weighted minimum distance estimator with a third-order polynomial in age. The cohort-adjusted VSL also includes indicator variables for year of birth.

Figure 2. Value of a Statistical Life-Year Based on Cohort-Adjusted and Cross-Section Value of Statistical Life, 1993–2000



NOTES: Value of statistical life-years based on an assumed 3 percent discount rate and average age-specific life expectancy and derived from the age-specific VSLs presented in Figure 1.

EPA NCER/NCEE Workshop

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

Empirical Issues Associated with Mortality Risk Valuation

Joseph Aldy and Kip Viscusi, “Adjusting the Value of a Statistical Life for Age and Cohort Effects”

George Van Houtven, Melonie Sullivan, and Chris Dockins, “Eliciting Tradeoffs for Valuing Fatal Cancer Risks”

Comments by Clark Nardinelli

April 11, 2006

The two papers in this session both explore differences in people’s willingness to pay for a small reduction in the risk of death, or what economists call the value of a statistical life. Joseph Aldy and Kip Viscusi look at differences in the values of statistical life across workers by ages, whereas George Van Houtven, Melonie Sullivan, and Chris Dockins look at the difference between the value of reducing fatal cancer risks and the value of reducing fatal accident risks. Because of the way I approached the papers, I will first discuss Aldy and Viscusi.

Aldy and Viscusi's work on the compensating differentials associated with occupational risks forms the basis for the most widely-used estimates of the value of a statistical life. Most regulatory economists use their estimates and will continue to do so. Their new study is especially welcome because it deals with the highly controversial topic of the so-called "senior discount", or more generally the effects of age on the value of a statistical life. The recent dust-up over regulatory analyses that used a lower value of statistical life for older persons, ensures that economists who analyze regulatory policies will pay close attention to the results of this study.

Aldy and Viscusi introduce age-specific fatal and non-fatal occupational risks to estimate the relationship between age and the value of a statistical life. The cross-sectional hedonic regression based on age-specific fatal accident risks generates an inverted U-shaped curve. The curve shows a steep decline from the peak value of $9.9 million per statistical life at age 39 to $3.8 million at age 62. Much of that decline, however, apparently reflects the rise in real incomes over time. Older workers come from generations with lower real earnings and therefore have lower values of statistical life. Aldy and Viscusi show that the steep decline after age 39 comes from the combination of the changes over time within an age cohort and the differences in lifetime earnings across cohorts. Including a cohort adjustment in the regressions substantially flattens the slope of the inverted U, particularly at older ages. In the cohort-adjusted estimates, the value peaks at $7.8 million at age 46, and then declines to $5.1 million at age 62. Indeed, the difference between maximum value and the value at age 62 in the cohort-adjusted estimates is not large enough to be raise serious doubts in someone who believes that the value of statistical life does not vary substantially across age groups. I would like to see if other adjustments would flatten the curve even more. Knowing what those adjustments were might help illuminate the difference between these results and the stated preference experiments that generate a constant value of a statistical life across ages.

As I read this paper and looked at the inverted U-shaped curve, I thought the curve looked familiar. I thought about it for a while and finally realized that the value of statistical life curve generated by their hedonic wage regressions has the same basic shape as a traditional lifetime age-earnings or age-productivity curve. Because they have the data on age and wage rates, I would like to see Aldy and Viscusi compare the age-earnings curve with the age-value of statistical life curve. Do they have similar or different shapes? Do they peak at the same age as earning or at a different age? By doing the comparison, they can show how adding age-specific fatal accident rates to the estimating equations alters the shape of the values of statistical life from that implied by the age-earnings profile alone.

As a regulatory economist I was asked to consider the implications of these results for my work. My first reaction was mild elation because we now have some empirical estimates on how the value of statistical life changes with age. The Aldy-Viscusi estimates cover ages 18 through 62 and most of the illnesses dealt with by my agency affect people younger than 18 and older than 62, but I thought that perhaps we could extend the estimating polynomial equations backward and forward out of sample to generates estimates for our analyses. But then I immediately got discouraged as I read Aldy and Viscusi's warning that "there is no support for the standard practice of transferring VSLs from studies based on the average of the labor market to risk contexts specific to the elderly population."

Feeling a little depressed because Aldy and Viscusi would not let me use their results, I turned to the paper by Van Houtven, Sullivan, and Dockins. I immediately felt better because Van Houtven, Sullivan, and Dockins promised to show me how to use a stated preference survey to derive a relationship between the willingness to pay to reduce the risk of fatal cancer and the willingness to pay to reduce the risk of a fatal automobile accident.

The paper's literature review surprised me. I did not know that some economists have failed to find a premium when estimating willingness to pay to reduce cancer risks compared with other risks. I am more familiar with the risk analysis research on cancer risks; that literature always finds a cancer effect – including more dread, higher aversion, steeper trade-offs, and skewed risk rankings when cancer is one of the risks. In studies of risk perception, cancer always generates a response that cannot be explained by the actuarial risk. Based on risk analysis literature, I did not think that the direction of the cancer effect was in doubt, just the size.

Van Houtven, Sullivan, and Dockins indeed find a cancer premium, which they model as the ratio of the value of a statistical cancer to the value of a statistical life as estimated by the willingness to pay to reduce the risk of a fatal automobile accident. The contrast between the near-instant death through automobile accident and the prolonged illness and other unpleasantness that accompanies death from cancer allows them to identify the full difference in willingness to pay as a cancer premium. They also show how latency (death from cancer occurs years after exposure) and the types of cancer influence the value of a statistical cancer.

Van Houtven, Sullivan, and Dockins extract the value of a statistical cancer and the value of a statistical life from the results of a probit analysis of stated preferences between two hypothetical locations with different risk characteristics. The survey respondents chose between moving to an area with fewer automobile accident deaths per million than their current location and moving to an area with fewer cancer deaths per million than their current location. Using a dichotomous choice to elicit preferences and then deriving the willingness to pay from the results makes fewer demands on participants than many stated preference methods but still gives the full continuous range of results. I like the method and was pleased to hear that the Office of Management and Budget has approved it in principle.

In the description of the participants, however, I noticed something strange in the reported personal experiences of the survey participants. Among the participants, 18 percent reported knowing someone who had died in an automobile accident and 12 percent reported knowing someone who had died of cancer. But the number of annual cancer deaths is 13 times larger than the number of annual automobile accident deaths. Unless people who die of cancer die without friends or relatives, there's something not quite right here. My guess is that the sample, drawn from a web-based national panel, is not in fact made up of persons with unusual life experiences. Instead, the result tells us something about the perceptions and recall biases associated with the risks of fatal cancer and fatal automobile accidents. I suggest that Van Houtven, Sullivan, and Dockins explore this result in later research. It may help them to explain more of the cancer premium itself.

Van Houtven, Sullivan, and Dockins find that, compared with the base case of a fatal automobile accident, the value of a statistical cancer ranges from 2 to 3 times the value of a statistical life, depending on the latency period – a large premium by any yardstick. This finding alone makes the study of value to those of us who must assess the benefits of policies designed to reduce the risks of cancer and other illnesses.

For policy analysis, however, it is important to identify the source of the cancer premium. Van Houtven, Sullivan, and Dockins do not find a strong effect from the period of morbidity that precedes death from cancer. This negative finding may reflect the difficulty of teasing out an estimate of morbidity's contribution to the cancer premium. For policy analysts, the more disturbing possibility is that the cancer premium is not due to morbidity but to something else. Does the cancer premium reflect some fear based not on actual but on imagined outcomes or superstition? The responses of people with some experience of cancer imply that much of the fear associated with cancer may stem from unfamiliarity with the illness.

We need some way to separate the real from the imaginary parts of the cancer premium. Morbidity must account for the real part of the premium. Morbidity can cause real losses above the value of a statistical death directly through the effects of illness on victims and perhaps indirectly through its effects on friends and relatives. Whatever generates the large cancer premium found here has to be related to something that happens before death, during the morbidity phase of the cancer. Once death occurs, the cause ceases to matter.

Many researchers apparently believe that we should treat different causes of death differently based solely on differences in willingness to pay, a practice difficult to justify for regulatory analysis. Suppose that we could survey a representative sample of dead people. If we asked them whether they found it worse to be dead because of cancer or worse to be dead because of an automobile accident, I doubt that we would find a significant difference between the cancer dead and the accident dead. Unless we have some survey evidence from dead persons saying that yes, it is far worse to be dead because of cancer than anything else, we have to find something that occurs before death that makes cancer worse than a fatal accident. The cancer premium derived from stated preference alone does not justify regulatory analysts placing a higher value of preventing statistical cancers.

To make these results of practical use for policy analysis, Van Houtven, Sullivan, and Dockins need to tease the mortality and morbidity effects out of the value of statistical cancers. Doing so would make it possible to de-compose the cancer premium into a realized utility loss and the superstition, stigma, or dread that generates the rest of the premium. I am not suggesting that superstition plays no role in real-world market valuation, only that it should play no role in the valuations used by public health agencies. Public health agencies exist partly because the general public does not always have adequate information on true actuarial probabilities and true severities. In valuing policy alternatives, regulators should ignore superstition, stigma, and irrational fear. As public health economists, we should measure human welfare with actuarially correct risks and real measures of severity, not with dread, superstition, or other imaginary effects. The Food and Drug Administration, for example, came into existence to reduce the consumption of snake oil. To assess the effects of that agency's regulations based on imaginary effects would be the equivalent of introducing snake oil into regulatory analyses. Public health agencies should stick to concrete, measurable health effects when assessing regulatory policies.

Let me conclude by saying that I am grateful for the opportunity to read and comment on these two fascinating papers.

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

Comments on VSL Papers

Maureen L. Cropper
University of Maryland and World Bank

April 11, 2006

Eliciting Risk Tradeoffs for Valuing Fatal Cancer Risks

- **Why This Paper is Important:**
- **SAB's Environmental Economics Advisory Committee determined in 2000 no valid estimates exist of the value of a fatal cancer case**
- **This paper fills this void by estimating the ratio of the value of a statistical fatal cancer (VSC) to the VSL associated with immediate, accidental death in an auto accident (VSL)**

$$\frac{VSC}{VSL} = \frac{-dP_D}{dP_C}\Big|_{E(U)=k}$$

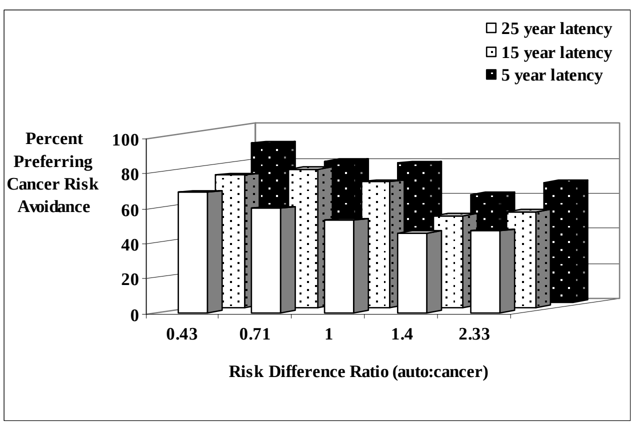
Answers Seem Generally Reasonable

- **78% of respondents pass probability choice quizzes**
- **In choice between City B (fewer Cancer deaths) and City A (fewer Auto deaths), proportion choosing City B FALLS as the relative death ratio (RDR)—the number of auto deaths saved for every additional cancer death—rises**
- **Latency reduces proportion choosing City B, holding the RDR constant**

BUT:

- Percent choosing City B never falls below 50% even with 25 year latency
- No sensitivity to length of morbidity preceding death

Effect of Risk Difference Ratio on P(Choose City B)



How to Value Non-Fatal Cancers?

- Risk-risk tradeoffs for non-fatal cancers effectively produce a QALY weight for cancer:

$$\frac{VSC}{VSL} = \left(1 - \frac{U(C,Y)}{U(H,Y)}\right)$$

- How does this compare with other elicitation methods for obtaining QALY weights?
- Does this effectively monetize QALYs?

Adjusting the Value of a Statistical Life for Age and Cohort Effects

- Why this paper is important:
  - Examines how hedonic wage function shifts in wage-risk space with worker age
  - Estimates how MWTP for a change in risk changes with age
  - Uses multiple cross-sections to disentangle age and cohort effects

- However, to use these estimates for policy, one must believe that hedonic wage equations provide unbiased estimates of a change in risk on the wage.

Should Hedonic Wage Equations Be Interpreted as Causal Relationships?

- How do we interpret a cross-sectional regression of infant mortality on air pollution levels?
- How do we interpret a regression of property values on air pollution levels using a single cross section of data?
- Due to omitted variable bias problems both results would be suspect: Need to find a natural experiment that causes an exogenous change in air quality (see e.g. Chay and Greenstone, QJE, August 2003; JPE, April 2005).
- Dan Black et al. (2003) raise similar concerns about hedonic wage equations: risk is likely to be correlated with the error term, causing results to be suspect
- Perhaps a natural experiment involving changes in road safety could be used to measure the impact of changes in fatal risk on wages of transport operators.

Summary of the Q&A Discussion Following Session V

J.R. DeShazo, (UCLA)
Directing his comments to Dr. Joe Aldy, Dr. DeShazo stated, "We do have some stated preference estimates that reflect almost exactly the same pattern of age-adjusted VSLs that you revealed—they're slightly lower, on average." Referring to comments made by discussant Clark Nardinelli, he added that because he and his colleagues had a large number of seniors in their sample, these age-adjusted VSLs "actually can be used to evaluate the senior population." He also stated that "the general pattern is very much the same, and I think the only difference is that our VSL estimate is about $2 million less, on average."

Saying that he had two questions, Dr. DeShazo posed the first: "Why do we see this change with age?" He cited Ehrlich's work as "the best theoretical study to date." He said that Ehrlich "shows that there are a variety of reasons that we might value reductions in health risks as we age. First and foremost, we value health in the current period, and as we age the marginal utility of that is going to increase as our health state declines." Other factors Dr. DeShazo identified include "changes in the remaining expected lifespan—changes in the marginal utility of income or consumption—changes in individuals' discount rates that you would, consistent with theory, expect to increase. Of course, for any given risk that you're focusing on, the background risk profile is changing, so that the other risks that you face are going up." Addressing the presenters, he asked, "Out of those things that vary with age, what do you think explains this decline?" He added that in their analysis he and his colleagues "were able to identify changes in the marginal utility of consumption, changes in the discount rate, and changes in the background risks that people face as they age, all of which might explain this decline."

The second question from Dr. DeShazo, which he classified as "much more fundamental" than the first, was "whether or not we should be applying hedonic estimates which give us current period values for a mortality risk reduction in efforts to value the types of health risk reductions that FDA and EPA focus on primarily, which follow, typically, years of chronic or severe morbidity. The basic question is: Is the marginal mortality risk reduction the same today, if you're perfectly healthy, as it would be if you've suffered for 10 years from chronic morbidity or maybe 3 years from severe morbidity?" He added that preliminary results from his studies "suggest that that's not the case—that the marginal value of a risk reduction is highly context dependent, and your willingness to trade off morbidity and mortality health states is such that your value of mortality reductions falls as you experience more prior morbidity." In closing, Dr. DeShazo asked, "So, what's the best argument for transferring the sort of hedonic wage analysis?"

Joe Aldy, (Resources for the Future)
"To get to the first question about why we think we see this kind of age profile with respect to the value of a statistical life—I think when we look at the young workers that there are two things driving that result. One is that for the 18- to 24-year-olds we're

focusing on just the full-time workers. That group is going to have a disproportionally large sample of full-time workers who do not have a college degree relative to older age groups in our sample. To the extent that those are people who never have a college degree, they have lower lifetime income, and we would expect them to have a lower risk-income tradeoff in the labor market. I think the other thing that's driving that is that you can't really borrow against future income. With the exception of college loans, it's really hard to be able to do that. This is why we see very little savings behavior among most households until they get into their late 30's or early 40's. You see a little bit of precautionary savings, but other than that, very little saving occurs early in life, and I think that's one reason we see the lower value for the younger workers." He added that the impact seen with older workers is, he feels, "being dominated by life expectancy." He also said he felt it would be great to get a sense of what's driving "stated preference results that show relatively small declines or no decline in the value of life," and he asked "is it because we see changes in discount rates as they get older, and we see differences in risk attitudes? Are there ways in which we can try to structure future surveys to try to get at those questions explicitly so we can have a better understanding of why we see that impact?" Citing existing literature and specifically naming Zeckhauser, Rosen, Ehrlich (two papers), and Johannson (several papers), Dr. Aldy stated that most of this work shows that the value of life is going to decline as people get older. He added, however, that almost all of these studies "have assumed that attitudes toward risk are constant across the lifecycle and the discount rate is constant over the lifecycle. Also, with the exception of the Ehrlich stuff, health doesn't really enter in at all. As we get more complex, there's the question: Are we able with a richer model and a richer theory to explain the fact that the value of life may not decline much with age? With what we're finding among the workers, though, we don't have any basis for saying it's because of health—their health can't be changing that much because they're still full-time workers. It might be declining some, but I think at the end of the day it's life expectancy that's really going to be driving the results on that."

Dr. Aldy then turned to the other question of why we should be using hedonic wage VSLs when we look at policies that have latent impacts. He commented that "part of the point we made at the end of our paper is that if most of those you are looking at are elderly who are enjoying the benefits—whether it's clear skies, whether it's the tier-2 rule that reduced sulfur in gasoline and had a lot of PM reduction benefits—in that context it's difficult to reconcile a VSL where the average age of the worker is 35-40 years old. You bring up the latency issue; I think the age issue makes it difficult." He went on to explain, "There's a question of whether or not in ours you say: Well, you come up with this value of life for someone who is 62—that still doesn't really help me much if the average age of the beneficiary is 70. I haven't even really gotten to that person yet, and if you think, for example, there may be differences in attitudes after one leaves the workforce. One can come up with plausible stories about how one's attitudes toward risk would vary from what they were before and raise questions about whether or not one should be trying to transfer a hedonic wage estimate over. So, I'm not going to come out and forcefully say that hedonic wage is the way to go. As I already mentioned, I have a personal bias towards revealed preference. My co-author may have a slight bias towards that, but he's done a good number of CV studies, too."

He closed by saying, “I think we’re getting closer to doing a better job in the hedonic wage literature of trying to get to interesting questions. For about 15 years, there wasn’t much that was very interesting going on. I think if you look at the last 5 years, it’s getting more interesting to try to better understand the heterogeneity in the value of life. I think that’s something that if you work through theory models, you start seeing that there should be a lot of heterogeneity in the value of life, not just with respect to age but to other issues and attributes as well. We’re moving in that direction, but I’m not standing up here and saying you should ignore all the stated preference stuff and go with hedonic wage, because I don’t think we’re really cracking that nut yet.”

Bryan Hubbell (U.S. EPA)
Dr. Hubbell stated, “Just for the record, we’re actually not using VSLY either anymore, even in sensitivity analyses,” and added “but what I really actually wanted to raise a question about is: One of the things I find most intriguing about your results were the graphs that showed that fatal risks increase with age.” Saying that this issue has bugged him for a number of years, Dr. Hubbell asked, “How well do we really understand the wage trajectory over the lifespan of an individual? I think about a person entering an occupation, and with that occupational choice they’re making a decision at that point about the level of risk they want to accept in the wage tradeoff. From that point forward, however, how much are they actually able to renegotiate based on their own individual age-level risk with their wage trajectory? . . . Say, for example, that risk didn’t change over your lifespan for the particular occupation that you’re in. You would then actually see an increase in VSL over time, simply because your skill level and wages are going up, and so forth, but your risk level is going to stay the same. So, you’re getting an implied VSL that perhaps would seem large if you didn’t adjust for individual specific factors well enough. So, one question that arises is: Without a panel study—if you’re not controlling random effects in panel fashion—are we getting confounding with individual-level effects in terms of the wage-risk relationship? The other question is: How would individuals actually understand how those risks change over time? Certainly, it was unexpected to see that change, and the question is how much is that information actually out there so there’s difference between perceived risk and actual risk in those particular cases.”

He closed by mentioning, “One of the things I think is interesting is that there are not a lot of studies out there looking at things other than hedonics as a way to identify these marginal values using the labor market decisions,” and he questioned whether hedonics were the only way to use this information or “are there other revealed-preference methods, such as discrete choice type models which look at occupational or job choices and job switching, that could help capture some of this information.” He stated that “hedonics tend to assume that there is no bundling of attributes, that you can have any kind of combination of experience with risk and everything else in a very continuous fashion so that you can get these derivatives—and if that *doesn’t* occur, you can actually end up with some biased results. Hence, the question is: How much have we explored the bundling of attributes and jobs and whether we can disentangle that.”

Joe Aldy
Dr. Aldy answered, “There at the end, Bryan, you started addressing how I would respond to the very first question that you raised, which is whether or not over their lifecycle workers can really adjust their wage or salary in response to changes in the risk. Clearly when one applies the model, we’re making the assumption that the labor market has enough freedom and mobility so that one *can* move—so that you can get these kind of equilibria. In the case of what we’ve done, these equilibria that are age specific, we looked at the relationship between what the firms offer in terms of a combination of safety and labor compensation and what the workers are demanding in terms of that combination of risk and income. We so see that labor income does increase over much of the lifecycle, but then it does start to decrease for some older workers in their 50’s. We actually see in our sample a slight decline in labor income for our oldest group.” He explained that this could be partly explained by “the standard story that for those who stay within one firm for a long time there’s sort of an agreement that they will be paid less than their marginal product when they are young and then will tend to be paid more than their marginal product when they’re older.” He added that “there’s some concern that because of this we’re not really getting the right measures. Having said that, we still should be seeing among workers that if they really don’t like what’s being offered to them they should be going to a different job. That does raise the question of whether workers are really that mobile when they’re at older stages of their lives.” This led back to the Dr. Hubbell’s comment regarding “if there isn’t sort of a continuous set of job market characteristic bundles, then you could have some potential problems with this.”

Dr. Aldy summarized that “unfortunately there’s not much one can do when looking at these cross sections. The benefit of using the CPS is that it’s a *massive* cross section; the downside is that it’s *just* a cross section. You could construct a quasi-two-year panel, but that’s actually very problematic with how they’ve designed the CPS. We’re actually thinking about trying to explore the PSID, where we could have a pretty long panel.” He added that he has not “seen any evidence of what perceived risks are and how they vary with age” and he said that he wasn’t sure “if in academia professors know how their risk profile changes with their age, but if you’re in a blue-collar job where there is a good number of injuries, there’s probably a decent sense of that.” He said he’s sure that there’s a sense of that within the firms, “because they’re the ones who have to pay workmans’ compensation premiums to the state governments, so they should have a sense of how the more serious incidents that can lead to either long-term hospitalization or fatality can vary with age.”

Mary Evans, (University of Tennessee)
Dr. Evans said that she first “wanted to applaud your efforts in this paper and other papers in refining the occupational job risk measure that we’re able to use—I think that’s an important contribution to the literature.” She then picked up on something that was mentioned in the response to J.R. DeShazo’s earlier question, which was “the issue of possible selection effects within the sample.” She said, “You focused on the lower age

range, the 18- to 24-year-olds, but my concerns are more about the upper end of the age distribution, the 55- to 62-year-olds. My question is: Are you able to estimate some sort of selection model?—Have you thought about doing that?—and how do you think doing so might impact your results?"

Joe Aldy
Dr. Aldy responded, "Again, the problem here is in using the CPS—it doesn't really give you anything to identify the decision to work or not." He went on to say that although they had not looked at non-labor income in the household, they did "try to look at non-head-of-household labor income" and added that "it yielded virtually no impact on our estimates, but it wasn't a good instrument—it clearly was not exogenous." Dr. Aldy closed by saying, "As I mentioned, we're thinking about trying to go with the PSID, where we can use a panel. There we can definitely use asset measures to try to identify that . . . it's a much, much richer data set that might enable us to identify selection. It's one reason why we decided to cut the age at 62, the age of early social security retirement. We recognize that there's still a potential problem there, but there are these tradeoffs with the sample that we wanted to use, because at the end of the day when you want to cut this thing by a specific age, it helps to have a 100,000 observation sample. You know, if you want to get the VSL for people who are just age 60, you're not going to get much if you're using the PSID. In the end, that's the tradeoffs one has to make when using a really large data set."

Greg Poe, (Cornell University)
Addressing his comment "to George [Van Houtven] and to the audience," Mr. Poe stated, "It really looks desirable that we're doing risk-risk tradeoffs, and that pulls out the money, and we immediately think that this is going to be a much simpler type decision framework and it might be better. However, a long body of literature from marketing to psychologists to political choice to even birds and bees has shown that these two choices, these tradeoffs, are not that stable. You can add a third choice, which would pass some sort of dominance test such as Maureen [Cropper] referred to, which nobody would choose, but it greatly changes the proportions of people who choose both of those. So, just because we're getting rid of money doesn't mean that we've solved everything and it immediately makes it a preferred technique—it's just *another* technique, and we need to investigate that."

George Van Houtven
"I would agree that it certainly doesn't solve everything, and I wouldn't want to make that claim. I do think, though, that the framework helps in terms of cognitive burden the way we've set it up—in terms of not having to spend as much time explaining the *absolute* value of the risks but rather the relative risks. It's easier for people to trade off—you know, when the denominators are the same, they sort of get canceled out of the equation as long as we're willing to assume and expect the utility framework or something close to that. *That's* the sense in which I think it maybe offers some advantage, but otherwise I agree—it's not a silver bullet."

Reed Johnson, (RTI)

Dr. Johnson commented that "both Joe [Aldy] and Maureen [Cropper] made passing reference to possible connections between the value of a statistical life year and willingness to pay for QALY. I just want to emphasize Alan's [Krupnick] point yesterday that it's important to be vigilant about keeping separate welfare theoretic measures from quality-adjusted health indices like QALY. We get hit over the head all the time by non-economists about this term "value of a statistical life." It's a bad choice of terms, and I think Trudy [Cameron] has advocated something that really describes what we're getting at, which is the willingness to pay for a small change in risk. I think we deserve to be ridiculed if we make the same mistake they make in thinking of the value of a statistical life year as the value of a life year, which of course is what willingness to pay for QALY is supposed to get at."

He went on to say that he's "not sure, though, about George's [Van Houtven] manipulation of ratios of values of a statistical life, whether there's some way of backing out some QALY-like measure out of that. I think it's worth thinking about that, but let's not make the same mistake non-economists make about dropping the statistical part of these value measures."

David Risley, (U.S. EPA)
Starting with the disclaimer that he just started with the Clean Air Markets division about a month ago, so this is all very new to him, Mr. Risley addressed this comment/question to Joe Aldy: "Maybe I'm just offended that my VSL seems to be lower than most peoples' but . . . I'm three years out of undergraduate studies; I have no savings; I moved to the most expensive part of D.C.; and I'm about to start grad school. I know that my debt will be growing, but I *hope* that in the future I'll have earnings potential. I was just wondering if there's any thought of perhaps adding my current VSL to some fractional VSL that represents the likelihood that I'll get to be 40 make more money and have a family."

Joe Aldy
Dr. Aldy replied, "The good news is that your value is going to go up for a while. When Kip [Viscusi] and I were working on this, he didn't like the fact that the peak was always at an age younger than his current age. . . When I think about whether or not the younger population should have a lower value of life, I sometimes wrestle with the question of—you know, this is reflecting imperfections in the labor market, in the capital markets, and that's why they have this lower value. Having said that, this is still what people are using to make actual decisions. Your compensating differential for mortality risk in your job at EPA I presume is probably pretty low—I actually haven't looked at the data closely enough to know how risky it is to work at EPA—I hope it's low. What one is able to infer from that suggests that you're making what is, for you, a rational decision. The idea here is that you're valuing your current consumption enough that you're willing to take less compensation for that probability of dying on the job right now—that's what's implicit in the modeling framework that we have."

Wrapping up, Dr. Aldy commented, "You can take some offense. I can tell you that my father, whom I've talked to about this, takes probably greater offense, for the same reason

Kip does. At the end of the day, what we're trying to say here is that these are the values through which people are trying to reveal their preferences about labor income and risk in their labor market decisions. There are a host of issues in terms of how we try to estimate this and interpret it, as we've already discussed, but at the end of the day that's what we're trying to achieve empirically. It would be nice if you could go to a bank right now and say, "Hey, I'm about to go to graduate school and I'm going to make a lot of money—why don't you give me a lot of money right now?" They're probably not going to do that, but if they did, then you would probably be demanding a larger compensation for the probability of dying at EPA sometime over the next couple of years."

END OF SESSION V Q&A