DISCOUNTING STATISTICAL LIVES

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Economists have come to accept the idea that placing a dollar value on life is unavoidable in evaluating projects that reduce mortality risks. A related and more controversial question, however, has now surfaced: How should the value of a future life be discounted? In other words, what is the present value of a risk reduction that occurs 20 years from now? If the value of future risk reductions is to be discounted, what discount rate should be used?

This question arises in decisions about when to undertake the clean-up of a toxic waste site, how to phase out the use of a dangerous pesticide, or what kind of sewage treatment plant to build. Consider, for example, a coastal city that has been undertaking primary treatment of its sewage and that is considering constructing a secondary sewage treatment facility. Secondary sewage treatment would reduce the morbidity and mortality risks to swimmers and consumers of seafood. The city could build one particular type of secondary sewage treatment plant that would begin operation almost immediately, or it could build another type of plant that would be more effective in reducing risks but that would require a longer time to construct.[1] Whether the construction delay is warranted by the greater risk reductions depends in part on the discount rate for mortality risks.

Environmental and other groups have argued that a zero discount rate should be used for public policies that reduce risk. The Office of Management and Budget, on the other hand, has adopted the position that a market rate is appropriate.[2] Proponents of this view point out that project funds could be invested at a market rate of interest and

[1] This scenario describes roughly the situation faced by the city of Los Angeles in the late 1970's with respect to the treatment of sewage emptied into Santa Monica Bay. In this case, the second type of plant had lower costs rather than improved effectiveness in treating sewage and reducing risks. The lower cost was due to the (anticipated) availability of federal funds that would reduce the city's share of the costs.

[2] Conflict between these two claims was highlighted in the 1987 nomination of Douglas Ginsburg to the U.S. Supreme Court. Ginsburg was brought under fire during his nomination hearings because while he was with the Office of Management and Budget he had applied a discount rate of 10% in evaluating the benefits from regulation of asbestos. Asbestosis bar a latency period of about twenty years between the time exposure occurs and the time the risk manifests itself (as mortality or morbidity). Because reduction of exposure to asbestos must be undertaken in the present but the benefits do not occur until the future, this is a prime example of a situation in which a discount rate might be applied. Several environmental groups argued in the hearings that it was unethical to use a positive discount rate in this situation. (See discussions in *Newsweek* (1987, 1988)).

the future revenue be used to buy (1+r) amounts of risk reduction in the following period. A third view which is sometimes espoused is that because many aspects of risk affect utility (see George Torrance, Michael Boyle, and Sargent Forward, 1982), an individual's discount rate for a particular risk is likely to depend on the characteristics of that risk. In this paper, we propose a survey method for eliciting discounting behavior, and we investigate these claims about the appropriate discount rate for statistical lives.

There is a large literature beginning with Thomas Schelling (1968) and Ezra Mishan (1971) on the value of a statistical life and willingness to pay for decreases in risk.[3] These works led to utility-based approaches to the value of life that included both atemporal models (Michael Jones-Lee, 1974, 1976; Bryan Conley, 1976) and intertemporal, life-cycle models in which the timing of risks could be considered (W. Brian Arthur, 1981; Theodore Bergstrom, 1982; Donald Shepard and Richard Zeckhauser, 1982). Virtually all of the empirical work on the value of risk reductions has been of the atemporal type, considering risks that occur entirely in the present, *e.g.* accidents (Glenn Blomquist, 1979; Jones-Lee, M. Hammerton, and P.R. Phillips, 1985). The few studies that have measured willingness to pay to avoid future risks, using exposure to carcinogens with a long latency period, have not varied the timing dimension and cannot directly estimate a discount rate (Robert Mitchell and Richard Carson, 1986; V. Kerry Smith and William Desvousges, 1987).[4]

Only recently has it been recognized that the life-cycle utility model can be used to derive a discount rate for risks. Theoretical work by Carson, John Horowitz, and Mark Machina (1987), Sherwin Rosen (1987), and Maureen Cropper (1988) uses this model to derive an individual's discount rate for risks in the absence of markets for health or

[3] The change in the probability of mortality multiplied by the number of individuals affected gives the number of statistical lives raved by a given project. Statistical lives are a common measure of policy effectiveness in reducing risk when small risks are borne by a large group of people rather than large risks by a few specific individuals (Bailey, 1980).

[4] Studies using future risks (Mitchell and Carson, 1986) as well as studier that have used actuarial risks, which combine both present and future risks (Thaler and Rosen, 1976), have tended to estimate lower values for A statistical life than studies in which only immediate risks are considered. This relationship suggests that future risks are discounted at A positive rate.

safety. They show that this discount rate may be greater or less than the market rate, depending, for example, on the form of the budget constraint or on the shape of the time stream of earnings. Such results suggest that empirical estimates, rather than a theoretical expression, may provide a more informative measure of an individual's discount rate.

Empirical estimates of the discount rate for risk reductions, like empirical estimates of values of other nonmarketed goods, can be obtained either by inferring a discount rate from market transactions or by eliciting it directly through the use of surveys.[5] The indirect market approach was recently adopted by Michael Moore and Kip Viscusi (1987) using wages for different occupations. They estimate an hedonic wage equation to derive age-specific wage premia for risks from accidental, job-related deaths. Age is converted into the number of years of life remaining and the age-specific wage premium then decomposed into a premium for each remaining year of life by specifying the functional form relating the value of future years to the value of present years. The relationship between premia is the estimated discount rate, which they find to be 12.2%.

In this paper we propose a survey method for estimating discount rates based on respondents' choices among policies that differ in the timing and number of the statistical lives that are saved. The choices contain information about respondents' discount rates. This occurs because, under a fairly weak set of assumptions on the utility function, we can calculate the unique discount rate that would make the individual indifferent between the two policies. By varying the time stream of statistical lives saved we can observe choices at different levels of the cut-off discount rate. We show that the median discount rate for the population sampled can be robustly estimated from these data, and that, under stronger assumptions, estimates of individual discount rates are possible.

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[5] The pioneering empirical work on inferring discount rates from market transactions, using air conditioner purchases, in Hausman (1979). The survey approach was first considered in this area by Victor Fuchs (1982) who found little evidence that an individual's health choices were related to his explicitly or implicitly expressed discount rate for financial assets.

Our method has a number of strengths and weaknesses relative to methods based on inference from actual market transactions, such as that used by Moore and Viscusi (1987). One the survey's major strengths is that it can be used to elicit discount rates for different types of risks, not just those for which close market substitutes exist. We can also specify the size of the risks, thereby assuring that all individuals have the same information and that the risk variable is measured correctly. Further, our method requires weaker assumptions than are necessary for estimation of an hedonic pricing equation.[6] The primary weakness of the survey method is that responses to hypothetical situations are often suspect relative to actual behavior. This problem can be minimized however through careful survey design and implementation, and survey instruments can be constructed to encourage realistic choices by the participants. For example, surveys can use a discrete choice framework that is similar to what individuals might face on a ballot and thus can induce observed choices to mimic voting behavior in a referendum.

To demonstrate our technique, we report the results of a survey using 75 undergraduate students and three policy scenarios with different types and timing of risks. We then investigate five questions: (i) Are individuals sensitive to the timing of life-saving projects? (ii) Is the median discount rate for risks equal to zero? (iii) Is the median discount rate equal to the market discount rate? (iv) How do discount rates compare for different types of risks? (v) What is the relationship between the discount rate and characteristics of the individual participants?

Section I sets out the assumptions and describes the estimation method. Section II describes our survey instrument. Section III presents our empirical results and Section IV gives a brief summary and some concluding remarks.

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[6] We Are able to experimentally impose reparability between the discount rate And the value of life. Because their study is based on A tradeoff of risk for money, Moore And Viscusi (1987) first estimate A value of life And then infer the discount rate from changes in this value. Thus it is not possible to estimate the discount rate without estimating the value of life. Our method trades off risk for risk and allows us to separate measurement of the discount rate from measurement of the value of life.

I. A Method for Estimating Discount Rates

A. *The Relationship between Discount Rates and Discrete Choice*

The value of a project that saves statistical lives over a period of time can be expressed as:

$$\sum_{t=0}^{T} L(t)\, V(t)\ , \tag{1}$$

where $L(t)$ is the number of statistical lives saved in year t, T is the duration of the project, and $V(t)$ is the present value of a statistical life saved in year t.[7] Estimates of V_0 = V(0) for a variety of situations are given by Jones-Lee (1974, 1976), Richard Thaler and Rosen (1976), Blomquist (1979), Robert Smith (1979), Rachel Dardis (1980), Jones-Lee, Hammerton, and Phillips (1985), and Mitchell and Carson (1986). The assumption of exponential discounting yields $V(t) = V_0/(1+\delta)^t$, where δ is the (constant) discount rate.[8]

To estimate an individual's discount rate, and to estimate the distribution of discount rates in the population, we introduce a discrete choice problem. Consider two projects that save statistical lives. One project saves L_1 lives per year for every year from the present to the end of the horizon T. The second project saves L_2 lives per year which has the same horizon T but which does not take effect until year $j > 0$. For individual i under the specification $V(t) = V_0/(1+\delta_i)^t$, the values of the two projects are:

$$\text{Value of present project} = \sum_{t=0}^{T} L_1 \frac{V_0}{(1+\delta_i)^t} \tag{2a}$$

and

[7] This model can be interpreted as a life-cycle model of preferences over personal risks. In this case, $V(t)$ is replaced by the individual's present willingness to pay for a reduction in the the conditional mortality risks for period t. A reasonable assumption is that fox small risks willingness to pay is linear in the risk change. For a given population at risk, the reduction in the individual's mortality risk is proportional to $L(t)$.

[8] The discount rate is, for an individual of a given age, one minus the marginal rate of substitution between risk reductions at times t and $t+1$, i.e., $V(t)/V(t+1)$ - 1. This definition is somewhat different from the discount rate definition used by Moore and Viscusi (1987) and Cropper (1988), which is based on how the value of a current risk reduction changes with age.

$$\text{Value of future project} = \sum_{t=j>0}^{T} L_2 \frac{V_0}{(1+\delta_i)^t} . \qquad (2b)$$

For these two projects we can define a "rate of return" or "equilibrating discount rate" as the discount rate an individual must have if he is indifferent between the two projects. We denote this equilibrating discount rate as δ^*, the level of δ such that the value of the present policy is equal to the value of the future policy,

$$\sum_{t=0}^{T} L_1 \frac{V_0}{(1+\delta^*)^t} = \sum_{t=j}^{T} L_2 \frac{V_0}{(1+\delta^*)^t} . \qquad (3)$$

Each survey participant is asked which of the two projects he prefers, given L_1, L_2, j, and T. A participant who prefers the present policy must have a discount rate δ_i greater than δ^*, since this is equivalent to $\sum_{t=0} L_1/(1+\delta_i)^t > \sum_{t=j} L_2/(1+\delta_i)^t$. A participant who prefers the future policy must have a δ_i smaller than δ^*. Note that under the specification $V(t) = V_0/(1+\delta)^t$, V_0 can be cancelled from the equation.[9] Preference depends only on the relationship between δ^* and δ_i. This allows us to separate discounting behavior from questions about the value of a statistical life.

The parameter δ^* provides either an upper or a lower bound on the individual's discount rate. We exploit this feature in the survey design by assigning a different value of L_2 to each participant. Because a one-to-one mapping exists between each L_2 and δ^*, given L_1, j, and T, this is equivalent to assigning a different δ^* to each participant.[10] We observe which of the two projects is preferred for the given value of L_2, and thus at the given δ^*. We then estimate a relationship between δ^* and the proportion of the individuals who were assigned that δ^* who were in favor of the future project.[11] This

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[9] If the two policies being compared are not for the same basic type of risk, our method requires that V_0 and δ_i be identical for the two types of risks.

[10] There are a number of roots to (3), but only the real root is relevant. Note that although we have described our method in terms of fixing L_1 and varying L_2, it is possible to carry out estimation by varying the other parameters of the time streams such at L_1 or j. The only requirement is that a unique real root to (3) exist.

[11] This procedure is analogous to that used in bioassays in which a stimulus is applied and the proportion of responses noted (David Finney, 1978). In our model δ^* operates as the stimulus and the choice between the projects an the response.

relationship is an estimate of the cumulative distribution function for discount rates in the population.

B. *Estimating the Relationship between Choice and* δ^*

Suppose that individual discount rates are distributed in the population according to the equation $g(\delta_i) = \mu + h(X_i,\gamma) + \epsilon_i$, where the function $g(\bullet)$ is increasing; the function $h(\bullet)$ is centered around zero with arguments X_i, a vector of individual taste variables, and γ, a vector of parameters; ϵ_i is a zero-mean disturbance term with variance σ^2; and μ is a location parameter, such as the mean or median, of the cumulative distribution of discount rates.

Following the argument presented in the preceding section, the individual chooses the future policy if his δ_i is less than his assigned $\delta_i{}^*$ or, equivalently, if $g(\delta_i)$ is less than $g(\delta_i{}^*)$. The probability that a randomly selected individual who faces a choice at $\delta_i{}^*$ chooses the future policy ($CHOICE_i = 1$) is:

$$P(CHOICE_i = 1 | \delta_i{}^*) = P(g(\delta_i{}^*) > g(\delta_i)) = P(g(\delta_i{}^*) - \mu - h(X_i,\gamma)) > \epsilon_i) \ . \qquad (4)$$

This probability P can be estimated in a straightforward manner once we make an assumption on the distribution of ϵ.[12] For example, if ϵ is distributed normally with standard deviation $\sigma = 1/\beta$, then this probability is:

$$P = P(CHOICE = 1 \,|\, \delta^*) = \int_{-\infty}^{\beta[g(\delta^*) - \mu - h(X,\gamma)]} \frac{1}{(2\pi)^{1/2}} EXP\left(-\frac{t^2}{2}\right) dt$$

$$= F[\, \beta g(\delta^*) - \beta\mu - \beta h(X,\gamma) \,] \ , \qquad (5)$$

where $F(\bullet)$ is the standard normal cumulative distribution function.

We can estimate (5) through maximum likelihood methods using the log likelihood function:

[12] From here on we suppress the i subscript whenever no possibility for confusion arises.

$$ln(L) = \sum_i CHOICE_i \; ln(F[\,\beta g(\delta^*) - \beta\mu - \beta h(X_i,\gamma)])$$
$$+ \; (1 - CHOICE_i)(1 - ln(F[\,\beta g(\delta^*) - \beta\mu - \beta h(X_i,\gamma)]) \; . \qquad (6)$$

Equation (5) can be estimated using a standard probit routine. A typical feature of probit models, however, is that only the product $\beta\mu$ can be estimated and not the individual parameters β and μ. In the formulation of our model, though, separate estimates for μ, β, and γ can be obtained. This property can be readily seen by examining (6). Because the treatment variable $g(\delta^*)$ enters linearly with respect to μ, we can estimate β as the coefficient on $g(\delta^*)$ and can estimate μ separately by dividing $\beta\mu$ by β (Trudy Cameron and Michelle James, 1987). We also note that random assignment of the δ_i^* implies that functions of δ_i^* are independent of $h(X_i,\gamma)$. This means that β and μ can be estimated from either the conditional distribution ($h(\bullet)$ included) or the unconditional distribution ($h(\bullet)$ excluded).

We estimate (6) under two different specifications for the functional form of $g(\bullet)$. The specification $g(\delta_i) = \delta_i$ implies that the unconditional distribution of discount rates in the population is:

$$\delta_i = \delta_m + \nu_i \; , \qquad (7)$$

where δ_m is the unconditional mean (and median) discount rate and $\nu_i = \epsilon_i + h(X_i,\gamma)$. If we instead use the specification $g(\delta_i) = ln(\delta_i)$ then discount rates are unconditionally distributed according to $ln(\delta_i) = ln(\delta_m) + \nu_i$. To allow for negative values of δ_i we shift the horizontal axis by 0.1 and let $g(\delta_i) = ln(\delta_m + 0.1)$ so that:[13]

$$ln(\delta_i + 0.1) \; = \; ln(\delta_m + 0.1) + \nu_i \; . \qquad (8)$$

[13] Negative discount rates are considered for two important reasons. First, negative discount rates have been observed elsewhere in experiments involving undesirable goods (Loewenstein, 1987; Horowitz, 1988). Second, by allowing the possibility of observing negative discount rates through the L_2 values assigned, we avoid the possibility of a corner solution at zero and thereby increase the statistical power of our hypotheses tests.

Note that while the assumptions that ϵ is normally distributed and that $g(\bullet)$ is either linear or logarithmic are convenient for estimating (6), they are not necessary. Assuming $g(\bullet)$ is known, estimates of the median (and the other central quantiles of the distribution of δ_i) using (6) will be relatively robust against reasonable alternative distributions for ϵ. On the other hand, if we assume the distribution of the error terms is known, then it is possible to estimate $g(\bullet)$ and $h(\bullet)$ in (4) semiparametrically using, for instance, smoothing splines (Robert Engle, Clive Granger, John Rice, and Andrew Weiss, 1986) or generalized additive models (Trevor Hastie and Robert Tibshirani, 1986). If one wants to avoid making assumptions about the functional forms of $g(\bullet)$ and $h(\bullet)$ and the distribution of ϵ, then a completely nonparametric approach such as the ACE algorithm proposed by Leo Breiman and Jerry Friedman (1985) can be used to estimate the entire cumulative conditional or unconditional distribution function for the δ_i.

II. An Empirical Application

To estimate discount rates for statistical lives, we conducted a survey using the discrete choice set-up described above. The survey was part of a larger series of surveys and experiments set up to investigate individual time-and-risk preferences and was conducted with undergraduates enrolled in an upper division environmental economics class at the University of California, San Diego, in June, 1987. Seventy-five individuals took part.

The survey portrayed three scenarios in which there was a choice between one policy that saved a given number of lives starting immediately and an alternative policy that saved a possibly different number of lives but started later.[14] The scenarios described projects that mitigated risks in air travel, the workplace, and at traffic intersections. In the air travel scenario, the policies were improvements in the design of

[14] As noted in the previous section, it is necessary that both projects have similar types of risk.

airplanes or airports that reduced the risk of fatal airplane collisions. In the worker scenario, the policies were improved ventilation systems that reduced the risk of death from spills of dangerous chemicals. In the traffic scenario, the policies were safety improvements at intersections to reduce the risk of automobile collisions.[15] These scenarios are typical of situations that have been used in contingent valuation surveys to place a dollar value on risk reductions.[16]

The scenarios further differed in the number of statistical lives at stake, the time of delay, and the length of time over which the policies would be effective. The range in the randomly assigned number of lives saved by the future policy (L_2) also varied across scenarios. These features of the scenarios are summarized in Table 1.

Table 1 -- Summary of Policy Choices, by Scenario

Scenario	beginning year j	ending year T	lives saved L_1; range of L_2
1. Air Travel (present)	0	15	20 (L_1)
(future)	5	15	29-54 (L_2)
2. Worker (present)	0	25	20 (L_1)
(future)	3	25	20-34 (L_2)
3. Traffic (present)	0	25	10 (L_1)
(future)	5	25	11-38 (L_2)

[15] Only 73 individuals completed the survey for the traffic scenario.

[16] Jones-Lee (1976), for example, uses airplane safety scenarios. The worker scenario is similar to real-life situations that have frequently been used in empirical hedonic pricing studies (Thaler and Rosen, 1976; Viscuri, 1979; Smith, 1983; Moore and Viscusi, 1987). Jones-Lee, Hammerton, and Phillips (1985) use automobile safety.

The text of the air travel scenario question is given here. The texts of the other two scenarios are presented in the Appendix.

> Airplane accidents result in a number of deaths each year, mostly from landings and takeoffs. One option to reduce the number of deaths is to require that a safety feature be placed on the existing fleet of airplanes. This feature will save an expected 20 lives per year over the next 15 years (the life of the safety feature). However, the government could instead require that a new radar system be installed at the airport. Construction of the radar system would take about 5 years and would be financed by the airlines. The radar will save about (L_2) lives per years over the next 10 years (year 5 to year 15).
>
> The costs of these two alternatives are the same. But because these costs are large, the government will not require both actions to be taken and it must make a choice about which one to use. Which action should the government require?
>
> ____ Airlines should be required to install the safety equipment immediately.
>
> ____ Airlines should be required to construct the radar system, to be ready in 5 years.

The first policy presented in this question involves the immediate installation of a safety feature on airplanes that is expected to prevent L_1=20 deaths per year for the next T=15 years, beginning immediately. The second, or “future”, policy involves the construction of a radar system that will be completed j=5 years from the present and will last for $T - j$ = 10 years.[17] This action is predicted to prevent L_2 deaths per year, with the value for L_2 randomly assigned to each participant. The variable L_2 ranged from 29 to 54 in the air travel scenario. The equilibrating discount rate when L_2 = 32, for example, is δ^* = 0.036, or 3.6%. Equilibrating discount rates in this scenario ranged from -1% to 20% with a mean of 6.6% and a median of 7.5%. The mean and median of the equilibrating discount rates for the worker and traffic scenarios were 7.0% and 6.7% (worker) and 11.6% and 9.9% (traffic).

[17] Although it is not necessary that both policies be effective until the same T for the estimation method to work, in a pretest we found that some respondents had difficulty understanding the choice if different T's were involved.

III. Results

A. *The Individual Scenarios*

Our data consist of each respondent's choice ($CHOICE_i$ = {0,1}) and the δ^* he or she was assigned through L_2. They also include the total number of participants who were assigned each value of δ^* and the proportion *p* of these that favored each policy.

Values of *p* for the air travel scenario are plotted against δ^* in Figure 1. Results from the probit estimation of (7) and (8) for this scenario are reported as (9) and (10) with the asymptotic *t*-statistics given in parentheses:

$$\Phi(\hat{p}) = \underset{(-1.71)}{-0.458} + \underset{(2.97)}{10.082}\,\delta^* \; ; \tag{9}$$

and

$$\Phi(\hat{p}) = \underset{(3.38)}{3.646} + \underset{(3.22)}{1.878}\, ln(\delta^* + 0.1) \; . \tag{10}$$

where $\Phi(\bullet)$ is the inverse of the standard normal cumulative probability function. Predicted probabilities from (9) and (10) are graphed in Figure 1 as the solid and dashed lines, respectively.

With δ^* as the independent variable, the estimated median (and by the symmetry of the normal distribution, the estimated mean) discount rate is 4.54%. With $ln(\delta^*$ + 0.1) as the independent variable the data yield a median discount rate of 4.35%. The log specification (10) yields an estimated mean discount rate of 5.00%.[18] These values are summarized below in (11) and (12):

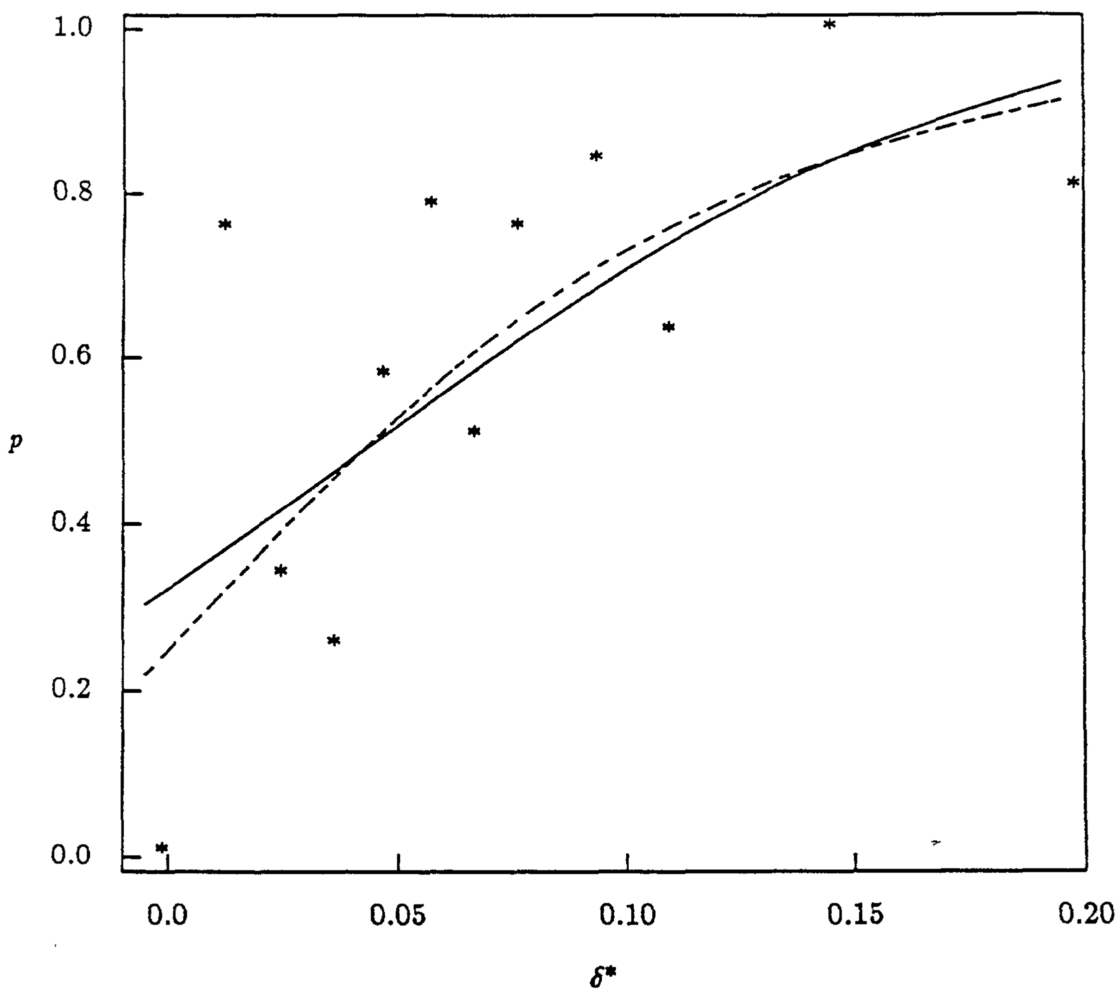
$$\hat{\delta}_m = \underset{(2.91)}{0.0454} \; ; \qquad \hat{\sigma}_\nu = \underset{(2.46)}{0.099} \; ; \tag{11}$$

and

$$ln(\hat{\delta}_m + 0.1) = ln(\underset{(4.02)}{0.0435} + 0.1) \; ; \qquad \hat{\sigma}_\nu = \underset{(2.70)}{0.532} \; . \tag{12}$$

[18] This reflects Arthur Goldberger's (1968) correction to obtain the mean from the median: $\overline{\delta} = \hat{\delta}_m\, EXP(1/(2\hat{\beta}^2))$.

Figure 1. Proportion of Individuals Choosing the Future Project as a Function of δ^* (Air Travel Scenario)



Each point represents the proportion of choices in favor of the future policy for the 3 to 7 individuals who were assigned that value of δ^*.

$$\Phi(\hat{p}) = -0.458 + 10.082\,\delta^* \quad \text{(solid line)} \tag{9}$$

$$\Phi(\hat{p}) = 3.646 + 1.878\,ln(0.1 + \delta^*) \quad \text{(dashed line)} \tag{10}$$

A common concern in all contingent valuation studies is that respondents' answers do not reflect economic behavior, or, more precisely, that answers are essentially random. We examine this issue by testing the hypothesis that individuals answer randomly against the alternative that they are sensitive to the timing and number of lives saved each period. The null here is not that individuals have a zero discount rate; even if they had a zero discount rate they would still be sensitive to the number of lives saved each year.

These hypotheses are:

$H1$: $\beta = 0$
$K1$: $\beta \neq 0$,

where β measures the response to δ^* in the probit estimation of (7) or (8). Values for $\hat{\beta}$ and the t-statistics are given in (9) and (10). $H1$ is rejected above the 99% level in favor of the alternative $K1$ that δ^* significantly predicts choices.

A useful measure of the ability of δ^* to explain choice is the percentage of additional correct predictions made when δ^* or a function of δ^* is added to the probit regression. Approximately 58.7% of all choices were in favor of the future policy. If choice were predicted without the treatment variable δ^*, the optimal prediction would be $CHOICE$=1, which would correctly forecast 58.7% of the observed choices. Using the estimated δ_m's allows us to predict 70.7% and 76.0% of observed choices in (9) and (10) respectively. These results imply that under the log specification, for example, roughly 42% or (76.0 - 58.7)/(100 - 58.7) of the unexplained choices can be explained on the basis of discounting.[19]

Having rejected random behavior, we can move to test our next hypothesis that the median discount rate is zero:

[19] Another common measure of goodness fit in probit models is the pseudo-R^2, 1 - $ln(L_u)/ln(L_r)$, where $ln(L_r)$ is the log-likelihood in the restricted equation (β = 0) and $ln(L_u)$ is the log-likelihood in the unrestricted equation. Pseudo-R^2's tend to be lower than R^2 for linear probability models. The pseudo-R^2's for the air travel scenario are 0.10 for (9) and 0.11 for (10).

$H2$: $\delta_m = 0$
$K2$: $\delta_m \neq 0$.

This is perhaps the most fundamental of the hypotheses we test. It tests the claim that individuals do not discount future reductions in risk; in other words, that future lives are equal in value to present lives.[20] Using (11), we reject $H2$ in favor of the alternative $K2$ with t = 2.91; the median discount rate is not equal to zero. A positive median discount rate, however, does not imply positive individual discount rates for all individuals. Under the assumption that the errors are normally distributed, approximately 32% of the population does implicitly espouse a discount rate of 0 or less.[21]

The next hypothesis we test is that the discount rate is equal to the market rate. This is formally stated as Hypothesis 3, where r represents the real market rate:

$H3$: $\delta_m = r$
$K3$: $\delta_m \neq r$.

A common measure of the real rate of return is the difference between the nominal rate of return on 25-year treasury bonds and the rate of inflation in the consumer price index. On June 4, 1987 (the day of the survey), the 25-year T-bond rate was approximately 9.01%, and the annual rate of inflation between April and June 1987 was roughly 3.85%. These give a value for r of 9.01 - 3.85 = 5.16%. Using this value, the t-statistic for $H3$ is 0.40 and thus we do not reject $H3$ for scenario 1. Although other definitions of the real rate could be used for this test, it is clear that we would not reject $H3$ for a wide range of plausible values for r since the 95% confidence interval for the median (and mean) discount rate in the air travel scenario includes rates from 1.42% to 7.66%.

[20] Note that our survey does not measure preferences about distant generations.

[21] Using the non-parametric estimation technique proposed by Breiman and Friedman (1985) yields a median discount rate of 0.041, and an estimated percentage of individuals with a discount rate less than zero of 23.6%. This suggests that while estimates of the median are robust estimates of more extreme quartiles are sensitive to assumptions about the distribution of ϵ and the functional form of $g(\bullet)$.

We next turn to results from the other two scenarios. Observed values of p are plotted against δ^* in Figures 2 and 3. Choices in favor of the future policy were 56.0% in the worker scenario and 48.0% in the traffic scenario. Results from the probit estimations are reported in (13) and (14), with predicted probabilities graphed as the solid and dashed lines in Figures 2 and 3.

The estimated median discount rate was 4.66% in the worker scenario,

$$\hat{\delta}_m = \underset{(2.44)}{0.0466}, \quad \hat{\sigma}_\nu = \underset{(3.37)}{0.124} \;; \tag{15}$$

and 12.80% in the traffic scenario,

$$\hat{\delta}_m = \underset{(5.09)}{0.1280}, \quad \hat{\sigma}_\nu = \underset{(2.30)}{0.210} \tag{16}$$

H1 and H2 are rejected in favor of the alternatives K1 and K2 for both scenarios since $\hat{\beta}$ and $\hat{\delta}_m$ are significantly different from zero in (13)-(16). The t-statistics for $H3$ using r = 5.16% are 0.26 and 3.04 for the worker and traffic scenarios respectively, leading us to accept the null hypothesis that the discount rate is equal to the market rate for the worker scenario but to reject it for the traffic scenario.

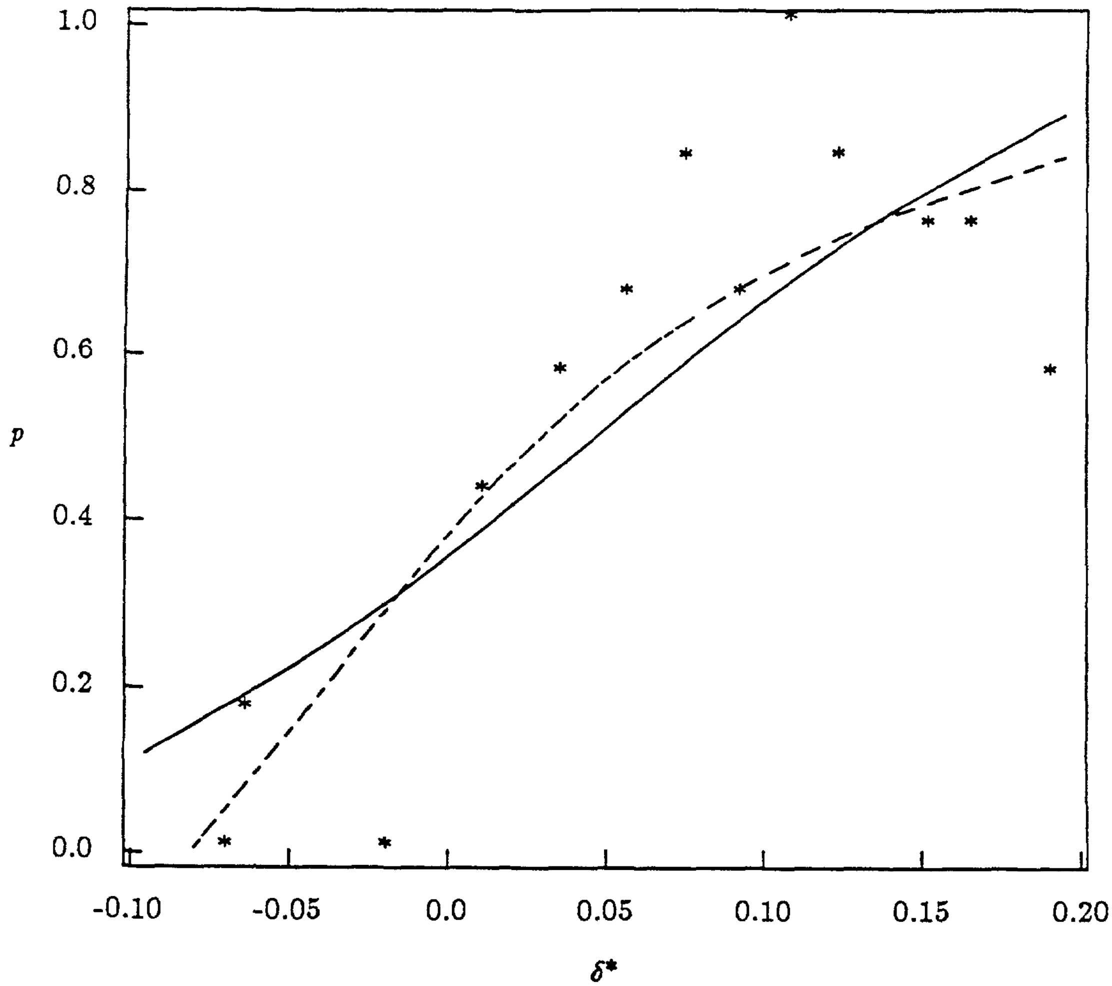
B. *Comparison of Choices in Different Scenarios*

One important hypothesis is that the discount rates are the same for all three scenarios. Such an hypothesis posits that a simple model such as (1) might be satisfactory for evaluating preferences for many different types of mortality risks. This hypothesis is formally expressed as Hypothesis 4:

$H4$: $\delta_m^{s} = \delta_m^{w} = \delta_m^{t}$

$K4$: $\delta_m^{s} \neq \delta_m^{w} \neq \delta_m^{t}$.

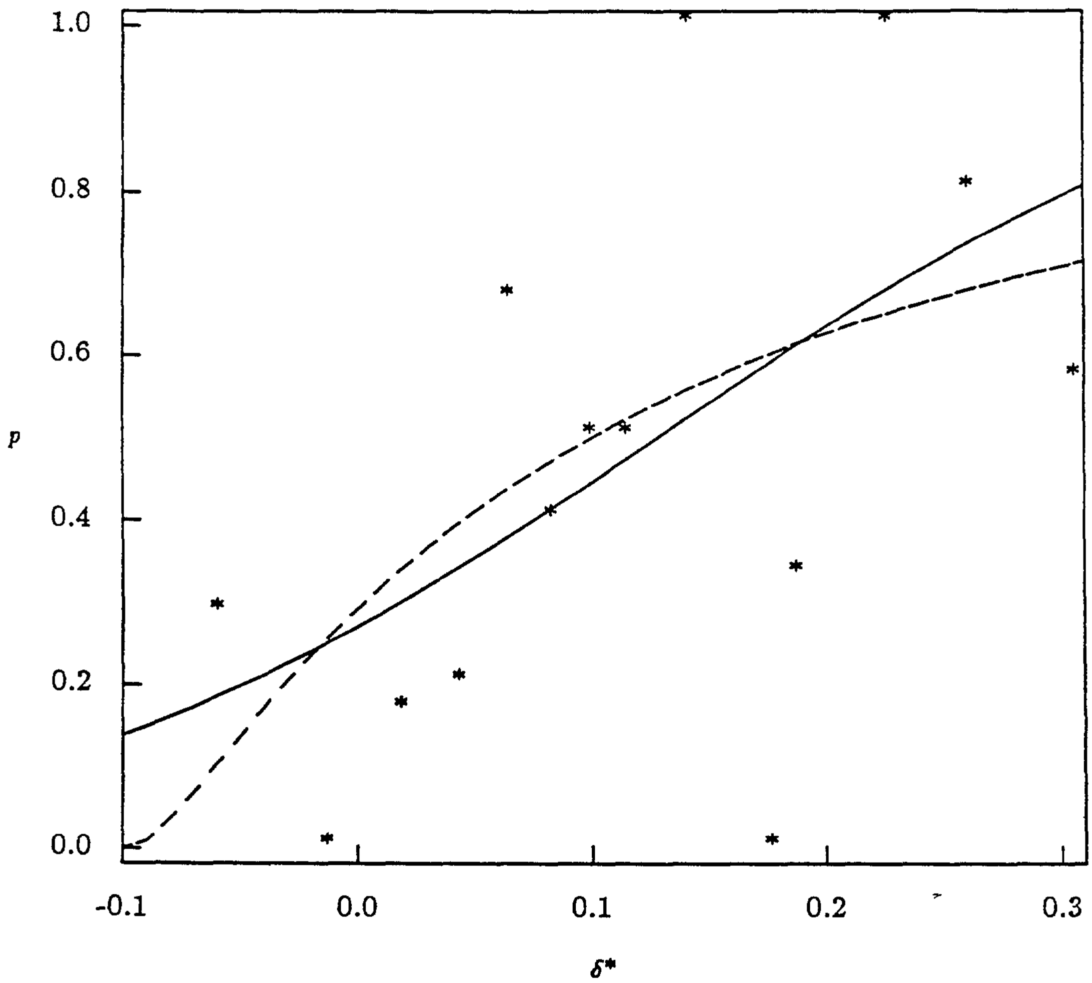
Figure 2. Proportion of Individuals Choosing the Future Project as a Function of δ^* (Worker Scenario)



$$\Phi(\hat{p}) = -0.375 + 8.057\,\delta^* \quad \text{(solid line)} \tag{13a}$$

$$\Phi(\hat{p}) = 2.396 + 1.162\,ln(0.1 + \delta^*) \quad \text{(dashed line)} \tag{13b}$$

Figure 3. Proportion of Individuals Choosing the Future Project
as a Function of δ^* (Traffic Scenario)



$$\Phi(\hat{p}) = -0.613 + 4.778\,\delta^* \qquad \text{(solid line)} \qquad (14a)$$

$$\Phi(\hat{p}) = 1.282 + 0.791\,ln(0.1 + \delta^*) \qquad \text{(dashed line)} \qquad (14b)$$

Estimated median discount rates for the three scenarios are 4.54%, 4.66%, and 12.80%. Hypothesis 4 is not rejected for the air travel and worker scenarios (t = 0.05). It is rejected for the worker and traffic scenarios (t = 2.58) and for the air travel and traffic scenarios (t = 2.79). This suggests that discount rates for the air travel and worker scenarios differ from the discount rate for the traffic scenario.

There are several reasons why the higher discount rate for the traffic scenario might be observed. We speculate on three here. The higher discount rate in the traffic scenario might be observed because the risks associated with traffic are more *familiar* to our survey participants than the risks associated with air travel or blue collar work; more familiar risks may induce a higher discount rate because individuals more clearly envision the present risk. A higher discount rate might also be held when risks are more likely to affect the participants personally, as traffic risks are likely to do. A higher discount rate for this reason is consistent with an argument that individuals discount risks to their own lives but hold a more altruistic view about risks to other individuals. Another possible explanation for the higher discount rate is that it is due to the size of the payoffs, since the traffic scenario is characterized by a smaller number of statistical lives at stake than either the air travel or the worker scenarios. Higher discount rates with smaller payoffs have also been observed for money payoffs in survey contexts by Thaler (1981) and George Loewenstein (1987).

C. *Estimating Individual Discount Rates*

Models such as the life-cycle utility model suggest that discount rates may differ across individuals because of different budget constraints or different time streams of income; the discount rate may also differ with age if discounting is influenced by the probability of reaching a particular age. Additional economic work also suggests that discount rates might differ across individuals according to socio-economic variables such as wealth (Emily Lawrance, 1987). The estimation of individual discount rates may thus be especially worthwhile since the attractiveness of different risk reduction policies may be affected by whom the policies affect.

Our final null hypothesis is that no relationship between X and revealed discount rates exists. If we assume individual discount rates follow a simple relationship between δ_i and individual characteristics X_i, $\delta_i = \mu + X_i\gamma + \epsilon_i$, then Hypothesis 5 can be stated formally as:

$H5$: $\gamma = 0$
$K5$: $\gamma \neq 0$,

Estimation results for X = *(GENDER, FGRADE)* are given in (17) for the air travel scenario, with asymptotic t-statistics in parentheses,[22]

$$\delta_i = \underset{(2.56)}{0.040} + \underset{(1.14)}{0.017}\ GENDER - \underset{(-1.13)}{0.047}\ FGRADE\ ; \qquad \hat{\sigma}_\epsilon = \underset{(1.43)}{0.10}\ . \tag{17}$$

Hypothesis $H5$ is accepted for X = *(GENDER, FGRADE)* in the air travel scenario using a likelihood ratio test. Similar acceptances are obtained for a number of other configurations of the vector X, other functional forms for $h(\bullet)$, and for choices in the other scenarios. Unfortunately, the homogeneity of the student population, which increases the power of the tests of hypotheses $H1$ through $H4$, greatly decreases the power of the test of $H5$.

IV. Conclusion

This paper proposes a survey approach for examining the question: What discount rate should be used for future reductions in mortality risks? Our method is based on a relationship between an individual's discrete choice between two policies that save statistical lives and the equilibrating discount rate at which the individual would be indifferent between the two policies. This relationship can be used under fairly general

[22] *GENDER* equals 1 if the respondent is male and equals -1 if the respondent is female. Approximately 2/3 of the respondents were male. *FGRADE* is the deviation of final course grade from the clear mean of 3.08 (on a scale of 0 to 4).

assumptions to estimate median discount rates and, under stronger assumptions, to estimate individual discount rates as well.

We present empirical evidence about individual preferences over the timing of projects that save statistical lives. We find strong evidence that individuals discount future statistical lives at a positive rate. The estimated median discount rates are 4.54% for the air travel scenario, 4.66% for the worker scenario, and 12.80% for the traffic scenario.

The 12.2% estimate of the discount rate made by Moore and Viscusi (1987) is close to our estimated discount rate for the traffic scenario. The risks posed in our traffic scenario are similar to the occupational risks in their model since traffic is perhaps the most common and most familiar risk to our student participants just as occupational risks are the most familiar risks to their blue collar workers.[23]

The discount rate is inherently unobservable. The validity of the indirect market approach for estimating δ as used by Moore and Viscusi (1987) rests on the appropriateness of two crucial sets of assumptions: those assumptions that underly a particular specification of the hedonic wage equation, and the assumption that workers correctly perceive job-related risk levels. Our survey approach avoids these critical assumptions but requires that individuals answer survey questions in a manner that reflects what their behavior would actually be if they faced temporal choices affecting these risks. The strengths and weaknesses of the two approaches are diametrical. Under the criterion of convergent validity, the fact that the two approaches obtain similar estimates is evidence that both are actually measuring the public's intertemporal risk preferences.

One of our goals in this paper has been to examine how discount rates differ for different types of risks. Our results suggest that a different discount rate might apply to each type of risk. We feel, however, that the discount rate is likely to be a function of

[23] Moore and Viscusi (1987) obtain an estimate for the discount rate of 9.6% in one specification of their model, which is closer to our estimates of discount rates in the air travel and worker acenarios

just a few key characteristics. Some characteristics that might affect the discount rate are the risk's familiarity, voluntariness, and sensationalism; the availability of substitutes; whether the risk has a latency period; whether a bad outcome from the risk is viewed as a catastrophe; and the magnitude of the base-line risk *(i.e.* the degree to which the risk affects the individual) (see Paul Slovic, Baruch Fischhoff, and Sarah Lichtenstein, 1982). Testing the effects of these characteristics is easily accommodated through our survey method by using scenarios with different mixes of characteristics.

While we rejected the hypothesis that different discount rates are held by different individuals for the same risk, this claim should be investigated further with a sample of participants from the general population. Our sample varied little in some of the attributes that might be expected to have an affect on risk preference such as age, income, education, or occupation; neither did we collect data on individual attitudes toward specific risks. An empirical estimate of interpersonal variability is important since it may explain why different discount rates for a given risk are supported by different groups. It is also important if different projects affect different groups of people.

In conducting our analysis we have maintained a number of traditional assumptions. The underlying utility function used to value statistical lives has been assumed to be time separable and linear in the number of lives saved and to exhibit exponential discounting. The assumption of exponential discounting is the most restrictive of these, and it can easily be tested in our framework by varying the time period between the instigation of the present project and the future project, or by varying the projects' duration. We also have not tested for the effect that the framing of the survey questions may have had on our results, although we have made an effort to minimize the influence of framing effects on our results. The most frequently cited framing effect in this area is the change in choices that often occurs when an identical problem is changed from being expressed in terms of lives saved to being expressed in terms of lives lost (Daniel Kahneman and Amos Tversky, 1981).[24] Changing the framing of the question in this manner has been shown to affect revealed risk preferences, and it remains to be examined whether it influences time preferences as well.[25]

Finally, we wish to note that there are two situations in which the discount rate is likely to be a more important factor in policy evaluation than the value of a statistical life. First, in many cases, the timing dimension is the key aspect of regulation that government agencies have jurisdiction over. This occurs for instance when a specific level of risk reduction has been mandated by legislation and what remains for the regulatory agency to decide is what technological changes should be required (which affects how quickly the technologies can be installed) or the timing with which a given technology should be adopted. Such decisions then involve questions of "when" rather than "whether" to undertake a particular project.

The second situation arises when the regulatory agency operates under fixed budget constraints. Consider the "drinking water problem" currently faced by the U.S. Environmental Protection Agency (EPA). In regulating drinking water quality, the EPA may be forced to choose between mandating reduced risks of contamination from active biological agents, which poses a risk of immediate illness and mortality, and reducing trihalomethane contamination, which poses a risk of future mortality from cancer. The limited financial resources of the municipalities involved generally prevents the adoption of both projects, even when both appear warranted. This tradeoff too can be seen as a tradeoff in the timing of the risks, rather than a tradeoff of risk for money.

[24] One possibility is that revealed discount rates vary according to whether the present policy is called an "advancement" or the future policy is called a "delay". Another potential source of framing effect is the size of the time units in which the choice is described, such as lives saved per year or lives saved per month.

[25] Thaler (1981) finds discount rates for money payoffs to be higher for gains than losses. This may, however, not be strictly a framing effect.

APPENDIX

Worker Safety

Each year a significant number of worker deaths occur due to dangerous vapors from spills of toxics. The government is considering two options to increase worker safety. One option is to require an adjustment to the existing ventilation system in the plants. This option will save an expected 20 lives per year over the next 25 years. A second option is to wait until a new technology currently being tested is ready for use. This technology will be ready for installation in about 3 years and will have a life span of about 22 years (The period of coverage is year 3 to year 25). It will save about lives per year once installed. The present-value cost of the options is about the same.

If the government requires the firms to make the adjustment to the existing ventilation system now, it will not be able to require them to install the new technology later. Which regulation should the government adopt?

____ Require an immediate improvement to the existing ventilation system.

____ Require use of the new technology when it becomes available 3 years from now.

Traffic Safety

Many traffic deaths occur each year because of problems at major intersections throughout the U.S. To reduce these deaths, the Federal government has made available two funds. One fund pays for the installation of better traffic signals. These can be installed immediately. The signals have a life of about 25 years and will save about 10 lives per year in each year of their existence. A second fund pays for a complete redesigning and reconstruction of the intersection, a process which takes about 5 years. The new design will save about lives per year for 20 years. After year 25, the intersection will have to undergo another renovation in either case.

A city can apply for only one of these funds. The amount of money that it must put up is the same in either case. Which option should the city choose?

______ Install better traffic signals now.

______ Redesign and reconstruct the intersection five years from now.

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