Valuation of Environmental Goods with Temporal Variation in Benefit and Payment Schedules

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Abstract: We analyze agent response to disparate payment schedules for protection of critical habitat units for the Seller sea lion in Alaska. The model allows for identification of implicit and explicit discount rates using information from a system of maximum likelihood equations. Testing is done using data for one, five, and fifteen-year payment treatments.

The temporal treatment of payment schedules in stated preference applications is a subject to be taken seriously by researchers attempting to value willingness to pay (WTP) for non-market goods. Much research has been directed towards sequencing and scope issues, as well as the properties of alternative payment mechanisms (Carson, 1997). Many of these studies pay particular attention to incentive structures inherent in the survey design, yet relatively little has been written about the time preference for payments of environmental goods. Especially when the program in question provides a pure public good, likely financed by tax dollars, it seems inappropriate to frame a dichotomous choice question in terms of a one-shot, lump-sum payment, when the true payment vehicle would likely be a stream of payments over time. Similarly, analysis of the benefits of the program should incorporate the temporal dimensions of the benefits stream, especially if the time periods differ between the two.

Much of the literature that does, in fact, mention bid treatment over time looks at sensitivity of summary measures of willingness to pay for a particular good or set of goods across the treatments. It was found that in eliciting willingness to pay for a toxic waste treatment facility in British Colombia, for example, respondents as a group did not distinguish between payment schedules of one and five years (Kahneman and Knetsch, 1992), violating the standard economic assumption of a positive discount rate. Expanding this idea, Stevens, DeCoteau, and Willis (1997) compared both scale and temporal embedding effects for both a public good (salmon restoration) and a private good (movie passes at a local theatre), and concluded that responses are not invariant to payment schedule. The authors also indicated in a footnote that an implicit assumption about the length of time the program provides benefits is necessary if one is to assume implicit discount rates from mean WTP estimates. Both of these studies used open-ended elicitation methods, with Kahneman and Knetsch conducting phone interviews and Stevens, et. al. collecting their data via a questionnaire.

Strumborg, Baerenklau, and Bishop (2001) studied temporal payment mechanism response in a contingent valuation study of Lake Mendota in Wisconsin, which elicited responses via a mail survey with a modified payment card and randomly split the sample into three and ten year treatment groups, with program benefits explicitly capped at ten years. They found that, if market discount rates are assumed, the ten-year subsample yields net present values that are higher than the three-year subsample.[1] Chavas and Mullarkey (2002) develop a model of valuation under temporal future learning uncertainty and irreversibility in the policy decision arena. They find that in the face of temporal uncertainty, there is a risk premium that is added to the willingness to pay for the option value of a natural resource. It seems logical that the higher the level of uncertainty, the larger the risk premium. Following this logic, it may be the case the risk premium may be higher for projects that extend further into the future because of the future learning that occurs with the resource under consideration. In other words, there may be a risk premium that has a negative correlation with future discounting because of uncertainty and irreversibility of the resource change. Finally, van der Pol and Cairns (2001) used discrete choice data to calculate implicit discount rates for health by collecting multiple data points on each respondent, and found that discounting varied by certain demographic and elicitation method characteristics.

This paper extends the line of research by analyzing willingness to pay and implicit discount rates when the periods of program benefit and payment schedule differ.

[1] The authors incorporated a discount rate of 4% into their regression equations.

We show how discount rates can be incorporated into the analysis in a conceptually rigorous way based on the principles of net present value analysis. The program we study concerns a pure public good, protection of critical habitat units for the Steller sea lion in Alaska, which generates an infinite stream of benefits. Three distinct subgroups in the population are studied that are likely to differ in their preferences for Steller sea lion protection: rural Alaska residents, other (predominantly urban) Alaska residents, and residents of the "Lower 48" states. Payment periods for the program are finite, with three variations: a lump sum (1-year), five years, and fifteen years. We show how comparisons of responses for the multi-year payment schedules to responses for the lump sum can be used to estimate the discount rates in addition to scale and location of willingness to pay.

The paper proceeds as follows. The next section develops the theoretical model, which incorporates the temporal variation in benefit and cost schedules by normalization to the one-year responses. The model is then implemented using the Steller sea lion data set. First, the standard equations using the lump-sum vehicle are estimated using the principles of maximum likelihood. Implicit discount rates are then calculated from mean willingness to pay results for the three payment horizons. Next, the discount rates are estimated explicitly as part of the model for the subgroups that exhibit significant differences in willingness to pay slope coefficients across treatments. Finally, we discuss the implications for future research and analysis.

MODEL DEVELOPMENT

Suppose an independent sample of respondents is presented with a survey that solicits willingness to pay for a public program with different repayment periods. Specifically, individual i is asked whether s/he is willing to pay B_i dollars per year for n_i

years for the provision of the public program. If the program is supplied, it provides a stream of benefits over an infinite time horizon.[2] As the program embodies costs and benefits over time, any expression for WTP necessarily embodies the individual's discount rate. Thus, we model the program choice as a comparison between the net present values (NPV) of the payments stream and the benefits stream.

The (finite) payment stream can be expressed as the difference between two infinite streams, one beginning in year 0, and the other beginning in year n_i*-1*. Assuming a discount rate *r*, the NPV of the infinite stream B_i beginning now is

$$PV_0^\infty(B_i) = B_i + \frac{1}{(1+r)}B_i + \frac{1}{(1+r)^2}B_i + \ldots \tag{1}$$

and

$$\frac{1}{(1+r)}PV_0^\infty(B_i) = \frac{1}{(1+r)^2}B_i + \frac{1}{(1+r)^3}B_i + \ldots \tag{2}$$

so that

$$PV_0^\infty(B_i) = B_i\frac{(1+r)}{r}. \tag{3}$$

Similarly, an infinite stream of payments beginning n_i years from now is worth

$$\begin{aligned} PV_{n_i}^\infty(B_i) &= \frac{1}{(1+r)^{n_i}}PV_0^\infty(B_i) \\ &= \frac{1}{(1+r)^{n_i}}B_i\frac{(1+r)}{r} \\ &= \frac{1}{(1+r)^{n_i-1}}B_i\cdot\frac{1}{r}. \end{aligned} \tag{4}$$

Subtraction of (2) from (1) yields the NPV to individual *i* of a finite stream of payments beginning now and ending in year n_i*-1*:

[2] Our analysis applies, more generally, to any cases where the benefit stream accrues over a period different than the repayment period.

$$\begin{aligned} PV_n(B_i) &= PV_0^{\infty}(B_i) - PV_{n_i}^{\infty}(B_i) \\ &= (B_i)\cdot\frac{(1+r)}{r}\left(1-\frac{1}{(1+r)^{n_i}}\right). \end{aligned} \tag{5}$$

Assuming the annual benefit received by the individual is given by the measure WTP_i, and the benefits accrue over an infinite time horizon, the NPV of the benefit stream is given by $\frac{WTP_i}{r}$. Thus, when faced with the hypothetical question of paying B_i dollars per year for n_i years for the program, the respondent votes yes so long as the NPV of benefits is at least equal to the NPV of the payment stream given by (5).

Of course, the researcher does not observe the true WTP_i as it is a latent variable. Instead, we define y_i as an observable binary variable with the following properties:

$$\begin{aligned} y_i &= 1 \text{ if } \frac{WTP_i}{r} \geq PV_n(B_i) \\ y_i &= 0 \text{ if } \frac{WTP_i}{r} < PV_n(B_i). \end{aligned} \tag{6}$$

Assuming that the true data generating process for annual individual benefits is $WTP_i = X_i\beta + \sigma\varepsilon_i$, where $\varepsilon_i \sim N(0,1)$,[3] the probability of observing a "no" response from an individual facing bid B_i^n can be written as

$$\begin{aligned} \Pr\{y_i = 0\} &= \Pr\left\{\frac{WTP_i}{r} < PV_n(B_i^n)\right\} \\ &= \Pr\left\{\frac{X_i\beta}{r} + \left(\frac{\sigma}{r}\right)\varepsilon_i < \frac{B_i^n}{r}\cdot\delta(r,n_i)\right\}, \end{aligned} \tag{7}$$

[3] Although this model assumes a single-index linear specification, generalization to non-linear functional forms is straightforward. Similarly, non-normal errors could be assumed.

where for simplicity, $\delta(r,n_i) \equiv \left(1 + r - \frac{1}{(1+r)^{n_i - 1}}\right)$. Since n_i is known, there is one unknown parameter in $\delta(r,n_i)$, the discount rate r.

The probability statement in (7) is a straightforward generalization of Cameron (1988), explicitly taking the time dimensions of the payment and benefit streams into consideration. Isolating B_i^n then yields

$$\Pr\left\{\frac{WTP_i}{r} < PV_n(B_i^n)\right\} = \Pr\left\{\frac{X_i\beta}{\delta(r,n_i)} + \left(\frac{\sigma}{\delta(r,n_i)}\right)\varepsilon_i < B_i^n\right\}, \tag{8}$$

which illustrates the impossibility of estimating and identifying β, σ, and r jointly without some sort of normalization.

Note that in the absence of the discount factor, the presence of the varying annual bid B_i^n would permit identification of both the β coefficient vector and σ, allowing for calculation of the scale of WTP directly from the latent variable formulation. While this is not be possible here, as there are three parameters of interest, it is nonetheless possible to identify the discount rate r and β up to a scale σ, as is typical in standard logit and probit analysis, by normalization of the variance parameter to 1. Cameron's approach, therefore, can be used to identify exactly one additional parameter of interest, although doing so results in limiting oneself to speaking in terms of probabilities without additional assumptions on scale.[4]

An alternative strategy, assuming at least two payment periods, is to normalize the parameter vector by r in estimation, thereby allowing for identification of location, scale, and the discount rate. This normalization allows the system of equations to be written

[4] Of course, this does not preclude using methods such as the familiar approach popularized by Hanneman (1984) to estimate mean WTP.

such that one equation identifies normalized location and scale, while the others identify r. Estimation then yields estimates of the discount rate and the normalized parameters, from which the underlying parameter vectors can be recovered.

To illustrate the approach, write (7) as

$$\Pr\left\{\frac{WTP_i}{r} < PV_n(B_i^n)\right\} = \Pr\left\{X_i\beta^* + \sigma^*\varepsilon_i < \frac{B_i^n}{r}\cdot\delta(r,n_i)\right\}, \tag{9}$$

where $\beta^* = \beta / r$ and $\sigma^* = \sigma / r$, and assume that we have data for two time treatments, $n_1 = 1$ and $n_2 > 1$. Then the probability of a no response for individuals asked to pay over the two time streams can be expressed as

$$\Pr\left\{\frac{WTP_i}{r} < PV_n(B_i^1)\right\} = \Pr\left\{X_i\beta^* + \sigma^*\varepsilon_i < B_i^1\right\} \tag{10}$$

$$\Pr\left\{\frac{WTP_i}{r} < PV_n(B_i^n)\right\} = \Pr\left\{X_i\beta^* + \sigma^*\varepsilon_i < \frac{B_i^n}{r}\cdot\delta(r,n)\right\}, \tag{11}$$

making use of the fact that $\delta(r,1) = 1$. Again isolating the annual bid payment, the system defined by (10) and (11) can be rewritten as

$$\Pr\left\{\frac{WTP_i}{r} < PV_n(B_i^1)\right\} = \Pr\left\{X_i\beta^* + \sigma^*\varepsilon_i < B_i^1\right\} \tag{12}$$

$$\Pr\left\{\frac{WTP_i}{r} < PV_n(B_i^n)\right\} = \Pr\left\{X_i\beta^*\cdot\frac{r}{\delta(r,n)} + \sigma^*\cdot\frac{r}{\delta(r,n)}\varepsilon_i < B_i^n\right\}, \tag{13}$$

or equivalently as

$$\Pr\left\{\frac{WTP_i}{r} < PV_n(B_i^1)\right\} = \Pr\left\{X_i\beta_1^* + \sigma_1^*\varepsilon_i < B_i^1\right\} \tag{14}$$

$$\Pr\left\{\frac{WTP_i}{r} < PV_n(B_i^n)\right\} = \Pr\left\{X_i\beta_2^* + \sigma_2^*\varepsilon_i < B_i^n\right\} \tag{15}$$

Clearly, (14) and (15) can be estimated by standard maximum likelihood procedures, although this in itself does nothing to identify the extra parameter. However, comparing (13) to (12) suggests that we can use the one-year treatment to identify β^* and σ^*, and differences in the parameters from (14) to (15) are due solely to the discount factor. For a given $r = \mathbf{r}$, then, one could test the hypothesis

$$H_0 : \beta_2^* = \beta_1^* \cdot \frac{r}{\delta(r,n)}, \sigma_2^* = \sigma_1^* \cdot \frac{r}{\delta(r,n)},$$

which would identify a range of r for which the data do not reject the hypothesis.

This methodology can be extended to directly estimate all of the parameters, including r, using equations (12) and (13) and restricting the parameter vectors to be identical, thus embodying the assumption that the same parameter vectors characterize annual WTP, and differences in the estimated coefficients are due to the discount factor alone. The log likelihood function can be developed by rewriting (13) so that

$$\Pr\{y_i = 0\} = \Pr\left\{\varepsilon_i < -\frac{X_i\beta^*}{\sigma^*} + \frac{B_i^n}{\sigma^*} \cdot \frac{\delta(r,n)}{r}\right\} \tag{16}$$

Assuming normal errors, taking logs, and summing over the sample, the log likelihood function becomes

$$\begin{aligned}\log L = \sum_{i=1}^{(N_1+N_n)} \Bigg\{ & y_i \ln\left[1 - \Phi\left(-\frac{X_i\beta^*}{\sigma^*} + \frac{B_i^n}{\sigma^*} \cdot \frac{\delta(r,n)}{r}\right)\right] \\ & +(1-y_i)\ln\left[\Phi\left(-\frac{X_i\beta^*}{\sigma^*} + \frac{B_i^n}{\sigma^*} \cdot \frac{\delta(r,n)}{r}\right)\right]\Bigg\}.\end{aligned} \tag{17}$$

Optimization of (17) by standard numerical procedures, such as the MAXLIK option in GAUSS, is straightforward, and asymptotic standard errors for the parameter estimates will be correct so long as the density is correctly specified. The usual hypothesis tests can then be performed to empirically investigate a number of issues regarding intertemporal preferences within a CVM framework, including sensitivity of responses to the temporal payment schedule and testing if rates of time discount are significantly different from zero. In addition, one can extend the model to allow for endogenous variation in the discount rate parameter r over individuals, simply by specifying an appropriate functional form for $r(z)$, such as the linear $r(z) = z'\gamma + \varepsilon_i$, where z is an n x k subset of the exogenous regressor set x. Through this specification, we can test for significant differences in the discount rate between categories of respondents.

SURVEY AND DATA

Giraud and Turcin (2001) collected referendum data on willingness to pay for a proposed expanded federal Steller sea lion recovery program off the coast of Alaska. This program consisted of increased restrictions on commercial fishing activity within the certain designated buffer zones around critical habitat units for the Steller sea lion, as well as a doubling of funding for research efforts to understand the ongoing population decline. Data was collected using the Dillman Tailored Design Method (2001) via a questionnaire that was mailed to random samples of 1,000 households in each of three regions: the Alaska Boroughs (rural areas that contain the critical habitat and buffer zones), the state of Alaska (whose population is highly concentrated in the cities of Anchorage, Fairbanks, and Juneau), and the United States as a whole. After describing the relevant background information, assessing the respondent's views on endangered species management and evaluating familiarity with the Steller sea lion and the associated fishery, the survey presented each agent with the following dichotomous choice question:

> "If the Expanded Federal Steller Sea Lion Recovery Program was the only issue on the next ballot and it would cost your household $____ in additional Federal taxes every year for the next ____ year(s), would you vote in favor of it? (By law the funds could *only* be used for the Steller sea lion program."

Bid amounts for each of the three stratifications varied from $1 to $350, a range established by extensive use of focus groups and pre-testing. In addition to the varying bid amounts, there were also three temporal treatments of one, five, and fifteen years. Each respondent was asked to vote only once, and associated demographic information was collected at the end of the survey. A summary of the geographically pooled data used for analysis for each of the three temporal treatment groups is presented in Table 1.

LUMP-SUM MODEL

Before proceeding directly to the discount model, it is useful to examine the results from the prototypical lump-sum payment vehicle model, which in the current context assumes $n_i = 1$. Table 2 reports the dependent and independent variables used in estimation of this model for the spatially pooled data, a subsample that excludes the Boroughs, a subsample that that excludes the rest of the United States, and each of the three geographic subsamples. The motivation behind this stratification, maintained throughout the paper, is explained primarily by differences in homogeneity of preferences among groups. Those in the rest of U.S. are not tied economically to the commercial fisheries that would be negatively affected by the Steller program, whereas a very high percentage of Alaskan residents, both in the Boroughs and statewide, are economically tied to the commercial fisheries either directly or through family members. As such, protection of the habitat units may, in fact, constitute a “bad” rather than a good for many respondents, and their compensating variation may be negative. Comments received in focus groups, pre-testing and on the survey itself indicate that some respondents viewed sea lions as a pest. Others thought that previous efforts by the government to protect the sea lion were unsuccessful and thus the protection program should not continue. The net effect is that even though the Alaska groups are separated geographically, they likely are quite heterogeneous in preferences for Steller protection, much more so than the Rest of U.S. group. It is therefore instructive to pool the non-Boroughs data to (somewhat) isolate the respondents not tied to the fisheries, and to pool the Alaska data to isolate the peculiar features of this population subset.

Table 3 reports the results of the estimation of the lump-sum model given by equation (10). Due to the linear functional form of the data generating process, the β coefficients give the marginal change in the estimated (net present value of) WTP for a one-unit change in each regressor, identified only up to location and scale, with no information regarding the temporal preferences of the agents. As is typical in single-bounded dichotomous choice contingent valuation (CV) studies, the standard errors on the coefficients are relatively large, yet most signs are as expected a priori. [5] The exceptions are the insignificant *Income* variable, which is positive for the Rest of U.S. subsample only, and the *Member* variable, which is also negative for all but the non-Alaskan stratifications. However, in light of the heterogeneity of preferences between

[5] As a result, the convention denoting statistical significance in the tables will be one star (*) for significance at the ten percent level, and two stars (**) for significance at the five percent level.

some Alaskans and the rest of the country, these results are not surprising. In addition, it has been argued that prior knowledge can influence WTP (Giraud, et al., 1999), so *KnowSSL* and *KnowVil* are included as explanatory variables in each model. The significance of each, however, tends to decline as familiarity with the issue increases, as residents of Alaska were inundated with information regarding this highly contentious program.

In fact, the Alaskan data appears to be extremely noisy, as none of the explanatory variables are individually statistically significant at the ten percent level in the Boroughs subsample, and only *Projobs* appears to be marginally non-zero for the Rest of Alaska model. The situation improves slightly when the Alaskan data is pooled, providing an additional benefit through increased degrees of freedom available for estimation. As such, the subsequent analysis focuses primarily on models estimated using the pooled data and each of the two pooled subsamples.

IMPLICIT DISCOUNT RATE MODELS

We next turn to the treatment of alternative payment schedules that has been presented in the previous literature, albeit in the context of an *infinite* benefits stream rather than a stream of benefits and costs of identical length. To do so, it is necessary to estimate at least one additional equation, which in conjunction with the lump-sum model creates a system described by equations (14) and (15) above. For this data set, we estimate additional equations for both the five-year and fifteen-year payment treatments. Pairwise comparisons between the lump-sum and each multi-year equation provide information regarding the size of the implicit discount rate r, as we use the relationship between the slope coefficients to provide point estimates of the parameter. Standard errors can then be computed through the Krinsky-Robb simulation procedure (Krinsky and Robb, 1986).[6]

As can be seen from equations (12) and (13), the predicted mean NPV WTP over the infinite time horizon for, say, the 5 year treatment is

$$\frac{\overline{\widehat{WTP}_{5yr}}}{r} = \frac{1}{N_5}\sum_{i=1}^{N_5} X_i^5 \hat{\beta}^* = \frac{1}{N_5}\sum_{i=1}^{N_5} X_i^5 \hat{\beta}_2^{\ *} \cdot \frac{\delta(\hat{r},5)}{\hat{r}}, \tag{18}$$

where N_5 is the number of observations in the particular five-year treatment and hats denote estimates. Similarly, predictions for the lump-sum treatment are

$$\frac{\overline{\widehat{WTP}_{1yr}}}{r} = \frac{1}{N_1}\sum_{i=1}^{N_1} X_i^1 \hat{\beta}^* = \frac{1}{N_1}\sum_{i=1}^{N_1} X_i^1 \hat{\beta}_1^{\ *}. \tag{19}$$

With consistent parameter estimates and a correctly specified model, differences in mean NPV WTP between the treatments are solely the result of discounting, substitution of (19) in (18) yields

$$\overline{X^5 \hat{\beta}_2^*} = \overline{X^1 \hat{\beta}_1^*} \cdot \frac{\hat{r}}{\delta(\hat{r},5)} \tag{20}$$

with the bar denoting the mean. Equation (20) can be solved to provide implicit estimates of *r*, much as the previous literature has done. Extending to *m* pairwise implicit equations for additional treatments is straightforward.

Results for each of the additional two regressions for each temporal treatment are reported in Table 4, and implicit discount rates calculated from both the sample mean and median $\left(X^m \beta_m^{\ *}\right)$ are reported in Table 5. Note that the value reported for the one-year treatment identifies the NPV WTP (*m*=1), while the estimates for the five and fifteen-year

[6] Pending from the author.

schedules (m=5 or m=15) are transformations of NPV WTP defined by (18) which implicitly define the magnitude (and variability) of the discount rate. Due to the considerable unexplained heterogeneity in the Alaskan data, we introduce an additional stratification to separate those respondents who may consider the program a public bad from those who consider it a good. Thus, we split the aggregate pooled, pooled subsample, and rest of U.S. groups into a "pro-species" and "pro-employment" dichotomy, defined by the ratio of *ProSpec* to *ProJobs*.[7] As can be seen in Table 5, this results in positive, statistically significant mean and median $\left(X^m \beta_m^*\right)$ estimates for each cost stream treatment in the "pro-species" category, while the "pro-employment" stratification results in insignificant, negative estimates. We thus restrict our attention to the former, and do not report the latter.

Furthermore, likelihood ratio tests were used to test joint significance of the imprecisely estimated parameters for each model, and the appropriate restrictions were imposed where appropriate. As such, the rest of U.S. and non-Boroughs and Alaskan models not stratified by preferences include three regressors (*ProSpec, ProJobs, and Constant*), while the rest of the equations are estimated using five regressors, excluding *Income* and *Age*.

Examination of Table 4 reveals that inclusion of the Boroughs data tends to deflate point estimates of NPV WTP for the pooled models not stratified by preference, and decreases the precision. Even utilizing the non-Boroughs data, the fifteen-year estimate of mean$\left(X^m \beta_m^*\right)$ is negative, in contrast to the one-year treatment, but is at least significant for the shorter periods. Restricting estimation to the less volatile rest of U.S.

[7] More specifically, if (*ProSpec/ProJobs)*>1 for an individual observation, that observation is considered "pro-species".

category increases precision and results in positive, significant, and feasible mean and median estimates, and using the "pro-species" data does the same for the pooled data and increases the overall magnitudes of WTP.

The revealed temporal preferences across the subsamples are intriguing as well. A priori, we expect mean/median $\left(X^m \beta_m^*\right)$ to be largest for the lump sum treatment and decline with the length of the payment horizon, in accordance with equation (13). This relationship is not observed between the lump sum and five year treatments for the pooled equations without preference stratification; in fact, in all but one case (non-boroughs), the five-year point estimates are actually greater. This implies a *negative* discount rate for those in the five-year sample. While irrational if the discount rate is interpreted narrowly as a market interest rate, *r* may more appropriately be interpreted as a social discount rate that expresses preferences for intergenerational consumption; in this context a negative *r* implies greater weight to future consumption. An alternative explanation, making use of the variability in the estimates of NPV WTP, is that respondents did not distinguish between the lump sum and five-year treatments, as found in Kahneman and Knetsch (1992). The latter argument is strengthened by examining the preference-stratified estimates for the five year treatment, which imply discount rates well over one (and in one case, ten times that).

It does appear, however, that respondents distinguish between the lump sum and fifteen year treatments in just about every case reported in Table 4. Due to the change in sign, implicit discount rates cannot be estimated for pooled samples not stratified by preferences, but the change in sign of $\left(X^m \beta_m^*\right)$ suggests that individuals revealed some form of discounting. The remaining models support this argument, with point estimates of discount rates ranging from 0.23 to 0.79. While these estimates are high with respect to market rates of interest, they are reasonable and in line with estimates from the previous literature (Stevens, DeCoteau, and Willis, 1997; Stumborg, Baerenklau, and Bishop, 2001; van der Pol and Cairns, 2001).

EXPLICIT DISCOUNT RATE MODELS

With these results in mind, we now move to explicit estimation of the discount rates, as given by maximization of the likelihood given by equation (17). This formulation has the advantage of not relying solely on consistent estimates of the central moment in order to estimate discount rates, potentially dampening the influence of outliers in the data, as well as the ability to take advantage of more than just pairwise comparisons in the data through joint estimation of the m equations in the system. Additionally, from a computational standpoint, we explicitly obtain point estimates and asymptotic standard errors from the optimization, rather than solving a series of implicit equations and using simulation to compute standard errors.

In order to explicitly identify the discount rate r with a relative degree of precision, there must be variation between a completely unrestricted model that allows for varying coefficients across treatments and a restricted model that imposes all slope coefficients equal, as can be seen from equations (12) and (13). If this is not the case, then the data suggests that $\frac{r}{\delta(n_i, r)} = 1$, i.e., $r = \infty$, and individuals do not distinguish between temporal treatments. Once again, these restrictions can be tested using likelihood ratio tests, as reported in Table 6.[8] In all but the preference-stratified non-Boroughs sample, the data supports evidence that respondents are distinguishing between payment schedules, although this seems to manifest itself through the fifteen-year rather than the five-year treatment. Additional testing confirms that restricting coefficients to be equal in the lump-sum versus five-year treatment model is not rejected at the 95% level for any of the models considered, yet four of the six reject equivalence of the discount rates from the five and fifteen year schedules. These results are in accordance with the implicit rates discussed above.

Tables 7 and 8 report the results of the explicit discount models and the revealed, internally consistent NPV WTP and annual WTP evaluated at both the mean and the median for those models that suggest some degree of discounting. The signs of the discount rate are all positive with magnitudes between zero and one, although the levels of statistical significance are disappointing for the treatments not stratified by preferences. Overall, the point estimates tend to be larger than the market rate of interest, and the (statistically significant) explicit rates for the fifteen-year treatment tend to be higher than the corresponding implicit rates. Perhaps surprisingly, the "pro-species" stratification has only slight effects on the point estimates for four of the six treatments, indicating some degree of robustness.

The WTP estimates exhibit the same general pattern as with the implicit discount rate models, as inclusion of the Boroughs without preference stratification significantly reduces NPV WTP. Median WTP is consistently greater than mean WTP without

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[8] See Table 7 for the model specification used. Likelihood ratio tests for the "Projob" stratification did not reject equivalence of slope coefficients at the 10% level, and thus are not reported here.

adjusting for the unexplained heterogeneity, but the reverse is true when looking at the "pro-species" group alone.

DISCUSSION AND IMPLICATIONS

The implicit and explicit discount rates from mean willingness to pay are quite high relative to market rates, but in line with those found by Stevens, DeCoteau, and Willis (1997) and Stumborg, Baerenklau, and Bishop (2001). Similarly, the results from the analysis support the Kahneman and Knetsch (1992) finding that five-year intervals make little difference in estimated mean willingness to pay, although the data here support the hypothesis of discounting for fifteen-year payment schedules.

We suspect the special population of Alaska is bifurcated into those with especially strong preferences towards environmental quality, and those whose preferences are the polar opposite and whose livelihoods and economic security are directly impacted by the fisher. As such, the models exhibited heterogeneity of parameters within the sample that cannot be explained by time preferences alone. To the extent that we controlled for this heterogeneity by focusing on a subsample stratified by preferences, it should be stressed that the results are conditional on this choice. However, this problem illustrates that models with larger sample sizes and greater efficiency will most likely have more success in identifying the underlying temporal preferences of respondents. This seems especially true in the case presented here, where a relatively contentious issue with potentially significant market effects may lead some individuals to view a program as a public bad rather than a public good.

Most fundamentally, a method of recovering the discount rate for differing program lengths and payment periods is identified. The empirical results suggest that respondents are, in fact, sensitive to temporal payment schedules in a discrete choice format, at least in the long run. It may be that the Chavas-Mullarkey argument about risk premia associated with longer, and inherently more risky, time periods plays a role. In any event, it seems clear that across the CV research to date, as in the marketable goods case, there is little empirical support for the theoretical argument that agents discount money streams at the market rate of interest. This raises important questions about the proper treatment of benefits in a public policy context when considering projects with a temporal component, as typically researchers and decision-makers compare net present values of benefits versus costs when making their recommendations or decisions.

Finally, as previously noted, expansion of the model to allow for the discount rate parameter to be a function of regressors is straightforward, presuming one achieves given sufficient variation in the slope parameters. Van der Pol and Cairns (2001), for example, found that discount rates tend to increase with increasing age, while Thaler (1981) found a negative relationship between dollar sums and discount rates. Furthermore, Stevens, DeCoteau, and Willis (1997) suggest that budget constraints may play a role in determining discount factors. One could, in principle, choose a functional form for these explanatory variables and let $r = f(\gamma \mid X_i)$, thus allowing the discount rate to differ between individuals.

CONCLUSIONS

This paper introduces a model that identifies the role of time preferences separately from program values in contingent valuation applications for which the time periods of program benefits and payment differ. It allows for explicit calculation of discount rate parameters given alternative temporal treatments of the bid vehicle, which is grounded theoretically in the principles of present value analysis. Results suggest that respondents are more sensitive to payment period variation in the long run, and rates of discount are significantly higher than the market rate of interest. These findings are especially relevant with regard to pure public goods, such as the protection of endangered species, as recovery programs may often take many years and are unlikely to be financed with a lump-sum payment vehicle. Proper experiment design and execution, therefore, requires serious consideration of temporal payment issues in order to credibly present respondents with a realistic vehicle and to provide researchers with the proper information necessary to inform and advise policy makers.

Table 1: Summary Statistics

	Vote	*Bid*	*ProSpec*	*ProJobs*	*KnowSSL*	*KnowVil*	*Gender*	*Member*	*Age*	*Inc*
One Year	0.4743	82.62	3.66	3.053	0.6799	0.7477	0.2360	0.1168	0.4941	0.6876
n = 428	(0.4999)[a]	(103.2)	(1.029)	(1.114)	(0.4671)	(0.4349)	(0.4251)	(0.3216)	(0.1255)	(0.4132)
Five Year	0.481	79.32	3.643	2.741	0.6557	0.7165	0.2709	0.1443	0.4954	0.6500
n = 395	(0.5003)	(104.2)	(1.063)	(0.6289)	(0.4757)	(0.4513)	(0.445)	(0.3518)	(0.135)	(0.3718)
Fifteen Year	0.3824	75.74	3.588	2.755	0.6873	0.7752	0.2248	0.1473	0.4968	0.7371
n = 387	(0.4866)	(100.8)	(1.084)	(0.5999)	(0.4642)	(0.418)	(0.418)	(0.3549)	(0.1298)	(0.4432)
Pooled Data	0.4471	79.34	3.632	2.856	0.6744	0.7463	0.2438	0.1355	0.4954	0.6911
n = 1210	(0.4974)	(102.7)	(1.057)	(0.8387)	(0.4688)	(0.4353)	(0.4296)	(0.3424)	(0.1299)	(0.4114)

[a] Standard errors in parentheses.

Table 2: Definition of Variables Used in Analysis

Variable Name	***Description***
Vote	=1 if respondent votes yes; 0 otherwise
Bid	Annual payment on which to vote, measured in dollars
ProSpec	Sum of three Likert-scale questions (Strongly Disagree = 1; Strongly Agree=5) regarding endangered species protection to asses preferences
ProJobs	Sum of three Likert-scale questions regarding preferences towards commercial fishing activity and employment
KnowSSL	=1 if individual has "read or heard anything about the endangered Steller sea lion in Alaska"; 0 otherwise
KnowVil	=1 if individual has "read or heard anything about the commercial Pollock fishery in Alaska"; 0 otherwise
Gender	=1if female; 0 otherwise
Member	=1 if respondent is a member of a conservation or environmental organization; 0 otherwise
Age	Age of respondent in years
Income	Total pre-tax household income, measured in tens of thousands of dollars elicited through choice of income category

Table 3: Lump-Sum Vehicle Estimation Results

	Pooled Data	***Non-Boroughs***	***Alaska***	***Rest of U.S.***	***Rest of AK***	***AK Boroughs***
ProSpec	179.7**	173.9**	258.0**	105.9**	323.0*	247.4
	(49.3)[a]	(53.28)	(109.2)	(46.92)	(194.3)	(190.5)
ProJobs	-146.8**	-85.98**	-202.7**	-101.8**	-94.36	-383.4
	(42.1)	(35.38)	(88.35)	(43.09)	(78.98)	(290.1)
KnowSSL	97.01	138.5**	66.65	93.33	170.7	-73.42
	(61.12)	(67.38)	(111.9)	(70.2)	(176.6)	(220.1)
KnowVil	-119.1*	-95.48	-278.2*	-52.57	-268.5	-226.3
	(63.21)	(59.59)	(167.2)	(58.42)	(222.)	(315.)
Gender	101.8*	96.92	200.4	22.4	328.1	210.3
	(59.92)	(62.82)	(123.6)	(62.88)	(221.)	(240.4)
Member	-152.9*	-134.4	-275.2*	18.53	-388.4	-282.9
	(80.17)	(94.04)	(155.5)	(117.6)	(291.2)	(287.)
Age	3.205	61.07	-185.4	175.4	-111.5	-391.5
	(140.7)	(190.5)	(355.4)	(206.3)	(527.8)	(698.2)
Income	-61.36	-39.19	-101.2	36.26	-162.	-171.7
	(60.05)	(60.36)	(110.4)	(66.7)	(168.7)	(259.5)
Constant	-109.2	-331.4	54.41	-145.7	-528.9	762.
	(187.1)	(231.3)	(319.1)	(248.2)	(528.4)	(828.6)
σ	306.8**	245.2**	433.0**	180.8**	377.3*	604.2
	(72.68)	(62.65)	(171.2)	(52.49)	(213.3)	(444.6)
n	428	254	316	112	142	174

* denotes significance at the 10% level of significance, ** denotes significance at the 5% level of significance.
[a] Standard errors in parentheses.

Table 4: Implicit Discount Rate Models
Joint Insignificance Restrictions Imposed

	Five-Year Treatment				*Fifteen-Year Treatment*			
	Pooled Data	***Non-Boroughs***	***Alaska***	***Rest of U.S***	***Pooled Data***	***Non-Boroughs***	***Alaska***	***Rest of U.S***
No Stratification by Preferences								
ProSpec	209.7**	184.1**	274.2**	129.9**	165.0**	129.2**	215.2**	122.1**
	(38.58)[a]	(34.83)	(68.31)	(35.89)	(28.51)	(26.35)	(48.25)	(31.64)
ProJobs	-209.9**	-189.9**	-225.0**	-166.0**	-116.5**	-134.0**	-86.72*	-158.7**
	(48.75)	(47.36)	(73.5)	(58.59)	(35.4)	(37.96)	(48.99)	(50.11)
Gender	-8.262	--	--	--	46.41	--	--	--
	(47.3)				(41.43)			
Member	-33.31	--	--	--	-48.62	--	--	--
	(62.89)				(54.75)			
Constant	-135.5	-90.62	-351.5	41.35	-311.1**	-126.8	-598.2**	-10.49
	(145.8)	(137.1)	(246.4)	(150.4)	(133.2)	(126.3)	(226.4)	(135.1)
σ	297.6**	237.3**	360.2**	210.6**	238.5**	195.6**	285.5**	176.7**
	(46.43)	(38.47)	(79.04)	(45.26)	(32.32)	(29.25)	(54.79)	(33.22)
n	424	271	304	120	417	247	305	112
"Prospecies" Stratification								
ProSpec	232.1**	252.7**	243.2**		176.8**	151.5**	237.0**	
	(48.11)	(55.4)	(71.61)		(37.2)	(37.7)	(67.02)	
ProJobs	-181.6**	-172.5**	-194.0**		-107.0**	-134.5**	-50.00	
	(50.14)	(55.93)	(72.21)		(38.64)	(41.83)	(56.06)	
Gender	-22.34	-38.52	46.35		67.82	57.82	38.32	
	(47.57)	(50.77)	(74.17)		(41.96)	(43.96)	(63.76)	
Member	-42.35	-28.36	-15.87		-15.29	-55.05	(44.56)	
	(61.46)	(68.59)	(89.79)		(57.6)	(61.14)	(82.25)	
Constant	-309.6	-408.9	-328.3		-400.5	-236.	-806.5**	
	(186.4)	(210.8)	(261.4)		(166.2)	(168.7)	(310.3)	
σ	264.9**	228.8**	316.6**		225.4**	180.9**	283.5**	
	(42.44)	(40.88)	(72.64)		(32.09)	(28.65)	(61.66)	
n	294	200	194		282	174	193	

* denotes significance at the 10% level of significance, ** denotes significance at the 5% level of significance.

[a] Standard errors in parentheses.

Table 5: Implicit Discount Rates and Mean and Median NPV WTP

	No Stratification by Preferences				*"Prospecies" Stratification*			
	Mean $Xi\beta^*$	*Implicit r^b*	*Median $Xi\beta^*$*	*Implicit r*	*Mean $Xi\beta^*$*	*Implicit r*	*Median $Xi\beta^*$*	*Implicit r*
Pooled Data								
One Year Treatment	29.37		49.96*		232.9**		191.6**	
	(23.89)[a]		(29.94)		(47.84)		(59.96)	
Five Year Treatment	35.65	-5.66	69.44**	-2.29	176.5**	3.12	168.7**	7.37
	(22.07)		(27.66)		(27.12)		(33.99)	
Fifteen Year Treatment	-47.1**	--	-9.324	--	73.79**	0.46	65.05**	0.51
	(23.3)		(29.2)		(18.43)		(23.1)	
Non-Boroughs								
One Year Treatment	83.2**		123.1**		220.8**		205.5**	
	(21.98)		(27.55)		(44.62)		(55.92)	
Five Year Treatment	75.58**	9.92	137.5**	-2.06	188.7**	5.88	187.6**	10.48
	(21.54)		(27.)		(30.53)		(38.26)	
Fifteen Year Treatment	-26.75	--	-10.32	--	60.83**	0.38	58.26**	0.39
	(22.75)		(28.51)		(19.23)		(24.1)	
Alaska								
One Year Treatment	-24.06		27.93		319.6**		226.7	
	(45.67)		(57.24)		(137.6)		(172.5)	
Five Year Treatment	-27.36	-8.29	-21.23	--	187.**	1.37	174.6**	3.34
	(38.45)		(48.2)		(40.53)		(50.8)	
Fifteen Year Treatment	-100.**	--	-69.25	--	62.95**	0.23	70.69**	0.45
	(40.21)		(50.39)		(27.76)		(34.79)	
Rest of U.S.								
One Year Treatment	106.5**		135.7**					
	(27.3)		(34.21)					
Five Year Treatment	122.**	-2.08	118.2**	6.75				
	(29.31)		(36.73)					
Fifteen Year Treatment	36.94	0.53	60.77*	0.79				
	(25.17)		(31.55)					

* denotes significance at the 10% level of significance, ** denotes significance at the 5% level of significance.

[a] Standard errors in parentheses.

[b] Standard errors forthcoming from the author.

Table 6: Likelihood Ratio Tests for Explicit Discount Model

	No Stratification by Preferences			***"Prospecies" Stratification***		
Temporal Treatment	*Pooled Data*	*Non-Boroughs*	*Alaska*	*Pooled Data*	*Non-Boroughs*	*Alaska*
1 v. 5 v. 15						
H_0: Equivalent β's	26.29**	28.58**	17.52**	22.7**	9.695	12.83**
d.f.	10	6	6	10	6	6
H_0: $r_5 = r_{15}$	9.767**	9.35**	3.150*	7.972**	0.001	1.532
d.f.	1	1	1	1	1	1
1 v. 5						
H_0: Equivalent β's	8.777	7.217*	4.862	7.619	5.356	0.9574
d.f.	5	3	3	5	3	3
1 v. 15						
H_0: Equivalent β's	17.29**	19.74**	12.84**	13.50**	5.096	9.091**
d.f.	5	3	3	5	3	3
Critical Chi-Squared	***90%***	***95%***				
chi-1	2.71	3.84				
chi-3	6.25	7.81				
chi-5	9.24	11.07				
chi-6	12.59	10.64				
chi-10	15.99	18.31				

* denotes significance at the 10% level of significance, ** denotes significance at the 5% level of significance.

Table 7: Explicit Discount Rate Models
Joint Insignificance Restrictions Imposed

	Five-Year Treatment			*Fifteen-Year Treatment*		
	Pooled Data	***Non-Boroughs***	***Alaska***	***Pooled Data***	***Non-Boroughs***	***Alaska***
No Stratification by Preferences						
ProSpec	643.6**	617.1**	877.3**	249.9**	216.4**	351.6**
	(233.5)	(222.2)	(357.9)	(63.6)	(61.31)	(140.9)
ProJobs	-479.2**	-452.3**	-516.8**	-162.6**	-128.3**	-184.2**
	(182.5)	(174.0)	(225.1)	(47.98)	(45.08)	(84.23)
Gender	168.7			104.6**		
	(112.5)			(52.25)		
Member	-241			-125.6*		
	(152.9)			(67.18)		
Constant	-963.**	-875.1**	-1736.0**	-434.7**	-382.7**	-753.6**
	(440.9)	(444.2)	(828.2)	(167.5)	(175.4)	(362.9)
r	0.2118	0.1662	0.1454	0.7855**	0.7259**	0.5263
	(0.1345)	(0.1133)	(0.1141)	(0.3535)	(0.3463)	(0.3225)
σ	962.2**	885.0**	1238.0**	376.0**	318.1**	510.9**
	(346.0)	(315.2)	(498.6)	(92.57)	(84.8)	(2.527)
n	1293	787	939	869	516	635
"Prospecies" Stratification						
ProSpec	611.1**	258.9**	743.8**	278.8**	245.6**	467.3*
	(242.2)	(99.81)	(316.3)	(81.35)	(81.6)	(267.2)
ProJobs	-403.5**	-162.4**	-418.3**	-171.**	-154.1**	-229.1
	(168.)	(68.42)	(192.7)	(57.2)	(59.35)	(142.2)
Gender	182.4			146.8**		
	(113.9)			(64.01)		
Member	-165.6			-94.21		
	(129.2)			(70.66)		
Constant	-1114.**	-475.0**	-1533.0*	-554.0**	-452.5*	-1082
	(532.2)	(234.8)	(785.4)	(229.4)	(241.7)	(709.4)
r	0.257	1.761	0.1934	0.7349**	0.7442*	0.3942
	(0.1714)	(2.019)	(0.1395)	(0.3526)	(0.3988)	(0.3139)
σ	779.4**	301.**	968.4**	366.9**	310.6**	614.2*
	(304.3)	(112.1)	(401.2)	(100.6)	(93.56)	(343.8)
n	858	547	577	564	347	383

* denotes significance at the 10% level of significance, ** denotes significance at the 5% level of significance.
[a] Standard errors in parentheses.

Table 8: Mean NPV WTP and Annual WTP
Explicit Discount Rate Models

	Five-Year Treatment			*Fifteen-Year Treatment*		
	Pooled Data	***Non-Boroughs***	***Alaska***	***Pooled Data***	***Non-Boroughs***	***Alaska***
No Stratification by Preferences						
Mean NPV WTP	-15.52	124.2**	-188.6	-5.509	44.94*	-77.26
	(51.7)[a]	(55.12)	(124.8)	(24.75)	(23.01)	(58.68)
Mean Annual WTP	-3.288	20.65	-27.43*	-4.327	32.62	-40.67*
	(10.35)	(12.75)	(15.55)	(19.0)	(20.81)	(24.05)
Median NPV WTP	118.9*	236.3**	-69.84	47.98	98.19**	-16.73
	(64.8)	(69.08)	(156.4)	(31.02)	(28.84)	(73.55)
Median Annual WTP	25.18	39.27	-10.15	37.69	71.28	-8.80
r	0.2118	0.1662	0.1454	0.7855**	0.7259**	0.5263
	(0.1345)	(0.1133)	(0.1141)	(0.3535)	(0.3463)	(0.3225)
"Prospecies" Stratification						
Mean NPV WTP	449.8**	209.4**	494.2**	213.9**	207.3**	286.5**
	(160.3)	(72.3)	(187.1)	(51.19)	(54.46)	(142.9)
Mean Annual WTP	115.6**	368.7	95.56**	157.2**	154.3**	113.**
	(39.45)	(304.8)	(37.54)	(46.45)	(52.33)	(41.99)
Median NPV WTP	393.5*	181.7**	435.5*	195.2**	170.5**	255.7
	(200.9)	(90.61)	(234.5)	(64.15)	(68.26)	(179.1)
Median Annual WTP	101.13[b]	319.97	84.23	143.45	126.89	100.80
r	0.257	1.761	0.1934	0.7349**	0.7442*	0.3942
	(0.1714)	(2.019)	(0.1395)	(0.3526)	(0.3988)	(0.3139)

* denotes significance at the 10% level of significance, ** denotes significance at the 5% level of significance.
[a] Standard errors in parentheses.
[b] Standard errors forthcoming from the author.

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