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A Bayesian Bioeconomic Model of Invasive Species Control:
The Case of the Hemlock Woolly Adelgid

Abstract

In this article we evaluate a US Forest Service plan to mitigate damages from an invasive insect on public, forested land. We develop a dynamic model of infestation and control to explicitly account for biological interactions, baseline conditions, and spillover effects creating a more complete picture of policy impacts than a static cost benefit analysis could provide. We combine the results of the dynamic model with an empirical study of nonmarket forest benefits to create a bioeconomic model of ecosystem management. Estimating the empirical model in a Bayesian framework allows us to treat the economic coefficients of the dynamic model as random variables. We specify distributions for the biological parameters and examine the effects of both types of uncertainty on the predictive distribution of net benefits. We find that the net benefits of the program are positive, and that uncertainty in the biological model contributes substantially more variance to our estimate than that which surrounds the valuation of the resource.

Keywords: bioeconometrics, ecosystem services, Gibbs sampling, hemlock woolly adelgid, invasive species, nonmarket valuation

1. Introduction

Mitigating the economic and ecological damages caused by invasive species is among the more challenging tasks faced by public resource managers. Control methods can be complicated and costly, their benefits are often non-market, and biological and economic concepts must be simultaneously considered. The management of invasives is also among the more important tasks, as evidenced by the billions of dollars spent annually to limit the impact of hundreds of invasive plants, animals, and microbes (Pimentel et al., 2005). The problem is likely to grow as populations and economies become more closely intertwined. The design of strategies to limit the risk of new entries, and for cost-effectively managing the damages from existing invasives, is therefore an increasingly important public policy challenge.

In this paper we examine the case of the hemlock woolly adelgid (*Adelges tsugae*), an invasive insect that is destroying stands of hemlock forest in the eastern United States. We present an empirical bioeconomic framework that integrates a dynamic biological model, control options and costs, and a non-market valuation study of control benefits. We use the framework to assess the cost effectiveness of mitigation strategies under consideration by the U.S. Forest Service in the southern Appalachian region.

The hemlock woolly adelgid (HWA) is native to East Asia, and was introduced to the eastern United States last century. It is now present in seventeen states, where it is systematically destroying hemlock forests in piedmont and highland ecosystems. Absent aggressive mitigation it is predicted that ninety percent of hemlock forests will be lost in the next twenty years.

Analysis of HWA mitigation strategies is complicated by two factors. First, the benefits of control are largely non-market. Hemlock forests provide aesthetic and recreation value, and

have cultural significance. They also protect fragile trout streams from heat and erosion, and are in general an important component of forest ecosystems. To measure the benefits of these hemlock forest services, we conducted a survey of North Carolina residents to value a US Forest Service program protecting hemlocks in a study area along the North Carolina-Tennessee border. Our stated preference questions provide multiple observations of interval-censored willingness to pay per respondent, which vary in the level of service provision. To analyze these data we develop a multiple equation Bayesian estimation approach that generalizes the model described by Fernandez et al. (2004). Estimates from our model can be used to provide posterior predictions for the value of different levels and configurations of hemlock forest protection in our study area. Our findings suggest that among the two types of sites eligible for protection – human use and ecologically important – the latter hold greater value. We also find that people with higher incomes and those with environmental preferences have greater willingness to pay for hemlock protection.

The second complicating factor is that analysis of control strategies requires an understanding of how hemlock forests and HWA interact over time, how they respond to available chemical and biological control methods, and how different controls produce different cost and hemlock forest outcomes. To address this we construct a three species, dynamic predator-prey model relating hemlock forests, HWA, and a predator beetle that is being introduced as a biological control. Data on the biological interactions between these species are sparse, making calibration of our biological model difficult. To reflect the uncertainty surrounding the parameters of the biological model we treat most of them as random, relying on recent studies of infested forests to specify their distributions.

Using information on the costs of the biological and chemical controls, and the results from our non-market valuation exercise, we solve an empirical version of the model to generate predictive distributions for the net present value of conservation strategies applied in our study area. By fixing alternately the economic and biological parameters, we isolate the effect of each type of uncertainty on the distribution of net benefits. In treating both sets of parameters as simultaneously random we demonstrate the combined effect of biological and economic uncertainty on the results. Qualitatively, we show that the net benefits from protecting hemlock forests from HWA are positive and may warrant expansion of existing programs. Quantitatively, there is a large degree of uncertainty about the magnitude of these benefits and most of this is due to limits on biological knowledge. Our results suggest that research into the effectiveness of introduced predators would yield greater precision gains than further study of economic benefits.

With our combined non-market valuation and bioeconomic modeling approach we make several contributions. We develop a Bayesian econometric framework that is useful in stated preference applications that collect multiple, bounded responses from sampled individuals. We integrate the results from our non-market valuation into a dynamic bioeconomic model, thereby combining econometric benefit estimates with a calibrated biological model. While this type of integrated analysis remains rare, our sense is that empirically grounded analyses of the type we present here - what Smith (2008) labels bioeconometric analysis - will grow in importance along with the invasive species problem. Finally, our case study of the hemlock woolly adelgid is a timely analysis of a large and growing invasive species problem.

2. Context

The hemlock woolly adelgid is a phytophagous insect native to Asia where it is a common and largely harmless pest. While western hemlock species are relatively immune, the HWA causes crown die-back and extensive mortality to stands of eastern hemlock. Two susceptible hemlock species are found in the eastern United States. The eastern hemlock (*Tsuga canadensis*) is a slow growing evergreen that can live for 800 years and reach heights of more than fifty meters. The Carolina hemlock (*Tsuga caroliniana*) is a closely related but less common species found only on the slopes of the southern Appalachian Mountains. Eastern and Carolina hemlocks rarely survive infestations, with mortality typically occurring four to ten years after colonization. Since its discovery in Virginia in the 1950s the HWA has spread to seventeen eastern states. Its rate of expansion suggests that absent aggressive mitigation, ninety percent of eastern and Carolina hemlocks will be lost in the next twenty years (Jacobs, 2005).

Three types of mitigation strategies are available to resource managers. Spraying trees with insecticidal soap and oil requires truck mounted equipment and is impractical for most stands of native hemlocks. A second and more feasible chemical control protects individual trees through an insecticide (Imidacloprid) that is injected into the soil at the base of the tree. Imidacloprid kills virtually all HWA feeding on that tree at the time of application and prevents re-infestation for up to three years. The risk of groundwater contamination, however, limits its use to a fraction of trees in a given stand. A third, biological, control has been developed and is under evaluation. There are many species of beetles that prey on the HWA. Among these, the Japanese lady beetle (*Sasajiscymnus tsugae*) has been found to be an effective predator with no known collateral risks (Cheah et al. 2004). Beetles are mass reared in laboratories using HWA-

infested foliage, and subsequently released onto individual trees. A total of 1,500 to 2,500 beetles are typically released on one to four trees per hundred acre area, from which they are expected to spread and colonize other nearby trees (Jacobs, 2005).

Hemlock wooly adelgid mitigation efforts are underway on three federal land management units in western North Carolina and eastern Tennessee: Great Smoky Mountains National Park, Nantahala National Forest, and Pisgah National Forest. These units comprise the study area for our research. The national park and two national forests together received approximately 15 million visitors in 2006 (National Park Service; US Forest Service). Of the nearly two million acres included in these federal lands, roughly 32,000 acres (1.8%) are hemlock-dominated forest. HWA infestations have been recorded throughout the study area and extensive damage is already apparent at many popular recreation sites.

While it is not currently possible to protect all or even most of the hemlocks in the study area, federal land managers have identified a network of 159 non-contiguous, high priority sites for targeted mitigation. Each site contains about 125 acres of hemlock-dominated forest and has been selected either for its ecological or human use importance. Human use sites typically have a long history of outdoor recreation or are used for nature-based learning programs. The chemical and/or biological controls will be applied to sites throughout the network. Approximately half of the sites will receive the chemical treatment, which involves treating twenty trees in the 125 acre area (about 0.5% of hemlock trees at a site). All of the sites will receive the biological control. The goal of the biological control effort is to provide long-term management of HWA populations, keeping densities low enough for hemlocks to survive mild infestations. The chemical insecticide is largely being used as a stop-gap measure to conserve a core population of

hemlocks until the beetles become established. Our research evaluates the cost effectiveness and efficiency of this effort.

3. Valuation Strategy

The first objective of our research is to measure the non-market benefits of the Forest Service's efforts to preserve hemlock stands. Our goal is to estimate households' willingness to pay for different aspects of the program, and then use the results to construct a benefit function for use with our bio-economic model. For these purposes we conducted a survey of North Carolina residents during 2006. Details on the survey design are contained in Moore (2008); Moore et al. (2009) provide a more complete summary of the resulting data. Here we sketch the main features of the survey and data before describing our modeling approach in detail.

Survey Instrument

The US Forest Service provided funding to complete an initial study of the non-market benefits of hemlock protection in the southern Appalachians. In cooperation with Forest Service economists, we designed and executed an internet-based, stated preference survey of North Carolina residents. Respondents were contacted using a random digit dialing protocol, during which they were asked to complete the online survey. Customer Insights Research, a marketing research firm, was contracted to complete the sample recruitment and manage the online data gathering. Among the 4,144 people contacted in the initial screen, 897 agreed to take the online questionnaire. Among these, 401 actually completed the survey, implying an effective response

rate of approximately ten percent. While Sax et al. (2003) show that web-based surveys tend to result in lower response rates than other modes, our response rate is low even by this standard. Nonetheless, comparisons to available demographic information for North Carolina in 2006 suggest our sample matches the population summary for income, though it over represents high school and college graduates. These latter findings are typical for internet surveys.

The core of the survey was a series of stated preference questions to elicit values for hemlock preservation as provided by the Forest Service program. Prior to answering the questions respondents were given information on the invasive, its impact on hemlock forests, the available control methods, and the actual program. Respondents were then asked to value the protection of a particular number of sites in the program network, divided between ecological and human use emphasis sites. Multiple versions of the survey and multiple questions per person were used to vary both the number of protected sites and the mix among site types.

Figure 1 shows an example of the contingent valuation questions individuals faced. The information section preceding the valuation questions explained that one hundred human use areas and one hundred ecologically important areas were under consideration for treatment. The question in figure 1 solicits the person's willingness to pay to protect 50 sites of each type¹. The payment vehicle is an increase in annual state taxes, and we have used the payment card method to record respondents' answers. The payment card presents a list of ascending dollar amounts ranging from \$2 to \$500 with an additional option of 'above \$500.' Respondents were asked to indicate whether or not they were willing to pay each amount to support the treatment program referenced by the question. Each person answered three different versions of the willingness to pay question, presented in succession, and therefore provided three valuation responses under varying protection levels. For each question, the payment card format provides upper and lower

bounds on the person's willingness to pay for the particular provision level. Our full sample consists of 1,203 responses. Table 1 summarizes respondents' answers by presenting the mean and median of interval midpoints, broken out by the eight provision levels that our experimental design included. The mean ranges from \$15 for protection of 50 human use and zero ecological sites, to nearly \$51 for protection of all 200 sites.

[Approximate Location of Figure 1]

[Approximate Location of Table 1]

Econometric Model

Two features of the design of our contingent valuation questions have implications for the development of our econometric model. Specifically, the payment card response format leads to interval censored dependent variables, and the use of multiple questions per individual implies correlation among answers from the same person. In what follows we describe an econometric model that accommodates both of these data features.

Consider a linear relationship for willingness to pay (WTP) given by

$$y_{ij}^* = \beta X_{ij} + \varepsilon_{ij}, \quad i = 1, \dots, 401, \quad j = 1, 2, 3, \quad (1)$$

where y_{ij}^* is the willingness to pay for person i on choice situation j , X_{ij} is a matrix of explanatory variables that includes the number and mix of protected sites, β is a vector of coefficients, and ε_{ij} is an element of $\varepsilon_i = (\varepsilon_{i1}, \varepsilon_{i2}, \varepsilon_{i3})'$, a vector of zero mean, normally distributed errors representing unobserved determinants of person i 's willingness to pay. The solicitation method we have used does not provide a point value for WTP. Rather, the payment card responses reveal an interval in

which the person's value lies. The highest dollar amount with an affirmative response and the lowest dollar amount that the respondent refused provide bounds on the latent WTP given by

$$y_{ij}^L \leq y_{ij}^* < y_{ij}^U, \quad (2)$$

where y_{ij}^L and y_{ij}^U are lower and upper bounds on respondent i 's WTP for question j , respectively.

Interval response models are typically estimated by maximum likelihood (Cameron and Huppert 1989). If we assume that the ε_{ij} are independent and identical $N(0, \sigma^2)$ then it is relatively easy to construct the likelihood function, since only a single dimension integral must be computed for each choice outcome. For our case with $N=401$ the likelihood function is

$$L(\beta, \sigma | X, Y) = \prod_{k=1}^{3N} \left\{ \int_{y_k^L}^{y_k^U} \frac{1}{\sigma\sqrt{2\pi}} \exp\left[-\frac{(y_k^* - x_k\beta)^2}{2\sigma^2}\right] dy_k^* \right\}, \quad (3)$$

where Y is a matrix of the upper and lower bounds on WTP observed in the sample, and the responses have been stacked and indexed by k . Maximization by standard numerical search routines provides easily obtained estimates for β and σ^2 . It is unlikely, however, that responses from the same person are independent. It therefore is desirable to allow for non-zero correlation among the elements of ε_i by assuming that $\varepsilon_i \sim N(0, \Sigma)$, where Σ is a three-by-three covariance matrix for a single person's answers. Under this generalization the likelihood function requires computation of three-dimensional integral probabilities for each person:

$$L(\beta, \Sigma | X, Y) = \prod_{i=1}^N \left\{ \int_{y_{i3}^L}^{y_{i3}^U} \int_{y_{i2}^L}^{y_{i2}^U} \int_{y_{i1}^L}^{y_{i1}^U} \frac{1}{|\Sigma|^{1/2} (2\pi)^{3/2}} \exp\left[-\frac{1}{2}(y_i^* - x_i\beta)' \Sigma^{-1} (y_i^* - x_i\beta)\right] dy_{i1}^* dy_{i2}^* dy_{i3}^* \right\}. \quad (4)$$

Maximizing (4) by numerical methods is challenging and time consuming, even though it is technically feasible to compute three dimensional integrals using standard quadrature methods. If additional stated preference questions were added the dimension of integration would increase, eventually to the point that maximization would become infeasible. In what follows we describe

a Bayesian approach to estimating the parameters in (1) that has several computational and conceptual advantages.

Estimation

Adopting a Bayesian perspective allows us to take advantage of computational methods that were originally developed for Bayesian inference, while maintaining the option of interpreting estimates from a classical perspective (see Train, 2003, pp. 291-295). In what follows, however, we develop and present our estimates using the Bayesian paradigm and terminology, since this will prove useful for combining our econometric and biological models into a unified framework for assessing benefit uncertainty.

Our objective is to characterize the posterior distribution for the unknown model parameters (β, Σ) , given by Bayes' Theorem as

$$p(\beta, \Sigma | X, Y) \propto L(\beta, \Sigma | X, Y) p(\beta, \Sigma), \quad (5)$$

where $L(\cdot)$ is the likelihood function given in equation (4) and $p(\beta, \Sigma)$ is the prior distribution for the unknowns. The posterior is proportional to the likelihood times the prior. To complete the model specification we need to choose a specific distribution for the prior. In what follows we assume β and Σ are *a priori* independent such that

$$\begin{aligned} p(\beta) &= N(b_0, M_0) \\ p(\Sigma) &= IW(\nu_0, S_0), \end{aligned} \quad (6)$$

where IW denotes the inverse Wishart distribution with degrees of freedom ν and scale matrix S , and (b_0, M_0, ν_0, S_0) are hyper parameters which we set to assure non-informative (flat) priors.

The posterior defined using the expressions in (4) and (6) has a non-standard form and analytical calculation of the moments of the distribution is not possible. Instead, we simulate values of (β, Σ) from the posterior distribution and use the resulting collection of draws to approximate the moments of interest. This requires a Monte Carlo Markov Chain (MCMC) method such as Gibbs sampling, since it is not possible to directly draw from the posterior. Fernandez et al. (2004) develop a Gibbs sampler with data augmentation for interval censored data when there is only one response per individual. We generalize their approach to cases such as ours, when there are multiple responses per individual, and in doing so demonstrate an econometric approach that may be valuable in other applications employing the payment card method.

Gibbs sampling is useful when a joint distribution of interest has a non-standard form, but the full set of conditional distributions can be drawn from directly (Train, 2003). Data augmentation (Tanner and Wong, 1987) is useful in latent variable situations when the observed dependent variables provide bounds on the values the unobserved latent variables can take. In our model the conditional posterior distributions for $\beta|X, Y^*, \Sigma$ and $\Sigma|\beta, X, Y^*$ have standard forms, where Y^* is a vector of actual (but unobserved) willingness to pay outcomes. Data augmentation involves treating Y^* as another set of unknowns in the model, deriving its conditional posterior $Y^*|\beta, \Sigma, X, Y$, and simulating values for Y^* as part of the Gibbs sampler. Draws from the unconditional posterior are obtained via Gibbs sampling by sequentially sampling from the conditional distributions, iterating through all elements of (β, Σ, Y^*) and always conditioning on the most recent draws of the other elements. After a suitably large number of iterations, draws taken in this way will converge to draws from the full posterior (Casella and George, 1992).

Using this logic, the Gibbs sampling algorithm we use to obtain draws from the posterior distribution is as follows:

Algorithm

To begin the chain, initialize values β^0 , Σ^0 , and y_i^{*0} . For iterations $s=1, \dots, B+R$, complete the following steps:

- i. For each person i draw $y_i^{*s} = (y_{i1}^{*s}, y_{i2}^{*s}, y_{i3}^{*s})'$ from the multivariate truncated normal distribution

$$y_i^{*s} \sim TN_{[y_i^L, y_i^U]}(x_i \beta^{s-1}, \Sigma^{s-1}),$$

where y_i^L and y_i^U are the truncation bounds from the person's payment card answers and x_i is a $3 \times K$ matrix of explanatory variables associated with the three questions, with K being the number of variables in the model. Stack these draws into a $3N$ dimensional vector Y^{*s} .

- ii. Draw β^s from a normal distribution $N(\beta^s, M^s)$ where

$$M^s = \left[M_0^{-1} + X'(\Omega^{s-1})^{-1} X \right]^{-1},$$

$$\beta^s = M^s \left[M_0^{-1} b_0 + X'(\Omega^{s-1})^{-1} X \right]^{-1} X (\Omega^{s-1})^{-1} Y^{*s}$$

and Ω^{s-1} is a $3N \times 3N$ matrix formed from the Kroneker product of Σ^{s-1} and an N -dimensional identity matrix.

- iii. Draw S^s from an inverse Wishart distribution $IW(N+3, S^s)$ where $N+3$ is the degrees of freedom and

$$S^s = \frac{1}{N+3} \left[v_0 S_0 + \sum_{i=1}^N (y_i^{*s} - x_i \beta^s)(y_i^{*s} - x_i \beta^s)' \right].$$

After a suitably large B (the burn in time) the draws of (β^s, Σ^s) for $s > B$ converge to draws from the posterior distribution given by equation (5), with no dependence on the initial values.

Steps (ii) and (iii) in the algorithm are straightforward to complete, while step (i) requires an iterative process discussed by Geweke (1991) and implemented by Huang (2001). We provide detail on this process in the Appendix. Koop (2003) and Train (2003) provide additional detail on derivations for the distributions in steps (ii) and (iii).

4. Estimation Results

The results for several models are shown in tables 2 through 5. We tested several functional forms and found that the log-linear specification produces coefficient estimates that are more often statistically significant and of the expected sign and relative magnitude. This specification is appealing because it imposes a non-negativity constraint on expected WTP, and the log-normal distribution is well suited to the right-skewed distribution of bids that are typically observed in CV studies. In all instances 1,000 draws from the posterior are used to summarize the posterior moments. These are obtained by discarding the first 1,000 iterations in the chain and then keeping every tenth of the next 10,000 draws. For each of the models the performance of the Gibbs sampler is assessed by the convergence diagnostic and inefficiency factor summaries. The latter describes the serial correlation in the posterior sample (Koop et al., 2007 p.144); values near one suggest draws that are independent (not serially correlated) for practical purposes. The convergence diagnostic (Geweke, 1992) reflects whether or not the draws kept for inference are drawn from a stationary distribution. Values less than two in

absolute value generally indicate that the sequence has converged and the draws were taken from the target distribution. We present these statistics for each element of the parameter vector as evidence of the validity of our inference using the draws obtained from the Gibbs sampler.

Table 2 contains estimation results from our most parsimonious specification. We include both level and quadratic terms for the number of human use and ecological sites protected, an interaction term between human use and ecological sites, categorical variables for different income levels, and a dummy variable equal to one if the person lives in western North Carolina, where the hemlock protection program is taking place. This specification allows us to examine sensitivity to scope (Smith and Taylor, 1996) and income effects (Diamond 1996; Brown 2003), and to test for a complement/substitute relationship between human use and ecological site protection. We find positive coefficient estimates for the number of both human use and ecological sites, and negative coefficients for their squares. This suggests our WTP estimates are sensitive to scope in that predictions increase at a decreasing rate in the level of provision. The coefficient on the cross product term is positive, suggesting that the services provided by ecological and human-use sites are complementary. We note, however, that the degree of complementarity is small in that the addition of one site to the network will increase the marginal value of the other type of site by only 0.0064%.

[Approximate Location of Table 2]

The coefficients on income levels provide a further validity test of our model. Dummy variables are included for each of four categorical income levels, where the omitted category is the lowest income (>\$15,000 per year). Our point estimates suggest that WTP is monotonically

increasing in income categories, and the mean-to-standard-deviation ratios imply effects that are economically sizeable relative to their precision. Figure 2 displays histograms of the marginal posterior distributions for the four income coefficients to see how income level effects differ from each other. The plot shows that the distributions shift to the right as income increases, though it is difficult to distinguish between the two middle distributions – implying people in the two ranges covering \$35-\$150 thousand have similar preferences. These estimates suggest that our WTP predictions have an expected relationship to income levels, lending further support to the validity of our model. Finally, we find that people living in western North Carolina have a higher willingness to pay for protection programs generally. This result is sensible, since this is the area of the state in which the program is concentrated.

[Approximate Location of Figure 2]

Our remaining models examine the role of additional covariates in explaining peoples' preferences for hemlock protection. In table 3 we report results for a specification that adds two more categorical variables. Responses to attitudinal questions were used to classify respondents as 'environmentalists' and 'recreationists.' The categories are neither mutually exclusive nor exhaustive. Respondents were asked to rate the importance of different objectives of mitigation programs and the importance of protecting hemlocks that provide different services. Individuals who rated environmental objectives as 'extremely important' *and* who rated hemlocks providing primarily ecological services as 'extremely important' to protect are placed in the environmentalist category. Individuals who rated recreational objectives as being 'extremely important' *and* rated hemlocks providing human-use services as 'extremely important' to protect

are categorized as recreationists. We find that members of the environmentalist group have systematically higher willingness to pay for hemlock protection, and belonging to the recreationist group tends to reduce bid responses. The latter result is counterintuitive, though the posterior mean to standard deviation ratio for the recreation coefficient suggests the effect is not sharply identified.

[Approximate Location of Table 3]

Our final specification adds income category and provision level interactions to examine how marginal willingness to pay varies with income levels. Estimation results are shown in table 4. We find that the coefficients on the income category variables are smaller but maintain their correct relative magnitudes, suggesting that some of the income effects are being folded into the interactions. The estimates for the provision and income category coefficients do not suggest any systematic differences in marginal willingness to pay among different income levels. For ecological site provision the marginal willingness to pay is larger for all income categories above the bottom level, but there is no notable difference among them. Coefficients on the terms interacted with the number of human-use sites have mixed signs and small mean-to-standard-deviation ratios, suggesting little evidence for an income effect on the marginal WTP for human-use sites. These estimates suggest that income is more relevant for explaining how much people value a program generally, and less so for explaining the incremental value generated by additional sites. Based on this reasoning we consider the first two models preferable to the last.

[Approximate Location of Table 4]

Our final set of posterior summaries looks at the distribution of the covariance matrix Σ . Table 5 summarizes the posterior distribution for the elements of Σ , based on the Gibbs sampler results from our first model as shown in table 2 (results from the other models are similar). The off-diagonal elements show there is substantial positive correlation in a given individual's response, suggesting that an assumption of independence for computational convenience is a misspecification. From a classical perspective, this can lead to inconsistent parameter estimates (since the model is non-linear) as well as an inaccurate assessment of their precision. The model we've proposed allows us to accurately reflect the additional information that multiple responses provide, without misrepresenting the precision of our willingness to pay estimates or risking inconsistent post-estimation predictions. As we show in more detail below, both of these features are important for our policy analysis.

[Approximate Location of Table 5]

Our analysis of the survey data allows us to state a few general conclusions regarding preferences among sampled individuals for hemlock protection. We find evidence that willingness to pay for the protection of ecologically important sites is generally larger and better defined than that for human-use sites but also diminishes more quickly. Furthermore, people with environmental interests are willing to pay more to support hemlock protection programs than are others. Finally, hemlock protection is a normal good in the sense that higher income households are willing to pay more to secure the service, and the value people hold for additional protection is positive but diminishing. These findings match our qualitative intuition and imply

sensible quantitative measures of value, supporting our claim of the application's validity and the potential usefulness of our econometric approach.

5. Net Benefit Function

Our ultimate objective is to combine the results of our willingness to pay analysis with a biological model to assess the net benefits of invasives control programs. For this we need to construct a net benefit function that temporally matches the time scale of the policies. In this section we describe the steps needed to predict the annual flow of benefits from woolly adelgid control and discuss our estimates of control costs.

Our survey solicited individuals' willingness to pay additional annual taxes for controls that would prevent hemlock mortality. The willingness to pay for the program is equal to the value of hemlock services only if respondents believed the program would be completely successful. While there are reasons to doubt the literal accuracy of this assumption (e.g. people may be willing to pay to protect more sites if they think some control efforts will fail), we assume for simplicity that the value of protecting a site is equal to its service value. We believe that this provides a conservative estimate of benefits if people responded assuming that control efforts would not be perfectly effective.

Our empirical specification implies that the predicted willingness to pay for hemlock services described by a single row of data \bar{x} and a parameter value indexed by s is

$$\widehat{WTP}^s = \exp\left[\bar{x}\beta^s + \frac{\sigma_s^2}{2}\right], \quad (7)$$

where σ_s^2 is the variance of the error in our regression equation. For our analysis we use the variance corresponding to the first equation such that $\sigma_s^2 = \Sigma^s(1,1)$. We obtain a posterior distribution for the prediction of hemlock benefits at the service level and respondent characteristics contained in \bar{x} by evaluating (7) at each of the values of β^s and σ_s^2 obtained from our posterior simulation.

The primary source for estimates of control costs is Appendix F of the *Environmental Assessment for the Suppression of Hemlock Woolly Adelgid* (Jacobs, 2005) distributed by the US Forest Service. This document presents the plan to control HWA and conserve hemlock resources in the study area via chemical and biological methods. The document provides fixed and average variable costs for using each type of control at a treatment site. Without specific information on marginal costs we assume they are constant and equal to average variable costs. We also maintain the following assumptions on cost levels: the Forest Service incurs an annual fixed cost of \$15,000 to identify and monitor treatment sites; biological control is applied to every site in the treatment network at a cost of \$2,200 per site; and a subset of sites receives three insecticide treatments spaced three years apart, each costing \$1,500. In a population including N individuals the per capita cost function for controlling HWA is

$$G(\text{chem}_t, \text{bio}_t) = \frac{1}{N} [\$15,000 + \$1,500 \times \text{chem}_t + \$2,200 \times \text{bio}_t], \quad (8)$$

where chem_t and bio_t are the number of sites receiving chemical and biological treatments in year t .

Net benefits from control in year t are calculated by subtracting the costs incurred in that year from the benefits realized as a result. By this logic the flow of benefits in year t to a specific person/program size described by \bar{x} , requiring chem_t and bio_t to provide, is

$$NB_t^s(\bar{x}, chem_t, bio_t, N) = \exp\left[\bar{x}\beta^s + \frac{\sigma_s^2}{2}\right] - \frac{1}{N}[\$15,000 + \$1,500 \times chem_t + \$2,200 \times bio_t]. \quad (9)$$

6. Dynamic Model of Infestation and Control

Our model of infestation and control is based on a three-species, predator-prey model and is meant to approximate the hierarchical relationship among hemlocks, HWA, and the introduced predators. The predator beetles prey upon HWA, which feed on the hemlocks. To capture these relationships we use a three-species generalization of the logistic Lotka-Volterra predator prey model (Berryman, 1992; Chauvet, Poullet, Previte, Walls, 2002). Lotka-Volterra models are attractive because the population of each species is bounded between zero and the carrying capacity of the environment, which in the case of predator species, is a function of prey population.

Model Specification

We adapt the three-species model to accommodate the chemical controls under use in the study area. Recall that soil injection of insecticide kills all HWA feeding on the treated tree *and* prevents re-infestation of the tree for about three years. To account for the persistent effectiveness of chemical control we treat it as a fourth state variable that increases at the time of treatment and then decays with time. The flow of chemical insecticide $chem_t$ reduces the adelgid population directly while the stock of chemical effectiveness C_t removes the treated proportion of hemlock trees from the adelgid's food supply. Differential equations for this and the three

other state variables track the interactions among hemlock health (H), woolly adelgid infestation (A), predatory beetles (B), and chemical insecticide effectiveness (C). The dynamic biological model is given by

$$\dot{H} = vH_t \left(1 - \frac{H_t}{K} \right) - \omega A_t H_t \quad (10)$$

$$\dot{A} = \alpha A_t \left(1 - \frac{\varepsilon_A A_t}{H_t - C_t} \right) - \xi B_t A_t - chem_t A_t \quad (11)$$

$$\dot{B} = \pi B_t \left(1 - \frac{\varepsilon_B B_t}{A_t} \right) + bio_t \quad (12)$$

$$\dot{C} = chem_t - \gamma C_t. \quad (13)$$

Because of the hierarchical structure of the predator prey model, choosing a value for the carrying capacity of hemlock health K scales the units of the other state variables in the model. To maintain consistency with the net benefit function we express the levels of state variables in treatment site-units. For hemlock health this is straightforward; a value of $H_t = 100$ means that the equivalent of 100 treatment sites (or 12,500 acres of hemlock-dominated forest) remain healthy at time t . Likewise, a value of $C_t = 10$ indicates that chemical insecticide is effective on the equivalent of 10 treatment sites at time t . For the other two state variables the units refer to the equivalent number of sites with fully established populations. For example a value of $A_t = 20$ means that the equivalent of 20 treatment sites are fully infested at time t .

Before the 159 treatment sites were chosen, an initial survey of the study area yielded a larger set of 351 potential treatment sites to be considered for treatment because they provide important ecological or human-use services (Jacobs, 2005). We use the larger set of potential treatment sites to set a value for K , a parameter that represents the maximum possible treatment sites of each type. Unfortunately, we are unable to determine how many of the 351 potential

sites were chosen for ecological or human-use reasons. We therefore make the admittedly arbitrary assumption that the set of potential sites consisted of equal numbers of ecological and human use sites, so that $K = 175.5$ for each type of site. The fact that K is not an integer has no impact on the simulation results.

Calibrating the biological model is difficult because very little data are available on the species and their interactions. To account for this uncertainty we treat the biological parameters as random in our dynamic simulation and specify their distribution based on what is known in the forestry and entomology literature. In some cases we have just one published study to provide a central estimate but no indication of variance for that estimate. However, all of the parameters have values beyond which the biological model does not behave in a realistic way - crashing, exploding, or producing other behavior that is inconsistent with what is known about the system. These bounds were found through trial and error, which eventually provided us with a plausible interval for each biological parameter. We use a triangular distribution to truncate the distribution of the parameters at their bounds and use the available data to specify the mode; this generally results in an asymmetric distribution. We use this approach for six of the biological parameters in equations (10) through (13) and treat the remaining parameters deterministically to ensure that the same scale is applied to all simulations.

Table 6 lists the biological parameters, their definitions, and the references used to specify the values used for simulation. For deterministic parameters table 6 lists the single value used to produce all time paths. Three values are listed for each of the uncertain parameters, these are the minimum, mode, and maximum of the triangular distributions. Figure 3 plots the densities of the random parameters. We have no reason to believe that the biological dynamics would differ between ecological and human-use treatment sites, so no distinction is made

between the two types of sites when specifying the dynamic model. Nor is it likely that state and control variables on any two sites will interact significantly due to large distances between sites (Jacobs, 2005). These assumptions allow us to conduct simulations for ecological and human-use sites independently, aggregate the values for each type of hemlock service, and use the aggregated values to calculate net benefits in a given time period.

[Approximate Location of Figure 3]

[Approximate Location of Table 6]

Simulation of the Dynamic Model

Simulation of infestation and control requires starting values for the state variables and time paths for the control variables. Starting values for predatory beetles B_0 and insecticide effectiveness C_0 are clearly zero, as neither would exist in the study area prior to treatment. Initial levels for HWA infestation A_0 and hemlock health H_0 are based on a survey of the study area conducted in the year prior to beginning treatment. At that time more human-use sites showed evidence of infestation than did ecological sites (Jetton, 2007, personal correspondence). Because HWA spread to previously unaffected areas by hitch-hiking on animals and people, sites that see more human traffic—such as picnic areas and trail heads—are more susceptible to infestation. Based on this information we assume that 15% of the human use areas in the study area are fully infested by hemlock woolly adelgid causing a reduction in forest health to 80% of carrying capacity. Expressing these conditions in treatment site-units we have $A_0 = 26$ and $H_0 = 140$ in the human-use areas of the forests. Ecological sites tend to be in remote areas that see

less human traffic so there is a smaller probability of introduction. We assume 10% of the ecologically important areas are fully infested resulting in forest health of 90% of potential so that $A_0 = 17.5$ and $H_0 = 158$ in the ecologically important areas.

Paths for the control variables are specified to mimic the actual mitigation strategy in the study area. They indicate how many ecological and human-use sites are included in the network, when each site will receive chemical or biological treatment, and how many trees on each site will be treated. Jacobs (2005) provides sufficient information to specify time paths of control. The treatment network includes 159 treatment sites: 130 human use sites and 29 ecological sites. Approximately half of each type of site will receive treatment with chemical insecticide (65 human-use sites and 15 ecological sites). However, the risk of ground water contamination limits the use of insecticide to about 20 trees or 0.5% of the mature hemlocks on a site. Predatory beetles will be released at all sites in the treatment network as they become available over the first two years of the program. About 2,000 beetles will be released at each site onto just one or two infested trees. The high density of beetles on so few trees aids in establishing a reproducing population at the site. From these trees the beetles are expected to spread to other infested trees in the area.

By taking draws from the distributions of the biological parameters we generate 1,000 time paths for the state variables. Prior to attaching dollar values to these time paths, we conduct two simulations: one to find the time path of hemlock health in the absence of mitigation effort, and another to simulate the proposed strategy. Our dynamic cost-benefit analysis will focus on the difference between these two scenarios.

The two panels in figure 4 use the simulated time paths for hemlock health in the human-use treatment areas to demonstrate the impact of biological uncertainty on the model. The left

panel plots the average time path for hemlock health under the status quo scenario, bounded by time paths representing the 10th and 90th percentiles. The right panel plots the same information but under the control scenario. Analogous plots for HWA density in human-use areas are shown in figure 5. While these plots show how the values of the state variables in the dynamic model are affected by uncertainty surrounding the biological parameters, they cannot show the impact that uncertainty has on the economic evaluation of the mitigation program.

[Approximate Location of Figure 4]

[Approximate Location of Figure 5]

7. Predictive Inference

In this section we integrate the findings from the economic and biological models to value the HWA control strategies. The result is a prediction of the distribution of net benefits that incorporates uncertainty over the parameters of the economic valuation model as well as uncertainty over the parameters of the biological model. We also examine the effect of each type of uncertainty individually by holding one set of parameters at their most likely values while allowing the other set to vary in generating the predictive distribution for net benefits.

To generate the full predictive distribution of net benefits, allowing for biological and economic uncertainty, we use the following procedure:

Algorithm

- i. Using the Gibbs Sampler (Section 3) obtain R draws from the joint posterior of β and Σ and label them $[\beta, \Sigma]^s$, for $s = 1, \dots, R$.

- ii. Using simulations of the biological model (Section 6) generate M time paths for hemlock health on ecological sites and human-use sites under the baseline and control scenarios for the years $t = 1, \dots, T$ and label them

$$\left[H_{baseline}^{eco}, H_{baseline}^{use} \right]^{(m,t)}, \left[H_{control}^{eco}, H_{control}^{use} \right]^{(m,t)}, m = 1, \dots, M, t = 1, \dots, T.$$

- iii. For each (m,s) pair, calculate the net present value of benefits as follows:

- a. For $t=1, \dots, T$ evaluate

$$WTP^s \left(\left[H_{control}^{eco}, H_{control}^{use} \right]^{(m,t)} \right) - WTP^s \left(\left[H_{baseline}^{eco}, H_{baseline}^{use} \right]^{(m,t)} \right) - G(chem_t, bio_t),$$

where $WTP^s(\cdot)$ refers to the willingness to pay measure in equation (8) and $G(\cdot)$ is given in equation (9).

- b. Discount the T net benefits calculated in step (a) and sum to obtain, for each (m,s) combination, a net present value of mitigation.

Performing steps (i)-(iii) results in $R \cdot M$ draws from the distribution of expected net present value of benefits. With $R=1000$ and $M=1000$, we have one million draws with which to characterize the predictive distribution of net benefits. Figure 6 plots a histogram of the draws and the first row of Table 7 summarizes the distribution. To compute these figures we use the estimation results from table 2, assume that the benefiting population is $N=3.13$ million (the number of households in NC in 2006), and weight the income dummy variable coefficients based on the distribution of income in the state in 2006. The mean of the distribution is nearly \$20 with an inner 90% percentile of \$6 to \$37.

[Approximate Location of Figure 6]

[Approximate Location of Table 7]

To examine the effect of biological and economic uncertainties individually we conduct the same calculations, but hold one set of parameters constant at their posterior means. To hold the biological parameters constant we run the simulation of the biological model holding the parameters at their modes and producing just one time path for hemlock health on ecological and human-use sites. The resulting distribution of net benefits reflects uncertainty in the economic parameters only. To hold the economic parameters constant we perform step (iii) using posterior mean values for β and Σ (tables 2 and 5). The resulting distribution of net benefits reflects uncertainty only in the biological parameters. The two panels of figure 7 compare the resulting predictive distributions and the last two rows of table 7 provide summary statistics.

[Approximate Location of Figure 7]

Figures 6 and 7 show that the distributions of net benefits are bounded from below at zero, which is not by construction. Our decision to use a log-linear functional form does impose a non-negativity constraint on willingness to pay. However, to calculate net benefits we subtract willingness to pay for baseline conditions and the costs of mitigation from willingness to pay for improved forest health. This calculation could result in negative benefits but, as can be seen from the predictive distributions, it does not for any of the predictive draws. As such, there is strong evidence that benefits from the mitigation strategy are positive. This qualitative result alone does not justify implementation, however. When other conservation projects are competing for the same funds the magnitude of net benefits (or the benefit-cost ratio) becomes important. In this case choosing among competing projects may require more precise estimates of net benefits.

Where should we look to improve the precision of our estimates? The summary statistics in table 7 make it clear that uncertainty in the biological parameters results in a much larger spread of net benefits and thus contributes more variance to the full predictive distribution than does uncertainty in the economic parameters. Comparing the plots in figure 7 confirms this observation. Based on this, research into the biological interactions among hemlocks, HWA, and the introduced predator is likely to yield larger precision gains for net benefit estimation than is further study into the valuation of forest services.

8. Conclusion

Invasive species management is a difficult and increasingly important policy challenge. Indeed, Pimentel et al. (2005) estimate damage costs of nearly \$120 billion per year from the over 50,000 non-native species established in the United States. Understanding causes of introduction, the geographical spread of populations, methods of control, and economically sensible policy action requires expertise from a range of disciplines that includes economics, entomology, forestry, and ecology. While carefully integrated modeling is needed for useful policy analysis, our sense is that this is the exception rather than the rule in most of the disciplinary literature on invasive species management. In this paper we have combined models and methods that are often separately employed to study the cost effectiveness of policies designed to control an important invasive. The Bayesian paradigm we've used is a useful tool for linking our model components in that it provides a systematic means of documenting sources of uncertainty and examining its impact on the precision of estimates. Via this strategy we find for our application that biological uncertainty is likely to be a larger constraint on the accuracy of

policy analysis than economic uncertainty.

Perhaps this is not surprising. While advances can still be made (a point to which we return below), economic methods for non-market valuation (and predicting behavior generally) are well established. Likewise, resource economists increasingly study dynamic problems using rich differential equation specifications that require simulation and numerical methods to solve. What is often lacking is empirical studies that can be used for confidently calibrating biological parameters, establishing baseline conditions, and estimating how proposed controls will affect populations of invasive and codependent species. To this we might add that biological, empirical economic, and calibrated dynamic models usually operate at different temporal and spatial scales. Our research suggests there is a need for coordinated biological and economic studies, in which model inputs and outputs are simultaneously designed to be compatible. While the study presented here does not fully achieve this high objective, it does provide tools and an organizing principle around which future studies can be designed.

None of this is to say that disciplinary advances are not important. An integrated model is only as good as its weakest component, and ideally each component would be state of the art. A main contribution of this paper is the presentation of an econometric approach suitable for estimating models with multiple responses per individual of interval censored data. Our Bayesian approach facilitates computational aspects of estimation, enables a rich model specification, and integrates readily into our study's larger objectives. Our sense is that the approach we have suggested will be useful in other contingent valuation applications using the payment card method.

Additional research along the themes discussed in this paper can go in many directions. There are likely to be substantial payoffs to continued development of Bayesian approaches to

model construction and combination. In instances where primary data for economic modeling is limited or lacking, informative priors based on existing valuation studies may be a viable option. Likewise the calibration of dynamic biological models might take a more formally Bayesian approach in which some primary data for an application area is gathered, and combined with priors on biological parameters gleaned from the literature and the analyst's judgments. Finally, our modeling approach in this paper does not have a spatial component. In applications where control sites are contiguous (causing control benefits to potentially spill over), or modeling the movement of invasive and predator populations is otherwise of interest, adopting the spatial spillover approaches seen, for example, in fisheries applications (e.g. Smith et al. 2009) may be useful.

Notes

1. The ecological and human use combinations referenced in the CV questions were: 0-50, 50-0, 0-100, 100-0, 50-50, 50-100, 100-50, and 100-100, where the first number is ecological sites and the second is human use sites.
2. A special issue of *Ecological Economics* with the theme 'Integrating ecology and economics to address bioinvasions' contains several papers combining both economic and biological modeling, though generally without the econometric rigor we have included. See Shogren and Tschirhart (2005) for an introduction and Finoff et al. (2005) as a specific example of work complementary to ours.

Appendix

Step (i) in our Gibbs sampler involves taking draws of $y_i^{*s} = (y_{i1}^{*s}, y_{i2}^{*s}, y_{i3}^{*s})'$ for $i=1, \dots, N$ from the truncated normal distribution given by

$$y_i^{*s} \sim TN_{[y_i^L, y_i^U]}(x_i \beta^{s-1}, \Sigma^{s-1}),$$

where y_i^L and y_i^U are the truncation bounds. Because it is not possible to draw directly from this distribution we use an iterative method that effectively expands the dimension of the Gibbs sampler to include the three elements of y_i^{*s} . Given the previous values β^{s-1} , Σ^{s-1} , and y_i^{*s-1} for all i , the following sub-steps are used for $i=1, \dots, N$:

- a. Derive the conditional distribution $y_{i1}^* | y_{i2}^{*s-1}, y_{i3}^{*s-1} \sim N(\mu_{1|23}, \sigma_{1|23}^2)$ where

$$\begin{aligned} \mu_{1|23} &= x_{i1} \beta^{s-1} + \Sigma_{1,23}^{s-1} (\Sigma_{23,23}^{s-1})^{-1} (y_{i,23}^{*s-1} - x_{i,23} \beta^{s-1}) \\ \sigma_{1|23}^2 &= \Sigma_{1,1}^{s-1} + \Sigma_{1,23}^{s-1} (\Sigma_{23,23}^{s-1})^{-1} \Sigma_{23,1}^{s-1}, \end{aligned}$$

x_{i1} is the first row of x_i , $x_{i,23}$ is a matrix holding the second and third rows of x_i , $y_{i,23}^{*s-1}$ is a 2×1 vector holding the second and third elements of y_i^{*s-1} , and subscripts on Σ^{s-1} indicate sub-matrices where, for example, $\Sigma_{23,1}^{s-1}$ is a 2×1 vector including the second and third rows and first column of Σ^{s-1} . Using this conditional distribution and the inverse method (see Train, 2003, p. 210-11), draw y_{i1}^{*s} from the single dimension truncated distribution

$$y_{i1}^* | y_{i2}^{*s-1}, y_{i3}^{*s-1} \sim TN_{[y_{i1}^L, y_{i1}^U]}(\mu_{1|23}, \sigma_{1|23}^2),$$

where y_{i1}^L and y_{i1}^U are the lower and upper bounds on y_{i1}^* , respectively.

- b. Derive the conditional distribution $y_{i2}^* | y_{i1}^{*s}, y_{i3}^{*s-1} \sim N(\mu_{2|13}, \sigma_{2|13}^2)$ where

$$\begin{aligned} \mu_{2|13} &= x_{i2} \beta^{s-1} + \Sigma_{2,13}^{s-1} (\Sigma_{13,13}^{s-1})^{-1} (y_{i,13}^{*s-1} - x_{i,13} \beta^{s-1}) \\ \sigma_{2|13}^2 &= \Sigma_{2,2}^{s-1} + \Sigma_{2,13}^{s-1} (\Sigma_{13,13}^{s-1})^{-1} \Sigma_{13,2}^{s-1}, \end{aligned}$$

and the notation follows from above, accept that $y_{i,13}^{*s-1} = [y_{i1}^{*s}, y_{i3}^{*s-1}]'$. Draw y_{i2}^{*s} from

$$y_{i2}^* | y_{i1}^{*s}, y_{i3}^{*s-1} \sim TN_{[y_{i2}^L, y_{i2}^U]}(\mu_{2|13}, \sigma_{2|13}^2),$$

once again using the inverse method univariate distributions.

c. Derive the conditional distribution $y_{i3}^* | y_{i1}^{*s}, y_{i2}^{*s} \sim N(\mu_{3|12}, \sigma_{3|12}^2)$, where

$$\mu_{3|12} = x_{i3}\beta^{s-1} + \Sigma_{3,12}^{-1}(\Sigma_{12,12}^{s-1})^{-1}(y_{i,12}^{*s} - x_{i,12}\beta^{s-1})$$

$$\sigma_{3|12}^2 = \Sigma_{3,3}^{s-1} + \Sigma_{3,12}^{-1}(\Sigma_{12,12}^{s-1})^{-1}\Sigma_{12,3}^{s-1},$$

and $y_{i,12}^{*s} = [y_{i1}^{*s}, y_{i2}^{*s}]'$. Draw y_{i3}^* from

$$y_{i3}^* | y_{i1}^{*s}, y_{i2}^{*s} \sim TN_{\left[\begin{smallmatrix} y_{i3}^L \\ y_{i3}^U \end{smallmatrix} \right]}(\mu_{3|12}, \sigma_{3|12}^2).$$

When (a) - (c) are completed for all people in the sample, step (i) is complete and the Gibbs sampler proceeds to steps (ii) and (iii).

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Table 1 Summary of willingness to pay responses

Combination of Sites Referenced in CV Question		Refused All Bid Amounts	Midpoint of WTP Interval		Chose 'More than \$500' response
Ecological Sites	Human Use Sites		Mean	Median	
0	50	32.1%	15.1	5.0	0.0%
0	100	35.8%	17.1	5.0	0.0%
50	0	17.9%	33.3	12.5	1.5%
100	0	24.1%	26.5	9.0	1.5%
50	50	11.2%	40.3	12.5	0.8%
50	100	10.5%	36.5	12.5	0.8%
100	50	12.0%	38.6	12.5	0.8%
100	100	10.8%	50.6	17.5	1.9%

* Mean and Median are calculated using 0 when all bid amounts were refused and \$600 when the response 'More than \$500' was chosen.

Table 2 Posterior distribution for the most restricted specification of WTP

Variable	Coefficient Mean	Coefficient Standard Deviation	Mean/Std Dev	Convergence Diagnostic	Inefficiency Factor
Constant	1.132	0.182	6.22	-1.21	1.05
Number of Ecological sites	0.028	0.003	9.40	0.69	1.06
Number of Human-use sites	0.013	0.003	4.30	0.97	1.10
Ecological ²	-2.09 x 10 ⁻⁴	1.90 x 10 ⁻⁵	-10.88	-0.07	1.04
Human-Use ²	-1.16 x 10 ⁻⁴	2.20 x 10 ⁻⁵	-5.53	-1.03	1.21
Ecological* Human-use	6.40 x 10 ⁻⁵	2.00 x 10 ⁻⁵	3.18	-0.79	1.01
Western North Carolina	0.230	0.047	4.89	1.81	1.08
\$15k-\$35k income	0.724	0.102	7.10	0.04	0.99
\$35k-\$75k income	1.226	0.098	12.46	0.03	1.02
\$75k-\$150k income	1.444	0.100	14.45	0.24	1.00
≥ \$150k income	1.992	0.188	10.62	-0.17	0.96

Table 3 Posterior distribution for the specification of WTP including attitudinal dummy variables

Variable	Coefficient Mean	Coefficient Standard Deviation	Mean/Std Dev	Convergence Diagnostic	Inefficiency Factor
Constant	0.927	0.182	5.11	1.05	0.99
Number of Ecological sites	0.027	0.003	9.71	-0.74	1.00
Number of Human-use sites	0.012	0.003	3.90	-0.60	0.97
Ecological ²	-2.04 x 10 ⁻⁴	1.90 x 10 ⁻⁵	-10.74	0.24	1.04
Human-Use ²	-1.14 x 10 ⁻⁴	2.10 x 10 ⁻⁵	-5.43	0.27	0.99
Ecological* Human-use	7.10 x 10 ⁻⁵	1.90 x 10 ⁻⁵	3.74	1.08	0.99
Western North Carolina	0.290	0.050	5.81	0.70	0.97
\$15k-\$35k income	0.755	0.102	7.43	-0.41	0.94
\$35k-\$75k income	1.216	0.099	12.34	-1.05	1.02
\$75k-\$150k income	1.515	0.103	14.76	-0.22	0.93
≥ \$150k income	2.147	0.190	11.33	0.36	1.02
Environmentalist	0.487	0.048	10.07	0.04	0.95
Recreationist	-0.124	0.061	-2.04	-0.58	1.00

Table 4 Posterior distribution for the specification of WTP including attitudinal dummy variables and income interaction variables

Variable	Coefficient Mean	Coefficient Standard Deviation	Mean/Std Dev	Convergence Diagnostic	Inefficiency Factor
Constant	1.251	0.278	4.51	-0.21	1.02
Number of Ecological sites	0.021	0.004	5.58	-1.28	0.97
Number of Human-use sites	0.012	0.004	3.16	0.07	1.06
Ecological ²	-2.05 x 10 ⁻⁴	1.90 x 10 ⁻⁵	-10.79	0.72	0.98
Human-Use ²	-1.13 x 10 ⁻⁴	2.20 x 10 ⁻⁵	-5.14	0.00	1.02
Ecological* Human-use	7.20 x 10 ⁻⁵	2.00 x 10 ⁻⁵	3.60	1.38	1.01
Western North Carolina	0.317	0.049	6.43	0.49	0.95
\$15k-\$35k income	0.480	0.264	1.82	0.69	0.94
\$35k-\$75k income	0.744	0.246	3.03	0.50	0.94
\$75k-\$150k income	1.295	0.267	4.84	0.63	0.95
≥ \$150k income	1.476	0.524	2.81	0.94	0.99
Environmentalist	0.010	0.003	3.65	0.57	0.99
Recreationist	0.005	0.002	2.13	0.72	0.98
Ecological* (\$15k-\$35k)	0.006	0.003	2.12	0.88	1.02
Ecological* (\$35k-\$75k)	0.018	0.005	3.37	-0.25	1.01
Ecological* (\$75k-\$150k)	-0.005	0.003	-1.92	-0.95	0.97
Ecological* (≥ \$150k)	0.003	0.002	1.08	-0.79	0.95
Use* (\$15k-\$35k)	-0.002	0.003	-0.65	-1.18	0.90
Use* (\$35k-\$75k)	-0.007	0.005	-1.35	-1.10	1.06
Use* (\$75k-\$150k)	0.494	0.051	9.69	-0.52	0.95
Use*(≥ \$150k)	-0.112	0.065	-1.72	-0.14	1.00

Table 5 Posterior distribution for the covariance matrix Σ

Element of Sigma	Coefficient Mean	Coefficient Standard Deviation	Mean/Std Dev	Convergence Diagnostic	Inefficiency Factor
Diagonal Elements – Own Variance					
1,1	2.293	0.176	13.05	-0.83	0.95
2,2	2.395	0.181	13.22	0.29	0.99
3,3	2.657	0.213	12.46	0.15	0.99
Off-Diagonal Elements - Covariance					
1,2	2.135	0.167	12.75	-0.41	0.97
1,3	1.711	0.161	10.64	-0.60	0.98
2,3	1.697	0.162	10.45	-0.15	0.99

Table 6 Biological Parameters

Symbol	Description	Deterministic Value or [min,mode,max]	Observation used for Deterministic Value or Parameters of Triangular Distribution
K	Carrying capacity for hemlocks	175.5	351 sites were considered for treatment before the 159 actual sites were chosen (Jacobs, 2005). We assume those potential sites included an equal number of ecological and human use sites so that $K=175$ for each type.
v	Intrinsic hemlock growth	[0.05, 0.157, 0.2]	Annual growth rate for the diameter of eastern hemlocks in the southern Appalachian Mountains is 0.11 (Teck and Hilt, 1991). Identification requires current proportion of hemlock carrying capacity: Hemlocks once made up about 20% of upland forests and land use over the past century has reduced this to 6% (McClure, Salom, Shields, 2003)
α	Intrinsic HWA growth	[2.5, 3.25, 5.5]	It takes about two years for a single tree to go from introduction to full-blown infestation in the absence of control measures (R. Jetton, personal correspondence, December 10, 2007). In the southern range of eastern hemlock, HWA spread at a rate of 15.6 km per year (Evans and Gregoire, 2007). These two observations are used in a reduced simulation to identify the parameter value.
π	Intrinsic growth of beetles	[0.1, 1.75, 2.0]	It generally takes six to ten generations of the prey species for a predator population to become established (DeBach 1964). Parameter identified via simulation.
ϵ_A	HWA sustenance parameter – units of hemlock needed to sustain a unit of HWA	1.0	Set to 1.0 by assumption. The implication being that a HWA population at carrying capacity requires a hemlock population also at carrying capacity to sustain that population level.
ϵ_B	Beetle sustenance parameter – units of HWA needed to sustain a unit of predatory beetles	1.0	Set to 1.0 by assumption. The implication being that a beetle population at carrying capacity requires a prey population also at carrying capacity to sustain that population level.
ω	HWA predation parameter – proportion of hemlock health consumed by a unit of HWA in a period	[2.0, 2.5, 8.0] $\times 10^{-3}$	Hemlock stands that initially had a moderate infestation experienced 5 to 15 % additional mortality per year reaching more than 50% in most stands over the 6 year observation period. (Jacobs, 2005). Parameter identified via simulation.
ξ	Beetle predation parameter – proportion of HWA consumed by a unit of predatory beetles in a period	[0.01, 0.085, 0.15]	Experiments conducted at four sites in Connecticut and two sites in Virginia revealed that releasing relatively few adult beetles (2,400-3,600) into an infested hemlock forest reduced adelgid densities by 47-88% on release trees in only five months with a median reduction of 52.9% (McClure, Cheah, Tigner, 1999). Parameter identified via simulation.
γ	Decay of Insecticide Effectiveness	[0.4, 0.45, 0.5]	A single application of imidacloprid will prevent HWA from infesting a hemlock for two to three years (Jacobs, 2005). Parameter identified via simulation.

Table 7 Predictive distribution of net present value

Source of Uncertainty	5th Percentile	95th Percentile	Median	Mean	Standard Deviation	Skewness
Biological and Economic	6.2	36.8	19.1	19.9	9.5	6.2
Economic	14.7	24.6	19.0	19.3	3.1	14.7
Biological	5.6	30.0	18.4	18.0	7.6	5.6

Figure 1 Example contingent valuation question

17. Consider a Program that would protect:

50 of the 100 ecologically important sites



and 50 of the socially important sites



In the table below indicate whether or not you would be willing to pay the listed amounts in increased annual taxes to support the treatment program. (Check 'Willing to pay' or 'Not willing to pay' for each amount.)

Increase in taxes in each year for the next three years	Willing to pay this tax	<u>Not</u> willing to pay this tax
\$2	<input type="checkbox"/>	<input type="checkbox"/>
\$4	<input type="checkbox"/>	<input type="checkbox"/>
\$6	<input type="checkbox"/>	<input type="checkbox"/>
\$8	<input type="checkbox"/>	<input type="checkbox"/>
\$10	<input type="checkbox"/>	<input type="checkbox"/>
\$15	<input type="checkbox"/>	<input type="checkbox"/>
\$20	<input type="checkbox"/>	<input type="checkbox"/>
⋮	⋮	⋮
\$450	<input type="checkbox"/>	<input type="checkbox"/>
\$500	<input type="checkbox"/>	<input type="checkbox"/>
More than \$500	<input type="checkbox"/>	<input type="checkbox"/>

Figure 2 Posterior distributions of coefficients on categorical income variables

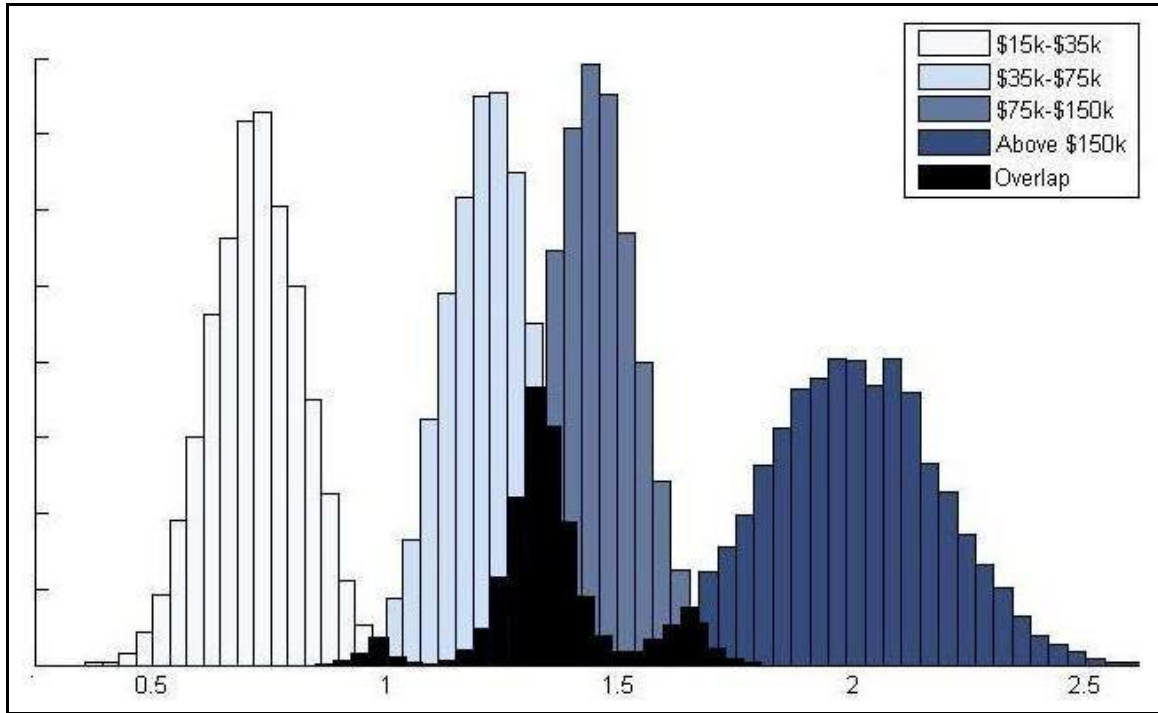


Figure 3 Probability densities for uncertain biological parameters

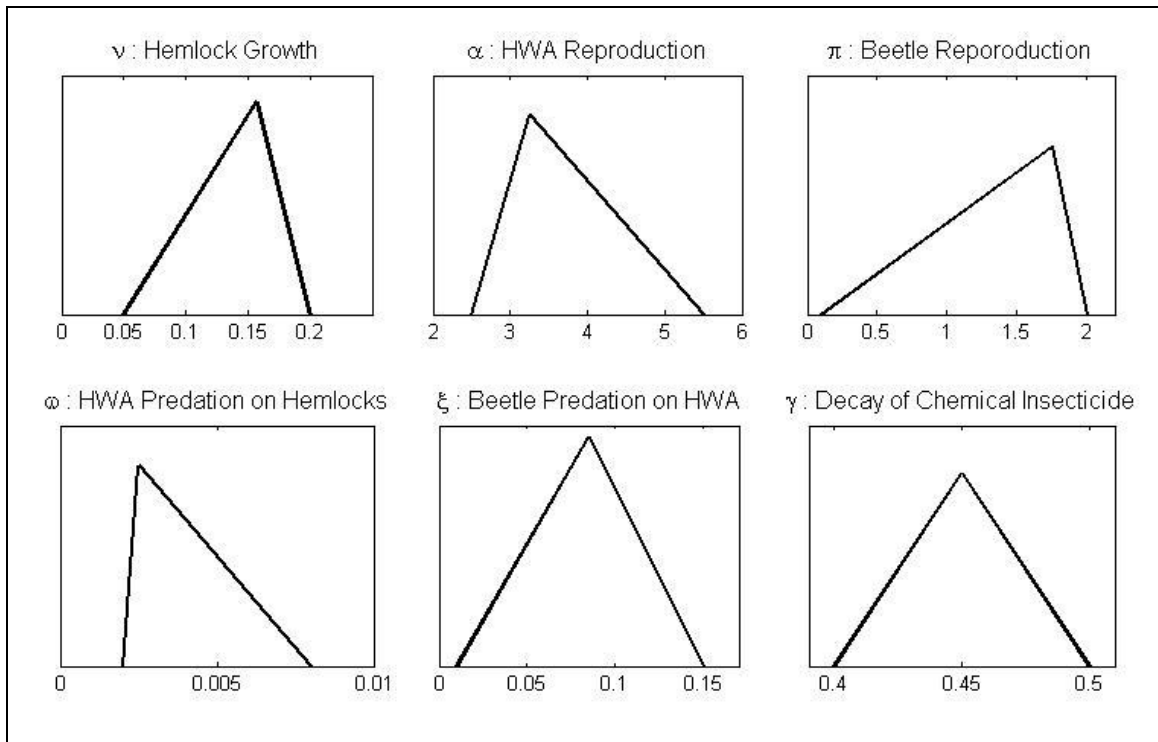


Figure 4 Hemlock health under baseline and control scenarios

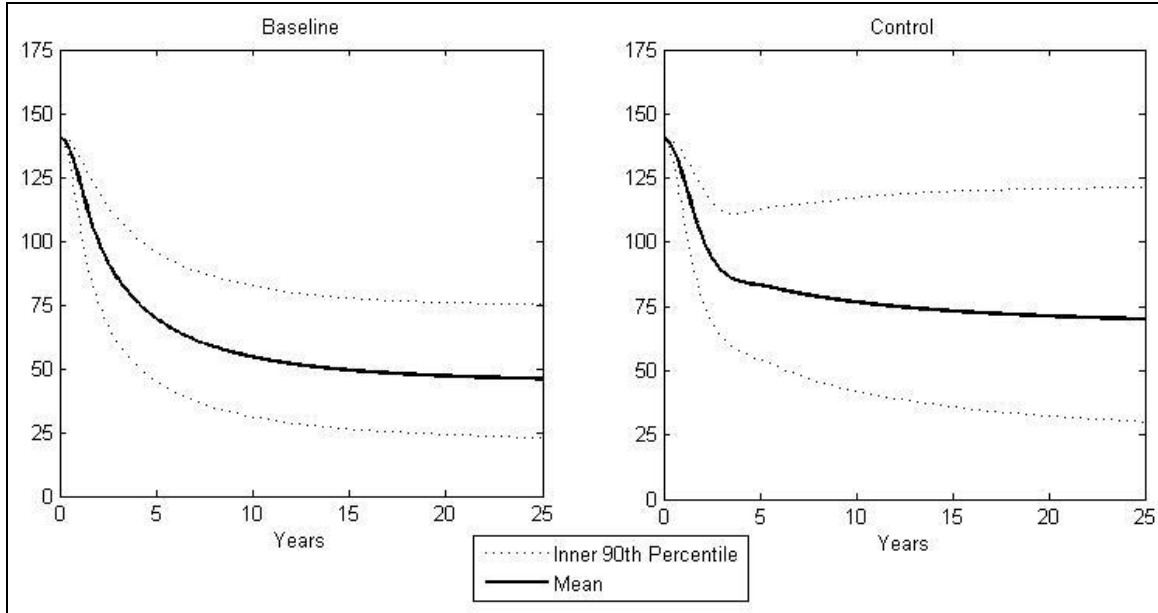


Figure 5 Hemlock Woolly Adelgid Density under Baseline and Control Scenarios

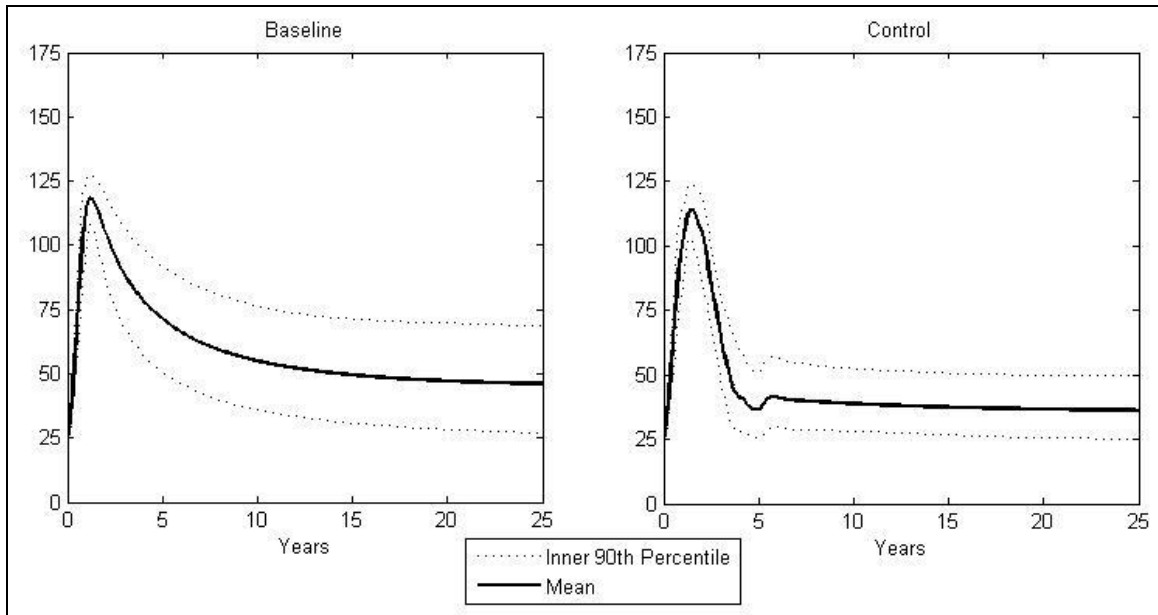


Figure 6 Predictive distribution of per household NPV with economic and biological uncertainty

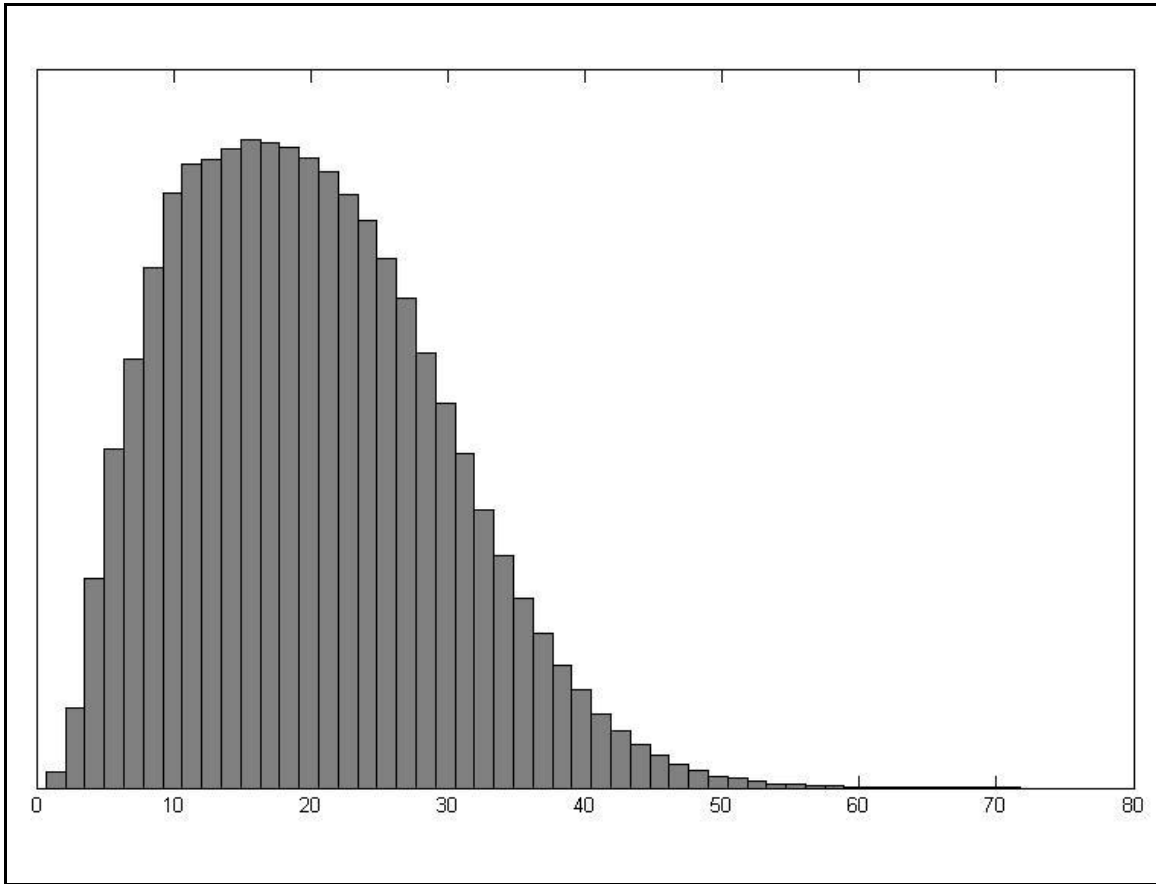


Figure 7 Predictive distribution of per household NPV given just one source of uncertainty

