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A Stochastic Bioeconomic Model with Research

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Abstract *This paper provides an incremental extension of a stochastic renewable resource model (Pindyck 1984) to include population dynamics research;* i.e.*, the rate of accrual of information regarding the stochastic evolution of the stock, as a dynamic choice variable. While Pindyck models variance in stock growth as an exogenous parameter, our formulation endogenizes this variance and characterizes the impact of scientific information accrual on both the harvest decision and the present value of rents resulting from harvest activity. We illustrate the theoretical existence of an internal optimum in research effort using a numerical example.*

Key words Stochastic bioeconomic model, stochastic control, fisheries management, population dynamics research, renewable resource, uncertainty.

JEL Classification Codes Q2, Q22, C61.

"Good fisheries management depends on acquiring high-quality information on an ongoing basis. These data provide the backbone of the science used in regulation" (NRC 2004).

Introduction

Any assessment of the efficiency of renewable resource use should include management costs, which can be significant relative to benefits flowing from the resource. For example, Arnason, Hannesson, and Schrank (2000) report management costs ranging from 3–25% of gross revenues from fishing in various European countries. Needless to say, the magnitude of such costs relative to rents is much higher. When fisheries management costs are significant, conventional bioeconomic models which ignore them may lead to seriously biased fishery policy recommendations (Arnason 2003).

The total cost associated with fisheries management typically includes three broad components: (*i*) research (*e.g.*, data collection and analysis), (*ii*) management

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(*e.g.*, formulation and implementation of management plans), and (*iii*) enforcement (of management rules).[1] According to a recent study of 11 OECD countries, these three components, on average, accounted for 34%, 26.4%, and 39.6%, respectively, of a total of US$2.45 billion in 1999 (OECD 2003).

In 1999, the total cost of U.S. fisheries management was $613.5 million, 17% of the value of total fish landings (OECD 2003). As shown in table 1, the cost associated with information collection and analysis accounted for 24% ($147 million) of the total. Clearly, the production of scientific information constitutes an important subset of management costs. A recent NRC (2004) report points out that the bulk of the cost of information gathering is borne by the central regulatory authority in U.S. fisheries through Congressional appropriations.

Governing agencies in fisheries and other natural resource systems are increasingly subject to criticisms regarding the efficacy of their actions and the accuracy of the information on which they are based. Arnason, Hannesson, and Schrank's (2000) analysis questions the cost effectiveness of management expenditures in general. Cost recovery programs cause the burden of government-led research programs to be borne by industry participants, therefore heightening the level of scrutiny. Since 1991, the Australian Fisheries Management Authority has faced the explicit objective of "efficient and cost-effective management," "accountability to the industry," and "achievement of government cost recovery targets" (Gooday and Galeano 2003), and the management agency carries out studies to ascertain whether these objectives are being met (Rohan 1999). Currently, cost recovery programs in Australia, Iceland, and New Zealand recoup a significant proportion of costs from industry. In 1999, the proportion of costs recovered was 23% in Australia, 37% in Iceland, and 50% in New Zealand (OECD 2003).

Alternatives to explicit and costly information gathering on the part of regula-

Table 1
U.S. Fisheries Management Cost in FY 2000

Category	Funding ($ million)	Percent
Research Services	202.5	33.01
Information collection and analysis	146.9	23.94
Fishing industry information	31.2	5.09
Information analyses and dissemination	24.4	3.98
Management Services	240.5	39.20
Conservation and management of the fishery	142.5	23.23
State and industry assistance program	12.4	2.02
Disaster assistance	64.7	10.55
Other	20.9	3.40
Enforcement Services	170.5	27.79
Total Cost	613.5	100.00

Source: OECD (2003).

[1] For detailed discussions, see OCED (2003) and Schrank, Arnason, and Hannesson (2003).

tors include the use of harvest (logbook) data (NRC 2004) as well as market signals, such as the price of transferable quotas (Batstone and Sharp 2003). In industries with low levels of rents, explicit scientific research may not be cost effective, and it may behoove regulators to opt for a conservative approach based on low-resolution estimates of stock abundance (Rose 2002).

This paper extends classical stochastic bioeconomic models (Andersen 1982; Andersen and Sutinen 1984; and Pindyck 1984) to include population research as a dynamic choice variable. There are typically two types of uncertainty associated with a resource stock (x): the uncertainty resulting from the inability to accurately measure stock size $x(t)$ at a specific point in time, and the uncertainty regarding the intertemporal stock growth from t to $t + \Delta t$. Fishery research involves various activities (*e.g.*, stock sampling and quantification *per se*, as well as data analysis, modeling, and biological research) to reduce these uncertainties. The current study focuses on the latter type of uncertainty (growth uncertainty) and considers the benefits associated with the production of scientific information related to stock dynamics. For example, research on the effects of changing environmental factors (*e.g.*, climate) on fish growth may reduce uncertainty regarding the growth process, and data collection and the development of statistical models increases the empirical understanding of stock-recruitment relationships.

The extended model presented here defines the optimal time path of research and identifies the relationship between the harvesting decision and improvements in information resulting from research. The model can be used to estimate the value of information regarding natural growth processes, which, in turn, may be used as a justification for cost recovery. While the most natural application of the following analysis is to fisheries, the concepts developed here are relevant to a variety of renewable resources, such as harvested forestlands, where growth may vary stochastically with climatic conditions and groundwater tables where regeneration rates are uncertain.

We limit our characterization of the benefits of population dynamics research to those emerging from extractive resource use, or “harvest.” It would be relatively straightforward to extend the analysis to a resource in which the stock has passive or non-extractive use, though it is not clear in those instances what policy variables would be affected by the improved information. Biological research also gives rise to other values not included in the present analysis.

The next section reviews the literature on bioeconomic analysis under uncertainty. The third section presents a model of a stock with known abundance but unknown growth (and hence unknown *future* abundance). Optimality conditions with respect to harvest and costly information gathering are derived, as well as a rate of return expression for such research. The fourth section illustrates the results with numerical simulations, and the final section concludes.

Literature Review

Bioeconomic models (Clark 1980, 1990) combine depictions of biological processes with representations of the behavior of economic agents. Because the behavior of a population of harvesters often deviates from social objectives (*e.g.*, aggregate dynamic efficiency), much of the literature focuses on strategies to mitigate the tendency toward rent dissipation (Gordon 1954). Stock dynamics constitute a dynamic biological constraint on the extractive process. The level of biomass is a stock, viewed by economists as a capital asset, which generates flows in the form of growth and harvest (*i.e.*, rents or consumer and producer surplus).

Renewable resource economics has largely assumed deterministic stocks and growth processes and focused on dynamically efficient or second-best harvesting policies. However, most natural systems exhibit stochasticity and/or imperfect information regarding either stocks or flows. Economic variables, such as output prices (Andersen 1982; McGough, Plantinga, and Provencher 2004), wages paid to labor and other factors, and the actual level of withdrawals are also stochastic in nature or imperfectly observed by decision makers. A growing body of literature explicitly models these sources of stochasticity and uncertainty, exploring their impact on system behavior and the effectiveness of different management approaches. Andersen and Sutinen (1984) provide a review of stochastic bioeconomic models. They conclude the effects of incorporating uncertainty into bioeconomic analysis are often ambiguous, but in some instances differ little from analogous deterministic results.

While the simplest models for stock and recruitment ignore year-to-year fluctuations in recruitment, fisheries data suggest that such fluctuations may be quite large. Ludwig and Walters (1982) examine optimal harvesting subject to imprecise parameter estimates for stock-recruitment relationships. They show the presence of such uncertainty can lead to striking changes in the estimated optimal escapement. When only a narrow range of spawning stocks has been observed, there is considerable uncertainty about how recruitment per spawner will vary with spawning stock. The optimal policy involves deliberate probing or experimentation with the spawning stock so as to improve the predictive ability of the model. The optimal number of spawners can be at least twice the number predicted by deterministic theory.

Pindyck (1984) examines the implications of uncertainty regarding the growth rate of stock for the optimal level of stock and harvest. The study shows that stochastic fluctuations add a risk premium to the rate of return required to keep a unit of stock *in situ*, and consequently a lower standing stock is maintained as variance increases. Optimal harvest can increase, decrease, or be left unchanged as the variance of the fluctuations increases, depending on the functional forms of biological growth and market demand.

As an alternative to a dynamic path of harvest and/or escapement, Sandal and Steinshamn (1997) extend Pindyck's analysis by developing a "feedback rule" for the management of stochastically evolving stocks; *i.e.*, a harvest policy that is dependent upon current stock levels. This "reactive" strategy mitigates the negative impacts of uncertainty compared to an open-loop solution in which a harvest path is determined in advance.

Saphores (2003) explores the effect of uncertainty on harvest decisions. In their model, uncertainty does not (as one might expect) lead to a monotonic change in the optimal harvest rate. Rather, increases in uncertainty at low levels lead to conservative behavior, but at high levels of uncertainty the possibility of extinction leads to more aggressive harvest.

Model

Following Pindyck (1984), we model the dynamics of an exploited biomass, x, as

$$dx = [f(x) - h]dt + \sigma(y)xdz, \tag{1}$$

where $f(\cdot)$ is the growth function, h is the rate of harvest, $\sigma(\cdot)$ is a deterministic function describing variance in stock growth, y is the accumulated knowledge regarding the growth function, and z is a Wiener process. Equation (1) implies the current fish stock is known with certainty, but the instantaneous change in the stock is, in part, random. That is, we consider only growth uncertainty; population dynamics research in our model constitutes an incremental improvement in the information regarding the stock level in subsequent periods.[2]

Knowledge reduces the uncertainty regarding evolution of the stock:

$$\frac{d\sigma(y)}{dy} \leq 0, \tag{2}$$

and the accrual of knowledge is linear in research effort, s, at time t:[3]

$$dy = s dt. \tag{3}$$

The social planner manages the stock as a capital asset so as to maximize the present value of social surplus; *i.e.*, the area under the demand curve for extracted stock minus the cost of extractive and other inputs (Miranda and Fackler 2002). For dynamic optimality, one must consider not only static costs incurred by harvesters, but also indirect ones (the stock externality and dynamic opportunity costs related to intertemporal allocation of resource; see equations (15) and (19) below). The social surplus function is:

$$\Pi(x, h, s) = \int_0^h [D^{-1}(\eta) - c(x)]d\eta - w(s), \tag{4}$$

where $D(p)$ (= h) is the demand for output as a function of its price, p; $c(\cdot)$ is the marginal cost of harvest, which varies inversely with stock size; and w is the total expenditure on research ($\partial w/\partial s > 0$ and $\partial^2 w/\partial s^2 \geq 0$).

The social planner's value function is:

$$V(x, y) = \max_{h,s} E_t \int_t^\infty \Pi(x, h, s)e^{-\delta(\tau - t)}d\tau, \tag{5}$$

where δ is the social discount rate. The manager's problem is to maximize V in equation (5), subject to stock dynamics (equation [1]) and the knowledge accrual process [equations [3]). The problem has two control variables, h and s, and two state variables, x and y.

The Bellman equation for this constrained optimization is:

$$\delta V(x, y) = \max_{h,s} \left\{ \Pi(x, h, s) + \frac{1}{dt} E[dV(x, y)] \right\}. \tag{6}$$

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[2] We understand that stock assessment generally covers many different forms of uncertainties. Indeed, the current fish stock is often uncertain.

[3] This specification is for simplicity. In some cases, knowledge accumulation may be nonlinear. For example, it may follow an S-shaped (logistic) path.

We use Ito's Lemma to expand dV and obtain:

$$dV = \frac{\partial V}{\partial t}\,dt + \frac{\partial V}{\partial x}\,dx + \frac{\partial V}{\partial y}\,dy + \frac{1}{2}\left[\frac{\partial^2 V}{\partial x^2}(dx)^2 + \frac{\partial^2 V}{\partial y^2}(dy)^2\right] + \frac{\partial^2 V}{\partial x \partial y}\,dxdy. \qquad (7)$$

Substituting equation (1) for dx and equation (3) for dy into equation (7), and noting that V is not an explicit function of t ($\partial V/\partial t = 0$),[4] we have:

$$dV = \left\{ \left[f(x) - h \right] \frac{\partial V}{\partial x} + s\,\frac{\partial V}{\partial y} + \frac{1}{2}\sigma^2(y)x^2\,\frac{\partial^2 V}{\partial x^2} \right\} dt + \sigma(y)x\,\frac{\partial V}{\partial x}\,dz. \qquad (8)$$

Next, substituting equation (8) into (6) and noting that $E(dz) = 0$, the optimization problem (equation [6]) becomes:

$$\delta V = \max_{h,s} \left\{ \int_0^h D^{-1}(\eta)d\eta - c(x)h - w(s) \right. \qquad (9)$$

$$\left. + \left[f(x) - h \right] \frac{\partial V}{\partial x} + s\,\frac{\partial V}{\partial y} + \frac{1}{2}\sigma^2(y)x^2\,\frac{\partial^2 V}{\partial x^2} \right\}.$$

Maximizing the right-hand side (RHS) of equation (9) with respect to harvest, h, and the research input, s, gives rise to the first-order conditions:

$$D^{-1}(h) - c(x) - \frac{\partial V}{\partial x} = 0, \qquad (10)$$

$$\frac{dw(s)}{ds} - \frac{\partial V}{\partial y} = 0. \qquad (11)$$

Since $D^{-1}(h) = p$, equation (10) is the standard optimality condition for h (Pindyck 1984, eq.12, p. 293): Under optimal management, the shadow value of stock x (*i.e.*, the social value of the marginal unit of *in situ* stock) is equal to the marginal net benefit (*i.e.*, surplus) from extraction.

Equation (11) is the optimality condition for population research (s). The marginal cost of research is equal to its marginal benefit; *i.e.*, the increase in value function, V, with respect to an increase in cumulative knowledge (y), resulting from instantaneous research effort, s.

The optimality conditions for state variables, x and y, illuminate the relationship between harvesting and research. Letting h^* and s^* be the solutions to equations (10) and (11), we can rewrite equation (9) as:

$$\delta V = \int_0^{h^*} D^{-1}(\eta)d\eta - c(x)h^* - w(s^*) + [f(x) - h^*]\,\frac{\partial V}{\partial x} + s\,\frac{\partial V}{\partial y} + \frac{1}{2}\sigma^2(y)x^2\,\frac{\partial^2 V}{\partial x^2}\,. \qquad (12)$$

[4] This is an autonomous infinite-horizon problem (Judd 1998).

Differentiating equation (12) with respect to x yields:

$$\delta \frac{\partial V}{\partial x} = \left[D^{-1}(h^*) - c(x) - \frac{\partial V}{\partial x} \right] \frac{\partial h^*}{\partial x} - \frac{dc(x)}{dx} h^* + \frac{df(x)}{dx} \frac{\partial V}{\partial x} \tag{13}$$

$$+ \sigma^2(y)x \frac{\partial^2 V}{\partial x^2} + [f(x) - h^*] \frac{\partial^2 V}{\partial x^2} + s \frac{\partial^2 V}{\partial x \partial y} + \frac{1}{2} \sigma^2(y)x^2 \frac{\partial^3 V}{\partial x^3},$$

noting that:

$$\frac{1}{dt} Ed \left(\frac{\partial V}{\partial x} \right) = [f(x) - h^*] \frac{\partial^2 V}{\partial x^2} + s \frac{\partial^2 V}{\partial x \partial y} + \frac{1}{2} \sigma^2(y)x^2 \frac{\partial^3 V}{\partial x^3}. \tag{14}$$

Substituting equations (10) and (14) into (13) yields the optimality condition for stock x:

$$\frac{1}{dt} Ed[p - c(x)] + \frac{df(x)}{dx} \frac{\partial V}{\partial x} - \frac{dc(x)}{dx} h^* = \delta \frac{\partial V}{\partial x} - \sigma^2(y)x \frac{\partial^2 V}{\partial x^2}. \tag{15}$$

The first term on the left-hand side (LHS) of equation (15) is the rate of appreciation of the *in situ* value of the stock; *i.e.*, the rate of growth in the marginal net rents associated with harvest. This is analogous to the rate of change in the co-state variable in an optimal control problem solved with a current-value Hamiltonian (Clark 1990, p. 107); Pindyck (1984) refers to this first term as "the absolute rate of capital gain." The second LHS term represents the gain in value from stock growth, and the last LHS term captures the stock externality—the reduction in harvest costs associated with a marginal unit of stock. The two terms on the RHS represent, respectively, the opportunity cost (*i.e.*, foregone interest earnings) of resource left *in situ* and the risk premium; *i.e.*, the amount the resource manager would pay for perfect information about stock growth.

Next, we derive the rate of return condition by rewriting equation (15) as:

$$\frac{\frac{1}{dt} Ed[p - c(x)]}{p - c(x)} + \frac{df(x)}{dx} - \frac{\frac{dc(x)}{dx} h^*}{p - c(x)} = \delta + \sigma^2(y)xA(x, y), \tag{16}$$

where $A(x, y) = -(\partial^2 V/\partial x^2)/(\partial V/\partial x)$ is the index of absolute risk aversion. Expression (16) is essentially the same as that in Pindyck (1984, eq.18, p. 294). In the presence of stock growth uncertainty, the social discount rate, δ, is effectively augmented by the risk premium (the last term on the RHS). In our case, this risk premium depends upon accrued knowledge, y. An increase in y leads to a decrease in stock growth variance, σ^2, according to equation (2), thus lowering the risk premium. According to Clark and Munro (1975), the rate of return condition specifies that the optimal stock, x^*, is the one at which the "own rate of return" of the stock[5] (LHS of equation [16]) equals the social rate of discount, augmented by the risk premium.

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[5] The return associated with holding a unit of stock (Pindyck 1984).

Differentiating equation (12) with respect to y, we obtain:

$$\delta \frac{\partial V}{\partial y} = \left[D^{-1}(h^*) - c(x) - \frac{\partial V}{\partial x} \right] \frac{\partial h^*}{\partial y} + \sigma(y) \frac{d\sigma(y)}{dy} x^2 \frac{\partial^2 V}{\partial x^2} \tag{17}$$
$$+ [f(x) - h^*] \frac{\partial^2 V}{\partial x \partial y} + s \frac{\partial^2 V}{\partial y^2} + \frac{1}{2} \sigma^2(y) x^2 \frac{\partial^3 V}{\partial x^2 \partial y}.$$

Noting that:

$$\frac{1}{dt} Ed(\frac{\partial V}{\partial y}) = [f(x) - h^*] \frac{\partial^2 V}{\partial x \partial y} + s \frac{\partial^2 V}{\partial y^2} + \frac{1}{2} \sigma^2(y) x^2 \frac{\partial^3 V}{\partial x^2 \partial y} \tag{18}$$

and substituting equations (10) and (18) into (17) gives the optimal condition for y:

$$\frac{1}{dt} Ed \left(\frac{\partial V}{\partial y} \right) = \delta \frac{\partial V}{\partial y} - \sigma \frac{d\sigma}{dy} x^2 \frac{\partial^2 V}{\partial x^2}. \tag{19}$$

The LHS of equation (19) represents the capital gain resulting from research. On the RHS, the first term is the opportunity cost of research, and the second term captures, in terms of reduction of the risk premium, what the resource manager would pay to eliminate stock growth uncertainty.

Again, we can obtain the rate of return condition for y by rewriting equation (19):

$$\frac{\frac{1}{dt} Ed \left(\frac{\partial V}{\partial y} \right)}{\frac{\partial V}{\partial y}} = \delta + \sigma \frac{d\sigma}{dy} x^2 A(x, y) \frac{\frac{\partial V}{\partial x}}{\frac{\partial V}{\partial y}}. \tag{20}$$

From equation (2), we know the last term on the RHS is negative. Thus, research lowers the risk premium and, in turn, the *total* discount rate. Equation (20) suggests that the optimal level of cumulative research input, y^*, is the one at which the "own rate of interest" of the total research input (LHS of equation [20]) is equal to the social rate of discount adjusted by the risk premium that is reduced by research.

A Numerical Example

The incorporation of scientific knowledge (y) makes analytic solution of the stochastic bioeconomic model infeasible. In theory, optimal solutions for h^*, s^*, x^*, and y^* might be obtained by solving equations (10), (11), (16), and (20) jointly. However, this is a nontrivial exercise, even with existing numerical solvers. Some useful insight is gained through partial numerical analysis of the stock (x), treating the level of knowledge (y) as exogenous.

We illustrate the impact of accrued knowledge (y) on optimal harvest (h) and stock level (x) using numerical simulation. Following Pindyck (1984, p. 295), we choose functional specifications as follows:

$$D(p) = bp^{-\alpha} \tag{21}$$

$$c(x) = cx^{-\gamma} \tag{22}$$

$$f(x) = qx(1 - x/K), \tag{23}$$

with $b = 1$, $\alpha = 0.5$, $c = 5$, $\gamma = 2$, $q = 0.5$, $K = 1$, and $\delta = 0.05$.[6] These functional forms correspond to an isoelastic demand function, an isoelastic marginal cost function, and a logistic growth function, respectively.

To assess the effect of reducing variance (σ) resulting from research (y), we use three values (0.05, 0.10, and 0.15, respectively) for σ in our analysis. Numerical results are generated using a MATLAB stochastic control routine.[7] The results are depicted in figures 1 through 3.

Figure 1 illustrates the impact of increased knowledge y (and hence decreased uncertainty $\sigma[y]$) on the indirect objective function; *i.e.*, the maximized value function in equation (5).[8] While the absolute difference between the value functions for

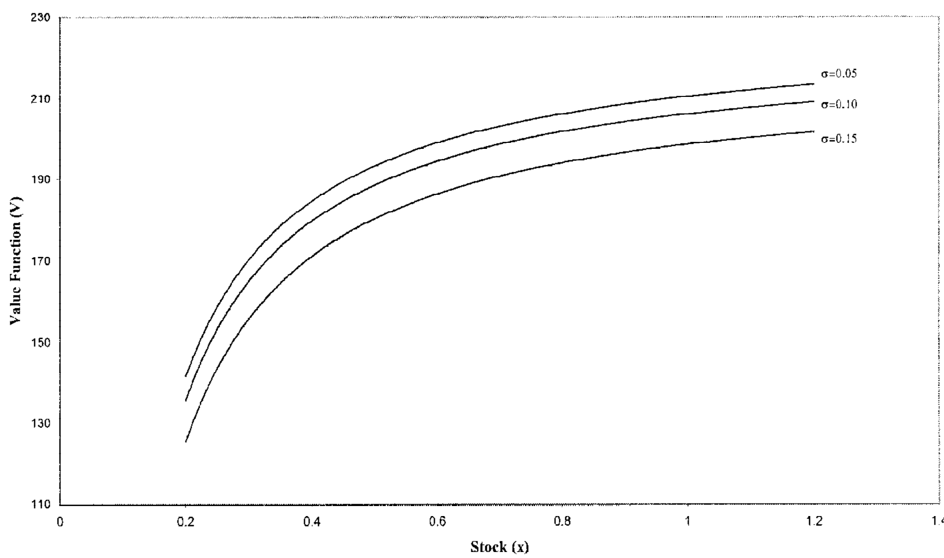

Figure 1. Value Function

[6] These parameters are from Miranda and Fackler (2002, p. 416).

[7] DEMSC02 (Renewable Resource Management Model) in the CompEcon Toolbox developed by Miranda and Fackler (2002, pp. 415–17).

[8] For the isoelastic demand function and $\alpha = 0.5$, the area under demand function is $\int_0^h D^{-1}(\eta)d\eta = -1/h + A$ (for relevant discussion, see Pindyck 1984; note 14, p. 302) with $A = \infty$ at $\eta = 0$. For empirical estimation, we specify η starts from 0.05 and thus $A = 20$. For $A = 20$, the arbitrary constant in the value function equals $A/\delta = 400$ (see Pindyck 1984; equations (21) and (22), p. 296).

different levels of uncertainty remains constant over different stock levels, it is clear that information is less valuable as a percentage of value as the stock size (and hence the value function) increases. It is also evident there are diminishing returns to information; *i.e.*, the value gain from decreasing σ from 0.15 to 0.10 is greater than the gain associated with moving from 0.10 to 0.05.

As shown in figure 2, the steady-state harvest level (h) increases as the stock growth uncertainty (σ) decreases. Figure 3 shows that it is efficient to maintain a larger standing stock, x^*, as uncertainty regarding the growth function is reduced. Improved information makes stock a less risky form of capital, and therefore the social planner wishes to hold more of this asset in her portfolio. While the response of harvest to changing variance can increase or decrease depending upon the functional form of the growth function and economic parameters (Pindyck 1984), the effect on steady-state stock size—barring the possibility of extinction—is insensitive to such factors (Saphores 2003).

Combining the results in figures 1 and 3, we see the benefit associated with a costly reduction in the uncertainty has two components: a movement (to the left) along a value function due to rising stock size and an upward shift of the value function. In our numerical example, the benefits associated with reducing σ from 0.15 to 0.10 and 0.05 are 8.75 (4.76%) and 13.40 (7.30%), respectively, as shown in table 2.[9]

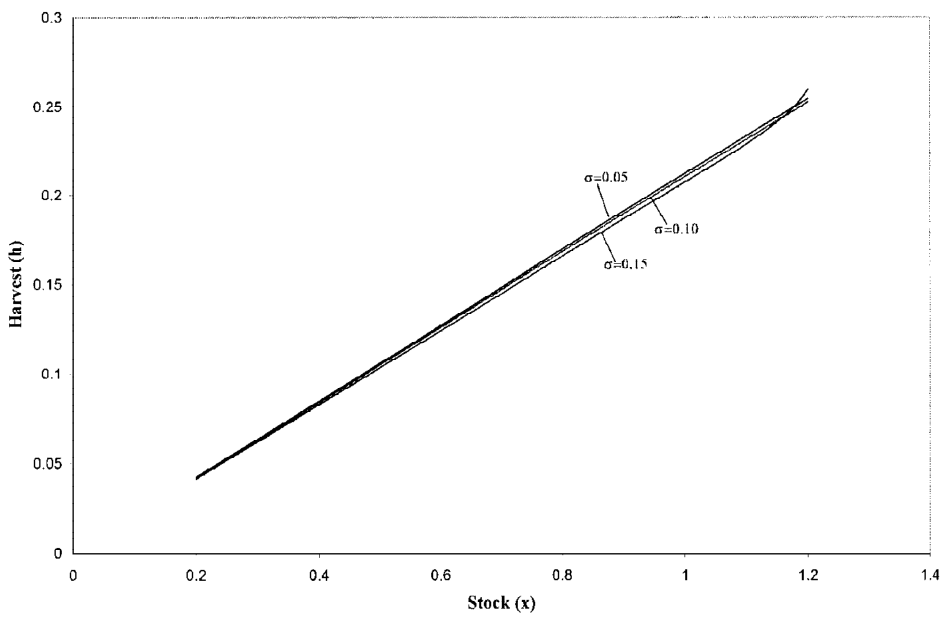

Figure 2. Optimal Harvest

[9] The percentage changes in the value function reported here are somewhat dependent upon the parameters and functional forms chosen, and should be regarded as illustrative only.

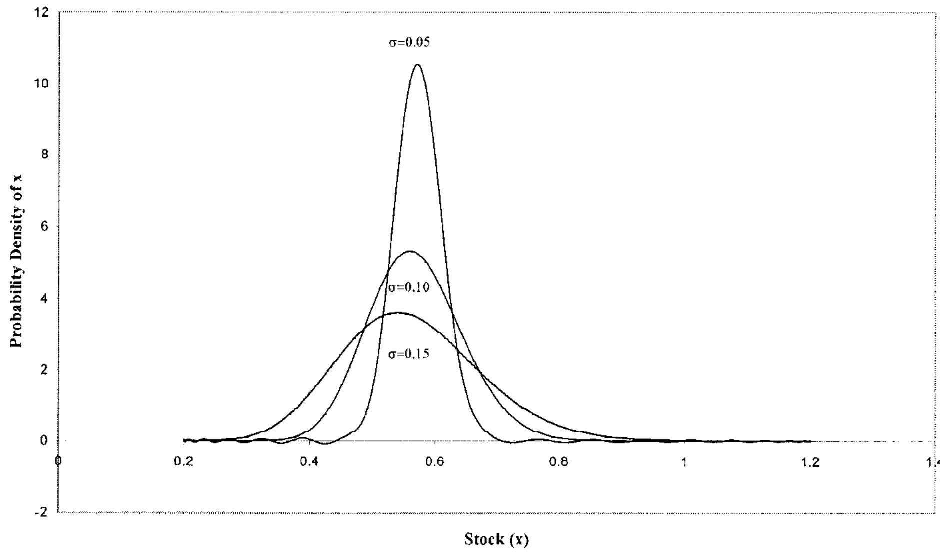

Figure 3. Long-Run Stock Density

Table 2
Benefit of Population Dynamics Research

Uncertainty	Expected Stock $E(x)$	Value V	Net Benefit ΔV (%)
$\sigma = 0.15$	0.54	183.68	—
$\sigma = 0.10$	0.56	192.43	8.75 (4.76)
$\sigma = 0.05$	0.57	197.08	13.40 (7.30)

Conclusions

This paper provides an incremental extension of a stochastic renewable resource model (Pindyck 1984) to include information gathering regarding the stochastic evolution of the stock as a dynamic choice variable. While Pindyck models variance as an exogenous parameter, our formulation endogenizes the level of variance and characterizes the impact of information gathering on both the harvest decision and the present value of rents resulting from harvest activity. The study contributes to the development of a theoretical framework for analyzing the efficiency of scientific information production in renewable resource industries.

As expected, we show that the research input s; *i.e.*, the incremental accrual of knowledge regarding stock evolution at time t should be chosen such that the marginal cost of research is equal to its marginal benefit. Marginal benefit in this case is defined as the increase in the social planner's value function, V, with respect to an incremental increase in cumulative knowledge (y), arising as a result of s.

Pindyck (1984) shows that under stock growth uncertainty, the social discount rate, δ, in the rate of return condition is effectively augmented by a risk premium. This premium is the maximum the resource manager would be willing to pay to eliminate the uncertainty. In our case, the risk premium is affected by cumulative research input, y, as an increase in y leads to a decrease in stock growth variance, σ^2. We show that population research influences the rate of return condition by lowering the premium.

Finally, we show that the optimal level of cumulative research input, y^*, is the one at which the "own rate of interest" of the total research input is equal to the social rate of discount adjusted by the risk premium which is reduced by research.

Our analysis illustrates the theoretical existence of an internal optimum in research effort, though we do not explicitly solve for the time path of such effort. The numerical procedure may be used to develop estimates of the benefit associated with information gathering to reduce scientific uncertainty. If the cost of research is known, a benefit-cost assessment may be conducted. Indeed, our results imply that research programs might, in fact, *not* be cost-effective; *i.e.*, if the increase in the value function arising from such a program is small relative to the fixed costs of implementation.

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