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WORKING PAPER NO. 819

BIOPROSPECTING WITH PRIOR ECOLOGICAL INFORMATION

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DEPARTMENT OF AGRICULTURAL AND RESOURCE ECONOMICS

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Abstract: The role of ecological and taxonomic knowledge in biodiversity prospecting is examined. A sequential-search model of biodiversity prospecting is developed in which genetic materials are differentiated by prior information. When search procedures are optimized to take account of available information, materials with unusually high priors command significant information rents. These rents can be large, even when genetic materials are not themselves scarce. When genetic materials are abundant, an increase in the potential profitability of product discovery has virtually no effect on the value of any site; and technology improvements that lower search costs induce a drop in the value of every promising site. Results of a numerical simulation suggest that bioprospecting information rents could, in some cases, be large enough to finance meaningful biodiversity conservation.

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BIOPROSPECTING WITH PRIOR ECOLOGICAL INFORMATION

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1. Introduction

What role does scientific knowledge plays in the field of natural products bioprospecting? How does information derived from scientific models -- particularly, from the fields of ecology and systematics -- affect the decisions facing profit-seeking firms, as they select whether and where to conduct bioprospecting searches? What does such knowledge imply for the value of genetic materials as a source of intellectual property? And is there any effect of such knowledge on the generatation of economic incentives for biodiversity conservation? With this focus, the central theme of this paper is the proposition that scientific information, regarding the location of plants, animals and microbes, and their ecological relationships, can and does play a fundamental role in the bioprospecting process. Information, when organized and made available to those conducting searches for genetic materials of potential interest, can offer guidance that improves the efficiency and effectiveness of bioprospecting.

Given that search is costly and that bioprospecting firms are rational and profit-seeking, they will optimize their search procedures to take account of scientific information, and will investigate the most promising opportunities before moving on to less likely sources. If their procedures for generating prior beliefs are sound, then using such information should, on average, increase the likelihood of making discoveries, and reduce the costs of search. Accordingly, scientific information can play a substantial role in determining the profitability and feasibility of bioprospecting as an economic activity.

Our work represents a conceptual departure from previous economic analyses of bioprospecting, in two principal respects. First, we argue that the discussion of bioprospecting as an economic activity should focus not on biologically-determined units such as genes or species, but on search opportunities that correspond, in practice, to geographic locations. The activities surrounding bioprospecting – the collection of scientific data, the collection and screening of samples, the development of local institutions, the negotiation of access agreements -- are all connected to particular places. Second, given the *site* as our unit of analysis, a strategy of measuring search opportunities in ways that are particular to locations is required. That is, we need to design frameworks that allow us to evaluate sites in terms of their chances of yielding a successful discovery, for a given project. There is an emerging scientific literature suggesting that for many applications this is, in fact, a viable strategy – that scientific frameworks could be developed to guide searches, based on site-specific data that can be collected at moderate cost (Dreyfuss and Chapela, 1994). In this vein, Sandoz Pharmaceuticals, Inc. (now Novartis) has recently launched a Biolead Project that will attempt to identify observable factors that correlate with biochemical "creativity" of microorganism, i.e. their fertility as sources of complex chemical structures (Möller, 1996). Such approaches stand to make bioprospecting a less random process in the future, elevating the importance of scientific information.

To take the metaphor of "prospecting" seriously, consider an analogy to the field of oil exploration. How much would an oil company be willing to pay for the exploration and drilling rights on a parcel of land drawn from the landscape entirely at random? Consider two polar cases. If the chance that an "average" parcel will yield a oil strike is very low, then under reasonable conditions of oil prices and drilling costs, the firm would not be willing to pay much for the opportunity to sink a well there. If, on the other hand, oil can be found, with high probability, under almost every undistinguished plot, then oil *in situ* will not be a scarce resource. In either case, when priors are uninformative – when sites are perfect substitutes *ex ante* – search opportunities command little, if any, scarcity value.

This is the central result of bioprospecting models based on an assumption of uninformative priors (Simpson, Sedjo and Reid, 1996; Polasky and Solow, 1995). As the analogy makes clear, the result is not really "about" biodiversity and technology discovery, *per se*. It is, instead, a negative result that highlights the central role of information, in any kind of search project: if the exploration rights to a parcel are valuable, there must be something that marks the location as having unusual promise, relative to alternative options. In the market for search opportunities, information turns sites from commodities into differentiated products.[1] The problems of prospecting are, substantially, problems of creating and managing information about potential leads.

To structure this theme formally, we present a sequential-search model of prospecting in which search opportunities are differentiated by prior information. A complete characterization is developed of the relationship between the costs and benefits of search, the quality of available information, and the value of options on search opportunities. Leads associated with unusually strong priors are shown to command *information rents*, a value that flows from the ability of information to lower the costs and risks of search. Undistinguished opportunities, on the other hand, typically command low values.

When genetic materials are viewed as opportunities to conduct searches for new products, this framework can be applied to biodiversity prospecting. In this context, genetic materials become genetic *resources* only in combination with distinguishing information. This analysis allows us to distinguish biodiversity prospecting, the economic activity, from biodiversity conservation, the social objective. Bioprospecting has generated excitement, both in the economics literature and elsewhere, largely because it appears to hold promise as a source of market-based incentives for biodiversity conservation. However, in order to estimate the potential conservation benefits of bioprospecting, we must first analyze the behavior of profit-seeking firms that desire access to genetic resources, but may not have an interest in conservation *per se*. If prior information cannot differentiate genetic materials, then

[1] Even in cases for which the base resource is homogeneous (e.g. elemental minerals).

Simpson et al. have settled the issue definitively: conservation efforts need to look for alternative sources of support. If, on the other hand, prior information can distinguish some materials as being unusually promising, then the connections between natural products R&D and biodiversity conservation incentives remain important areas for research, and retain at least some promise as the basis for a conservation strategy. The first task is to understand the incentives facing outside firms and local institutions, and to analyze the properties of equilibria that result in markets for search opportunities.

Five sections comprise the paper. Section 2 presents the conceptual foundation of our model. In section 3, we present a model of bioprospecting in which scientific information suggests habitat locations that are especially creative. Assuming optimal search behavior, we derive a formula that expresses the value of differentiated habitats to a bioprospecting firm, and show that this value depends sensitively on the quality of available information. Section 4 presents a numerical example that demonstrates how our formula could be used to incorporate ecological information into an economic valuation function. In section 5, we discuss how our model would need to be extended to address two related economic and policy issues: the analysis of equilibria in the market for search opportunities; and institutional arrangements for biodiversity conservation. We argue that the broad qualitative implications of the basic model are robust to various generalizations. A concluding section summarizes our findings.

2. A Conceptual Framework for the Economic Analysis of Bioprospecting

In this section a brief description of bioprospecting is provided, followed by a survey of the economic literature on the topic. The conceptual and empirical evidence in support of the presuppositions upon which our model is based is then examined.

2.1 A brief history of bioprospecting

While humans have used living materials as sources of natural products since time immemorial, the beginning of bioprospecting as the deliberate activity of profit-seeking private firms could reasonably be dated from the World War II era discovery of penicillin antibiotics from bread molds. This event set off expansive, albeit scattershot, attempts to find other naturally-occurring organic chemicals with therapeutic properties. Further discoveries included immunosuppressants developed from soil microbes growing in remote regions of Norway and Japan (Werth, 1994). Selected commercial products isolated from natural sources are reported in Table 1. No obvious geographic or other patterns emerged that correlated the source of materials to their therapeutic potential.

[INSERT HERE TABLE 1: Selected Commercial Products Derived From Natural Sources]

In recent years, technical advances have dramatically reduced the labor inputs, and hence the expense, of natural products screening. Many firms and other organizations have pushed into the hunt for new drugs, insecticides, oils, and other natural products. Moreover, firms and other institutions have emerged that specialize in the collection, preparation and initial assaying of living materials. (See Table 2.)

[INSERT HERE TABLE 2: Examples of Companies Active in Natural Product Collection and Screening]

The increasing pace of bioprospecting, and the implied increase in its profitability, has driven parallel changes in the institutional environment surrounding the activity. Under the United Nations Convention on Biological Diversity, the principle was established that nation-states are sovereign over the genetic resources found within their borders. Many bioprospecting activities are now governed by

contracts with national governments or their representatives; contracts that specify fees, royalty payments, and other obligations that private firms much accept as the price of access to potentially valuable genetic materials.

2.2 The economic literature on bioprospecting

While bioprospecting has generated a great deal of published literature (see, for example, Reid et al. (1993), Vogel (1994), Pan American Health Organization (1996), and the references therein), only a few articles have appeared on the topic in the refereed economics journals. These have emerged out of an antecedent literature on biodiversity conservation and the non-market valuation of environmental resources and amenities. The earliest work to draw an explicit link between biodiversity conservation and the development of new goods was made by Weisbrod (1964), whose arguments led to the formal articulation of the concept of biodiversity option value (Arrow and Fisher, 1974; Conrad, 1980). Using this framework, Fisher and Hanemann (1986) developed an explicit, quantified link between the value of a genetic resource and the uncertainty surrounding its potential benefits. While this literature has considered the links between information, conservation, and the discovery of valuable natural products, it has not yet incorporated an explicit role for agents who must expend effort in order to carry out searches and identify these options.

Brown and Goldstein (1984) were the first to model bioprospecting explicitly as an economic activity. In their model, biodiversity appears as an aggregate, undifferentiated stock variable; it plays a role exactly analogous to that of capital in standard neoclassical production theory. The authors address the question of how large this stock should be, given a relationship of diminishing returns between the size of this stock and the benefits of a search effort. Barbier and Aylward (1996) extended this approach to address the role of information in bioprospecting, through a model in which "knowledge" is represented by a second state variable that complements biodiversity in the production of new product discoveries.

They consider the trade-offs associated with the allocation of a fixed amount of public resources to the competing claims of conservation and knowledge-accumulation.

Simpson et al. (1996) introduced more explicitly the potential importance of redundancy across species as sources of valuable compounds. Analyzing a sequential-search model of bioprospecting, they argue that the "marginal species" should contribute little to the value of a bioprospecting project. The result appears as a version of the water-diamond paradox: material can be extremely valuable in the aggregate, yet still contribute only a very little to utility at the margin. Polasky and Solow (1995) generalized this approach to consider the case in which hit probabilities are equal *ex ante*, but correlated to a degree that depends on a measure of genetic distance. They also refine the assumption of redundancy, allowing for the possibility that one discovery in a product class could be surpassed by another of greater effectiveness. Results derived from these search models depend critically on the assumption that every species has, *ex ante*, an equal probability of yielding the sought-after compound.[2]

2.3 Units of analysis for bioprospecting

Discussions of biodiversity and its conservation, investigation, and use, have been conducted with many different units of analysis. Brown and Goldstein (1984), for example, initiated the economic analysis of bioprospecting by treating biodiversity as an undifferentiated stock, an approach adopted by Barbier and Aylward (1996). Ecologists have studied biodiversity in terms of large-scale geographic and functional concepts – the ecosystem, the bioregion, the biodiversity "hot spot" – while systematics organizes the web of life according to phenotypic characteristics of organisms. These fields are the primary sources for organized information about the properties of organisms, and their relations

[2] Artuso (1996) also considered how information increases the value of genetic materials. His focus, however, is on how value is added to genetic materials as they clear the various stage-hurdles in the process of drug discovery (e.g. successfully passing clinical trials of efficacy and safety), not on the *ex ante* differentiation of genetic materials based on

amongst each other and their environments. Political debate about access to genetic resources, on the other hand, has tended to focus on institutionally-defined units, emphasizing the split between the "technology-rich" countries of the North vs. the "gene-rich" countries of the South; the prerogatives of individual nation-states; or the pros and cons of *ex situ* vs. *in situ* conservation.

The United States Endangered Species Act views the *species* as the fundamental unit of conservation, a focus that also characterizes much of the recent search literature on bioprospecting. Discussion of agricultural genetic resources tends to focus on fine-scale intra-species distinctions, at the level of the *variety* or breed. Others have advocated an even finer scale of resolution, insisting that conservation must assure the viability of every gene or "genetically coded function" (Vogel, 1994) in the gene pool. Still others have proposed that conservation be based on abstract measures of diversity (Weitzman, 1992; Solow, Polasky and Broadus, 1993; Weitzman, 1993). None of these concepts can assert a dominant claim as the "right" unit of analysis for all discussion about biodiversity; each has an appropriate role in some contexts, while also raising its own challenges of definition and measurement.

2.3.1 The *search opportunity* as the basic unit of analysis in bioprospecting

In analyzing bioprospecting as an economic activity, it is necessary to assume the perspective of the agents who conduct transactions in this "market." In particular, we need to analyze the incentives facing bioprospecting firms, the "consumers" of genetic resources. A firm carrying out a bioprospecting project has no financial stake in conservation *per se*. Nor, in practice, will its information about testing opportunities be organized in the form of a matrix showing the pairwise genetic distances between all species, or as a catalog of genetically coded functions. Nor does the firm care about the national origins of the organisms it examines. To the firm, only three questions matter:

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prior scientific information. Nor does his framework incorporate the possibility that species could be redundant as sources of novel compounds, and the consequent distinction between average and marginal values for genetic materials.

how much will a search program cost? What are the chances for its success? And, what benefits will be realized in case of a successful discovery?

From the perspective of the firm, therefore, genetic materials can be represented formally as *search opportunities*. Each opportunity is a certain type of lottery ticket, characterized by a price (the cost of testing), a probability of winning, and a jackpot that is paid in the case of a lucky draw. In order to analyze firm behavior, we need to describe the menu of search opportunities available to the firm, the information it has about the value of these opportunities, and the incentives that drive the selection of one option over another. Other concepts related to biodiversity and genetic resource management (from conservation biology, political economy, etc.) enter our analysis only indirectly, insofar as they have an impact on the options, information, and incentives of economic agents.

2.3.2 Search opportunities as geographic locations

What objects comprise the search opportunities? In approaching this issue, three questions are operative: how is the information about search opportunities organized? How are access agreements negotiated and transacted? And, what objects are, ultimately, investigated?

Much of the discussion of this question in the literature has treated search opportunities as being embodied by individual species. However, although screening programs are in some cases organized to test individual species sequentially and randomly, this paradigm is far from universal. Commonly, the objects tested are complexes of organisms, large and lumpy aggregates of living material. In some screening programs (e.g. of microbial communities in soil, leaf litter, etc.), the firm may not even know the identity of the species in a sample it screens – nor need it directly care. The question, from the firm's perspective, is whether *something* in the sample can generate a chemical compound with desired properties. From this perspective, the individual species is merely an intermediate carrier of chemical

creativity; its identity has no direct bearing on the firm's problem. In fact, an "atomistic" focus on individual species, in abstraction from ecological and environmental relationships, can interfere with the discovery process. For example, in some cases, micro-organisms will produce certain proteins only in certain strains, only in symbiosis with certain plants, or under particular conditions of temperature and humidity. A plant may produce defensive chemicals only in its stems or leaves, or only when under attack from insects. If such relationships are ignored, the true capacities of organisms may be misjudged. By equating search opportunities with species, we in effect presume that screening is carried out in an impoverished informational context.[3]

What is required is a characterization of ecological knowledge that allows a bioprospector to form informative prior beliefs that serve to guide the product discovery process. In this setting, search opportunities should be described not with biological units of conservation (species or genes), but with geographic locations, defined primarily by ecological and institutional boundaries. Our reasoning finds support on both scientific and institutional grounds.

Scientific information suggesting the potentially valuable uses of organisms comes from many branches of the biological and social sciences, including ecology, systematics, cell biology, and ethnobotany. Myers (1997) notes that plants, which cannot flee from predatory attacks, have developed instead a wide array of complex chemical defenses. These are especially well-developed in deserts, rainforests and coral reefs – zones of "biological warfare" where biotic and environmental stresses are particularly acute. The insight that, "plants of this ecosystem have developed a great variety of defenses against insects" can suggest, to an agrochemical firm, a place on which to focus a search for insecticides.

[3] It is important to distinguish the treatment of these two points in the literature. The formal claim that tests are best viewed as search opportunities is acknowledged, implicitly or explicitly, in several published works on bioprospecting (Fisher and Hanemann, 1986; Simpson, Sedjo and Reid, 1996; Polasky and Solow, 1995; Simpson and Sedjo, 1996). The limitation of these studies, we argue, stems from their empirical claims that search opportunities should be identified with individual species, or that there exist no basis for the formation of informative priors that distinguish opportunities from one another.

Similarly, the observation that people native to one area use the roots of a certain red plant as a treatment for diarrhea, can generate informative priors to a firm investigating therapeutics. Environmental indicators can in some cases give far more specific direction. Frogs, lacking a hard defensive shell, are unusually prolific generators of toxins. One anit-coagulant, approved for human trials, was developed after screening venom from only seventy species of snakes (Pollack (1992), as cited in Artuso (1996)).

By far the most prolific source of new drugs, however, is the world of micro-ogranisms (Werth, 1994). The diversity of micro-organisms also dwarfs that of the "macrobial" world of plants and animals (Pace, 1997). To a pharmaceutical firm looking for compounds to screen against a set of target cancer cell lines, it would be of great interest to know that micro-organisms congregated at a certain location, growing in soils under rotting wood of a certain type of tree, and under specific conditions of temperature and soil moisture, produce an unusually large variety of complex proteins. The hot springs at Yellowstone National Park, USA, were the source of a heat-resistant bacterium that produces Taq polymerase, an enzyme that forms the basis for the Polymerase Chain Reaction, a DNA replication method. PCR now generates millions of dollars in annual licensing revenues for the patent holder, Hoffmann-La Roche. Several firms have since searched for similar compounds in these springs (Milstein, 1995), which contain the deepest known evolutionary divergences of the bacterial domain (Pace, 1997).

As the above examples illustrate, product leads come organized in a variety of formats, making use of data across many dimensions. A characteristic they all share, however, is a reference to geography. To take advantage of an informative prior, a firm must ultimately collect, or have collected, samples of organic material from a particular location. Of all the dimensions along which ecological information could be organized, geography provides the best – perhaps, the only – common denominator. This conclusion suggests that, as an operational stance, search opportunities be treated as sites.

Institutional considerations reinforce this position. When we speak of a "search opportunity" as an economic object, we mean an opportunity to make an investment, to trade an expenditure of resources for a reduction in uncertainty. By this definition, a single species or sample extract does not represent a search opportunity. Firms do not in practice revisit, after each assay, the decision whether or not to screen additional samples. The firm's effective decisions, rather, concern how and where to allocate resources (equipment, personnel, etc.) in pursuit of samples to screen. The analyses that form the basis for these decisions will draw on information that comes in many forms, but will hinge ultimately on an estimate of the probable costs and benefits of dispatching resources to particular places from which materials can be collected.

The delineation of search opportunities along geographic lines is strengthened by property rights considerations. When a bioprospecting firm must negotiate its access to genetic resources, the local institution on the other side of the table – be it a host country government, a non-governmental representative (e.g. Costa Rica's INBio), or the manager of a botanical garden – will control an area that typically will be defined by geographic boundaries.[4] Concretely, we propose that economic search frameworks be organized in terms of *sites*, conceived of as relatively small parcels described in terms of local institutional boundaries and firm investment decisions.[5]

2.4 Measuring Information, in the Context of Bioprospecting

Closely related to the question of how units of analysis are defined, is that of how they should be dimensionalized or measured. The units of measurement must be developed according to the use to

[4] In addition, conservation efforts are often organized along geographic lines.

[5] While there is, for most purposes, no need to specify spatial scales exactly, we can think loosely of a site as comprising an area on the order of 1,000 hectares, or 10 km^2, a figure that corresponds, within a rough order of magnitude, to the scale at which bioprospecting expeditions are carried out.

which the information will be put. For a bioprospecting program, sites are measured, ultimately, in terms of *discovery probabilities*, for a particular search project, using a particular search technology or system. Many other variables can be incorporated into such an evaluation, but all such information ultimately needs to be framed into a site-specific chance of discovery. In essence, a bioprospecting firm must decide where and whether to pitch its tent, and begin searching for something it thinks might be valuable.

In this context, the term *information* is used to refer to anything that reduces the uncertainty inherent in a search process, and that thereby increases the chance of making a discovery, or reduces, in expectation, the time or effort required for the project. In this usage, the term is very general. It encompasses the results of massive screening programs carried out by large pharmaceutical firms, fundamental advances in ecology and systematics, and knowledge about the medicinal properties of plants carried by local users of traditional therapeutics.[6]

To summarize, an appropriate economic analysis of bioprospecting starts with a description of the objects being transacted. Formally, these objects are search opportunities, not genetic materials *per se*. Opportunities to search are typically defined by institutional and geographic boundaries, which are dimensionalized in terms of success probabilities. In the next section, the incentives that confront firms in this market are analyzed within a formal model of bioprospecting.

[6] Dreyfuss and Chapela (1994), to note one example, propose a systematic method for generating prior beliefs, for the case of screening microbial fungi for new drug leads. Defining the chemical "creativity" of micro-organisms as their propensity to produce a variety of different types of complex molecules (especially, proteins), they note that creativity can, in some cases, be correlated with observable "macroscopic" data (humidity, temperature, etc.), and with the phylogenetic features of the microbial communities examined *in vitro*. These correlations could be employed as the basis for forming priors about hit rates in pharmaceutical screening programs.

3. A Model of Bioprospecting, Using Ecological Information

We present a sequential-search model of bioprospecting, considering the case in which success probabilities vary across test sites. The model is a generalization of the Simpson-Sedjo-Reid model of sequential search, in which we allow prior probabilities to differ across sites, and assume that firms optimize their search strategies taking this information into account. We then analyze the model to address the question, what is the incremental contribution of a site to the value of a bioprospecting program, and how is this value affected by the availability of useful prior information?[7]

3.1 The Model

A bioprospecting firm conducts a search for a compound that will make possible the development of a new product. There are a large number N of sites where the compound might be found. Using scientific models, site-specific data, and ethnobotanical knowledge that are assumed to be available freely, the firm is able to assign to each site a number that represents the probability that a test of the site will generate a discovery that leads ultimately to the development of the product.[8] A test of the n^{th} site is thus treated as a Bernoulli trial with probability p_n of successfully scoring such a "hit." The hit

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[7] The theory of valuing search options appears to have received relatively little attention in the economics literature, particularly in the context of technology development. There does exist a large body of work on the theory of search, both within economics (Lippman and McCall, 1979) and elsewhere (Stone, 1975; DeGroot, 1970; Ahlswede and Wegener, 1987). Work in the area has focused, however, on the identification of optimal selection and stopping rules (Weitzman, 1979), and on how these rules are affected by changes in parameters describing the search space (the probability distributions of rewards, agents' appetites for risk, time preferences, Bayesian updating, etc.). Further, much of this work is based on an assumption that per-trial rewards are identically distributed, or that the number of search opportunities is unlimited (Kohn and Shavell, 1974).

Our focus is on a related but distinct issue: assuming optimal search behavior, what is the value to the researcher of preserving a quality-differentiated search opportunity, when "success" is an all-or-nothing property, and when multiple successes are strictly redundant? This question does not appear to have been explored to date (although Simpson et al. (1996) and Simpson and Sedjo (1996) analyze the case with uninformative priors. Also, Seo (1995) examines the value of an option to "recall" an opportunity after it has been tested, in a context where test results take on a range of possible values).

[8] By "probability," we mean subjective probability, i.e. a degree of reasonable belief, in the view of the firm. These parameters are to be interpreted as reduced-form expressions based on potentially complicated evaluations of search opportunities.

probabilities of different sites are assumed to be statistically independent. Without loss of generality, we can assign labels to sites in order of decreasing hit probability, so that $p_1 \geq ... \geq p_N$. In order to avoid trivial cases, we assume that no site contains the desired compound with certainty ($p_n < 1$ for all n). We refer to the ordered list $\{p_n\}$ as the *information structure* of the bioprospecting problem.

The firm tests sites sequentially, at a cost c per site, where c is a positive constant.[9] The regime is open-access: the firm can search at any site, without paying access fees or other contract-specific costs.[10] When a test is successful, a payoff R is realized.[11] Multiple hits are redundant. Our sole behavioral assumption is that the firm selects the order in which it tests sites so as to maximize the payoff to the search project.

3.2 Scarcity Rents and Information Rents for Genetic Resources

Given our assumptions about the incentives facing the bioprospecting firm, its behavior is fully characterized by the following result, a well-known application of the theory of search:

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[9] Many bioprospecting projects involve multi-stage testing, in which samples that show promise in an initial screening are subjected to more rigorous, and expensive, follow-on testing and investigation. (For a discussion of how this multi-stage process works in drug discovery, see Artuso (1996).) Samples, and hence sites, can thus differ with respect to their ultimate cost of testing. In this case, however, the researcher will typically not know *ex ante* which samples will require additional expense. For the purpose of modeling the researcher's incentives, we can, therefore, treat c as constant, the average (or expected) cost per test, and p_n as the *ex ante* probability that a sample from site n will clear all the stage-hurdles associated with research and development, leading ultimately to the marketing of a new product.

[10] We assume an open-access regime with common knowledge and complete appropriability of discoveries, so that all rents accrue to the prospecting firm. This regime represents an institutional "baseline case." If we instead assumed that host countries held enforceable property rights to sites, our analysis would be complicated by the need to consider the strategic behavior of firms and site-owners in the resulting market for search opportunities.

[11] In practice, this payoff is likely to be uncertain at the outset of a product-development process. The payoff ultimately realized will depend on the resolution of multiple contingencies (the outcome of clinical trials, the size of consumer demand, the activities of competitors, etc.). It is assumed, however, that the firm has the capacity to formulate beliefs about its payoffs over such a rich set of contingencies, to represent those beliefs in the form of a probability distribution, and to calculate R as the expected value of that (subjective) distribution. Assuming the firm to be risk-neutral, its approach to the project will be the same in either case, and the use of the reduced-form expression is justified. More generally, we can view R as the certainty equivalent of the payoff distribution under the objective function of a risk-averse firm.

Proposition 1: *An optimal search program involves testing, at each stage, a site with maximal hit probability amongst those not yet examined. Search terminates either when a hit is reached, or when no sites remain for which testing promises a non-negative return in expectation.*

In other words, optimal search involves checking the most promising sites first – a highly intuitive result previously recognized by Weitzman (1979), amongst others.

Proof: all proofs are included in an Appendix.

In light of the result, the probability ordering $(p_1, p_2, ..., p_N)$ is also the order in which sites are examined: the information structure determines a *search queue*.[12] This concept is central to our results. The stopping rule implies that sites for which $p_n < c/R$ are never tested under any conditions, and have no effect on search behavior or payoffs. Without violence to our results, therefore, we assume in what follows that $p_n \geq c/R$ for all n.[13]

Using the proposition, we compute a value function that determines the expected payoff of the search at each stage, conditional on results at previous stages. Let V_n denote the *ex post* expected value of continuing the search, after n-1 sites have been tested unsuccessfully. Applying Bellman's Principle of Optimality, this continuation value is characterized by the recursive relationship

$$V_n = p_n R + (1 - p_n)V_{n+1} - c \quad , \quad n = 1, \ldots, N \tag{1}$$

where $V_{N+1} \equiv 0$. This equation can be interpreted as follows. With probability p_n, the n^{th} test is successful, a payoff R is realized, and search terminates; with probability 1 - p_n, the test is a failure, and

[12] More exactly, the information structure determines the order of the queue, up to a permutation of sites with equal hit probabilities. As we show (Corollary 2.1), any such permutation yields equivalent analytic results.

[13] More generally, we can interpret the stopping rule as defining, endogenously, the effective number of available sites: let $\tilde{N}$ denote the total number of potential sites, and let $N \leq \tilde{N}$ be defined as the largest integer such that $p_N \geq c/R$.

search proceeds to the n+1st site. The "consolation prize" in case of failure is the opportunity to continue the search with the n+1st site, the value of which is, by definition, V_{n+1}. In either event, a cost c is incurred for the test. Solving, the expected payoff to the search at its outset is given by

$$V_1 = \sum_{n=1}^{N} a_n (p_n R - c) \qquad (2)$$

where $a_n \equiv \prod_{i=1}^{n-1}(1-p_i)$ is the probability that the search is carried to the nth stage, i.e. the probability of failure in each of the first n-1 tests; and p_nR-c is the expected return to a test of the nth site.[14]

An expression for the expected incremental contribution of the nth site to the overall value of the search process can now be derived. First rewrite V_1 in the form

$$V_1 = \sum_{i=1}^{n-1} a_i (p_i R - c) + a_n V_n$$

$$= \sum_{i=1}^{n-1} a_i (p_i R - c) + a_n \left[p_n R - c + (1-p_n) V_{n+1} \right]$$

where the recursive definition of V_n from equation (1) is introduced. Now define V_{-n} as the expected value of the search process, for the case in which the nth site is skipped:

$$V_{-n} = \sum_{i=1}^{n-1} a_i (p_i R - c) + a_n V_{n+1} \quad . \qquad (3)$$

The *incremental value* of the nth site, denoted v_n, is defined as the difference between these two terms:

$$v_n \equiv V_1 - V_{-n}$$
$$= a_n(p_n R - c) + a_n(1-p_n)V_{n+1} - a_n V_{n+1} \ ,$$

[14] Here, $a_n p_n$ is the probability that the search ends with a success at the nth site. If we treat the event "the project fails" as an N+1st site, then the vector $\langle a_1 p_1, \ldots, a_N p_N, a_{N+1} \rangle$ forms a probability distribution over the set {1, ..., N, N+1} (specifically, a truncated nonhomogeneous geometric distribution, so that $\sum_{i=1}^{n} a_i p_i = 1 - a_{n+1}$ is the cumulative probability of success in the first n trials) with associated payoffs <R-c, R-2c, ..., R-Nc, -Nc>.

which simplifies to

$$v_n = a_n\left[p_n(R - V_{n+1}) - c\right] \quad . \tag{4}$$

The incremental value v_n can be interpreted as the maximum a firm will be willing to pay at the start of a search project, to insure that a site will be available if it should be needed (i.e. if all tests of more promising sites end in failure). The formula is interpreted as follows: With probability a_n, the first n-1 tests are unsuccessful, and search proceeds to site n, which is tested at cost c. With probability p_n, this test is successful, a reward R is realized, and search terminates. The effective payoff in this case is, however, net of the continuation value V_{n+1} that would have applied if the search had instead skipped over the n^{th} site. That is, since multiple discoveries are redundant, a success at the n^{th} stage destroys the value associated with the opportunity to continue searching.[15]

In abstract terms, we can view the incremental value function as a transformation v that maps a sequence p_n of technical parameters, onto another sequence v_n of economic values. The definition of this functional is conditioned on the parameters c and R, on the assumption of an open-access, common-knowledge search regime, on the assumption that the order of search is optimized to take advantage of available information, by searching higher-probability sites before moving on to low-probability alternatives. The search rule does not, however, determine the order of testing uniquely, since it does not determine the order in which sites of equal probability are examined. We show (Corollary 2.1) that our definition of incremental value does not depend on this arbitrary choice and, therefore, that the functional v is well-defined. The intuition is straightforward: since a site's

[15] The incremental value is not exactly the same as the firm's willingness to pay a gatekeeper for access to the site. As discussed in Section 5, this willingness to pay depends on how access rights are defined, and on the degree of competition amongst suppliers and consumers of search opportunities. For example, if, in place of open-access, we assumed that local institutions were able to exclude prospectors selectively, then the firm's maximal willingness to pay for access would depend on the fees charged by competing suppliers of search opportunities. This value would increase with each unsuccessful test of an alternative site. Nor does the expected value of the project equal the sum of the incremental values. Indeed, $\sum v_n = V_1 - \sum a_n p_n V_{n+1}$; the sum of site values equals the expected value of the project, less the expected "redundancy cost" that a discovery at one site imposes on its competitors. This latter term is analogous to the social welfare cost associated with redundant R&D programs in patent races.

incremental value is defined as the difference in expected returns with the site and without it, the removal of any two sites with equal probability will yield the same effect on returns.

A central result concerns the case in which the researcher has heterogeneous (i.e. informative) priors. It can be shown that sites toward the front of the search queue add more to the project's expected return than do those further back. In other words, sites of unusual promise are strictly more valuable to the prospector, than are alternative areas. This result holds due to two factors. First, the early, high-probability sites contribute more than the others to the chance of an eventually successful outcome for the project. As repeated failures push investigators to pick through lower-grade "ore," it becomes increasingly unlikely that a hit will ever be scored. Second, the opportunity to test the high-probability sites first increases the chance that a discovery will be made early in the process. In case of a discovery, the costs of continued search are avoided. If high quality sites are removed from the menu of search options, the shift to low-quality sources implies an increase in the expected number of trials-to-discovery. For this reason, sites toward the front of the queue are valuable because of their capacity to reduce *ex ante* search costs.

The intuition behind this claim can be strengthened by expressing V_1, the *ex ante* returns to search, as a difference between expected benefits and costs:

$$V_1 = \left(\sum_{n=1}^{N} a_n p_n\right) R - \left(\sum_{n=1}^{N} a_n\right) c \qquad (5)$$
$$= \mu R - Tc$$

The first term denotes the *ex ante* expected benefit of the project: the probability μ of a successful conclusion, times the payoff R in case a hit is scored. The second term denotes the *ex ante* expected cost, expressed as the expected number T of trials carried out, times the per-trial cost c. The removal of a site from the search queue lowers the expected value of the project both by reducing the chance of

making a discovery (i.e. by lowering μ), and increasing the expected length (hence, cost) of the search (represented by an increase in T). As will be shown, both effects are more pronounced for sites early in the search queue. This holds because these sites, if available, are more likely to be tested. Removal of sites toward the back of the queue has an effect on search payoffs only in cases in which all early tests end in failure.

Example. We examine the Simpson-Sedjo-Reid model, with the single refinement that one site is known to have a higher success probability than all the others. That is, consider the special case where $p_1 > p_2 = p_3 = \ldots = p_N \equiv p$, a constant. The incremental contribution v_1 of the first site can be shown (see Appendix) to have the form

$$v_1 = \left(\frac{p_1}{p}\right)\left(\frac{1-p}{1-p_1}\right)v_N + \left(\frac{p_1 - p}{p}\right)c \quad ,$$

where v_N is the incremental contribution made by each "marginal" site with hit probability p. Interpreting the expression on the right, an improvement in the chance of success at the first site generates value in two ways. First, it increases the chance that a hit will be scored eventually, and so acts like an increase in the number of sites available to check. Second, it increases the chance that a hit will be scored *early*, thereby lowering total search costs.

In sum, when search procedures are optimized to incorporate useful prior information, high-probability sites command *information rents* associated with their unusual contribution to the chance of success, and to the avoidance of search costs.[16] These information rents apply in addition to any *scarcity rents* resulting from a limit on the total number of sites available for testing.

[16] As the discussion makes clear, the magnitude of the information rent associated with a given site depends not only (or even, primarily) on the site's own hit probability, but also on how this value compares with those of other sites. This is because a site's hit probability determines not only the chance of a successful test, but also the site's position in the search queue (and, therefore, the probability that the site will ever be tested at all).

This distinction between scarcity and information rents is formalized in the following proposition, which characterizes completely the relationship between the costs and potential benefits of search, the quality of available information, and the value of differentiated search opportunities. Here, a site n is referred to as *marginal* if its hit probability is equal to that of the lowest-quality viable alternative, i.e. if $p_n = p_N = \min \{p_i \mid p_i R - c \geq 0, i = 1, ..., N\}$.

Proposition 2: *Let* $\{p_n\}_{n=1}^{N}$ *be the sequence of hit probabilities on a collection of sites, indexed in order of decreasing probability. Let the incremental value* v_n *of the* n^{th} *site be defined as in (4) above. Then* v_n *can be decomposed into components* $v_n = v_n^I + v_N$, *where*

$$v_n^I \equiv \left(\frac{a_N}{1-p_n}\right)(p_n - p_N)R + \left[\sum_{i=n+1}^{N-1} \frac{a_i}{1-p_n}(p_n - p_i)\right]c \text{ , and}$$

$$v_N = a_N(p_N R - c) \text{ is the value of a marginal site.}$$

We refer to these components, respectively, as the information rent *and the* scarcity rent *of site n.*

A site's scarcity rent can be interpreted as the expected amount it would contribute to the value of the project if it were undistinguished from the mass of other leads and was, therefore, a perfect substitute for any other marginal site, *ex ante*. Scarcity rents can be positive if the project is constrained by a technical bound on the number of feasible research opportunities – that is, if N is finite, and if marginal sites carry a positive expected return ($p_N R - c > 0$), so that random screening is, in expectation, profitable.[17]

[17] In many cases, however, it is natural to think of search as limited, not by any physical constraint on the number of sites that might be tested, but by a potential economic exhaustion of sufficiently promising leads. For the interpretation that the firm's stopping rule determines endogenously the effective number of available sites (i.e. if $p_N R - c \approx 0$), then $v_N \approx 0$; marginal search opportunities command zero scarcity rents. In this case, a site only commands a value when it is associated with a success probability above the "average background" level: all rents are information rents.

The information rent captures the degree to which a distinguishing prior increases a site's expected incremental value. The expression for v'_n can be interpreted with the aid of a thought experiment. Suppose that a researcher who is seeking a treatment for muscle spasms learns that people of a particular location, when thus afflicted, boil the roots of a certain plant to make a tea that is locally renowned for its soothing powers. Although she had planned to visit the area eventually to conduct random screening of samples, she had previously thought it unpromising for her purpose, assigning it the lowest probability, p_N. On hearing the news, she raises her expectation that the region will provide what she seeks, increasing her prior to $p_n > p_N$. She also rearranges her search queue so that the area now occupies the prominent n^{th} position on her itinerary, where $n < N$. What effect does the change in her prior entail for her expected return to the research project?

There are two effects. First, there is an increase in the expected probability that she will find what she seeks before exhausting all her leads. The amount of the consequent rise in expected benefits is represented by the first term in the expression for v'_n, the probability $a_N/1-p_n$ that no other site contains the discovery, times the increase in the expected benefit of testing this remaining site. Second, if this n^{th} test is successful, then she will have avoided the cost of visiting at least some of the sites that now occupy positions n+1, ..., N-1. The second term in the expression for v'_n represents the drop in her expected costs of search.

3.3 Resource Abundance, Research Costs and Payoffs, and Resource Value

Under what conditions are information rents large enough to carry significant weight in land use and conservation decisions? In particular, can genetic resources have significant value, in their role as bioprospecting search opportunities, even when genetic materials are abundant? The characterization

of information and scarcity rents allows several general results to be proved that bear on these questions.

Inspection of the formulae in Proposition 2 shows that scarcity and information rents have non-negative values ($v_N \geq 0$, and $v'_n \geq 0$ for all n), and that marginal sites command zero information rents. More importantly, it confirms the claim advanced earlier that sites of unusual promise have strictly greater value than do their less promising neighbors:

Corollary 2.1: *For all m, n = 1, ..., N, if $p_n = p_m$, then $v_n = v_m$, and if $p_n > p_m$, then $v_n > v_m$. Thus, the sequence $\{v_n\}$ of incremental values is monotone decreasing in n (i.e. the transformation v is order-preserving). In particular, information rents are everywhere zero if and only if priors are uninformative.*

The comparative static effects on site values of changes in the parameters describing search benefits and costs can also be examined. To facilitate the discussion, let $B_n \equiv \left(\frac{a_N}{1-p_n}\right)(p_n - p_N)R$, the first, "benefit-increasing" term in our expression for v'_n. Note that the payoff R from a success enters into the expression for v_n only through v_N and B_n and that both these terms are linear in a_N, the probability of reaching the last site in the search queue. Since $p_n \geq c/R$ for all n, a_N is bounded above by $(1 - c/R)^{N-1}$, which becomes small as N grows large. Hence, the size of project rewards has only a limited effect on site values, a claim formalized in the following result.

Corollary 2.2: *The effect on site values of a change in the payoff level R is given by* $\frac{\partial v_n}{\partial R} = a_{N+1}\left(\frac{p_n}{1-p_n}\right)$. *Hence,* $\frac{\partial v_n}{\partial R}$ *is strictly positive, and is independent of R and c.*

For $p_n \leq \frac{1}{2}$, *it is bounded above by* a_{N+1}, *the probability of project failure.*

Interpreting the expression for $\partial v_n / \partial R$, an increase in project rewards induces an increase in a site's value only in proportion to the probability that the site contains the discovery uniquely (i.e. in proportion to p_n, the probability of success at site n, times $a_{N+1}/1-p_n$, the probability that tests at all other sites would result in failure). Therefore, when the expected probability of an eventual discovery is high, site values are largely insensitive to changes in the potential payoff. This result may seem counter-intuitive; one might expect that large increases in potential project rewards would generate substantial increases in the value of a chance to realize those rewards. However, once the prize attains a certain size, the researcher may find it rational to undertake a search so expansive as to make success a virtual certainty. Further increases beyond this threshold may have a large impact on the expected value of the project overall, but not on the *ex ante* contribution of any one site to the realization of those benefits. This effect is particularly strong for sites of low quality (for which p_n is very small).

Note, however, that the "cost-reducing" term $\left[\sum_{i=n+1}^{N-1} \frac{a_i}{1-p_n}(p_n - p_i)\right]c$ in the expression for information rents, remains positive even if N is large. Indeed, this term is increasing in N: as the haystack grows, information on the whereabouts of the needle becomes increasingly valuable. This observation is fundamental to the relationship between search costs and site values.

Corollary 2.3: *The effect on site values of a change in search costs c is given by*

$\frac{\partial v_n}{\partial c} = \left[\sum_{i=n+1}^{N-1} \frac{a_i}{1-p_n}(p_n - p_i)\right] - a_N$. *In particular,* $\frac{\partial v_n}{\partial c}$ *is independent of R and c, and is negative if and only if* $\sum_{i=n+1}^{N} a_i \left(\frac{p_n}{1-p_n}\right) < a_n$.

The last clause of the statement suggests a second surprising result. Intuitively, we might expect that the value of a search opportunity to increase with any drop in the unit-cost of search effort. Such a change, after all, increases the expected return to any trial. However, for the relatively promising sites (i.e. for cases in which n is relatively small, as a fraction of N), there is a second, counter-veiling effect. As shown in Proposition 2, a large fraction of the value of these sites is associated with their potential help in avoiding the costs of resorting to low-quality alternative sources. As unit search costs decline, the value of this "competitive advantage" is eroded. Hence, an improvement in search technology increases (weakly) the value of the lowest-quality sites, but can reduce the value of high-quality sites.

As viable search opportunities become increasingly abundant, these counter-intuitive features of the value function become dominant. To show this, consider the case in which there are a relatively small number of sites known to be specially promising, and a larger number that share an "average background" probability of making a discovery at a site sampled at random from a large pool of potential sources.[18] Concretely, let $M << N$ be given, and suppose that $p_M = p_{M+1} = ... = p_N = p$, where p is a constant such that $pR - c \geq 0$; and suppose that $p_n > p$ for all $n = 1, ..., M-1$. We refer to sites 1, ..., M-1 as "promising," while sites M, ..., N are called "marginal," as above. The following proposition characterizes the value of genetic materials as marginal sites become abundant, i.e. as N grows without bound.

Proposition 3: *Let sites 1, ..., M-1 be promising, and sites M, ..., N be marginal, as defined above. Then for n = 1, ..., M-1, the incremental value of v_n has a strictly positive lower bound, given by the relation*

$$v_n \geq \left[\sum_{i=n+1}^{M-1} \frac{a_i}{1-p_n}(p_n - p_i) + \left(\frac{a_M}{1-p_n} \right) \left(\frac{p_n - p}{p} \right) \right] c \quad .$$

Further, this relation becomes an equality in the limit as N goes to infinity.

Accordingly, a site that is worth testing at all and is more promising than at least some of its "competitors" commands a rent that is strictly positive and bounded away from zero. The bound obtains no matter how many other sites are available, no matter what the size of the potential reward for success. The lower bound can be interpreted as the *ex ante* reduction in search costs associated with the opportunity to test the n^{th} site before moving on to the pool of less promising sources, a pool that includes an infinite number of sites with hit probability p. The bound of this proposition allows a value to be assigned to promising locations that depends neither on the degree of resource abundance, nor on potential rewards (beyond a threshold level of project viability), but only on search costs and prior information.[19, 20] The final claim of the proposition, concerning the limiting behavior as N grows to infinity, leads immediately to several striking results about the value of genetic resources under conditions of abundance.

Corollary 3.1: *Let sites 1, ..., M-1 be promising, and sites M, ..., N be marginal, as defined above. Suppose that the payoff from a successful discovery is large enough to make random sampling of marginal sites profitable in expectation (i.e. $R \geq c/p$). Then as genetic materials become abundant (i.e. in the limit as $N \rightarrow \infty$), the following hold:*

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[18] Again, we assume away the trivial case in which one or more sites contain the desired compound with certainty.

[19] In the language of Weitzman (1979), the threshold reward level, c/p, is the called the "reservation price" of the marginal sites.

[20] Proposition 3 and Corollary 3.1 can be generalized to cover the case in which $p \geq p_n \geq c/R$ for all n = M, ..., N. All results hold, except that v_n does not converge to the lower bound given in Propositon 3 as $N \rightarrow \infty$. See Corollary 4.4.

(i) *Marginal sites have zero value.*

(ii) *An increase in the potential profitability of product discovery has no effect on the incremental value of any site.*

(iii) *A technology improvement that lowers search costs induces a drop in the incremental value of every promising site.*

Thus, if search opportunities are in effectively unlimited supply, then scarcity rents are negligible. In this case, the value of a site is, to a very good approximation, entirely a function of the quality of information associated with it.[21] The composite good (material plus information) enhances the profitability of the project not so much by creating success, as by aiding the avoidance of failure.

3.4 The Effect of Exogenous Changes in Prior Beliefs

Improvements in ecological, taxonomic, and ethnobotanical knowledge can lead to changes in researchers' priors. The next proposition clarifies how a site's value is affected by changes in its perceived hit probability, when all other parameters of the problem are held fixed.

Proposition 4.1: *The value of a site is a piecewise linear, continuous, increasing, and weakly convex function of its own hit probability. Furthermore, on the interval* $p_{n-1} > p_n > p_{n+1}$, *the elasticity of* v_n *with respect to* p_n *is given by* $\frac{\partial v_n}{\partial p_n} \cdot \frac{p_n}{v_n} = 1 + \frac{a_n c}{v_n}$.

[21] Our analysis has thus far ignored the effects of time discounting. Incorporating a role for discounting should, however, only strengthen these results: if benefits decay with time, then information that enables rapid discovery becomes even more important.

Interpreting the elasticity formula, the twin effects of value-enhancement and cost-reduction are identified. A pair of analogous results characterizes the effect of changes in hit probabilities at other areas.

Proposition 4.2: *The value of a site is a piecewise linear, decreasing function of the hit probability of every other site. For $m \neq n$, v_n is continuous in p_m except where $p_m = p_n$. Furthermore, the following hold:*

(i) For $m = 1, \ldots, n-1$, on the intervals $p_{m-1} > p_m > p_{m+1}$, the elasticity of v_n with respect to p_m is given by

$$\frac{\partial v_n}{\partial p_m} \cdot \frac{p_m}{v_n} = -\left(\frac{p_m}{1-p_m}\right).$$

(ii) For $m = n+1, \ldots, N$, on the interval $p_{m-1} > p_m > p_{m+1}$, the elasticity of v_n with respect to p_m is given by

$$\frac{\partial v_n}{\partial p_m} \cdot \frac{p_m}{v_n} = -\left(\frac{p_m}{1-p_m}\right)\left[1+\left(a_n - p_n \sum_{i=n+1}^{m} \frac{a_i}{1-p_n}\right)\frac{c}{v_n}\right].$$

The form of the equation in point (i) reflects the fact that, conditioned on the superiority of site m over site n, a further increase in p_m reduces the chance that site n will ever be tested. (Interestingly, this effect depends only on the magnitude of p_m, and not on the position of m in the list 1, ..., n-1.) For $m > n$, an increase in p_m reduces the perceived probability that, if the n^{th} site provides a success, then it would have done so uniquely. It also reduces the expected cost savings associated with the opportunity to test the n^{th} site before the m^{th}.

The claims in Propositions 4.1 and 4.2 are conditioned on constraints in the ordering of the search queue. It turns out that the qualitative results do not depend on this restriction.[22] As a result, a general claim about the impact of research that refines or sharpens priors can be advanced.[23]

[22] Showing this requires that certain technical complications be negotiated. These involve the fact that the valuation function is not differentiable at points where the search ordering changes.

Corollary 4.3: *An increase in the hit probability of a site induces a more-than-proportionate increase in the value of that site, and a decrease in the value of every other site.*

This corollary implies in turn that the lower bound described in Proposition 3 applies to all information structures (and not just in the special case for which hit probabilities are constant for all but a few superior sites).

Corollary 4.4: *Let* $\{p_n\}_{n=1}^{N}$ *be an information structure for the bioprospecting problem, and let p be a constant with* $1 > p \geq p_N$. *Let* $M(p) = \min\{m \mid p_m \leq p\}$. *Then for* $n = 1, \ldots, M-1$, *the incremental value of* v_n *has a strictly positive lower bound given by*

$$v_n \geq \left[\sum_{i=n+1}^{M(p)-1} \frac{a_i}{1-p_n}(p_n - p_i) + \left(\frac{a_{M(p)}}{1-p_n}\right)\left(\frac{p_n - p}{p}\right) \right] c \quad .$$

Further, in the limit as $N \to \infty$, *the conclusions of Corollary 3.1 hold.*

Obviously, this formula is useful for empirical valuation studies.

4. Using the Model as the Basis for a Valuation Approach: A Numerical Example Based on Data from the Pharmaceutical Industry

Implications of our model for valuing intellectual property can be revealed through a numerical simulation. The exercise has two purposes. First, to demonstrate how the framework of Section 3 could be used, in the context of suitable scientific information, as the basis for assigning economic

[23] Our discussion has been based on an implicit assertion that improved information always increases the values of the hit probabilities p_n. Conceptually, of course, this needn't be true -- new research could reveal that sites which had been thought promising are actually of low quality. More commonly, however, it will be the poorly-understood sites that are assigned low priors, at some "average background" level. Improved knowledge will serve mainly to sharpen priors upward.

value to genetic resources. Second, to offer support for the claim that, under a range of plausible parameter choices, information rents for high-probability sites could be large enough to generate significant incentives for conservation. In order to facilitate a side-by-side comparison that highlights the importance of information in the search process, we adapt our simulation from the similar exercise of Simpson et al. (1996).

We consider our model in the case in which the bioprospecting firm is confronted with a menu of K ecosystems where it can choose to conduct a search. Each ecosystem comprises a number N_k of search opportunities, where k = 1, ..., K. To simplify the discussion, a search opportunity corresponds to a geographically-defined parcel (or site), of a standard size. Based on scientific and ethnobotanical knowledge, ecosystems are differentiated from each other by the per-site hit rate: all sites within the k^{th} ecosystem have the same probability π_k of generating a discovery, with $\pi_1 > \ldots > \pi_K$.[24] As above, the per-site cost of testing is a constant c, the payoff in case of success is a constant R, and multiple hits are redundant. The values of these parameters are chosen to assure that all tests yield positive returns *ex ante*: $\pi_k > c/R$ for all k = 1, ..., K.

Given these assumptions, the firm's optimal search program (Proposition 1) involves the sequential testing of each site in the first ecosystem, then each site in the second, and so on. Testing stops either when a hit is reached or when all viable search opportunities have been exhausted. The incremental value of each site to the total value of the search is given by equation (4).

To implement this simulation, incremental values for sites in each of eighteen biodiversity "hot spots" are computed using data from Myers (1988, 1990) (see Table 3). The density of endemic species of higher plants is used as a proxy for the fertility of the ecosystem as a source of new drug leads. These

densities are assumed to be proportional to the per-test hit rate for sites in each ecosystem.[25] Other parameters on the drug discovery process are based those used by Simpson et al.[26] Hit rates in differentiated ecosystems are based on their rate of 1.2×10^{-5} hits/species, implying that 37% of search projects end successfully, with a drug discovery. We assume that ten new drugs based on natural sources are released per year. To achieve this yield, an average of twenty-six projects per year are undertaken. Each successful discovery generates a return of R = $450,000,000. Firms discount future costs and benefits at 10% per year. Cost are set at $485 per test, at which level both formulae generate equal per-site values for the least promising ecosystem (California Floristic Province). Results of the simulation are presented in Table 3 and in Figure 1. The values generated in the Simpson-Sedjo-Reid calculation are presented to facilitate comparison.

Figure 1 shows the relationship between ecosystem size, hit rate, and incremental value. As we see, information rents can be several orders of magnitude larger than scarcity rents, and can be substantial even when scarcity rents are negligible. Indeed, the values associated with the highest-quality sites (on

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[24] Note that π_k refers to the hit rate, not for the site at the k^{th} position in the search queue, but for each of the N_k sites in the k^{th} ecosystem.

[25] It should be emphasized that we are not staking out an empirical claim that the density of endemic species is a good indicator of chemical creativity, nor that these simulated values be taken as rigorous empirical estimates of bioprospecting values for these geographic areas. The derivation of such estimates will depend on the development of scientific and ethnobotanical bases for assigning priors to search opportunities, over a range of potential natural products. Rather, we use these figures simply in order to demonstrate how the technique would be used, given an appropriate scientific basis for assigning hit probabilities to locations.

[26] It is important to distinguish our calculation from the one carried out by Simpson et al. In their formulation, tests are conducted on individual species. Since each species carries an equal chance of success, each is associated with the same marginal value. A parcel of habitat is characterized by the number of species it contains uniquely; the cost of its destruction is given by that number of endemic species per hectare, times the (extremely low) value of each "marginal" species. In other words, the loss of a habitat has an effect on the realized costs and benefits of search only in those cases when all tests of the surviving species end in failure.

In our model, by contrast, tests are conducted on sites. By treating the hit rate as proportional to the density of endemic species, we use this density as a proxy for site quality. The constant of proportionality could then be interpreted as the effective hit rate per species, but this parameter has no direct effect on the results. In our model, destruction of high-quality habitat is deleterious not only because it implies a loss of search opportunities, but also because the surviving opportunities may be less productive than those that were lost.

the order of $9,000/hectare in our simulation, for rainforest in Western Ecuador) can be large enough to motivate conservation activities.[27]

If large differences in hit probabilities generated only small differences in site valuations, then our approach would offer no substantive improvement over the Simpson-Sedjo-Reid results. Our numerical results, however, suggest the opposite. Comparing the most promising sites in the queue (Western Ecuador) with the least promising (California Floristic Province), for example, we see that a two-orders-of-magnitude difference in hit probability translates into a four-orders-of-magnitude difference in incremental values. Here, a given difference in site quality leads to a more-than-proportionate difference in site value.

5. Policy Implications

The model is intentionally simple, treating many relevant considerations (the scientific basis for the formation of priors, market structure and competition, etc.) in reduced form. Nonetheless, it incorporates several essential features of bioprospecting: search is sequential; total costs increase with each failure; multiple hits are redundant; and prior information can differentiate search opportunities. Formally, the model is the equivalent to that of Simpson-Sedjo-Reid, except that it allows for heterogeneous priors. In the framework presented here, however, search opportunities are associated with sites, rather than species. The claim is that a geographic definition of the set of testable objects makes more compelling the assignment of heterogeneous priors (and, incidentally, makes the results more readily applicable to conservation policy). Nonetheless, it should be noted that our analytic results do not turn on this choice of interpretation. The model applies equally well to any ordered set of

[27] A sensitivity analysis shows that these qualitative results are robust with respect to the selected parameter values. In particular, a ten-fold increase in the cost per test raises the net present value of the highest quality sites to approximately

testable objects (e.g. species) with specified hit-rates. There are two distinct but related claims: an analytic claim that heterogeneous priors lead to information rents; and an empirical argument that the real world is properly portrayed by a model exhibiting heterogeneous priors.

Two policy issues link closely to bioprospecting: the definition of property rights in genetic materials; and market-based incentives for biodiversity conservation. The key question is whether the refinements to our model needed to address these policy issues would still leave the fundamental results intact, i.e. whether the model presented here is, in fact, robust.

5.1 Definition of Access Rights, and the Emergence of a Market in Search Opportunities

Our analysis assumed an open-access regime. Suppose instead that local institutions had enforceable property rights over genetic resources, allowing them to restrict access selectively, and only in exchange for payment of access fees. In this case, a market for search opportunities emerges, in which local institutions act as suppliers, and transact with private-sector buyers. We consider what equilibria would emerge in this market.

Since access fees increase the full cost of carrying out a test, they necessarily reduce expected returns to search. The key observation is that the research firm will test sites in decreasing order of expected value: as the local institution raises its access price, the firm-customer will move that search opportunity further back in its search queue.[28] By setting prices aggressively, therefore, local institutions jockey for positions near the front of the queue. Each balances the benefit of high fees

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$11,000.

[28] For example, suppose the local institution that controls site n requires, in return for access to its resources, the payment of an up-front fee c_n (which includes the transaction costs of negotiating a detailed agreement), plus a fraction r_n of the firm's profits as royalties, in case the search is successful. Then the firm's expected return to conducting the search is $p_n(1-r_n)R - c - c_n$. The research firm will, therefore, test this site only after testing others with probability greater than $p_n(1-r_n) - c_n/R$, for which no access fees are charged.

against the risk that, if it does not sell its wares early in the process, a discovery may be found elsewhere that renders its resources redundant, and hence valueless, to the firm in question. In equilibrium, in a competitive market for search opportunities, access prices will be determined by a marginal condition that balances the benefits of increasing access fees against the risks of losing all revenues to a competitor. Analyzing these interactions would require the development of a framework allowing for heterogeneous costs between sites, multiple firms and search projects, and strategic interactions between site-owners and firms.

5.2 Bioprospecting and Conservation Incentives

Given the demand for search opportunities, is is possible to identify conditions under which bioprospecting generates incentives for biodiversity conservation? The operational importance of this question follows from the United Nations Convention on Biological Diversity, which assigns property rights over genetic resources to nation-states. This institutional innovation, it was argued, would help to internalize the externality associated with the status of biodiversity as a common-property resource. The framers imagined that the definition of these property rights in these resources would foster the creation of a market in genetic materials, and would thus accomplish two objectives simultaneously: the creation of market-based incentives for biodiversity conservation, and the transfer of wealth to developing countries.

It remains an open question whether and to what degree these outcomes will obtain in practice. Our results suggest that if ecological and taxonomic knowledge can assist the search process, then firms may, under some conditions, be willing to the underwrite the conservation of certain well-investigated sites shown to hold special promise. This conclusion stands in opposition to the result of Simpson, Sedjo and Reid, who find that, when priors are uninformative, biodiversity prospecting creates extremely weak conservation incentives.

Whether prior discovery probabilities should be modeled as equal or heterogeneous, is an empirical question that cannot be answered through *a priori* theorizing. Yet key policy choices turn on its resolution. One such link concerns the accumulation of data that allow prior beliefs to be sharpened. For countries offering germplasm services on a competitive market, our results highlight the importance of investing in complementary information assets.[29] Biological inventories and bioinformatic databases that improve priors serve to move genetic wares up toward the front of firms' search queues. Investments in information will only be profitable in the long term, however, if the base material is conserved. By collecting information, therefore, a local institution signals its commitment to a conservation strategy.

At a global level, it is important to know how, or even whether, property rights over genetic resources should be defined. If the goal in doing so is to create incentives for conservation, then these rights must be described and assigned in ways that are well-aligned with opportunities for effective conservation. The United States' Endangered Species Act provides a cautionary illustration of the point. Many of the problems with the Act can be traced to the framers' insistence that the *species* be used as the unit of conservation. This stance ignores ecological realities, including the dependence of species on one another and on the maintenance of habitats. It also creates perverse economic incentives: land-owners who discover endangered species on their property have an interest in destroying, rather than nurturing, the creatures. A potentially important line of research would explore the effect on conservation incentives of the choice of units for the definition of property rights.

[29] This result is in line with that of Barbier and Aylward (1996). The analysis may help to explain a noted shift in the movement of bioprospecting projects to botanical gardens and other *ex situ* collections. Some advocacy groups have decried this trend as evidence of a move to subvert the benefit-sharing provisions of the UN Convention on Biological Diversity (Rural Advancement Foundation International, 1996). It may be, instead, that the move is motivated by the value associated with the information these institutions have about their collections. This interpretation seems particularly strong in light of the fact that, in many cases, bioprospecting contracts with these institutions call for up-front fees and royalty payments, just as do those with host countries, and so are not necessarily "cheaper" for the firms involved.

6. Summary and Conclusions.

A sequential-search model of biodiversity prospecting in which testing is guided by useful prior information has been analyzed. When search procedures are optimized to take advantage of this information, high-probability sites command *information rents* associated with their unusual contribution to the chance of success, and to the avoidance of search costs. These rents apply in addition to any *scarcity rents* resulting from a limit on the total number of sites available for testing. The magnitude of information rents depends on the degree to which fundamental ecological and taxonomic knowledge turns sites into "differentiated products." These rents can be significant even when genetic material is itself abundant. When genetic materials are abundant, an increase in the potential profitability of product discovery has virtually no effect on the value of any site; and technology improvements that lower search costs induce a drop in the value of every promising site. Results of a numerical simulation suggest that bioprospecting information rents could, in some cases, be large enough to finance meaningful biodiversity conservation.

The analysis shows that, for the purposes of natural products prospecting, we must treat biodiversity as a composite good: genes bound up inseparably with knowledge of them. It is only in this combination that genetic materials become resources that can reliably add value to the natural-products discovery process. These results have important implications for future work on the economics of bioprospecting. They suggest that empirical work should focus relatively heavily on the formation and updating of prior beliefs, and on estimating search costs, rather than on the ultimate demand for natural products. They also suggest that the institutional context for bioprospecting, including systems of intellectual property rights, should reward the provision of information, as well as the provision of the base biological material. Theoretical research in the area could be extended profitably to investigate statistical dependence between success probabilities; option values when conservation decisions are endogenous; contracting relations between prospecting firms and host countries; and the implications of these

considerations for optimal design of institutions for the conservation and management of biodiversity. The goal, ultimately, is to develop a valuation technique for genetic resources that incorporates site-specific information, the search behavior of firms, and the dynamic effects of biodiversity conservation by local institutions.

Appendix: Mathematical Results

Proposition 1: *An optimal search program involves testing, at each stage, a site with maximal hit probability amongst those not yet examined. Search terminates either when a hit is reached, or when no sites remain for which testing promises a non-negative return in expectation.*

Proof: The proof of the first sentence, which relies on the independence of the Bernoulli trials, involves a straightforward confirmation that no alternative search sequence can improve payoffs in expectation; see Weitzman (1979). Given that multiple discoveries are strictly redundant, the stopping rule is obvious. ■

Example. Given $p_1 > p_2 = p_3 = \ldots = p_N \equiv p$, we wish to show that

$$v_1 = \left(\frac{p_1}{p}\right)\left(\frac{1-p}{1-p_1}\right)v_N + \left(\frac{p_1 - p}{p}\right)c .$$

Proof: By equation (4), $v_1 = p_1(R - V_2) - c$. In this case,

$$V_2 = (pR - c)\left(\sum_{n=2}^{N}(1-p)^{n-2}\right) = \left(\frac{pR-c}{p}\right)\left(1-(1-p)^{N-1}\right) .$$

We also have that $v_N = (1-p_1)(1-p)^{N-2}[pR - c]$. Substituting, we get

$$\begin{aligned} v_1 &= p_1\left[R - \left(\frac{pR-c}{p}\right)\left(1-(1-p)^{N-1}\right)\right] - c \\ &= p_1 R - \left(\frac{p_1}{p}\right)(pR-c) + \left(\frac{p_1}{p}\right)(pR-c)(1-p)^{N-1} - c \\ &= \left(\frac{p_1}{p}\right)c + \left(\frac{p_1}{p}\right)\left(\frac{1-p}{1-p_1}\right)v_N - c \\ &= \left(\frac{p_1}{p}\right)\left(\frac{1-p}{1-p_1}\right)v_N + \left(\frac{p_1 - p}{p}\right)c \end{aligned}$$

proving the result. ■

Proposition 2: *Let* $\{p_n\}_{n=1}^{N}$ *be the sequence of hit probabilities on a collection of sites, indexed in order of decreasing probability. Let the incremental value* v_n *of the* n^{th} *site be defined as in equation (4). Then* v_n *can be decomposed into components* $v_n = v_n^I + v_N$, *where*

$$v_n^I \equiv \left(\frac{a_N}{1-p_n}\right)(p_n - p_N)R + \left[\sum_{i=n+1}^{N-1}\frac{a_i}{1-p_n}(p_n - p_i)\right]c \text{ , and}$$

$$v_N = a_N(p_N R - c) .$$

Proof: Repeated application of the recursive relationship in equation (1) yields a closed-form expression for the continuation value V_{n+1} of site n+1:

$$V_{n+1} = \sum_{i=n+1}^{N}\left(\frac{a_i}{a_{n+1}}\right)(p_i R - c) \tag{6}$$

where $a_i/a_{n+1} = (1-p_{n+1})(1-p_{n+2})\ldots(1-p_{i-1})$ is the probability that the search will reach the i^{th} stage, conditioned on having previously reached the $n+1^{st}$. Separating benefits from costs gives

$$V_{n+1} = \left[\sum_{i=n+1}^{N}\frac{a_i p_i}{a_{n+1}}\right]R - \left[\sum_{i=n+1}^{N}\frac{a_i}{a_{n+1}}\right]c \tag{7}$$

which can be substituted into equation (4) to give an expression for the incremental value of site n, expressed as a function of fundamental model parameters:

$$v_n = a_n p_n\left[1 - \sum_{i=n+1}^{N}\frac{a_i p_i}{a_{n+1}}\right]R + a_n\left[p_n\left(\sum_{i=n+1}^{N}\frac{a_i}{a_{n+1}}\right) - 1\right]c \tag{8}$$

Since $a_{i+1} = a_i(1-p_i)$, the identity $a_i p_i = a_i - a_{i+1}$ can be applied to simplify the first expression in brackets:

$$a_n p_n\left[1 - \sum_{i=n+1}^{N}\frac{(a_i - a_{i+1})}{a_{n+1}}\right]R = a_n p_n\left[1 - \frac{(a_{n+1} - a_{N+1})}{a_{n+1}}\right]R = \left(\frac{a_{N+1}}{1-p_n}\right)p_n R \tag{9}$$

where $a_{N+1} \equiv \prod_{i=1}^{N}(1-p_i)$ is the probability of project failure (i.e. of failure in all tests), and hence $a_n\left(a_{N+1}/a_{n+1}\right) = a_{N+1}/1-p_n$ is the probability of failure at all sites except the n^{th}, i.e. that if the n^{th} site contains the desired discovery, then it does so uniquely. Rewriting equation (8), we find that

$$
\begin{aligned}
v_n &= \left(\frac{a_{N+1}}{1-p_n}\right)p_nR + a_n\left[p_n\left(\sum_{i=n+1}^{N}\frac{a_i}{a_{n+1}}\right)-1\right]c \\
&= \left(\frac{a_{N+1}}{1-p_n}\right)(p_nR-c)+\left(\frac{a_n}{a_{n+1}}\right)\left[p_n\left(\sum_{i=n+1}^{N}a_i\right)+a_{N+1}-a_{n+1}\right]c \\
&= \left(\frac{a_{N+1}}{1-p_n}\right)(p_nR-c)+\left(\frac{1}{1-p_n}\right)\left[p_n\left(\sum_{i=n+1}^{N}a_i\right)-\left(\sum_{i=n+1}^{N}p_ia_i\right)\right]c \\
&= \left(\frac{a_{N+1}}{1-p_n}\right)(p_nR-c)+\left[\sum_{i=n+1}^{N}\frac{a_i}{1-p_n}(p_n-p_i)\right]c \quad .
\end{aligned}
\tag{10}
$$

Now,

$$
\left(\frac{a_{N+1}}{1-p_n}\right)(p_nR-c)=\left(\frac{a_N}{1-p_n}\right)(p_n-p_np_N)R-\left(\frac{a_N}{1-p_n}\right)(1-p_N)c
$$

and

$$
v_N = a_N(p_NR-c)=\left(\frac{a_N}{1-p_n}\right)(p_N-p_np_N)R-\left(\frac{a_N}{1-p_n}\right)(1-p_n)c \quad .
$$

Hence

$$
\begin{aligned}
v_n - v_N &= \left(\frac{a_N}{1-p_n}\right)(p_n-p_N)R+\left[\sum_{i=n+1}^{N-1}\frac{a_i}{1-p_n}(p_n-p_i)\right]c \\
&\quad +\left(\frac{a_N}{1-p_n}\right)\left[(1-p_n)-(1-p_N)+(p_n-p_N)\right]c \quad ;
\end{aligned}
$$

since the last term disappears, the proposition is shown. ■

Corollary 2.1: *For all m, n = 1, ..., N, if $p_n = p_m$, then $v_n = v_m$, and if $p_n > p_m$, then $v_n > v_m$. Thus, the sequence $\{v_n\}$ of incremental values is monotone decreasing in n. In particular, information rents are everywhere zero if and only if priors are uninformative.*

Proof: Let m and n be given, and consider first the case $p_n = p_m \equiv p$. Without loss of generality, we can assume $n \le m$. By Proposition 2,

$$
v_n - v_m = \sum_{i=n+1}^{m}\frac{a_i}{1-p}(p-p_i)c \, .
$$

But by Proposition 1, $p_n = p$ and $p_m = p$ implies $p_i = p$ for all intermediate $i = m+1, m+2, ..., n-1$. Hence the first claim is shown. For the case $p_n > p_m$, Proposition 1 implies $n < m$. Hence

$$
v_n - v_m = \left(\frac{p_n-p_N}{1-p_n}-\frac{p_m-p_N}{1-p_m}\right)a_NR+\sum_{i=n+1}^{m}\frac{a_i}{1-p_n}(p_n-p_i)c+\sum_{i=m+1}^{N-1}a_i\left(\frac{p_n-p_i}{1-p_n}-\frac{p_m-p_i}{1-p_m}\right)c \, .
$$

Since $p_n > p_m$ implies $1/1-p_n > 1/1-p_m$, all three terms in the expression on the right hand side are positive, and the second claim is proven. The last two sentences are then immediate from Proposition 1 and the definition of information rents. ■

Corollary 2.2: *The effect on site values of a change in the payoff level R is given by* $\frac{\partial v_n}{\partial R} = a_{N+1}\left(\frac{p_n}{1-p_n}\right)$. *Hence,* $\frac{\partial v_n}{\partial R}$ *is strictly positive, and is independent of R and c. For* $p_n \leq 1/2$, *it is bounded above by* a_{N+1}, *the probability of project failure.*

Proof: Immediate from equation (10) in the proof of Proposition 2. ■

Corollary 2.3: *The effect on site values of a change in search costs c is given by* $\frac{\partial v_n}{\partial c} = \left[\sum_{i=n+1}^{N-1} \frac{a_i}{1-p_n}(p_n - p_i)\right] - a_N$. *In particular,* $\frac{\partial v_n}{\partial c}$ *is independent of R and c, and is negative if and only if* $\sum_{i=n+1}^{N} a_i\left(\frac{p_n}{1-p_n}\right) < a_n$.

Proof: By equation (10) in Proposition 2,

$$\frac{\partial v_n}{\partial c} = a_n\left[p_n\left(\sum_{i=n+1}^{N}\frac{a_i}{a_{n+1}}\right) - 1\right] = \sum_{i=n+1}^{N} a_i\left(\frac{p_n}{1-p_n}\right) - a_n$$

since $a_n/a_{n+1} = 1/1-p_n$. ■

Proposition 3: *Let sites 1, ..., M-1 be promising, and sites M, ..., N be marginal, as defined in the text. Then for n = 1, ..., M-1, the incremental value of* v_n *has a strictly positive lower bound, given by the relation* $v_n \geq \left[\sum_{i=n+1}^{M-1} \frac{a_i}{1-p_n}(p_n - p_i) + \left(\frac{a_M}{1-p_n}\right)\left(\frac{p_n - p}{p}\right)\right]c$. *Further, this relation becomes an equality in the limit as N goes to infinity.*

Proof: It suffices to show that v_n is decreasing, as a function of N, and that the sequence $\{v_n(N)\}$ converges to the above limit as N goes to infinity. To prove the first claim, we use equation (10) to express v_n as a function of N:

$$v_n(N) = \left(\frac{a_{N+1}}{1-p_n}\right)p_n R + \left[\sum_{i=n+1}^{N}\frac{a_i}{1-p_n}p_n - a_n\right]c \quad . \qquad \textbf{(11)}$$

For $i > M$, we have $a_{i+1} = (1-p)a_i$, so that

$$v_n(N) - v_n(N+1) = \left(\frac{a_{N+1}}{1-p_n}p_n\right)pR - \left(\frac{a_{N+1}}{1-p_n}p_n\right)c \ ,$$

which is positive by the assumption pR - c > 0. Hence $v_n(N)$ is decreasing in N. To prove the convergence claim, we use the relation $a_{i+1} = (1\text{-}p)a_i$ to rewrite the formula in Proposition 2:

$$\begin{aligned} v_n(N) &= v_N(N) + v_n^I(N) \\ &= a_M(1-p)^{N-M}(pR-c) + \left(\frac{a_M(1-p)^{N-M}}{1-p_n}\right)(p_n-p)R \\ &\quad + \left[\sum_{i=n+1}^{M-1}\frac{a_i}{1-p_n}(p_n-p_i) + \sum_{i=M}^{N-1}\frac{a_M(1-p)^{i-M}}{1-p_n}(p_n-p)\right]c \end{aligned}$$

As $N \to \infty$, $(1\text{-}p)^{N-M} \to 0$, and $\sum_{i=M}^{N-1}(1-p)^{i-M} = \frac{1-(1-p)^{N-M}}{p} \to \frac{1}{p}$, so

$$\lim_{N\to\infty} v_n(N) = \left[\sum_{i=n+1}^{M}\frac{a_i}{1-p_n}(p_n-p_i) + \left(\frac{a_M}{1-p_n}\right)\left(\frac{p_n-p}{p}\right)\right]c \ . \qquad \textbf{(12)}$$

Since convergence is monotonic, the expression on the right forms a lower bound for all terms in the sequence. The bound is strictly positive for n < M, and zero for n ≥ M. ■

Corollary 3.1: *Let sites 1, ..., M-1 be promising, and sites M, ..., N be marginal, as defined in the text. Suppose that the payoff from a successful discovery is large enough to make random sampling of marginal sites profitable in expectation (i.e. R ≥ c/p). Then as genetic materials become abundant (i.e. in the limit as N → ∞), the following hold:*

(i) *Marginal sites have zero value.*

(ii) *An increase in the potential profitability of product discovery has no effect on the incremental value of any site.*

(iii) *A technology improvement that lowers search costs induces a drop in the incremental value of every promising site.*

Proof: Claim (i) restates equation (12) for the case n = N. Claims (ii) and (iii) follow since $\lim_{N\to\infty} v_n(N)$ does not depend on R and is increasing in c. ■

Proposition 4.1: *The value of a site is a piecewise linear, continuous, increasing, and weakly convex function of its own hit probability. Furthermore, on the interval $p_{n-1} > p_n > p_{n+1}$, the elasticity of v_n with respect to p_n is given by* $\frac{\partial v_n}{\partial p_n}\cdot\frac{p_n}{v_n} = 1 + \frac{a_n c}{v_n}$.

Proof: To carry out the proof, we expand the notation to allow for variability in the ordering of the search queue. Given cost and benefit parameters c and R, let I = [c/R, 1) be the interval of hit

probabilities on which sites are viable, as test opportunities. Then $\mathbf{p} \in I^N$ is a vector corresponding to an assignment of hit probabilities to an unordered collection of N sites, such that each site is viable. Let p_1 be variable, and let $p_{-1} \equiv \langle p_2, p_3, \ldots, p_N \rangle$ be a fixed vector of the other hit probabilities. Without loss of generality, we can label sites so that $p_2 \geq \ldots \geq p_N$.

Now let Z be the set of all N! permutations of the set $\{1, 2, \ldots, N\}$, and let the function $s: I \times I^{N-1} \rightarrow Z$ be a rule for ranking the collection of N sites into a search queue, defined as follows: for $n = 2, \ldots, N$, let the position $s_n(p_1 \mid p_{-1})$ be given by

$$s_n(p_1 \mid p_{-1}) = \begin{cases} n-1 & \text{if } p_1 \leq p_n \ ; \\ n & \text{if } p_1 > p_n \ . \end{cases}$$

By exhaustion, this expression determines the position $s_1(p_1 \mid p_{-1})$ of the site with index 1. Thus sites are examined in the order $2, 3, 4, \ldots, s_1, 1, s_1+1, \ldots, N$. In particular, if $s_1 > 1$, the site with index s_1 occupies the s_1-1st position in the queue, immediately preceding the site with index 1. Since, for $n > 1$, $s_1 > s_n$ if and only if $p_1 \leq p_n$, this queuing rule satisfies the optimality condition of Proposition 1.

Now let $u_n(p_1) \equiv v_{s_n(p_1 \mid p_{-1})}$ denote the value of the site with index n, viewed as a function of p_1. By Corollary 2.1, this value depends only on the magnitudes of the components of $\mathbf{p}$: any other queuing rule $s(\mathbf{p})$ that satisfies the optimality condition of Proposition 1 (i.e. any involving a permutation of equi-probable sites) will yield the same values. Hence u_n is well-defined, for all $n = 1, \ldots, N$.

We can now prove the proposition. Rewriting equation (11) in terms of our new notation, the value of the site with index 1 can be expressed as a function of its own hit probability:

$$u_1(p_1) = \left(\prod_{i=2}^{N}(1-p_i)\right)p_1 R + \sum_{i=s_1}^{N}\left(\prod_{j=2}^{i}(1-p_j)\right)p_1 c - \left(\prod_{i=2}^{s_1}(1-p_i)\right)c \quad . \qquad \textbf{(13)}$$

By inspection, u_1 is linear in p_1 on all intervals for which s_1 is constant. Hence, u_1 is continuous on intervals of the form $p_n > p_1 > p_{n+1}$ for $n = 2, \ldots, N-1$, and on the interval $p_N > p_1 \geq c/R$. In addition, since $s_1 > s_n$ whenever $p_1 = p_n$, s_1 is constant on intervals $p_1 \in [p_n - \varepsilon, p_n]$ for ε sufficiently small. Hence u_1 is continuous from the left at the finitely-many "switching points" at which $p_1 = p_n$, for some $n > 1$.

To prove continuity from the right, suppose that $p_{n-k} > p_{n-k+1} = \ldots = p_n > p_{n+1}$. Then $s_1(p_1 = p_n \mid p_{-1}) = n$, and for positive $\varepsilon < p_{n-k} - p_n$, $s_1(p_1 = p_n + \varepsilon \mid p_{-1}) = n-k$. Applying equation (13), we have

$$u_1(p_n + \varepsilon) - u_1(p_n) = \left(\prod_{i=2}^{N}(1-p_i)\right)R\varepsilon + \sum_{i=n-k}^{N}\left(\prod_{j=2}^{i}(1-p_j)\right)c\varepsilon + \sum_{i=n-k}^{n-1}\left(\prod_{j=2}^{i}(1-p_j)\right)p_n c$$
$$+\left[\left(\prod_{i=2}^{n}(1-p_i)\right) - \left(\prod_{i=2}^{n-k}(1-p_i)\right)\right]c \quad .$$

Since $p_{n-k+1} = p_{n-k+1} = \ldots = p_n$, the third and fourth terms cancel:

$$\sum_{i=n-k}^{n-1}\left(\prod_{j=2}^{i}(1-p_j)\right)p_n c = \left(\prod_{i=2}^{n-k}(1-p_i)\right)\left[\sum_{j=0}^{k-1}(1-p_n)^j\right]p_n c$$

$$= \left(\prod_{i=2}^{n-k}(1-p_i)\right)\left[1-(1-p_n)^k\right]c$$

$$= \left[\prod_{i=2}^{n-k}(1-p_i) - \prod_{i=2}^{n}(1-p_i)\right]c \quad .$$

Hence $u_1(p_n+\varepsilon) \to u_1(p_n)$ as $\varepsilon \to 0$, and so u_1 is continuous for all $p_1 \in I$. Equation (13) also implies that, on any open interval of arguments p_1 for which s_1 is constant, u_1 is differentiable, with

$$\frac{du_1(p_1|s_1)}{dp_1} = \left(\prod_{i=2}^{N}(1-p_i)\right)R + \sum_{i=s_1}^{N}\left(\prod_{j=2}^{i}(1-p_j)\right)c \qquad \textbf{(14)}$$

Since the expression on the right is positive, u_1 is increasing on each such open subinterval. Continuity then implies that u_1 is increasing on the entire interval I. Further, since du_1/dp_1 is monotone decreasing in s_1, and s_1 is monotone decreasing in p_1, u_1 is weakly convex on I. Finally, equation (14) implies that

$$\frac{du_1(p_1|s_1)}{dp_1}\cdot p_1 = \left(\prod_{i=2}^{N}(1-p_i)\right)p_1 R + \sum_{i=s_1}^{N}\left(\prod_{j=2}^{i-1}(1-p_j)\right)p_1 c = u_1 + a_{s_1}c$$

where, following our established conventions, $a_{s_1} = \prod_{i=2}^{s_1}(1-p_i)$ denotes the probability that the site with index 1 is tested. ■

Proposition 4.2: *The value of a site is a piecewise linear, decreasing function of the hit probability of every other site. For $m \neq n$, v_n is continuous in p_m except where $p_m = p_n$. Furthermore, the following hold:*

(i) *For $m = 1, \ldots, n-1$, on the intervals $p_{m-1} > p_m > p_{m+1}$, the elasticity of v_n with respect to p_m is given by*

$$\frac{\partial v_n}{\partial p_m}\cdot\frac{p_m}{v_n} = -\left(\frac{p_m}{1-p_m}\right).$$

(ii) *For $m = n+1, \ldots, N$, on the interval $p_{m-1} > p_m > p_{m+1}$, the elasticity of v_n with respect to p_m is given by*

$$\frac{\partial v_n}{\partial p_m}\cdot\frac{p_m}{v_n} = -\left(\frac{p_m}{1-p_m}\right)\left[1+\left(a_n - p_n\sum_{i=n+1}^{m}\frac{a_i}{1-p_n}\right)\frac{c}{v_n}\right] \quad .$$

Proof: Let $n \in \{2, 3, \ldots, N\}$ be the index for a given site. We use the notation developed for the proof of Proposition 4.1 to derive a formula for $u_n(p_1)$, the value of the site with index m, expressed as a function of the hit probability p_1. For arguments $p_1 > p_n$ (so that $s_n = n > s_1$), this value is given by

$$u_n(p_1|p_1 > p_n) = \left(\prod_{\substack{i=1\\ i\neq n}}^{N}(1-p_i)\right)p_n R + \sum_{i=n}^{N}\left(\prod_{\substack{j=1\\ j\neq n}}^{i}(1-p_j)\right)p_n c - \left(\prod_{i=1}^{n-1}(1-p_i)\right)c \quad , \qquad (15)$$

so u_1 is linear, and hence continuous, in p_1 on the interval $1 > p_1 > p_n$. Further, since $\frac{du_n(p_1|p_1 > p_n)}{dp_1} = -\frac{u_n}{(1-p_1)}$, the elasticity relation claimed in point (i) is shown.

For $p_1 \leq p_n$ (so that $s_n = n\text{-}1 < s_1$), the value is given by

$$u_n(p_1|p_1 \leq p_n) = \left(\prod_{\substack{i=1 \\ i\neq n}}^{N}(1-p_i)\right)p_n R + \left[\sum_{i=n}^{s_1}\left(\prod_{\substack{j=2 \\ j\neq n}}^{i}(1-p_j)\right) + \sum_{i=s_1}^{N}\left(\prod_{\substack{j=1 \\ j\neq n}}^{i}(1-p_j)\right)\right]p_n c - \left(\prod_{i=2}^{n-1}(1-p_i)\right)c. \tag{16}$$

This function is linear, hence continuous, in p_1 on subintervals for which s_1 is constant. On each such subinterval, we have that

$$\begin{aligned}\frac{du_n(p_1|s_1 > s_n)}{dp_1} &= -\left(\frac{1}{1-p_1}\right)\left[\left(\prod_{\substack{i=1 \\ i\neq n}}^{N}(1-p_i)\right)p_n R + \sum_{i=s_1}^{N}\left(\prod_{\substack{j=1 \\ j\neq n}}^{i}(1-p_j)\right)p_n c\right] \\ &= -\left(\frac{1}{1-p_1}\right)\left[u_n + \left(\prod_{i=2}^{n-1}(1-p_i)\right)c - \sum_{i=n}^{s_1}\left(\prod_{\substack{j=2 \\ j\neq n}}^{i}(1-p_j)\right)p_n c\right].\end{aligned} \tag{17}$$

which expresses the elasticity relation of claim (ii) in the new notation. That u_n is continuous at points $p_1 = p_m$, for $p_m < p_n$, follows from an argument entirely analogous to the one used in the proof of Proposition 4.1. (A similar argument shows that $\lim_{\varepsilon \to 0} u_n(p_n + \varepsilon) < u_n(p_n)$, so u_n is discontinuous at $p_1 = p_n$.)

To complete the proof, it must be shown that u_n is decreasing in p_1. Equation (15) implies that u_n is decreasing in p_1 on the interval $1 > p_1 > p_n$. For $p_1 < p_n$, equation (17) implies that u_n is decreasing on subintervals of $[c/R, p_n]$ on which s_1 is constant. But since u_n is continuous on $[c/R, p_n]$, this implies that u_n is decreasing on any interval not containing p_n. Finally, at the point of discontinuity $p_1 = p_n$, we have $\lim_{\varepsilon \to 0} u_n(p_n + \varepsilon) < u_n(p_n)$. Thus u_n is decreasing for all $p_1 \in I$. ■

Corollary 4.3: *An increase in the hit probability of a site induces a more-than-proportionate increase in the value of that site, and a decrease in the value of every other site.*

Proof: We showed in Proposition 4.1 that the elasticity of a site's value u_1 with respect to its own hit probability p_1 is greater than unity on subintervals of I for which the search ordering is constant. The first claim of the corollary then follows from the fact that u_1 is continuous, increasing and convex in p_1. The second claim, that u_n is decreasing in p_1 for $n > 1$, was proven in Proposition 4.2. ■

Corollary 4.4: *Let* $\{p_n\}_{n=1}^{N}$ *be an information structure for the bioprospecting problem, and let p be a constant with* $1 > p \geq p_N$. *Let* $M(p) = \min\{m \mid p_m \leq p\}$. *Then for* $n = 1, \ldots, M-1$, *the incremental value of* v_n *has a strictly positive lower bound given by*

$$v_n \geq \left[\sum_{i=n+1}^{M(p)-1} \frac{a_i}{1-p_n}(p_n - p_i) + \left(\frac{a_{M(p)}}{1-p_n}\right)\left(\frac{p_n - p}{p}\right)\right]c \quad .$$

Further, in the limit as $N \to \infty$, *the conclusions of Corollary 3.1 hold.*

Proof: Consider a second information structure $\{p'_n\}_{n=1}^{N}$, in which $p_n' = p_n$ for $n < M$, and $p_n' = p$ for $n \geq M$, and let v'_n be the value of site n with respect to this new structure. Then for $n < M$,

$$v'_n \geq \left[\sum_{i=n+1}^{M-1} \frac{a_i}{1-p_n}(p_n - p_i) + \left(\frac{a_M}{1-p_n}\right)\left(\frac{p_n - p}{p}\right)\right]c$$

by Proposition 3, and $v_n \geq v'_n$ by Proposition 4.2. To prove the limit results, note that $p_n \geq c/R$ for all n implies $a_N \leq (1-c/R)^{N-1}$. Hence $a_N \to 0$ as $N \to \infty$. Then by Proposition 2 and the above inequality, $\lim_{N\to\infty} v_n(N)$ does not depend on R, is increasing in c for $n < M(p)$, and is zero for $n = N$. ■

REFERENCES:

AHLSWEDE, Rudolf and Ingo WEGENER, 1987. Search Problems. New York: Wiley.

ARROW, Kenneth J. and Anthony C. FISHER, 1974. "Environmental Preservation, Uncertainty, and Irreversibility," Quarterly Journal of Economics 88:312-319.

ARTUSO, Anthony, 1996. "Economic Analysis of Biodiversity as a Source of Pharmaceuticals." in Biodiversity, Biotechnology, and Sustainable Development in Health and Agriculture: Emerging Connections. PAHO Scientific Publication No. 560. Washington, D.C.: Pan American Health Organization.

BARBIER, E. B. and Bruce A. AYLWARD, 1996. "Capturing the Pharmaceutical Value of Biodiversity in a Developing Country." Environmental and Resource Economics 8:157-181.

BROWN, Gardner and Jon H. GOLDSTEIN, 1984. "A Model for Valuing Endangered Species," Journal of Environmental Economics and Management 11:303-309.

CONRAD, Jon M., 1980. "Quasi-Option Value and the Expected Value of Information," Quarterly Journal of Economics 94:813-820.

de SOUZA SILVA, José, 1996. "From Medicinal Plants to Natural Pharmaceuticals: The Commercialization of Nature." in Biodiversity, Biotechnology, and Sustainable Development in Health and Agriculture: Emerging Connections. PAHO Scientific Publication No. 560. Washington, D.C.: Pan American Health Organization.

DeGROOT, Morris H., 1970. Optimal Statistical Decisions. New York: McGraw Hill.

DREYFUSS, M.M. and Ignacio H. CHAPELA 1994. "Potential of Fungi in the Discovery of Novel, Low-Molecular Weight Pharmaceuticals." in Vincent P. Gullo, ed., The Discovery of Natural Products with Therapeutic Potential. Boston: Butterworth-Heinemann.

FISHER, Anthony C. and W. Michael HANEMANN 1986. "Option Value and the Extinction of Species," in V.K. Smith, ed., Advances in Applied Micro-Economics, vol. 4, JAI Press, Inc. pp 169-190.

KOHN, Meir G. and Steven SHAVELL 1974, "The Theory of Search," Journal of Economic Theory 9(2):93-123.

LIPPMAN, S.A. and J.J. McCALL, eds., 1979. Studies in the Economics of Search. Amsterdam; New York: North-Holland Pub. Co.

MILSTEIN, Michael 1995. "Yellowstone Managers Stake a Claim on Hot-Springs Microbes." Science 270:226. 13 October.

MÖLLER, Christine, 1996. "Biolead: A New Approach to Drug Discovery." Presentation at Seminar on Biotechnology and Genetic Resources, College of Natural Resources, University of California at Berkeley.

MYERS, N. 1988. "Threatened Biotas: 'Hot Spots' in Tropical Forests," The Environmentalist 8:197-208.

_____ 1990. "The Biodiversity Challenge: Expanded Hot-Spots Analysis." The Environmentalist 10:243-256.

_____ 1997. "Biodiversity's Genetic Library." In G.C. Daily, ed., Nature's Services. Washington: Island Press. pp 255-273.

PAN AMERICAN HEALTH ORGANIZATION, 1996. Biodiversity, Biotechnology, and Sustainable Development in Health and Agriculture: Emerging Connections. PAHO Scientific Publication No. 560. Washington, D.C.: PAHO.

PACE, Norman R. 1997. "A Molecular View of Microbial Diversity and the Biosphere." Science 276:734-740, May 2.

POLLACK, A., 1992. "Drug Industry Going Back To Nature." The New York Times, 3 March 1992.

POLASKY, Stephen and Andrew SOLOW, 1995. "On the Value of a Collection of Species." Journal of Environmental Economics and Management 29:298-303.

REID, Walter V., Sarah A. LAIRD, Carrie A. MEYER, Rodrigo GAMEZ, Ana SITTENFELD, Daniel H. JANZEN, Michael A. GOLLIN, and Calestous JUMA, eds. 1993. "Biodiversity Prospecting: Using Genetic Resources for Sustainable Development." Washington, D.C.: World Resources Institute (WRI).

RURAL ADVANCEMENT FOUNDATION INTERNATIONAL, 1996. "Pharmaceutical Companies Bid for Northern Botanical Garden Collections in Attempt to Avoid the Biodiversity Convention." RAFI Communique, July/August 1996. Toronto: Web site http://www.rafi.ca.

SEO, Junghwan, 1995. Holding Options in a Theory of Search. Ph.D. dissertation, Dept. of Economics, University of California at San Diego.

SIMPSON, R. David, Roger SEDJO, and J. REID 1996. "Valuing Biodiversity for Use in Pharmaceutical Research." Journal of Political Economy 104(1):163-185.

_____ and _____ 1996. "Valuation of Biodiversity for Use in New Product Research in a Model of Sequential Search." Discussion Paper 96-27, Resources for the Future, Washington, D.C.

SOLOW, Andrew, Stephen POLASKY, and James BROADUS, 1993. "On the Measurement of Biological Diversity." Journal of Environmental Economics and Management 24: 60-68.

STONE, Lawrence D., 1975. Theory of Optimal Search. New York: Academic Press.

VOGEL, Joseph H., 1994. Genes for Sale: Privatization as a Conservation Policy. New York – Oxford: Oxford University Press.

WEISBROD, Burton A., 1964. "Collective-Consumption Services of Individual-Consumption Goods," Quarterly Journal of Economics 78:471-477.

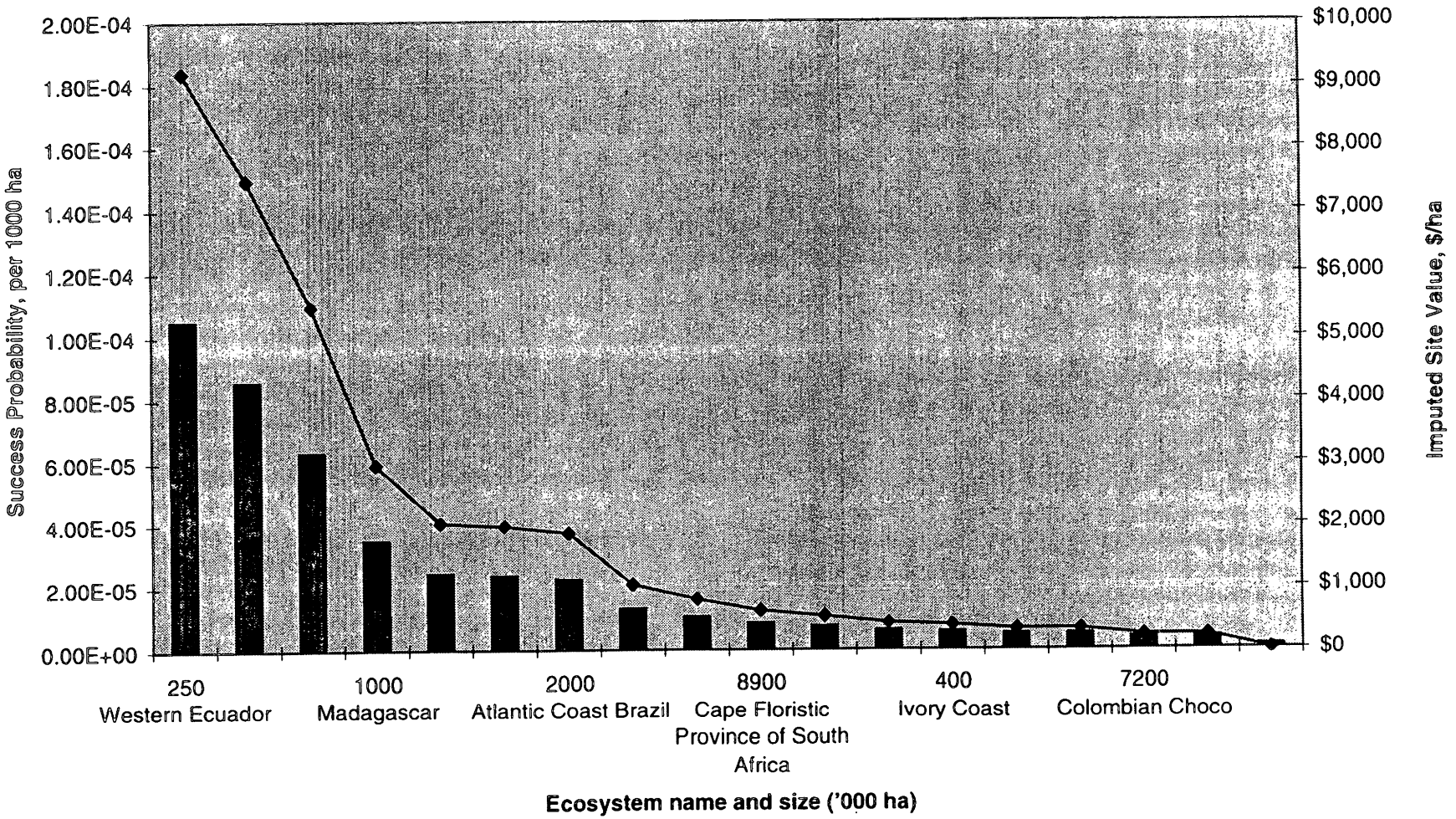
WEITZMAN, Martin L. 1979. "Optimal Search for the Best Alternative." Econometrica 47(3):641-654.

_____, 1992. "On Diversity." Quarterly Journal of Economics CVII (2): 363-405.

_____, 1993. "What To Preserve? An Application of Diversity Theory to Crane Conservation." Quarterly Journal of Economics CVIII (1): 157-183.

WERTH, Barry 1994. The Billion-Dollar Molecule. New York: Simon & Schuster.

Figure 1: Bioprospecting Values in Several Ecosystems, as a Function of Success Probabilities



Assumes 10 successes/year, revenues $450,000,000/success, cost $483/test, hit rates based on 1.2 E-05 per species, discount rate 10%. Source: Myers (1988, 1990); Simpson, Sedjo and Reid (1996), and authors' calculations.

Table 1: Selected commercial products derived from natural sources

Product	Use	Natural source	Source location
Vinblastine	Treatment, Hodgkin's disease, leukemia	Rosy periwinkle (flower)	Madagascar
Tubocurarine	Muscle relaxant	Chondodendron tomentosum	
Quinine	Anti-malarial	Cinchona ledgeriana	
Pilocarpine	Glaucoma	Jaborandi	
Morphine	Analgesic	Opium poppy	
Scopolamine	Motion sickness	Hyoscyamus niger	
Taxol	Ovarian cancer	Pacific yew	Pacific Northwest, USA
Erythromycin	Anti-biotic	Tropical fungi	
Oubain	Heart medicine	Strophanthus gratus (vine)	West Africa
Penicillin	Anti-biotic		
Taq polymerase	Polymerase chain reaction	Aquatic microbes	Yellowstone National Park, USA
Cyclosporine	Immunosupressant	Soil microbes	Norway
FK-506	Immunosupressant	Soil microbes	Japan

Sources: Reid et al. (1993); Milstein (1995); Werth (1994).

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Table 2: Examples of Companies Active in Natural Product Collection and Screening

COMPANY	COLLECTORS	NATURAL PRODUCT FOCUS	THERAPEUTIC GROUP
Abbott Laboratories	University of Illinois	Microbes, plants	Anti-infective, cardiovascular, neuroscience, immunoscier
CIBA-GEIGY	Chinese Academy of Sciences Harbor Branch Oceanographic Institute	Microbes, marine, plants	Cancer, cardiovascular, anti-inflammatory, CNS, respiratc anti-allergy
Eli Lilly	National Cancer Institute (U.S.) Shaman Pharmaceuticals	Plants, algae	Anti-infective, diabetes, cardiovascular, cancer, CNS, pulmonary, anti-viral, skeletal diseases
Merck & Co., Inc.	INBio New York Botanical Garden MYCOsearch	Fungi, microbes, marine, plants	Respiratory, anti-allergy, anti-inflammatory, cancer, cardiovascular, anti- infective, antiviral, others
Monsanto	Missouri Botanical Garden	Plants, microbes	Anti-infectants,cardiovascular, anti-inflammatory
Pfizer	Natural Product Sciences New York Botanical Garden	Plants, spiders, venom	
Pharma Genesis	In-house collectors. Asian independent collectors	Natural products used in traditional Asian medicine	N/A
Rhone-Poulenc Rorer	University of Hawaii Beijing Medical University Shanghai Medical University Tianjin Plant Institute, China independent collectors	Plants, marine organisms, and microbes	
Shaman Pharmaceuticals, Inc.	In-house botanists, independent collectors	Plants used in traditional therapeutics	various
SmithKline Beecham	Biotics, Ltd. Royal Botanic Garden, Kew University of Virginia Scripps Institution of Oceanography University of Pennsylvania MYCOsearch	Microbes, plants, marine	Anti-infective, cardiopulmonary, CNS, gastrointestinal, anti-inflammatory

Sources: Reid et al. (1993), de Souza Silva (1996)

Table 3: Bioprospecting Values in Several Ecosystems, as a Function of Density of Endemic Species

Biodiversity "Hot Spots"	Forest Area (1000 ha)	Density, endemic species / 1000 ha	Hit Probability (/ 1000 ha)	Incremental Value ($/hectare)	SSR Scarcity Rent ($/hectare)
Western Ecuador	250	8.75	1.05E-04	$9,177	$20.63
Southwestern Sri Lanka	70	7.14	8.57E-05	$7,463	$16.84
New Calendonia	150	5.27	6.32E-05	$5,473	$12.43
Madagascar	1000	2.91	3.49E-05	$2,961	$6.86
Western Ghats of India	800	2.03	2.44E-05	$2,026	$4.77
Philipines	800	1.98	2.38E-05	$1,973	$4.66
Atlantic Coast Brazil	2000	1.88	2.26E-05	$1,867	$4.42
Uplands of Western Amazonia	3500	1.10	1.32E-05	$1,043	$2.59
Tanzania	600	0.88	1.06E-05	$811	$2.07
Cape Floristic Province of South Africa	8900	0.71	8.52E-06	$632	$1.66
Peninsular Malaysia	2600	0.62	7.44E-06	$539	$1.47
Southwestern Australia	5470	0.52	6.24E-06	$435	$1.22
Ivory Coast	400	0.48	5.76E-06	$394	$1.14
Northern Borneo	6400	0.42	5.04E-06	$332	$0.99
Eastern Himalayas	5300	0.42	5.04E-06	$332	$0.98
Colombian Choco	7200	0.32	3.84E-06	$231	$0.75
Central Chile	4600	0.32	3.84E-06	$231	$0.74
California Floristic Province	24600	0.09	1.08E-06	$0	$0.20

Assumes 10 successes/year, revenues $450,000,000/success, cost $485/test, hit rates based on 1.2 E-05 per species, discount rate 10%.
Source: Myers (1988, 1990); Simpson, Sedjo and Reid (1996); and authors' calculations.