On Sustainability and the Economics of Survival

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This paper investigates the implications of sustainability and survival strategies for economic analysis. It reviews connections between the approaches used by economists and biological scientists in the study of survival. The paper emphasizes the role of irreversibility and uncertainty in the investigation of sustainability issues. Implications of the results for the analysis of economic behavior are discussed.

Key words: adaptation, irreversibility, survival, sustainability, uncertainty.

The relationship between economic analysis, sustainability, and survival is a subject of interest among biologists (e.g., Wilson), ecologists (e.g., Constanza) and social scientists (e.g., Alchian; Nelson and Winter). Sustainable development is an important focus of resource management and agricultural policy (Pearce; Conway and Barbier). Conway and Barbier define agricultural sustainability as the ability of the agro-ecological system to maintain productivity in the face of stress or shocks. This ability is adversely affected by uncertainty or by the existence of irreversibilities (e.g., as a result of extinction). While issues such as environmental preservation (Arrow and Fisher), endangered species (Bishop), sustainable farm practices (Paolletti, Stinner, and Lorenzoni) or environmental policy evaluation (Barbier) have been analyzed, there is a need for comprehensive analyses of the relationships between economic analysis, sustainability and survival issues.

The primary objective of the present paper is to investigate some of the implications of sustainability and long-term survival for economic analysis. The focus is on sustainability issues in the context of a general dynamic model under uncertainty and irreversibility. A secondary objective is to explore connections between the economics approach and the biological approach to the study of survival issues to build better communications between disciplines interested in sustainability issues.

The Last Four Billion Years

Paleontologists believe that life began on earth about 4 billion years ago. Since then, fossil records (which cover the last 800 million years) indicate that many animal species have become extinct. It is estimated that extinction has claimed 99% of all species (Gore). Many of these species disappeared as a result of small or local environmental changes. Others perished during periods of mass extinctions.

One of the great extinctions was caused by gas pollution. The toxic gas was, paradoxically, what supports animal life today: oxygen. Indeed, 4 billion years ago, earth’s oceans and atmosphere were virtually oxygen-free, or anaerobic. Carbon dioxide dominated the planet and primitive forms of life were anaerobic. Then about 3 billion years ago, certain bacteria developed photosynthetic capabilities, using sunlight, water and carbon dioxide to sustain plant life while releasing oxygen as a waste product. As the oxygen waste built up, the oceans were oxygenated, then the atmosphere. As a result, new aerobic bacteria developed in the sunlight, while their anaerobic competitors were driven underground or into extinction. Oxygen-producing bacteria dominated the world between 2.5 billion and 600 million years ago. Then, like the anaerobic life they displaced, they almost disappeared.

That was the time when animal life developed. The appearance of animals was associated
with a different approach to survival. Photosynthesis enabled organisms to make their own food from sunlight, carbon dioxide, and water, whereas animals use other organisms as a source of food. Because grazing or hunting requires energy, animals needed a high-powered metabolism; this was provided by an aerobic oxygen-burning metabolism. After oxygen accumulation crossed some threshold, animal life spread quickly around 570 million years ago. Since then, the number of animal species on earth has in general increased over time, except during periods of mass extinctions.

Over the last 240 million years, 12 mass extinctions have been identified from fossil records, each wiping out a large proportion of existing species (Gore). Paleontologists agree that mass extinctions are associated with important changes in the earth’s environment. Such changes may be triggered by cataclysmic events (such as the impact of a large meteorite or intense volcanic activities) or by more gradual environmental changes (such as climatic fluctuations). During mass extinction, as the environment changed, extreme specialization was a liability. In general, spatially widespread species or species with the ability to adapt weathered mass extinction better than other species. For example, in the face of strong climatic swings, survivors were in general smaller and more warm-blooded and thus dealt better with cold climates. Humans are relative newcomers in the evolution of species, appearing on earth only 2 million years ago.

Some believe that earth is currently experiencing its greatest mass extinction in 66 million years (e.g., Myers). For example, many large mammals became extinct in America about 11,000 years ago. Since then, human interventions have wiped out other species through hunting, through destruction of habitat, or through the more indirect impacts of human activities on the earth’s environment. The severity of the situation is perhaps best known in countries like Brazil or Madagascar, where expanding human populations and economic pressures contribute to rapid destruction of the forest and its wildlife.

On the one hand, the influence of humans on the biosphere is an indication of the success of human survival strategies, as people develop and use new technologies that improve control of the environment. On the other hand, humans might also take irreversible steps that could threaten the long-term future of many species, possibly including the human species. The extinction rate over the last 11,000 years is sometimes seen as a warning that we should take a more cautious approach to life management on earth.

A General Approach

This section develops a general survival model. The discussion of survival issues covers both living organisms (as in ecology or evolutionary biology) and economic institutions.

Assume a dynamic system represented by the state variables \( y \) which evolve over time according to the first order difference equations

\[
y_{t+1} = F(y_t, z_t, x_t, e_t), \quad x_t \in X, \quad e_t \in E
\]

where \( z_t \) denotes resource availability indices influencing \( y_t, \) \( x_t \) is a vector of control variables reflecting alternative actions that may be taken at time \( t, \) \( e_t \) is a vector of random variables representing exogenous uncertainty, and \( X \) and \( E \) denote the feasible sets of \( x_t \) and \( e_t \).

The state variables \( y \) in (1) include all relevant variables influencing the dynamics of the system. The vector \( y \) includes basic variables such as energy and other resources. It also includes alternative forms of organizations. In general, (1) can represent complex dynamic systems consisting of a network of interacting organizations with many levels of aggregation and interactions, each level having its own time scale and characteristic behavior. For example, biologists study how molecules are organized to make cells, how cells are organized to make plants or animals, how individuals are organized to make populations, and so forth. Similarly, social scientists study how humans are organized to make households, firms, and nations, and how such organizations influence the allocation of resources. Our focus here is on the survival of complex forms of organization. Thus, this paper pays particular attention to the state variables that represent the dynamics of such organizations.

The resource availability indices \( z_t \) in (1) indicate how the nature of the environment affects the evolution of the state variables \( y. \) In turn, the resource availability indices may be influenced by the state variables \( y \) and by the control variables \( x. \) This is expressed in the following relationship

\[
z_t = g(y_t, x_t), \quad x_t \in X.
\]

Note that the resource availability indices \( z_t \) in equation (1) could be eliminated from the analysis by substituting equation (2) into equation (1). However, the explicit consideration of equation (2) will prove useful in the discussion presented in below.
Consider a particular organization \( J \) and denote by \( y_{jt} \) the state of this organization at time \( t \). We assume that the state variable \( y_{jt} \) represents a measure of the strength of this organization, using a cardinal scale. Moreover, we assume that organization \( j \) survives at time \( t \) if and only if \( y_{jt} > 0 \). Thus, \( y_{jt} \leq 0 \) implies that organization \( j \) did not survive at time \( t \).

Here, we are interested in the survival of a group of organizations denoted by \( J \), a subset of all possible organizations. The group \( J \) will be defined according to common characteristics across organizations. This set of characteristics depends on the interest of the investigator. For example, the group may be a species for a biologist (i.e., a group of similar living organisms that can reproduce) or an industry for an economist (i.e., a group of firms selling similar outputs in a given market).

Note that the nonsurvival of some members of group \( J \) does not imply the extinction of the group, as long as some members of the group are not eliminated. Also, having \( y_{jt} \leq 0 \) for all \( j \in J \) at some time \( t \) does not imply the extinction of the group. For example, living organisms may die in an unfavorable environment; but they may also develop resistant forms (e.g., spores, seeds) that generate new organisms at later time periods after the environment becomes more favorable. This suggests the following definition.

**Definition 1:** Given some initial conditions \( y_{0t} \) at time \( t = 0 \), the critical period \( M \) for group \( J \) is the smallest number of consecutive time periods beyond which \( \text{prob}(y_{jt} > 0) = 0 \) for all \( j \in J \) and all \( t > M \). More formally, the critical period \( M \) is given by

\[
M(y_{0t}, J, x, e) = \min\{s: \text{eq. (1) and (2); } y_{0t}; x, e; \text{prob}(y_{jt} > 0) = 0 \text{ for all } j \in J, \text{ and all } t > s\}
\]

where \( x = (x_1, \ldots , x_M) \), \( x_i \in X \), and \( e = (e_1, \ldots , e_M) \), \( e_i \in E \).

In general, the value of \( M \) depends on the initial conditions \( y_{0t} \), on the nature of the group \( J \), on the control variables \( x \), and on the random variables \( e \). Note that a finite value of \( M \) in equation (3) implicitly assumes an irreversible situation that implies a zero probability of survival for all future organizations in group \( J \) for all \( t > M \). In the absence of irreversibility, the value of \( M \) in (3) would be infinite whenever there is a nonzero probability that some value of \( x_i \in X \) and \( e_i \in E \) would make \( y_{jt} \) strictly positive for some \( j \in J \) and for some arbitrarily large time period \( t \). In this case, \( M = \infty \), and the definition of the critical period \( M \) given in (3) loses its empirical usefulness.

The definition of extinction for a group \( J \) is given as follows.

**Definition 2:** The group \( J \) is said to become extinct under initial conditions \( y_{0t} \) if it faces the situation \( x = (x_1, \ldots , x_M) \) and \( e = (e_1, \ldots , e_M) \), where the value of \( M(y_{0t}, J, x, e) \) given in (3) is finite.

The above definition indicates that extinction of group \( J \) depends on the initial conditions \( y_{0t} \), on the decision variables \( x \) as well as on luck (as represented by the random variables \( e \)). It also shows the temporal dimension of extinction depending on the number of time periods \( M \) needed to eliminate group \( J \). In particular, definition 2 excludes the case of reversible situations where \( M \) would be infinite. Our definition of extinction thus makes sense only in situations exhibiting some form of irreversibility.

Given initial conditions \( y_{0t} \), the probability of extinction of group \( J \) over \( T \) successive time periods is

\[
P(y_{0t}, J, x, T) = \text{prob}(M(y_{0t}, J, x, e) \leq T)
\]

where the probability is based on the joint probability distribution of the random variables \( e \). Note that the probability \( P(\cdot) \) in (4) depends on the control variables \( x \). Some of the properties of \( P(\cdot) \) are presented next.

**Proposition 1:** The probability of extinction given in (4) satisfies:

\[
(5a) \quad P(y_{0t}, J, x, T) \geq P(y_{0t}, J', x, T)
\]

for any \( J \subset J' \)

\[
(5b) \quad P(y_{0t}, J, x, T) \geq P(y_{0t}, J, x, T')
\]

for any \( T > T' \).

**Proof:** Let \( J \) be any subset of \( J' \). The feasible region in problem (3) is smaller when \( j \in J \) than when \( j \in J' \). Because a smaller feasible region can only either maintain or increase the value of the objective function in a minimization problem, it follows that

\[
(6) \quad M(y_{0t}, J, x, e) \geq M(y_{0t}, J', x, e)
\]

for any \( J \subset J' \).

This implies expression (5a). Expression (5b) follows directly from the property that the distribution function \( P(T, \cdot) \) is a nondecreasing function of \( T \).
The results in proposition 1 are intuitive. Expression (5a) states that the probability of extinction of a group increases as the group is more narrowly defined. It says, for example, that the probability of extinction of all animal life is lower than the probability of extinction of any particular animal species. Also, expression (5b) states that the probability of extinction of group \( J \) increases over time: as \( T \) increases, group \( J \) has some chance of facing adverse situations that it cannot survive. This is consistent with previous models of extinction (e.g., Pielou, p. 19) and with the observation that 99% of all animal species have become extinct over the last 4 billion years (see above). Given that the odds of survival of any species may be quite low in the long term, it is useful to investigate factors that contribute to improving these odds.

The choice of the control variables \( x \in X \) can influence the survival odds. In general, a strategy \( x \in X \) that improves the probability of survival \( P(y_0, J, x, T) \) will contribute to the adaptiveness of group \( J \). This adaptiveness depends on the feasible set \( X \); i.e., on the mechanisms used by group \( J \) to register signals, to process them, and to react to them through the choice of the control variables \( x \). The nature of the mechanisms used in the decision-making process is discussed below.

Adaptive Strategies of Living Organisms

For living organisms, adaptive mechanisms are many. They can be classified according to response time. In a sequence of increasingly fast response, the following mechanisms can be identified: (i) genetic; (ii) developmental; and (iii) physiological.

For any particular organism, the genetic mechanism is slow. Although the gene pool provides a storage of information for all living organisms, it provides no possibility of adaptation within a generation. The speed of genetic adaptation across generations depends on the genetic system. One of these systems is asexual vegetative reproduction, which provides little possibility of genetic adaptation over time. Alternatively, sexual reproduction allows possibilities of mutations and extensive recombination of genes from one generation to the next. The resulting genetic variations provide new options for species to either manage unexploited locations, or survive successfully in a changing environment.

Developmental adaptation takes place during a life cycle. As such, it is quicker than a genetic mechanism. It involves a response to the environment through some developmental changes. It consists of situations where a young organism facing alternative paths of development is triggered by the environment toward a particular path (Bonner, p. 59).

Physiological adaptation includes immune response, hormonal response, muscular contraction, as well as neural response. Physiological adaptation can provide a relatively fast response of an organism to environmental stimulus (Bonner, p. 57). The fastest response comes from the neuromuscular system, which allows organisms to move. Mobility plays an important adaptive role by allowing an organism to escape from an undesirable place or move toward a desirable one.

Most living organisms rely on more than one adaptive mechanism and integrate them in some ways. For example, under asexual reproduction, organisms can still preserve flexible phenotypes through developmental or physiological adaptation. Also, any adaptive mechanism is influenced by genes and thus subject to genetic selection. In general, smaller or more primitive organisms with short life cycles use genetic response as an adaptation to a changing environment. In contrast, larger or more developed organisms rely more on physiological response.

The role of the nervous system as an adaptive tool for animals is worth noting here. In particular, the brain has evolved as an effective way of processing signals, information, and thoughts, and of generating quick reactions. Multiple choice behavior and flexible response to the environment make it easier to adapt to new habitats and to find new sources of food. The ability of the brain to process large amounts of information and to make decisions in complex situations contributes to developing improved adaptive strategies. Moreover, the ability to store and retrieve information allows the accumulation of knowledge by particular individuals (learning through experience) as well as the transmission of knowledge across individuals (teaching and education). The human species uses learning ability to help control the environment in ways that no other species has matched.\(^2\) The adaptive power of the human brain has allowed humans to survive in almost any habitat.

\(^2\) The invention of spoken and written language has greatly improved human ability to store information over time and to transmit it among individuals.
Adaptive Economic Behavior

The power of the human brain has generated a debate among social scientists. On the one hand, economists developed a theory of rational choice based on optimizing individuals. In such a case, economic behavior is assumed to be the product of the optimization process of a human decision-maker given his/her stable preferences. On the other hand, psychologists argue that the brain has some limited capacity that affects the way it processes information. As a result, human preferences may be neither stable nor consistent (e.g., Hogarth and Reder).

Consider $J$ to be a set of organizations, each member of the set being denoted by $j \in J$. Assume that equation (1) takes the form:

\[ y_{j,t+1} = \max\{0, y_p + f_j(h_{j,t}, y_t, x_t, e_t)\} \]

where

\[ h_{j,t} = h_j(z_{j,t}, x_{j,t}) \]

is a performance measure of the $j$th organization at time $t$, $j \in J$. Also, let equation (2) be

\[ z_{j,t} = g(y_{j,t}, x_{j,t}) > 0 \]

where $z$ is a scalar measure of resource availability for group $J$.

Assume that $y_p$ is a scalar representing the state of organization $j$ at time $t$, $y_p > (\approx) 0$ implying that the $j$th organization survives (does not survive) at time $t$. In an economic context, the state variable $y_p$ measures the amount of physical and human capital characterizing the $j$th economic organization. The set $J$ includes current organizations (for which $y_p > 0$) as well as potential entrants (for which $y_p = 0$ at time $t$, but possibly $y_p > 0$ at some $\tau > t$). Thus, equations (7)-(8) allow the modeling of entry (when a zero $y_p$ becomes positive) as well as exit (when a positive $y_p$ becomes zero) in the group of interest.

The following assumptions are made:

**A1:** The functions $h_j(\cdot)$ are nonstochastic; i.e., they do not depend on the random variables $e$, (although they can depend on the probability distribution function of $e$, $j \in J$).

**A2:** The function $f_j(h_{j,t}, \cdot)$ is an increasing function of $h_{j,t}$ and satisfies $f_j(0, \cdot) = 0$ for all surviving organizations as well as potential entrants, $j \in J$.

**A3:** The function $h_j(z_{j,t}, \cdot)$ is an increasing function of $z_{j,t}$, $j \in J$.

**A4:** The function $g(y_{j,t}, \cdot)$ is a decreasing function of $y_{j,t}$, $j \in J$.

In an economic context, equations (7)-(8) represent institutions involved in the production of private or public goods. For private goods, the institutions could be private firms involved in the production of particular goods or services sold in the market place. The performance measure $h_{j,t}$ in (7) is then a measure of net benefit obtained by firm $j$ at time $t$. By assumption (A1), this net benefit depends on the probability distribution of $e$, but not on the realized values of the random variables $e$; i.e., the net benefit to the firm is measured *ex ante*. In the absence of uncertainty, $h_{j,t}$ is firm profit. Alternatively, in the presence of uncertainty, the net benefit $h_{j,t}$ is the "certainty equivalent of net benefit," an *ex ante* measure of benefit that includes a risk premium accounting for risk aversion (Pratt). In the context of private firms, the index variable $z_t$ is the market price for output. Then, assumption (A3) reduces to profit being an increasing function of output price. Assumption (A4) states that increasing the capital used in production of a given output puts downward pressure on output price. This indicates that equation (8) plays a role similar to the downward sloping aggregate demand function commonly found in economic analysis.

The organizations could also be public institutions providing some collective goods. The value $h_{j,t}$ in (7) would then be a measure of the aggregate net benefit provided by the $j$th institution. Again, assumption (A1) implies that this benefit is measured *ex ante* (because it does not depend on the realization of the random variables $e$). In the absence of uncertainty, this aggregate net benefit is the sum of the willingness-to-pay across all individuals affected by the public goods, minus the cost of providing those goods. This corresponds to standard benefit-cost analysis commonly found in economics (e.g., Mishan). Under uncertainty, the value $h_{j,t}$ would be the aggregate sure net benefit proposed by Graham. Assumption (A3) states that increasing resource availability (as measured by $z$) increases the aggregate net benefit $h_{j,t}$. Similarly, assumption (A4) indicates that any increase in $y_{j,t}$, $j \in J$, used in the production of public goods reduces the resource availability index $z_t$.

Assumption (A2) implies that any positive net benefit ($h_{j,t} > 0$) stimulates the accumulation of capital by the $j$th institution over time. Al-

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1 Assumption (A4) implicitly assumes that the various organizations in $J$ are competitors. It rules out the possibility of beneficial interactions among organizations in $J$ that would improve their effectiveness in the use of available resources. It is a crucial assumption for the analysis presented below.
ternatively, any negative net benefit \( h_j(\cdot) < 0 \) reduces the capital of institution \( j \) over time. This assumption represents a simple feedback mechanism that stimulates the activities generating a reward and reduces the activities generating a penalty. Assumption (A2) applies only to surviving organizations and potential entrants. It is not assumed to apply to extinct organizations for which entry is no longer possible no matter how large the net benefit function \( h(\cdot) \) becomes. This is a crucial point that needs to be kept in mind if model (7)–(8) is to exhibit the kind of irreversibility that makes extinction possible (see above).

Equations (7)–(8) are a simplified version of model (1) and (2). They include as special cases the formulations commonly used in dynamic analysis of populations (Pielou). Some of the simplifying restrictions imposed on the specification (7)–(8) allow the derivations of more specific implications of the model. In general, equations (7)–(8) generate a variety of short-run dynamics depending on the functional forms \( f(\cdot) \), \( h(\cdot) \) and \( g(\cdot) \). In contrast, we show that model (7)–(8) yields rather precise implications for long run economic behavior (as reflected in the choice of the control variables \( x \)).

Equations (7)–(8) provide useful insights on the sustainability of group \( J \). Sustainability has been defined broadly as the ability to maintain some activity in the face of stress or shocks (e.g., Conway and Barbier; Pierce). Interpreting \( y \) as a measure of the particular activities to be maintained over time, then from (7a), sustainability of group \( J \) corresponds to the situation where \( y_j(t) = y_j(t-1) \) for all \( j \in J \) and all \( t \). In other words, sustainability within group \( J \) is identified with the existence of a steady state long run equilibrium (assuming that it exists\(^4\)) in equations (7)–(8). From (7a) and assumption (A2), this implies zero net benefit for surviving organizations; i.e., \( h(z_j, x_j) = 0 \) for all \( t \). The implications of the existence of a sustainable long run equilibrium for group \( J \) are investigated next.

By assumption (A3), the equation \( h_j(z_j, x_j) \) is an increasing function of \( z_j \). Define the survival index \( z_j(x_j, y_j) \) to be the inverse function of \( h_j(z_j) = h_j', \) where \( z_j(x_j, y_j) = [z_j: h_j(z_j, x_j) = h_j'(x_j)] \). Of particular interest here is the critical survival index \( z_j^* = z_j(x_j, y_j) \). This index measures the lowest level of resource availability that generates a zero net benefit to the \( j \)th organization at time \( t \). From (7a), any resource availability index higher (lower) than \( z_j^* \) stimulates the growth (the decline) of the \( j \)th organization (as measured by \( y_j \)). The lower the critical survival index \( z_j^* \), the better the \( j \)th organization survives in situations with low resource availability (as measured by \( z \)). In other words, the lower the critical survival index \( z_j^* \), the better the \( j \)th organization competes against others.\(^5\) For example, in the context of a firm, \( z_j^* \) is the lowest output price that leaves firm \( j \) with zero profit. In other words, given \( x_j^*, z_j^* \) is the average cost that generates zero profit. Then, (7) and (A2) imply that the \( j \)th firm facing an output price equal to \( z_j^* \) has no incentive to change its capital \( y_j^* \).

Without a loss of generality, let \( J = \{1, 2, 3, \ldots \} \) and reorder the organizations so that \( z_{1j} = z_{2j} = \ldots = z_{mJ} = \ldots \). Let \( y = \{y_j, j \in J\} \) where \( y_j = \{y_{ji}, j \in J\} \) represents the set of organizations belonging (not belonging) to group \( J \). Then equation (8) becomes \( z_j = g(y_{i1}, y_{i2}, \ldots, y_{im}, 0, 0, \ldots, y_{iJ}, x_j) \), where \( y_{ji} > 0 \) for \( j = 1, 2, \ldots, m \) being the number of surviving organizations at time \( t \). The \( m \)th organization is the marginal organization: it is the least competitive of all surviving organizations (because it has the highest critical survival index).

Then the following result is obtained:

**PROPOSITION 2:** A sustainable long run equilibrium can exist for (7)–(8) only if

\[
(9a) \quad z^* = z_{1j} = z_{2j} = \ldots = z_{mj} \leq z_{m+1,j} \leq z_{m+2,j} \leq \ldots
\]

and

\[
(9b) \quad y_{m+1,j} = y_{m+2,j} = \ldots = 0,
\]

for all \( t \), where \( z^* \) is the long run equilibrium resource availability index.

**PROOF:** In a long run equilibrium, it must be that \( y_{j,t+1} = y_j \) for all \( j \in J \).

From (7a) and (A2), it follows that \( h_j(z_j, x_j) = 0 \) for all surviving organizations (with \( y_j > 0 \)) and \( h_j(z_j, x_j) \leq 0 \) for nonsurviving organizations (with \( y_j = 0 \)). This implies that the critical sur---

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\(^4\) It should be emphasized that a long-run equilibrium may not always exist, including in situations where the state variables \( y \) in equation (7a) may be unbounded, be characterized by limit cycles, or be characterized by chaos (i.e., by aperiodic but bounded cycles that are locally divergent). In such cases, a number of results presented in this section would not apply.

\(^5\) Our survival index would be the inverse of the fitness index commonly found in biology: the higher the fitness index of a particular organization, the better it can compete against others.
vival index \( z_p = z(x_p, 0) \) for nonsurviving organizations is at least as large as the survival index for surviving organizations. Also, from (7)–(8), all surviving organizations face the same value \( z_i = g(y_i, x_i) \). Combining the two results gives (9a) and (9b).

Note that result (9) holds, no matter how the controls \( x \) are chosen. In particular, it does not require that organizations exhibit optimizing behavior. Proposition 2 indicates that, under the stated conditions, a sustainable long-run equilibrium exists only when the surviving organizations have the same critical survival index \( z_p \), and that this index must be the lowest among all current as well as potential organizations. Because \( z_i = g(y_i, x_i) \) where \( y_i = [Y_i, \bar{Y}_i] \), the long run equilibrium \( z^* \) in (9) depends in general on \( \bar{Y}_i = (y_j, j \notin J) \), the set of organizations not belonging to group \( J \). This situation indicates that group \( J \) will, in general, be influenced by the situation of organizations outside group \( J \) which stresses the importance of linkages among systems in the investigation of sustainability issues. This point is made by Norgaard (1984a, 1984b), who emphasizes the coevolutionary linkages between social and ecological systems. Similarly, Conway and Barbier argue that sustainable agricultural development must be viewed within the context of the overall agroecological system as it is transformed by people in the process of producing food and fiber.

The following result is obtained as a special case of proposition 2.

**COROLLARY 1:** Assume that no two organizations have the same critical survival index \( z_p \). Then a sustainable long run equilibrium must satisfy \( y_{i, t} > 0 \) and \( y_{2i} = y_{3i} = y_{4i} = \ldots = 0 \) for all \( t \).

Corollary 1 implies that, if no two organizations have the same critical survival index, then only one organization can survive in the long run. This is the principle of competitive exclusion in biology.

Dropping the \( j \) and \( t \) subscripts for convenience, recall the definition of the survival index \( z(x, h) = \{ z: h = h(z, x), x \in X \} \). Then, assuming that they have a solution, consider the two following problems.

**Optimizing Behavior**

(10a) \( h^*(z) = \max \{ h(z, x): x \in X \} \)

which has for solution \( x^*(z) \).

**Minimization of the Survival Index**

(10b) \( z^*(h) = \min \{ z(x, h): x \in X \} \)

which has for solution \( x^*(h) \).

Because the functions \( h(z, x) \) and \( z(x, h) \) are inverse functions of each other, the following result is obtained.

**PROPOSITION 3:** The optimization problems (10a) and (10b) are dual to each other in the sense that they satisfy the following:

(11a) \( z^*(h) \) and \( h^*(z) \) are inverse functions of each other,

(11b) \( x^*(z^*(h)) = x^+(h) \)

(11c) \( x^+(h^*(z)) = x^*(z) \)

Proposition 3 states that the minimization problem (10b) is consistent with optimizing behavior (10a), as stated in (11b) and (11c). In the context of a sustainable long run equilibrium (where \( h(z) = 0 \), this result takes the following form.

**COROLLARY 2:** In a sustainable long run equilibrium, optimizing behavior by any organization is consistent with the minimization problem

(12) \( z^*_p = \min \{ z(x_p, 0): x_p \in X \} \)

\( = \min \{ z(z): h(z, x_p) = 0, x_p \in X \} \)

for all \( t, j \in J \).

Equation (12) defines \( z^*_p \) as the critical survival index corresponding to optimizing behavior as stated in (10a). Then, the following result is obtained.

**PROPOSITION 4:** Assume that the \( j \)th organization chooses \( x_j \in X \) (which may or may not be an optimizing choice for \( x \)).

Then, a sustainable long run equilibrium must satisfy

(13) \( z^*_j = z(x_p, 0) = z^*, j = 1, \ldots, m, \) for all \( t \).

**PROOF:** Note that \( z(x_p, 0) = z^*, i = 1, \ldots, m, \) follows from proposition 2. Also, \( z^*_j \leq z(x_j, 0) \) follows from the definition of \( z^* \) in corollary 2.

This suggests that the survival index defined above provides a convenient basis for measuring the behavioral efficiency of surviving organizations in the set \( J \).

**DEFINITION 3:** Consider the set of surviving organizations in a sustainable long run equilibrium: \( y_j = y_{j,t+1} > 0 \) for all \( t, j \in J \).

Then,

(14) \( z^*_j/z^* \)
is an index of behavioral efficiency, with \( 0 < \frac{z^*_j}{z^*_j} \leq 1 \).

Equation (14) defines behavioral efficiency in terms of a ratio of the survival index of the \( j \)th organization assuming that it would optimize, to the equilibrium resource availability index. If the \( j \)th surviving organization does optimize according to (10a), then corollary 2 and proposition 5 imply a behavioral efficiency index equal to 1. Alternatively, if the \( j \)th organization does not optimize, then equation (13) implies that the behavioral efficiency index is bounded between 0 and 1. In this case, the behavioral efficiency index (14) measures the largest percentage reduction in the resource availability index that the \( j \)th surviving organization can face before its survival became threatened. It provides a simple measure of the potential gains that optimizing behavior can generate. Note that the efficiency index (14) is consistent with the analysis of productive efficiency typically found in the literature (e.g., Farrell; Kopp). To see that, interpret \( z(x_j, 0) \) as an average cost function for a firm. Then, from corollary 2, the minimization of the average cost function in (12) implies cost minimizing behavior, which can be used as a basis for analyzing technical efficiency, allocative efficiency as well as scale efficiency (e.g., Kopp).

Note that proposition 4 does not assert that the surviving organizations are identical, nor that they exhibit optimizing behavior. However, placing restrictions on the distribution of the critical survival indices \( z^*_j \) across organizations yields some rather strong predictions as stated in the following two propositions.

**Proposition 5:** Assume that all surviving organizations have the same critical survival index \( z^*_j \). If (at least) one of them exhibits optimizing behavior, then a sustainable long run equilibrium can exist only if all surviving firms also exhibit optimizing behavior.

**Proof:** In a long run equilibrium (where \( h_j(\cdot) = 0 \) for all surviving organizations), the assumption of identical survival indexes implies that \( z^*_j = \frac{z_m}{z_{j,t}} \) for all \( j = 1, \ldots, m - 1 \), and all \( t \). Without a loss of generality, assume that the optimizing organization is the mth one. It follows that \( z_m(x_m, 0) = \frac{z_m}{z_{m,t}} \). But proposition 4 implies that \( \frac{z^*_j}{z^*_j} = \frac{z(x_j, 0)}{z^*_j} \), for all \( j = 1, \ldots, m \). It follows that \( \frac{z^*_j}{z^*_j} = \frac{z(x_j, 0)}{z^*_j}, j = 1, \ldots, m \). Corollary 2 then implies that all firms must optimize in a long run equilibrium.

Proposition 5 applies to the case where all organizations have the same critical survival index \( z^*_j \) as defined in (12). This is clearly satisfied if all organizations in \( J \) are identical. But this is also satisfied if the organizations are different (i.e., with different performance measures \( h_j(z, x_j) \)) as long as their \( z^*_j \) is the same across \( j \in J \). Proposition 5 shows that, in a sustainable long run equilibrium, optimizing behavior by any one organization would lead all surviving organizations to optimize as well, if they have the same critical survival index \( z^*_j \). Any organization exhibiting nonoptimizing behavior would necessarily not survive in the long run. This can be interpreted in terms of the survival of the fittest. In other words, the struggle for survival would eventually select only the organizations that optimize according to (10a).

The assumption of identical organizations is commonly made in economic analysis. For example, it can be found in the long run theory of the firm under certainty (Silberberg), as well as under uncertainty (Chavas et al.). It is also a central assumption in the theory of contestable markets (Baumol, Panzar, and Willig). Thus, proposition 5 can be seen as a possible way to justify the assumption of optimizing behavior by economic agents. This includes profit maximization (where \( h_j(\cdot) \) is firm profit) or expected utility maximization (where \( h_j(\cdot) \) is the certainty equivalent of profit). This also includes dynamic models under uncertainty and irreversibility (e.g., as discussed in section 3 in the context of extinction). In this case, we will argue below that the benefit function \( h_j(\cdot) \) would include an “adaptive value” that gives some incentive to implement conservation strategies that decrease the odds of facing irreversible states. Finally, in the case of public goods, optimizing behavior together with zero aggregate net benefit (\( h_j(\cdot) = 0 \)) implies a Pareto optimal allocation of resources by the \( j \)th public institution (Graham). Therefore, from proposition 5, model
(7)–(8) can be useful in comparative institutional analysis: in the long run, it can generate a Pareto optimal allocation of resources by surviving organizations.

Proposition 5 indicates that restricting the critical survival indexes to be the same across organizations generates rather strong long run predictions. However, relaxing this restriction can lead to quite different results, as stated next.

**Proposition 6:** Assume that all surviving organizations do not have the same critical survival index $z_{i}^{*}$. Then in a sustainable long run equilibrium, it must be that at least one organization $j$ does not exhibit optimizing behavior. Moreover, such an organization necessarily satisfies $z_{j}^{*} < z^{*}$.

**Proof:** By assumption, $z_{i}^{*} < z_{j}^{*}$ for some $i$ and $j \leq m$. From proposition 4, we have $z_{i}(X_{i}, 0) = z_{j}(X_{j}, 0) = z^{*}$. But this implies that $z_{i}^{*} < z_{j}^{*}$. It follows from corollary 2 that optimizing behavior of the $j$th organization is not consistent with long run equilibrium.

Proposition 6 states that in the long run, surviving organizations with different critical survival indices $z_{i}^{*}$ is inconsistent with optimizing behavior by all organizations. This suggests that there are reasons why the long run behavior of particular organizations may systematically depart from optimization. Moreover, it indicates that it is the organizations with lower critical survival index $z_{i}^{*}$ that would depart from optimizing behavior. This can provide new insights in the analysis of economic efficiency.

Casual observations in economics (or ecology) suggest that surviving organizations in any particular economic (or ecological) niche are typically neither single nor identical. In a steady state equilibrium, this could happen under optimizing behavior provided that the organizations have the same critical survival index $z_{i}^{*}$ (as stated in proposition 5). But if the ability to compete (as measured by $z_{i}^{*}$) varies across $j \in J$, this would imply that some surviving organizations do not optimize (as stated in proposition 6). In this case, the organizations with a better ability to compete (i.e., with a lower $z_{i}^{*}$) would fail to optimize and be found behaviorally inefficient according to the efficiency index (14). Then, the allocation of resources in this long run equilibrium would not be Pareto optimal. These results suggest that empirical economic analyses of long-term resource management should not rely exclusively on the assumption of optimizing behavior. More specifically, it may be that many behavioral decisions involved in sustainability issues are not the outcome of an optimizing process.

**The Role of Irreversibility and Uncertainty**

Irreversibility and the ability to react to unexpected shocks have been identified as important factors in the investigation of environmental preservation and sustainability issues (e.g., Arrow and Fisher; Pearce; Conway and Barbier). Thus, we now turn our attention to the role of irreversibility and uncertainty in the evaluation of resource management policy. In order to do that, define the indicator variable $I_{j}$ as

$$I_{j} = \begin{cases} 0 & \text{if the organization } j \text{ becomes extinct at any time before time } t \\ 1 & \text{otherwise.} \end{cases}$$

Denote the measure of net benefit generated by organization $j$ during period $t$ by

$$I_{j} \cdot b_{j}(z_{j}, x_{j}, e_{j})$$

where $b_{j}(z_{j}, x_{j}, e_{j})$ is the net benefit from the $j$th surviving organization during period $t$. This net benefit can be estimated by any of the direct or indirect valuation techniques typically used in benefit-cost analysis (such as the travel cost method, contingent valuation, hedonic regression, etc.). Note that the above specification implies that no net benefit can be generated without the existence of the organization.

Assume that the performance measure (7b) is given by the standard present value formula:

$$h_{j}(x_{j}, \cdot) = E_{\Delta} \sum_{t=0}^{\infty} \beta^{t} I_{j,t+1} b_{j,t+1}(z_{i,t+1}, x_{j,t+1}, e_{j,t+1})$$

$$= I_{j} E[b_{j}(z_{j}, x_{j}, e_{j})] + \beta E[h_{j,t+1}(x_{j,t+1}, \cdot)]$$

where $E_{\Delta}$ is the expectation operator based on the information available at time $t$ and $\beta$ is a discount factor ($0 < \beta < 1$). The expected present value of benefits (15) from organization $j$ can be alternatively written as

$$h_{j}(x_{j}, \cdot) = I_{j} E[b_{j}(z_{j}, x_{j}, e_{j})] + \beta[1 - P_{j}(x_{j})] E[h_{j,t+1}(\cdot)]$$

where $P_{j}(x_{j}) = E_{\Delta}(1 - I_{j,t+1})$ is the probability that organization $j$ becomes extinct during period $t + 1$ based on the information available at

\[\text{Footnote 8: Under a situation involving risk and risk aversion, the net benefit } h_{j}(\cdot) \text{ would include a risk premium as a measure of the cost of risk bearing.}\]
time \( t \) (see equation (4)), and \( E_t^j \) is the expectation operator based on the information available at time \( t \) conditional on \( I_{j,t+1} = 1 \) (i.e., conditional on the organization \( j \) surviving at time \( t+1 \)). Equation (16) shows that a positive probability of extinction tends to reduce the effects of expected future benefit \( E_t^j[h_{j,t+1}(\cdot)] \) on the performance measure \( h_j(\cdot) \). This implies the following result.

**Proposition 7:** The possibility of extinction has a negative (positive) impact on the performance measure \( h_j(\cdot) \) if and only if the expected future benefit \( E_t^j[h_{j,t+1}(\cdot)] \) is positive (negative).

Proposition 7 indicates that extinction has the desirable characteristic of increasing the expected present value of benefits for organizations that generate large and negative future benefits. From a human viewpoint, this is the case for microorganisms causing diseases such as cholera, yellow fever, or malaria. Alternatively, proposition 7 implies that the possibility of extinction has the undesirable characteristic of decreasing the expected present value of benefits whenever future expected benefits are positive. This would be true whether current benefit \( b_j(\cdot) \) is zero, positive or negative. This illustrates the importance of incorporating the irreversibility of extinction in benefit evaluation. This may be especially crucial for organizations that generate no current benefit but have the potential of producing positive future benefits (e.g., the case of some endangered species).

This raises the question of how to evaluate future benefits. First, it involves choosing the discount rate \( \beta \) in equation (16). Much debate has focused on this issue in the benefit-cost evaluation of environmental policies. Unfortunately, no consensus currently exists on the most appropriate measure of the discount rate (Markandya and Pierce).\(^{10}\) Second, the measurement of future benefits raises the problem of the proper handling of future uncertainties and the role of adaptive strategies as a response to new information. We now turn our attention to this issue.

Let \((0,1,\ldots, S)\) denote a set of \((S + 1)\) mutually exclusive states of nature at each time period. The element \(0\) represents the situation where no new information is obtained on the state of nature beyond time \( t \), while each of the elements \(1, \ldots, S\) corresponds to a different observation on the state at time \( \tau \geq t \). At each time period \( \tau \), organization \( j \) is assumed to receive a signal \( s_\tau \), indicating which of the \((S + 1)\) states actually occurred. Then a general strategy for choosing the control variables \( x_p \) can be denoted by some rule \( x_p(s_\tau) \) which maps the observation on the state of nature into the behavior of organization \( j \) at time \( \tau \). This allows for information feedback as the organization can react to new information represented by \( s_\tau \). Note that the behavioral rule \( x_p(s_\tau) \) may or may not correspond to optimizing behavior (as defined in (10a)). From equation (16), the expected present value of benefits under the behavioral rule \( x_p(s_\tau) \) is

\[
\begin{align*}
(17) \quad h_j(x_p(s_\tau)) & = I_j E_t^j[b_j(z, x_p(s_\tau), e)] \\
& + \beta [1 - P_j(x_p(s_\tau))] E_t^j[h_{j,t+1}(x_{j,t+1}(s_{t+1}))].
\end{align*}
\]

We are interested here in providing a measure of the value of adaptation. Let \( s_{0\tau} \) represent the situation where the state \( (0) \) is observed at time \( \tau \geq t \) (i.e., where no new information becomes available for decision making beyond time \( t \)). We propose to use as a reference point the behavioral rule \( x_p(s_{0\tau}) \) corresponding to a non-adaptive choice of \( x_p \) (i.e., a choice of \( x_p \) without information feedback). This leads to the following definition.

**Definition 4:** The adaptive value of the behavioral rule \( x_p(s_\tau) \) is given by

\[
(18) \quad V_j(x_p(s_\tau)) = h_j(x_p(s_\tau)) - h_j(x_p(s_{0\tau})).
\]

In general, the adaptive value \( V_j(x_p(s_\tau)) \) of the behavioral rule \( x_p(s_\tau) \) can be positive, zero, or negative. This value is used to measure the adaptability of the associated strategy. A positive adaptive value indicates that, compared to a situation where new information is neglected, the organization \( j \) improves its performance (as measured by (17)) by reacting to new information through the rule \( x_p(s_\tau) \). Alternatively, a negative value shows that, according to the benefit measure (17), the behavioral rule \( x_p(s_\tau) \) is inferior to the rule \( x_p(s_{0\tau}) \) where no information feedback is used beyond time \( t \).

The value \( V_j(\cdot) \) in (18) provides useful insights in the role of adaptation in dealing with the irreversibility of extinction. To see that, substitute equation (18) evaluated at time \((t+1)\) into (17) to obtain

\[
(19) \quad h_j(x_p(s_{t+1})) = I_j E_t^j[b_j(z, x_p(s_{t+1}), e)] \\
+ \beta [1 - P_j(x_p(s_{t+1}))] E_t^j[h_{j,t+1}(x_{j,t+1}(s_{t+1})) + V_j(t+1)].
\]
The performance measure (19) is made based on the information available at time \( t \). It does not allow for information feedback beyond time \( t \) while compensating the performance measure for this lack of adaptivity (through the term \( V_{j,t+1}(\cdot) \)). It shows that the adaptive value \( V_{j,t+1} \) contributes to increasing the expected present value of benefits to organization \( j \). This gives the following result.

**Proposition 8:** A behavioral rule \( x_j(s_t) \) exhibiting a positive adaptive value \( V_{j,t+1} > 0 \) tends to improve the performance of the organization \( j \) (as measured by \( h_j(\cdot) \)).

Thus, adaptive behavior tends to improve performance. It should be emphasized that this result is obtained whether or not the organization exhibits optimizing behavior (as stated in (10a)). It holds under general conditions (including nonoptimizing short run situations). However, additional results are obtained if the organization exhibits optimizing behavior (e.g., as implied by proposition 5).

**Proposition 9:** If the behavioral rule \( x_j(s_t) \) corresponds to optimizing behavior (10a), then its adaptive value \( V_{j,t} \) is necessarily nonnegative.

**Proof:** Under optimizing behavior (10a), equation (17) becomes Bellman's equation of dynamic programming. The adaptive value (18) is then the difference between a closed loop solution and an open loop solution to a stochastic dynamic programming problem. This difference has been shown to be always nonnegative (Bertsekas, p. 192).

The implications of the above results become more apparent if we examine the following example. Consider an organization \( j \) existing at time \( t \) \( (I_j = 1) \) and faced with the problem of choosing between two strategies: (i) a strategy \( x_{j,t}^*(s_t) \), which leads to extinction with probability one between time \( t \) and \( t+1 \); and (ii) a strategy \( x_{j,t}^*(s_t) \), which exhibits a positive probability of survival to period \( t + 1 \). In other words, the decision rule \( x_{j,t}^*(s_t) \) corresponds to an irreversible situation while the decision rule \( x_{j,t}^*(s_t) \) does not. The question is: what is the role of irreversibility and adaptation in the evaluation of these two strategies? This question can be answered using the performance index (19). Given that \( I_j = 1 \) and noting that \( P_j(x_{j,t}^*(s_t)) = 1 \) and \( P_j(x_{j,t}^*(s_t)) < 1 \), we have

\[
(20a) \quad h_j(x_{j,t}^*(s_t)) = E_l[b_j(z_t, x_{j,t}^*(s_t), e_t)]
\]

and

\[
(20b) \quad h_j(x_{j,t}^*(s_t)) = E_l[b_j(z_t, x_{j,t}^*(s_t), e_t)] + \beta[1 - P_j(x_{j,t}^*(s_t))] + E_l[h_j(\cdot) + V_{j,t+1}(\cdot)].
\]

This shows that the value of adaptation plays no role in the evaluation of the irreversible move \( x_{j,t}^*(s_t) \) in (20a) while it gives a positive contribution to the evaluation of the strategy \( x_{j,t}^*(s_t) \) in (20b). This implies that adaptive strategies exhibiting \( V_{j,t+1}(\cdot) > 0 \) contribute to the survival of organizations. In other words, adaptive strategies can improve the resilience of a system and improve its ability to sustain stress or shocks (Pearce; Conway and Barbier). In economic terms, the adaptive value \( V_{j,t+1}(\cdot) \) gives some incentive to implement the strategy that avoids the irreversibility of extinction. This result does not require optimizing behavior. However, under optimizing behavior (10a), the adaptive value \( V_{j,t+1}(\cdot) \) becomes equivalent to the “quasi-option” value proposed by Arrow and Fisher in their investigation of environmental preservation under uncertainty and irreversibility. From proposition 9, the “quasi-option value” \( V_{j,t+1}(\cdot) \) is necessarily nonnegative (Fisher and Hame\(n\)mann) and gives an incentive to implement conservation strategies that decrease the odds of facing the irreversible state (Arrow and Fisher; Bishop). Thus, our results stress the importance of incorporating an adaptive value in the evaluation of sustainability issues. They generalize the concept of “quasi-option” value proposed by Arrow and Fisher. This generalization appears attractive to the extent that many behavioral decisions involved in sustainability issues may not be the outcome of an optimizing process.

**Concluding Remarks**

This paper has explored some of the common ground that exists between social scientists, ecologists, and evolutionary biologists concerning the study of survival issues. Our analysis focused on various aspects of resource sustainability and the economics of survival, stressing the importance of irreversibility issues. It identified some linkages between long-term survival and optimizing behavior. It was shown how optimizing behavior (as commonly assumed in economics) can be generated from a long run equilibrium involving competing organizations. Conditions were also derived under which long run equilibrium is necessarily inconsistent with optimizing behavior. This suggests that the em-
pirical analysis of sustainability and resource policy should not rely exclusively on the assumption of optimizing behavior. In this context, an adaptive model was presented under uncertainty and irreversibility. It was shown that, even in the absence of optimizing behavior, adaptive strategies can improve the resilience of a system and its ability to sustain shocks. In benefit-cost analysis, this can be handled through the incorporation of an "adaptive value" in benefit evaluation. Ignoring this adaptive value under irreversibility would understate the benefits of conservation strategies and bias decisions against conservation. A failure to implement conservation strategies would lead to higher probability of the irreversible states. At stake may be the long-term survival of the organizations of interest. Thus, the explicit incorporation of this adaptive value in economic analysis appears to be a crucial step in the evaluation of sustainability issues.

The results presented here appear applicable to a broad range of policies related to the long-term sustainability of various economic institutions and biological organizations. It is hoped that they will help stimulate additional research on this important topic.

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