The Role of a Dynamic Marketplace in the Adoption of Industrial Efficiency Innovations

Stephen J. DeCanio, University of California, Santa Barbara
John A. "Skip" Laitner, U.S. Environmental Protection Agency

ABSTRACT

The failure of business and industry to adopt profitable energy-saving innovations and the apparent ability of some businesses to transform environmental concerns into a competitive advantage are just two of the instances of firm behavior that are not captured in standard economic policy models. Indeed, the evidence is mounting that the typical economic description of business behavior — in which firms are assumed to follow strict principles of profit maximization subject only to a production function and budget or regulatory constraints — is ready for transformation.

The conventional theory of corporate behavior is challenged by a wide range of phenomena that range from capital budgeting and technology choice to transaction costs, market uncertainty, and organizational structure. In this paper we will explore alternatives to the pure maximization approach that have been suggested in the literature on the behavior of firms. In particular, we show how an evolutionary perspective can lead naturally to dynamic models that exhibit the kind of open-endedness that actually characterizes the real world. This, in turn, may highlight the opportunities that encourage or accelerate the adoption of profitable energy innovations within industrial firms.

Introduction

The proper characterization of technology and how its performance changes over time are both critical elements of energy modeling. Equally important, however, are the behavioral responses of individuals and firms. Before new technologies can be adopted firms must learn about them, and the investment process is mediated by the organizational structures that guide corporate decision-making and the flow of information. Brynjolfsson and Hitt (1996), for example, showed that the productivity gains from computerization could not be realized until firms reorganized to take advantage of the new information-processing technology. Yet the standard modeling treatment assumes that technology can be adequately represented by some form of a production function that transforms various commodity inputs into a given output.[1] The behavioral assumption is limited to the highly abstract idea of profit maximization, an assumption that is largely unexamined in conventional energy-economic modeling.

Although managers are very much concerned with the economic survival and profitability of their enterprises, their activities are not well described as the solving of the kinds of maximization problems that lie at the heart of most economic modeling exercises.

[1] This is true whether technology is represented in specific technology choice models or in more stylized econometric or equilibrium models.

Managers do not primarily work with mathematical representations of their production processes or the availability of resource inputs. Instead, the most challenging elements of their jobs involve strategic planning, human relations, organizational design, and bureaucratic politics. While it is true that some elements of operations research (and more recently, mathematical finance) are important components of management expertise, these by no means embody the full set of tools that have been devised to enhance business leadership.

It is not an adequate response to argue, as Friedman did in an influential methodological article in the early 1950s, that the details of management practices can be ignored because firms can be analyzed "as if" they conform to the profit-maximization paradigm (Friedman 1953). Friedman's argument rests on an appeal to the selection pressures of evolution (i.e., if firms did not maximize profits they would be driven out of business), but in fact the evolutionary argument, while being correct in pointing out that market survival does require that firms earn positive profits, is not the same thing as an argument for *optimization* (Alchian 1950). Evolution is a non-teleological process, and the fact that it is never "finished" implies that evolving populations are always susceptible to improvement. The evolutionary outlook does offer insights into industrial dynamics (see below), but does not constitute justification for ignoring the nature of the particular activities undertaken by management. Rather than using the "as if" argument to avoid close examination of the activities and practices of firms, it is necessary, as Simon observed some time ago, to "make the observations necessary to discover and test true propositions….Then let us construct a new market theory on these firmer foundations" (1963, p. 230).

The modern theory of the firm has been developed in a number of disciplines. The technical literature spans the fields of economics, management science, sociology, and organization theory. No attempt will be made to survey that literature comprehensively here.[2] The significant point is that disregarding how firms actually operate can lead to misconceptions about both the likelihood that the firms will adopt profitable energy-saving technologies and the mechanisms by which policy can influence those decisions. The consequence of ignoring the modern theory of the firm is a pervasive bias in policy analysis that underestimates the potential for energy savings that are consistent with strengthening the economic performance of industrial organizations.

Energy Policy Models and the Modern Theory of the Firm

The heart of the production function/profit maximization story is the assumption that the firm is *efficient*. No stone is left unturned in the search for profits, and all investments that yield a return greater than or equal to the cost of capital for projects of comparable risk are undertaken. This view treats the firm as though it were a unitary entity capable of single-minded pursuit of its formal objective – profitability for the shareholders. However, the "rationality of individuals" making up an organization does not easily translate into the "rationality of the organization" as a whole. The way the organization behaves depends on its decision-making procedures, or on how the preferences of the individuals who comprise it are aggregated to produce collective action. There are both theoretical and practical reasons to doubt that the behavior of groups has the same desirable qualities as individual rationality. Thus, Olson (1965) showed that the "logic of collective action" is such that groups will not

[2] Some of the authors' own contributions, which include references to the wider literature, can be found in DeCanio (1993, 1994a, 1994b, 1994c, 1998, and 2000) and Laitner et al. (2000).

ordinarily generate outcomes that are optimal, and Arrow (1951) proved that there is no mechanism that can aggregate individual preferences into a collective decision rule that preserves the minimum requirements for individual rationality. The divergence between the interests of the individuals making up a firm and the formal profit-maximizing objective of the firm fall under several categories that more or less correspond to the observations of practical experience. These include principal/agent problems, issues of control, and limitations due to bounded rationality. We will discuss each of these in turn.

Principal-Agent Problems

This type of barrier to optimization arises because the members of any organization (and, in the case of business corporations, the employees and owners) are likely to have, at least to some degree, differences in interests. The shareholders of a firm are primarily interested in the firm's net profitability. Because they can diversify their holdings by owning the shares of many different firms, even risk-averse shareholders would like the managers of the firms in the shareholders' portfolios to behave in a risk-neutral manner, seeking the highest expected return regardless of the risk associated with any particular projects. Working conditions experienced by the employees of the firm are of secondary importance to the shareholders because the employees (along with the capital, intellectual property, and other assets of the firm) are purely instrumental to the goal of maximum profits. The perspective of the employees is different. For them, working conditions, employment perquisites, and job security are as important as the rates of compensation or the quality of the benefits package. This leads to a potential conflict of interest between the shareholders and the employees.

There is no easy way out of this conflict. The owners cannot be aware of all the information (from customers, suppliers, and internal to the firm) that is pertinent to efficient operation of the firm – that is why they hire mangers in the first place. The consequences of this "separation of ownership and control" were commented upon by Berle and Means in the 1930s (1932).[3] Given this asymmetric possession of information, the owners have no way of assessing whether the managers' decisions are self-serving or are based on information held only by the managers. For example, shareholders may be unable to ascertain the true rate of return on various investment projects available to the firm. This inability gives them a reason to set a "hurdle rate" for investments undertaken by the firm's managers that is higher than the appropriate risk-adjusted cost of capital (Antle and Eppen 1985). If the principals (the shareholders) do not know the true rate of return on projects, they have no way of knowing how the profits generated are allocated between dividend payout (which is received by the principals) and management perquisites (including reduced levels of effort by the managers). Setting an artificially high hurdle rate for projects guarantees that (1) only highly profitable investments will be undertaken, and (2) the returns from the projects will accrue to the firm (because the managers must demonstrate *ex post* that the hurdle rate target has been met). This means that some profitable projects with rates of return below the high hurdle rate will be foregone, but the principals may judge that the resulting inefficiency is preferable to allowing the managers to appropriate the lion's share of the profits earned by the projects that are undertaken. This is one possible explanation for the common observation that companies require extremely short paybacks (on the order of one or two years) and/or unreasonably high

[3] But see also the earlier references in Jensen and Meckling (1976).

internal rates of return for even the simplest kinds of energy-saving investments. Lighting and motor system upgrades or right-sizing of heating, ventilation, and air conditioning systems are not technologically or economically risky, and there is no *economic* reason why such projects should have to meet high hurdle rates to be adopted.[4]

Problems of Management Control

Even if principal/agent conflicts of interest were not a problem, the modern complex organization would be difficult to manage in a profit-maximizing way. It is not a simple matter to coordinate the multifarious activities of the employees of a firm. A balance must be struck between giving instructions (and seeing that they are carried out) and reliance on the specialized skills and initiative of the individuals who contribute to production. It is not sufficient to issue a general directive to "maximize profits." At the most basic level, it is difficult to know exactly how much any particular subunit is contributing to the overall profitability of a firm, and even more difficult to know each individual employee's contribution. Compensation and other rewards need to be connected to performance, but the measurement of performance inevitably entails setting targets and standards that are measurable and concrete. In a complex organization, these standards may be only partially related to total profitability.

Many of the functions of the organization are part of overhead and therefore cannot be tied directly to a particular profit center. Even if a group's costs and returns can be separated from general returns in an accounting sense, the group may benefit (or suffer) from reputational or brand-name identification effects that are common to the whole organization (or to segments much larger than the team or group under review). The costs of the legal department, government relations, human resources, and capital management are not easily allocated across subunits.

Instead of a general instruction to "maximize profits," the members of the firm have to be given incentives to perform and measures by which their performance can be evaluated. The principals of the firm (whether shareholders or top management) are not entirely free in setting these objectives and evaluation tools, however, because the firm is embedded in the larger society's labor and capital markets. The existence of a labor market means that the overall mix of compensation and terms of employment has to be competitive with that offered by other firms. At the same time, attracting and retaining quality employees offers one of the dimensions along which management ingenuity can pay off in terms of economic performance. The difficulties of balancing incentives and performance, central control and individual employees' discretion, and knowledge of operations without succumbing to "information overload," are part of the reason management is such a demanding task, and why good managers are so highly compensated. If management entailed only the kind of maximization calculations expressed in conventional energy-economic models, the ideal manager would be a fresh college graduate who had done well in calculus. High-priced MBA programs would go out of business, and there would be no extensive displays of management self-help books in airport bookstores.

[4] It should be noted that the discussion so far has been cast in terms of conflicts between shareholders and employees; the same reasoning applies to potential conflicts between different layers of management. Top management and middle management (as well as management and line employees) are plagued by the same information asymmetries and divergent incentives as the shareholders and "management" as a group.

Bounded Rationality

So far, the discussion has assumed that the individuals making up the firm are perfectly rational, but that the necessity of their taking collective action to make the organization work is a potential source of sub-optimality. This assumption of perfect rationality on the part of the individual agents is itself suspect. Herbert Simon first drew attention to the fact that individual agents are only boundedly rational, that is, they do not have unlimited information processing and computational capabilities.[5] The result is that individuals "satisfice" rather than optimize. Recently, some economists (and others) have questioned whether the traditional economic dimensions are adequate to capture key elements of behavior even in a market setting. This has led to a proliferation of work on "behavioral economics," "behavioral finance," and the like.[6] These inquiries start from experimental evidence in psychology, sociology, and economics that runs counter to the way *homo economicus* is "supposed" to behave, and attempts to derive models that are consistent with what is known about individual behavior.

Furthermore, the fact that firms take actions only in accordance with their own internal rules of procedure and decision-making processes places additional limitations on the kinds of outcomes that will be observed. The firms' rules and procedures are often complex, and are adhered to for non-economic reasons (such as maintaining hierarchical power relationships or satisfying cultural preferences). In addition, full optimization by firms would require very high-quality forecasting of future events that are essentially impossible to predict. Thus, the criterion that a profitable investment must have a positive expected net present value requires forecasting cash flows and costs far into the future. Both streams are subject to the uncertainty of future prices, and the expected revenues typically depend on macroeconomic or aggregate demand conditions as well. Even requiring that the firm's forecasts take account of all the information available (a minimum requirement for the kind of "rational expectations" posited in many economic models) imposes an insuperable computational burden (Spear 1989; DeCanio 1999).

Nor are the difficulties inherent in forecasting the only source of bounded rationality in the firm's calculations. Many modern management problems, such as inventory control, production scheduling, and organizational design can be solved only approximately using reasonable amounts of computational resources and time (Garey and Johnson 1991; Papadimitriou 1996). Any time the decision-making of a firm must be mediated by some kind of communications network (because it is too costly or difficult for all members of the organization to be simultaneously in touch with all others), the question arises of what the optimal network structure might be, and finding that structure can be extraordinarily difficult. Managers constantly must wrestle with the problem of how best to organize activities, and significant amounts of time within organizations are devoted to meetings, memos, and other mechanisms for the transmission of information up and down the bureaucracy.

Even when posed in abstract form, problems of this sort are intractably difficult mathematically. Perhaps the most famous example is the "traveling salesman problem." A salesman has the task of visiting each of the cities in his territory and then returning to his

---

[5] A comprehensive review of the bounded rationality literature is given by Conlisk (1996).

[6] For a starting point to the literature on behavioral economics, see the Russell Sage Foundation Project Review (http://www.russellsage.org/programs/proj_reviews/behavioral.htm). For behavioral finance, see Barberis and Thaler (2002).

starting point. The distance (or cost of traveling) between each pair of cities is known. What route minimizes the total cost of travel? This problem is quite easy to state and obviously corresponds to a practical management issue, yet it is an instance of one of the most difficult outstanding problems in mathematics. While approximations can be made, an algorithm that would determine the optimal solution in a length of time that grows only "polynomially" with the number of cities has yet to be found (and is widely believed to be impossible to find).[7] An indication of the difficulty of this problem is that the Clay Mathematics Institute has offered a $1 million prize for a valid proof of a polynomial-time algorithm (or for a demonstration that no such algorithm can be found in the general case).[8]

A strong implication is that there is no way around the limits that "bounded rationality" place on human economic activity. The finite processing capacities of individuals are mirrored in computational limits on the decision-making of firms. In addition to dealing with principal/agent and control problems, management must cope with the reality that only approximate solutions can be found to many practical operations problems. To formulate such problems as calculus maximization problems that can be solved exactly does violence to the underlying reality. Mathematical models that accurately represent the kinds of decisions industrial managers must make will necessarily reflect these limitations.

The Evidence

The discussion to this point has been largely theoretical. Yet there is also a substantial body of evidence that attests to the fact that firms and other productive organizations fall short of complete optimization. The most obvious and compelling evidence is our own personal experience working in organizations. Each person has direct knowledge of the ways his or her own firm (or university, government agency, or non-profit group) could improve its performance. "Bureaucracy" is a ubiquitous epithet, despite the fact that hierarchies and formal decision-making procedures are necessary to the functioning of modern complex organizations. Knowing that bureaucracies give rise to various kinds of inefficiencies does not mean that we could get along without them.

Formal empirical literature on the measurement of efficiency (or inefficiency) is also extensive. One strand centers on the concept of "X-efficiency" (and its companion "X-inefficiency) that was introduced by Harvey Leibenstein in a series of papers beginning in 1966. Leibenstein contrasted "X-efficiency" (management or organizational efficiency)[9] with allocative efficiency (the traditional kind of efficiency in which, for example, marginal factor productivities are equated to factor prices). He concluded that X-efficiency is more important than allocative efficiency in determining profitability.[10] Leibenstein's initial paper contained a large body of information (drawn from surveys of industrial establishments, the

---

[7] This means that if T is the running time of the algorithm on a standard computer and N is the number of cities, T grows no faster than some polynomial function of N. (Polynomial functions are functions involving sums of terms like N^a, where a is an integer.) An example of a function that is not polynomial in N is an exponential function such as $2N$.

[8] For details, and a more general statement of the problem, see www.claymath.org/prizeproblems/index.htm.

[9] Leibenstein identifies three elements as being "significant in determining…X-efficiency: (1) intra-plant motivational efficiency, (2) external motivational efficiency, and (3) nonmarket input efficiency" (Leibenstein 1966, pp. 406-407).

[10] Leibenstein's papers through 1989 have been collected in Button (1989), but Leibenstein continued to explore the issues through the 1990s (Leibenstein and Maital, 1992, 1994).

lag time between invention and the adoption of new technologies, and the return to management consulting services) that supported his theoretical argument. The concept and measurement of technical efficiency has been generalized through application of "Data Envelopment Analysis" (DEA). This technique measures the distance of a firm or facility from its potential production-possibilities frontier by benchmarking the facility against the most efficient facilities in the same industry. As currently practiced, DEA identifies the efficient facilities by means of a linear programming calculation of the minimum combination of inputs sufficient to produce various combinations of output, as indicated by the input and output data of firms currently in the market. Even though this represents a lower bound on efficient combinations (it is always possible that techniques more efficient than any currently seen in the market are feasible), DEA provides a standardized way to compare the technical efficiencies of a set of facilities.

The DEA technique was originally introduced in the 1950s (Koopmans 1951; Farrell 1957), but several modern treatments are available (Cooper, Seiford, and Tone 2000; Charnes et al. 1994; Sengupta 1995). The empirical DEA literature is extensive; the CD-ROM bibliography (Seiford 2000) accompanying Cooper et al. (2000) covering the period 1978 through September 1999, contains over 1,500 entries, excluding technical reports and working papers. A recent non-systematic compilation of 26 such studies revealed an average efficiency level of 86% (compared to the efficiency of firms on the DEA production-possibilities frontier of 100%) (DeCanio 1997).

DEA is not the only approach to the measurement of relative efficiency. For example, Marc Ross and his colleagues at the University of Michigan have developed the Long-term Industrial Energy Forecasting (LIEF) model that has established a so-called efficiency gap — in effect, the difference between average and best practice — that ranges as high as 40 percent.[11] In light of all these indications of the failure of firms to optimize, the question needs to be asked: "How can standard economic models ignore such extensive and diverse evidence in favor of an unsubstantiated preference for the unadorned profit maximization model of firms and production?"

Evolutionary Models of Production and Markets

If the representation of production in energy/economic models is to progress beyond the "profit maximization subject to the production function" characterization, new approaches need to be incorporated into the modeling framework. There is room for improvement both in how the internal decision-making of firms is characterized and in the portrayal of market dynamics. Modern computational tools show promise for representing both elements in an evolutionary perspective.[12] A suitable model has to have two elements: (1) a population of firms, with some characterization of the decision processes of those firms, and (2) specification of the dynamics through which market pressures shape the evolutionary process. Why many firms? A standard optimizing model will show perhaps 35 sectors of the

[11] See, Ross et al (1993) for the background and development of the LIEF model, and Cleetus et al (2003) for an updated treatment and use of the model. Førsund (1999) contains a discussion of other methodologies to measure relative efficiency.

[12] For what is still the best general introduction to evolutionary models in economics, see Nelson and Winter (1982). For an historical treatment, see Hodgson (1997). For a description of both the overlapping elements and differences in the traditions of evolutionary biology and neoclassical economics see Krugman (1996).

economy, with only one typical "firm" representing each sector. In other words, in the standard models there is the equivalent of a "representative agent" deciding on all matters affecting each sector. Moreover, the only basis for decisions within a given sector is the information contained in the prices faced by the sector.

But relying on the purely mathematical convenience of a representative agent is to abstract away from the diversity of the industrial economy — a social system in which there are more than 1.1 million industrial establishments and 25 million people employed in those establishments. Decisions are made within those and other organizations that affect more than more than $1.2 trillion in annual capital expenditures.[13] The preferences, expectations, and other characteristics of individual firms affect their investment choices and the consequent impact on aggregate energy use. Assuming that an average firm will adequately represent the spectrum of behaviors and investment choices unnecessarily limits the full set of choices. Perhaps just as important, it will provide little insight into the range of policies that might positively impact both energy use and the output or profitability of individual firms. Thus, if we break from the modeling limitations of a representative agent who makes average decisions based on prices alone, we may be able to explore a richer set of opportunities for industrial energy users and policy makers.

One way to represent the diversity of firms is to simulate the dynamics of the population of firms with a Genetic Algorithm (GA). This is a technique that has found application in widespread areas. It can be used to search a large and complicated parameter space for good solutions to optimization problems. For example, using Sun Microsystems workstations, researchers at the University of Wisconsin's Energy Research Center employed a genetic algorithm to design truck engines that pollute less while also consuming less energy. Usually, the engineers will optimize system design for either fuel efficiency or for reduced pollution levels, but the genetic algorithm was able to help engineers simultaneously improve both attributes. The new engine design cut nitric-oxide emissions by three times and soot emissions by 50 percent while simultaneously reducing fuel consumption by 15 percent (Colin 2000).

The GA technique can also be used to create a more general model of industrial dynamics. The GA begins with a population of entities (stylized representations of firms in a particular sector, for example) and mimics biological evolution by allowing those entities to mutate, merge, and adopt some of the characteristics of the other members of the population, all the while allowing the more fit members of the population to have a differential advantage in survival and/or in passing their characteristics on to members of succeeding generations of the population. What is required is a scheme to encode the "genetic information" of the firms (their operating procedures, decision-making rules, organizational structures, etc.). The algorithm creates "offspring" of the parent entities through mutation and exchange of genetic information (analogous to what happens in biological sexual reproduction), subjecting the entire population to selection pressure over time (see Holland 1975; Goldberg 1989; and Mitchell 1996 for standard treatments of the computational techniques).

To provide a sketch of how this search technique might work for industrial energy models, suppose we initialize a relatively large number of firms with a variety of characteristics. These may include organizational structure, capacity for learning by doing, expectations formation mechanisms, and other elements that affect investment decisions. Each of these characteristics might be encoded in a set of bits that form a larger

[13] See Tables 601, 714, and 736 in the *U.S. Statistical Abstract* (U.S. Census Bureau 2002)

"chromosome" embodying the particular characteristics of the firm. Fitness of the organization is determined by normal profitability conditions that depend on how the firm responds to external market conditions. Two members of this evolving population can produce an offspring by "crossover" exchange of genetic information. This is illustrated in Figure 1 below.

Figure 1. Chromosomes of Two Parents and Offspring

Genes	***a***	***b***	***c***	***d***	***e***	***f***	***g***	***h***	***i***	***j***	***k***	***l***	***m***	***n***
Firm 1	***1***	***0***	***0***	***0***	***0***	0	0	1	0	0	0	0	0	1
Firm 2	1	1	1	0	0	***1***	***0***	***1***	***0***	***0***	***0***	***1***	***1***	***0***
Offspring	***1***	***0***	***0***	***0***	***0***	***1***	***0***	***1***	***0***	***0***	***0***	***1***	***1***	***0***

In this example, each gene on the 14-bit chromosome indicates a specific condition or characteristic of the firm that shapes decisions about energy investments. For example, gene ***a*** might represent whether the firm uses NPV or payback to evaluate investments (with "1" coding the use of NPV and "0" the use of simple payback); gene ***b*** could represent whether the firm uses in-house forecasting of future market conditions or contracts it out to a consulting firm; gene ***c*** might indicate whether the firm behaves in a risk-neutral or risk-averse manner in evaluating the projects, etc. A string of genes might represent the organizational structure of the firm, using the elements of the adjacency matrix of the firm's network structure to map out the communications links (see DeCanio et al. (2000) for an illustration of how this can be done). If these two firms are selected to reproduce (via merger, buyout, or spinoff) because their fitness is relatively high compared to the other firms in the population, the resulting offspring organization could be as shown. The offspring takes genes ***a*** through ***e*** from Firm 1 and genes ***f*** through ***n*** from Firm 2. (These are indicated in bold italics in Figure 1.) The genetic algorithm operates on the whole population of organizations, differentially selecting members of the population for reproduction according to their relative fitness (profitability), creating new firms over time as illustrated in Figure 1, and repeats the steps in each successive generation. Mutations can also occur at random if genes are probabilistically switched.

Models of this type have the great advantage that they can be used to study the behavior of *populations* of firms, not just the equilibrium conditions for a representative firm. The first consequence is that it becomes possible to analyze the distributions of various characteristics in the evolving population. Evolving populations can be expected to display varying levels of profitability (or technical efficiency), just as we observe among firms in the real world.

A number of promising results have been derived using this type of framework. Consider the problem of searching for the best organizational structure. Amir-Atefi (2001) has explored a simulation model in which some of the firms search over the entire space of potential structures, while others restrict their search to "divisional" structures only. He finds that although it is known that the optimal structure must lie in the unrestricted search space, the firms that restrict their search may gain enough of a temporary advantage (because they evolve more quickly) to drive the unrestricted searchers out of the market. This can result in a permanent inefficiency, at least until some kind of shock or policy signal would open up a wider range of possible structures for examination. Some such mechanism may account for the widespread adoption of the divisional corporate form.

Similarly, DeCanio et al. (2001) developed a model in which firms perform two stylized tasks, one corresponding to the adoption of a profitable energy-saving innovation and the other corresponding to assembly of a finished product. The most surprising result was that alternative organizational structures could produce almost identical net fitness (profitability). In particular, two different organizational forms emerged as high performers: one in which total costs were relatively high but performance (gross revenue) from both the assembly and energy-efficiency investment tasks was also high, and the other in which the revenues from both tasks were relatively low but total costs were also low. In other words, the market could support equally well a "high cost, high performance" and a "low cost, low performance" solution to the competitive puzzle. This outcome is quite suggestive of the "Porter hypothesis" that improved environmental performance brought on by appropriate regulations need not have an adverse impact on profitability or productivity (Porter 1991, Porter and van der Velde 1995).

Using a different framework, Mitchell (2001) shows how an evolutionary process by which agents choose their degree of connectedness to other agents may or may not lead to optimal network configurations, depending on the initial conditions and the property-rights features of the costs and benefits of technology adoption. Mitchell's model is in the tradition of evolutionary game theory (Weibull 1995), while those of Amir-Atefi and DeCanio et al. have kinship with the "organizational demography" literature (Carroll and Hannan 2000).

Conclusions and Policy Implications

A clear implication of the modern theory of the firm, the empirical evidence on relative efficiencies of firms, and the properties of evolutionary models is that the assumption of optimization should be questioned and, in some cases, abandoned. There is no scientific reason to presume that the technology choices of firms could not be improved in such a way as to increase both their energy efficiency and their economic performance. Of course, to say that there is room for improvement is not the same thing as saying that such improvements can come easily or automatically. Management faces a series of tests, generated by competitive market pressures, changes in the legal and regulatory environment, and the opportunities afforded by technological progress, and making decisions about energy investments is just one element of that set.

This perspective also has policy implications. If optimization cannot be assumed, the range of potential policies that can provide net social and economic benefits is widened. Price (which can be affected mainly through the tax structure) is no longer the only channel through which policies can be effective. Measures that increase the salience of energy efficiency, voluntary pollution-prevention programs, labeling, smart standards, government demonstrations, information-gathering initiatives, and the facilitation of inter-firm and interpersonal networking[14] are examples of the extended set of possibilities. The presence of path dependence and the persistence of random effects in evolutionary models means that *early action* to change the course of technological development may have effects that are amplified over time.

[14] See Canan and Reichman (2002) for an analysis of the importance of leadership and intragroup network structures in the success of the Montreal Protocol on Substances that Deplete the Ozone Layer.

The key is to avoid modeling choices that abstract from essential features of the system being studied. Representative agent models that rule out the irreducible diversity of industrial firms cannot be expected to yield reliable or informative predictions. The assumption of optimization, while useful in some settings because it provides restrictions that have testable implications, should not be maintained in the face of overwhelming evidence to the contrary. Doing so undermines the credibility of the modeler, and detracts from the weight that might properly be given to model results. A refocusing of theoretical attention to the tangible realities of industrial behavior will be difficult, and may require years of effort before yielding sharp numerical results. However, these disadvantages are far outweighed by the gain in reliability and realism that would accompany such an effort.

References

Alchian, Armen A., 1950. "Uncertainty, Evolution, and Economic Theory," *Journal of Political Economy*, Vol. 58, No. 3 (June): 211-221.

Amir-Atefi, Keyvan, 2001. "Bounded Rationality, Rules of Thumb, and Organizational Design," unpublished manuscript, 2001 (October 16).

Antle, Rick, and Gary D. Eppen, 1985. "Capital rationing and organizational slack in capital budgeting," *Management Science*, Vol. 31, No. 2 (February): 163-174.

Arrow, Kenneth J., 1951. *Social Choice and Individual Values*. New York: John Wiley & Sons.

Barberis, Nicholas, and Richard Thaler, 2002. "A Survey of Behavioral Finance," NBER Working Paper 9222. Cambridge, MA: National Bureau of Economic Research.

Berle, Adolf A., and Gardiner C. Means, 1932. *The Modern Corporation and Private Property*. New York: The MacMillan Company.

Brynjolfsson, Erik, and Loren Hitt, 1996. "Paradox Lost? Firm-Level Evidence on the Returns to Information Systems Spending," *Management Science,* 42(4), 541-558.

Button, Kenneth, ed., 1989. *The collected essays of Harvey Leibenstein. Volume 2. X-efficiency and micro-micro theory*. Aldershot: Elgar.

Canan, Penelope, and Nancy Reichman, 2001. *Ozone Connections: Expert Networks in Global Environmental Governance.* Sheffield, UK: Greenleaf Publishing.

Charnes, A., W.W. Cooper, A.Y. Lewin, and L.M. Seiford, 1994. *Data Envelopment Analysis: Theory, Methodology and Applications*. Norwell, MA: Kluwer Academic Publishers.

Cleetus, Rachel, Stephen Bernow, Neal Elliott, Anna Shipley, and Elizabeth Brown, 2003. "Explorations with the LIEF 2002 Model," *Proceedings of the 2002 ACEEE Summer*

Study on Industrial Energy Efficiency, American Council for an Energy Efficient Economy, Washington, DC.

Coase, R., 1937. "On the nature of the firm," *Economica*, n.s. 4(16): 386-405.

Colin, J., R. 2000. "Genetic algorithms design low-emission engine," *EETimes*. www.eetimes.com/story/OEG2000630S0041. Accessed August 12, 2000.

Conlisk, J., 1996. "Why Bounded Rationality?" *Journal of Economic Literature*, Vol. 34, No. 2: 669-700.

Cooper, William W., Lawrence M. Seiford, and Kaoru Tone, 2000. *Data Envelopment Analysis: A Comprehensive Text with Models, Applications, References and DEA-Solver Software*. Boston: Kluwer Academic Publishers.

DeCanio, Stephen J., 1993. "Barriers within firms to energy-efficient investments," *Energy Policy*, Vol. 21, No. 9 (September): 906-914.

_____________, 1994a. "Agency and Control Problems in U.S. Corporations: The Case of Energy-efficient Investment Projects," *Journal of the Economics of Business*, Vol. 1, No. 1: 105-123.

_____________, 1994b. "Why Do Profitable Energy-Saving Investment Projects Languish?" Journal of General Management, Vol. 20, No. 1 (Autumn): 62-71.

_____________, 1994c. "Energy Efficiency and Managerial Performance: Improving Profitability While Reducing Greenhouse Gas Emissions," in David L. Feldman, ed., *Global Climate Change and Public Policy*. Chicago: Nelson-Hall Publishers.

_____________, 1997. "Economic Modeling and the False Tradeoff Between Environmental Protection and Economic Growth," *Contemporary Economic Policy*, Vol. 15: 10-27.

____________, 1998. "The efficiency paradox: bureaucratic and organizational barriers to profitable energy-saving investments," *Energy Policy*, Vol. 26, No. 5: 441-454.

_____________, 1999. "Estimating the Non-Environmental Consequences of Greenhouse Gas Reductions Is Harder Than You Think," *Contemporary Economic Policy*, Vol. 17, No. 1 (July): 279-295.

_____________, 2000. "The Organizational Structure of Firms and Economic Models of Climate Policy," in Stephen J. DeCanio, Richard B. Howarth, Alan H. Sanstad, Stephen H. Schneider, and Starley L. Thompson, *New Directions in the Economics and Integrated Assessment of Global Climate Change*. Washington: Pew Center on Global Climate Change.

_____________, 2003. *Economic Models of Climate Change: A Critique*. Basingstoke, UK: Palgrave-Macmillan (forthcoming).

DeCanio, Stephen J., and William E. Watkins, 1998. "Information Processing and Organizational Structure," *Journal of Economic Behavior and Organization*, Vol. 36, No. 3 (August 1998): 275-294.

DeCanio, Stephen J., Catherine Dibble, and Keyvan Amir-Atefi, 2000. "The Importance of Organizational Structure for the Adoption of Innovations," *Management Science*, Vol. 46, No. 10 (October 2000): 1285-1299.

DeCanio, Stephen J., Catherine Dibble, and Keyvan Amir-Atefi, 2001. "Organizational Structure and the Behavior of Firms: Implications for Integrated Assessment," *Climatic Change* 48: 487-514.

DeCanio, Stephen J., William E. Watkins, Glenn Mitchell, Keyvan Amir-Atefi, and Catherine Dibble), 2001. "Complexity in Organizations: Consequences for Climate Policy Analysis" in *Advances in the Economics of Environmental Resources*, Vol. 3, *The Long-Term Economics of Climate Change: Beyond a Doubling of Greenhouse Gas Concentrations*, eds. Darwin C. Hall and Richard B. Howarth. Amsterdam: JAI/Elsevier Science.

Farrell, M.J., 1957. "The Measurement of Productive Efficiency," *Journal of the Royal Statistical Society, Series A*, Vol. 120, No. Part 3: 253-290.

Førsund, F.R., 1999. "The Evolution of DEA – The Economics Perspective," paper presented to the Sixth European Workshop on Efficiency and Productivity. Copenhagen, 29-31 October.

Friedman, Milton, 1953. *Essays in Positive Economics*. Chicago: University of Chicago Press.

Garey, Michael R., and David S. Johnson, 1979 [updated 1991]. *Computers and Intractability: A Guide to the Theory of NP-Completeness*. New York: Freeman.

Goldberg, David E., 1989. *Genetic Algorithms in Search, Optimization, and Machine Learning*. Menlo Park, CA: Addison-Wesley Publishing Company, Inc.

Hannan, Michael T., and John Freeman, 1989. *Organizational Ecology*. Cambridge: Harvard University Press.

Hodgson, Geoffrey M., 1997. *Economics and Evolution: Bringing Life Back into Economics*. Ann Arbor: University of Michigan Press.

Holland, J.H., 1975. *Adaptation in natural and artificial systems*. Ann Arbor: University of Michigan Press.

Jensen, Michael C., and William H. Meckling, 1976. "Theory of the firm: managerial behavior, agency costs and ownership structure," *Journal of Financial Economics*, Vol. 3, No. 4 (October): 305-360.

Koopmans, T.C., 1951. "Analysis of Production as an Efficient Combination of Activities," in T.C. Koopmans, ed., *Activity Analysis of Production and Allocation*. New York: Wiley.

Krugman, Paul, 1996. "What Economists Can Learn from Evolutionary Theorists," talk given to the European Association for Evolutionary Political Economy (November). http://web.mit.edu/krugman/www/evolute.html (accessed 5/8/03)

Laitner, John A. "Skip," Stephen J. DeCanio, and Irene Peters, 2000. "Incorporating Behavioral, Social, and Organizational Phenomena in the Assessment of Climate Change Mitigation Options," in *Society, behavior, and climate change mitigation,* eds. E. Jochem, D. Bouille, and J. Sathaye. New York: Kluwer Academic Press.

Leibenstein, Harvey, 1966. "Allocative Efficiency vs. 'X-efficiency,'" *American Economic Review*, Vol. 56, No. 3 (June): 392-415.

Leibenstein, Harvey, and Shlomo Maital, 1992. "Empirical Estimation and Partitioning of X-Inefficiency: A Data-Envelopment Approach," *American Economic Review*, Vol. 82, No. 2 (May): 428-33.

_____________, 1994. "The Organizational Foundations of X-Inefficiency: A Game-Theoretic Interpretation of Argyris' Model of Organizational Learning," *Journal of Economic Behavior and Organization*, Vol. 23, No. 3 (May): 251-68.

Mitchell, Glenn T., 2001. "Evolution of Networks and The Diffusion of New Technology," Chapter 1 of Ph.D. dissertation "Technology, Energy and the Environment," University of California, Santa Barbara, 2001.

Mitchell, Melanie, 1996. *An Introduction to Genetic Algorithms (Complex Adaptive Systems)*. Cambridge, MA: MIT Press.

Nelson, Richard R., and Sidney G. Winter, 1982. *An Evolutionary Theory of Economic Change*. Cambridge: The Belknap Press of Harvard University Press.

Nelson, Richard R., 1995. "Recent Evolutionary Theorizing About Economic Change," *Journal of Economic Literature*, Vol. 33, No. 1 (March): 48-90.

Olson, Mancur, Jr. 1965. *The Logic of Collective Action: Public Goods and the Theory of Groups*. Cambridge, Mass., Harvard University Press.

Papadimitriou, Christos H., 1996. "Computational Aspects of Organization Theory (Extended Abstract)," in Josep Diaz and Maria Serna, eds., *Algorithms – ESA '96:*

Fourth Annual European Symposium, Barcelona, Spain, September 1996 Proceedings. New York: Springer.

Porter, Michael E., 1991. "America's Green Strategy: Environmental Standards and Competitiveness," *Scientific American*, Vol. 264, No. 4 (April): 168.

Porter, Michael E., and Claas van der Linde, 1995. "Green and Competitive: Breaking the Stalemate," *Harvard Business Review*, Vol. 73, No. 5 (September-October): 120-134.

Robinson, Joan, 1953. "The Production Function and the Theory of Capital," *Review of Economic Studies*, Vol. 21, No. 2 (1953-54): 81-106.

Ross, M., P. Thimmapuram, R. Fisher, and W. Macioroski. *Long-Term Industrial Energy Forecasting (LIEF) Model (18-Sector Version)*, ANL/EAIS/TM-95, Argonne National Laboratory, May.

Seiford, Lawrence M., 2000. "A Cyber-Bibliography for Data Envelopment Analysis (1978-1999) (September, 1999)," in Cooper et al., 2000, *Data Envelopment Analysis: A Comprehensive Text with Models, Applications, References and DEA-Solver Software*. Boston: Kluwer Academic Publishers.

Sengupta, Jati K., 1995. *Dynamics of Data Envelopment Analysis: Theory of Systems Efficiency*. Dordrecht: Kluwer Academic Publishers.

Simon, Herbert A., 1963. "Discussion," *American Economic Review*, Vol. 53, No. 2: 229-231.

Spear, Stephen E., 1989. "Learning Rational Expectations under Computability Constraints," *Econometrica*, Vol. 57, No. 4: 889-910.

U.S. Census Bureau, 2002. *Statistical Abstract of the United States: 2002*, 122nd Edition, Washington, DC.

Weibull, Jörgen W., 1995. *Evolutionary Game Theory*. Cambridge, MA: The MIT Press.