3 Technological choices and the inevitability of errors

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It seemed like a marvelous idea at the time: Grocery shoppers would use an ID card that, combined with the electronic scanners at the checkout line, would tell marketers exactly who bought what. But six years later, the effort looks as if it could turn out to be one of Citicorp’s biggest follies. The POS (for point-of-sale) Information Services unit has spent about $200 million, generated just $20 million in revenue at best and made a mess of relationships with many grocery chains and consumer goods producers.

Other direct marketers . . . saved millions of dollars in being able to see where Citicorp went wrong. (Bleakley, 1991)

My biggest mistake was failing to get Data General into the PC business. (Mr. de Castro, Chairman and co-founder of Data General Corp., quoted in Wilke, 1990)

Technology is a double-edged sword. While it can create wealth, it can also consume and destroy it. This duality strikes at the very heart of strategic management because technological changes offer firms some of the most important opportunities for revitalization. Entire industries can emerge from new technologies, as illustrated by the overnight delivery and video games businesses. At the same time, however, technological changes can threaten firms’ very existence. New technologies can make products obsolete, as illustrated by the audio cassette recorder’s superiority over phonograph records.

Despite the importance of technological change for corporate vitality, there are several instances of decision makers failing to recognize and capitalize on technological opportunities and of decision makers failing to recognize technological threats. For instance, RCA, a recognized leader in broadcasting, chose not to invest in FM technology, which was successful later (Hughes, 1989). Xerox developed the first personal computer in 1976 but decided not to commercialize it (Smith & Alexander, 1988). Sony chose not to adopt the ultimately successful VHS format for video tape recorders (Nayak & Ketteringham, 1986). In contrast, there are also several examples of firms exploiting technological opportunities. For instance, Sun Microsystems was among the first few firms in the computer industry to initiate the development of RISC chips that are now revolutionizing the computer industry (Alster, 1987; Wilke, 1992). The 3M Corporation has reaped benefits from Post-It notes as has Sony from its Walkman, despite gloomy forecasts (Nayak & Ketteringham, 1986).

These specific instances are symptomatic of a more general phenomena that we label as technological “oversights” and “foresights.” A technological oversight occurs when a firm adopts a technology that is eventually unsuccessful (for example, the unsuccessful Videodisc developed by RCA) or when a firm does not adopt a technology that is eventually successful (such as the CT scanner that was invented yet spurned by EM). In contrast, a technological foresight occurs when a firm adopts a technology that is eventually successful (Xerox’s decision to commercialize xerography) or when it does not adopt a technology that is eventually unsuccessful (several banks chose not to invest in the apparently unsuccessful point-of-sale information systems adopted by Citicorp).

We treat oversights and foresights as consequences of choices by firms to invest, or withhold investment, in a particular technology. Investment decision making is a complicated, protracted process of gathering and processing data to make, accept or reject decisions under conditions of uncertainty (Ali, Kraljic & Kovenock, 1993; Amit & Schoemaker, 1993; Galle & Shapira, 1989). Under such conditions, there is only a partial correlation between actions and outcomes. The likelihood of success of an investment in a project can be only partially predicted. Hence, one of two errors is likely to occur. First, some projects selected will turn out to be failures. Second, in retrospect it can be determined that some rejected projects would have actually been successful.

How should strategic management theories deal with these two errors? Uncertainty about future outcomes cannot be eliminated, only reduced. Therefore, these two errors can never be completely eliminated when decisions are undertaken under conditions of uncertainty. In fact, whether an error has been made is only revealed ex-post. However, it is possible to improve predictive validity (within certain limits) to aid investment decisions ex-ante. In addition, as discussed later, reducing one type of error without improving the predictive validity of project-selection mechanisms will increase the other type of error. Existing strategic-management paradigms (for example, resource-based and industry-structure views) do not address this dilemma as they ignore cognitive elements implicit in every resource-allocation process. Yet, these elements are particularly relevant in contemporary environments characterized by rapid technological change, wherein complex technologies place tremendous cognitive demands on decision makers.
We develop our argument by first offering a brief description of the extant literature on technological choices. To extend this literature, we next introduce a selection model that has previously been applied in different contexts to explore the relationships between false positives and false negatives. Next, we discuss limits to improvements in the predictability of technological outcomes and therefore the inevitability of errors. As an example of how firms may deal with the inevitability of errors, we discuss how incentives should be designed to accomplish two outcomes. First, incentives can be designed to encourage innovation-team members to learn from their mistakes and improve predictability. Second, incentives can be designed to ensure that the appropriate type of error (Type I or Type II) is minimized.

Technological choice

Technology-choice issues are becoming increasingly important in contemporary environments characterized by rapid technological change. In such environments, the notion of sustainable advantage is inextricably linked with a firm's ability to introduce new products. No longer can decision makers sit on their laurels by creating defensible niches through first-movement. Instead, they must continually choose between technologies. This task is made all the more difficult because of the complexity associated with modern technologies (Weick, 1990) and the rapidity with which decisions have to be made (Eisenhardt, 1989).

We suggest that the technology-choice literature can broadly be classified into three interrelated streams—the technological, the economic and the institutional. The technological perspective focuses on technical determinants—how well a technology performs in comparison to others (for example, Farrell, 1993), its future potentials (for example, Foster, 1986), and the interrelationships between form and function (for example, Petrofski, 1992). Consistent with this perspective is the “technology-push” hypothesis (for example, Comroe & Dripps, 1976), which suggests that advances in science and technology will lead to superior technologies that will most likely be adopted.

The marketing and economics perspective focuses not so much on scientific determinants but on economic ones. This perspective suggests that there are a number of strong economic issues that encourage the acceptance of certain technologies over others. These economic issues include: (1) the extent to which resources are available for any technology (for example, Kay, 1979), (2) potential returns from an investment (Bower, 1970; Brealey & Myers, 1984), and (3) the reluctance to adopt new technologies that cannibalize earlier investments (for example, Connor, 1988). Consistent with this perspective is the “market-pull” hypothesis that suggests that customer needs will shape technological choices.

Appreciating the polar extremes for the genesis of these two perspectives, many have adopted a techno-economic perspective to guide techno-

logical choices (for example, White & Graham, 1978; Freeman, 1986; Cooper, 1986). Others, who have adopted an institutional perspective, offer other social, cognitive, and political forces that shape the evolution and adoption of technologies that develop in a path-dependent, cumulative manner (David, 1985; Arthur, 1988; Powell, 1991). This perspective recognizes that institutionalized rules and practices create a context that shapes the cognition of technology champions (Garud & Rappa, 1994). Those operating within such a professionalized field choose within a set of institutional beliefs, not simply because they are the best, but because conformance confers legitimacy (Scott, 1987). Consequently, the “best technology” may not necessarily be chosen.

These viewpoints are not mutually exclusive. Technological, economic and institutional forces are all-important in determining technology assessment and adoption. We choose technologies that work, but within a “choice set” prescribed by institutionalized fields (Scott, 1991). Economic forces play a role, but have power to dislodge entrenched trajectories only occasionally (Rosenberg, 1982). Together, these forces create what have been labeled as technological trajectories (Dosi, 1982). Trajectories represent paths along which a technology develops based on previous choices and on future expectations (Dosi, 1982; Nelson & Winter, 1982). These paths build up in a cumulative manner as initial choices dictate future opportunities; some or all of the investments are irreversible and may not be easily deployed to pursue other approaches. Moreover, these paths require distinct institutionalized practices that emerge through a socio-political process.

Thus, there are significant technological, economic, and institutional forces that compels innovation makers to persist with a technological trajectory. This “stickiness” associated with these trajectories places a premium on how, what, and when we choose. An inappropriate choice of technological trajectory will result in the expenditure of considerable resources leading to an “oversight by commission.” One may argue that such an oversight by commission could be eliminated by deciding not to choose any technology at all—in itself a choice decision. But then, in this age of rapid technological change, such a course would increase “oversight by omission.” Somewhere between these two extremes we must be able to create choice rules that allows us to trade off between these two types of errors. To understand these issues, we first discuss a choice model.

False negatives and false positives in technology choices

The importance of analyzing the effects of judgmental processes and cognitive biases on strategic management has been examined by several authors (Amit & Schoemaker, 1993; Hoskisson, Hitt, & Hill, 1991; Schwenk, 1984; Zajac & Bazerman, 1991). While part of the effects stem from the underlying structure and features of the human judgmental system (Tversky & Kahneman, 1974), other potential determinants of “biased” decisions are the in-
centives and penalties associated with the outcomes of strategic decisions. Executive’s decisions in situations of uncertainty appear to be affected more by attempts to avoid failure rather than by attempts to pursue risky alternatives whose potential success can be described as only probabilistic (Shapira, 1993). When faced with the need to make decisions on risky projects, managers are worried about making one of two errors. They may accept a project that should have been rejected, or reject a project that should have been accepted.

Decision makers involved with technology choices are aware of the two potential errors and their implications for risk-taking. On the one hand there is a tendency for decision makers to behave in a risk-averse manner. Pursuing this avenue is manifested by attempts to continue building on alternatives that proved successful in the past without exploring new avenues through innovation. However, firms operating in dynamic environments soon discover that avoiding the challenge of dealing with innovations may prove dangerous. As March (1991) noted, firms often get caught in a conflict between the need to explore new opportunities and the tendency to exploit existing resources.

Consistent with March’s focus, the framework of aspirations and resources may be used to analyze intrafirm decisions as well. Following the analysis of risk perceptions and attitudes in a large sample of managers, March and Shapira (1987, 1992) developed a model that relates risk tendencies to resources and attention to a target such as an aspiration level. If decision makers perceive their resources to be below their aspiration level, their consequent behavior is likely to be risk seeking. If, on the other hand, they perceive their resources to be above their aspiration level, their behavior is likely to be risk averse.5

Suppose these decision makers consider investing in a particular project. They face an accept-or-reject decision that may lead them either to success or failure. This decision situation is best exemplified by the selection model depicted in Figure 3.1. In this project-selection decision, a critical value \( x_c \) for a predictor variable is determined such that if the ex-ante evaluation of a project yields a value \( x \) where \( x \geq x_c \), the project is accepted. A project is rejected if \( x < x_c \). After the project is complete, its performance is measured against a critical value, \( y_c \). If the ex-post realized value is equal to or greater than \( y_c \), the project is considered a success. Otherwise, the project is classified a failure. The degree to which the ex-post realization of a project is predicted by a selection criterion is referred to as the predictive validity of the model and is described by the correlation coefficient \( R_{xy} \). The ellipse in Figure 3.1 is an illustration of the boundary surrounding actual data points \( (x_i, y_i) \) where \( x_i \) is the measure of the project on the predictor variable while \( y_i \) is its subsequent performance level.

Figure 3.1 describes the four potential categories that may result from a selection decision. Two categories designate success (“positive hits” and “negative hits”) and the other two designate failure. The latter two regions, labeled as “false positives” and “false negatives,” are the most problematic for decision makers. The former designates the failure of a project that had been accepted while the latter describes the success (eventually elsewhere) of a project that had been rejected. “False positives” and “false negatives” are called Type I and Type II errors, respectively, in the statistical-inference literature.6

As Figure 3.1 suggests, the only way to minimize both types of errors is by increasing the predictive validity of the model. In the limit, when \( R_{xy} = 1 \), the ellipse turns into a straight line and both errors are eliminated. At the other end, when \( R_{xy} = 0 \), the ellipse becomes a perfect circle and predictability vanishes. In most personnel-selection studies, it has been found that \( R_{xy} \) does not exceed 0.5 (Casino, 1991), as illustrated by the elliptical boundary surrounding the data points in Figure 3.1. This limit to the improvement of predictability is illustrated by the fact that even 3M Corporation, which is an exemplar of continual innovation, is unable to perfectly predict the outcomes of its technological choices.

Managers who are driven primarily by concerns about failure may put a greater emphasis on minimizing Type I errors (i.e., false positives), since
they are visible. In contrast, Type II errors (i.e., false negatives) are often not visible, since rejected projects may not be pursued by anyone. Consequently, decision makers may choose to commit Type II errors even though these errors may be more detrimental to firms than Type I errors due to opportunity costs. Decision makers' risk tendencies are, in fact, determined by the utilities of the two errors. Important to firms are the costs associated with the two errors. At times, the costs of committing Type I errors may be more salient, since shareholers may be troubled with investments in "white elephants." However, consistent with March's (1991) notion of exploration, reducing Type II error (while increasing Type I error) may be the right avenue in many situations characterized by rapid change and innovation.

Minimizing Type I error can be achieved by putting a higher hurdle on the decision criteria. This is exemplified by the line labeled \( x_0 \) (where \( x_0 > x_e \)) in Figure 3.2. By shifting \( x_e \) to the right of its position in Figure 3.1, the area designated "false positives" is smaller but the area representing "false negatives" is larger in comparison to the same areas in Figure 3.1. Similarly, Type II errors would be reduced if \( x_e \) is moved to the left of its position in Figure 3.1. However, note that the area depicting the sum of Type I and Type II errors does not decrease by mere changes in the value of \( x_e \). Shifting

\[ y \text{ (performance)} \]

\[ \text{"Success"} \quad (y \geq y_e) \]

\[ y_e \]

\[ \text{False Negatives} \]

\[ \text{Positive Hits} \]

\[ \text{"Failure"} \quad (y < y_e) \]

\[ y \]

\[ \text{False Positives} \]

\[ \text{Negative Hits} \]

\[ \text{Reject} \quad (x < x_e) \]

\[ x_e \]

\[ x_0 \]

\[ \text{Accept} \quad (x \geq x_0) \]

Figure 3.2. Project selection and variations in decision criteria.

\[ x_e \] changes only the relative frequencies of the two errors, namely, following a shift in \( x_e \), one error goes down but the other goes up.

It is not possible, therefore, to reduce both errors by merely changing the decision criteria, \( x_e \). It should also be noted that simply restricting the range on the predictor variable (\( x \)) by considering a narrow range of projects will also not reduce errors. The probability of committing either a Type I or a Type II error is a function of the area that falls into the false-positive or false-negative regions, respectively, relative to the total area of the ellipse. Thus, reducing the total area of the ellipse does not necessarily decrease the relative area of the two errors. On the contrary, since predictive validity is measured by the correlation coefficient \( R_{xy} \) restricting the range of \( x \) (for example, by constraining the set of projects being considered) will result in a lower \( R_{xy} \). This is due to the fact that correlation is actually a standardized covariation measure. If the variance of one of the variables is reduced, covariation is reduced as well. This phenomenon is labeled "restriction of range" and may actually lead to more (rather than less) error.

This discussion should not be confused with the desire to reduce variance for better measurement. In the selection model, an observed score is a combination of a true score and an error term. Reducing the variance of the error term is highly desirable. However, merely restricting the range of the observed score will not reduce error variance. In the extreme case, if all projects get exactly the same score (that is, variance is zero), the correlation between project scores and any other measure is zero. In sum, the only way to reduce both errors is by increasing the predictive validity of the model (\( R_{xy} \)). This can be achieved by collecting data and refining the measures used, not by arbitrary moves of the decision criterion \( x_e \).

**Applying the model**

Several considerations are important in applying the model in technology-choice decisions. Appropriate measures are required to discriminate between projects that should be accepted from those that should be rejected. Similarly, appropriate measures are required to discriminate between success and failure. While it may be easier to employ a common measure across time, the realities of the technology-development process compel decision makers to choose measures that are different across time. This is because selection measures are used to help in resource allocation among competing technologies. Later, other measures are often used to gauge the success of a project in comparison to competition. For example, net present value (NPV) and internal rate of return (IRR) are well accepted selection measures for evaluating projects (Brealey & Myers, 1984). In contrast, return on investment (ROI), profitability, and market share are widely used measures of success.

In addition to choosing measures, decision makers need to choose an appropriate criterion for each measure to discriminate between the accept and
reject regions and between success and failure. Since decision makers seek to increase their ability to choose technologies that are likely to be successful, they also need to establish the relationship between selection criteria and indicators of success.

In the context of evaluating technological projects in organizations, decision makers frequently lack ex-ante criteria that are valid predictors of future success. Confronting this challenge, decision makers frequently employ the same criterion that they would use to measure the success of the project ex-post, and make an estimation of the projects' performance in the future to make accept-or-reject decisions. This practice is inappropriate for two reasons: judgmental and political. First, it is problematic vis-a-vis the nature of the selection model. In this model, we proposed identifying predictors that can be used to predict future success. By using estimates of future ROI, we rely on the judgment of the persons making the estimate. Their estimate is based on some other underlying variables (such as expertise and reputation of the project team). In a sense, they are integrating information on these variables to produce the estimate. However, it has been shown (Dawes & Corrigan, 1974) that humans do a poor job of information integration (and hence of forecasting). Therefore, using the actual underlying variables may be a more reliable way of establishing a selection measure. If, however, a single selection criterion is needed, the ranking of projects by a few evaluators could be more reliable than ROI estimates.

Second, using the same criterion ex-ante and ex-post may lead to political games between top management and project sponsors. Decision makers and project proposers may represent the value of a project differently (Bower, 1970; Williamson, 1975). For instance, project proposers may be overly optimistic and aggressive in promoting the benefits of their project while being blind to or silent about the potential costs involved. In anticipation of this possibility, those who evaluate projects for funding may discount claims made by project proposers. The traditional way to accomplish this is by placing higher hurdles on the selection criteria (Brealey and Myers, 1984).

However, there are situations in which it is beneficial to have relaxed selection criteria. These are situations in which an individual project proposal would by itself appear nebulous and be unattractive on any criterion. But a collectivity of such nebulous proposals may lead to the creation of significant technological breakthroughs. As Nelson (1959) pointed out, this is frequently the case when considering advances in basic science. The problem here is one of motivating researchers to pursue activities that individually would not meet overall corporate-investment criteria. Under these conditions, setting selection criteria that are less strict than success criteria would increase the flow of proposals.

The practice of encouraging "bootlegging" among researchers at firms such as 3M and Hitachi illustrates how these criteria may be chosen to foster innovation. These firms have implicitly set \( x_1 = 0 \) for a portion of each researcher's time. For instance, researchers at 3M are permitted to pursue any project they desire for up to 15% of their time. The success of 3M at introducing a stream of new and innovative products attests to the value of such a strategy.

**Limits to predictability and the inevitability of errors**

Realizing that errors are inevitable, decision makers may undertake two initiatives. First, they may try to learn from their mistakes to reduce the number of errors in the future. Second, they may trade off one type of error at the expense of the other, depending upon the technology context they confront. We discuss these two initiatives in greater detail below.

**Learning from mistakes**

The sum of the two errors can be reduced by increasing the predictive validity of the criterion chosen to accept or reject projects. To accomplish this, decision makers need to establish a relationship between selection criteria (for example, NPV or IRR) and measures of success (for example, ROI or market share). Once this is accomplished, decision makers can be more confident in their ability to accept or reject a project based on an estimate of NPV or IRR, as the case may be. Ideally, of course, selection measures should be perfectly correlated with measures of success. Since this is seldom the case in practice, decision makers should collect historical data on previous accept-or-reject decision criteria and the outcomes of projects funded and not funded. If these experiments using different values of the selection criteria to establish the level of correlation between selection and success measures in their experience.

Such experimentation may seem unusual to an uninformed observer and it may suggest a somewhat arbitrary decision-making process, since decision criteria would appear to shift idiosyncratically. To ensure that such experiments are not perceived as reflecting an arbitrary decision-making process, it is important to clarify that experiments will be undertaken to gather data to improve the decision-making process. By this means, the predictive validity of selection criteria could be improved.

As we are dealing with decisions in situations where there is considerable uncertainty, improving predictability may not be easy. Most likely, the conflict between the two risk tendencies (risk seeking versus risk averse) and the two judgmental errors (Type I versus Type II) may be present most of the time, highlighting the dual nature of technology-development decisions. However, since we advocate a dynamic framework, learning from the past becomes important. Collecting data and experimenting may be necessary to counteract the tendencies to search for confirming evidence only (Einhorn & Hogarth, 1978), and to fall prey to reasoning by hindsight (Fischhoff, 1975). Data on all four quadrants of Figure 3.1 are needed for learning and for improving predictability. Obviously, there are other vari-
ablees that can confound learning. For instance, a project that is selected may get considerable funding it would otherwise not have received, thereby increasing the chances for its success beyond what would be predicted by the model. This may lead to what Einhorn and Hogarth (1976) called a “treatment effect,” which may hinder our ability to improve judgmental predictability. For instance, Hirsch (1972) demonstrated that predicting successful records in the music-publishing industry is extremely difficult; since records that get selected initially are given tremendous publicity (a treatment effect). Nevertheless, in this industry, Type II errors cannot be ignored, since rejected records often get produced by other firms and, therefore, become visible.

Trade-offs between errors

Decision makers can make trade-offs between Type I and Type II errors through their choice of decision criteria and incentive schemes. This trade-off depends upon the technological context surrounding choices. For instance, several scholars suggest two broad technological contexts—an era of ferment, wherein multiple technological approaches exist, and an era of incremental change, wherein technological activities take on the form of product elaboration and improvements (Anderson & Tushman, 1990; Utterback & Abernathy, 1975). The era of ferment is characterized by the presence of a number of alternative trajectories (Dosi, 1982), each one of which could eventually be successful. Each trajectory incorporates designs that emphasize certain dimensions of technological merit while compromising on others (Tushman & Rosenkopf, 1992).

Since information about these technological trajectories increases over time, it might be argued that decision makers within firms could postpone their technology adoption decisions. There are, however, other aspects of technological change that drive firms to choose from technological trajectories even during the presence of multiple trajectories that offer conflicting benefits. First, technology develops in a cumulative fashion, making it increasingly difficult over time for a firm to enter into a technology race begun by others. Second, technological opportunities dwindle over time as technology options become fewer and as specialized assets required for the successful commercialization of the technology are foreclosed (Teece, 1987). As a result, postponing technology-adoption decisions may lock out a firm from a technological field (Cohen & Levinthal, 1990; Ghemawat, 1991).

Thus, the timing of technology-choice decisions is a key issue. Very early choices may not provide the opportunity to generate organizational intelligence about alternative trajectories, thereby locking in the firm to a trajectory early in the development of a technology. Very late choices, on the other hand, may lock out a firm. Consequently, there is a window of opportunity within which firms must decide on the specific technological trajectory they wish to pursue. During this window of opportunity, the firm may wish to generate information about various trajectories so as to make an informed choice. This requires that managers encourage researchers to take risks in order to explore alternative paths, even though only one of them will eventually be chosen. Besides enhancing organizational intelligence, exploring alternative paths also hedges the firm’s bets by creating options that it might pursue in the future when information about trajectories increases. In the context of our framework, this implies minimizing Type II errors—encouraging risk taking and exploration.

For example, in supercomputing, IBM and Cray Research are both actively developing three different technologies: vector machines, massively parallel processors, and workstation clusters. Seymour Cray, the founder of Cray Research, believed, however, that “his company’s decision to bet on MPP simply ‘diluted’ its support for future vector-processor machines” (Mitchell, 1993, pp. 80–90). In new audio recording and playback technologies, Sony has hedged its bets by licensing Philips’ Digital Compact Cassette technology and by promising to sell digital cassettes even as it continues to develop its own Mini Disc technology (Therrien, 1992). In the development of the videocassette recorder, “the successive heads of RCA research for years had to orchestrate a competition between several videocassette technologies inside the Laboratories, unsure which one would, or should, win out . . . each element of the system could be approached in several possible ways” (Graham, 1986, pp. 5–15).

An era of incremental change follows the era of ferment. During this era, the direction of technical change is relatively more predictable. For firms, a challenge during the era of incremental technological change is one of appropriating the benefits that a technology offers (Ghemawat, 1991; Teece, 1987). Although a firm may have “picked the winner,” its ability to benefit from a technology may be compromised if rival firms enter the industry with substitute products. Firms confront this challenge by engaging in activities that improve product performance and process efficiencies. Technological choices now are between alternative courses of action within a path that improve its performance and quality and reduce its cost. That is, there is inadequate knowledge of how path-specific outcomes can be accomplished.

A part of this technological uncertainty is stochastic and cannot be reduced through experimentation (Nelson & Winter, 1977). However, another part of this technological uncertainty represents preliminary ignorance that can be reduced by trial-and-error learning. Trial-and-error learning is an adaptive process wherein researchers generate information that guides their future actions. As cost reduction is important during this stage of technology development, an important consideration during this trial-and-error learning process is to avoid alternatives that consume more resources than they save. This suggests that the type of decisions made during the era of incremental change would be different from those made during the era of
ferment. In particular, during the era of incremental change, most of a firm’s resources should be allocated to exploit its relative advantage. In the context of our framework, this implies creating sequential hurdles for the chosen technology (so as to arrive at the best design). This would mean, in general, minimizing Type I errors.

In practice, determining the technological context when making a choice is a big challenge. There are many indicators—such as the presence or absence of multiple technological trajectories and the emergence of a dominant design—to help make this determination. However, this determination is not only difficult but also dangerous. Misjudging the technological context could lead to an inappropriate trade-off between Type I and Type II errors, resulting in greater technological oversights and fewer foresights.

Fortunately, we do not need clear cut-off points in time during the evolution of a technology in order to apply the proposed model. In the presence of multiple technological trajectories, the model suggests that firms must first create options by exploring alternative technological trajectories. As information about each of the alternative technological trajectories unfolds, firms can begin prioritizing and focusing their resources. Rather than selecting specific trajectories to pursue, this process is one that progressively rejects those trajectories that clearly appear not to be worth pursuing, thereby eventually narrowing a firm’s options to those that are more likely to be viable in the future.

For instance, George Poste, chairman of pharmaceutical research at SmithKline Beecham PLC, noted that “there’s a limit to how many (medical research programs) any company, no matter how large, can afford to be in” (Moore, 1992, p. 85). The company has decided to reallocate funds previously spent on gastrointestinal research among five different priority therapeutic areas. Similarly, Honda is reported as “putting 67 percent of its R&D budget into improving gas engines, 28 percent for electric vehicles, and the remaining 5 percent for more far-off possibilities, such as hydrogen and methanol” (Miller, 1992, p. 46).

Role of incentives

A contemporary view is that incentives are needed because the interests of principals and agents are often not aligned. Therefore, incentives are designed to align interests. If alignment cannot be achieved, controls are instituted to prevent any opportunistic behavior on the part of agents. These controls often take the form of indirect and direct supervision. Further, it has been widely recognized that appropriate incentives and control systems must be instituted to encourage risk-seeking and innovation. For instance, a lack of formal structure, and extrinsic and intrinsic rewards in the form of autonomy, recognition, special compensation, and dual ladders have been suggested (Galbraith & Kazanjian, 1986). Consistent with this advice, General Electric selectively rewards innovators and entrepreneurs who try and fail (Aguilar & Hammermesh, 1985). However, it appears that most managers reduce Type I errors by instituting incentive schemes that carry a more direct link to compensation (Shapira, 1994).

The literature on the role of incentive and control systems, however, does not consider which type of error should be minimized at the expense of the other through the reward system. Specifically, the conditions under which different types of risk taking should be encouraged is not addressed. Thus, to foster innovation, firms are only advised to institute systems to encourage risk taking. The model developed in this chapter shows, however, that one type of error should be encouraged while the other discouraged, depending upon the technological context. This observation has important implications for the design of appropriate incentives. For example, as Galai and Shapira (1985) have shown, it is more appropriate to seek a balance between Type I and Type II errors, namely between investment and opportunity losses, to foster a more rational approach to risk taking.

Further, not discriminating between error types may lead to some unfortunate consequences. Type I errors are visible and they are often punished. In other words, risk-seeking behavior is penalized. Witness, for example, the recent firing of three senior executives of Maytag’s Hoover unit in the United Kingdom for perceived errors in designing a sales-promotion program (Miller, 1993). In contrast, Type II errors are invisible and they often go unpunished, thereby inappropriately rewarding risk-averse behavior, as is illustrated by the long tenures of several senior managers who appear to have missed opportunities (Andrews, 1990; Wilke, 1990).

One way to try to affect executives’ strategic decisions is by structuring their incentives (and penalties) in a flexible way in terms of minimizing Type I and Type II errors. Minimizing one error versus the other may lead to differential strategies in line with the exploration and exploitation strategies. We do not argue for the advantage of one strategy over the other. Instead, our analysis suggests that the choice of strategy and the related incentive schemes depend on the technological context.

Specifically, during the era of ferment, when a number of alternative technologies are competing for predominance, decision makers need to encourage the exploration of all alternatives. In other words, Type II errors are to be reduced so that consideration of potentially promising technologies is not prematurely foreclosed. To this end, relatively greater autonomy to pursue research, and recognition for reaching-out, should be provided. In addition, incremental innovations to existing technologies should not be emphasized and may even be discouraged.

During the era of incremental change, decision makers need to encourage many incremental innovations. In other words, Type I errors are to be reduced so that corporate resources are not misdirected towards trying to develop alternatives to the already dominant technology. To this end, relatively less autonomy to pursue research is appropriate, and autonomy should be centered around the dominant technology. In addition, recog-
tion should be provided for achieving improvements in existing technologies that result in improved performance measured by, say, market share or return on investment.

**Conclusion**

Strategic-management theories focus on the creation and sustenance of wealth. New technologies, if successful, provide some of the most important sources of wealth. However, if not successful, new technologies can drain firms of their valuable resources. In this way, new technologies can act as both a source and a sink.

To explore this duality, this chapter attempts to link risk taking by decision makers to the context of technological development. First, we explored Type I and Type II decision errors and pointed out the trade-offs that exist between them. Next, we argued that decision makers can reduce the sum of the two errors. Paradoxically, this requires making errors with a view to improving the predictive validity of project-selection measures, a process that Einhorn (1986) called “accepting error to make less error.” An inadequate consideration of this fact may lead to certain dysfunctional actions that detract from learning through innovation. For instance, a propensity to automatically ascribe blame for performance below expectations may stifle creativity.

Considering the conflict between exploration and exploitation, there are many forces in firms that push for exploitation rather than exploration. Amongst them are the nonrational escalation of commitment (Staw, 1981) and the inertial tendencies not to engage in cannibalization of existing technologies. However, cannibalization is often required for innovation or for preventing a competitor from innovation that may render the firm’s technology obsolete (Conner, 1988). In this context, we suggested that decision makers may want to reduce one type of error even at the expense of increasing the other depending upon the stage of technology development. Specifically, exploration requires that decision makers reduce Type II errors, while exploitation requires that they reduce Type I errors.

These technology-choice issues are becoming increasingly important in contemporary environments characterized by rapid change. The increasing pace of technological change and the associated complexity places a premium on understanding how decisions are made and what can be done to improve them. This requires that behavioral aspects of decision making should be included in any theory of strategic management (Zajac & Baezerman, 1991). However, decision makers are missing in many theories of strategic management that have focused on positioning or imitability. For instance, the structure-conduct-performance paradigm (see, for example, Porter, 1980) has been articulated at the firm and industry levels, thereby precluding an analysis of decision makers and decision-making processes. Moreover, this paradigm does not explicitly incorporate the time dimension in its construction, a facet that is critical to understanding how firms can create and sustain a competitive advantage through the choice of technologies.

The resource-based view is another perspective that does not include decision makers in its formulation (see Peteraf, 1993 for a recent review). This perspective has examined how firms might develop a sustainable competitive advantage through the creation of inimitable resources. However, this perspective has largely ignored how these resources can entrap firms in the past even as new technologies make old inimitable resources worthless. In this context, Elster (1983) pointed out that through their choices, humans can avoid being trapped by the past. Therefore, they can escape the inevitability of the future.

This paper is one effort to accomplish the task of bringing the decision maker back into a theory of strategic management. By focusing on decision makers and coupling them with their changing technological context, our framework suggests new avenues of inquiry. For instance, a key question for strategic management pertains to the creation of organizational intelligence. Variability and errors in outcomes usually evoke negative reactions from managers. We tend to penalize people for errors and attempt to eliminate variability in outcomes. However, variability and errors are the very attributes that make learning possible in the context of innovation. As Walter Wriston, former CEO of Citibank, noted, “good judgment comes from experience; experience comes from bad judgment” (Kearns & Nadler, 1992, p. 267). Variability and errors help us to learn and develop valid predictors of successful innovations, thereby creating organizational intelligence. Without this organizational intelligence, the process of innovation cannot be institutionalized (Schumpeter, 1975). Whether we explore or exploit, errors are inevitable. We must learn from, reduce, and make appropriate trade-offs between errors. Strategic management theories must grapple with these issues.

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**Notes**

1. As Graham noted, “R&D is still an enigma. . . . But R&D’s strangeness and remoteness to the rest of the organization affects not only its effectiveness as a support function, but its credibility as a generator and implementor of strategic opportunities . . . . The need for general managers to concern themselves with R&D is becoming more compelling . . . . When R&D allocates its resources and assigns priorities to one area of research over another, it is inevitably predetermining corporate strategy” (1986, pp. 220-229).

2. Beder noted that “corporate histories are replete with good ideas that lan-
guished on the shelf. . . . Such oversights are to some extent unavoidable, if only because once an industry matures there’s a tendency to think the big inventions have already been made and to focus instead on small improvements” (1993, p. 80). Europe’s EUREKA program, encompassing 650 projects, is expected to cost $15 billion, but only 17% of corporate participants claim that it has helped improve competitiveness; the ESPRIT program, expected to cost nearly $10 billion, has a hit rate of only 50% in 915 projects; only one-third of 1330 projects in the $3.2 billion BRIT program have shown any commercial value (Levin, 1993). Quiana, a synthetic silk introduced by Du Pont, cost about $200 million to develop and market. It was abandoned for natural fibers and died. Electronic imaging businesses have cost Du Pont over $600 million since the mid-60s yet have yielded only red ink. After 10 years and $1 billion, Du Pont officials admit that pharmaceuticals take longer and cost more to develop and market than they anticipated (McMurray, 1992).

3 The saga of the initial development of xerography and personal computers is well known. Markoff (1991) chronicles 13 technologies conceived at Xerox’s Palo Alto Research Center that were rejected by Xerox and later successfully developed by other firms. However, not surprisingly, data on the extent of such occurrences is rarely collected.

In the motion picture production industry, about two-thirds of the top-100 wide-release films (those released simultaneously in more than 500 theaters in the U.S.) during 1985-1991 had below average gross box-office receipts. Interestingly, some studios such as Paramount and 20th Century Fox had significantly better “hit rates.” Sixty percent of Paramount’s releases had above average gross box-office receipts, whereas 50% of 20th Century Fox’s were above average. In contrast, Disney and Warner Brothers had only 33% of their releases grossing above-average receipts (Movie Stats, 1991).

In industries such as oil and gas exploration, the occurrence of outcomes that in retrospect may be considered to be oversights or foresights seems almost taken for granted because of the low success rates. About a third of all wells drilled in the United States during the period 1986-1990 yielded neither oil nor gas (American Petroleum Institute, 1990).

In consumer goods, new product introductions are singularly unsuccessful. For example, a noted annual industry survey reported that of all products introduced into the market in 1991, only 17% met their business objectives. In other words, the failure rate after product introduction was 83% (Group EFO Limited, 1992). A study by Arthur D. Little found that only 8% of new cereals introduced succeed (Zangwill, 1993). Given such low odds for success, it is a wonder that firms still try at all.

4 Graham noted that “during the mid-70s, RCA’s decision not to stick with Magtape was received by the press and the industry as a healthy focus of the company’s effort on a product with higher potential. Only later, when it would become apparent that RCA’s decision had in effect determined that no American company would be able to compete with the Japanese in manufacturing videotape recorders, would the press, in its customary fickle way, ask how such a thing could have happened. How could RCA, the American consumer electronics industry’s traditional pionees, fail to produce a magnetic tape player of its own making?” (1996, p. 149).

5 March and Shapira (1992) do recognize that at a “survival” point, firms will exhibit risk-seeking behavior (exploration) irrespective of whether performance is below or above aspiration levels. Firms with few resources but high aspirations may also engage in exploration to compete with rivals possessing greater resources.

6 A similar model is frequently used in the psychometric literature and has been adopted for the study of individual decision making by Einhorn and Hogarth (1978).

7 Note that although we developed the model using a single measure, decision makers may, in fact, employ multiple measures. This may introduce trade-offs among measures.

8 Collecting data on the outcomes of projects that were funded may be relatively easy. Collecting data on the outcomes of projects that were not funded by the firm but were, perhaps, funded by competitors is possible, but is rarely done. In fact, seldom are any records maintained of alternatives that were considered and not funded. To improve predictive validity, however, such data must be collected and analyzed.

9 Experimentation is possible in established firms that confront several technology choice decisions over time. By creating a database on successes and failures, decision makers in established firms may create organizational intelligence that start-up firms do not have.

10 Torres noted that professional investors favor firms that still “possess the savage entrepreneurial appetite with which they were founded. They want companies willing to innovate. They want cannibals that will cheerfully destroy the past in order to feed the future... Intel is a model cannibal, some pros say” (1992, p. CI).

References


Rational entrepreneurs or optimistic martyrs? Some considerations on technological regimes, corporate entries, and the evolutionary role of decision biases

Giovanni Dosi and Dan Lovallo

I. Introduction

This is a rather conjectural report on the evolutionary role of decision biases—at both the level of individuals and of organizations—and, in particular, on their importance to the processes of corporate entry and the evolution of industrial structures. A growing and quite robust body of evidence highlights the pervasiveness of various types of biases in individual decision making, which accounts for systematic departures from predictions of the canonical model of rational choice (see, for example, Kahneman & Tversky, 1973, 1986, Shafir & Tversky, 1992). For our purposes, we will mainly concern ourselves with overconfidence or optimism, which frequently leads to bold forecasts of the consequences of one’s own actions. Also, by way of example, we will examine risk seeking in the domain of losses, which often yields escalating commitments in the face of failures. Interestingly, these biases appear to carry over from the level of individuals to that of groups and organizations and, indeed, might even be amplified in the latter circumstances (see, for example, Kahneman & Lovallo, 1993, Lovallo, 1996a, and the literature discussed there). In this respect, a challenging domain of investigation—with vast ramifications into the analyses of the nature of entrepreneurship, technological change, and industrial dynamics—is that of corporate entry into an industry.

Numerous studies have shown that the vast majority of entrants fail (see, for example, Dunn, Roberts, & Samuelson, 1988). Furthermore, there are significant interindustry differences in failure rates. Evidence of high-level firm failure rates appears to be consistent with experimental data showing that, typically, people are unrealistically optimistic, exhibit illusions of control in even modestly complex environments, and systematically neglect the statistics of previously observed performances.

In this study, we report some preliminary results and conjectures from an ongoing investigation of corporate entry, postentry performances, and the
Technological innovation
Oversights and foresights

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