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A Theoretical Framework for Managing the New Product Development Portfolio: When and How to Use Strategic Buckets

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Developing the "right" new products is critical to firm success and is often cited as a key competitive dimension. This paper explores new product development (NPD) portfolio strategy and the balance between incremental and radical innovation. We characterize innovative effort through a normative theoretical framework that addresses a popular practice in NPD portfolio management: the use of *strategic buckets*. Strategic buckets encourage the division of the overall NPD resource budget into smaller, more focused budgets that are defined by the type of innovative effort (incremental or radical). We show that time commitment determines the balance between incremental and radical innovation. When managers execute this balance, they are often confounded by (i) environmental complexity, defined as the number of unknown interdependencies among technology and market parameters that determine product performance; and (ii) environmental instability, the probability of changes to the underlying performance functions. Although both of these factors confound managers, we find that they have completely opposite effects on the NPD portfolio balance. Environmental complexity shifts the balance toward radical innovation. Conversely, environmental instability shifts the balance toward incremental innovation. Risk considerations and implications for theory and practice are also discussed.

Key words: new product development; NPD portfolio strategy; incremental innovation; radical innovation; strategic buckets; complex systems; evolutionary systems
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1. Introduction

Developing the "right" new products is critical to firm success and is often cited as a key competitive dimension (Roussel et al. 1991, Cooper et al. 1998). Companies that make poor choices with respect to their new product development (NPD) portfolio run the risk of losing their competitive advantage. Examples abound in practice: DuPont experienced trouble because the company diverted the majority of its $2 billion annual research and development (R&D) budget to improve established product lines (*Business Week* 2003). Drug maker Novartis established an advantage over close rival Roche by shifting resources toward incremental NPD programs; their advantage eroded due to the lack of early stage development projects and the subsequent drying up of their pipeline (*Financial Times* 2000). Kodak shifted resources toward developing breakthrough technologies in order to catch up in the digital photography market, despite the fact that the company was synonymous with photography for the better part of the twentieth century (*Forbes* 2003).

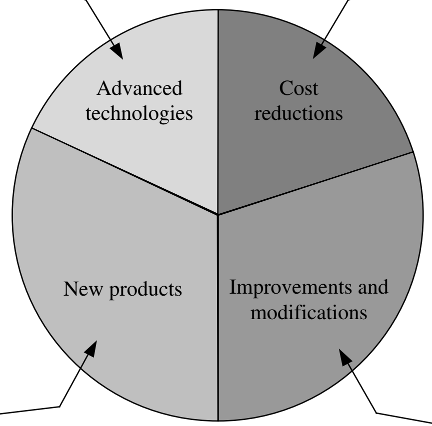
NPD portfolio management presents a difficult challenge because resources must be allocated between innovation programs and each program may represent conflicting directions in terms of corporate strategy. Success then requires a fundamental trade-off: short-term benefits accrued through incremental improvements versus long-term benefits achieved through radical or new-to-the-world products and services (Tushman and O'Reilly 1996). A report from the Product Development Management Association (PDMA) paints a bleak picture with respect to this challenge (Adams and Boike 2004). According to the report, the majority of firms overemphasize incremental innovation efforts, which exhibit negative correlation with firm performance. The PDMA study indicates that success is strongly linked to a mix of efforts that devote resources to "fundamentally new" or "new-to-the-world" products and services in addition to minor product extensions.

Managers have adopted several methods that aim to increase effectiveness when allocating resources across NPD initiatives of varying degrees of novelty.

Figure 1 NPD Portfolio Strategy and Strategic Buckets

Program	Rank	Score
Walden	1	92
Proteus	2	85
Gamma	3	79
Sanaco	4	75

Program	Rank	Score
1267-F	1	89
98-DD	2	85
150-C	3	81
97-D	4	77
0919-K	5	65



Program	Rank	Score
Midget	1	89
Kool-K	2	85
Essy	3	81
Pop-up	4	77
Tri-123	5	65

Program	Rank	Score
X-Tra	1	92
NaCl	2	85
GamX	3	79
Mini	4	75

A number of case-driven frameworks address the trade-offs between product and process innovation, risk and reward, and market and technology risk (Roussel et al. 1991, Wheelwright and Clark 1992, Cooper et al. 1998). These tools summarize best practices for dividing resources and achieving "balance" across a portfolio of NPD endeavors. Though the tools have different names, they all encourage the division of the overall resource budget into smaller, more focused budgets. The result is a set of *strategic buckets* for managing the NPD portfolio. A strategic bucket is a collection of NPD programs that are aligned with a particular innovation strategy. The NPD programs in a strategic bucket may involve process improvements and cost reductions, minor product modifications, radical next-generation technological research, or groundbreaking R&D initiatives, among others. Figure 1 depicts an NPD portfolio strategy with four strategic buckets.

Strategic buckets create nonpermeable partitions between dissimilar NPD programs to ensure access to resources for projects that are seemingly unattractive to commonly used project valuation methods. Net present value (NPV) or real options analyses tend to disfavor advanced technology projects due to the long-term payoffs and high likelihood of failure. In addition, project valuation tools are difficult to use when it comes to radical projects because data may be unreliable or highly biased (Kavadias et al. 2005). In light of these challenges, the goal of a strategic bucket is to earmark resources for radical NPD programs. In the absence of mechanisms that protect resources, managers often sway the result of an NPV analysis in favor of a more radical project by increasing its estimated payoff (the infamous $10 billion market opportunity). Of course, any NPV analysis can sway in the opposite direction by lowering the probability of success for radical NPD initiatives. Such ad hoc decision making results in intraorganizational suspicion and lack of transparency (Wu et al. 2008). Ultimately, the suggested portfolio balance remains a vague guideline, which is resolved on a case-by-case basis. To the best of our knowledge, decisions regarding strategic buckets and the protection of resources have little or no theoretical foundation.

The goal of this paper is to provide a theory that explains when and how strategic buckets should be used. We begin by characterizing the behavior of the individual NPD programs that comprise a strategic bucket. Our analysis highlights the subtle role of two strategic factors and how they impact the value of a NPD program: (i) the degree of change sought by the innovative activity (how novel should the target solution be?) and (ii) the time during which product improvements and extensions take place (for how long does management commit resources to the program?). Radical innovation efforts require a window of time in order to realize positive outcomes. We establish how interactions between performance drivers impact this window of time. In complex business environments with numerous interactions, radical innovation efforts pay off earlier. Conversely, environments with little or no interactions favor incremental innovation efforts. The ability to commit to an innovation initiative depends on environmental instability (likelihood of major technological or market disruptions). A higher degree of environmental instability favors incremental efforts. We show how individual NPD programs drive overall portfolio decisions and we shed light on the appropriate "balance" between incremental and radical innovation in the NPD portfolio. Although environmental complexity and instability both confound managers, we find that they have completely opposite effects on the NPD portfolio balance. Environmental complexity shifts the balance toward radical innovation. Conversely, environmental instability shifts the balance toward incremental innovation.

The remainder of this paper is organized as follows: In §2, we review the relevant literature, and in §3, we introduce theoretical foundations. In §§4 and 5, we build, respectively, analytic and evolutionary models of NPD program performance. In §6, we extend our analysis from the single NPD program to the NPD portfolio, and we draw conclusions for theory and practice in §7.

2. Literature Review

There is an abundance of literature that analyzes the resource allocation and portfolio problem at the operational level (for a review, see Kavadias and Chao 2007). Analysis at the operational level often consists of mixed integer programming techniques due to the "in" or "out" nature of projects at this level of decision making. These models are highly sensitive to parameter changes and practitioners often doubt their results due to the lack of robustness and transparency (Loch et al. 2001, Shane and Ulrich 2004, Kavadias et al. 2005). These limitations are discussed in a review paper for the technological innovation and product development area of *Management Science*. According to the department editors, "A substantial body of research has been focused on the question of which innovation projects to pursue .... Surveys have shown that these models have found very little use in practice. If 50 years of research in an area has generated very little managerial impact, perhaps it is time for new approaches" (Shane and Ulrich 2004, p. 136).

In light of these limitations, practitioners often prefer multidimensional decision-making tools (Liberatore 1987, Saaty 1994, Hammonds et al. 1998) or ranking methods (Brenner 1994, Loch 2000). The popularity of these methods stems from the explicit consideration of metrics that are difficult to quantify (e.g., strategic alignment). Unfortunately, these tools rely on an ad hoc list of dimensions, and decision makers often manipulate the methods to generate desired outcomes instead of using them as true decision support tools. There also exists significant research that specifically addresses the practice of strategic buckets as an NPD portfolio management tool (Roussel et al. 1991, Wheelwright and Clark 1992, Cooper et al. 1998). This research provides descriptive evidence of the use, benefits, and popularity of strategic buckets.

A number of normative models address the issue of return on investment from NPD programs. Ali et al. (1993) consider a competitive setting where firms decide to invest in a single incremental or radical product idea. They focus on a single project and consider project completion to be an exogenous random variable. Kauffman et al. (2000) analyze the return from search efforts that vary with respect to the distance of search within a performance landscape. They do not account for the portfolio decision that includes multiple innovation efforts, and they consider the time horizon to be fixed. Loch and Kavadias (2002) focus on the optimal resource allocation across NPD programs. They do not consider how the type of the NPD investment or the investment horizon impact the allocation decision. In a follow up to the previous study, Bhattacharya and Kavadias (2007) account for the dynamic allocation of a fixed budget over research opportunities that become available at different points in time. They do not characterize the nature of innovation, and they assume a particular structure for the return on investment curves.

From a methodological standpoint, a large body of literature has examined the mathematical properties of resource allocation models beginning with Smith (1959), followed by Gittins (1989). This work is based on the dynamic scheduling of critical resources across a set of potential tasks (for an excellent review, see Van Mieghem 1995). The dynamic scheduling literature considers a fixed time horizon, which is an appropriate assumption because task returns do not change over time (at most they get discounted). Given the fixed time horizon length, these studies determine an allocation or scheduling policy. We borrow a simple mathematical structure from the dynamic scheduling literature—the well known "treasure hunt" problem (for a recent analysis, see Denardo et al. 2004). We use this structure as a basis to examine the effects of the horizon length on the best choice for the type of innovative effort. We do not make a methodological contribution to the dynamic scheduling literature (i.e., our goal is not to develop new index policies). Still, we analyze a key trade-off regarding the investment horizon and the choice of program innovativeness, which is beyond the scope of the dynamic scheduling literature.

An important aspect of our study is that the structure of the return on investment curves emerges endogenously. This occurs because of our characterization of commitment time and innovation strategy. We also build upon previous normative work and explicitly account for the allocation decision across NPD programs. In the latter part of our analysis, we employ performance landscapes to extend our basic model setup and obtain managerially relevant insights.

3. Theoretical Foundations

In this section, we formally define the concepts of innovative effort and NPD programs. To begin, we provide a definition of a product and the performance it delivers to the firm. We then characterize innovation and NPD as an attempt to alter product attributes and improve product performance. Two concepts are central to our analysis: (i) NPD programs are more or less innovative depending on the degree of change created by the program. Each type of innovative effort is characterized by its potential value, risk, and cost depending on the degree of change. (ii) Managers commit to NPD programs for a given amount of time. The time commitment reflects their belief that the firm will be able to continue to operate according to the status quo.

3.1. Products, NPD Programs, and Innovative Effort

Borrowing from the marketing and engineering design literatures, we define a product as a bundle of technology and market attributes, $\omega = (x_1, x_2, \ldots, x_N)$. The attributes represent key product parameters such as core product architecture, component technologies, design features, and manufacturing process specifications, among others. N represents the size of the technology feasibility set (the number of attributes that affect product performance). We define an NPD program as an initiative that strives to alter product attributes to enhance existing product performance or create an altogether new product. An NPD program need not alter all of the technology and market attributes. In fact, in many cases, NPD managers are not aware of the entire technology feasibility set. In such settings, managers alter a proper subset of the technology feasibility set, $\bar{\omega} = (x_1, x_2, \ldots, x_{\bar{N}})$, where $\bar{N} < N$.

With this definition in mind, we note that an NPD program begins with a product, ω, and creates a different product, ω'. In doing so, the NPD program can be characterized by a change metric, $d = |\omega' - \omega|$, which defines the type of innovative effort pursued by the program. For any existing product ω and type of innovative effort d, we define the set of potential new product ideas as $N_d(\omega) = \{\omega' \colon |\omega' - \omega| \le d\}$. In our framework, innovation is equivalent to stating that an NPD program changes product attributes over time and drives performance improvement.

Product performance (net revenue generated by a product) is a function of the technology and market attributes and is given by $F^K(\omega)$, where K specifies the underlying complexity of the performance function. Complexity in this context refers to performance interactions between technology and market attributes. For any NPD program, $F^K(\omega') - F^K(\omega)$ is the performance change as a result of the innovative effort. For the time being we assume that the function $F^K(\cdot)$ itself is not altered as a result of innovative effort and we restrict our analysis to the case in which technology and market complexity is negligible. We relax these assumptions in §5 where we analyze complex performance functions that may change over time. We define a performance improvement function $V(\cdot)$ such that $F^K(\omega') - F^K(\omega) = V(d)$. Let $\widehat{V}(d)$ be the maximum potential performance improvement possible within $N_d(\omega)$ and note that $\widehat{V}(d)$ is nondecreasing in d. This follows immediately from our definition of $N_d(\omega)$ because for any $d_1 < d_2$, $N_{d_1}(\omega) \subset N_{d_2}(\omega)$.

In addition to the value created by NPD programs, innovative activity also involves risk. We characterize risk based on the probability that an NPD program achieves $\widehat{V}(d)$. This probability is given by $p(d)$, which is decreasing in d. Finally, the cost associated with innovative effort that transforms ω to ω' is also a function of the degree of change sought by the NPD program. The cost of innovation is given by $c(d)$, which is increasing in d.

3.2. Incremental and Radical Innovation

For any $d_1 < d_2$ we say that d_1 represents incremental innovation and d_2 represents radical innovation, and we note the following: (i) $|N_{d_1}(\omega)| < |N_{d_2}(\omega)|$. The number of solutions possible through radical innovation is greater than the number of solutions possible through incremental innovation. (ii) $\widehat{V}(d_1) \le \widehat{V}(d_2)$. The maximum potential performance for radical innovation is at least as big as the maximum potential performance for incremental innovation. (iii) $p(d_1) > p(d_2)$. Radical innovation is more risky (has lower probability of success) compared to incremental innovation. (iv) $c(d_1) < c(d_2)$. The cost of incremental innovation is less than the cost of radical innovation.

According to our framework, an NPD program may be more or less incremental or radical depending on the number of attributes that are actually altered. Furthermore, our definition of innovative effort extends beyond the standard notion of technological change. Because a product is defined as a collection of technology and market attributes, and an NPD program alters d attributes, innovation takes on a spatial quality similar to the Schumpeterian definition of innovation: "To produce means to combine forces and materials within our reach…to produce other things…means to combine these materials and forces differently" (Schumpeter 1934, p. 65).

4. An Analytic Model of NPD Program Performance

To capture the dynamic nature of innovation, we consider that the firm attempts to improve product performance over a given interval of time, $t = 0, 1,$

$2, \ldots, m$. As described in §3, an NPD program exists with the express purpose of improving product performance and we assume that performance is normalized such that $F(\omega) = 0$ at $t = 0$. A number of questions arise immediately, such as how much performance improvement can the NPD program realize within a given time frame, m? Should the firm attempt an incremental improvement strategy (relatively minor benefits achieved with higher probability of success and lower cost) or should the firm pursue efforts that attempt to radically improve performance (potentially large benefits with lower probability of success and higher cost)?

The answers to these questions depend on the overarching goals of the NPD manager. Formally, let the random variable $V_m(d)$ represent the performance of a NPD initiative of type d after m periods. NPD managers are concerned with maximizing a general utility function, $U(V_m(d))$, where $U(\cdot)$ is assumed to have a certainty equivalent that is increasing in the expected performance (reward) and decreasing in the variance in performance (risk). Thus, NPD managers seek to maximize expected reward while reducing risk. Throughout the remainder of §4 we focus our attention on the issue of expected performance. In §5 we extend our analysis to explicitly consider the risk inherent in NPD programs.

4.1. Expected Performance for a Single NPD Program

The commitment to a particular type of innovative effort for a given interval of time captures precisely the intuition behind strategic buckets. For any $d \in \{1, 2, \ldots, N\}$, the firm invests $c(d)$ dollars per period and improves product performance to $\widehat{V}(d)$ with probability $p(d)$ in each period.[1] Of course, if the attempted NPD effort is not successful, product performance remains unaltered. We can express the expected performance after n periods for an NPD program of type d through the following recursive equation:

$$J_n^d = \max\{0, -c(d) + rp(d)\widehat{V}(d) + r[1-p(d)]J_{n+1}^d\}, \quad (1)$$

where r is the one-period discount factor. Equation (1) represents a search for the best-performing product configuration.[2] For example, an NPD team working on a new design of an iPod conceives a prototype that is flat, white, weighs 8 oz, and has a color screen. The probability that this set of attributes is the best-performing solution is given by p. If "flat, white, 8 oz, and color screen" is not the best-performing solution, then the team must continue to search and they face a similar problem in period $n+1$ (this occurs with probability $1-p$).

Because the firm commits to the NPD program for m periods, we have the boundary condition $J_m^d = 0$. The boundary condition reflects the reality that managers terminate the NPD program and it no longer drives performance improvement once the commitment time has passed. Working backwards, if we assume that $-c(d) < rp(d)\widehat{V}(d)$, the expected performance in period $m-1$ is $J_{m-1}^d = -c(d) + rp(d)\widehat{V}(d)$. Similarly, the expected performance in period $m-2$ is $J_{m-2}^d = [-c(d) + rp(d)\widehat{V}(d)][1 + r(1-p(d))]$. Continuing in this fashion the expected performance for an m period commitment (considered at $t = 0$) to an NPD initiative of type d is

$$J_0^d = [-c(d) + rp(d)\widehat{V}(d)]\frac{1 - r^m[1-p(d)]^m}{1 - r[1-p(d)]}. \quad (2)$$

For a given type of innovative effort, Equation (2) defines the expected return curve for the NPD program as a function of the time commitment, m. The following proposition describes the behavior of the NPD program return curves (all technical details can be found in the online technical appendix).

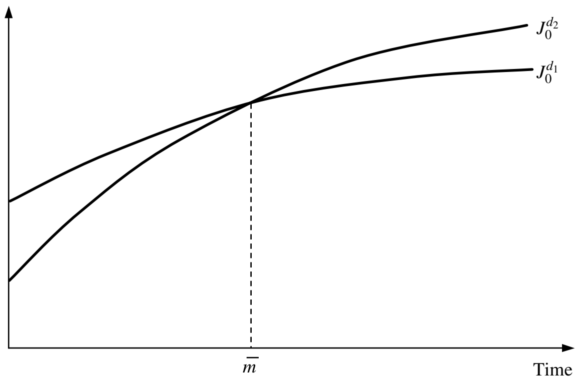
Proposition 1 (Behavior of NPD Program Return Curves). *J_0^d is increasing and concave in m. Furthermore, for $d_1 < d_2$, $J_0^{d_1} > J_0^{d_2}$ for $m = 1$ provided that $p(d_1)\widehat{V}(d_1) > p(d_2)\widehat{V}(d_2)$ and $c(d_1) < c(d_2)$. Additionally, there exist threshold values $\bar{p}$ and $\underline{p}$ such that $p(d_1) > \bar{p} > \underline{p} > p(d_2) \Rightarrow J_0^{d_1} < J_0^{d_2}$ as $m \to \infty$.*

The conditions described in Proposition 1 intuitively capture the key differences between incremental and radical innovation. The requirements $p(d_1)\widehat{V}(d_1) > p(d_2)\widehat{V}(d_2)$ and $c(d_1) < c(d_2)$ simply translate to higher net payoff for incremental innovation on a short-term (one-period) basis. Furthermore, $p(d_1) > \bar{p}$ and $\underline{p} > p(d_2)$ are aligned with the fact that incremental innovation has higher probability of success relative to radical innovation. Figure 2 depicts a schematic representation of Proposition 1. The expected performance for both incremental and radical NPD programs increases with time commitment. In the short run, incremental NPD programs deliver higher expected performance—a "sure bet" relative to radical NPD programs. However, if given enough time, radical NPD programs overcome the low probability of success and deliver higher expected performance because of their high potential value.

[1] We assume that the duration of each period does not depend on d. In reality, a radical NPD program may have an inherently longer overall time frame due to the need to refine underlying technologies or fully understand new markets. Our formulation captures these possibilities through the lower probability of success for radical NPD programs.

[2] In the online technical appendix (provided in the e-companion) we provide two alternative formulations of our model. An electronic companion to this paper is available as part of the online version that can be found at http://mansci.journal.informs.org/.

Figure 2 **Schematic Representation of Proposition 1**



The structure of the return curves $J_0^{d_1}$ and $J_0^{d_2}$ leads to a unique *crossing time*, $\overline{m}$, which allows managers to evaluate different types of innovative effort. If the firm commits to the NPD program for $m < \overline{m}$ periods, then incremental innovation is the best choice. Conversely, if the firm is willing to commit to the NPD program for $m > \overline{m}$ periods, then radical innovation is the best choice. An alternative interpretation highlights a different side of the commitment decision: if management holds the belief that the firm can only continue to operate for an amount of time less than $\overline{m}$, radical innovation does not make sense because radical innovation requires at least $\overline{m}$ periods to deliver higher payoff relative to incremental innovation. In contrast, if management holds the belief that the firm can continue to operate longer than the crossing time, radical innovation becomes more attractive. Thus, the importance of protecting resources for an interval of time depends not only on the parameters of the alternative types of innovation, but also on the belief that management holds with respect to viability of the firm (identified through the commitment time).

Having described the structure of the NPD program return curves, we now turn our attention to a comparative statics analysis of $\overline{m}$ to understand the factors that make incremental or radical innovation more favorable.

Proposition 2 (Comparative Statics Analysis for $\overline{m}$). *The crossing time, $\overline{m}$, is higher when* (i) $\widehat{V}(d_1)$ *is higher,* (ii) $p(d_1)$ *is higher,* (iii) $c(d_1)$ *is lower,* (iv) $\widehat{V}(d_2)$ *is lower,* (v) $p(d_2)$ *is lower, and* (vi) $c(d_2)$ *is higher.*

A higher $\overline{m}$ is synonymous with more favorable circumstances for incremental innovation because the time interval during which incremental innovation dominates radical innovation is longer (from the viewpoint of expected performance). Innovative activity of type d becomes more attractive when $\widehat{V}(\cdot)$ or $p(\cdot)$ is higher and $c(\cdot)$ is lower. The former make innovative activity attractive by increasing the expected value of a NPD program whereas the latter makes innovative activity attractive by lowering the cost of a NPD program. The effect due to expected value is more nuanced because it includes a trade-off: higher d implies lower $p(d)$ and higher $\widehat{V}(d)$.

4.2. Can the Firm Commit to the NPD Program?

The preceding analysis is based on the fact that the firm makes an m period commitment to the NPD program. In reality, there are firm level factors that influence whether the firm is *able to commit* to the NPD program for a given interval of time. Commitment to an NPD program is based on the belief that management holds regarding the ability of the firm to continue to generate adequate performance. From a practical standpoint, this observation echoes managerial concerns such as "How long will it take for innovation efforts to pay off?" Theoretically, the question translates to "Do managers believe that the firm will continue to operate under the status quo beyond the interval $[0, \overline{m}]$?" Unfortunately, the ability to generate adequate performance may be beyond the control of managers. The technology and market environment that defines product performance may be subject to disruptions (e.g., dramatic technological leaps or shifts in customer preferences). Disruptions alter the underlying relationship between product attributes and product performance and therefore alter the expected performance of any NPD program meant to improve a product. In this section we extend the previous analysis to account for the fact that the firm may experience disruptions in NPD program performance.

Let $f(m) = J_0^{d_1} - J_0^{d_2}$ represent the difference between incremental and radical NPD program performance for a given time commitment, m. Note that when $f(m) > 0$ ($f(m) < 0$) incremental (radical) innovation is the preferred type of innovation for the NPD program. When the technology and market environment is subject to potential disruptions, the underlying relationship between product attributes is altered and product performance is negatively affected. We assume that a technology or market disruption is defined by a renewal process so that when a disruption occurs the firm's performance is relegated to the performance at $t = 0$ and the firm faces the same decision problem once more. Let ΔJ represent the difference between incremental and radical NPD program performance for the renewal process defined by technological and market disruptions. Suppose that a disruption occurs after t periods with probability q. Letting r be the one-period discount factor, we can write $\Delta J = q[f(t) + r^t \Delta J] + (1-q) f(m)$, which simplifies to

$$\Delta J = \frac{q}{1 - qr^t} f(t) + \frac{1-q}{1-qr^t} f(m). \qquad (3)$$

When $\Delta J > 0$ ($\Delta J < 0$), incremental (radical) innovation is the preferred type of innovation for the NPD program. The choice depends on the probability of technological and market disruptions.

Proposition 3 (Technological and Market Disruptions). *For $t < \bar{m} < m$, ΔJ is a increasing function of q. Furthermore, there exists a $\bar{q}$ such that $q < \bar{q} \Rightarrow \Delta J < 0$ and $q > \bar{q} \Rightarrow \Delta J > 0$.*

Proposition 3 states that as the probability of an *imminent* technology or market disruption increases, incremental innovation becomes more attractive because it allows the firm to reap quick rewards before another disruption occurs.[3] Conversely, as the probability of technology or market disruption decreases, radical innovation becomes more attractive because the effort should pay off if given enough time. An alternative interpretation is that a turbulent environment (i.e., an environment in which customer preferences are not well defined) drives firms to seek incremental changes. Note, that an incremental strategy does not imply homogeneity with respect to the actual changes in technology or market attributes. Instead, different firms may use different technologies or conquer different market segments so long as their innovative efforts remain closely associated with their current product offerings. Note that $\bar{m}$ depends on the attributes that define an individual product, whereas q is a firm level parameter common across all products. The importance of this observation will become obvious once we extend our analysis to the portfolio level.

5. An Evolutionary Model of NPD Program Performance

Our evolutionary model shares many characteristics with the analytic model. Both frameworks use similar notions of products, NPD programs, and innovative effort. The evolutionary model adds to the analytic model along two important lines. First, the evolutionary model provides a more realistic characterization of the performance landscape. To remain tractable, the performance landscape for the analytic model consists of a single product definition that delivers an acceptable performance value (all remaining product definitions are assumed to deliver unacceptable performance values). The evolutionary model extends the notion of performance landscape to allow for intermediate performance values, which are acceptable until a better-performing solution is found. Furthermore, our analytic model assumes that the performance functions are characterized by negligible complexity. In reality, performance functions are extremely complex as multiple technology and market attributes interact in significant and unknown ways resulting in nonuniform values for $\widehat{V}(d)$ and $p(d)$. This is particularly so at a strategic level of decision making.

The second, and perhaps most important difference between the two frameworks lies in our conceptualization of managerial rationality and behavior. The model presented in §4 is difficult to use in practical optimization problems. For even a small number of possible outcomes and periods, it is unlikely (if not impossible) that managers possess the computational capability to determine the best choice of strategic buckets. Previous work on the optimal balance between incremental and radical innovation highlights this fact and proposes solution algorithms for $m > 1$ (Macready and Wolpert 1998). Unfortunately, it is well documented that algorithmic approaches are not used in practice (Loch et al. 2001, Shane and Ulrich 2004).

In this section we extend our analytic model to account for the fact that managers do not have the ability to optimize an m period commitment decision at $t = 0$ and the performance functions they face are complex. Based on these observations, we take an evolutionary perspective on this problem (Nelson and Winter 1982). That is to say, NPD program performance evolves over time based on variation, selection, and retention mechanisms (Loch and Kavadias 2007).

5.1. A Complex Performance Landscape

Recall that we define a product as $\omega = (x_1, x_2, \ldots, x_N)$ and product performance as a function of the technology and market attributes given by $F^K(\omega)$. To specify our model and allow for further analysis assuming that $F^K(\cdot)$ is a complex function, we employ the NK model of tunable fitness landscapes (Kauffman 1993). A number of researchers have employed complex performance landscapes to model managerial problems such as organizational design and evolution (Levinthal 1997, Rivkin and Siggelkow 2003, Siggelkow and Levinthal 2003, Siggelkow and Rivkin 2005), problem solving (Gavetti and Levinthal 2000, Sommer and Loch 2004), and technological innovation (Kauffman et al. 2000, Fleming and Sorenson 2004).

Let $x_j \in \{1, 2, \ldots, S\}$ and assume that each attribute j contributes individually to the overall product performance. The performance contribution of attribute x_j is not necessarily independent from the other performance determinants; rather, it may depend on $K \in \{0, 1, \ldots, N-1\}$ other attributes through a function $f_j(x_j, x_{j_1}, x_{j_2}, \ldots, x_{j_K})$. The number of interactions, K, is a modeling convention that proxies the underlying complexity of the technology-market setting in which the firm operates. Interaction complexity is a result of

[3] We focus on the case of $t < \bar{m} < m$ because any case in which $m < t$ is trivial. Also, the cases in which $\bar{m} < t < m$ and $t < m < \bar{m}$ result in a straightforward choice between incremental and radical innovation regardless of the disruption probability.

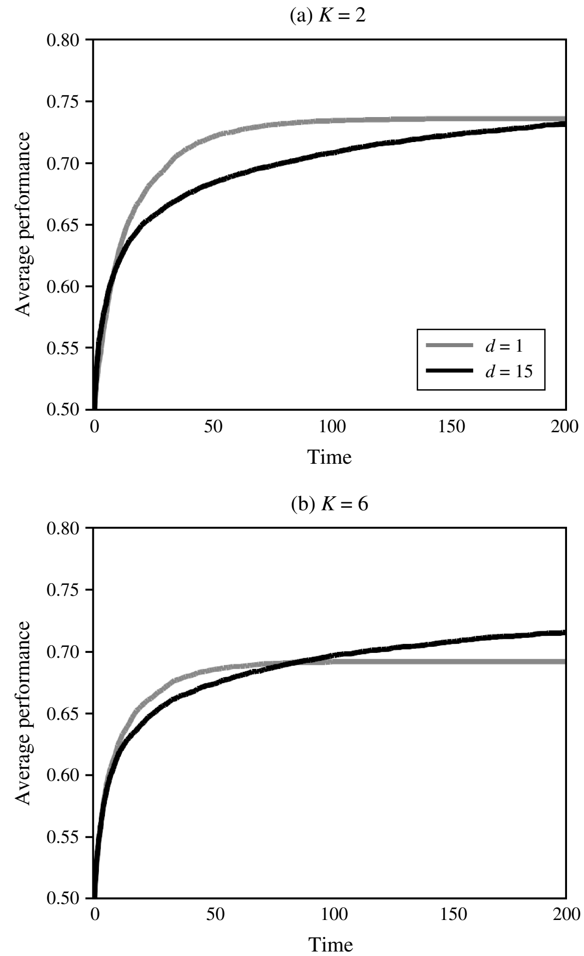
"a large number of parts that interact in non-simple ways [such that] given the properties of the parts and the laws of their interactions, it is not a trivial matter to infer the properties of the whole" (Simon 1969, p. 195).

We assume that each f_j is a random draw from a $U(0, 1)$ distribution to account for the fact that managers do not know the payoff structure for the performance landscape. Product performance is the average of the performance contributions from each attribute: $F^K(\omega) = (1/N)\sum_{j=1}^{N} f_j$. Two structural properties merit discussion here. First, the fact that each f_j is a random draw from a $U(0, 1)$ is not restrictive. Extant research has shown that complex performance landscapes retain their form under a wide variety of distributions for the f_j (Kauffman 1993, Sommer and Loch 2004). Second, we model product performance as the average of the performance contributions from each attribute. We adopt this convention so that the system size (N) does not drive our results.

Aligned with the theoretic foundation established in §3, we now adopt an evolutionary view of innovation and we simulate the behavior of NPD programs over time. To initialize our simulation ($t = 0$) we randomly define a product, $\omega = (x_1, x_2, \ldots, x_N)$. In each period ($t = 1, 2, 3, \ldots$), an NPD program of type d drives a change in product attributes. We implement this change by allowing the NPD program to randomly search for one new product configuration, ω', within $N_d(\omega)$. If $F^K(\omega') > F^K(\omega)$, the new product configuration is adopted. This process of variation, selection, and retention is repeated in each period.

We compare different types of innovative effort by simulating the performance of an NPD program of type d (averaging over 500 runs in each landscape and 100 landscapes). For each experiment, we let $N = 15$ and $S = 2$ and we vary K and d. To conserve space, we do not show results for every value of K or d (please see the online technical appendix for details).

Figure 3 **Average Performance Over Time for Incremental and Radical NPD Programs**



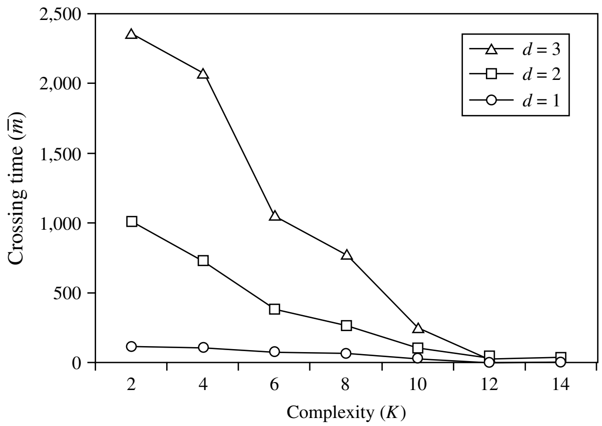
Notes. Average is over 500 runs per landscape and 100 landscapes. For all experiments, $N = 15$ and $S = 2$.

5.2. NPD Program Performance

Figures 3(a) and 3(b) illustrate how complexity impacts NPD program performance (for $K = 2$ and $K = 6$, respectively). For a given level of K, incremental NPD programs achieve short-term performance whereas radical NPD programs achieve long-term performance. Once again, this gives rise to a crossing time and defines a window of time during which radical innovation underperforms on average. More importantly, the crossing time occurs earlier as K increases.

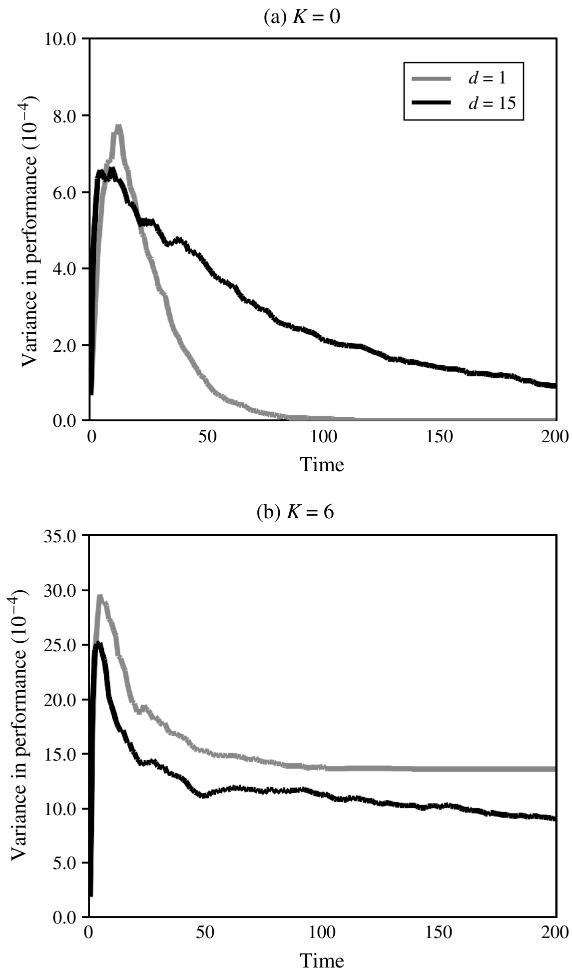
The existence of a crossing time is a direct outcome of the "rugged" nature of the performance functions in environments with significant interaction complexity. In complex technology-market environments, incremental NPD programs offer an initial advantage because they improve performance with higher probability relative to radical NPD programs. Unfortunately, the advantage is short-lived because incremental efforts are not able to benefit from a holistic approach and they get trapped in local performance optima (lower $\widehat{V}$). Radical NPD efforts take more time to improve performance. The time inefficiency of radical NPD programs is due to the fact that they seek riskier solutions based on drastic product alterations. However, the holistic approach and perspective of radical NPD programs (expressed through the number of potential solutions in $N_d(\omega)$) allows them to escape local optima. Figure 3 shows that interaction complexity increases the attractiveness of radical NPD programs. In the absence of complexity, there is no need for radical innovation. Thus, our simulation identifies performance function complexity as another feature that drives the value of radical innovation. In a complex environment, the value of radical innovation is realized faster and the crossing time is reduced.

Figure 4 **Crossing Time ($\bar{m}$) as a Function of Complexity (K) for Different Values of d**



Notes. Average is over 500 runs per landscape and 100 landscapes. For all experiments, $N = 15$ and $S = 2$. Crossing times for $d = 1$, $d = 2$, and $d = 3$ are relative to $d = 15$.

Figure 5 **Variance Over Time for Incremental and Radical NPD Programs**



Notes. Variance is over 500 runs per landscape and 100 landscapes. For all experiments, $N = 15$ and $S = 2$.

The preceding analysis was based on the extreme cases of $d = 1$ and $d = 15$. Figure 4 depicts the crossing time ($\bar{m}$) as a function of complexity (K) for different values of d. For a given d the crossing time is a decreasing function of complexity. Thus, our results are robust with respect to d. Of course, for a given level of complexity, the crossing time is an increasing function of d because higher d implies more radical innovative effort. Note that the extreme case in which all NPD programs are defined by $d = 15$ would result in $\bar{m} \to \infty$.

Although average performance is an important metric, it is also insightful to consider the issue of risk (proxied through variance of NPD program performance). Figures 5(a) and 5(b) show the variance of NPD program performance as a function of time for environments with no complexity and high complexity ($K = 0$ and $K = 6$, respectively). In the absence of complexity, incremental NPD programs reduce risk immediately as the product configuration converges to the globally optimal configuration (note that the variance for incremental NPD programs is zero after approximately 100 periods). However, in a complex environment, incremental NPD programs converge to multiple local optima and thus do not reduce variance as quickly as radical NPD programs. The radical programs continue to reduce variance over time, as they are able to escape locally optimal product configurations and further improve performance. Thus, when risk is taken into account, radical innovation delivers a secondary benefit in the presence of complexity: it *reduces* NPD program risk. The observation is of significant managerial value because it illustrates an environmental aspect of risk in addition to the typical considerations. Previous research stresses that managers should be aware of individual program risk due to the probability of success in any given period. We extend the consideration of risk and recognize the effect of time and interaction complexity on NPD program risk. Of course, a radical innovation strategy reduces risk in the long term if and only if the program continues to operate under the same environmental conditions in the future.

5.3. Can the Firm Commit to the NPD Program?

Our base-case results reveal the critical role of time when evaluating the effectiveness of a NPD program. The option to pursue different degrees of incremental or radical innovation creates tension with respect to the amount of time that it takes to fully realize the benefits of a particular NPD program. The fact that radical NPD programs take longer to deliver results poses an additional challenge to managers who must ensure that the firm remains viable during this critical time window. As with the analytic model of §4, we now turn our attention toward potential disruptions to the technological and market environment.

Environmental instability represents the likelihood of structural changes in the underlying program performance functions. Low (high) stability implies that the probability that the firm faces the same performance function in subsequent periods is low (high). In practice, several exogenous factors may reshape the performance functions. The technology management literature highlights the effects of competence-destroying changes that redefine an industry (Tushman and Anderson 1986). Another possibility is the periodic shift in market preferences, a phenomenon that Christensen observed in the hard-disk industry (Christensen et al. 1998). The landscape may also change as a dominant design emerges in an industry and the competitive dimensions are altered (Henderson and Clark 1990), or because governmental regulation resets the rules of competition.

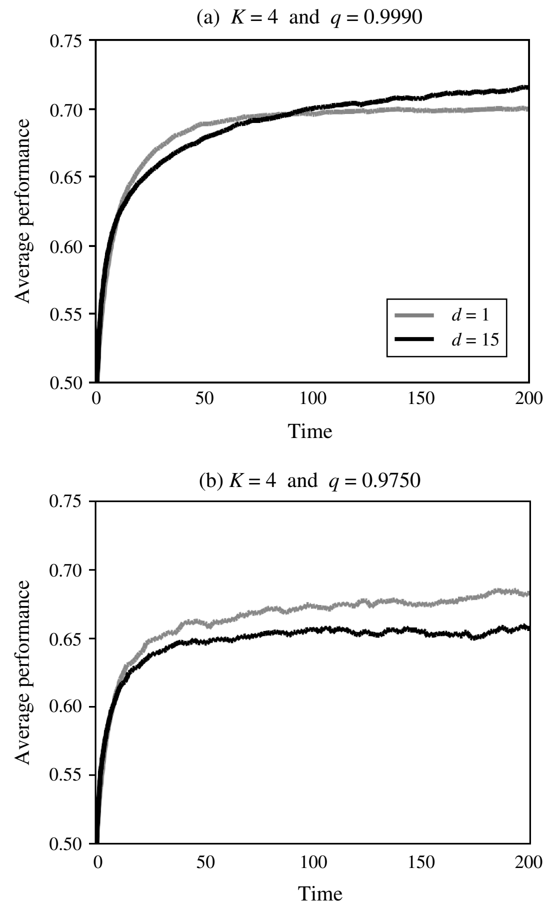
Similar to the analytic model setup, let the likelihood q determine the performance function $F^K(\cdot)$ in period $t+1$ conditioned on the performance function in period t as follows:

$$F^K(\omega \mid \vec{f}) = \begin{cases} (1/N)\sum_{j=1}^{N} f_j & \text{w.p. } q \\ (1/N)\sum_{j=1}^{N} f'_j & \text{w.p. } 1-q, \end{cases} \tag{4}$$

where $\vec{f}$ is the vector of attribute contribution functions in period t. Thus, we model environmental disruptions by changing the performance functions that firms face. A disruption in our setting does not alter the firm's product configuration; rather, the performance contribution of each attribute, f_j, is randomly redefined by a new $U(0,1)$ random number. However, we maintain the same level of complexity to isolate the effects of environmental instability. The simulation proceeds according to the same mechanics as the base case with the exception that a disruption occurs in every period with probability $(1-q)$. Thus, the time of disruption is a random variable. Figure 6(a) depicts the average performance for $K=4$ and $q=0.9990$ (high complexity and high stability). Radical innovation dominates after the crossing time, although the steady-state performance is dampened due to the lack of environmental stability. Figure 6(b) shows the average NPD program performance over time when $K=4$ and $q=0.9750$ (high complexity and low stability). Despite the presence of complexity, low stability undermines the effectiveness of a radical innovation strategy because radical NPD programs do not have time to improve performance between disruptions.

The result bears managerial significance because it alludes to the notion of turbulence in an environment. Utterback (1994) characterizes different phases of industrial evolution (fluid, transitional, and specific) and he emphasizes that the rate of technological change is high during the predominant design (fluid) phase. Christensen et al. (2002) also address the fact that different strategies are successful early versus later in the industry lifecycle—the former being defined by high complexity while the latter is defined by low complexity. Our analysis of stability adds to these insights and highlights the fact that managers must assess the level of environmental instability when determining innovation strategy. The critical issue is whether the firm has enough time to allow radical NPD programs to achieve superior performance relative to incremental NPD programs. Once again, the crossing time is of critical importance when determining an innovation strategy.

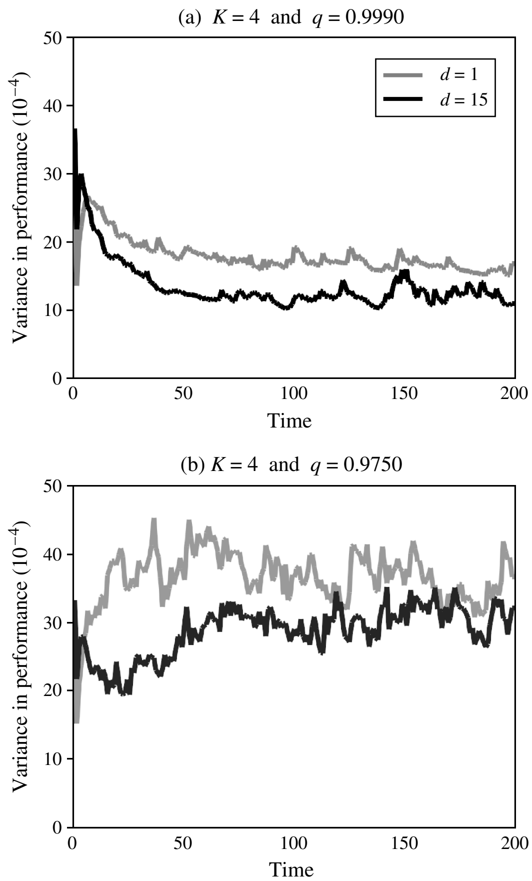
Figure 6 **Average Performance Over Time in the Presence of Technological or Market Disruption**



Notes. Average is over 500 runs per landscape and 100 landscapes. For all experiments, $N = 15$ and $S = 2$.

Analysis of the variance in performance (risk) under environmental instability offers a different insight. Figures 7(a) and 7(b) show the variance of NPD program performance as a function of time in a complex environment ($K=4$) with high stability ($q=0.9990$) and low stability ($q=0.9750$), respectively.

Figure 7 Variance Over Time in the Presence of Technological or Market Disruption



Notes. Variance is over 500 runs per landscape and 100 landscapes. For all experiments, $N = 15$ and $S = 2$.

In the presence of complexity, a higher probability of disruption creates additional risk for both types of NPD programs. Despite the environmental instability, variance is still lower for radical NPD programs because of their ability to escape local optima.

Conventional wisdom states that incremental innovation efforts deliver low value and low risk whereas radical innovation efforts deliver high value and high risk. The insights from Figure 6(b) and Figure 7(b) challenge this wisdom. In an environment characterized by high instability, incremental innovation ($d = 1$) delivers *higher* average performance and *higher* variance relative to radical innovation ($d = 15$). Thus, environmental complexity coupled with environmental instability reverses the commonly accepted value/risk profiles of incremental and radical innovation.

6. Extension to a Portfolio of NPD Programs

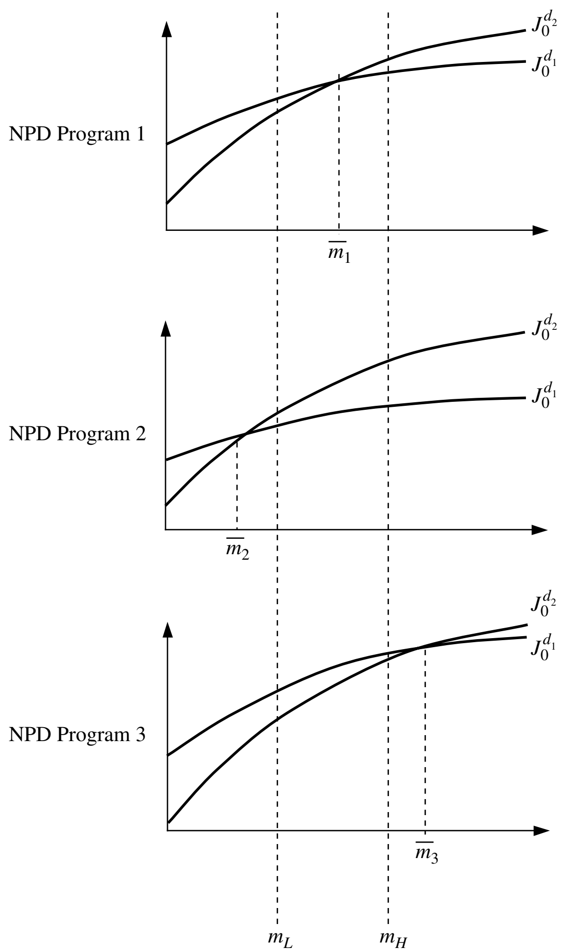
To this point we have considered the value generated by a single NPD program both from an analytic and evolutionary lens. We now discuss the performance of a portfolio that consists of $M > 1$ NPD programs, each geared toward improving a particular product. At the NPD portfolio level, each NPD program will be defined by a particular type of innovative effort. A strategic bucket is a collection of NPD programs that are similar with respect to the type of innovative effort. We will show that the simple structure defined in this paper leads to an NPD portfolio that is more or less incremental or radical depending on the environment in which the firm operates. Furthermore, this observation is true whether one considers the rational analytic model described in §4 or the evolutionary simulation described in §5.

There is no reason to believe that every NPD program in the portfolio will have the same expected return curve. In fact, because the NPD programs each target a different product, and each product is defined by a different set of technology and market attributes, there is strong evidence that the NPD program return functions will be distinct. Based on this observation, the NPD portfolio problem is defined by a set of crossing times $\{\overline{m}_1, \overline{m}_2, \ldots, \overline{m}_M\}$ and a choice of the type of innovation (incremental or radical) for each of the M programs. Once again, potential disruptions to the technology and market environment dictate the amount of time available to the firm. Based on our previous discussion, our intuition is that if the amount of time available is short, the NPD portfolio balance will shift toward incremental innovation, whereas if the amount of time available is long, the balance will shift toward radical innovation.

6.1. The Analytic Reason to "Balance" Strategic Buckets

Building on our analytic model, let $f_i(m)$ be the difference between incremental and radical NPD program performance for the ith NPD program in the portfolio. A simple example highlights the shifting balance in strategic buckets for a portfolio with $M = 3$ NPD programs (Figure 8). Suppose a disruption occurs at time m_L with probability q (with probability $1 - q$ there is no disruption). When $q = 1$ we have $f_1(m_L) > 0$, $f_2(m_L) < 0$, and $f_3(m_L) > 0$. In this case, Program 1 should pursue incremental innovation, Program 2 radical innovation, and Program 3 incremental innovation. The resulting strategic buckets policy is 33% radical. Conversely, suppose that a disruption occurs at time m_H with probability q (again, with probability $1-q$ there is no disruption). In this case, when $q = 1$ we have $f_1(m_H) < 0$, $f_2(m_H) < 0$, and $f_3(m_H) > 0$. Program 1 should pursue radical innovation, Program 2 radical innovation, and Program 3 incremental innovation. The resulting strategic buckets policy is 66% radical. This example highlights the fact that different degrees of environmental instability lead to different "balance" in the NPD portfolio. In fact, for any $q \in (0, 1)$, as

Figure 8 An Example of the Shifting Balance in the NPD Portfolio



q becomes lower (higher), the NPD portfolio should include more radical (incremental) innovation efforts. Of course, if $q = 0$ there is no disruption and the best choice is 100% radical programs in the NPD portfolio. As the probability of a technological or market disruption increases, the "balance" shifts toward incremental innovation in the NPD portfolio because radical innovation does not have time to deliver results.

6.2. The Evolutionary Reason to "Balance" Strategic Buckets

Based on the results from our evolutionary model, we now present a simple example that explains the balance between incremental and radical innovation in the NPD portfolio. Each NPD program is geared toward improving a product and the performance of each product may be defined by a different level of complexity. With this in mind, each NPD program in the portfolio will have a different crossing time. Figure 9 depicts a sample NPD portfolio with $M = 3$ NPD programs. The left column depicts an environment with relatively high stability ($q = 0.9990$) whereas the right column depicts an environment with relatively low stability ($q = 0.9750$).

When the firm is operating in an environment with high stability ($q = 0.9990$), the best strategy in terms of long-run expected performance is that Program 1 pursues incremental innovation whereas Programs 2 and 3 pursue radical innovation. This results in an NPD portfolio that is 66% radical. Conversely, when the firm is operating in an environment defined by low stability ($q = 0.9750$), the best strategy in terms of long-run expected performance is incremental innovation for all of the NPD programs. This results in an NPD portfolio that is 0% radical.

Once again, different degrees of environmental instability lead to different "balance" in the NPD portfolio. If NPD managers care about long-run expected return more than they care about risk, we can safely conjecture that as the probability of technology or market disruptions becomes lower (higher), the NPD portfolio should include more radical (incremental) innovation efforts. As with our analytic model, if $q = 1.000$, the environment is fully stable and the best choice is a NPD portfolio that is 100% radical. As the probability of a technological or market disruption increases, the "balance" shifts toward incremental innovation in the NPD portfolio. Conversely, if managers would rather reduce risk than increase expected performance, then a higher probability of technological or market disruption coupled with a complex performance landscape may call for an NPD portfolio that includes a *greater* number of radical programs. This final insight is important as it challenges commonly accepted wisdom regarding NPD portfolio strategy and risk.

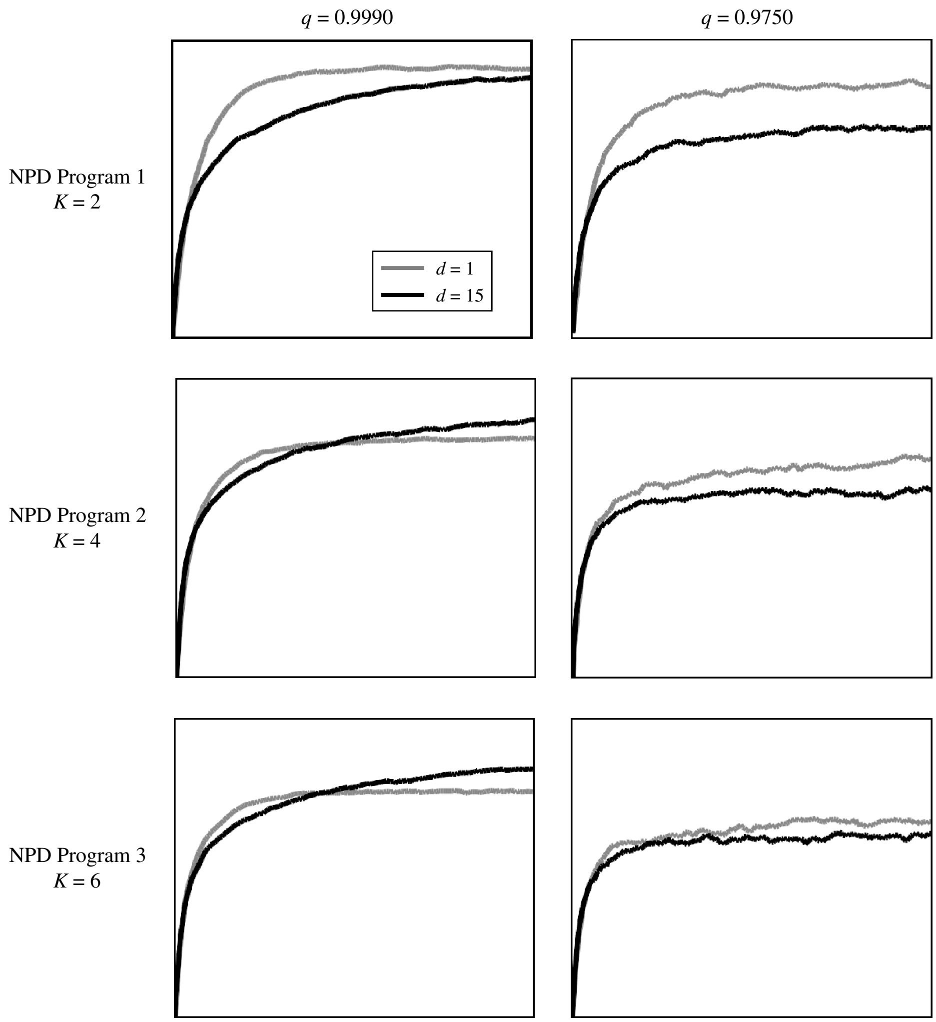
7. Conclusions and Implications of the Research

To date, NPD portfolio considerations at the strategic level are for the most part qualitative. The need for a solid theoretical framework is imperative because NPD portfolio decisions serve to execute innovation strategy. We offer a rigorous treatment of the long-proposed method of dividing the NPD portfolio into innovation-focused strategic buckets. The practitioner literature describes multiple cases of successful implementation and highlights the importance of protecting resources. Unfortunately, specifics are not offered aside from a consistently repeated suggestion to "balance" the NPD portfolio. Our analysis reveals a robust structure for the strategic buckets problem—the existence of a crossing time that defines the relative value of incremental and radical innovation.

7.1. When and How to Use Strategic Buckets

Effective use of strategic buckets requires a deeper understanding regarding two factors that confound decision making: environmental complexity and environmental instability. Complexity between performance attributes and instability in the performance

Figure 9 An Example of the Shifting Balance in the NPD Portfolio



Notes. Each graphs depicts the average NPD program performance over time. Average is over 500 runs per landscape and 100 landscapes. For all experiments, $N = 15$ and $S = 2$.

landscape both make the performance function more difficult to understand in the eyes of the decision maker. However, the former increases the value of radical innovation, whereas the latter increases the value of incremental innovation. The rationale behind these effects is of significant managerial value. Higher complexity implies a performance landscape with multiple local performance peaks where incremental innovation strategies may get trapped. On the other hand, high instability reduces the critical time necessary to achieve high value from radical innovation efforts. When complexity and instability are present together, we find that common notions of risk and reward are reversed: incremental innovation delivers *higher* performance and *higher* risk relative to radical innovation. If the NPD manager cares enough about risk relative to average performance, our insights may result in a complete flip of the NPD portfolio balance. Table 1 summarizes these conclusions.

7.2. Unraveling Complexity and Coping with Bounded Rationality

Managers can benefit from clearly identifying a set of key design, technology, and market variables that affect the overall NPD program performance function *even if their exact performance contribution is not known*. Identifying key product attributes can help managers decipher the nature of the technological and market environment and assess whether the program performance functions are governed by low or high interaction complexity.

One of the primary challenges to understanding complexity and its effects on NPD program performance is that technology and market attributes are often qualitative and difficult to operationalize. To grasp the complexity of the technological and market environment, decision makers must unravel dependencies between the attributes that determine product performance. The design structure matrix (Eppinger et al. 1994) is a tool that has predominantly

Table 1 When and How to Use Strategic Buckets

Environment characterized by...	Best strategy to maximize expected return	Best strategy to reduce risk (variance)	"Balance" in the NPD portfolio should shift toward...
High complexity only	Radical	Radical	Radical
High instability only	Incremental	Incremental	Incremental
Neither complexity nor instability	Incremental	Incremental	Incremental
Both complexity and instability	Incremental	Radical	Depends on $U(\cdot)$

been used by designers to map dependencies between design attributes. We posit that similar thinking can be applied to performance dependencies between technological and market attributes of a product.

Although the design structure matrix can help managers decipher the complexity of the environment, questions still remain with respect to the performance functions for each of the technology and market attributes, and the extent to which these performance functions change over time. Various market research techniques such as conjoint analysis or choice modeling can be used to uncover the evolution of performance functions (Ofek and Srinivasan 2002). In conjunction with traditional market research methods, the use of these tools on a periodic basis can help managers understand how the performance functions change over time. This exercise goes a long way toward helping managers understand the notion of environmental instability.

Our study of strategic buckets coupled with methods that shed light on environmental complexity and stability can form the basis for more effective NPD portfolio strategy. We view our work as an important step that can help academics and practitioners develop a better understanding of portfolio decisions at a strategic level.

8. Electronic Companion

An electronic companion to this paper is available as part of the online version that can be found at http://mansci.journal.informs.org/.

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