A THEORETICAL FRAMEWORK FOR MANAGING THE NPD PORTFOLIO: WHEN AND HOW TO USE STRATEGIC BUCKETS

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Abstract

Developing the "right" new products is critical to firm success and is often cited as a key competitive dimension. This paper addresses the link between new product development (NPD) portfolio strategy and firm performance. To do so, we first characterize resource allocation and NPD portfolio strategy in a general theoretical framework. We then proceed to use our framework to analyze a popular practice in NPD portfolio management: the use of *strategic buckets* for managing the NPD portfolio. Strategic buckets encourage the division of the overall NPD resource budget into smaller, more focused budgets. Our results indicate that the "optimal" strategic bucket size depends on *environmental complexity* (defined as the number of unknown interdependencies among technology and market parameters that determine product performance). As complexity increases, portfolios that include a greater number of revolutionary programs perform better. We also explore conditions that create a need to balance the NPD portfolio: *competition intensity* (the probability of firm extinction) and *environmental instability* (the probability of changes to the underlying performance functions) prompt for a balanced portfolio. We conclude by presenting specific methods that can aid strategic level decision-making in NPD portfolio management.

Keywords: New Product Development; NPD Portfolio Strategy; Resource Allocation Strategy; Strategic Buckets; Incremental and Revolutionary Innovation; Complexity; Bounded Rationality.

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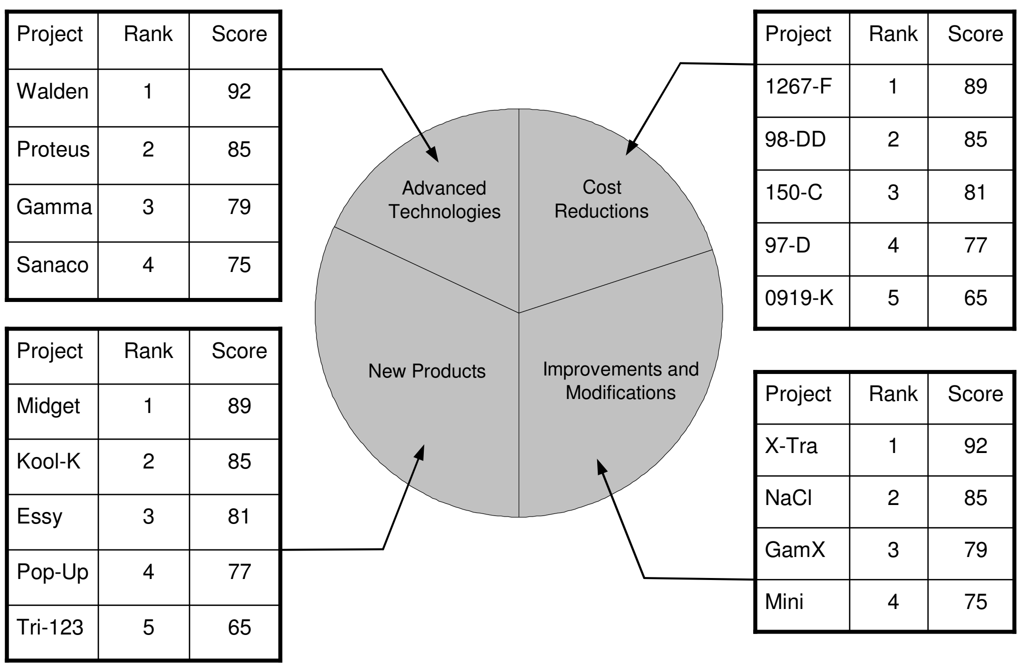
1. INTRODUCTION

Developing the "right" new products is critical to medium and long-term success of firms (Roussel et al. 1991, Cooper and Kleinschmidt 1996, Miller and Morris 1999). 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 estimated $2 billion yearly R&D budget to improving established business lines (Barrett 2003). Drug maker AstraZeneca revealed the decision to restructure its portfolio to include more incremental projects (Pilling 2000). Kodak is investing resources in revolutionary new technologies 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 (Schoenberger 2003). These cases underscore the reality that effective resource allocation and NPD portfolio strategy profoundly impact firm success.

Managing the NPD portfolio is a challenge because of scarce resources, market and technical uncertainties, product/project complexities and interactions, and the desire to achieve strategic alignment, among other difficulties (Kavadias and Loch 2003). The Product Development Management Association (PDMA) recently issued a report that paints a bleak picture with respect to this challenge (Adams and Boike 2004). According to the report, the majority of firms emphasize incremental innovation efforts in their NPD portfolio. Such emphasis appears to be negatively correlated with firm performance. Indeed, the PDMA study goes on to indicate 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 incremental improvements.

Practitioners have developed several methods that aim to increase effectiveness when allocating resources across NPD initiatives of varying degrees of innovativeness. A number of case based frameworks cite the trade-offs between product and process innovation, risk and reward, and market and technology risk among others (Roussel et al. 1991, Wheelwright and Clark 1992, Cooper et al. 1998). These tools summarize best practices for dividing resources and achieving "balance" across R&D endeavors. Though the tools may have different names, all of these practices encourage the division of the overall R&D resource budget into smaller, more focused budgets. The result is a set of *strategic buckets* for managing the R&D portfolio (Cooper and Edgett 2003, Cooper et al. 2004).[2] A strategic bucket is money set aside for R&D projects aligned with a particular strategy (Roussel et al. 1991, Wheelwright and Clark 1992, Cooper et al. 1998). The strategies addressed by different strategic buckets may involve process improvements and cost reductions, minor product modifications, revolutionary next generation technological research, or groundbreaking R&D initiatives, among others.[3] Figure 1 depicts a NPD portfolio strategy with four strategic buckets.



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

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

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

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

Figure 1: An example of a strategic buckets strategy comprised of four buckets: cost reductions, improvements and modifications, new products, and advanced technologies (adapted from Cooper et al. 2001).

[2] Depending on the study such buckets are named process or product innovation buckets, or high-risk versus low-risk buckets, etc. All of these terms are centered on the degree of innovation pursued by the programs in the strategic bucket.

[3] Strategic buckets may also address specific market segments (e.g., industrial, retail, consumer) or specific geographic focus (e.g., North America, Latin America, Asia). The framework presented in this paper subsumes all of these possibilities.

The primary goal of strategic buckets is to create non-permeable partitions between R&D 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 and new-to-the-world projects due to the increased risk (high likelihood of failure) and the long-term payoffs associated with these revolutionary projects. In addition, these tools are difficult to use when it comes to cutting-edge projects because data may be unreliable or highly biased (Kavadias et al. 2005). In summary, the goal of a strategic bucket is to "protect" resources for revolutionary R&D projects. As an alternative to protecting resources, managers can sway the result of a NPV analysis in favor of a more revolutionary project by increasing the value of the project (the infamous $10 billion market opportunity). However, the results can just as easily be swayed in the opposite direction by lowering the probability of success for a revolutionary project. Such lack of transparency in decision-making creates problems for managers (Loch et al. 2001). Strategic buckets avoid these problems by earmarking resources for revolutionary R&D projects from the beginning.

The main idea underlying the strategic buckets methodology is relatively straightforward. However, in practice, the decision is ad-hoc with minimal theoretical foundation. Resource allocation according to a strategic buckets rule suffers limitations because it is difficult to operationalize and obtain robust NPD data at the strategic level. Thus, the suggested balance in resource allocation remains merely a guideline. Despite the widespread use of strategic buckets in practice, we lack rigorous theoretical understanding about the drivers of resource allocation strategy in NPD and the need for strategic buckets.

The difficulty inherent in the use of strategic buckets stems from underlying decision problem characteristics. The resource allocation decision at the strategic level exhibits *complexity* and is influenced by decision maker's *bounded rationality* (Simon 1982, Hagel 1988). Complexity may exist due to a variety of reasons including market and technological uncertainty, and the existence of multiple technology and market variables that define overall product performance (Leonard-Barton 1995, Pich et al. 2002). In addition, these factors may interact to some degree, as exemplified by market cannibalization phenomena or technical design dependencies (Moorthy 1988, Smith and Eppinger 1997, Brown and Eisenhardt 1998, Kavadias and Loch 2003). Along similar lines, lack of available information, data processing limitations, and knowledge limitations restrict decision-maker's ability to optimize resource allocation decisions (Simon 1955). The inability to optimize results in bounded rationality – the fact that decision-makers have inadequate information regarding the precise structure of product performance functions, e.g., how the relevant performance drivers interact to determine performance (Simon 1982, Kahneman 2003). Despite the complexity of the problem and their bounded rationality, managers must still make decisions with respect to R&D resource allocation.

Academic research stresses the importance of establishing "the right balance" between resource funding for incremental and revolutionary NPD efforts. Classic studies use mathematical programming techniques that focus on individual projects as the unit of analysis and model the interplay between capacity availability and project value (knapsack problems). This research stream seldom accounts for strategic variables due to their intangible nature, and managers rarely adopt the resulting suggestions (Loch et al. 2001, Shane and Ulrich 2004). In addition, mathematical programming efforts do not disentangle the drivers of project performance and they subsume all knowledge into a single parameter: the project value. This practice ignores the fact that project value is a result of decisions made during the design and development of a new product (Fleming 2001, Ulrich and Eppinger 2004). Several case studies and field research efforts have addressed strategic issues, but unfortunately these efforts do not offer theoretical background regarding the existence of strategic buckets, or their proposed size (Roussel et al. 1991, Wheelwright and Clark 1992, Cooper et al. 1998).

The goal of this manuscript is twofold. First, we develop a theoretical framework that addresses resource allocation and NPD portfolio strategy. Second, we use our framework to provide a rigorous theoretical foundation for the strategic bucket methodology. Our theory highlights the subtle, yet fundamental role of interactions between technology and market performance drivers. We show that complex business environments with numerous interactions call for more resources allocated to revolutionary innovation efforts while environments with little or no interactions favor incremental projects. In addition, our framework emphasizes the central role of time in evaluating the efficiency of a strategic bucket. Revolutionary efforts require a window of time in order to realize positive outcomes. We show that the number of interactions directly impacts this window of time and we illustrate how different strategic bucket strategies pay off more or less during the window of time. The time element of an innovation outcome sheds light on two additional factors: competition intensity (likelihood of firm extinction) and environmental instability (likelihood of major technological or market disruptions). Higher levels for either of these two factors favors smaller allocation to revolutionary efforts. These results stem from the direct impact of competition and environmental instability on the time window required for revolutionary efforts to pay off.

The remainder of this paper is organized as follows: in section 2 we review the relevant literature, and in section 3 we introduce our model of R&D resource allocation. The results are presented in section 4 beginning with the base result that shows why strategic buckets are a necessity in the presence of complexity, and continuing with the analysis of additional resource allocation drivers. In section 5, we synthesize our findings into a framework that describes the effectiveness of strategic buckets of different sizes in various industrial environments.

2. LITERATURE REVIEW

In this section we briefly review the relevant literature. Two research streams relate to our study: i) research on resource allocation and NPD portfolio management and ii) research on complexity and bounded rationality in strategic decision-making.

2.1 Resource Allocation and NPD Portfolio Management

There is an abundance of literature that analyzes the resource allocation problem at the operational level (Beged-Dov 1965, Souder 1973 and 1978, Fox & Baker 1984, Czajikowski & Jones 1986, Schmidt & Freeland 1992, Benson et al. 1993, Dickinson et al. 2001). 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. This methodology is highly sensitive to parameter changes and practitioners often ignore the results because they lack robustness and transparency (Loch et al. 2001, Kavadias and Loch 2003). These limitations were recently 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 multi-dimensional 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 ability to explicitly include metrics for market risk, technical risk, strategic alignment, and customer preferences. Still, these methods rarely exhibit rigorous theoretical foundations (Calantone et al. 1996, Kavadias and Loch 2003) and they cannot avoid the limitations associated with mixed integer programming.[4] As a result, decision-makers often manipulate the methods to generate desired outcomes rather than using them as true decision support tools.

A number of theoretic models have addressed the choice of R&D projects at the strategic level. Ali et al. (1993) consider a competitive setting where firms decide whether to invest in a single incremental or revolutionary product. They identify return on investment as a primary decision driver but they do not address a portfolio decision. Furthermore, we consider a dynamic search setting and managerial bounded rationality (both of which are more consistent with NPD in practice). Loch and Kavadias (2002) focus on the single firm optimal investment in NPD programs. They do not explicitly account for the nature of the R&D investment (incremental or revolutionary) and they assume perfect knowledge of the program payoff functions and the existing interactions between programs. This assumption excludes truly innovative efforts, since the managers cannot realistically have perfect knowledge regarding such efforts. Adner and Levinthal (2001) consider the balance between product innovation and process innovation in technology development. They focus on demand side effects (e.g.

[4] Ranking methods apply simplifying heuristics similar in nature to those used in mixed integer programs.

customer adoption), and they assume that the payoff structure contains a unique optimum. We allow for a payoff structure that exhibits multiple local optima and changes dynamically.

There exists significant research that specifically addresses the practice of strategic buckets as a resource allocation tool (Roussel et al. 1991, Wheelwright and Clark 1992, Cooper et al. 1997, Cooper et al. 2004). These papers provide descriptive evidence of the use of strategic buckets and the resulting benefits. They often take the form of survey questionnaires that ask practitioners to name the tools used in R&D portfolio management (e.g. benchmarking best practices). These studies clearly point to the importance of strategic buckets and they are our starting point. We aim to enhance our understanding of the need for strategic buckets and provide rigorous theoretical foundation for their use in practice.

2.2 Complexity, Bounded Rationality, and Firm Strategy

Academic research recognizes the fact that many decision problems found in practice exhibit complex structure (Nelson and Winter 1982) and decision makers often exhibit bounded rationality (Simon 1982 and references therein, Kahneman 2003). To model these problem characteristics, researchers treat decision-makers as myopic (i.e. they exhibit limited cognition regarding future outcomes when faced with a performance function). A simple yet rigorous methodology that addresses the analysis of such decision-making situations is the NK model of complex performance landscapes. This methodology builds upon the seminal work of Stuart Kauffman (Kauffman and Levin 1987, Kauffman 1993) and employs fitness (correlation) landscapes to model performance functions. In doing so, the NK model considers a set of agents that "move" around a landscape from point to point based on a predetermined strategy.[5]

A number of researchers have adopted complex performance landscapes to model various managerial problems such as organizational design and evolution (Levinthal 1997, Rivkin and Siggelkow 2003, Siggelkow and Levinthal 2003, Ethiraj and Levinthal 2004, Siggelkow and Rivkin 2005), problem

[5] Along similar lines, researchers in the geological sciences have developed a method called RSM (Response Surface Methodology; see Kushner 1964, Betro 1991, Jones 2001). The goal of RSM is to establish efficient search techniques for complex functionals; yet this stream focuses more on deriving heuristic rules of search and with respect to our problem it does not provide additional insights compared to the simpler and straightforward NK methodology.

solving (Gavetti and Levinthal 2000, Rivkin 2000, Sommer and Loch 2004, Mihm et al. 2003), and technological innovation (Kauffman et al. 2000, Fleming and Sorenson 2001, Sorenson 2002, Fleming and Sorenson 2004). Kauffman et al. (2000) is the work most closely related to our study. They analyze the degree of search effort (more or less revolutionary) as a function of the firm's current performance; however, they do not account for the resource allocation decision across multiple innovation efforts. We build upon their work since we explicitly account for the resource allocation decision in the NPD portfolio. In addition, our search strategies are not simply random draws from a distance related payoff distribution. Rather, we assume that managers have myopic decision-making capabilities with respect to product development choices.

Although the above researchers have contributed to our understanding of organizational design and evolution, problem solving, and technological innovation, none have addressed the important issue of effective resource allocation in the NPD portfolio. We differ from the extant literature in that we develop a general model of resource allocation decisions taking into account the notions of complexity among performance drivers and bounded rationality – two critical elements that define this problem at the strategic level of decision-making. We use the NK methodology to analyze our model and obtain results. However, our fundamental contributions are to provide a theoretical framework that operationalizes NPD portfolio strategy and to provide a theoretical foundation for the use of strategic buckets in managing the NPD portfolio.

3. A MODEL OF THE NPD PORTFOLIO

In this section we introduce a general model of the NPD portfolio and the strategic resource allocation decisions that managers must make. At the strategic level, decision makers do not know exactly how product specific market or technology attributes impact performance (Pich et al. 2002), yet they are still forced to make decisions regarding investment in NPD projects and they are subject to the performance outcomes (e.g. product revenue). Anecdotal evidence from practice (Cooper et al. 2004) and the relevant practitioner literature both highlight the fact that managers create strategic buckets to address the challenges associated with resource allocation strategy. Our goal is to offer a theoretically sound foundation for the existence of strategic buckets, and explore how different factors determine the size and nature of the buckets.

3.1 Individual Products, the Portfolio, and Performance

Borrowing from the engineering design and marketing literature (Urban and Hauser 1993, Ulrich 1995, Srinivasan et al. 1996, 1997, Maier and Rechtin 2000), we model each of the firm's *M* products, ω_i**,** as a bundle of technology and market attributes, $(x_1, x_2, ..., x_N)$. The technology and market attributes combine to deliver economic benefit to the firm (Krishnan and Ulrich 2001). The attributes represent parameters such as the core product architecture, component technologies, design choices, manufacturing process specifications, customer preferences, and customer demographic information, among others. We assume that each technology or market attribute takes one of *S* discrete values so that $x_j \in \{1, 2, ..., S\}$.

The economic benefit (performance) of a product is a function of the technology and market attributes. Each attribute *j* contributes individually to product performance. The performance contribution of attribute x_j may depend on $K \in \{0, 1, ..., N-1\}$ other attributes through a function $f_j(x_j, x_{j1}, x_{j2}, ..., x_{jK})$. This modeling convention captures potential design or market interactions (Smith and Eppinger 1997, Loch and Kavadias 2002, Mihm et al. 2003). For example, in the automotive industry, the contribution of vehicle design characteristics (shape, aerodynamics, aesthetics) to product sales may depend on customer technology awareness in the target market segment (Thomke and Nimgade 1998, Eppinger et al. 1994). The number of interactions per attribute need not be the same for each product. However, the average number of interactions, *K*, offers a surrogate metric for the underlying complexity of the technology-market setting in which the firm operates. Interaction complexity is a result of "*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). Note, that there is a distinct conceptual difference between an unknown yet robust underlying structure that determines the interactions among the technology and market attributes, and the likelihood that this underlying structure is subjected to fundamental changes that alter the interactions and consequently change the performance functions (Tushman and Anderson 1986). We define product performance as a general function of the performance contributions from each technology and market attribute: $F(\omega_i) = G(f_1, f_2, ..., f_N)$ for $i = 1,2,...,M$, and firm (portfolio) performance as the sum over the M products in the portfolio: $\Pi = \sum_{i=1}^{M} F(\omega_i)$.

3.2 Strategic Buckets: Incremental and Revolutionary Innovation

A strategic bucket rule consists of allocating resources to a subset of R&D programs with a common purpose (strategy-driven scope). Similar to Loch and Kavadias (2002) we define an R&D program as an initiative whose goal is to improve an existing product line or develop a new product line. R&D programs entail innovative efforts that strive to alter the product attributes in order to enhance existing product performance or create a new product all together. An individual R&D program may target any number $\Delta \in \{1,2,...,N\}$ product attributes. A set of programs may attempt to improve performance through small changes to product or process design. For these R&D programs, we let $\Delta \in \{1,2,...,d\}$ with $d << N$ and we define the innovation effort as *incremental*. Other programs may pursue long-term development entailing greater risk but higher potential reward. For these programs, we let $\Delta \in \{d+1, d+2,...,N\}$ and the innovation is defined as *revolutionary*. Thus, d determines the degree of innovation for each R&D program. According to our formal definition, R&D programs may be "more" or "less" incremental or revolutionary depending on the number of attributes that are actually altered. Furthermore, our definition of innovative effort extends beyond the standard notion of technological change. Since a product is defined as a collection of technology and market attributes, and R&D programs alter Δ 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, page 65). Figure 2 is a schematic representation of incremental and revolutionary R&D programs.

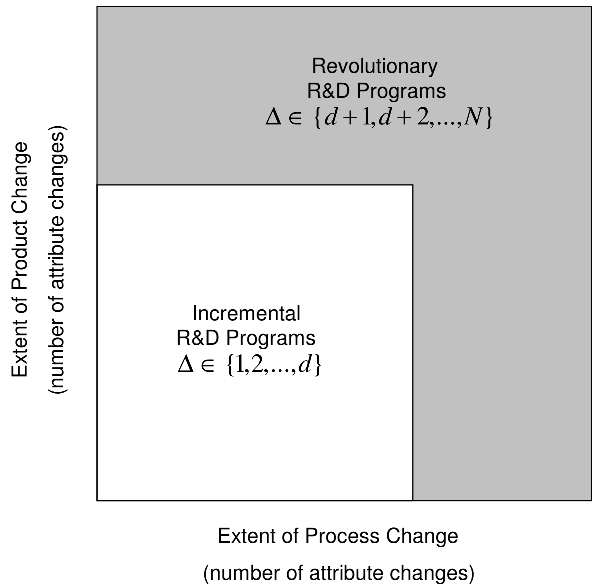


Figure 2: Schematic representation of incremental and revolutionary innovation efforts (adapted from Cooper et al. 2001).

Decision-makers are faced with the problem of allocating resources into R&D programs. Prompted by significant empirical and anecdotal evidence, we focus on resource allocation according to a *strategic buckets rule* (Roussel et al. 1991, Wheelwright and Clark 1992, Cooper et al. 1998). A strategic buckets rule allocates the R&D resources into broad categories such as cost reductions, minor product modifications, and major R&D initiatives. The categories discriminate between types of innovative search, such as incremental (relatively low risk, easy to complete projects with lower payoffs) or revolutionary (higher risk projects that are more difficult to complete but may provide greater payoff potential). Let p be the proportion of revolutionary R&D programs in the portfolio – thus p determines the size of the revolutionary strategic bucket. The remaining R&D programs in the portfolio are assumed to be incremental.[6]

[6] Our model can be extended to include multiple strategic buckets with varying degrees of incremental or revolutionary search (in which case d is a function of the bucket type). Our fundamental insights are not altered by this extension, hence we have chosen to keep the analysis straightforward and we focus on one incremental and one revolutionary strategic bucket.

Once the strategic bucket decision is made, R&D programs are funded and they progress over time. A time period in our model corresponds to a portfolio review period in practice (e.g. quarterly or semi-annually). Between every portfolio review period incremental and revolutionary R&D programs modify technology and market attributes to potentially improve product performance. Since innovation activities require time to realize significant progress, we assume that the strategic bucket allocation does not change from period to period; rather each bucket reflects a strategic vision that pertains to future products.[7] A good example is the development of alternative fuel engines in the auto industry. Companies have funded R&D programs in this specific technological area for several years, if not decades, resulting in hybrid forms that offer distinct competitive advantages (Scientific American 1998). Taking this practice into account, we assume that firms make long-term commitments to the incremental and revolutionary R&D programs in each strategic bucket. Our model is aligned with the common notion that an R&D program may consist of several projects that are reviewed in each portfolio review meeting.

Incremental projects improve product performance through changes to a small number of product attributes, leading to new products that are closely related to the existing products (e.g. product extensions or derivative products). Due to the configuration proximity, and the fact that R&D engineers have some basic decision-making ability, we assume they can test a large number of product configurations within a distance d and adopt the product configuration with the highest performance.

Revolutionary innovation entails higher risk and potentially higher reward. Programs funded by the revolutionary strategic bucket lead to products that are entirely different (in terms of their attribute configuration) to the firm's existing products. We consider that revolutionary R&D programs are not as systematic as incremental R&D programs. Thus, in each period, R&D staff are able to conceive a few new (random) configurations of technology and market attributes beyond a distance d. The new product configurations are tested and the best option is adopted only if it results in higher performance compared to the existing product configuration.

[7] In fact, the possibility of quick re-allocation of resources is cited in the literature as the fundamental reason for the use of strategic buckets (Cooper et al. 1997). As mentioned previously, the purpose of a strategic bucket is to protect resources from short-term based re-allocation.

Thus, incremental innovation allows managers to explore a large number of potential product configurations in a single period while revolutionary innovation constrains managers to explore only a few potential product configurations. Since the M programs exist in the same technology-market environment, they may share common technology and market attributes, and are subject to potential interactions. Still, each R&D program evolves independently. Figure 3 provides schematic representations of the stochastic paths of performance over time for incremental and revolutionary programs. Note that our model captures the stochastic advancement of R&D programs in a manner that is consistent with practice: incremental programs improve performance easily in every period (although the performance improves in relatively small increments) while revolutionary programs may advance several periods without success, but the payoff potential in any given period is greater. Revolutionary innovation is also more risky than incremental innovation because revolutionary programs randomly search for new product solutions while incremental programs systematically alter product attributes. Thus, the probability of finding a successful new product solution is smaller for revolutionary projects compared to incremental projects.

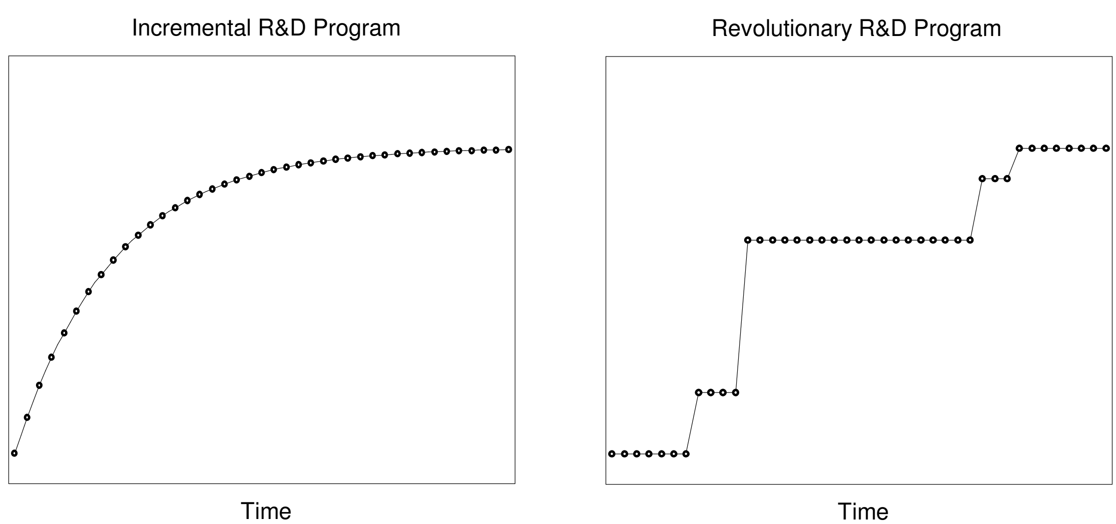


Figure 3: Schematic representation of the stochastic paths for incremental and revolutionary innovation.

The choice of a strategic bucket size translates into costs as follows: assume that the firm's budget in each portfolio review period is Nc for each R&D program.[8] The cost difference between incremental and revolutionary innovation is captured at the implementation level. An incremental program searches a large subset of the $\sum_{k=1}^{d}\binom{N}{k}$ different product solutions within d (and the best option is chosen). A revolutionary project results in only a few new product solutions (and the best option is chosen only if performance is better than the existing product solution). Thus, incremental innovation is less expensive than revolutionary innovation on a *per solution* basis. These assumptions are consistent with R&D portfolio practice as evidenced by the following statement: "*Money invested in R&D can be spent either in incremental projects or revolutionary projects – it's just a matter of what we tell our scientists to look for. Of course, in terms of implementation they are not equivalent. Over an equal period of time, incremental projects generate more [easy] feasible solutions and are less risky than revolutionary projects.*" (Kloeber 2005). A similar distinction between types of innovative activity is evidenced in Sosa (2005), where a firm that specializes in developing cosmetics faces a challenging portfolio decision. In that context, chemists perform "search iterations" in the same amount of time independently of the type of innovation that is pursued. However, the likelihood that each search is successful differs significantly depending on whether the search is incremental or revolutionary.

3.3 Model Analysis

We have developed a general model of the R&D portfolio and the strategic decisions facing managers. In order to specify our model and allow for analysis, we borrow from Kauffman and Levin's (1987) and Kauffman's (1993) NK model of tunable fitness landscapes. The NK model is appropriate in situations where decision-makers exhibit bounded rationality and the performance functions are complex.

We assume without loss of generality that $G(\cdot)$ is a simple average so the performance of each product is: $F(\omega_i) = N^{-1}\sum_{j=1}^{N} f_j$ for $i = 1,2,\ldots,M$. Note that each individual attribute contribution, f_j, is

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[8] The parameter c proxies the cost of innovation in terms of the "average cost to explore an attribute change".

weighed equally in $F(\omega_i)$. Still, that does not imply equal contribution from each attribute to product performance. On the contrary, through f_j and the interdependencies between product attributes, different attributes will result in different impact on product performance. We let $N = 15$ so that each product is defined by 15 key technology or market attributes. Without loss of generality, let $S = 2$ and assume that each attribute can take a value of 0 or 1, leading to a total of 2^N potential configurations for each product.[9] Each individual performance contribution f_j is a random $U(0,1)$ number that corresponds to a particular substring $(x_j, x_{j1}, x_{j2}, ..., x_{jK})$.[10] We assume that each f_j value is randomly generated to account for the fact that managers have limited knowledge (i.e. bounded rationality) regarding the payoff structure. We assume that each firm has $M = 20$ programs in the NPD portfolio and we let $d = 1$ so that each incremental program alters $\Delta = 1$ product attribute in each period. We assume that each incremental program can search all 15 potential product configurations within *d*, and each revolutionary program can generate one potential solution. We have chosen to focus on the extreme case defined by $d = 1$ in order to stress the importance of resource protection. In addition, any $d > 1$ poses issues concerning the ability to fully optimize over all incremental product configurations.

4. RESULTS AND DISCUSSION

In this section we provide theoretical foundation for the use of strategic buckets and we outline necessary conditions for the effectiveness of strategic buckets as a tool for managing the NPD portfolio. We then proceed to discuss various factors that influence how strategic buckets should be used.

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[9] Neither the structural properties of our problem, nor the qualitative nature of our results are altered by the binary value assumption (Kaufmann 1993).

[10] Without loss of generality, we assume that the performance contribution of each attribute depends on the K successive attributes. For example, if $K = 3$ then x_1 contributes $f_1(x_1, x_2, x_3, x_4)$. If $j + K > N$, the interaction substring is treated as circular without loss of generality (Levinthal 1997).

4.1 The Theoretical Foundation for Strategic Buckets

Initially, we consider firms that operate in an environment with minimal interactions between technology and market parameters. Figure 4 depicts average firm performance (for 500 sample paths) when there is no interaction complexity ($K = 0$). Each firm is defined by the size of its revolutionary strategic bucket, which may range from $p = 0\%$ to $p = 100\%$. The figure depicts 10%, 50%, and 90% strategies, although our analysis includes the full range of revolutionary strategic bucket sizes. We choose to focus on small, medium, and large revolutionary bucket sizes to facilitate exposition. The nature of our results is consistent across the continuous range of p.

The amount of time required for a firm to reach the maximum performance is increasing in the size of the revolutionary strategic bucket.[11] This intuitive result highlights the advantage of incremental innovation strategies (small size revolutionary bucket) in environments with no complexity. When $K = 0$, every point (global optimum excluded) has at least one adjacent point with higher performance.

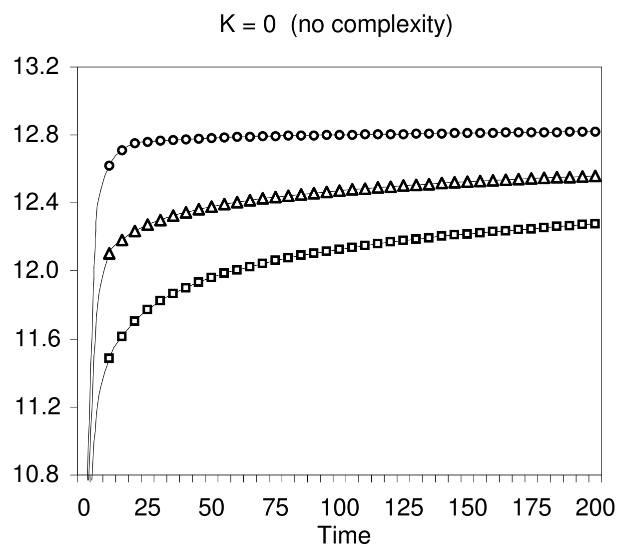

Figure 4: Average firm performance as a function of time for different size revolutionary buckets in an environment with no complexity (K = 0).

% Revolutionary Projects: —o— 10% —△— 50% —□— 90%

[11] To ease exposition we have terminated the simulation after 200 periods. In a $K = 0$ environment all firms will eventually reach the global optimum if given enough time. The notion of time plays an important role in subsequent result, thus we have chosen to remain consistent in our presentation for $K = 0$.

NPD programs that focus effort on incremental improvements advance quickly towards the maximum performance. In contrast, firms with medium to large size revolutionary buckets suffer a time disadvantage because of unsuccessful revolutionary programs. Thus, for $K = 0$, incremental innovation strategies dominate and revolutionary innovation strategies under-perform due to the risk that they bear.

The effectiveness of the revolutionary bucket increases as the technology-market interaction complexity increases. Figures 5(a) and 5(b) illustrate the impact of complexity (for $K = 6$ and $K = 10$ respectively). Higher levels of complexity render resource allocation towards revolutionary NPD programs more effective in the long-term. The fact that incremental NPD programs increase short-term performance while revolutionary NPD programs achieve long-term performance gives rise to a *crossing time*. We define a crossing time as the period in which a strategy with larger size revolutionary bucket (greater number of revolutionary programs) begins to outperform a strategy with a smaller size revolutionary bucket (lesser number of revolutionary programs). The crossing time defines a window of time during which revolutionary innovation efforts under perform on average, and potentially hamper firm performance.

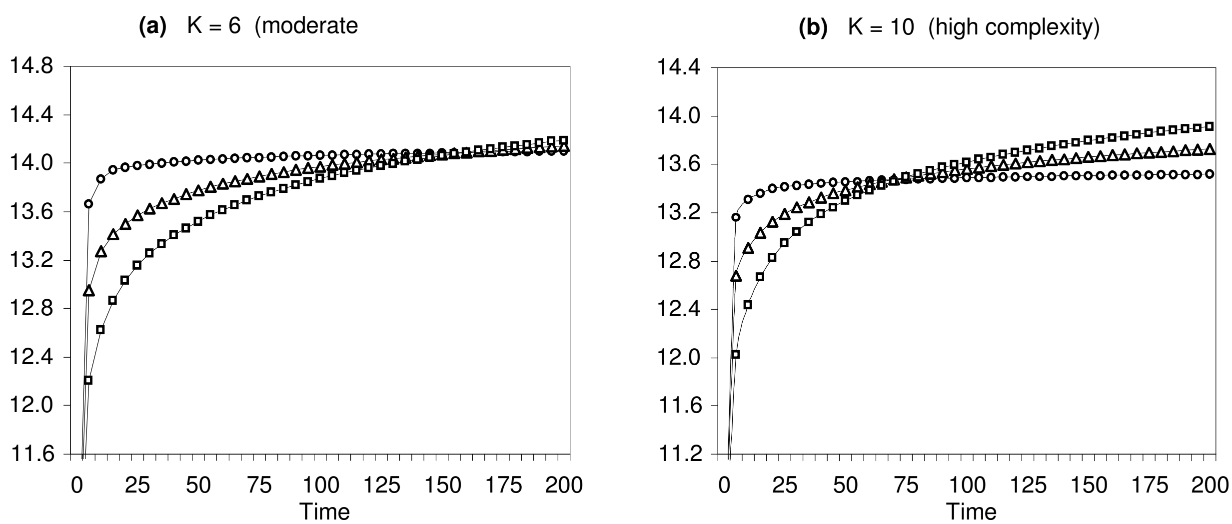

Figure 5: Average firm performance as a function of time for different size revolutionary buckets.

% Revolutionary Projects: 10% 50% 90%

The existence of a crossing time is a direct outcome of the "rugged" nature of the performance functions in environments with significant interaction complexity (Kauffman 1993). In complex technology-market environments, incremental NPD programs offer an initial advantage because they quickly develop solutions that allow them to obtain higher performance relative to revolutionary NPD programs. Unfortunately, the advantage is short-lived because incremental efforts are not able to benefit from a holistic approach (Ulrich and Ellison 1998) and they become "trapped" in local performance optima. Revolutionary NPD efforts improve performance slower on average. The time inefficiency of revolutionary programs is due to the fact that they entail risky solutions resulting from drastic product alterations. However, the holistic approach and perspective of revolutionary programs (expressed through the extended distance of search) allows them to escape local optima. Thus, firms with larger revolutionary buckets benefit from exploring distant parts of the environment.

Figures 4 and 5 show that interaction complexity creates the need to protect resources for revolutionary NPD programs. In the absence of complexity, there is no need for a strategic bucket.[12] Thus, our theoretical framework identifies complexity as the underlying structural feature that drives the need for strategic buckets when managing the NPD portfolio. The following Proposition formalizes the result:

PROPOSITION: *For any $K > 0$, there exists a time, $t(K)$, at which a strategy with larger size revolutionary strategic bucket outperforms any strategy with smaller size revolutionary strategic bucket. Furthermore, $t(K)$ is a decreasing function of the interaction complexity K.*

PROOF: provided in the appendix.

Note that despite the generality of our assumptions, the average return curves depicted in Figures 4 and 5 exhibit properties first assumed by Loch and Kavadias (2002). Our framework highlights the theoretical reasons for the emergence of these curves and how the curves are interrelated.

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[12] Note that an environment with $K = 0$ demands a strategy of 0% revolutionary programs. Although a firm with a strategy of $p > 0\%$ will eventually reach the same performance as a firm with a strategy of $p = 0\%$, the efficiency in terms of time is far greater for the $p = 0\%$ strategy.

The base-case results presented thus far highlight the benefit of revolutionary innovation strategies in complex environments. Furthermore, we see that these benefits increase (relative to incremental innovation) as complexity increases. Although average performance is an important metric, it is also insightful to consider the issue of firm risk (proxied through variance) and the strategic bucket. Research in economics and finance has highlighted the important role of risk-aversion in managerial decision-making (Pratt 1964, Arrow 1965, Kimball 1993, Holt and Laury 2002). Figure 6(a) and 6(b) show the variance of firm performance as a function of time for environments with no complexity and high complexity ($K = 0$ and $K = 8$ respectively). In the absence of complexity, firms with an incremental strategic bucket strategy reduce risk immediately as all products converge to the globally optimal configuration. However, in a complex environment, incremental NPD programs converge to multiple local optima and thus do not reduce variance as quickly as revolutionary NPD programs. The revolutionary 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, a revolutionary strategic bucket delivers a secondary benefit in the presence of complexity – it *reduces* portfolio risk. The observation is of significant managerial value because it illustrates an "environmental"

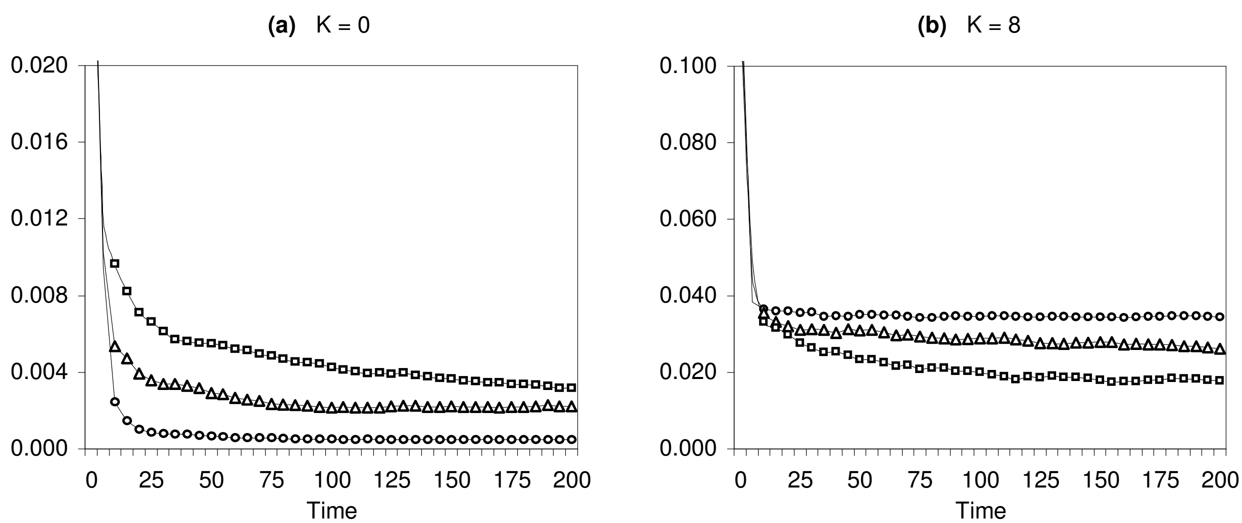

Figure 6: Variance of firm performance as a function of time for different size revolutionary buckets. % Revolutionary Projects: 10% 50% 90%

aspect of portfolio risk in addition to typical considerations of risk. Previous research stresses that managers should be aware of individual program risk (due to the nature of search of an individual program). We extend the consideration of risk and recognize the effect of interaction complexity on the *overall* portfolio risk. Thus, our theoretical framework is able to distinguish between individual program risk and overall firm risk in a straightforward manner. Of course, a strategy of larger size revolutionary bucket reduces portfolio risk in the long-term *if and only if* we assume that the firm will continue to operate under the same environmental conditions in the future.

Our base-case results reveal the critical role of time when evaluating the effectiveness of a strategic bucket strategy. The use of strategic buckets creates a mix of incremental and revolutionary innovation. The combination of innovation efforts in turn 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 revolutionary NPD programs take longer to deliver results poses an additional challenge to managers who must ensure that the firm remains financially viable during this critical time window. From a practical standpoint, our question echoes managerial concerns such as, "what size bucket ensures that the company *survives long enough* to seize the benefits of revolutionary innovation efforts?" Theoretically the question translates into, "what size revolutionary bucket guarantees survival during the interval $[0, t(K)]$?" In that light, the *bang-bang* nature of our base case result should not concern the reader.[13] Thus far we have addressed only the effects of complexity on the strategic bucket. In reality, there are a number of factors that create the need for "balanced" resource allocation in the NPD portfolio (Wheelwright and Clark 1992). We address the issue of firm survival and "balance" in the NPD portfolio in the section that follows.

4.2 How to Use Strategic Buckets: Factors That Influence Balance in the NPD Portfolio

The preceding section demonstrated that complexity is an underlying phenomenon that drives the existence of strategic buckets. Furthermore, our results highlight the importance of time in evaluating the effectiveness of strategic buckets: as the technological and market complexity increases, revolutionary

[13] The most effective strategy in the long-run is $p = 0\%$ for $K = 0$ and $p = 100\%$ for $K > 0$.

NPD programs pay dividends earlier in time. However, managers must ensure that the firm survives until the crossing time to increase the probability that revolutionary NPD programs deliver beneficial results. There has been substantial research that deals with firm evolution and survival and the reasons for firm failure (Hannan and Freeman 1977, Nelson and Winter 1982). Many of these reasons can be attributed to the level of competition faced by the firm (Porter 1985).

In this section we focus on the effect of firm survival (or conversely the probability that the firm becomes extinct) on the strategic bucket size. We enrich our basic model setup by explicitly considering the relative performance of the firm with respect to other firms within the same environment. Because of competition, the firm may become extinct if performance is extremely low. Our experimental structure proceeds as follows: we consider a population of 500 firms in which the size of the revolutionary bucket is evenly distributed throughout the population (i.e. equal number of firms with 10%, 50%, and 90% revolutionary buckets). In each period, the lowest δ firms in terms of performance become extinct. When a firm becomes extinct it is replaced by a new firm with randomly placed products and the same revolutionary bucket size. Our assumption that the overall population of firms remains unchanged is consistent with research in evolutionary economics and population dynamics (Levinthal 1997, Rivkin 2000). Note that we allow for the entire range of firm extinction possibilities through δ. For example, a large number of firms may become extinct in every period (high levels of incessant competition) or a small number of firms may become extinct in every period (negligible competition levels).

Figure 7(a) depicts average firm performance over time in an environment with no complexity ($K = 0$) and enough competition to render 10% of the firms extinct in each period ($\delta = 50$). Firms with small revolutionary buckets are the most resilient in technology-market environments that do not exhibit complexity. As explained previously, firms with small revolutionary buckets progress directly towards the global optimum very quickly in an environment with K = 0. Conversely, firms with larger revolutionary buckets do not improve performance quickly and become extinct. Thus, in settings with negligible complexity, even in the presence of competition, the basic result of §4.1 holds.

The effect of competition is more intricate in the presence of complexity. Figure 7(b) shows average firm performance over time in a complex environment ($K = 8$) in the presence of competition. There is a significant interval of time during which a "balanced" portfolio strategy (i.e. 50% revolutionary projects) outperforms the 10% or 90% revolutionary bucket strategy. Firms with a balanced portfolio (medium size revolutionary bucket) are able to exploit a mix of innovation efforts that delivers long-term performance while ensuring that the firm survives until the crossing time $t(K)$. The result is of managerial importance because it enforces the need for "balanced" portfolio strategies, a realistic consideration that is confirmed by anecdotal evidence in past studies (Cooper et al. 1997, Cooper et al. 2004). Furthermore, the presence of competition together with complexity gives rise to *multiple* crossing times rather than a single crossing time. The existence of multiple crossing times leads us to another critical question that impacts the use of strategic buckets: how long will the technology and market interactions that determine performance remain stable? The answer to this question determines the degree of balance in the NPD portfolio necessary to achieve effectiveness in the long run.

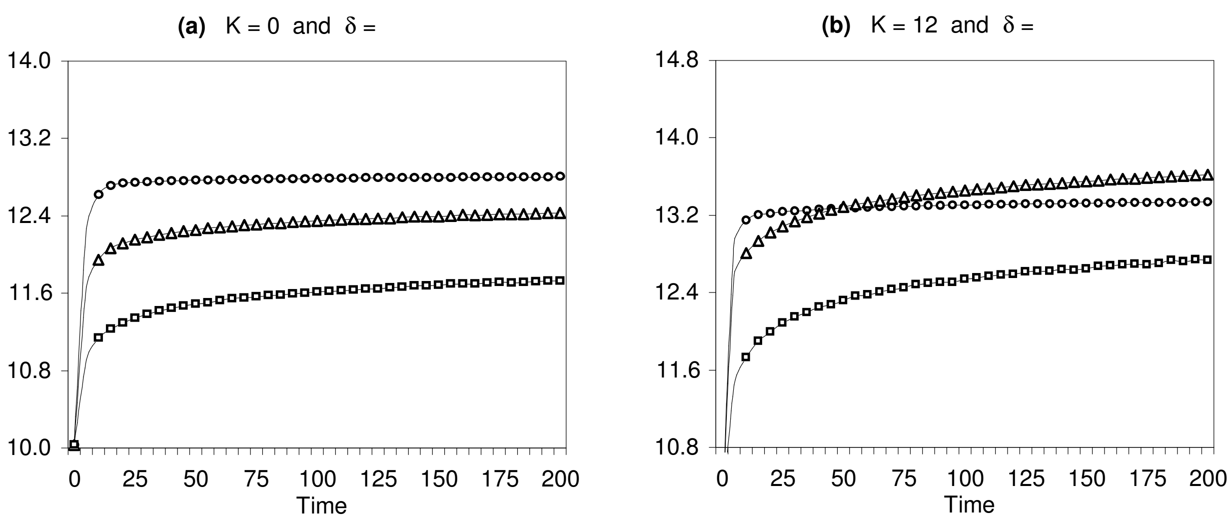

Figure 7: Average firm performance as a function of time for different size revolutionary buckets in the presence of competition.

% Revolutionary Projects: —o— 10% —△— 50% —□— 90%

Based on the above observations, *environmental stability* emerges as an important consideration for determining the most effective allocation across strategic buckets. Environmental stability 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 functions in subsequent review meetings is low (high). In practice, several exogenous factors may reshape the performance functions. The technology management literature highlights the effects of competence destroying changes (Tushman and Anderson 1986), i.e. breakthrough inventions that redefine an industry. Note that our framework does not discount such a case. It could very well be that an environmental disruption is created by the adoption of a new product configuration by a firm. Another possibility is the periodic shift in market preferences, a phenomenon that Christensen observed in the hard-disk industry (Christensen 1997, Christensen and Raynor 2003). The landscape may also change as a dominant design emerges in an industry and the competitive dimensions are altered (Henderson and Clark 1990, Abernathy 1994), or because governmental regulation resets the rules of competition. An example of the latter is the Bayh-Dole Act passed in 1980, which allowed the commercialization of federally funded university research. This legislation increased the creation of R&D consortia and immediately redefined the rules of competition (Thursby and Thursby 2002).

To gain insight into the effects of environmental stability, we extend our model setup. We define the likelihood *s*, which determines the payoff for the firm's products in period $t+1$ conditioned on the performance functions in period t as follows:

$$F(\omega_i \mid \tilde{\mathbf{f}}) = \begin{cases} G(f_1, f_2, \ldots, f_N) & \text{w.p. } s \\ G(\tilde{f}_1, \tilde{f}_2, \ldots, \tilde{f}_N) & \text{w.p. } 1\text{-}s \end{cases} \quad \text{for } i = 1, 2, \ldots, M \tag{1}$$

where $\tilde{\mathbf{f}}$ is the vector of attribute contribution functions.[14] 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

[14] Our model of environmental stability can be equivalently stated by a probabilistic change from $G(\cdot)$ to $\tilde{G}(\cdot)$.

a new $U(0,1)$ random number. However, we maintain the same level of complexity in order to isolate the effect of portfolio strategy on firm performance.[15] 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 – s). Thus, we allow the time of disruption to be a random variable.

Figure 8(a) shows the average firm performance over time when K = 12 and s = 0.975 (high complexity and low stability). The figure highlights the significance of environmental stability. Despite the presence of complexity, low stability emphasizes the need for an incremental portfolio strategy. The result stems from the inability of revolutionary NPD programs to reap benefits between environmental disruptions. Figure 8(b) depicts the average performance for K = 12 and s = 0.995 (high complexity and high stability). In this case, firms with larger size revolutionary buckets dominate in the long run, although the steady-state performance is dampened due to the lack of stability.

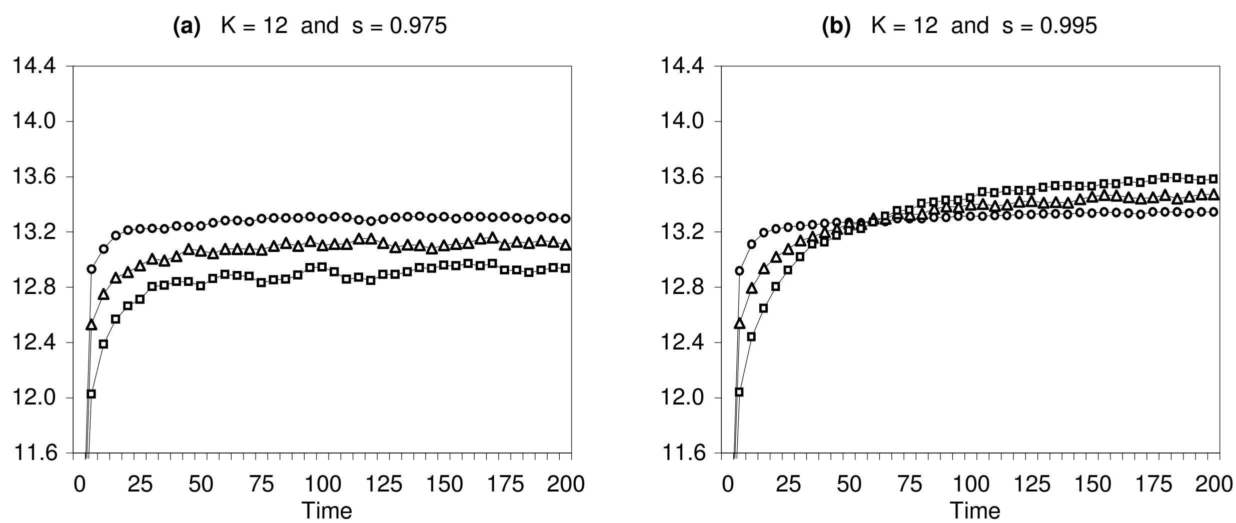

Figure 8: Average firm performance as a function of time for different size revolutionary buckets in the presence of environmental instabilty.

% Revolutionary Projects: 10% 50% 90%

[15] The modeling setup described here assumes uncorrelated landscapes in order to capture the extreme phenomena. We also conducted disruption experiments in which the landscapes were correlated. As expected, correlated landscapes mute the effects of disruptions since product configurations with high performance in one landscape will also achieve high performance on the other landscape (details are available from the authors).

The result bears managerial significance since it alludes to the notion of "turbulence" in an environment (Ansoff 1979, Mintzberg 1979 and 1993, Eisenhardt 1989, Brown and Eisenhardt 1998, Rivkin and Siggelkow 2005). 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 pre dominant design phase (the "fluid" phase). Cristensen 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 instability when making portfolio decisions. Moreover, the need for resource protection (strategic buckets) depends on the level of instability. Our results highlight that the critical issue is whether revolutionary NPD programs can return significant benefits within the crossing times that determine overall portfolio performance.

Analysis of firm risk (variance in performance) under environmental instability offers a different insight compared to the results presented in the §4.1. Figure 9 shows the variance of firm performance as a function of time in an environment with high complexity (K = 12) and high stability ($s = 0.995$). In the

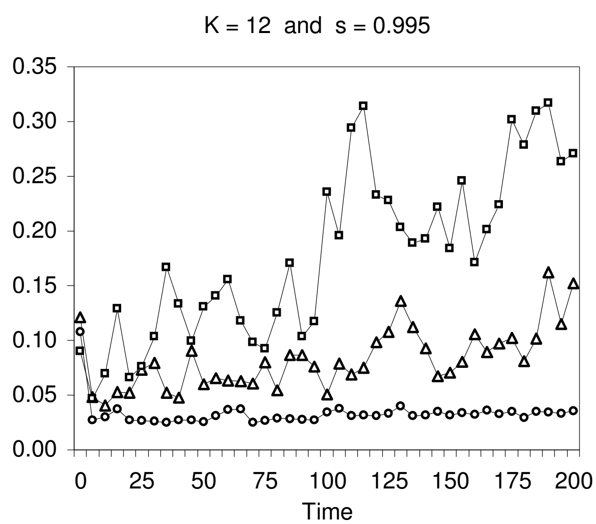

Figure 9: Variance of firm performance as a function of time for different size revolutionary buckets in the presence of environmental instabilty.

% Revolutionary Projects: —o— 10% —Δ— 50% —□— 90%

presence of complexity, even the slightest probability of technological and market disruption creates additional risk for firms with large revolutionary strategic buckets, and this portfolio risk is increasing over time.[16] Thus, high levels of instability prompt for incremental innovation strategies (smaller size revolutionary bucket) both from the perspective of average firm performance and variance of firm performance. Although variance reduction is often cited as an appropriate goal, it should be noted that variance also creates opportunities. Higher instability identifies a subset of firms with large revolutionary buckets that may be the most successful (since we have a high mean low variance set compared to a set with lower mean but much higher variance). The presence of instability defines a clear trade-off between how much risk the firm willing to accept and the relative average payoff, particularly in terms of long-run performance.

5. CONCLUSIONS AND MANAGERIAL IMPACT

We have introduced a theoretical framework that makes two contributions to existing knowledge. First, we operationalize incremental innovation (systematic search for similar product configurations), revolutionary innovation (random search for entirely different configurations), environmental complexity (interactions between product performance drivers), bounded rationality (lack of knowledge regarding performance functions and the inability to fully optimize), and environmental instability (the probability that performance functions change). 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 operationalize firm strategy. Second, we offer a rigorous treatment of the long proposed method of dividing resources into innovation-focused strategic buckets. The practitioner literature describes multiple cases of successful implementation, yet no specifics are offered aside from a consistently repeated suggestion to "balance" the NPD portfolio.

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[16] We measured variance of firm performance over time for various levels of complexity and stability. The results were consistent with those presented here (details are available from the authors).

5.1 *Managerial Insights: When and How to Use Strategic Buckets*

Our theoretical framework highlights the fact that the underlying interaction complexity among attributes that determine product (and subsequently overall portfolio) performance is a necessary condition for the employment of strategic buckets. This is particularly true given the fact that managers exhibit bounded rationality. The size of incremental and revolutionary strategic buckets depends not only on complexity, but also on competition and stability of the technology-market environment.

Our results show that firms that find themselves in low complexity environments should always pursue incremental innovation strategies (i.e., there is no need for a revolutionary strategic bucket). Conversely, firms that find themselves in complex environments must consider additional issues. If the likelihood of a technological or market disruption is high, an incremental strategy is once again advocated. However, if the probability of technological or market disruptions is relatively low, firms benefit from "protecting" resources through the use of revolutionary strategic buckets. Low probability of environmental disruption coupled with high levels of competition prompt for a balanced strategic bucket strategy. On the other hand, low probability of environmental disruption coupled with relatively low levels of competition prompt for significant investment in the revolutionary strategic bucket. These findings are summarized in Figure 10.

5.2 *Unraveling Complexity and Coping with Bounded Rationality*

The proposed framework and subsequent results have important implications for managers. First, the framework allows managers to operationalize incremental and revolutionary innovation, and apply the results to their NPD portfolio strategy. Management can benefit form 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 easily uncovered). Second, managers must decipher the nature of the technological and market environment and assess whether the program performance functions are governed by low or high interaction complexity.

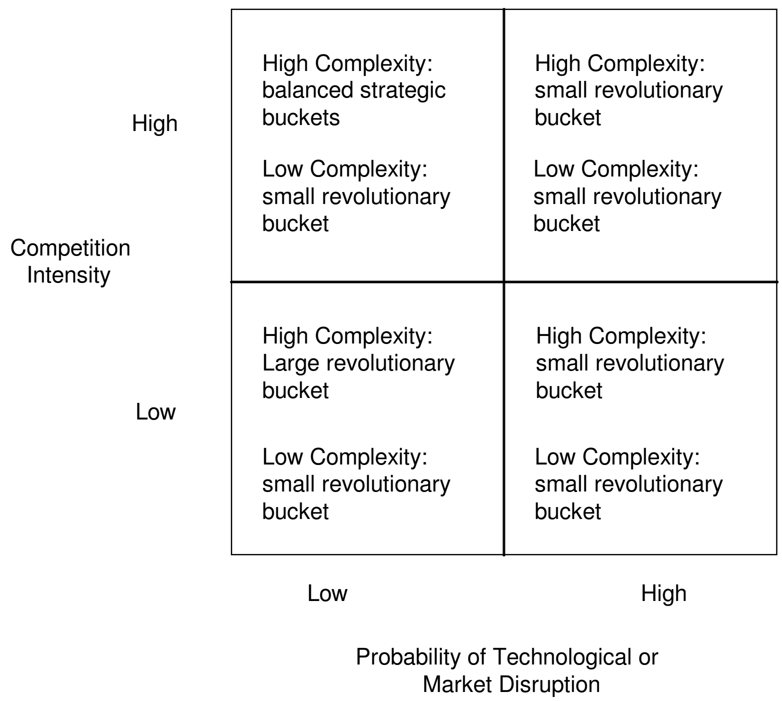

Figure 10: Complexity, competition, environmental instability, and the use of strategic buckets for the NPD portfolio.

One of the primary challenges with understanding complexity and its effects on the NPD portfolio is the lack of available tools/methods in practice. A reason for the lack of methods is that strategic NPD portfolio decisions are qualitative and difficult to operationalize. In order 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 (DSM) proposed by Eppinger and extended by other researchers (Eppinger et al. 1994, Smith and Eppinger 1997, Sosa et al. 2004 among many others) is a tool that can help managers map dependencies between attributes. Although the DSM was originally conceived strictly to highlight technical dependencies between product components and modules, the same thinking can be applied to performance dependencies between technological and market attributes of a product. It has already been shown that the DSM can be used in various contexts. Sosa et al. (2004) offer a good example of the DSM applied to organizational dependencies and Siggelkow (2002) uses a longitudinal study to map attributes of organizational design and understand organizational complexity.

Although the DSM can help managers decipher the complexity of their 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 (Ben-Akiva and Lerman 1985, McFadden 1986, Green and Srinivasan 1990, Train 2003, Verma and Plaschka 2003). Conjoint analysis and choice modeling are experimental methodologies that allow managers to predict the performance of new products by asking potential customers to make choices regarding specific configurations of technology and market variables that define the product. 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 – thus operationalizing the notion of technological-market stability.

Our theoretical framework for strategic NPD portfolio decisions coupled with methods that shed light on complexity and stability can form the basis for more effective resource allocation. We view our work as an important first step towards developing a better understanding of portfolio decisions at a strategic level. Since our perspective is relatively high-level we make assumptions that capture the essence of NPD program behavior without delving into details that would lead to burdensome derivations without additional insights. Still, future research can explore different structures of interaction between technology and market variables (Rivkin and Siggelkow 2006), as well as richer search strategies that can incorporate more complex optimization techniques for incremental innovation.

APPENDIX

To establish the existence of a crossing time and prove the proposition stated in the text, we first derive expressions for the expected performance of incremental and revolutionary NPD programs over time. Define the index sets $I_{\text{inc}} = \{i : \omega_{i,t} \in \text{ the incremental bucket}\}$ and $I_{\text{rev}} = \{i : \omega_{i,t} \in \text{ the revolutionary bucket}\}$ where $\omega_{i,t}$ is the product configuration (solution) adopted in period *t*.

LEMMA 1: *performance of incremental NPD programs.* Incremental NPD programs improve performance in each period through systemic changes to the product attributes. For any random initial product configuration, $\omega_{i,0}$, let w be the number of attribute changes required to achieve a locally optimal configuration. Note that for $K = 0$, $E[w] = N/2$ since half of the product attributes will already be set to the optimal value, and the other half can be altered in sequential periods until the (global) optimum configuration is achieved. For any $K>0$, $E[w]<N/2$ because the number of local optima is higher and thus, the probability that a random initial product configuration is close to a local optimum is higher. Therefore, for $K>0$ incremental NPD programs are able to quickly reach local optima. For $t>E[w]$, $E[F(\omega_{i,t})]$ is equal to the expected performance of a local optimum. Let F_{local} be this value. For $t<E[w]$, $E[F(\omega_{i,t})]<F_{\text{local}}$ and $\Pr\{F(\omega_{i,t+1})>F(\omega_{i,t})\}=1$.

LEMMA 2: *performance of revolutionary NPD programs.* Revolutionary NPD programs improve performance in each period by randomly selecting one random product configuration and adopting the new configuration only if performance is higher compared to the performance of the existing configuration. For any period *t*, the performance of a revolutionary NPD program is given by the recursion $F(\omega_{i,t})=\max\{F(\omega_{i,t}),F(\omega_{i,t-1})\}$ with $F(\omega_{i,o})$ defined as the performance of the initial product configuration. For a revolutionary NPD program, each period is independent of previous periods and the recursion can be rewritten as $F(\omega_{i,t})=\max\{F(\omega_{i,t}),F(\omega_{i,t-1}),...,F(\omega_{i,o})\}$. Note that $E[F(\omega_{i,t})]$ is concave increasing in *t* because the expectation of the maximum of t i.i.d. random variables is concave increasing in t (Srinivasan et al. 1997, p. 162). As $t\to\infty$, $E[F(\omega_{i,t})]$ is equal to the performance of the global optimum. Let F_{global} be this value. For $t<E[w]$, $\Pr\{F(\omega_{i,t+1})>F(\omega_{i,t})\}<1$.

PROPOSITION: *For any K > 0, there exists a time, t(K), at which a strategy with larger size revolutionary strategic bucket outperforms any strategy with smaller size revolutionary strategic bucket. Furthermore, t(K) is a decreasing function of the interaction complexity K.*

PROOF: For any *K > 0* existence of the crossing time *t(K)* follows directly from Lemmas 1 and 2. Consider a portfolio strategy of $p=0\%$. For such a strategy, $I_{\text{inc}}=\{1,2,...,M\}$ and $I_{\text{rev}}=\{\varnothing\}$ and the expected firm (portfolio) performance for $t>E[w]$ is $E[\Pi \mid p=0\%]=\sum_{i=1}^{M}E[F(\omega_{i,t})]=MF_{\text{local}}=(M-1)F_{\text{local}}+F_{\text{local}}$. Next, consider any strategy with a single revolutionary program indexed by *m*. For such a strategy firm (portfolio) performance for $t\geq E[w]$ is $E[\Pi \mid p>0\%]=(M-1)F_{\text{local}}+E[F(\omega_{m,t})]$. Since $E[F(\omega_{m,t=E[w]})]<F_{\text{local}}$ and $E[F(\omega_{m,t\to\infty})]=F_{\text{global}}>F_{\text{local}}$, the existence of a crossing time follows since $E[F(\omega_{m,t})]$ is concave increasing in *t*. The same argument can be repeated for comparing any strategy with higher *p* to a strategy with lower value *p*.

To show that *t*(*K*) is decreasing in *K*, we first characterize the performance distribution for all potential product configurations within a given landscape. Recall that product performance is defined as $F(\omega_i)=N^{-1}\sum_{j=1}^{N}f_j$ where each f_j is drawn from a $U(0,1)$ distribution. As highlighted in Skellett et al. (2005), for sufficiently large *N*, $F(\omega_i)\sim N(\mu,\sigma^2)$ where μ and σ^2 are the landscape mean and variance. Without loss of generality, assume that the landscape is appropriately scaled so that $\mu=0.5$. Note also that, due to our definition of $F(\omega_i)$, $\sigma^2=1/(12N)$. An important result is that σ^2 is independent of the interaction complexity, *K*. Thus the underlying probability distribution that determines the performance of a revolutionary project over time is the same for all *K*. This fact along with the basic result that the expected performance of a local optimum, F_{local}, is decreasing in *K* (Kauffman 1993) implies that *t*(*K*) is decreasing in *K*.

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