STRATEGIC NPD PORTFOLIO MANAGEMENT IN COMPLEX ENVIRONMENTS

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ABSTRACT
We analyze how various new product development (NPD) portfolio strategies succeed in complex environments. At the strategic level managers may not have the information necessary to optimize future decisions and they exhibit bounded rationality. Yet, they need to decide on incremental vs. revolutionary project investment. We view firms as "agents searching for the best outcome in a complex and unknown landscape" (Kaufmann 1993). Each firm advances through a portfolio mix of incremental and revolutionary projects. Since bounded rationality renders classic optimization infeasible, we simulate and analyze the efficacy of various NPD portfolio strategies. Our results indicate that the notion of "optimal balance" in the NPD portfolio is dependent on the "environmental complexity" (i.e.: the unknown interdependencies between determinants of firm performance) and on the "industry lifecycle" (i.e. the amount of time that these interdependencies remain constant). Moreover, we discuss circumstances under which learning from industry leaders improves firm performance.

Keywords: New Product Development, Project Portfolios, Complexity.

INTRODUCTION
The development of 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). Senior managers often set ambitious goals for future revenue generated from new products and statements such as "innovate or die" overflow the popular business press and verify the importance of new product development (*Harvard Business Review*, August 2002). At the same time, companies that hold on to "cash cows" run the risk of losing their competitive advantage (O'Reilly and Tushman 2004).

The NPD portfolio decision is complex due to: i) market uncertainty, ii) scarcity of resources, iii) alignment with overall firm strategy, iv) dynamic nature of the phenomenon, and v) project interactions (Roussel et al. 1991, Cooper et al. 1998, Brown and Eisenhardt 1998). In a recent example, DuPont ran into trouble when the company diverted the majority of its estimated $2 billion yearly R&D budget to improving established business lines (BusinessWeek, January 27, 2003). DuPont's problems highlight the fact that R&D investment embodies speculation – where to allocate resources today in order to realize rewards in the future. Furthermore, the technological, industrial, and social complexities make the NPD portfolio decision intractable from an optimization viewpoint (Brown and Eisenhardt 1998).

The academic literature stresses the importance of achieving "balance" between incremental and revolutionary projects in NPD portfolios (Roussel et al. 1991, Wheelwright and Clark 1992, Cooper et al. 2001, Kavadias and Loch 2003). NPD portfolio research at the operational level uses mathematical programming techniques that hardly include strategic variables and are rarely adopted by practitioners (Loch et al. 2001, Shane and Ulrich 2004). At the strategic level, case studies and field research highlight several drivers of successful portfolio management and propose qualitative guidelines such as "balancing" the portfolio (Roussel et al. 1991) and learning from successful leaders in the industry (Cooper and Kleinschmidt 1996).

Despite the merit that these managerial guidelines bear, they fail to enrich our theoretical foundations concerning the successful portfolio choice and its dependence on industry characteristics. This paper attempts to shed light onto questions such as: how does the optimal portfolio balance depend on industry characteristics? And, when is learning from the leaders a successful strategy?

We divert from the classic optimization approach to account for the complexity of the portfolio decision and the bounded rationality of managers (Simon 1982). Following the lead of Kaufmann (1993), we view firms as "agents searching for the best outcome in a complex and unknown landscape." We employ the widely used NK landscape structure to represent industrial environments with differing degrees of complexity. Complexity is defined as the interactions between attributes that determine firm performance. Decision makers are assumed to exhibit limited knowledge regarding the structure of the payoff function (Simon 1982, Kahneman 2003). Yet, at the strategic level managers rarely delve into the details of individual projects, and decide despite the incomplete information. They mainly focus on resource allocation between incremental and revolutionary projects (Roussel et al. 1991, Loch and Kavadias 2003).

Our results highlight the importance of two dimensions: i) *environmental complexity*, expressed as the interdependencies between determinants of firm performance, and ii) *industry lifecycle*, i.e. the period of time for which these interdependencies do not change. Industry lifecycle offers an intuitive way to represent distinct phases in the evolution of an industry – fluid, transitional, and specific period (Utterback 1994). We show that successful portfolio strategies vary depending on complexity and industry lifecycle. Higher complexity dictates more revolutionary projects while short industry lifecycles prompt incremental projects. Our results also point out that classic managerial guidelines such as "learn from the industry leaders" do not always lead to success.

The rest of the paper is structured as follows. In §2 we review the relevant literature. We introduce the modeling setup and the basic notion of an NK landscape in §3. Results and discussion follow in §4, and we conclude in §5 by outlining managerial guidelines and future research.

LITERATURE REVIEW

Strategic NPD portfolio management

Academics and practitioners primarily use case studies and field research to address the strategic issues of portfolio selection. At a strategic level, operational suggestions are hard to quantify due to the intangibility of parameters. Hence, the literature relies on qualitative suggestions such as the need to balance risk and reward, product and process improvement, revolutionary and incremental projects (Roussel et al. 1991, Wheelwright and Clark 1992, Cooper et al. 2001). Practitioners use multi-dimensional decision making tools (Liberatore 1987, Saaty 1994, Hammonds et al. 1998) or ranking methods (Brenner 1994, Loch 2000). Still, these methods assume that key parameters such as market risk, technical risk, and customer preferences can be accurately estimated.

Normative models attempt to operationalize the portfolio decision. However, accurate data estimates are feasible only at the project level and not necessarily along all dimensions, e.g. strategic alignment (Calantone et al. 1996, Schmidt and Calantone 1998; Kavadias and Loch 2003, Chapter 2). Some quantitative models address the strategic choice of projects. Ali et al. (1993) consider a competitive setting where firms decide whether to launch an incremental or a revolutionary product. Loch and Kavadias (2002) focus on the single firm optimal investment in NPD programs, accounting for market changes and program interactions. They do not explicitly account for the incremental versus revolutionary tradeoff. None of the above address industry characteristics. Our work is closely related to that of Adner and Levinthal (2001). They consider the balance between product innovation and process innovation in technological development, but they focus on demand side effects without considering the role of complexity or the adaptation of firm strategy.

"Search" on a rugged landscape

The innovation process is often modeled as random draws from a fixed set of possibilities (e.g. Weitzman 1979, Levinthal and March 1981, Nelson and Winter 1982, Cohen and Levinthal 1989, Marengo 1992). These models do not consider limited information due to factors that are unknown to decision makers or factors that are not accounted for but have significant influence on payoffs (Schrader et al. 1993, Sommer and Loch 2003). Furthermore, classic innovation models overlook the path dependency that innovation efforts exhibit (Kaufman and Lobo 2000).

Fitness landscapes model complex environments, while taking into account the fact that firms do not entirely know the space of potential outcomes. A number of attributes (N) determine the agent (firm) performance level through a fitness function. The number of interactions (K) among attributes defines the inherent complexity in the landscape. No interactions define a "smooth" landscape that has a unique global optimum. Increased interaction makes the landscape "rugged" with multiple peaks and valleys.

Building upon the original work of Kaufman (1993), researchers have extended simple landscape models into various contexts. Levinthal (1997) explores the effects of complexity and adaptation on the convergence of organizational forms and finds that learning leads to the imitation of successful peers. Gavetti and Levinthal (2000) and Sommer and Loch (2003) examine the effects of past experience and limited agent cognition (ambiguity) on the search process. Rivkin and Sigelkow (2003) characterize the balance between search for optimal outcomes and stabilization around good but sub-optimal outcomes. Ethiraj and Levinthal (2003) analyze modularity as a mechanism for reducing the complexity of an interdependent system. Our agents conduct both local and global search as a representation of the NPD portfolio mix. We extend previous search models by considering issues of environmental instability and disruption (changing landscapes).

NPD PORTFOLIO STRATEGIES IN COMPLEX ENVIRONMENTS

In this section we introduce our model of NPD portfolio strategies in complex environments.

The environment

We build upon the NK Model developed by Stuart Kaufmann (1993). Assume that N attributes, $(a_1,...,a_N)$, determine overall firm performance. Attributes represent factors such as technological advance of products, pricing and promotion variables, customer preferences from various market segments, and development team structure, among others. These attributes affect overall firm performance in both known and unknown ways. Without loss of generality, we assume that each attribute can take a value of 0 or 1, leading to a total of 2^N total performance outcomes.

Attribute i contributes to the overall firm performance through its individual performance contribution f_i, which may depend on the value of K other attributes, $(a_{i1}, a_{i2},..., a_{iK})$. K characterizes the environment complexity. If $K = 0$, f_i depends only on a_i and the landscape is characterized by a single performance peak. If $K > 0$, f_i depend on other attribute values and the landscape is characterized by multiple peaks. Hence, the industrial environment is fully determined by N and K.

We generate a random $U(0,1)$ number to define f_i for a particular vector $(a_i, a_{i1}, a_{i2},..., a_{iK})$. The random mapping stems from our original assumption that firms cannot predict how attributes interact to determine performance. Note that f_i is a *different* $U(0,1)$ number if *any* of the attributes $(a_i, a_{i1}, a_{i2},..., a_{iK})$ changes values. Overall firm performance is the average of the performance contributions of each attribute:

$$F = \frac{1}{N}\sum_{i=1}^{N} f_i(a_i, a_{i1}, a_{i2},..., a_{iK}) \quad [1]$$

NPD portfolio strategies

A set of the NPD portfolio projects aims to improve performance through upgrades to current product lines or small changes to component designs. Other projects focus on long-term development with greater risk and reward. We model these groups of projects by two distinct search modes: local moves and random long jumps. Local moves approximate incremental projects. Random long jumps represent revolutionary projects, e.g. introducing a completely new product to an unknown customer segment. Without loss of generality we assume that local moves focus on single steps (i.e.: only one attribute changes value) and random long jumps may alter every attribute simultaneously.

Incremental product development allows firms to consider surrounding "neighborhood" improvements. The firm then chooses the best overall performance once incremental projects materialize (i.e.: the firm conducts a local move). Similarly, if a revolutionary project is completed, a new potential for the firm is revealed which the firm compares to current performance (i.e.: revolutionary product development may not necessarily result in better performance due to high risk).

At the strategic level, the amount of resources committed to different types of projects defines the portfolio strategy. We define firm strategy through the percentage of resources invested in revolutionary projects, namely $P_j \in [0,1]$. A firm with $P_j = 0$ pursues only incremental projects, while $P_j = 1$ defines a firm that pursues only revolutionary projects.

We also consider the fact that system level adaptation and firm learning may take place. System level adaptation refers to the extinction of firms that under perform, and the entrance into the population of new firms by random regeneration. Surviving firms strive for improvement and attempt to learn from the top performing firms. We assume that firms adjust their portfolio allocation by a factor of $\pm\Delta$ closer to the portfolio allocation of the top performing firms. In practice, gradual shifts in resources are common strategy resulting from benchmarking. Practice also confirms that firms do rarely know project details about top performers' portfolio, or their exact combination of attributes.

Finally, over time, the performance definition may change (fluid vs. transitional period). Such disruptions fundamentally change the manner in which attributes interact causing performance redefinition (Tushman and Anderson 1986). We model disruptions by periodically changing the landscape on which firms are moving.

Summary of the Simulation

We create several landscapes with constant N=15 and K varying from 0 to 12. Landscapes are held constant across replications to ensure validity in terms of comparisons. In each experiment we randomly place 1000 firms at different initial points in the landscape in order to avoid any initialization bias. For the same reason, we report average performance across 1000 firms. Each firm begins with a distinct portfolio index. In every period, the results of the firm's innovative activity are realized and firms conduct a local move with probability $1-P_j$. The type of project completed in each period is random and subsumes the uncertainty inherent in new product development. At the end of each period, we compare the relative performance of all firms, and the bottom 10% become extinct. New firms enter the environment through a random regeneration. Survivors learn from the best performers by adjusting their portfolio indices by $\Delta = \pm 0.05$. Firms move, become extinct, and learn for 100 periods.

RESULTS AND DISCUSSION

In this section we analyze in turn: i) the effectiveness of static portfolio strategies and ii) the improvement introduced by dynamic portfolio strategies.

Static NPD portfolio strategies

We define a static portfolio strategy as one that does not adapt or change over time. We proceed with the static strategies for two reasons: i) to identify average firm performance in the presence of limited information (e.g. pre-dominant design periods in an industry), and ii) to establish a solid base case for comparison with respect to dynamic NPD portfolio strategies. In the base case, all firms survive extinction in every period, regardless of their performance.

Figure 1(a) shows the average performance over time for 1000 firms with NPD portfolio allocations ranging from 10% revolutionary projects to 90% revolutionary projects in an environment with no complexity (*K*=0). The time required to reach the maximum performance increases with the percentage of revolutionary projects and all firms eventually reach the global optimum. This behavior is intuitive since an environment with no complexity has a single global maximum, and there exists a path to that maximum from every point in the environment. Firms with incremental portfolio strategies spend more time making successful local moves while firms with revolutionary portfolio strategies suffer a time-loss disadvantage through possibly unsuccessful long jumps. Thus, in the absence of complexity, incremental-oriented strategies dominate.

The situation changes dramatically as we introduce complexity into the environment. Figure 1(b) shows the average firm performance over time in an environment with high complexity (*K*=12). For higher levels of complexity, we observe that higher resource allocation in revolutionary projects leads to higher performance. Furthermore, different allocations dominate in different periods. These domination periods occur earlier as complexity increases. The result stems from the "rugged" nature of complex environments. Firms with incremental strategies quickly move to the closest peak, only to get trapped in one of the local optima. These firms have lower likelihood of moving out of local optima because they exercise long jumps with less frequency. Therefore, the benefit associated with a high-risk strategy increases as complexity of the environment increases. Our results contrast previous research in the area of complex environments (Kaufmann 1993). The difference stems from the fact that we assume agents can perform a mix of local moves and long jumps, according to their portfolio allocation. Our assumptions about the setting are more consistent with NPD portfolio management in practice, where different types of projects are not mutually exclusive.

The results shown in Figure 1 suggest that success is also driven by "industry lifecycle". We define industry lifecycle as the duration of time during which interdependencies between attributes remain constant. Periodic disruptions offer more insight into the effects of industry lifecycle on portfolio strategy. We simulate disruptions by randomly changing landscapes while maintaining the same level of complexity.

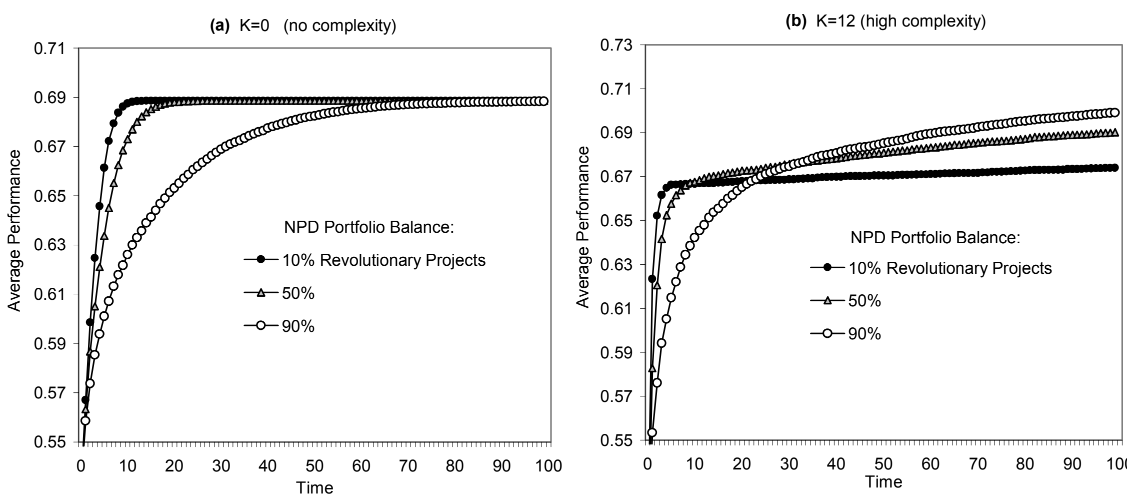

Figure 1: Average Performance Over Time for Static Portfolio Strategies

Figure 2(a) shows the average performance over time for firms with incremental portfolios and firms with revolutionary portfolios in an environment with no complexity (K=0). Every ten periods we introduce a disruption. In low-complexity environments, the incrementalist strategy performs better during stable periods and there is no advantage in the post-disruption period. The same cannot be said when complexity increases. Figure 2(b) shows the average performance over time in a complex environment (K=8). When complexity increases, incremental firms (low P_j) enjoy a higher level of post-disruption performance compared to revolutionary firms. This result holds true regardless of the frequency of the disruptions. At first glance, the result is counterintuitive, however, the result is driven by firm behavior immediately after the disruption. Firms with incremental projects have higher probability of improving performance immediately while firms with more revolutionary projects do not. Firms with incremental projects can quickly improve performance compared to their firms with more revolutionary projects because disruptions effectively re-start the competitive landscape.

Dynamic NPD portfolio strategies

Learning or benchmarking is often cited as a method of mitigating the effects of lack of knowledge (Leonard-Barton 1992). In this section we consider dynamic portfolio strategies as a method of counteracting to limited knowledge. We begin by randomly placing 1000 firms with uniformly distributed portfolio indices in the environment. After a delay of 5 periods, to avoid any initialization bias, firms observe the top 10% in terms of performance and adjust their innovativeness mix towards the portfolio strategy that is most common among the top firms. Adjusting the portfolio index implies that firms gradually shift resources in order to imitate the "successful" portfolio strategy.

Figure 3 illustrates the final distribution of firm strategies for environments with no complexity and high complexity. The final distribution is heavily skewed towards an incrementalist strategy when complexity is low (K=0). In environments with no complexity, the base case analysis shows that firms with incremental strategies enjoy longer periods of dominance before firms with revolutionary strategies surpass them. Figure 3 verifies that learning from industry leaders is helpful in environments with no

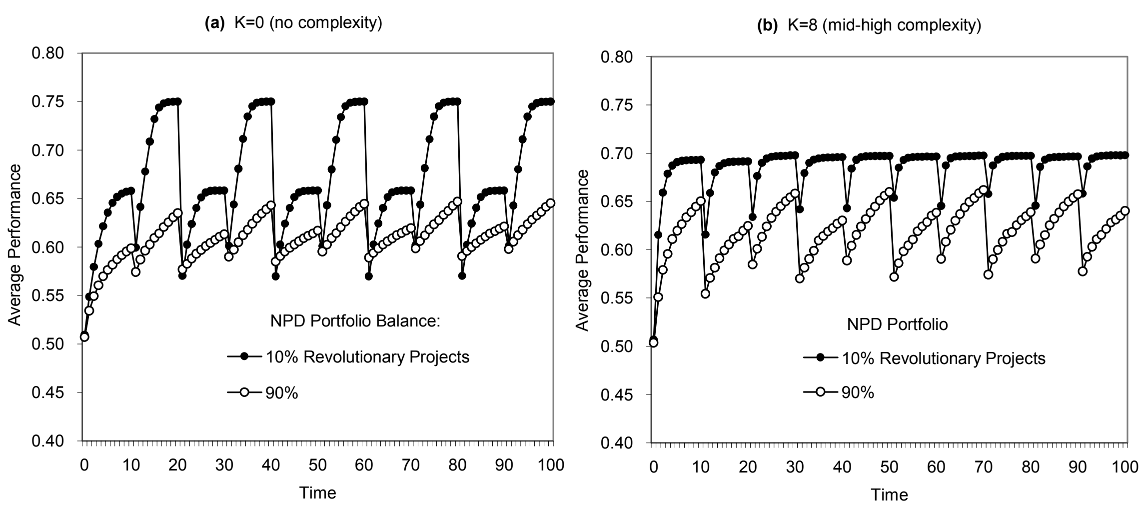

Figure 2: Average Performance Over Time with Periodic Disruptions

complexity.

As the complexity of the environment increases, the effectiveness of learning is reduced. The final distribution of firm strategies is shifted more towards revolutionary projects for *K*=12. Still, the majority of firms lag behind the dominant strategy (90% revolutionary projects) observed in the previous section. Furthermore, the final distribution of firm strategies has a high variance due to the numerous strategies that dominate at different points in time. It should be noted that an *extreme* static strategy (i.e.: $P_j = 0.1$ in simple environments and $P_j = 0.9$ in complex environments) outperforms other strategies that attempt to hedge against complexity by learning.

CONCLUSIONS AND FUTURE RESEARCH PATHS

We have explored the effects of complexity and learning on static and dynamic portfolio strategies. Our results highlight the importance of two dimensions: i) environmental complexity stemming from interdependencies between determinants of firm performance, and ii) industry lifecycle, defined as the period of time for which these interdependencies do not change. These results bear significance because both high complexity and short industry lifecycle can occur during the fluid period in the evolution of an industry (Utterback 1994). Our results also point out that applying common managerial practices such as learning from the top performers may be dangerous in complex environments.

A valuable direction for future research lies in developing methods that can reliably operationalize the level of complexity in an industry. The difficulty for managers then becomes to dictate strategy not based on imitation, but rather based on solid long-range forecasting and analysis. A second extension exists by considering how a firm should develop its project portfolio in uncertain or complex environments. In this paper we consider firms that already have various projects in a portfolio, but an interesting question remains for growing firms in terms of *how* an NPD portfolio should be developed. Finally, an empirical test of incremental and revolutionary product development in settings of varying complexity and industry lifecycle merits attention. We believe that these ideas are but a few that will add to the research of NPD portfolios in complex environments.

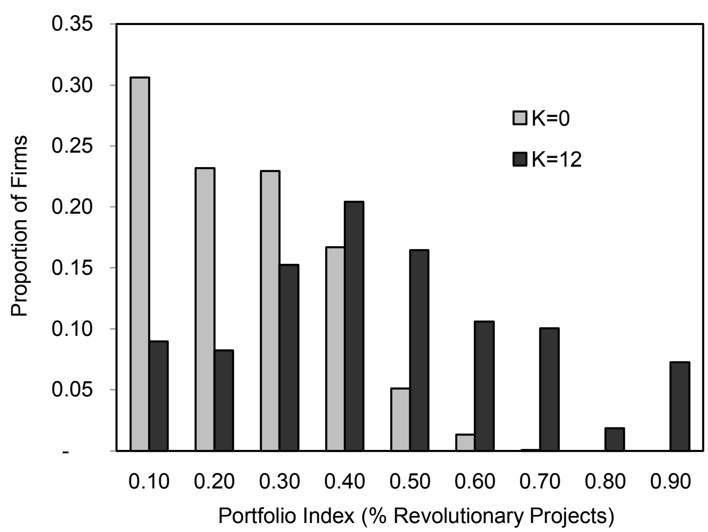

Figure 3: Final Distribution of Firm Strategies for Dynamic Portfolio Strategies

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