

**STRATA, STRUCTURE, AND STRATEGY FOR
RESOURCE ALLOCATION AND NEW PRODUCT DEVELOPMENT
PORTFOLIO MANAGEMENT**

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**STRATA, STRUCTURE, AND STRATEGY FOR
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PORTFOLIO MANAGEMENT**

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SUMMARY

Innovation and new product development (NPD) are critical to firm success and are often cited as means to a sustained competitive advantage. Unfortunately, the question of which innovation programs to pursue and how they should be funded is not trivial. This thesis examines the resource allocation and NPD portfolio problem. Special emphasis is placed on the organizational and behavioral factors that influence this problem. In doing so, we adopt a hierarchical perspective and posit that the resource allocation and NPD portfolio problem acquires a unique structure depending on the level at which the problem is considered. Beginning at the firm level, each study attempts to break open a black box to understand the drivers of effective resource allocation and NPD portfolio decisions at successively more detailed levels of analysis. We begin with an analysis of the firm's total R&D investment and we show how R&D intensity (the percentage of revenue that is reinvested in R&D) depends on a combination of NPD portfolio metrics and operational variables. We then extend the analysis to reveal how an evolutionary process explains the often cited consistency in R&D intensity at the industry level. Next, we analyze how the R&D investment is partitioned into "strategic buckets" consisting of NPD programs that are characterized by type of innovative activity (incremental or radical). We show how time commitment, technological/market complexity, and potential disruptions to the technology/market environment influence the balance between incremental and radical programs in the NPD portfolio. Finally, we analyze how individual NPD programs are funded and how they evolve over time in an organization setting that is defined by more or less autonomy. We find that how best to allocate resources depends on two types of autonomy bestowed upon managers: autonomy with respect to NPD funding and autonomy regarding how the NPD budget is monitored and controlled. We conclude with a discussion of the theoretical and managerial implications of our work.

CHAPTER I

INTRODUCTION

“For the past 25 years, we have optimized our organizations for efficiency and quality. Over the next quarter century, we must optimize our entire society for innovation.” U.S. Council on Competitiveness.

To innovate is to make changes to something established, especially by introducing new ideas, methods, products, or services (Oxford American Dictionary). Innovation may take a number of forms such as new packaging for existing products, new processes for manufacturing or delivering existing products, product line extensions through minor modifications to existing products, or radical changes that involve development of new methods, products, or services that differ markedly from the existing in terms of technology and market attributes. In practice, firms rely on new product development programs to drive innovation. A new product development (NPD) program is typically composed of multiple projects with a common overarching purpose (Loch and Kavadias 2002). Each NPD program addresses a clear goal such as cost reduction initiatives, minor product improvements, product line extensions, or the development of entirely new products or services (Cooper et al. 1998).

Innovation and NPD generate organic growth, which is particularly valuable to firms. Consider the following statements: *“Over the next 10 or 20 years the economy will be driven by innovation, and a premium will be placed on companies that can generate their own growth.”* (Jeffrey Immelt, CEO, General Electric Corporation). *“The most precious kind of growth is organic growth - top line expansion of your core business without reliance on acquisition.”* (A.G. Lafley, CEO, Procter & Gamble). These sentiments are echoed by a large number of senior executives. In fact, managers often set ambitious goals for future revenue generated from new products. Statements such as *“innovate or die”* overflow the popular business press and confirm the importance of effective new product development.

The question of which innovation programs to pursue is critical to firm success and is often cited as a key competitive dimension (Rousell et al. 1991, Wheelwright and Clark 1992, Cooper et al. 1998). The answer depends to a great extent on the firm’s corporate strategy. Firms that choose to compete based on novel designs and trend-setting technologies typically invest in radical product development efforts as opposed to process improvement initiatives (Von Hippel et al. 1999). In contrast, the latter investment benefits firms that compete based on conformance quality and cost (Li and Rajagopalan 1998, Schilling 2005). The first step in transforming corporate strategy from a hopeful statement about the future to an operational reality is to allocate resources (human or capital) to innovation programs. Of course, developing the “right” new products and determining the “right” level of funding for innovation programs is not trivial. This is particularly so when resources must be allocated between innovation programs and each program may represent conflicting directions in terms of corporate strategy. Success then requires a fundamental trade-off: short-term benefits accrued through incremental innovation efforts versus long-term benefits achieved through radical, new-to-the-market, or new-to-the-world products and services (Tushman and O’Reilly 1996). This trade-off implores managers to think about NPD programs collectively as a portfolio.

Every firm faces the critical problem of allocating resources between innovation initiatives in a portfolio. For this reason, *NPD portfolio management* is a competency that cannot be ignored. NPD portfolio management can be defined as, “. . . a *dynamic decision process, whereby a business’s set of new product development projects is systematically evaluated and resources are allocated between projects.*” (Copper et al. 1997). Figure 1 depicts a common view of the NPD portfolio and how the programs in the portfolio evolve from idea to reality.

Effective resource allocation and NPD portfolio management directly impact firm 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 (Business Week 2003). Kodak is investing resources in revolutionary new technologies to catch up in the digital photography market, despite the

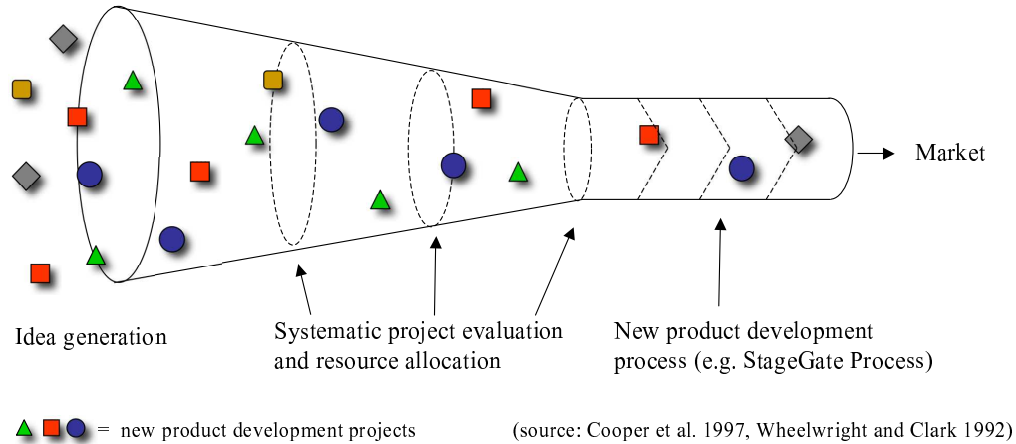


Figure 1: Resource allocation and NPD portfolio management.

fact that the company was synonymous with photography for the better part of the twentieth century (Forbes 2003). Toyota Motor Corporation has strengthened its competitive position relative to General Motors due in great part to more effective resource allocation and NPD portfolio strategy (Financial Times 2005). Drug maker Novartis established an advantage over close rival Roche by shifting resources towards new product introductions; that advantage eroded due to a lack of early stage development projects and a subsequent drying up of the pipeline at Novartis (Financial Times 2000). These cases underscore the reality that effective resource allocation and NPD portfolio management profoundly impact firm success.

From the dawn of Operations Research in the early 1950s, to the emergence of managerial frameworks (such as the BCG matrix) in the 1970s through today, the problem of developing the right new products has motivated academics and practitioners to propose a number of solutions. Several tools and theories have been developed by different constituencies, resulting in an interesting dichotomy: a collection of rigorous analytic efforts with minimal adoption and minimal practical impact (Loch et al. 2001, Shane and Ulrich 2004), and a variety of managerial frameworks grounded in individual case studies with widespread impact but little theoretical foundation (Cooper et al. 2004). In either case, managerial guidelines are limited to a generic notion of “balance” among different value determinants

A shift in focus towards more incremental innovation...

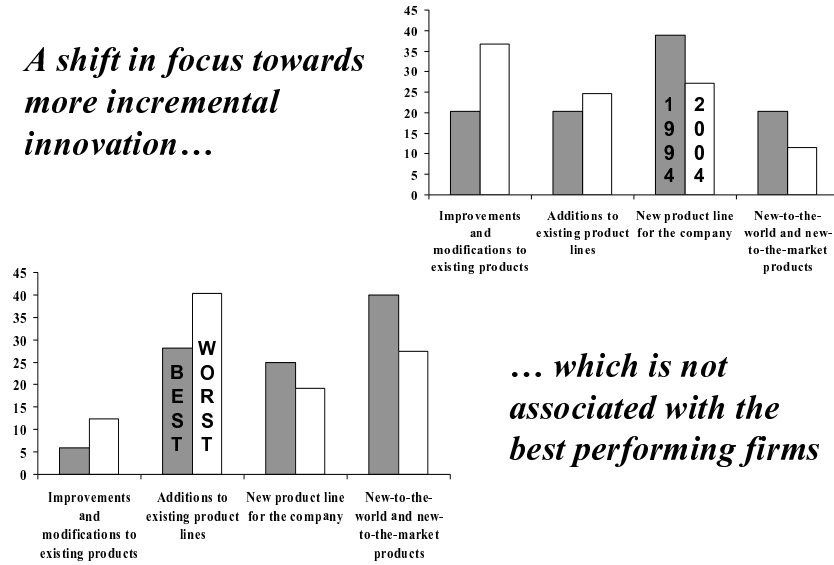


Figure 2: Product Development Management Association (PDMA) report on NPD portfolio focus and performance.

due to the confusion regarding fundamental problem drivers. Hence, senior managers, R&D managers, and project managers are forced to make resource allocation decisions based primarily on intuition or heuristic rules.

Recent data verify that the overall impact of NPD portfolio methods and research remains largely in doubt. A study conducted by the Product Development Management Association (PDMA) reveals an interesting result: between 1994 and 2004 development cycle times improved significantly. A portion of this effect is due to overall improvement in the management of the product development process. However, the percentage of resources allocated to minor product changes and small improvements also increased significantly during the same period of time. Thus, there is evidence that firms are increasingly focused on incremental NPD efforts. The bad news is that high performing firms emphasize diverse portfolios that include cutting edge, new-to-the-market, and new-to-the-world initiatives in addition to incremental efforts (Adams and Boike 2004). Figure 2 illustrates these results.

Collectively these facts indicate that a deeper understanding of resource allocation and NPD portfolio management is necessary. This thesis provides a theoretical framework to study resource allocation and NPD portfolio management. The remainder of this chapter

lays the groundwork for the in-depth studies that comprise the bulk of this thesis. In §1.1 we discuss a number of factors that make NPD portfolio difficult. In §1.2 we introduce a theoretical framework wherein we posit that the resource allocation and NPD portfolio decision acquires a unique structure depending on the level at which the problem is considered. Finally, in §1.3, we provide a set of concepts that will be of value as one reads through the thesis.

1.1 What Makes NPD Portfolio Management So Difficult?

The NPD portfolio determines the minor improvements, new product introductions, or radical breakthrough developments associated with the product mix of a company. In doing so, portfolio decisions influence the balance over market segments and the time to market profile of the firm. The essential feature that defines the NPD portfolio problem is that projects should be viewed *collectively* rather than in isolation. The portfolio view necessarily gives rise to several considerations:

- *Organizational and behavioral issues.* Resource allocation and NPD portfolio decisions take place in a setting defined by organizational (hierarchy) and behavioral issues. While this fact is obviously not unique to the NPD portfolio problem, it has been largely ignored by almost 50 years of academic work on resource allocation and NPD portfolio management.
- *Strategic alignment.* The NPD portfolio allows a firm to operationalize and implement strategy over time. This point implies that the NPD portfolio problem entails a large component of ambiguity and complexity, since the determinants of firm success and their interactions are rarely known. Moreover, successful NPD portfolio management rests upon the ability to effectively communicate firm strategy and cascade it down to an implementable NPD program or project level (Loch and Tapper 2002).
- *Strategic tension.* NPD portfolio decisions are defined by the tension that exists between multiple projects that often conflict in terms of corporate strategy. For any set of potential projects in the NPD portfolio, a number of projects will be geared

towards relatively minor, safe, low cost endeavors, while other projects will be geared towards relatively major, risky, high cost initiatives.

- *Project interactions.* Companies often develop multiple products and services in closely related technological areas. Hence, development efforts may exhibit synergies or incompatibilities in their technical aspects. Similarly, on the market side, products may substitute or complement one another. Interactions play a critical role in the resource allocation decision because they are a proxy for decision complexity.
- *Outcome uncertainty.* NPD projects are characterized by imprecise knowledge regarding outcomes. Managers face uncertainty in terms of potential market value and technical output for any given project. NPD managers face risks related to the overall functionality of the product (technical risk) and to the adoption of the product by end customers (market risk).
- *Dynamic nature of the problem.* Decision makers must allocate resources over time and NPD programs evolve over time. Therefore, managers must take into account future values and risks when allocating resources to a promising idea. However, it is often difficult to quantify the potential of promising ideas or precisely measure the risks involved. Furthermore, the various innovation initiatives in a portfolio typically evolve at different speeds.
- *Resource scarcity.* Scarce resources often critically constrain the NPD portfolio problem. Indeed, if a firm were to have infinite resources, there would not be a NPD portfolio problem. It is common practice to pursue many projects in parallel in order to achieve broader product lines (mass customization) and higher market share (Reinertsen 1997, Ulrich and Eppinger 2003, Cusumano and Nobeoka 1998). In multi-project environments, scarce resources render the resource allocation decision a critical factor for success (Adler *et al.* 1995). Scarcity may involve the total R&D budget, testing equipment availability, or specialists with unique areas of expertise (analogous to bottleneck machines in production scheduling). In several contexts, project managers must “queue” for access to these specialized resources.

The issues outlined above highlight the difficulties associated with NPD portfolio management. Moreover, they illustrate that resource allocation and NPD portfolio decisions, like several other NPD decisions, are not necessarily centralized decisions; rather, they span different levels of management. As the locus of decision-making moves from strategic to tactical to operational, resource allocation decisions are driven by more tangible and specific project metrics. However, at the operational level decisions are constrained by significantly less flexibility (Anderson and Joglekar 2005). In this thesis we present a general framework for resource allocation and NPD portfolio management, and we will link these decisions to different organizational levels.

1.2 Strata, Structure, and Strategy

The fundamental contribution of this thesis is the explicit treatment of organizational and behavioral elements that impact the resource allocation and NPD portfolio problem. We adopt a hierarchical perspective and posit that the resource allocation and NPD portfolio problem acquires a unique structure depending on the level at which the problem is considered (Figure 3). The hierarchical perspective allows us to provide a rigorous link between strategy (vision) and execution (money).

Beginning at the firm level, each question we address attempts to break open a black box and understand the drivers of effective resource allocation and NPD portfolio decisions at successively more detailed levels of analysis. We begin with an analysis of the firm’s total R&D investment and we show how R&D intensity (the percentage of revenue that is reinvested in R&D) depends on a combination of NPD portfolio metrics and operational variables. We then extend the analysis to reveal how a simple evolutionary process explains the often cited consistency in R&D intensity at the industry level (Chapter 3). Next, we analyze how the R&D investment is partitioned into “strategic buckets” consisting of NPD programs that are characterized by type and degree of innovative activity (incremental or radical). We show how time commitment, technological/market complexity, and potential disruptions to the technology/market environment influence the balance between incremental and radical programs in the NPD portfolio (Chapter 4). Finally, we analyze how

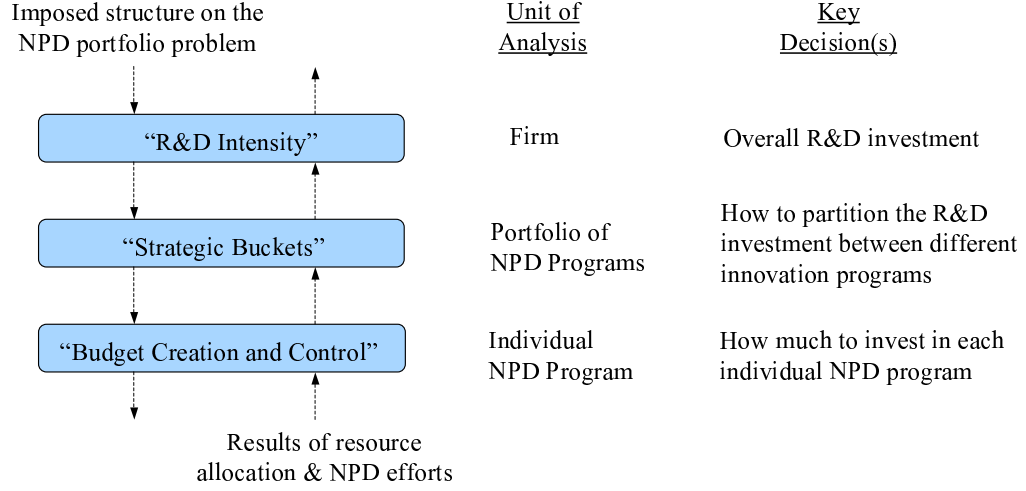


Figure 3: Strata, Structure, and Strategy for Resource Allocation and NPD Portfolio Management

individual NPD programs are funded and how they evolve over time in an organization setting that is defined by more or less autonomy. We find that how best to allocate resources depends on two types of autonomy bestowed upon managers: autonomy with respect to NPD funding and autonomy regarding how the NPD budget is monitored and controlled (Chapter 5).

1.3 Definitions and Preliminary Considerations

In this section, we introduce a number of concepts that are relevant for the studies considered in Chapters 3, 4, and 5 of this thesis. These concepts provide a general structure for mechanisms that are employed in subsequent chapters. We first define a product and then proceed to describe how the innovative effort embodied in NPD programs leads to a new product. In doing so, we highlight the fundamental issues of value, risk, and cost associated with NPD programs.

Borrowing from the marketing and engineering design literatures, we define a product as a bundle of technology and market attributes, $\omega = (x_1, x_2, \dots, x_N)$. The attributes represent key product parameters such as the core product architecture, component technologies,

design features, and manufacturing process specifications among others. We define a NPD program as an initiative that strives to alter product attributes in order to enhance existing product performance or create an altogether new product. With this definition in mind we note that a NPD program begins with a product, ω , and creates a different product, ω' . In doing so, the NPD program can be characterized by a change metric, $d = |\omega' - \omega|$. The metric d defines the type of innovative effort pursued by the NPD program (Kavadias and Chao 2006). Lower d implies incremental innovation and higher d implies radical innovation from the viewpoint of “degree of change”. For any product ω and type of innovative effort d we define the set of potential new product ideas as $N_d(\omega) = \{\omega' : |\omega' - \omega| \leq d\}$. Innovation is equivalent to stating that a NPD program changes product attributes over time and drives performance improvement.

Product performance (net revenue generated by a product) is a function of the technology and market attributes and is given by $F(\omega)$. For any NPD program, $F(\omega') - F(\omega)$ is the performance change as a result of the innovative effort. We define a performance improvement function $V(\cdot)$ such that $F(\omega') - F(\omega) = V(d)$. Let $\hat{V}(d)$ be the maximum potential performance improvement possible within $N_d(\omega)$ and note that $\hat{V}(d)$ is non-decreasing in d . This follows immediately from our definition of $N_d(\omega)$ because for any $d_1 < d_2$, $N_{d_1}(\omega) \subset N_{d_2}(\omega)$.

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

Based on the above, for any $d_1 < d_2$ we say that d_1 represents incremental innovation and d_2 represents radical innovation. Furthermore, based on the preceding arguments we note the following properties: (i) $|N_{d_1}(\omega)| < |N_{d_2}(\omega)|$. The number of solutions possible through radical innovation is greater than the number of solutions possible through incremental innovation. (ii) $\hat{V}(d_1) \leq \hat{V}(d_2)$. The maximum potential performance for radical innovation

is at least as big as the maximum potential performance for incremental innovation. (iii) $p(d_1) > p(d_2)$. Radical innovation is more risky (has lower probability of success) compared to incremental innovation. (iv) $c(d_1) < c(d_2)$. The cost of incremental innovation is less than the cost of radical innovation.

CHAPTER II

LITERATURE REVIEW

This chapter offers a comprehensive review of the existing knowledge regarding resource allocation and NPD portfolio management. We categorize extant research along two broad dimensions: the unit of analysis (NPD portfolio, NPD program, individual project) and the time element considered in each work (static versus dynamic). Chapters 3, 4, and 5 provide a more detailed analysis of the related literature for each study.

Figure 4 provides an outline of the existing work and immediately highlights an interesting insight: there appears to be an inverse relationship between the amount of theoretical work performed and the level of analysis. At the strategic (firm) level of decision making the amount of work is significantly less than the work at the operational level of project selection. In fact, the work at the operational level of decision making is so voluminous that it must be further classified into sub areas. Despite the volume of work at the operational level of decision making, the research has not delivered substantial impact to upper levels of the managerial community. This reflects the misalignment between the complex reality of the NPD portfolio problem and the simplifications necessary for modeling abstraction. This observation was first recorded by Souder (1973), and Schmidt and Freeland (1992); and iterated by Loch *et al.* (2001), Kavadias and Loch (2003b) and most recently by Shane and Ulrich (2004) in a review paper for the 50th anniversary of technology management and product development research in *Management Science*.¹ Below, we discuss the key findings and limitations of existing work in each of the groups identified in Figure 4.

¹“A substantial body of research has focused on which innovation projects to pursue... surveys have shown that these models have found very little use in practice... If 50 years of research on an area has generated very little managerial impact, perhaps it is time for new approaches.” (Shane and Ulrich 2004 p.136)

	Static	Dynamic
Firm Level	<ul style="list-style-type: none"> • Roussel et al. (1991) • Wheelwright and Clark (1992) • Ali et al. (1993) • Adler et al. (1995) • Cooper et al. (1997) • Comstock and Sjolseth (1999) 	<ul style="list-style-type: none"> • Balasubramanian et al. (2004) • Girotra et al. (2007) • Pisano and Gino (2005) • Chao and Kavadias (2007)
NPD Program Level	<ul style="list-style-type: none"> • Analytical Hierarchy Process Models, Liberatore (1987) • Jones (1999) • Fridgerisdottir and Akella (2005) 	<ul style="list-style-type: none"> • Chikte (1977) • Nobeoka and Cusumano (1997) • Loch and Kavadias (2002) • Ding and Eliashberg (2002) • Blanford (2004) • Setter and Tishler (2005) • Chao et al. (2006) • Bhattacharya and Kavadias (2007)
Project Level	<ul style="list-style-type: none"> • Mathematical Programming Formulations, Fox, Baker and Bryant 1984, Loch et al. 2001 • Multi-criteria decision making tools, Brenner 1994 • Net Present Value (NPV) analysis, Hess (1993), Sharpe and Kellin (1998) • Break-Even Times (BET), House and Price (1991) 	<ul style="list-style-type: none"> • Multi-Armed Bandit (MAB) models, Gittins and Jones 1972, Gittins 1989, Whittle 1980, Asawa and Teneketzis 1996 • Dynamic Scheduling Models, Smith 1956, Harrison 1975, Wein 1992, Van Mieghem 2000, Kavadias and Loch 2003 • Optimal admission models, Stidham 1985, Kleywegt and Papastavrou 1998, Lewis et al. 1999 • Economic models, Weitzmann 1979, Fox and Baker 1985, Vishwanath 1992

Figure 4: Overview of the resource allocation and NPD portfolio literature.

2.1 NPD Portfolio Management at the Strategic Level

The NPD portfolio problem consistently attracts strategy and management research interest, reflecting its importance for senior management. Because of the complexity of the decision at this level of decision making the literature has mainly grown to a set of “best practices” recorded through case studies. Recently, several theoretical studies have tried to open the “black box” of the $V(\omega)$ product performance functions. We begin by presenting the former group, which has shaped managerial decision making in a significant way. We then proceed to discuss the more recent studies.

Roussel *et al.* (1991) popularized the importance of portfolio selection for top management in organizations. Cooper *et al.* (1997) and Liberatore and Titus (1983) carried out a large survey of top management decision making concerning their NPD portfolios. Wheelwright and Clark (1992) also recognized the importance of portfolio selection for strategic decision making. Most of these studies confirm a general trend: senior managers tend to

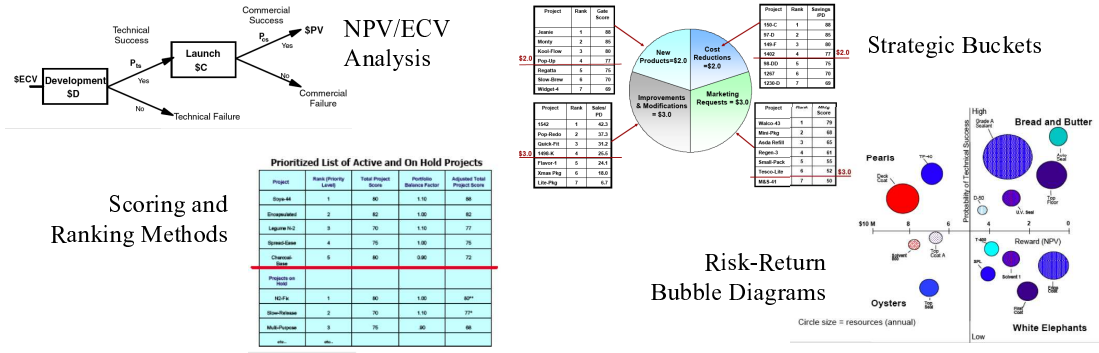


Figure 5: NPD portfolio management tools (source: Roussel et al. 1991, Wheelwright and Clark 1992, Cooper et al. 1997).

complement financial project evaluations with *ad hoc* tools. These tools often advocate resource allocation balance between the different types of innovation, or they suggest a comparison across market competition and technology newness and/or technological risk (Wheelwright and Clark 1992a, Cooper et al. 1998). We depict some representative managerial tools for NPD portfolio management in Figure 5.

In *scoring and ranking models* (lower left of Figure 5), projects are ranked based on a weighted average of their performance across multiple criteria as defined by management. The n best projects, according to their overall score, comprise the portfolio. The *risk-return bubble diagram* (lower right of Figure 5) categorizes each R&D program along its technology risk and potential return (discounted net present value). The size of the bubble indicates funding level. The objective for senior management is to achieve balance between the overall risk and the return of the portfolio. An efficient frontier could characterize the maximum return obtained at given risk levels. This tool is perhaps the most widely used in practice (Cooper et al. 1998). Finally, the *strategic buckets* tool (top right of Figure 5) aims to protect resources for NPD programs that differ with respect to their degree of innovation. This protection is necessary because long term programs with very risky outcomes will always be undermined when compared financially with short term quick cash initiatives. Various case studies have made arguments regarding what constitutes a strategic bucket (Cooper et al. 1998). The only framework that has managed to achieve an

abstract approach to this issue is that of Wheelwright and Clark (1992a). They identify the (manufacturing or sales) process change versus the extent of product change as the classification factors. Their idea is that a large change in either of these two dimensions increases risk, which must be balanced in order to achieve better “planning, staffing, and guiding of individual projects” (Wheelwright and Clark 1992a).

The fundamental insight of these studies is the notion of balance across different dimensions that determine product performance and subsequently overall portfolio performance. However, these tools can only generate *ad hoc* rules of thumb. They help managers think through the factors that influence the resource allocation decision, but they lack additional theoretical or empirical basis for further recommendations. Still, we must recognize the fact that these methods are heavily used in practice because they facilitate useful discussions in portfolio review meetings. Loch (1996) describes the challenges that often arise in portfolio review meeting. These tools represent an effort to understand the implications of multi-period effects, market variables, technology factors, and additional performance determinants, as well as their interactions. Due to the lack of a theoretical focus, these methods are necessarily at an aggregate level, and they cannot assess the “optimal” balance that management should strive for contingent on contextual factors. However, this stream of work is essential because it illustrates that further work should be performed to analyze the trade-offs between the various performance determinants (the x_1, x_2, \dots, x_N identified earlier).

As a response to the difficulty of assessing all potential NPD portfolio factors a relatively new approach has promoted the idea that generic criteria (such as risk, return, or any score) are not sufficient. Rather, NPD activities should be explicitly linked to business strategy (Kaplan and Norton 1996, Wheelwright and Clark 1992b, Comstock and Sjolseth 1999). In this sense, R&D strategy must cascade down to individual activities instead of allocating a given budget according to generic or customized scores (Loch and Tapper 2002).

A few normative studies have tried to uncover potential trade-offs at the strategic level. Ali *et al.* (1993) model an R&D race between two firms that choose between two different

types of innovation. They show the effect of competition on project choice given heterogeneous firm innovation capabilities (i.e. time and resource effectiveness). Although their approach is static, they highlight the importance of environmental factors and identify the fact that strategy is contingent on environmental conditions.

Two studies from the strategy area emphasize the effects of capacity choice on portfolio success (Adler *et al.* 1995, Gino and Pisano 2005). Both of these works view the R&D department of a firm as a manufacturing shop floor where different servers (individuals or teams) process each project before it is completed. Congestion effects lead to internal delays, revealing the latent technical interactions across innovation efforts that should be considered when defining the portfolio. Gino and Pisano (2005) also argue for the behavioral component in the decision of which projects should be admitted in each stage. In a pioneering empirical effort, Girotra *et al.* (2007) try to draw a systematic link between the portfolio choices and the overall value of the firm. They conduct an event study in the pharmaceutical industry, and they show that project failure without the appropriate build-up of back-up alternative compounds (capacity) may result in high company value loss. We believe that such studies are of crucial importance in order to truly uncover the performance drivers and apply optimization techniques to product portfolio management. Along similar premises Balasubramanian *et al.* (2004) analyze the changes in the product portfolio breadth over time within several high-tech industries, as a response to environmental factors like market opportunities and uncertainty. Although their work focuses on R&D program choices we classify it here due to the firm level data and the effort to once more quantify the trade-offs between performance determinants.

Chao and Kavadias (2007) introduce a theoretical framework that relies upon similar premises as the general model presented in Chapter 4 of this thesis. They explore factors that shift the proposed balance in the NPD portfolio, and they attempt to offer a theoretical basis for the strategic buckets tool presented above. Their findings show that the interactions among the performance drivers has a significant impact on the portfolio balance. Highly coupled marketing and technology performance determinants prompt for the

existence of strategic buckets (the protection of resources) aimed at radical innovation efforts. They also show that environmental turbulence (likelihood that the $V(\cdot)$ may change) shifts the balance towards more incremental resource allocation.

2.2 Resource Allocation and NPD Programs

The decision regarding how to allocate resources among NPD programs necessarily operates under a set of constraints: (i) the type of innovation balance as defined at the strategic level, and (ii) scarce resources that can be flexibly assigned. Studies at the NPD program level entail the flexibility of varying investment because different individual projects may be started or stopped within the program. Due to the focus on a single product line the complexity is reduced. Furthermore, due to the organizational proximity (hierarchy) between the R&D program manager and his/her project managers, there is a finer understanding of the underlying performance structure. Thus, the value of an NPD program can be better estimated given a specific product configuration $\omega = (x_1, x_2, \dots, x_N)$ and the issue turns to one of investment in different programs that can gradually (over time) capture the potential value.

Liberatore and Titus (1983) advocate the use of an Analytic Hierarchy Process (AHP).² AHP allows managers to break down the difficulty associated with the combinatoric nature of the problem at the single-project level. At the same time, it encompasses a similar notion as the strategic buckets - resources are divided based on a hierarchy of criteria. First a division based upon the upper level criteria is completed and then each subset of resources is allocated across individual projects.

A number of empirical studies suggest the formation of “within product line” development strategies (Nobeoka and Cusumano 1997, Jones 1999). They highlight the importance of product line management for firm performance and they focus on the value of product

²AHP is a methodology for structured (hierarchical) analysis and is not to be confused with the organization hierarchy that is discussed throughout this thesis.

platforms.³ These studies offer empirical evidence from the automotive and the telecommunications industries. Along similar lines Setter and Tishler (2005) try to estimate the technology investment curves in the defense industry context, and Blanford and Weyant (2005) analyze technology investments in climate change prevention initiatives.

At the NPD program level, the number of studies that consider a dynamic context are limited. This is due to the fact that uncertainty leads to changes in the optimal allocation over time. Chikte (1977) models parallel development activities and corresponding resource allocation strategies. He assumes that investment in an innovation effort impacts its likelihood of success and he analyzes general structural properties without any attempt to outline managerial decision rules. In the same category, there is extensive literature on the dynamic financial portfolio investments (Merton 1969, Constantinides and Malliaris 1995, Samuelson 1969). These financial models generally assume linear returns (equity position multiplied by stochastically changing prices). However, the returns from NPD investments are typically non-linear in the amount of resources dedicated to the NPD program (Arthur 1994, Brooks 1975).

Loch and Kavadias (2002) develop a dynamic allocation model that addresses the challenges of non-linear returns. They focus on NPD program investments and account for the carry over feature of the investment (i.e. the fact that investments within the product line may build up gradually over time). They assume knowledge of the potential value and of the interactions across product lines rendering the applicability of the model limited in cases of radical innovation efforts where both the value and the potential interactions are unknown. They show that the investment should follow a marginal benefit logic in which management should try to invest the next available dollar in the program with the highest *overall* marginal benefit (that is the benefit in the current and the subsequent periods). Along similar lines, Ding and Eliashberg (2002) analyze the number of parallel efforts in each stage within an R&D pipeline (they assume that all efforts aim at obtaining the same goal). Their main insight prompts for over-investment in each stage due to the potential

³The notion of a platform and its derivative products aligns very well with the definition of an NPD program. The key concept here is the fact that all platform efforts revolve around a specific configuration ω or its close neighbors.

failure of individual projects. Fridgeirsdottir and Akella (2005) explore capacity optimization decisions given the congestion effects that may arise within an NPD program. They assume that all projects are of the same type (same processing rate) with different payoffs. Their insight links idea arrival rates to an *ex-ante* capacity division, a notion that is related to the hierarchical suggestions by Liberatore and Titus (1983). Recently, Blanford (2004) analyzes dynamic resource allocation between two innovation endeavors, an incremental one and a radical one. Chao *et al.* (2006) build along the same notion. They consider the problem of dynamic investment in NPD programs under the assumptions that the overall budget depends on how cash is generated over time, and that resource availability may be constrained at different points in time as the programs evolve. They analyze how the investment in incremental or radical NPD programs depends on the level of autonomy given to decision makers.

2.3 Project Selection at the Operational Level

At the operational level of decision making, a fixed budget must be allocated among multiple ongoing projects, both statically (one-time) and dynamically (repeatedly, once per review period, or whenever a new project idea emerges). The fact that the single project may focus on a smaller subset of performance drivers (i.e. a small number of the x_j as opposed to x_1, x_2, \dots, x_N) as dictated by the NPD program decisions, implies that the associated complexity is significantly reduced. This results in more accurate value estimates and resource requirements. However, at the same time the rigidity of the resource requirements and the fixed outcome (value) lend a combinatoric nature to the problem and do not allow standardized solution processes. Thus, the majority of the proposed solutions reside on algorithms and heuristic methods.

From a practice-oriented standpoint, such approaches encompass findings from the financial literature such as net present value (NPV) analysis (Hess 1993, Sharpe and Kellin 1998) and break-even time (House and Price 1991) applied at the operational level of a single project. Each project is assigned an index (its financial value), and these indices are ranked to determine the n best candidates. Decision theorists have also proposed project

ranking via a composite average score of qualitatively assessed dimensions (Brenner 1994, Loch 2000). Similarly, the analytical hierarchy process (Liberatore 1987, Saaty 1994, Hammonds et al. 1998, Henriksen and Traynor 1999) is a structured process of multi-criteria decision making. However, the multi-dimensional decision making methods lack a significant determinant of project choice, namely interactions among projects, both on the technical and on the market side.

The majority of the normative literature has treated the problem at hand through two different lenses: (i) the “knapsack problem”⁴ and (ii) the dynamic allocation of a critical resource across projects (dynamic scheduling literature). Along the first category, there have been many attempts to model the selection problem with different mathematical programming formulations. Hence, formulations such as knapsack have been examined in depth in Operations Research (OR) and they have utilized many variants of mixed-integer programming heuristics for their solutions. Several of these efforts were applied in specific companies (Beged-Dov 1965, Souder 1973, Fox *et al.* 1984, Czajkowski and Jones 1986, Schmidt and Freeland 1992, Benson *et al.* 1993, Dickinson et al. 2001, Belhe and Kusiak 1997, Loch et al. 2001). Although mathematical programming is a sound methodology for optimization problems, and it has been successfully applied in several specific cases, it has not found widespread acceptance by practitioners (Cabral-Cardoso and Payne 1996, Gupta and Mandakovic 1992, Loch et al. 2001). This gap stems partly from the complexity and sophistication of the methods, which are difficult to understand and to adopt for people who are not trained in OR, and partly from the lack of transparency and from the sensitivity of the results to changes in the problem parameters (a mixed-integer programming application example can be found in Loch et al. 2001). In order to retain some level of analytical tractability, mathematical programming formulations rarely account for dynamic decision making, such as the option to abandon some of the projects during development, or the fact that different projects start and end at different points in time. Recently, Beaujon *et al.* (2001) made the observation that project funding is not a “zero or one” decision, but that it

⁴The *knapsack problem*, proposed by Operations Research theorists, considers a set of projects with specific resource requirements and value propositions and a fixed total budget (i.e. the knapsack). The objective is to maximize the value in the knapsack

can be continuously adjusted. Kavadias *et al.* (2005) rely upon the observation of Beaujon *et al.* (2001) but consider upper and lower limits of funding. They propose a heuristic method that relies upon a marginal benefit ranking. Still, the fundamental message from this literature is how difficult it is to obtain high diffusion due to the lack of managerial buy-in.

With respect to the dynamic scheduling literature, several authors have explored the dynamic portfolio selection decision emphasizing optimal policies rather than algorithmic solutions. This work mostly considers stochastic settings due to the uncertainty in projects. This literature comprises four groups. The largest group is the multi-armed bandit (MAB) problem literature, which has strongly influenced the scheduling literature in Operations Research (OR). It was first solved by Gittins and Jones (1972), and since then, many variants have been proposed and solved by other researchers. The general formulation concerns K projects proceeding in parallel, and a critical resource that should be devoted to only one project at a time. Gittins and Jones formulated the well-known *Gittins index*, a number that can be assigned to each project at each time t , and that characterizes the optimal policy. At any time t , it is optimal to work on the project with the highest Gittins index, which depends only on each individual project's state (Bertsimas and Niño-Mora 1996, Whittle 1980, Ross 1982) and corresponds to the reward that would make the decision maker indifferent as to whether to continue the project or exchange it for that reward.

The MAB policy rests upon a number of assumptions which make extensions to more realistic settings extremely difficult and which revert us back to algorithmic approximations. Gittins (1989) shows that for differing general discount functions there is no general index (Gittins 1989, pp. 27-29). Banks and Sundaram (1994) prove that the existence of switching costs across projects leads to the absence of a general index solution. The characteristics of NPD projects (payoffs are earned only after the product is launched into the market) challenge as well the basic premises of MAB. Moreover, projects tend to be interdependent due to prioritization. The latter causes penalties due to delayed market launch.⁵ Kavadias

⁵Which violates the basic MAB assumption that a project's value function remains unchanged while it is not worked on.

and Loch (2003a) expand existing results to incorporate these characteristics of NPD, and provide a useful discussion on the limitations for policy extensions.

The second group of dynamic scheduling models approaches the project prioritization problem as a multiclass queueing system, where different classes of jobs (i.e. types of projects) share a common server. Each job class requires a stochastic time on the server and incurs a linear delay cost. The main result is the “ $c\mu$ rule” (Smith 1956, Harrison 1975): give priority to the job with the highest delay cost divided by the expected processing time (marginal cost c , over time $\tau = \frac{1}{\mu}$). The rule is optimal for linear delay cost structures in various applications (Wein 1992, Ha 1997, Van Mieghem 2000).⁶ For non-linear delay costs, the “generalized $c\mu$ rule” ($G\text{-}c\mu$) has been shown to be asymptotically optimal in heavy traffic (Van Mieghem 1995).

The third group of dynamic scheduling model outline optimal admission rules when a budget has to be allocated over time to several project ideas⁷. Kavadias and Loch (2003b) present such an NPD setting (for an overview of the general problem, see Stidham 1985, Miller 1969). The NPD reality differs from manufacturing settings in two aspects: (i) The project attractiveness measure is continuous (there are uncountably many customer classes). (ii) The NPD system has a waiting buffer of size 1, from which the waiting project disappears when a new project idea arrives. In other words, the new idea is not turned away, but the old idea is superseded. This assumption represents project obsolescence, which is more important in NPD than in manufacturing. These model features lead to results that are consistent with recent literature (more available capacity lowers the threshold for acceptance, see, e.g., Stidham 1985, Lewis *et al.* 1999).

Finally, the stochastic and dynamic version of the knapsack model. Kleywegt and Papastavrou (1998) show that if all items are of the same size, a threshold policy is optimal, the value function is concave in the remaining amount of resource, and the threshold increases

⁶The $c\mu$ rule is a “continuous time” approximation of the Gittins index. Van Oyen *et al.* 1992 among others have pointed out the similarity between bandit policies and the $c\mu$ rule.

⁷The third and second groups of work share methodological foundations, but differ in the main research question: prioritization versus admission.

as the resource is depleted. Kleywegt and Papastavrou (2001) show that the results generalize to the case of stochastic resource requirements of the items, but only if the resource requirement distribution fulfills certain conditions (concavity), and the terminal value function is concave non-decreasing. Still, the NPD context imposes additional constraints on the problem, including the fact that investment in a given project may not be a one shot decision but may progress through milestones (i.e. StageGates) where additional action may be taken.

CHAPTER III

R&D INTENSITY

3.1 *Introduction*

A key metric for the assessment of innovative activity at the firm level is *R&D intensity*. R&D intensity is the ratio of a firm's R&D investment to its revenue (the percentage of revenue that is reinvested in R&D). In subsequent chapters we discuss more detailed issues related to resource allocation and NPD portfolio management. However, it makes sense to discuss where the firm's R&D investment comes from before analyzing how it should be allocated between projects.

The consistency in R&D spending within an industry is remarkable. As an example, consider the R&D intensity for Pfizer, Inc. (Figure 6). Over a 10 year span between 1995-2005, Pfizer's quarterly revenue grew from approximately \$2 Billion to over \$15 Billion. Over the same period of time, Pfizer's R&D intensity was approximately 13-15%. Despite an eight fold increase in revenue, the *percentage* of revenue invested in R&D remained relatively constant. Consistency in R&D intensity is not unique to Pfizer. Figure 7 provides the distribution of R&D intensities for firms in the automotive and pharmaceutical industries. The data show that consistency in R&D intensity is a common trait across these industries. In the automotive industry, R&D intensity typically falls between 3-5%. In the pharmaceutical industry, R&D intensity is approximately 14-16%.

On the managerial front, interactions with senior executives suggest that the R&D intensity phenomenon is robust (Freyre 2006, Kloeber 2007). However, the same executives recognize that firms adopt significantly different resource allocation and NPD portfolio strategies *despite* the drive to maintain a more-or-less constant R&D intensity. It is common to hear a manager say that R&D intensity is simply the result of the "cost of doing business" in a particular industry. Nevertheless, it would be beneficial to provide a more detailed and rigorous explanation for this phenomena. On the academic front a number of researchers,

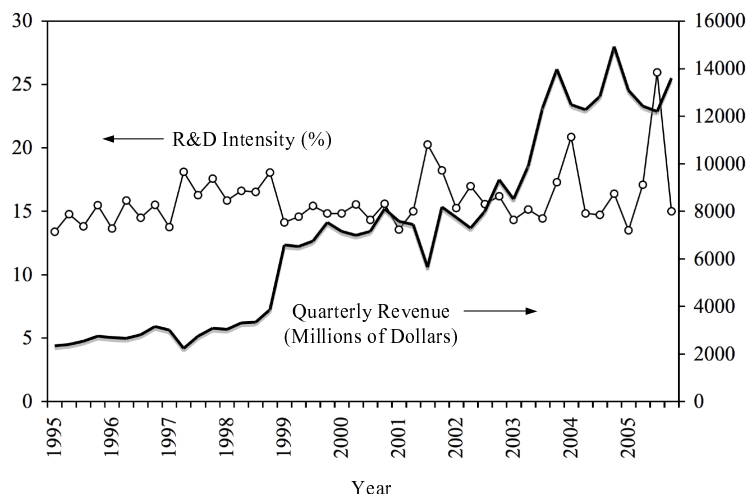
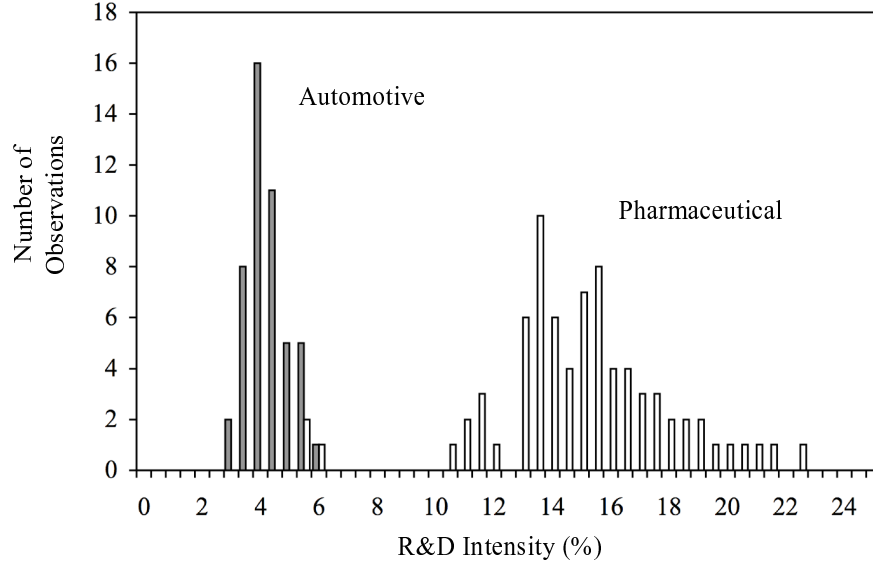


Figure 6: Pfizer Inc. R&D intensity and revenue over time (source: U.S. Securities and Exchange Commission and COMPUSTAT North America Industrial Database).

primarily in the area of economics, have studied related questions. Almost without exception this research is focused at an extremely high level and does not provide insights with respect to operational variables such as cost of sales or NPD portfolio composition. An interesting observation from practice and theory is that firms are differentiated with respect to NPD portfolio strategy. This implies that firms operate according to different potential reward, timing, and risk considerations for R&D investments. The different NPD portfolio strategies and the reward, timing and risk that accompany each strategy certainly require different resource allocation and NPD portfolio decisions.

In light of these observations, what are the factors that explain the consistency in R&D intensity for firms within a given industry? That is to say, why is the within-industry variance in R&D intensity typically less than the between-industry variance? This study builds upon prior research in economics and attempts to shed light on the factors that give rise to the often-cited consistency in R&D intensity for firms within a given industry. We begin our analysis at the individual firm level taking into account the firm's R&D investment decision (including the overall makeup of the NPD portfolio) and its effect on sales growth. We then extend our analysis to the industry level where multiple firms conduct R&D in the face of competition. A key component of our analysis lies in understanding how the R&D



Note: The data consist of firm R&D intensity (R&D/Revenue) for each firm in each year between 2000-2005. The automotive sample consists of the largest 9 companies in NAICS code 336111 (these companies account for 98.9% of industry sales between 2000-2005). The pharmaceutical sample consists of 14 companies in NAICS code 325412 (these companies account for 79.3% of industry sales between 2000-2005). Source: COMPUSTAT North America Industrial Database.

Figure 7: Distribution of R&D intensities in the automotive and pharmaceutical industries.

investment, the NPD portfolio composition, and the associated sales and profit evolve over time.

We find that R&D intensity for the single firm depends on a combination of portfolio metrics (i.e. expected portfolio productivity and uncertainty) and operational variables such as cost of sales and per-period decline in sales. Lower R&D productivity, uncertainty, and cost of sales drive higher R&D intensity. Conversely, lower per-period decline in sales drives lower R&D intensity. At the industry level, we show that a simple evolutionary process drives the consistency in R&D intensity. The evolutionary model suggests that multiple firms within an industry tend to converge to an equilibrium R&D intensity. Our study has important implications for theory and practice. From the theoretical side, we “break open the black box” and explain the consistency in R&D intensity for firms that compete in a particular industry. Thus, we bridge the gap between high-level economic research and detailed operations research. From the practical side, our study takes an important step

toward identifying potential metrics to evaluate R&D investment strategy. These metrics can help managers understand whether firms are under or over investing in R&D given their particular industry and NPD portfolio characteristics.

The remainder of this chapter is structured as follows: in Section 3.2 we discuss the related literature, primarily from the vantage point of economics and finance. In Section 3.3 we present an analytic model of R&D investment for the single firm and in Section 3.4 we extend this model to a competitive setting. We conclude in Section 3.5 with a discussion of the implications of this research for theory and practice.

3.2 Related Literature

In this section we review the literature related to R&D intensity. The overwhelming majority of this research stems from economics and industrial organization. There is an extensive literature in industrial organization that is focused on understanding two hypotheses advanced by Joseph Schumpeter (1950) and refined by John Galbraith (1957). These hypotheses are often referred to as the “Schumpeterian Hypotheses” and they are concerned with R&D spending and innovative performance of firms (Schumpeter 1950). The first hypothesis deals with the effects of competition (market concentration) on R&D spending. The second hypothesis relates firm size (sales or revenue) to R&D spending. A number of economic scholars have re-examined these hypotheses using varied methods and data (Kamien and Schwartz 1982, Levin et al 1985, Cohen et al. 1987, Cohen and Levin 1989).

The second Schumpeterian Hypothesis is the one most closely associated with our work. This hypothesis states that economies of scale drive R&D investment - larger firms will invest more in R&D because they have the necessary assets to take advantage of the investment and earn disproportionate rents. Although this premise is rather intuitive, its validity has sparked intense debate among industrial organization and innovation scholars. In any case, the argument does not explain why firms within a given industry, regardless of size, share a *common* R&D intensity. Furthermore, because of its focus on economic level attributes, this literature does not provide insights with respect to the *management* of the R&D investment and how it emerges from a consistent R&D intensity.

A number of economic researchers have studied problems that are closely related to the issue of R&D intensity (Kamien and Schwartz 1978, Nelson 1988, Cohen and Klepper 1996). Similar to our work, the majority of these efforts are based on analytic models of R&D spending. However, with rare exception, these efforts decouple revenue from the R&D investment. This decoupling transforms the problem from one of R&D investment and innovation to one of consumption and wealth accumulation. The focus on consumption and wealth accumulation is justified because the goal of the economic research is to provide guidelines for long-term economic growth.

The interest in long-term economic growth and the need to better understand what drives this growth has given rise to endogenous economic growth theory. Endogenous economic growth theory has an important relationship with our study. Whereas neoclassical economic growth models assume that the long-run rate of growth is exogenously determined (i.e. it is determined by an exogenous rate of technological progress or an exogenous rate of labor force growth), endogenous growth theory presumes that firm activity impacts the rate of technological progress. One important factor that drives this is investment in R&D and innovation. Beginning with the work of Solow (1956) and advanced through the work of Romer (1990), Aghion and Howitt (1992), Aghion and Tirole (1994), and Barro and Sala-i-Martin (1998), the endogenous growth literature attempts to explain long-term economic growth rates. Still, the high-level macro-economic view does not describe the operational details of R&D investment and the NPD portfolio decisions made by managers.

There is an abundance of research in finance that is tangentially related to the R&D intensity question primarily from the viewpoint of investment (Bradley et al. 1984, Myers 1984). The focus of the finance literature is capital structure (debt to equity ratio and dividend payments). In that light, R&D is conceptually related to finance in the sense that an investment decision is made taking into account potential returns (Hall 1992, Shyam-Sunder and Myers 1999, Hall 2002). However, R&D investment is defined by a number of properties that go beyond standard financial modeling. The most important of these properties are non-linear returns and the fact that R&D investment can alter potential value and probability of success (Loch and Kavadias 2002).

Relative to the existing research in economics and finance, this study will explain why R&D intensity exhibits such consistency within an industry. In particular, we hope to provide a greater level of operational detail with respect to the drivers of the R&D investment decision. Thus, our analysis is similar in terms of the level of detail to previous work in R&D portfolio management (Loch and Kavadias 2002, Setter and Tishler 2005, Blanford and Weyant 2007). This detail allows us to make the necessary link between economic factors, firm strategy, and the NPD portfolio.

3.3 A Model of R&D Investment for the Single Firm

Our study consists of two distinct but related levels of analysis. In this section we develop a model of R&D investment for a single firm. In section 3.4 we use the single firm results in an evolutionary analysis at the industry level. Thus, our study can be thought of as a nested analysis in which the single firm results exist within the evolutionary structure of the industry. Evolutionary perspectives have recently been advocated in managerial settings characterized by technological innovation and change (Hannan and Freeman 1977, Tushman and Anderson 1986, Stuart and Podolny 1996, Teece et al. 1997, Loch and Kavadias 2007)

3.3.1 R&D Investment and Sales Growth

Our analysis is focused on the firm's total R&D investment and how this investment impacts sales growth and profitability. We begin by considering the infinite horizon problem of investing in R&D to drive sales growth. The infinite horizon structure is appropriate since senior managers are expected to make investment decisions and face the same problem for the foreseeable future. Let $r(t)$ be the firm's R&D investment at time $t \in (t_0, \infty)$. The R&D investment has a positive impact on sales through an R&D productivity function $f(r)$, which is increasing and concave on $(0, \infty)$ with $f'(0) = \infty$ and $f'(\infty) = 0$. Of course, R&D investments require time to materialize and often fail before delivering results. To capture the time lag in effectiveness of R&D investments we define $\omega(t - \tau) \in (0, 1)$ as the portion of the R&D investment made at time τ that has an impact on sales at time $t \geq \tau$. With this definition in hand, we can write the total portion of the R&D investment made at τ that has an impact on sales at *any time* in the future as $\int_{\tau}^{\infty} \omega(t - \tau) dt = \mu \in (0, 1)$. Note that

$0 < \mu < 1$ implies that some R&D dollars are not effective and are lost without ever having an impact on sales. In this sense, μ is a proxy for the uncertainty in R&D investment. Lower μ results from more uncertain (higher risk) R&D investments while higher μ results from less uncertain (lower risk) R&D investments.

The triplet $\pi = \{f(\cdot), \omega(\cdot), \mu\}$ is a broad characterization of the firm's R&D portfolio. Given the level of analysis in this study we treat each element of the NPD portfolio as an aggregate measure (chapters 4 and 5 of this thesis will look into more detailed structural elements of the NPD portfolio problem). Each of the elements of π represents a combination of product development functions that together characterize the overall NPD portfolio. For example, if the firm has a preponderance of incremental NPD programs in its portfolio, then $f(\cdot)$ will be relatively small, $\omega(\cdot)$ will be such that the time lapse from R&D investment to payoff is relatively short, and μ will be relatively large. This structure for π is aligned with a low risk, low reward strategy. Conversely, a firm that has a substantial number of radical NPD programs in the portfolio will have $f(\cdot)$ that is relatively large, $\omega(\cdot)$ such that the time lapse from R&D investment to payoff is relatively long, and μ that is relatively small. This characterization of π embodies a high risk, high reward NPD portfolio strategy.

Given the firm's R&D investment and portfolio structure, we can define the impact of R&D on sales. Let $\dot{S}(t) = \int_{-\infty}^t f[r(\tau)]\omega(t - \tau)d\tau - \delta S(t)$ be the change in sales at t . The change in sales is the difference between *growth* due to previous R&D investments and *decline* due to lost sales in the absence of R&D activity (in this formulation, $\delta \in [0, 1]$ is the per-period percentage loss in sales that would be suffered if the firm did not invest in R&D). Note that growth in sales at time t depends on R&D investments made prior to t . The time at which the R&D investments actually deliver results (if they deliver results at all) depends on the form of $\omega(\cdot)$ and the value of μ . Having defined the firm's R&D investment and its impact on sales, we can write the firm's profit as

$$V(S_0) = \max_{r(t)} \int_{t_0}^{\infty} \{[1 - c(t)]S(t) - r(t)\}e^{-\rho t}dt \quad (1)$$

where $c(t)$ is the cost of sales (as a percentage of sales) and $\rho \in (0, 1)$ is the discount factor. We allow process improvement and learning to take place so that $\dot{c} < 0$, $\ddot{c} > 0$, and $c(\infty) = \bar{c}$. Thus, the cost of sales is decreasing over time, but cannot be reduced beyond a limiting

value \bar{c} . The maximization in Equation 1 is subject to $\dot{S}(t) = \int_{-\infty}^t f[r(\tau)]\omega(t-\tau)d\tau - \delta S(t)$, $S(t_0) = S_0 > 0$, and $\int_{\tau}^{\infty} \omega(t-\tau)dt = \mu \in (0, 1)$.

3.3.2 Equilibrium R&D Intensity

In this section we discuss the analytic solution to the problem presented above. To ease exposition, all technical details are presented in Appendix A.1 and functional notation is suppressed when the intended meaning is clear. In describing the analytic solution, we first characterize the firm's optimal R&D investment and then proceed to analyze the equilibrium values for R&D investment, sales, and R&D intensity. The problem stated in Equation 1 results in an intuitive solution for the firm's optimal R&D investment over time. We state this formally in Proposition 1.

Proposition 1. *Optimal R&D Investment.* The optimal R&D investment, $r^*(t)$, is defined implicitly by $\partial f / \partial r^* \int_t^{\infty} \lambda(\tau)\omega(\tau-t)d\tau = 1$.

The optimal R&D investment equates the expected marginal benefit from R&D (i.e. the expected impact that R&D investment has on sales including all future benefits) to the marginal cost of R&D at time t . This insight is aligned with previous work in economics (Cohen and Klepper 1992, 1996). Based on this result, we seek long-run equilibrium values for the firm's R&D investment and sales rate. An equilibrium is achieved when two conditions are satisfied. First, the marginal benefit from all future sales (discounted to t) is balanced against the marginal benefit at t . Second, the expected increase in sales at t (due to all previous R&D investments) is balanced against the decline in sales (due to δ). Together these conditions define a stationary equilibrium. Proposition 2 characterizes the equilibrium conditions.

Proposition 2. *Equilibrium R&D investment:* $\bar{r} = g^{-1}[(\rho + \delta)/(1 - \bar{c})\mu]$ where $g^{-1}(\cdot)$ is a decreasing and convex function defined by $g(r) = \partial f / \partial r$. *Equilibrium Sales Rate:* $\bar{S} = f(\bar{r})\mu/\delta$ where $f(\cdot)$ is an increasing and concave function. *Equilibrium R&D Intensity:* There exists an equilibrium R&D intensity given by: $\bar{\beta} = \bar{r}/\bar{S}$.

The equilibrium R&D investment balances the marginal expected benefit from R&D expenditure (in terms of R&D productivity and higher sales) with the cost of the investment. Because $c(t)$ is decreasing over time, it can be shown that the R&D investment increases over time until reaching the equilibrium value. This R&D investment drives sales growth over time. The equilibrium sales rate is defined at the point at which the expected sales growth due to R&D expenditure offsets the sales decline. Because the R&D expenditure increases towards the equilibrium, it follows that the sales rate increases until reaching the equilibrium value \bar{S} . Given the equilibrium R&D expenditure and sales rate, we define the equilibrium R&D intensity as the ratio of R&D expenditure to sales.

The existence of an equilibrium R&D intensity is guaranteed if the firm optimally invests in R&D at the point at which the benefits from the R&D expenditure balance against the cost of the investment. An important element of our analysis lies in understanding the factors that drive lower or higher R&D intensity. We state this formally in Proposition 3.

Proposition 3. *Comparative Statics Analysis for R&D Intensity:* $\bar{\beta}$ is higher if: (i) δ is higher, (ii) μ is lower, (iii) $f(\cdot)$ is lower, (iv) \bar{c} is lower, (v) ρ is lower.

The comparative statics results in Proposition 3 outline the factors that drive R&D intensity lower or higher for firms within an industry. Equilibrium R&D intensity is higher, *ceteris paribus*, if the firm is subject to conditions that result in lower sales (i.e. higher δ , lower $f(\cdot)$, and lower μ). In such cases, the firm must invest more in R&D to maintain a comparable level of sales and the result is a higher equilibrium R&D intensity. Lower cost of sales (\bar{c}) drives higher R&D intensity because the firm can invest more dollars in R&D without sacrificing profit.

The results discussed above apply to a single firm. Because firms have different NPD portfolio strategies (π) and operational variables (\bar{c} and δ), we would expect R&D intensity to differ across firms. However, theory and practice point to a consistency in R&D intensity for firms within a particular industry. In the analysis that follows we build upon our analytic model to explain the factors that drive this *consistency in R&D intensity*. Consistency in

this context refers to the premise that the within-industry variance of R&D intensities is less than the between-industry variance in R&D intensities.

3.4 *An Evolutionary Model of R&D Investment*

The equilibrium value of R&D intensity implies that there exists an optimal rate at which firms should invest in R&D (as a percentage of sales). Firms that invest beyond $\bar{\beta}$ will have lower profits because R&D productivity is subject to diminishing returns. Firms that invest below $\bar{\beta}$ will have lower profits because potential sales remain untapped. Of course, R&D investment is a risky business since investment decisions must be made today but sales growth is realized in the future. The decisions are exacerbated by competition intensity that may render the firm extinct before its R&D investment pays dividends.

In this section we extend the analytic model presented above to account for the fact that multiple firms coexist in a competitive environment. Based on this observation we take an evolutionary perspective on the R&D investment problem (Nelson and Winter 1982). That is to say, firm performance evolves over time based on variation, selection, and retention mechanisms. Evolutionary perspectives have recently been advocated in settings characterized by technological innovation and change (Tushman and Anderson 1986, Stuart and Podolny 1996, Teece et al. 1997, Loch and Kavadias 2007). Furthermore, an evolutionary perspective is appropriate given the fact that firms must often make R&D investment decisions without knowing the strategies or decisions made by competitors. Indeed, corporate R&D investments and NPD portfolio decisions are highly guarded secrets and are only common knowledge *ex post*.

3.4.1 **The Competitive Environment**

Suppose that a population of N firms exists at $t = t_0$. Each firm $i = 1, 2, \dots, N$ is differentiated with respect to π_i , $S_i(t_0)$, \bar{c}_i , and δ_i . The discount factor ρ is assumed to be the same for all firms. Given the initial conditions faced by each firm in the population, it should be obvious that the initial R&D intensity for each firm, β_i , will be different.

Our interest lies in understanding whether or not the distribution of R&D intensities converges to a value, and if so, what value does it converge to? Similar to the analytic model

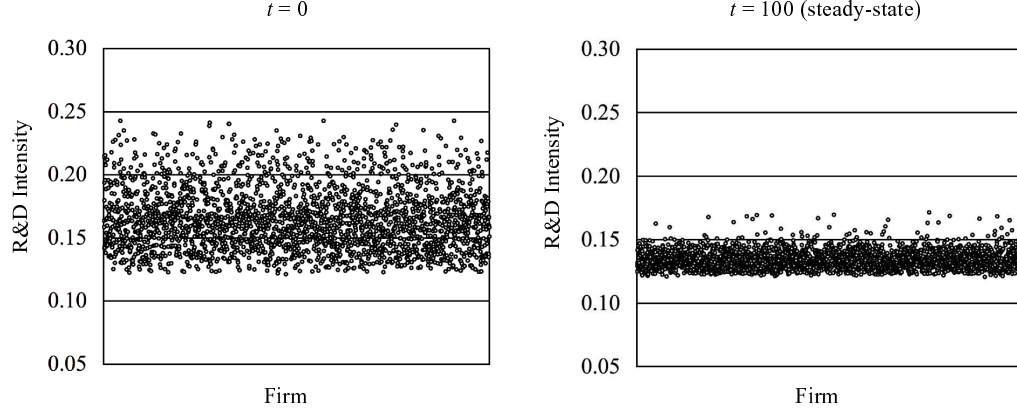
of Section 3.3, we look for equilibrium (steady-state) values for the β_i . An evolutionary perspective dictates that variation, selection, and retention mechanisms will lead to an equilibrium distribution for the β_i that is characterized by lower variance (relative to the initial distribution). Furthermore, the mean of the distribution should follow the insights described in Proposition 3.

To implement the evolutionary model, we must define variation, selection, and retention mechanism for the population of firms. The following activities take place in period $t = 0, 1, 2, \dots$ for each firm $i = 1, 2, \dots, N$: Firm i determines its R&D investment as $r_i = \beta_i S_i$ where β_i is calculated as $\beta_i = \bar{r}/\bar{S}$. *Variation* occurs as firm i 's R&D investment has an impact on sales: $S_i(t+1) = (1-\delta_i)S_i(t) + \sum_{\tau=t_0}^t f_i[r_i(\tau)]\omega_i(t-\tau)$. Note that $\omega_i(\cdot)$ determines the “weights” that past R&D investments have on current sales. In that light, $\omega_i(\cdot)$ behaves in a similar fashion to a probability mass function. *Selection* occurs in each period based on firm profit. Profit for firm i is calculated as $\Pi_i(t) = (1 - \bar{c}_i)S_i(t) - r_i(t)$ and the lowest $x\%$ of firms (in terms of profit) are eliminated from the population. New firms enter the population with random $S_i(t)$, \bar{c}_i , and δ_i . *Retention* occurs as portfolio strategies for the new firms (π_i) are benchmarked from the highest $x\%$ (in terms of profit). We repeat these steps until the system reaches an equilibrium (steady state). Complete details regarding the implementation of the evolutionary model, including functional forms and parameter distributions, can be found in Appendix A.2.

3.4.2 Equilibrium R&D Intensity

In analyzing the results of the evolutionary model we first confirm that R&D intensity indeed reaches as equilibrium. We then concern ourselves with the value of the equilibrium R&D intensity. Figure 8 depicts the distribution of R&D intensities at $t = 0$ and $t = 100$ (steady-state) for the base case analysis.¹ Figure 8 confirms that an equilibrium R&D intensity exists when a population of firms is subject to competition and evolutionary mechanisms. Note that the initial ($t = 0$) distribution of R&D intensities ranges from approximately

¹Extensive experimentation confirms that the convergence result depicted in Figure 8 is robust. In particular, the steady state ($t = 100$) variance in R&D intensity was substantially lower than the variance at $t = 0$ for all experiments.



Note: The graphs depict R&D intensity for each firm in the base case experiment. The sample consists of $N = 500$ firms per replication and 100 replications.

Figure 8: Distribution of Firm R&D Intensities at $t = 0$ and $t = 100$ (steady-state).

0.10 to 0.25. This reflects the fact that firms are initially differentiated with respect to cost and portfolio parameters. At $t = 100$ (steady-state) the distribution of R&D intensities is characterized by substantially lower variance. This result shows a strong convergence of R&D intensities.

The steady-state distribution of R&D intensities provides convincing support for the existence of an equilibrium R&D intensity. We now turn our attention to *the value of the equilibrium R&D intensity*. Figure 9 shows the mean of the distributions at $t = 100$ (steady-state) for profit, sales, R&D investment, and R&D intensity. Each experiment (E1-E5) highlights a changed parameter relative to the base case experiment. We also report the standard errors for each output measure to highlight the fact that convergence is robust and the steady-state ($t = 100$) variance of each output measure is relatively small.

The results in Figure 9 mirror the comparative statics analysis of Proposition 3. As with the analytic result, we note that the equilibrium R&D intensity is lower if cost of sales is higher, per-period sales decline is lower, R&D productivity is higher, and uncertainty is lower. Based on the results in Figure 9, we can explain the factors that drive a change in equilibrium R&D intensity for a population of firms. In experiment E1, both the equilibrium sales and equilibrium R&D investment are lower relative to the base case. The

Experiment	Effect	<i>Profit</i>	\bar{S}	\bar{r}	$\bar{\beta}$
Base Case	-	13.174 (0.098)	18.161 (0.131)	2.432 (0.016)	0.1344 (0.0004)
E1 (higher \bar{c})	Higher cost of sales	1.311 (0.011)	12.328 (0.085)	0.944 (0.006)	0.0768 (0.0003)
E2 (lower δ)	Lower per-period sales decline	33.497 (0.634)	42.531 (0.753)	2.752 (0.025)	0.0702 (0.0008)
E3 (higher $f(\cdot)$)	Higher R&D productivity	36.205 (0.444)	46.164 (0.549)	3.107 (0.031)	0.0686 (0.0005)
E4 (higher μ)	Lower uncertainty	30.062 (0.400)	38.933 (0.492)	3.084 (0.027)	0.0814 (0.0006)
E5 (higher ρ)	Higher discount factor	13.043 (0.092)	17.612 (0.101)	2.072 (0.011)	0.1183 (0.0004)

Note: Each experiment consists of $N = 500$ firms per replication and 100 replications. The entry in each cell is the average of the output measure (standard error provided in parentheses). Please see Appendix A.2 for details regarding the experimental design.

Figure 9: Equilibrium profit, sales, R&D investment, and R&D intensity at $t = 100$ (steady-state).

equilibrium R&D intensity is lower because the R&D investment effect dominates the sales effect (the same reasoning is true for experiment E5). Conversely, experiments E2, E3, and E4 result in higher equilibrium R&D investment and higher equilibrium sales. For these experiments R&D intensity is lower because the sales effect dominates the R&D investment effect. Interestingly, experiments E2, E3, and E4 consist of factors that have a direct impact on sales growth or decline.

For the majority of experiments we note that the distribution of firm portfolio variables ($f_i(\cdot)$, $\omega_i(\cdot)$, and μ_i) converges to a low $f(\cdot)$, an $\omega(\cdot)$ that delivers results earlier in time, and a higher μ relative to the base case. Note that all of these changes in the portfolio suggest that firms tend to converge to incremental portfolio strategies in the face of competition (in order to conserve space we do not report these results in Figure 9. Details are available from the author).

3.5 Conclusions and Implications

The goal of this chapter was to understand an often-observed phenomenon regarding the consistency in R&D intensity. To accomplish this goal we developed an analytic model of R&D investment for a single firm. We then extended the analytic model to a competitive setting in which a population of firms evolves over time until reaching an equilibrium state. Our results show that R&D intensity for the single firm depends on a combination of portfolio metrics (i.e. expected portfolio productivity and uncertainty) and operational variables such as cost of sales and per-period decline in sales. Lower R&D productivity and cost of sales drive higher R&D intensity. Conversely, lower uncertainty and per-period sales decline drive lower R&D intensity. At the industry level, we show that a simple evolutionary process drives the consistency in R&D intensity. The evolutionary model suggests that multiple firms within an industry tend to converge to an equilibrium R&D intensity. In an evolutionary setting, per-period sales decline, R&D productivity, and uncertainty drive the equilibrium R&D intensity through their effect on sales. The cost of sales and the discount factor drive R&D intensity through their effect on the R&D investment.

Our results contribute to both the theory and practice of R&D investment. From the theoretical side, we “open the black box” to discuss how the NPD portfolio impacts the consistency of R&D investment within an industry. We believe that this study is an important first step to bridge the gap between high-level economic research and detailed operations research. This is an important theoretical contribution as it sheds additional light on a long standing question in the economics of R&D investment. From the practical side, this study opens the door for managers to understand the long-run impact of NPD portfolio strategy. Specifically, firm level data such as cost of sales, per-period sales decline, and overall NPD portfolio composition can be used to estimate an equilibrium R&D intensity, which in turn can be used to estimate whether firms are over or under investing in research and development.

We view our work as an important step that can help academics and practitioners develop a better understanding of an often-observed phenomenon in R&D investment. Based on our analysis we outline a number of fruitful avenues for future research:

- *Empirical Validation.* The results of our analytic and evolutionary models can be tested using publicly available data on firm R&D investment and sales. Because of the relatively high level of analysis adopted in this study, the possibilities for empirical validation are plentiful.
- *Competition.* The evolutionary model presented in Section 3.4 consists of a simple mechanism that serves as a proxy for competition: firms become extinct if their profit is among the lowest in the population. What this mechanism gains in simplicity and effectiveness, it loses in terms of detail and explanatory power. It would be beneficial to treat the effects of competition through a more detailed mechanism. Extensions along these lines should include specific market mechanisms that determine sales (i.e. Cournot competition or market share attraction models). Nevertheless, one must take caution in defining a precise form for the effects of one company's R&D investment on another company's sales.
- *Uncertainty.* The portfolio variables considered in this study account for uncertainty in terms of the expected impact on sales. That is to say, $\omega(\cdot)$ and μ together act as a probability density function to determine the expected effect of R&D investment on future sales. Still, it would be beneficial to define the outcome from R&D investment as a true random variable. Previous work in economics (primarily in the area of R&D races) offers a good starting point for a true stochastic analysis.

The above issues merit rigorous study and are sure to enhance our understanding of innovation and economic growth. Indeed, knowing where the R&D investment comes from and what drives this investment at an aggregate level is the first step towards effective resource allocation and NPD portfolio management.

CHAPTER IV

STRATEGIC BUCKETS

4.1 *Introduction*

Managers have adopted several methods that aim to increase effectiveness when allocating resources across NPD initiatives of varying degrees of novelty. A number of case driven frameworks address the trade-offs between product and process innovation, risk and reward, and market and technology risk (Roussel et al. 1991, Wheelwright and Clark 1992, Cooper et al. 1998). These tools summarize best practices for dividing resources and achieving “balance” across a portfolio of NPD endeavors. Though the tools have different names, they all encourage the division of the overall resource budget into smaller, more focused budgets. The result is a set of *strategic buckets* for managing the NPD portfolio (Cooper and Edgett 2003, Cooper et al. 2004). A strategic bucket is a collection of NPD programs that are aligned with a particular innovation strategy (Roussel et al. 1991, Wheelwright and Clark 1992, Cooper et al. 1998). The NPD programs in a strategic bucket may involve process improvements and cost reductions, minor product modifications, radical next generation technological research, or groundbreaking R&D initiatives, among others. Figure 10 depicts a NPD portfolio strategy with four strategic buckets.

Strategic buckets create non-permeable partitions between dissimilar NPD programs to ensure access to resources for projects that are seemingly unattractive to commonly used project valuation methods. Net present value (NPV) or real options analyses tend to disfavor advanced technology projects due to the high likelihood of failure and long-term payoffs. In addition, project valuation tools are difficult to use when it comes to radical projects because data may be unreliable or highly biased (Kavadias et al. 2005). In light of these challenges, the goal of a strategic bucket is to earmark resources for radical NPD programs. In the absence of mechanisms that protect resources, managers often sway the result of a NPV analysis in favor of a more radical project by increasing its estimated payoff

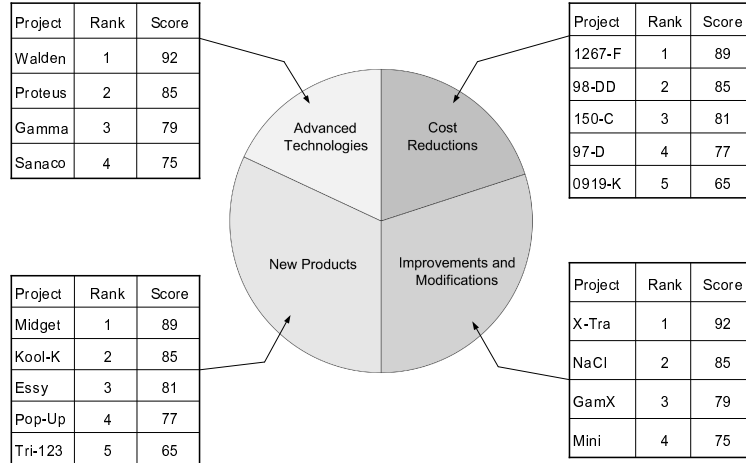


Figure 10: NPD portfolio strategy and strategic buckets.

(the infamous \$10 billion market opportunity). Of course, any NPV analysis can sway in the opposite direction by lowering the probability of success for radical NPD initiatives. Such ad-hoc decision-making results in intraorganizational suspicion and lack of transparency (Wu et al. 2006). Ultimately, the suggested portfolio balance remains a vague guideline, which is resolved on a case-by-case basis. To the best of our knowledge, decisions regarding strategic buckets and the protection of resources have little or no theoretical foundation.¹

The goal of this manuscript is to provide a theory that explains strategic buckets. We begin by characterizing the behavior of the individual NPD programs that comprise a strategic bucket. Our analysis highlights the subtle role of two strategic factors and how they impact the value of a NPD program: (i) the degree of change sought by the innovative activity (*how novel should the target solution be?*) and (ii) the time during which product improvements and extensions take place (*for how long does management commit resources to the program?*). Radical innovation efforts require a window of time in order to realize positive outcomes. We then establish how interactions between performance drivers impact this window of time. In complex business environments with numerous interactions radical innovation efforts pay off earlier. Conversely, environments with little or no interactions favor incremental innovation efforts. The ability to commit to an innovation initiative

¹Special thanks to J. Kloeber, J. Scott and P. Freyre for detailed discussions and insights regarding NPD portfolio strategy and the use of strategic buckets.

depends on environmental instability (likelihood of major technological or market disruptions). Higher degree of environmental instability favors incremental efforts. In conclusion, we show how individual NPD programs drive overall portfolio decisions and we shed light on the appropriate “balance” between incremental and radical innovation in the NPD portfolio. Although environmental complexity and instability both confound managers, we find that they have completely opposite effects on the NPD portfolio balance. Environmental complexity shifts the balance towards radical innovation. Conversely, environmental instability shifts the balance towards incremental innovation.

The remainder of this paper is organized as follows: in §4.2 we review the relevant literature and in §4.3 we introduce the theoretical foundations for our problem. In §4.4 we use the theoretical foundation to build an analytic model of NPD program performance, and we show how this performance leads to a tradeoff between different types of innovative effort. In §4.5 we show that insights from the analytic model are robust through a representation of NPD as an evolutionary process of performance improvement in complex technology-market environments. This is important because two very different views of the problem (analytic and evolutionary) lead to similar insights. In §4.6, we extend our analysis from the single NPD program to the NPD portfolio and we show how different problem contexts drive different strategic bucket policies. Finally, we draw conclusions for theory and practice in §4.7.

4.2 Related Literature

In this section we briefly review the relevant literature. Our focus is on resource allocation models that address the NPD portfolio problem. There is an abundance of literature that analyzes the portfolio selection problem at the operational level (Beged-Dov 1965, Souder 1973 and 1978, Fox and Baker 1984, Czajkowski and Jones 1986, Schmidt and 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. These models are highly sensitive to parameter changes and practitioners often doubt their results due to the lack of robustness and transparency (Loch

et al. 2001, Shane and Ulrich 2004, Kavadias et al. 2005). These limitations 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 explicit consideration of metrics that are difficult to quantify (e.g., strategic alignment). Unfortunately, these tools rely on an ad-hoc list of dimensions, and decision-makers often manipulate the methods to generate desired outcomes instead of using them as true decision support tools. There also exists significant research that specifically addresses the practice of strategic buckets as a NPD portfolio management tool (Roussel et al. 1991, Wheelwright and Clark 1992, Cooper et al. 1997, Cooper et al. 2004). This research provides descriptive evidence of the use and benefits of strategic buckets and clearly outlines the popularity of strategic buckets. We build upon these observations to provide a rigorous theoretical foundation for the existence and use of strategic buckets.

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

(2007) account for the dynamic allocation of a fixed budget over research opportunities that become available at different points in time. Once more they do not characterize the nature of innovation and they assume a particular structure for the return on investment curves.

From a methodological standpoint, a large body of literature has examined the mathematical properties of resource allocation models beginning with Smith (1959), and followed by Gittins and Jones (1974) and Gittins (1989). This work is based on the dynamic scheduling of critical resources across a set of potential tasks (for an excellent review see Van Mieghem 1995). These models consider a fixed time horizon, which is an appropriate assumption for dynamic scheduling because task returns do not change over time (at most they get discounted). Given the fixed time horizon length, these studies determine an allocation or scheduling policy. We borrow a simple mathematical structure from the dynamic scheduling literature - the well-known “treasure hunt” problem (for a recent analysis see Denardo et al. 2004). We use this structure as a basis to examine the effects of the horizon length on the best choice for the type of innovative effort. We do not make a methodological contribution to the dynamic scheduling literature (i.e. our goal is not to develop new index policies). Still, we analyze a key trade-off regarding the investment horizon and the choice of program innovativeness, which is beyond the scope of the dynamic scheduling literature.

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

4.3 Theoretical Foundations

In this section we formally define the concepts of innovative effort and NPD programs. To begin, we provide a definition of a product and the performance it delivers to the firm. We then characterize innovation and NPD as an attempt to alter product attributes and improve product performance. Two concepts are central to our analysis: (i) NPD programs

are more or less innovative depending on the degree of change created by the program. Each type of innovative effort is characterized by its potential value, risk, and cost depending on the degree of change (Kauffman et al. 2000). (ii) Managers commit to NPD programs for a given amount of time. The time commitment reflects their belief that the firm will be able to continue to operate according to the status quo. In the analysis that follows, our goal is to identify the minimum set of assumptions that demonstrate why strategic buckets exist and how they should be managed.

4.3.1 Products, NPD Programs, and Innovative Effort

Borrowing from the marketing and engineering design literatures, we define a product as a bundle of technology and market attributes, $\omega = (x_1, x_2, \dots, x_N)$. The attributes represent key product parameters such as the core product architecture, component technologies, design features, and manufacturing process specifications among others. We define a NPD program as an initiative that strives to alter product attributes in order to enhance existing product performance or create an altogether new product. With this definition in mind we note that a NPD program begins with a product, ω , and creates a different product, ω' . In doing so, the NPD program can be characterized by a change metric, $d = |\omega' - \omega|$, which defines the type of innovative effort pursued by the program (Kauffman et al. 2000, Kavadias and Chao 2006). For any existing product ω and type of innovative effort d we define the set of potential new product ideas as $N_d(\omega) = \{\omega' : |\omega' - \omega| \leq d\}$. In our framework, innovation is equivalent to stating that a NPD program changes product attributes over time and drives performance improvement.

Product performance (net revenue generated by a product) is a function of the technology and market attributes and is given by $F(\omega)$. For any NPD program, $F(\omega') - F(\omega)$ is the performance change as a result of the innovative effort. We define a performance improvement function $V(\cdot)$ such that $F(\omega') - F(\omega) = V(d)$. Let $\hat{V}(d)$ be the maximum potential performance improvement possible within $N_d(\omega)$ and note that $\hat{V}(d)$ is non-decreasing in d . This follows immediately from our definition of $N_d(\omega)$ because for any $d_1 < d_2$, $N_{d_1}(\omega) \subset N_{d_2}(\omega)$.

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

4.3.2 Incremental and Radical Innovation

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

According to our definition, a NPD program may be more or less incremental or radical depending on the number of attributes that are actually altered. Furthermore, our definition of innovative effort extends beyond the standard notion of technological change. Since a product is defined as a collection of technology and market attributes, and a NPD program alters d attributes, innovation takes on a spatial quality similar to the Schumpeterian definition of innovation (“To produce means to combine forces and materials within our reach... to produce other things... means to combine these materials and forces differently.” Schumpeter 1934, page 65). Figure 11 is a schematic representation of incremental and radical innovation.

4.4 An Analytic Model of NPD Program Performance

In this section we build an analytic model of NPD program performance and we show how this performance leads to a tradeoff between incremental and radical innovation. To capture

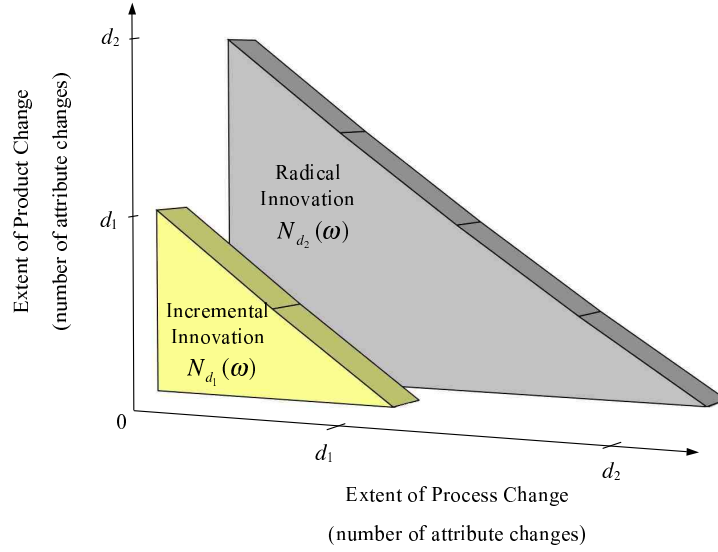


Figure 11: Incremental and radical innovation (adapted from Wheelwright and Clark 1992).

the dynamic nature of innovation we consider that the firm attempts to improve product performance over a given period of time, $t = 0, 1, 2, \dots, m$. As described in Section 3, a NPD program exists with the express purpose of improving product performance and we assume that performance is normalized such that $F(\omega) = 0$ at $t = 0$. A number of questions arise immediately, such as, how much performance improvement can the NPD program realize within a given time frame, m ? Should the firm attempt an incremental improvement strategy (relatively minor benefits achieved with higher probability of success and lower cost) or should the firm pursue efforts that attempt to radically improve performance (potentially large benefits with lower probability of success and higher cost)?

4.4.1 Expected Performance for a Single NPD Program

The commitment to a particular type of innovative effort captures precisely the intuition behind strategic buckets. For a given $d \in \{1, 2, \dots, N\}$ the firm invests $c(d)$ dollars per period and improves product performance to $\hat{V}(d)$ with probability $p(d)$ in each period.²

²Our model of probabilistic search assumes that firm is searching for a target value of $\hat{V}(d)$. In Appendix B.2 we provide an alternative formulation based on a search for the highest performance possible within a finite time interval.

Of course, if the attempted NPD effort is not successful, product performance remains unaltered. We can express the expected performance after n periods for an NPD program of type d through the following recursive equation:

$$J_n^d = \max \left\{ 0, -c(d) + rp(d)\hat{V}(d) + r[1 - p(d)]J_{n+1}^d \right\} \quad (2)$$

Where r is the one-period discount factor. Because the firm commits to the NPD program for m periods we have the boundary condition $J_m^k = 0$.³ The boundary condition reflects the reality that managers terminate the NPD program and it no longer drives performance improvement once the NPD program achieves $\hat{V}(d)$. Working backwards, if we assume that $-c(d) < rp(d)\hat{V}(d)$, the expected performance in period $m-1$ is $J_{m-1}^d = -c(d) + rp(d)\hat{V}(d)$. Similarly, the expected performance in period $m-2$ is $J_{m-2}^d = [-c(d) + rp(d)\hat{V}(d)][1 + r(1 - p(d))]$. Continuing in this fashion the expected performance for an m period commitment (considered at $t = 0$) to an NPD initiative of type d is

$$J_0^d = [-c(d) + rp(d)\hat{V}(d)] \frac{1 - r^m[1 - p(d)]^m}{1 - r[1 - p(d)]} \quad (3)$$

For a given type of innovative effort, Equation 3 defines the expected return curve for the NPD program as a function of the time commitment, m . The following proposition describes the behavior of the NPD program return curves (technical details and proofs for all propositions can be found in the Appendix).

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

Figure 12 depicts a schematic representation of Proposition 1. The structure of the return curves $J_0^{d_1}$ and $J_0^{d_2}$ leads to a unique *crossing time*, \bar{m} , which allows managers to

³The assumption regarding an m period commitment reflects our effort to model the managerial decisions we observed in practice. In the event that we allow for period-by-period switching between types of innovation, the simple dynamic program presented here results in a two-armed bandit which we solve in Appendix A.3. For a complete discussion on the multi-armed bandit, the reader is referred to Kavadias and Loch 2003 or the classic two-armed bandit proof in Gittins 1989.

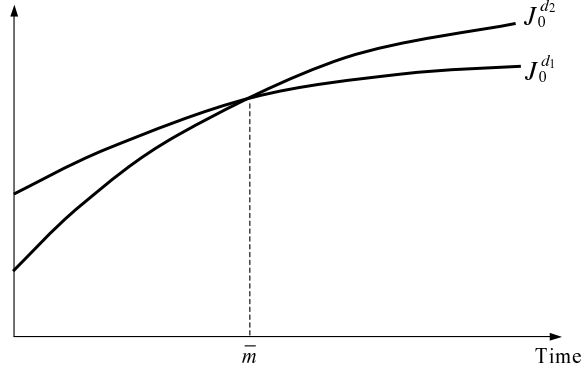


Figure 12: Schematic representation of proposition 1.

evaluate different types of innovative effort. If the firm commits to the NPD program for $m < \bar{m}$ periods, then incremental innovation is the best choice. Conversely, if the firm is willing to commit to the NPD program for $m > \bar{m}$ periods then radical innovation is the best choice. An alternative interpretation highlights a different side of the commitment decision: if management holds the belief that the firm will only continue to operate for an amount of time less than the crossing time, radical innovation does not make sense because radical innovation requires at least \bar{m} periods to deliver higher payoff relative to incremental innovation. In contrast, if management holds the belief that the firm can continue to operate longer than the crossing time, radical innovation becomes more attractive. Given these results, we see that the importance of protecting resources for an interval of time depends not only on the parameters of the alternative types of innovation, but also on the belief that management holds with respect to viability of the firm (identified through the commitment time).

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

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

Higher \bar{m} is synonymous with more favorable circumstances for incremental innovation since the time interval during which incremental innovation dominates radical innovation is longer (from the viewpoint of expected performance). Thus, incremental innovation becomes more favorable when $\hat{V}(\cdot)$ or $p(\cdot)$ is higher and $c(\cdot)$ is lower. The former make innovative activity attractive by increasing the expected value of a NPD program while the latter makes innovative activity attractive by lowering the cost of a NPD program. The effect due to cost is straightforward. However, the effect due to expected value ($p(\cdot)\hat{V}(\cdot)$) is more nuanced because it includes a tradeoff: higher d implies lower $p(d)$ and higher $\hat{V}(d)$.

4.4.2 Can the Firm Commit to the NPD Program?

The preceding analysis is based on the fact that the firm makes an m period commitment to the NPD program. In reality there are firm level factors that influence whether or not the firm *is able to commit* to the NPD program for a given interval of time. The ability to commit to a NPD program is based on the belief that management holds regarding the ability of the firm to continue to generate adequate performance. From a practical standpoint, this observation echoes managerial concerns such as, “How long will it take for innovation efforts to pay off?” Theoretically the question translates to, “Do managers believe that the firm will continue to operate under the status-quo beyond the interval $[0, \bar{m}]$?” Unfortunately, the ability to generate adequate performance may be beyond the control of managers. The technology and market environment that defines product performance may be subject to disruptions (e.g. dramatic technological leaps or shifts in customer preferences). Disruptions alter the underlying relationship between product attributes and product performance and therefore alter the expected performance of any NPD program meant to improve a product. In this section we extend the previous analysis to account for the fact that the firm may experience disruptions in NPD program performance.

Let $f(m) = J_0^{d_1} - J_0^{d_2}$ represent the difference between incremental and radical NPD program performance for a given time commitment, m . Note that when $f(m) > 0$ ($f(m) < 0$) incremental (radical) innovation is the preferred type of innovation for the NPD program.

When the technology and market environment is subject to potential disruptions, the underlying relationship between product attributes is altered and product performance is negatively affected. We assume that a technology or market disruption is defined by a renewal process so that when a disruption occurs the firm's performance is relegated to the performance at $t = 0$ and the firm faces the same decision problem once more.⁴ Let ΔJ represent the difference between incremental and radical NPD program performance for the renewal process defined by technological and market disruptions. Suppose that a disruption occurs after t periods with probability q . Letting r be the one-period discount factor, we can write $\Delta J = q[f(t) + r^t \Delta J] + (1 - q)f(m)$, which simplifies to

$$\Delta J = \frac{q}{1 - qr^t} f(t) + \frac{1 - q}{1 - qr^t} f(m) \quad (4)$$

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

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

Proposition 3 states that as the probability of an *imminent* technology or market disruption increases, incremental innovation becomes more attractive because it allows the firm to reap quick rewards before another disruption occurs. Conversely, as the probability of technology or market disruption decreases radical innovation becomes more attractive because the effort should pay off if given enough time. An alternative interpretation is that an environment defined by a turbulent phase (i.e. an environment in which customer preferences are not well defined) drives firms to seek incremental changes. Note, that an incremental strategy does not imply homogeneity with respect to the actual changes in technology or

⁴We recognize that the firm's decision problem may not be identical after a disruption. For example, competition intensity that renders the firm extinct is an extreme form of technological disruption. Nevertheless, our objective is to describe the effects of disruption frequency, which is an appropriate proxy for environmental instability.

market attributes. Instead, different firms may use different technologies or conquer different market segments so long as their innovative efforts remain closely associated with their current product offerings. It is important to note that \bar{m} depends on the attributes that define an individual product, while q is a firm level parameter common across all products in the portfolio. The importance of this observation will become obvious once we extend our analysis to the portfolio level.

4.5 An Evolutionary Model of NPD Program Performance

The previous framework is limited by a number of realistic considerations that merit discussion. First, for even a small number of possible outcomes and periods, it is difficult, if not impossible, for managers to possess the computational capability to determine the best choice of strategic buckets. Previous work on the optimal balance between incremental and radical innovation highlights this fact and proposes solution algorithms for $m > 1$ (Macready and Wolpert 1995). Unfortunately, it is well documented that algorithmic approaches are not used in practice (Loch et al. 2001, Shane and Ulrich 2004). Second, the analysis in the previous section is informed by a very specific structure for the performance $\hat{V}(d)$ and the probability $p(d)$. In reality, there is reason to believe that performance functions are extremely complex as multiple technology and market attributes interact in significant and unknown ways resulting in non-uniform values for $\hat{V}(d)$ and $p(d)$. This is particularly so at a strategic level of decision making, where a multitude of factors must be taken into account.

In this section we extend the analytic model presented above to account for the fact that managers do not have the ability to optimize an m period commitment decision at $t = 0$ and the performance functions they face are complex. Based on these observation we take an evolutionary perspective on this problem (Nelson and Winter 1982). That is to say, NPD program performance evolves over time based on variation, selection, and retention mechanisms. Evolutionary perspectives have recently been advocated in managerial settings characterized by technological innovation and change (Tushman and Anderson 1986, Stuart and Podolny 1996, Teece et al. 1997, Loch and Kavadias 2007).

4.5.1 A Complex Performance Landscape

Recall that we define a product as $\omega = (x_1, x_2, \dots, x_N)$ and product performance as a function of the technology and market attributes given by $F(\omega)$. In order to specify our model and allow for further analysis assuming that $F(\cdot)$ is a complex function, we employ the NK model of tunable fitness landscapes (Kauffman and Levin 1987, Kauffman 1993). A number of researchers have employed complex performance landscapes to model managerial problems such as organizational design and evolution (Levinthal 1997, Rivkin and Siggelkow 2003, Siggelkow and Levinthal 2003, Ethiraj and Levinthal 2004, Siggelkow and Rivkin 2005), problem 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). The majority of these studies employ the NK formulation to model a complex performance landscape and we follow along these lines.

Let $x_j \in \{1, 2, \dots, S\}$ and assume that each attribute j contributes individually to the overall product performance. The performance contribution of attribute x_j is not necessarily independent from the other performance determinants; rather, it may depend on $K \in \{0, 1, \dots, N-1\}$ other attributes through a function $f_j(x_j, x_{j_1}, x_{j_2}, \dots, x_{j_K})$.⁵ The number of interactions, K , is a modeling convention that proxies the underlying complexity of the technology-market setting in which the firm operates. Interaction complexity is a result of, “a large number of parts that interact in non-simple ways [such that] given the properties of the parts and the laws of their interactions, it is not a trivial matter to infer the properties of the whole.” (Simon 1969, p. 195).

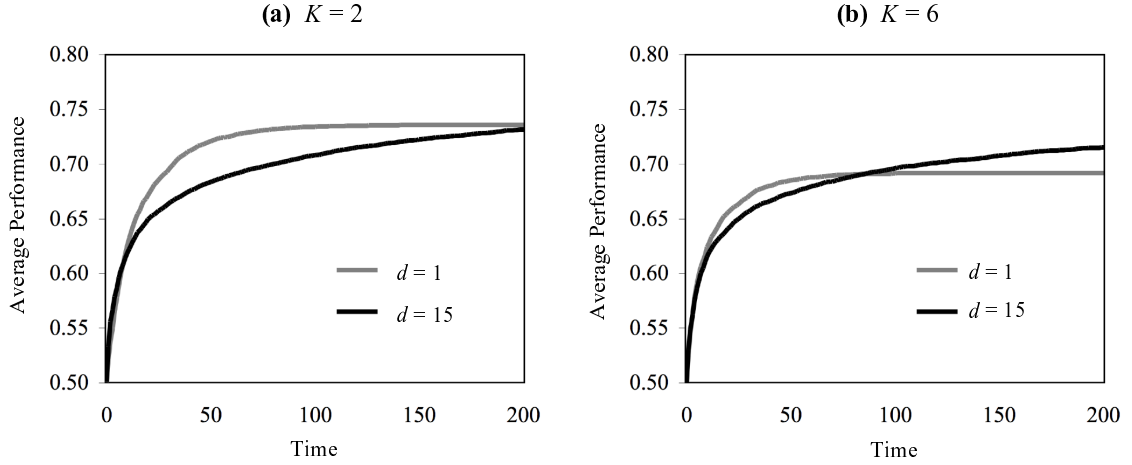
We assume that each f_j is a random draw from a $U(0,1)$ distribution to account for the fact that managers do not know the payoff structure for the performance landscape. Product performance is the average of the performance contributions from each attribute: $F(\omega) = 1/N \sum_{j=1}^N f_j$. Two structural properties merit discussion here. First, the fact that

⁵Without 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 $f_1(x_1, x_2, x_3, x_4)$ to product performance. If $j + K > N$ the interaction vector is treated as circular (Levinthal 1997).

each f_j is a random draw from a $U(0, 1)$ is not restrictive. Research on complex performance landscapes has shown that the performance landscapes retain their form under a wide variety of distributions for the f_j (Kauffman 1993, Ethiraj and Levinthal 2004, Sommer and Loch 2004). Second, we model product performance as the average of the performance contributions from each attribute. We adopt this convention so that the system size (N) does not drive our results.

Aligned with the theoretic foundation established in Section 3, we now adopt an evolutionary view of innovation and we simulate the behavior of NPD programs over time. To initialize our simulation ($t = 0$) we randomly define a product, $\omega = (x_1, x_2, \dots, x_N)$. In each period ($t = 1, 2, 3, \dots$), a NPD program of type d drives a change in product attributes. We implement this change by allowing the NPD program to randomly search for one new product configuration, ω' , within $N_d(\omega)$. If $F(\omega') > F(\omega)$ the new product configuration is adopted. This process of variation, selection, and retention is repeated in each period. We compare different types of innovative effort by simulating the performance of an NPD program of type d (averaging over 500 runs in each landscape and 100 landscapes). For each experiment we let $N = 15$ and $S = 2$ and we vary K and d . To conserve space, we do not show results for every value of K or d (please see Appendix B.4 for details regarding the full experimental design).

We characterize innovative effort as a random search within $N_d(\omega)$ to highlight the fact that managers cannot optimize the NPV of an m period commitment in a complex performance landscape. Alternatively, we could allow the incremental NPD programs to explore more than one ω' within $N_d(\omega)$ reflecting the lower per solution cost of incremental innovation. Any such mechanism would improve the performance of incremental NPD programs relative to radical NPD programs without altering the qualitative insights of our study. Furthermore, we focus our analysis on expected performance of a NPD program without including costs in our simulation. Our results regarding NPD program performance are robust despite the exclusion of costs in the simulation (for a discussion on the effects of cost, please see Appendix B.4).



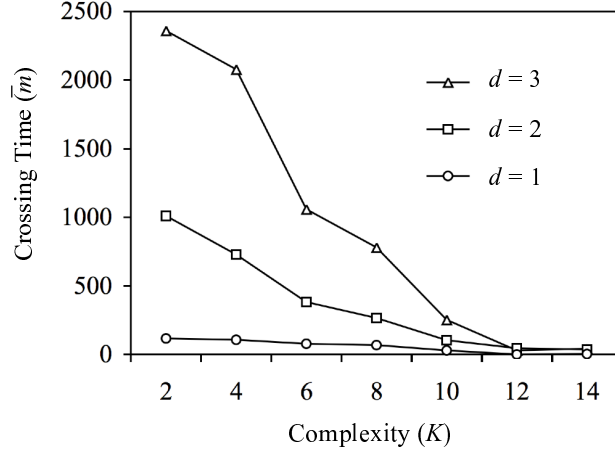
Note: Average is over 500 runs per landscape and 100 landscapes. For all experiments, $N = 15$ and $S = 2$.

Figure 13: Average performance over time for incremental and radical NPD programs.

4.5.2 NPD Program Performance

Figures 13(a) and 13(b) illustrate how complexity impacts NPD program performance (for $K = 2$ and $K = 6$ respectively). For a given level of K , incremental NPD programs achieve short-term performance while radical NPD programs achieve long-term performance. Once again, this gives rise to a crossing time and defines a window of time during which radical innovation under performs on average. More importantly, the crossing time occurs earlier as K increases.

The existence of a crossing time is a direct outcome of the “rugged” nature of the performance functions in environments with significant interaction complexity (Kauffman 1993). In complex technology-market environments, incremental NPD programs offer an initial advantage because they improve performance with higher probability relative to radical NPD programs. Unfortunately, the advantage is short-lived because incremental efforts are not able to benefit from a holistic approach (Ulrich and Ellison 1998) and they get trapped in local performance optima (lower \hat{V}). Radical NPD efforts take more time to improve performance. The time inefficiency of radical NPD programs is due to the fact that they seek riskier solutions based on drastic product alterations. However, the holistic approach



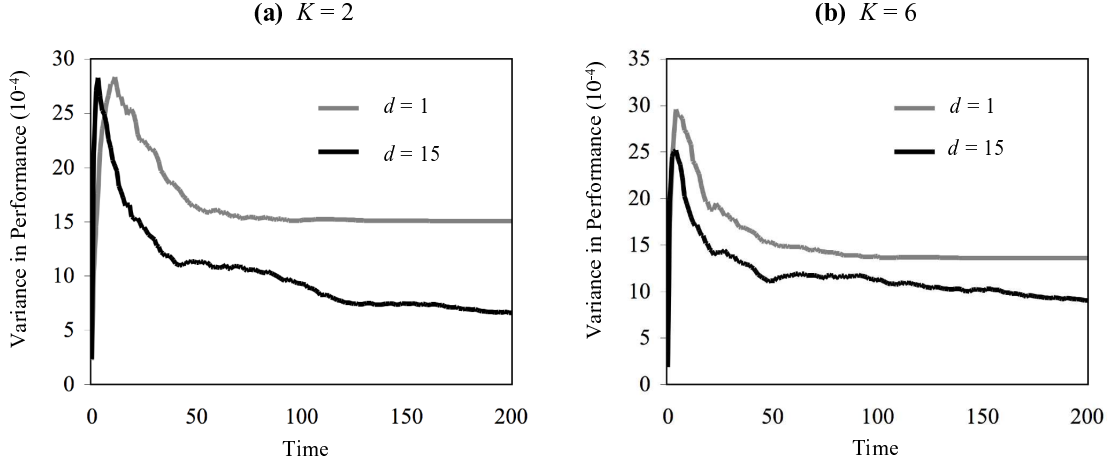
Note: Average is over 500 runs per landscape and 100 landscapes. For all experiments, $N = 15$ and $S = 2$. Crossing times for $d = 1$, $d = 2$, and $d = 3$ are relative to $d = 15$.

Figure 14: Crossing time (\bar{m}) as a function of complexity (K) for different values of d .

and perspective of radical NPD programs (expressed through the number of potential solutions in $N_d(\omega)$) allows them to escape local optima. Figure 13 shows that interaction complexity increases the attractiveness of radical NPD programs. In the absence of complexity, there is no need for radical innovation. Thus, our simulation identifies performance function complexity as another feature that drives the value of radical innovation. In a complex environment, the value of radical innovation is realized faster and the crossing time is reduced.

The preceding analysis was based on the extreme cases of $d = 1$ and $d = 15$. Figure 14 depicts the crossing time (\bar{m}) as a function of complexity (K) for different values of d . For a given d the crossing time is a decreasing function of complexity. Thus, our results are robust with respect to d . Of course, for a given level of complexity, the crossing time is an increasing function of d because higher d implies more radical innovative effort. Note that the extreme case in which all NPD programs are defined by $d = 15$ would result in $\bar{m} \rightarrow \infty$.

Although average performance is an important metric, it is also insightful to consider the issue of risk (proxied through variance of NPD program performance). Figure 15(a) and 15(b) show the variance of NPD program performance as a function of time for environments with no complexity and high complexity ($K = 0$ and $K = 6$ respectively). In the



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

Figure 15: Variance over time for incremental and radical NPD programs.

absence of complexity, incremental NPD programs reduce risk immediately as the product configuration converges to the globally optimal configuration (note that the variance for incremental NPD programs is zero after approximately 100 periods). However, in a complex environment, incremental NPD programs converge to multiple local optima and thus do not reduce variance as quickly as radical NPD programs. The radical programs continue to reduce variance over time, as they are able to escape locally optimal product configurations and further improve performance. Thus, when risk is taken into account, radical innovation delivers a secondary benefit in the presence of complexity - it *reduces* NPD program risk. The observation is of significant managerial value because it illustrates an environmental aspect of risk in addition to the typical considerations. Previous research stresses that managers should be aware of individual program risk (due to the probability of success in any given period). We extend the consideration of risk and recognize the effect of time and interaction complexity on NPD program risk. Of course, a radical innovation strategy reduces risk in the long-term if and only if the program continues to operate under the same environmental conditions in the future. We examine this caveat in the section that follows.

4.5.3 Can the Firm Commit to the NPD Program?

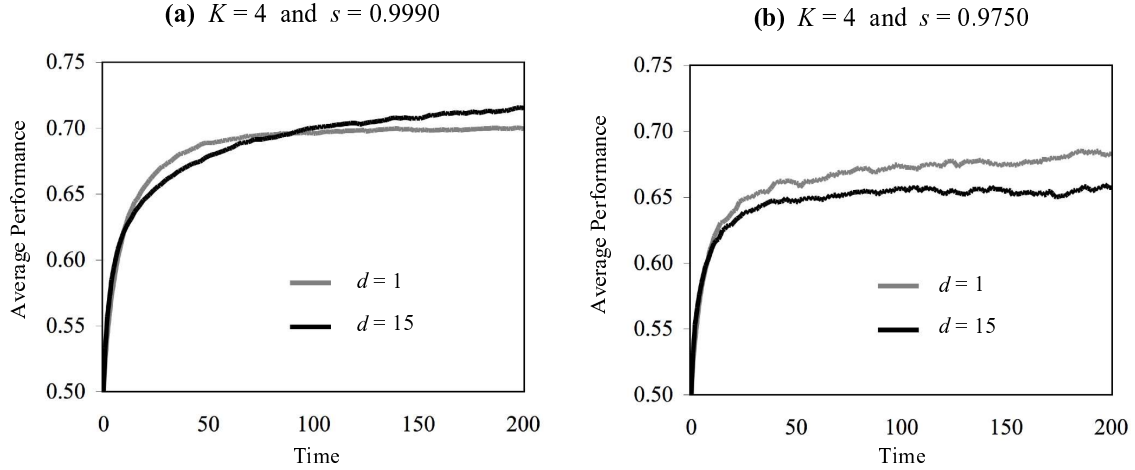
Our base-case results reveal the critical role of time when evaluating the effectiveness of a NPD program. The option to pursue different degrees of incremental or radical innovation creates tension with respect to the amount of time that it takes to fully realize the benefits of a particular NPD program.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

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

Let the likelihood s determine the performance function $F(\cdot)$ in period $t+1$ conditioned on the performance function in period t as follows:

$$F(\omega|\vec{f}) = \begin{cases} 1/N \sum_{j=1}^N f_j & \text{w.p. } s \\ 1/N \sum_{j=1}^N f'_j & \text{w.p. } 1-s \end{cases} \quad (5)$$

where \vec{f} is the vector of attribute contribution functions in period t . Thus, we model environmental disruptions by changing the performance functions that firms face. A disruption



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

Figure 16: Average performance over time in the presence of technological or market disruption.

in our setting does not alter the firm’s product configuration; rather the performance contribution of each attribute, f_j , is randomly redefined by a new $U(0,1)$ random number. However, we maintain the same level of complexity in order to isolate the effects of environmental instability. The simulation proceeds according to the same mechanics as the base-case with the exception that a disruption occurs in every period with probability $(1-s)$. Thus, we allow the time of disruption to be a random variable. Figure 16(a) depicts the average performance for $K = 4$ and $s = 0.9990$ (high complexity and high stability).⁶ In this case, radical innovation dominates after the crossing time, although the steady-state performance is dampened due to the lack of environmental stability. Figure 16(b) shows the average NPD program performance over time when $K = 4$ and $s = 0.9750$ (high complexity and low stability). Despite the presence of complexity, low stability undermines the effectiveness of a radical innovation strategy because radical NPD programs do not have time to improve performance between disruptions.

The result bears managerial significance since it alludes to the notion of “turbulence”

⁶It is worth pointing out that “high” or “low” stability is a relative measure. Stability can be interpreted as the number of disruptions that take place within an interval of time. For example, $s = 0.80$ ($1 - s = 0.20$) implies that a disruption will occur in 20% of the periods. Over an interval that contains 100 time periods, this implies that a disruption will occur on average every 5 periods.

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). Christensen et al. (2002) also address the fact that different strategies are successful early versus later in the industry lifecycle - the former being defined by high complexity while the latter is defined by low complexity. Our analysis of stability adds to these insights and highlights the fact that managers must assess the level of environmental instability when determining innovation strategy. The critical issue is whether the firm has enough time to allow radical NPD programs to achieve superior performance relative to incremental NPD programs. Once again, the crossing time is of critical importance when determining an innovation strategy.

Analysis of risk (variance in performance) under environmental instability offers a different insight compared to previous results. Figure 17(a) and 17(b) show the variance of NPD program performance as a function of time in a complex environment ($K = 4$) with high stability ($s = 0.9990$) and low stability ($s = 0.9750$) respectively. In the presence of complexity, a higher probability of technological and market disruption creates additional risk for both incremental and radical NPD programs. Despite the environmental instability, variance is still lower for radical NPD programs because of their ability to escape local optima.

Conventional wisdom states that incremental innovation efforts deliver low value and low risk while radical innovation efforts deliver high value and high risk. The insights from Figure 16(b) and Figure 17(b) challenge this wisdom. In an environment that is characterized by high instability, incremental innovation ($d = 1$) delivers *higher* average performance and *higher* variance relative to radical innovation ($d = 15$). Thus, environmental complexity coupled with environmental instability reverses the commonly accepted value/risk profiles of incremental and radical innovation.

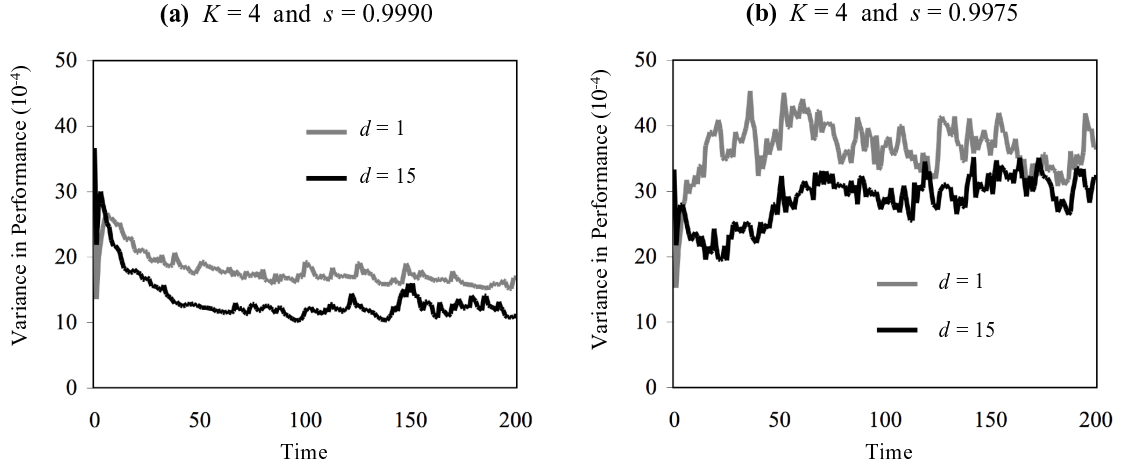


Figure 17: Variance over time in the presence of technological or market disruption.

4.6 Extension to a Portfolio of NPD Programs

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

There is no reason to believe that every NPD program in the portfolio will have the same expected return curve. In fact, since the NPD programs each target a different product, and each product is defined by a different set of technology and market attributes, there is strong evidence that the NPD program return functions will be distinct. Based on this observation, the NPD portfolio problem is defined by a set of crossing times $\{\bar{m}_1, \bar{m}_2, \dots, \bar{m}_M\}$ and a choice of the type of innovation (incremental or radical) for each of the M programs. Once

again, potential disruptions to the technology and market environment dictate the amount of time available to the firm. Based on our previous discussion, our intuition is that if the amount of time available is short, the NPD portfolio balance will shift towards incremental innovation whereas if the amount of time available is long, the balance will shift towards radical innovation.

4.6.1 The Analytic Reason to “Balance” Strategic Buckets

Building upon our analytic model, let $f_i(m)$ be the difference between incremental and radical NPD program performance for the i th NPD program in the portfolio. A simple example highlights the shifting balance in strategic buckets for a portfolio with $M = 3$ NPD Programs (Figure 18). Suppose a disruption occurs at time m_L with probability q (with probability $1 - q$ there is no disruption). When $q = 1$ we have $f_1(m) > 0$, $f_2(m) < 0$, and $f_3(m) > 0$. In this case, program 1 should pursue incremental innovation, program 2 radical innovation, and program 3 incremental innovation. The resulting strategic buckets policy is 33% radical (66% incremental). Conversely, suppose that a disruption occurs at time m_H with probability q (again, with probability $1 - q$ there is no disruption). In this case, when $q = 1$ we have $f_1(m) < 0$, $f_2(m) < 0$, and $f_3(m) > 0$. Program 1 should pursue radical innovation, program 2 radical innovation, and program 3 incremental innovation. The resulting strategic buckets policy is 66% radical (33% incremental). This simple example highlights the fact that different degrees of environmental instability lead to different “balance” in the NPD portfolio. In fact, for any $q \in (0, 1)$, as q becomes lower (higher), the NPD portfolio should include more radical (incremental) innovation efforts. Of course, if $q = 0$ there is no disruption and the best choice is 100% radical programs in the NPD portfolio. As the probability of a technological or market disruption increases, the “balance” shifts towards incremental innovation in the NPD portfolio because radical innovation does not have time to deliver results.

4.6.2 The Evolutionary Reason to “Balance” Strategic Buckets

Based on the results from our evolutionary model, we now present a simple example that explains the balance between incremental and radical innovation in the NPD portfolio. Each

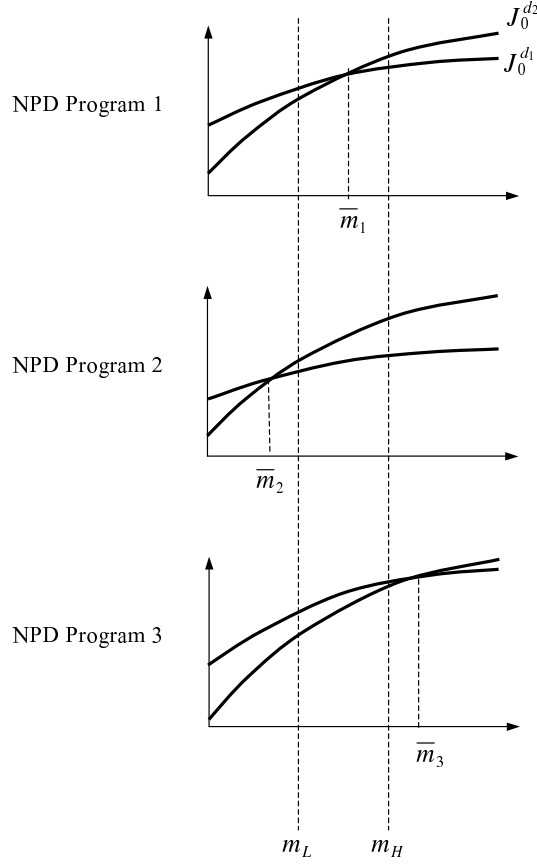
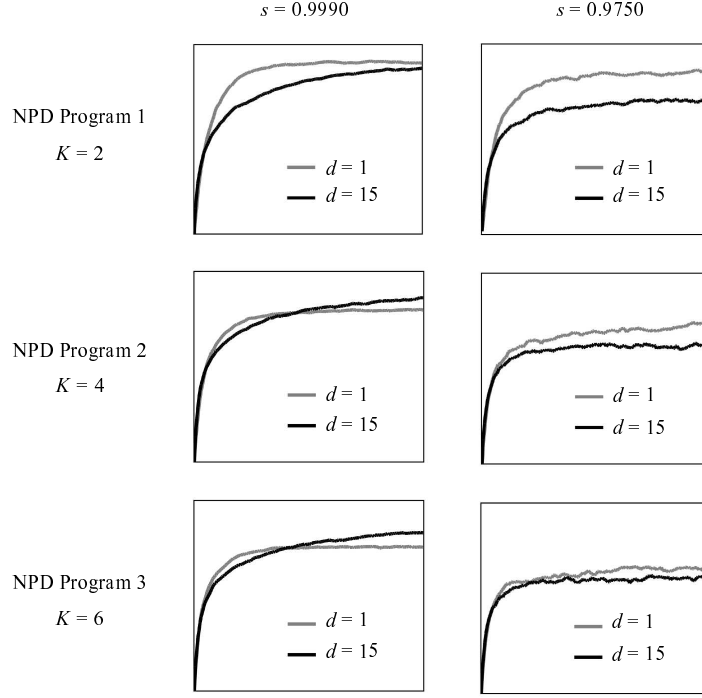


Figure 18: A example of the shifting balance in the NPD portfolio.

NPD program is geared towards improving a product and the performance of each product may be defined by a different level of complexity. With this in mind, each NPD program in the portfolio will have a different crossing time. Figure 19 depicts a sample NPD portfolio with $M = 3$ NPD programs. The left column depicts an environment with relatively high stability ($s = 0.9990$) while the right column depicts an environment with relatively low stability ($s = 0.9750$).

When the firm is operating in an environment with high stability ($s = 0.9990$), the best strategy depends on the commitment time. Given a long commitment time, the best strategy is that program 1 pursue incremental innovation while programs 2 and 3 pursue radical innovation. This results in a NPD portfolio that is 66% radical (33% incremental). Conversely, when the firm is operating in an environment defined by low stability ($s =$



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

Figure 19: A example of the shifting balance in the NPD portfolio.

0.9750), the best strategy regardless of the commitment time is incremental innovation for all of the NPD programs. This results in a NPD portfolio that is 0% radical (100% incremental).

Once again, different degrees of environmental instability lead to different “balance” in the NPD portfolio. Based on these arguments, we can safely conjecture that as the probability of technology or market disruptions becomes lower (higher), the NPD portfolio should include more radical (incremental) innovation efforts. As with our analytic model, if $s = 1.000$ the environment is fully stable and the best choice is a NPD portfolio that is 100% radical. As the probability of a technological or market disruption increases, the “balance” shifts towards incremental innovation in the NPD portfolio.

4.7 *Conclusions and Implications*

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

4.7.1 **When and How to Use Strategic Buckets**

Effective use of strategic buckets requires a deeper understanding regarding two factors that confound decision-making: environmental complexity and environmental instability. Complexity between performance attributes and instability in the performance landscape both make the performance function more difficult to understand in the eyes of the decision maker. However, the former increases the value of radical innovation, while the latter increases the value of incremental innovation. The rationale behind these effects is of significant managerial value. Higher complexity implies a performance landscape with multiple local performance peaks where incremental innovation strategies may get trapped. On the other hand, high instability reduces the critical time necessary to achieve high value from radical innovation efforts. When complexity and instability are present together, we find that common notions of risk and reward are reversed: incremental innovation delivers higher performance and higher risk relative to radical innovation.

4.7.2 **Unraveling Complexity and Coping with Bounded Rationality**

Managers can benefit from clearly identifying a set of key design, technology, and market variables that affect the overall NPD program performance function *even if their exact performance contribution is not known*. Identifying key product attributes can help managers

decipher the nature of the technological and market environment and assess whether the program performance functions are governed by low or high interaction complexity.

One of the primary challenges to understanding complexity and its effects on NPD program performance is that critical technology and market attributes are often 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 has predominantly been used by designers to map dependencies between design attributes. We posit that the same thinking can be generalized to performance dependencies between technological and market attributes of a product. It has already been shown that the DSM can be used in various managerial decision 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 the environment, questions still remain with respect to the performance functions for each of the technology and market attributes, and the extent to which these performance functions change over time. Various market research techniques such as conjoint analysis or choice modeling can be used to uncover the evolution of performance functions (Ben-Akiva and Lerman 1985, McFadden 1986, Green and Srinivasan 1990, Ofek and Srinivasan 2002). 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. This exercise goes a long way towards helping managers understand the notion of environmental instability.

Our study of strategic buckets coupled with methods that shed light on environmental complexity and stability can form the basis for more effective NPD portfolio strategy. We

view our work as an important step that can help academics and practitioners develop a better understanding of portfolio decisions at a strategic level. Since our perspective is relatively high-level we make assumptions that capture the essence of NPD program behavior without delving into details that 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 programs.

CHAPTER V

BUDGET CREATION AND CONTROL

5.1 Introduction

As discussed throughout this thesis, strategy formulation, resource allocation, and program implementation occur in a top-down hierarchical manner within the firm (Loch and Tapper 2002). Decisions and rules outlined by senior executives define the operating environment for subordinate levels of decision-making (Anderson and Joglekar 2005, Kavadias and Chao 2006). Consider the following example typical of any large corporation: senior executives of the firm set broad goals regarding corporate strategy (e.g., five years from today, 30% of revenue will be derived from new products; over the next year, costs will be reduced by 5%). Business unit managers are charged with the responsibility to transform that strategy to a reality.¹ To do so, they make funding decisions with respect to broad programs within the portfolio (e.g., cut funding from next generation technological development and increase funding for product line extensions; or increase funding for manufacturing process improvements and decrease funding for radical NPD initiatives).

The hierarchical nature of the resource allocation and NPD portfolio problem implies that decisions span various organizational levels and highlights the importance of organization design mechanisms for effective management. Organization design mechanisms are rules, controls, or parameters that define the means by which organizational work gets done (Galbraith 1977, Mintzberg 1979, Ouchi 1979, Eisenhardt 1985). In the context of NPD, organization design mechanisms take on a particularly important role, as innovation and NPD are often critical to a firm's competitive advantage (Wheelwright and Clark 1992). Recent work in NPD planning theory highlights this fact and stresses the need for a deeper understanding of the impact that organizational structure has on NPD decisions (Anderson

¹We use the term “business unit” to refer to any operating unit, division, or group within a firm that has profit and loss responsibility but reports to a senior executive of the firm.

and Joglekar 2005).

In practice, firms seem to follow various policies with respect to funding and control routines for NPD budgets (Christensen 1996). The hierarchical structure of the resource allocation and NPD portfolio problem, the concomitant existence of organization design mechanisms, and the fact that practice varies so widely with respect to those design mechanisms prompt us to ask the following questions: what types of organization design mechanisms drive effective resource allocation and NPD portfolio strategy? How does the choice of organization design mechanism influence the effort invested in improving an existing product versus effort aimed at developing an altogether new product? To shed light on these questions we examine organization design mechanisms that impose varying degrees and types of control on the manager responsible for resource allocation decisions. In particular, we study the source of a business units NPD resources as well as the monitoring (control) mechanisms that achieve effective resource allocation.

Consistent with extant theory, the objective of our model is net value maximization. Our results can be interpreted from the viewpoint of the business unit manager and the senior manager that is responsible for choosing the design mechanism. We find that higher autonomy in terms of how the NPD budget is funded drives higher resource expenditure towards improving an existing product. In contrast, the primary force that drives resource expenditure towards developing the new product is the type of budget control used. We find that effort aimed at developing the new product is strictly higher when the manager is forced to account for budget overruns throughout the development cycle as opposed to only at the end of the development cycle. In addition, we are able to show that the balance of resources across programs exhibits a gradual shift over time from incremental efforts to radical efforts. The shift is characterized by a switching point, which is delayed when the business unit has more autonomy. Thus, from a portfolio perspective we conclude that autonomy may lead to a NPD portfolio that is biased towards incremental projects. This insight challenges existing claims regarding autonomy, creativity, and innovation. Finally, we characterize situations in which a higher marginal cost of capital drives higher resource expenditure for existing product improvement. This occurs when a manager is given autonomy in terms of

budget creation and there is sufficient time remaining in the development cycle to reap the benefits from the increase in effort.

The remainder of this chapter is structured as follows: in Section 2 we review the related literature, particularly in the domains of organization design and new product development. In Section 3 we introduce our model. In Sections 4 and 5 we discuss the results and Section 6 we draw conclusions and discuss the theoretical and managerial implications of our work.

5.2 *Related Literature*

There is an extensive literature on organization design theory that focuses on the link between organization structure and performance (Galbraith 1977, Mintzberg 1979, Ouchi 1979, Eisenhardt 1985, Tushman and O'Reilly 1996). Much of this work is aimed at understanding design mechanisms that dictate the physical structure of work teams or business units (e.g., matrix, functional, or decentralized structure). Although structure is an important determinant of success, organization theorists note that control is also an important organization design mechanism (Ouchi 1979, Eisenhardt 1985). Control refers to monitoring and evaluation of behavior or processes. Eisenhardt (1985) succinctly states that, Control is an important, if sometimes neglected, facet of organization design. (Eisenhardt 1985, p. 134). Two decades of scholarly work in organization design takes note of this observation (Mintzberg 1980, Lewin and Minton 1986, Barley and Kunda 1992, Ghoshal et al. 1994, Kumar and Seth 1998, Levinthal and Warglien 1999, Bate et al. 2000). An important theme common to this body of research is the degree and nature of autonomy employed by the various organization design mechanisms.

Autonomy is defined as, the quality or state of being independent, free, and self-directing; independence in the capacity of a part for growth, reactivity, or responsiveness (Merriam-Webster). In the context of an organization, higher degree of autonomy is associated with increased flexibility, creativity, and empowerment (Kirkman and Rosen 1999). Unfortunately the benefits do not come without costs. When operating units are given autonomy, senior managers lose control over the decisions made within a business unit and they are subject to the outcomes resulting from these decisions. Autonomous business units may

also become entrenched and may not see themselves as part of a greater whole (Wheelwright and Clark 1992). The extent of control imposed or autonomy delegated to a business unit is an important issue in organization design, as autonomy is often used as an incentive to encourage creativity and innovation (Zajac 1991, Boudreau 2004, Shane and Ulrich 2004).

A number of researchers have studied the impact of autonomy and control on the new product development process. Cohen, Eliashberg, and Ho (2000) study the impact of predetermined NPD metrics such as time to market, quality, and cost. Tatikonda and Rosenthal (2000) study project management methods that focus on formality, autonomy, and flexibility. Olsen et al. (1995) study the effects of organization design mechanisms on NPD project effectiveness. Gerwin and Moffat (1997) study the role of autonomy in concurrent engineering. Bonner et al. (2002) study the impact of upper management control in new product development projects. Souder (1974) studies the effect of autonomy in an applied R&D laboratory. Hoskisson and Hitt (1988) and Hoskisson et al. (1993) study managerial control systems and incentives for NPD in large multiproduct firms. Collectively, this body of work finds that a higher degree of autonomy results in higher NPD effectiveness (measured as technical performance and quality, lower product development costs, and shorter NPD cycle times). The underlying reason for this finding is that higher autonomy gives the project team the flexibility needed to create solutions when obstacles are encountered. However, an important caveat is that extant research on autonomy and NPD project management uses the individual project as a unit of analysis. A focus on the individual project ignores the reality that multiple projects must be managed simultaneously in a portfolio of NPD programs. The portfolio imposes interplay between NPD programs as they compete for scarce resources. We build upon previous work by extending the theory to a higher level of responsibility within the organization. Namely, we study how organization design mechanisms and autonomy impact resource allocation and NPD portfolio strategy.

There is extensive literature in strategy and new product development that highlights the importance of resource allocation for effective NPD (Bower 1986, Rousell et al. 1991, Wheelwright and Clark 1992, Cooper et al. 1998, Kavadias and Loch 2003 and references therein). With few exceptions, the existing research on NPD resource allocation overlooks

the organizational elements that play an important role in defining success versus failure. It primarily focuses on net value maximization assuming that the decision-maker operates with a tight budget constraint (Kavadias and Loch 2003, Kavadias and Chao 2006). Practice defies these modeling assumptions since managers may or may not have the flexibility to request additional resources, particularly at the business unit level of decision-making (Pollack and Zeckhauser 1996). Along similar lines, the performance of the business unit may be monitored based on frequent milestone meetings or at the end of a development project (Loch and Terwiesch 1998).

Our efforts enrich the NPD portfolio literature along three dimensions. First, we explicitly consider the fact that organization hierarchy forces business unit managers to operate in a constrained environment with respect to how things are done. Second, we explicitly account for the realistic notion that NPD budgets are not always exogenously determined; rather they may be endogenously determined by the ability to generate revenue. Finally, we consider the fact that managers may tap resources that are external to the firm (e.g. financial markets) to remedy short-term cash constraints. We also contribute to the organization design literature by developing a normative study in which we model and analyze different control and autonomy mechanisms within the context of innovation. Since we include organization design mechanisms and resource allocation decisions in one model we are able to uncover the interaction between two important processes that impact firm competitive advantage.

5.3 A Model of Organization Design and Resource Allocation

In this section we introduce a dynamic model of resource allocation and NPD portfolio strategy. Our model examines how autonomy (or lack thereof) affects the managers decision to balance resource allocation between incremental product improvement effort and radical new product development effort. Incremental effort delivers an immediate but limited impact on revenue while radical effort has no immediate benefit but delivers a substantial impact on future value. To model the tradeoff between these two types of effort in the NPD portfolio, we consider a business unit that attempts to develop a new product over a finite

development cycle, $t \in [0, T]$. The end of the development cycle (T) may be either fixed or a decision variable. The former is a situation in which external market forces dictate product launches (e.g. holiday seasons in December and January drive new product introductions for firms in the consumer electronics industry). The latter is a setting in which the manager determines an optimal new product launch time. In addition to developing the new product, the business unit produces and sells a single existing product throughout the development cycle.²

5.3.1 Improving the Existing Product and Developing the New Product

During the development cycle, the business unit can make incremental improvements to the existing product in order to sustain or enhance its revenue generating potential. Incremental improvements include minor technological upgrades (e.g., larger storage capacity in a laptop computer), small modifications of market attributes (e.g., changes to product packaging), or process improvements leading to lower manufacturing and distribution costs. Let $p_1(t) \geq 0$ be the rate of effort expended on making incremental improvements to the existing product at time t . In practice, managers often use metrics such as the rate of effort to describe investment in NPD (e.g., engineering-hours per week). The cumulative level of effort expended on improving the existing product at time t is defined as $P_1(t) = P_1(0) + \int_0^t p_1(s)ds$. Since the business unit is producing and selling the existing product at $t = 0$, the initial cumulative level of effort is known and satisfies $P_1(0) > 0$.

In addition to making incremental changes to the existing product, the business unit also expends effort to develop a new product that is fundamentally different from the existing product in terms of underlying technology and market attributes (Chao and Kavadias 2006). Let $p_2(t) \geq 0$ be the rate of effort expended on developing the new product at time t . The effort undertaken to develop the new product includes concept generation, design, and testing activities to ensure manufacturing and market viability (Ulrich and Eppinger 2004). Early in the development cycle there is considerable technical and market uncertainty

²We assume that the business unit has a single existing product in order to facilitate exposition. Our analysis is easily extended to multiple existing products whose sales are lumped together into a single revenue stream.

regarding the viability of the new product and the uncertainty is resolved as the development cycle progresses. For example, in the pharmaceutical industry, the likelihood of successful development increases (uncertainty decreases) as a new drug progresses through the various stages of the FDA approval process (Girotra et al. 2006). Let $\alpha(t) \in [0, 1]$ represent the level of uncertainty that the manager faces at time t during the development cycle with $\dot{\alpha}(t) < 0$ and $\ddot{\alpha}(t) > 0$. Our definition of $\alpha(t)$ is similar to the uncertainty evolution in concurrent engineering models (Krishnan 1996, Krishnan et al. 1997). Uncertainty moderates the effectiveness of effort expended on developing the new product. Effort is less effective early in the development cycle when uncertainty is higher and more effective later in the development cycle when uncertainty is lower. Thus, we define the cumulative effective level of effort expended on developing the new product at time t as $P_2(t) = \int_0^t [1 - \alpha(s)] p_2(s) ds$.

5.3.2 The Cost of New Product Development

The manager responsible for resource allocation determines a dynamic strategy that maximizes the net value resulting from existing product improvement efforts and new product development efforts. Driving the investment strategy are the relative costs and benefits associated with the existing product and the new product over the development cycle.

Let $C_1[p_1(t)] \geq 0$ be the cost incurred for $p_1(t)$ units of effort aimed at improving the existing product. We assume that $C_1[0] = 0$ and $C_1[p_1(t)]$ is increasing and convex with respect to $p_1(t)$, reflecting diseconomies of scale with respect to effort at any instant of time (e.g., coordination costs or capacity constraints with respect to specialized resources). Similarly, let $C_2[p_2(t)] \geq 0$ be the cost incurred for $p_2(t)$ units of effort geared towards developing the new product. Assume that $C_2[0] = 0$ and $C_2[p_2(t)]$ is increasing and convex with respect to $p_2(t)$. Although $C_1[p_1(t)]$ and $C_2[p_2(t)]$ are both increasing and convex, the value and rate at which they increase may be unequal, reflecting the difference in the nature of the work undertaken by engineers or product development managers for each type of effort. The new product is defined by fundamentally different technology and market variables that are typically unknown and more difficult to manipulate. Therefore, it is reasonable to assume that $C_1[p_i(t)] \leq C_2[p_i(t)]$ for a given rate of effort $p_i(t)$.

5.3.3 Existing Product Revenue and New Product Payoff

The revenue (net of manufacturing and distribution costs) generated at time t from the existing product is given by $R[P_1(t), t]$. The revenue function for the existing product is comprised of two elements that are common in NPD. First, higher cumulative effort towards improving the existing product results in increased revenue with diminishing returns. Therefore, it is reasonable to assume that $R[P_1(t), t]$ is a positive increasing function of $P_1(t)$ with $\partial^2 R / \partial P_1^2 \leq 0$. Second, forces external to the business unit (such as increased competition intensity and shifting customer preferences) may make the existing product obsolete. Increasing competition intensity implies that the ability to earn revenue from the existing product decreases over time due to an increased likelihood of imitation or substitute products (Moorthy 1988, Ali et al. 1993, Dhebar 1996). In addition, consumer preferences may shift over time and thereby reduce the ability to earn revenue from the existing product (Christensen and Raynor 2003). Therefore, we assume that $\partial R / \partial t \leq 0$. Finally, we recognize that the existing product may have value beyond the end of the development cycle. Let $V_1[P_1(T), T]$ be the future revenue generated by the existing product beyond time T . $V_1[P_1(T), T]$ is a positive increasing function of $P_1(T)$ with $\partial V_1 / \partial T \leq 0$. It is natural to assume that the value of the existing product beyond time T also exhibits diminishing returns ($\partial^2 V_1 / \partial P_1^2 \leq 0$).

The value of effort expended on developing the new product is captured at the end of the development cycle when the business unit receives a payoff of $V_2[P_2(T), T]$. The new product payoff at T represents the value of revenue generated by the new product over its lifetime. Our characterization of the new product payoff reflects the estimates made by senior managers when assessing the “future market potential” of a new product. We assume that $V_2[P_2(T), T]$ is a positive increasing function of $P_2(T)$ with $\partial V_2 / \partial T \leq 0$. Therefore, a higher cumulative effort $P_2(T)$ increases the new product payoff. However, a delay in the new product launch may result in lower value for various reasons such as competition intensity or first-mover advantage for competing firms (see Hendricks and Singhal 1997 for a discussion on the market value of delayed product launch). Similar to the existing product payoff, the new product payoff exhibits diminishing returns ($\partial^2 V_2 / \partial P_2^2 \leq 0$).

5.3.4 Organization Design Mechanisms for Budget Creation and Control

A novel aspect of our model is the explicit consideration of the organization design mechanisms that drive resource allocation and NPD portfolio strategy. We assume that an organization design mechanism is jointly defined by two functions, $\pi = \{B(\cdot), C_3(\cdot)\}$, which determine the degree and nature of autonomy given to the manager of the business unit. The organization design mechanism determines how the budget is made available and how the budget is accounted for during the development cycle.

The function $B(\cdot)$ represents budget creation and defines how resources are made available for improving the existing product and developing the new product. The literature on resource allocation and NPD portfolio management typically assumes that budgets are set *exogenously*, by a higher level corporate authority. In such cases, $B(\cdot) = B$ and the manager does not have control over the manner in which the budget is created. We enrich the literature by considering organizational settings in which the manager is given autonomy with respect to budget creation. For such cases, we assume that the revenue earned from existing product sales *endogenously* funds product improvement and development efforts. We define the endogenous budget as $B(\cdot) = \beta R[P_1(t), t]$ where β is the percentage of existing product revenue that is made available for improving the existing product and developing the new product.³ Hence, for an endogenous budget, NPD funding changes dynamically depending on the revenue generated by the existing product.

The NPD budget and the allocated efforts $p_1(t)$ and $p_2(t)$ together determine the cumulative net budget at any time, $Z(t) = \int_0^t \{B(\cdot) - C_1[p_1(s)] - C_2[p_2(s)]\} ds$. Without loss of generality, we assume that the cumulative net budget at the beginning of the development cycle is normalized to zero. Note that $Z(t)$ may be positive or negative at any moment in time. We allow for instances when exceeds what is needed for existing product improvement and new product development and the result is a net budget surplus. Alternatively, $B(\cdot)$ may under fund the required improvement and development efforts, in which case the

³ β represents the business units R&D intensity. Empirical research has shown that a firms R&D intensity is relatively constant, and it emerges as a result of underlying industry characteristics (Cohen and Klepper 1992). For that reason, we assume that β is constant in our model.

business unit resorts to external sources of funding.

A second aspect of autonomy deals with how resources are controlled. The function $C_3(\cdot)$ represents the budget control dimension of the organization design mechanism. Budget control defines whether the manager is forced to account for the net budget at each instant of time throughout the development cycle (lower autonomy) or only at the end of the development cycle (higher autonomy). Accountability can be measured in practice through proxies such as frequency of meetings with NPD teams or extent of documentation required for NPD processes (Loch and Terwiesch 1998). If the manager is held accountable for budget overruns throughout the development cycle, $C_3(\cdot) = \int_0^T C_3[Z(t)]dt$. The term $C_3[Z(t)]$ denotes the cost (benefit) when the cumulative net budget is negative (positive) at time t . We assume that $C_3(0) = 0$, $\partial C_3/\partial Z \geq 0$, and $\partial^2 C_3/\partial Z^2 \leq 0$. Thus, when the available budget is not sufficient to fund the required NPD effort, $Z(t)$ is negative and the business unit pays a cost of $C_3[Z(t)]$. In this situation, $C_3[Z(t)]$ is a proxy for the cost of capital for product improvement and development. If $Z(t)$ is positive, the business unit benefits from slack resources. This benefit may represent surplus budget invested at the risk-free rate or intangible benefits extolled on the manager for generating a budget surplus. Alternatively, the manager may be held accountable for budget overruns only at the end of the development cycle. In such cases, $C_3(\cdot) = C_3[Z(t)]$ and the cost (benefit) when the cumulative net budget is negative (positive) is incurred only at the end of the development cycle. This mechanism offers the manager more autonomy since it simply requires a balanced budget at the end of the development cycle as opposed to requiring a balanced budget throughout the development cycle.

Figure 20 illustrates the functional forms that define budget creation and budget control. The notation π_i refers to organization design mechanism $i \in \{LOW, M1, M2, HIGH\}$. For the design mechanism that results in low autonomy (π_{LOW}) the budget is not determined by the business unit manager; rather, senior managers external to the business unit determine the budget. In addition, for the low autonomy case, the manager must account for the use of the budget at each moment in time throughout the development cycle. Conversely, for the design mechanism that results in high autonomy (π_{HIGH}) the budget is endogenously

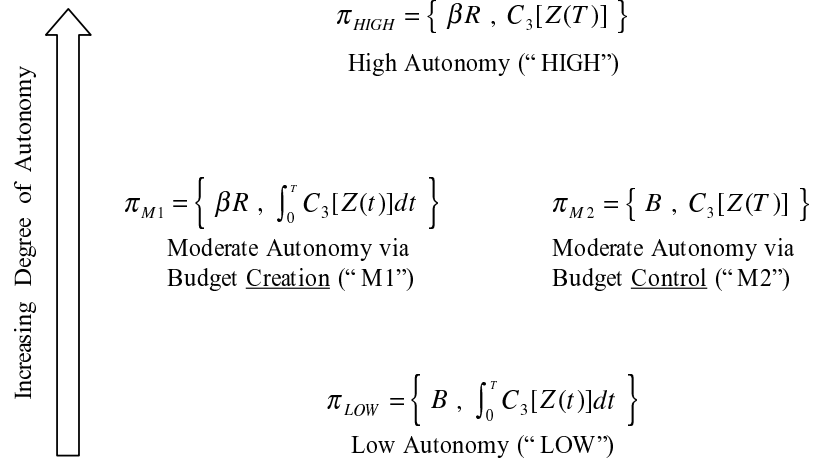


Figure 20: Organization design mechanisms that define business unit autonomy.

determined as a percentage of the revenue generated by the existing product. Furthermore, the manager operating under high autonomy is not required to account for the use of the budget until the time at which the new product is launched. Of course, the organization design mechanisms π_{LOW} and π_{HIGH} are extreme cases. Moderate levels of autonomy can be granted to the manager via budget creation (π_{M1}) or budget control (π_{M2}).

5.3.5 The Objective

Given the organization design mechanism π_i that determines the functional forms of $B(\cdot)$ and $C_3(\cdot)$, the business units profit maximizing objective is defined as:

$$\max_{p_1(t), p_2(t), T} \int_0^T \{ R[P_1(t), t] - C_1[p_1(t)] - C_2[p_2(t)] \} dt + C_3(\cdot) + V[\cdot] + Z(T) \quad (6)$$

subject to the dynamic equations that define $P_1(t)$, $P_2(t)$, $Z(t)$, and their initial conditions. The term within the integrand is the net benefit from resource allocation over the development cycle (total revenue earned from the existing product minus the total cost of effort for improving the existing product and developing the new product). $C_3(\cdot)$ determines the cost (benefit) of capital in addition to the principal amount, and it can be thought of

as interest paid (earned) on the cumulative net budget. The function $V[\cdot]$ represents collectively the value of the existing product and the new product beyond time T . We include $Z(T)$ in the objective to ensure that the manager is held accountable for (or receives benefit for) the principal amount of the cumulative net budget at T , although our insights are not altered if $Z(T)$ is removed from the objective function.

5.4 *Analytic Results and Analysis*

The model presented above is meant to identify potential organizational factors that drive resource allocation strategy towards existing product improvement or new product development. In this section we discuss insights obtained from the analytic solution of the problem presented above. To facilitate exposition, all technical details are presented in Appendix C.1 and functional notation is suppressed when the meaning is unambiguous.

5.4.1 **Improving the Existing Product and Developing the New Product**

The choice of organization design mechanism directly impacts resource allocation strategy within the business unit. Proposition 1 introduces three factors that drive the optimal allocation: the marginal value of cumulative effort towards improving the existing product, the marginal value of cumulative effort towards developing the new product, and the marginal value of cumulative net budget.

Proposition 1. *Marginal value functions. (i) For all organization design mechanisms, the marginal value of cumulative effort towards improving the existing product, λ_1 , is positive and convex-decreasing in time. (ii) For all organization design mechanisms, the marginal value of cumulative effort towards developing the new product, λ_2 , is positive and constant in time. (iii) For organization design mechanisms π_{LOW} and π_{M1} , the marginal value of cumulative net budget, λ_3 , is positive and decreasing in time while for organization design mechanisms π_{HIGH} and π_{M2} , the marginal value of cumulative net budget is positive and constant in time.*

The behavior of λ_1 reflects the revenue generating potential of the existing product. A unit of cumulative effort aimed at improving the existing product is more valuable early in

the development cycle because the revenue generated by this unit of effort will positively impact the objective function for a longer period of time compared to the same unit applied later in the development cycle. Similarly, λ_2 reflects the revenue generating potential of the new product. Since the payoff from the new product is not realized until T , a unit of cumulative effort aimed at developing the new product has the same value regardless of when it is invested during the development cycle. While the above insights regarding λ_1 and λ_2 hold for all organization design mechanisms, the behavior of λ_3 depends on the form of budget control. For organization design mechanisms π_{LOW} and π_{M1} budget control occurs throughout the development cycle. In these cases, the marginal value of cumulative net budget decreases in time because a unit of $Z(t)$ that is available early in the development cycle positively impacts the objective function for a longer period of time compared to the same unit later in the development cycle. Alternatively, a unit of debt that is created earlier in the horizon negatively impacts the objective function compared to the same unit of debt later in the development cycle. Conversely, for organization design mechanisms π_{HIGH} and π_{M2} budget control occurs only at the end of the development cycle. In these cases the marginal value of cumulative net budget is constant in time because the cost (benefit) of negative (positive) $Z(T)$ is not realized until the end of the development cycle.

The optimal rates of effort for improving the existing product or developing the new product are determined by the ratio of the marginal value of each respective effort to the marginal value of cumulative net budget. Therefore, based on Proposition 1, it is obvious that the optimal rates of effort depend on the choice of design mechanism. In Proposition 2 we provide a result that highlights the balance between effort aimed at improving the existing product and effort aimed at developing the new product.

Proposition 2. *Dynamic behavior of the decision variables. (i) For organization design mechanisms π_{HIGH} and π_{M2} , the optimal rate of effort expended on improving the existing product, p_1^* , is convex-decreasing in time. (ii) For organization design mechanisms π_{LOW} and π_{M1} , the optimal rate of effort expended on improving the existing product, p_1^* , is convex-decreasing in time if $E_{\lambda_1} > 1$ and convex-increasing in time if $E_{\lambda_1} < 1$ where*

$E_{\lambda_1} = \dot{\lambda}_1 \lambda_3 / (\dot{\lambda}_3 \lambda_1)$. (iii) For all organization design mechanisms, the optimal rate of effort expended on developing the new product, p_2^* , increases in time.

Under organization design mechanisms π_{HIGH} and π_{M2} the manager does not have to account for the NPD budget until the end of the development cycle and p_1^* decreases throughout the development cycle, directly mirroring the behavior of λ_1 . For organization design mechanisms π_{LOW} and π_{M1} , p_1^* decreases (increases) in time whenever the percentage change in λ_1 is greater than (less than) the percentage change in λ_3 over a given interval of time. The design mechanisms π_{LOW} and π_{M1} require the manager to account for the NPD budget throughout the development cycle. In such cases, E_{λ_1} captures the instantaneous tradeoff between the benefit from a unit of effort aimed at improving the existing product versus the cost of that unit of effort in terms of $Z(t)$. When $E_{\lambda_1} > 1$, λ_1 decreases at a faster rate compared to λ_3 and the manager optimally decreases p_1^* over time. In the spirit of realism and relevance to our research, we assume that $E_{\lambda_1} > 1$ throughout the development cycle, which implies that a unit of effort geared towards improving the existing product always has higher value compared to simply holding the unit as cash in the cumulative net budget. Note that with $E_{\lambda_1} > 1$, p_1^* decreases throughout the development cycle.

The effort allocated to improving the existing product decreases over time reflecting the decreasing revenue generating potential of the existing product over the development cycle. Because the existing product generates revenue at each instant of time throughout the development cycle, the value of this effort is higher early in the development cycle when it can impact the objective function for a longer period of time compared to the same unit of effort applied later in the development cycle. The primary force that drives the dynamic behavior of p_2^* is uncertainty resolution. Effort aimed at developing the new product increases over time because this effort is more effective later in the development cycle when a significant portion of the uncertainty is resolved.

In addition to the first order effects cited above, the interaction between p_1^* and p_2^* in determining the cumulative net budget also drives their dynamic behavior. The marginal value of λ_3 is non-increasing over the development cycle reflecting the fact that any cost or

benefit associated with $Z(t)$ has greater impact when there is more time remaining in the development cycle. Because p_1^* and p_2^* serve to lower the net cumulative budget, a higher marginal value of $Z(t)$ drives lower p_1^* and p_2^* (stated differently, a higher marginal value of $Z(t)$ drives the manager to reduce the costs associated with p_1^* and p_2^*). Moreover, for organization design mechanisms π_{HIGH} and π_{M1} , effort aimed at improving the existing product results in higher revenue, which in turn results in higher cumulative net budget. These results bear managerial significance for two reasons. First, they point out the different focus of resource allocation throughout the development cycle. There is a smooth transition of effort from improving the existing product towards developing the new product. Second, the results identify an intuitive index as a key driver of the optimal allocation: the marginal value of the investment (value created for each dollar of invested effort). The result complements previous findings in the NPD portfolio literature (Loch and Kavadias 2002) and verifies their intuition.

5.4.2 Comparative Statics

The previous analyses focused on the dynamic behavior of p_1^* and p_2^* . In this section we turn our attention to how the optimal rates of effort vary with key problem parameters. Results of a comparative statics analysis are presented in Propositions 3 and 4 below.

Proposition 3. *Comparative Statics Analysis for p_1^* . At time t during the development cycle, the optimal rate of effort expended on improving the existing product is higher if: (i) $\partial C_1/\partial p_1$ is lower, (ii) $\partial R/\partial P_1$ is higher, (iii) $\partial R/\partial t$ is lower, (iv) $\partial V_1/\partial P_1$ is higher, (v) $\partial V_1/\partial T$ is lower, (vi) β is higher, or (vii) $\bar{c}_{3,LOW}$ or $\bar{c}_{3,M2}$ is lower, where $\bar{c}_{3,i}$ is defined as $\partial C_3/\partial Z$ for organization design mechanism π_i . For organization design mechanisms π_{HIGH} and π_{M1} there exist threshold times t_{HIGH}^c and t_{M1}^c before (after) which, higher $\bar{c}_{3,HIGH}$ or $\bar{c}_{3,M1}$ causes p_1^* to be higher (lower). Furthermore, $t_{HIGH}^c \geq t_{M1}^c$.*

For organization design mechanisms that employ an exogenous budget, higher marginal cost of capital ($\partial C_3/\partial Z$) always results in lower effort expended on incremental product improvement. Conversely, for organization design mechanisms that employ an endogenous

budget there exists an interval of time early in the development cycle when a higher marginal cost of capital calls for *higher* effort expended on incremental product improvement. This result is due to the fact that the endogenous budget allows the manager to generate additional resources through incremental improvements to the existing product. The additional resources have value because they can be deployed in response to an increased cost of being over budget. Of course, increased effort towards improving the existing product makes sense only if there is enough time remaining in the development cycle to reap the rewards, thus the existence of threshold times for design mechanisms π_{HIGH} and π_{M1} .

Proposition 4. *Comparative Statics Analysis for p_2^* . At time t during the development cycle, the optimal rate of effort expended on developing the new product is higher if: (i) $\partial C_2/\partial p_2$ is lower, (ii) $\alpha(t)$ is lower, (iii) $\partial V_2/\partial P_2$ is higher, (iv) $\partial V_2/\partial T$ is lower, (v) $\bar{c}_{3,LOW}$, $\bar{c}_{3,M1}$, $\bar{c}_{3,M2}$, or $\bar{c}_{3,HIGH}$ is lower, where $\bar{c}_{3,i}$ is defined as $\partial C_3/\partial Z$ for organization design mechanism π_i .*

In the case of p_2^* , a higher marginal cost of capital results in lower effort expended on developing the new product regardless of the organization design mechanism. This insight coupled with results for the marginal cost of capital in Proposition 3 lead to the conclusion that a higher marginal cost of capital drives the business unit to a more incremental resource allocation strategy, particularly if the marginal cost of capital is higher early in the development cycle. To understand this result, note that the manager has two levers that can offset the higher cost of capital: increase resource expenditure for the existing product in order to generate more revenue and increase the cumulative net budget; or lower resource expenditure for existing product improvement, new product development, or both in order to increase the cumulative net budget. If there is sufficient time remaining in the development cycle the former strategy is advocated so long as the manager is operating with an endogenous budget. The result is a shift towards incremental projects in the NPD portfolio since p_1^* is higher and p_2^* is lower. Later in the development cycle the latter strategy is advocated regardless of the organization design mechanism employed, which is the intuitive

result consistent with observations from practice when a portfolio of NPD programs is considered. Chao and Kavadias (2006) discuss a situation in which managers of a business unit within a beverage company (operating under a mechanism similar to π_{m1}) cite the high cost of capital as the reason for their focus on incremental product improvement effort as opposed to radical new product development effort.

Propositions 3 and 4 highlight the direct impact of model parameters on p_1^* and p_2^* . In addition, p_1^* and p_2^* interact due to their combined effect on the cumulative net budget. They may act as substitutes or compliments depending on the choice of organization design mechanism. The interaction takes the form of a tradeoff between p_1^* and p_2^* based on the marginal value of cumulative net budget. When the manager operates under an exogenous budget, any effect that drives lower p_1^* will subsequently lead to lower $C_1[p_1^*]$ and higher $Z(t)$. Since $\partial^2 C_3 / \partial Z^2 \leq 0$, a higher value of $Z(t)$ will lead to lower $\partial C_3 / \partial Z$ and the result is lower λ_3 . Since p_2^* is optimally determined by the ratio of λ_2 to λ_3 , lower λ_3 implies higher p_2^* . Thus, under an exogenous budget any model parameter that directly impacts p_1^* has the opposite effect on p_2^* because of their interaction through $Z(t)$. On the other hand, p_1^* and p_2^* act as compliments when the manager operates under an endogenous budget. In these cases higher p_1^* may lead to higher $Z(t)$ because the endogenous budget increases $\beta R[P_1(t), t]$. Higher $Z(t)$ implies lower $\partial C_3 / \partial Z$ and lower λ_3 . Again, since p_2^* is optimally determined by the ratio of λ_2 to λ_3 , lower λ_3 implies higher p_2^* .

5.4.3 Crossing Times and the Balance Between p_1^* and p_2^*

In this section we consider how organization design mechanisms impact the balance between p_1^* and p_2^* at the portfolio level. Before we embark on this analysis, we note that several results stated below require that $C_3(\cdot)$ be a linear function of its argument (we relax this assumption in Section 5.5). Linear $C_3(\cdot)$ is necessary for the sake of mathematical tractability and in order to make meaningful comparisons across organization design mechanisms. Note that for π_{HIGH} and π_{M2} , linear $C_3(\cdot)$ corresponds to a constant marginal cost (benefit) paid only at the end of the development cycle based on the value of $Z(T)$. For π_{LOW} and π_{M1} , linear $C_3(\cdot)$ corresponds to a constant marginal cost (benefit) based on the average amount

by which $Z(t)$ is negative (positive) during the development cycle.⁴

The fact that p_1^* decreases over the development cycle while p_2^* increases leads to the possible existence of a *crossing time*. We define a crossing time, t^* , as the time during the development cycle when $p_1^* = p_2^*$. Before the crossing time, $p_1^* > p_2^*$ and the focus of the NPD portfolio is geared towards incremental improvements for the existing product. After the crossing time, $p_1^* < p_2^*$ and the focus of the NPD portfolio shifts towards developing the new product. In the following proposition we show that the choice of organization design mechanism affects the NPD portfolio by means of the crossing time. Formally, we can state the result as follows.

Proposition 5. *Autonomy impacts the crossing times as follows: $t_{LOW}^* = t_{M2}^* \leq \{t_{M1}^*, t_{HIGH}^*\}$ where t_i^* denotes the crossing time under organization design mechanism π_i . In addition, for the case of linear $C_3(\cdot)$, $t_{M1}^* \leq t_{HIGH}^*$.*

Recall that under organization design mechanisms π_{HIGH} and π_{M1} budget creation is endogenous. Proposition 5 states that an endogenous budget causes the crossing time to occur later in the development cycle. In such cases the manager optimally remains focused on improving the existing product for a longer period of time relative to cases in which the budget is exogenously determined. A later crossing time can be interpreted as an incremental strategy compared to an earlier crossing time since improvements to the existing product are relatively incremental compared to developing the new product. The endogenous budget drives an incremental strategy because existing product revenue is used to directly fund both types of effort, regardless of when the manager must account for the budget. The NPD literature contends that autonomy (freedom from control) is preferred when managing radical development projects while control (lack of autonomy) is preferred when managing incremental projects (Tatikonda and Rosenthal 2000). Our results add to these guidelines in cases that extend beyond the single project. In particular, we show how

⁴For organization design mechanisms π_{HIGH} and π_{M2} , the linear cost (benefit) function is $C_3[Z(T)] = \bar{c}_3 Z(T)$. For organization design mechanisms π_{LOW} and π_{M1} , the linear cost (benefit) function is $C_3[Z(t)] = (\bar{c}_3/T)Z(T)$, which implies that $C_3(\cdot) = \bar{c}_3(1/T) \int_0^T Z(t)dt = \bar{c}_3 \bar{Z}(t)$ where $\bar{Z}(t)$ is the average level of $Z(t)$ during the development cycle.

autonomy can be used to dictate the nature of innovation when resources must be allocated between multiple NPD programs in a portfolio.

5.4.4 The magnitude of p_1^* and p_2^* for Different Organization Design Mechanisms

Analysis of the crossing time hints at the relative priority given to multiple efforts in the NPD portfolio. However, the magnitude of p_1^* and p_2^* throughout the development cycle provides a more detailed view of how the choice of organization design mechanism impacts incremental and radical innovation.

Proposition 6. *For the case of linear $C_3(\cdot)$, when the development cycle begins ($t = 0$), $p_{1,LOW}^* = p_{1,M2}^* < p_{1,M1}^* < p_{1,HIGH}^*$. When the development cycle ends ($t = T$), $p_{1,LOW}^* = p_{1,M1}^* > p_{1,M2}^* = p_{1,HIGH}^*$. Furthermore, $p_{1,M2}^* < p_{1,LOW}^* < p_{1,M1}^*$ for $t \in (0, T)$, where $p_{1,i}^*$ denotes the optimal rate of effort towards improving the existing product under organization design mechanism π_i .*

The result established in Proposition 6 together with the fact that p_1^* is convex-decreasing throughout the development cycle allows us to draw additional conclusions regarding the dynamic behavior of p_1^* for different organization design mechanisms (Figure 21). The design mechanism π_{M2} results in the lowest p_1^* throughout the development cycle. In contrast, π_{M1} results in p_1^* that is strictly higher compared to π_{M2} . The design mechanism π_{LOW} results in p_1^* that falls between π_{M1} and π_{M2} . Finally, relative to the other design mechanisms, π_{HIGH} results in a rate of effort that is higher early in the development cycle and lower later in the development cycle. Together these results demonstrate that an endogenous budget drives a form of *front-loading* for existing product improvement. Front-loading describes increased resource expenditure early in a development cycle and it is advocated in the literature as an effective strategy to identify potential design errors at the minimum redesign cost (Cooper and Kleinschmidt 1994, Thomke and Fujimoto 2000). Our analysis reveals that organization design choices may drive a front-loading strategy (even in a deterministic setting) in the context of the NPD portfolio. The driving force behind this phenomenon is that a manager operating under an endogenous budget optimally expends more effort

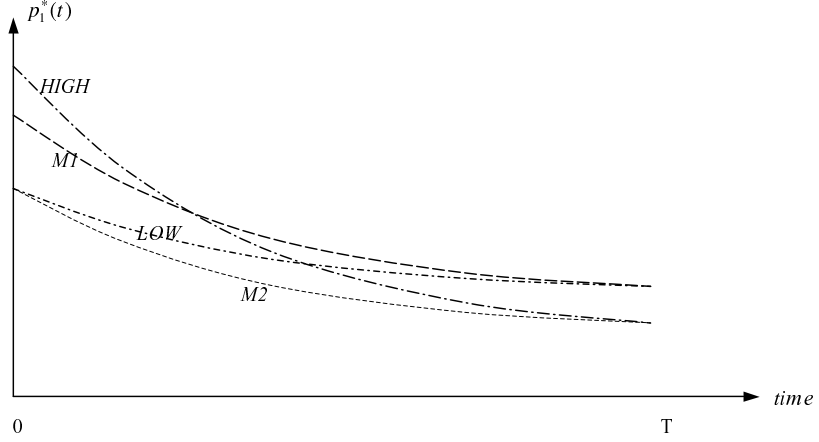


Figure 21: Dynamic behavior of p_1^* .

on improving the existing product in order to increase revenue generated by the existing product, which in turn increases the cumulative net budget under design mechanisms π_{M1} and π_{HIGH} . Our findings echo those of Loch and Kavadias (2002). They highlight cases under which a carryover benefit may lead to front-loading for an existing product.

The choice of organization design mechanism also impacts the effort expended on developing the new product. The following proposition establishes the result:

Proposition 7. *For the case of linear $C_3(\cdot)$, when the development cycle begins ($t = 0$), $p_{2,LOW}^* = p_{2,M1}^* < p_{2,M2}^* < p_{2,HIGH}^*$. Throughout the remainder of the development cycle ($t \in (0, T]$), $p_{2,LOW}^* = p_{2,M1}^* > p_{2,M2}^* = p_{2,HIGH}^*$, where $p_{2,i}^*$ denotes the optimal rate of effort towards developing the new product under organization design mechanism π_i .*

The result established in Proposition 7 together with the fact that p_2^* is increasing over the development cycle allows us to examine the dynamic behavior of p_2^* for different organization design mechanisms (Figure 22). First, the optimal rate of effort expended on developing the new product is equal for each organization design mechanism at the beginning of the development cycle ($t = 0$). After $t = 0$ and for the remainder of the development cycle, $p_{2,LOW}^* = p_{2,M1}^*$ and $p_{2,HIGH}^* = p_{2,M2}^*$. Furthermore, effort expended on developing the new product is higher when the manager is forced to account for budget

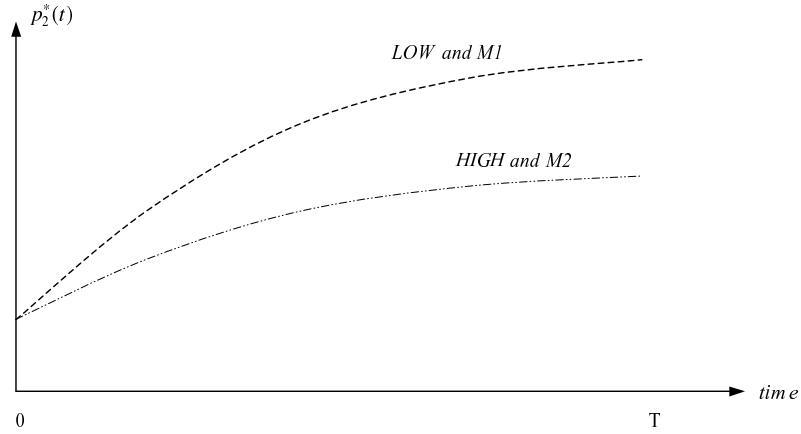


Figure 22: Dynamic behavior of p_2^* .

overruns throughout the development cycle compared to only at the end of the development cycle. Thus, for the new product, increased budget control drives a form of front-loading.

The driving force behind this result is that under organization design mechanisms π_{LOW} and π_{M1} , the marginal value of cumulative net budget decreases during the development cycle driving higher $p_{2,LOW}^*$ and $p_{2,M1}^*$ later in the development cycle. Alternatively, the result can be interpreted as less benefit to lower values of $p_{2,LOW}^*$ and $p_{2,M1}^*$ in terms of cumulative net budget later in the development cycle. These insights taken together lead us to the conclusion that strict budget control ensures a higher rate of effort towards developing the new product.

5.5 Choosing an Appropriate Design Mechanism

In this section we turn our attention towards factors that drive the choice of design mechanism. The problem is analogous to the extensively studied principal-agent problem (Grossman and Hart 1983, Gibbons 2005) in which a senior manager outside the business unit (the principal) decides on π_i , and the manager within the business unit (the agent) decides on p_1^* , p_2^* , and T in order to maximize profit for the business unit. Note that we do not explicitly model the principal's decisions; rather, we focus on the properties of the resource allocation strategy and the managerial actions that accompany each organization design mechanism. Nonetheless, the principal's decision is subsumed in the organization design

mechanism and it is important to understand what drives this choice.

Two features that are implicit in our model are of interest to our analysis. First, the principal and the manager share the same information with respect to uncertainty (risk). Second, the manager's effort is observable, which is embodied in the budget control mechanism (control throughout the development cycle or control only at the end of the development cycle). Given these two model features agency theory advocates that the principal should compensate the agent through a fixed wage. However, our analysis shows that not all organization design mechanisms result in the same profit. In addition, there may exist strategic choices beyond the business unit that encourage the principal to seek accelerated or delayed new product launch from the business units under his command (Gibbons 2005).

5.5.1 Numerical Analysis

Although we can obtain expressions for the total profit and the new product launch time, their mathematical complexity precludes managerial interpretation (please see the Appendix C for details). Instead, we develop insights with regard to these metrics through a numerical analysis of the model (Gaimon 1989 and 1997, Gaimon and Carillo 2000). Furthermore, through numerical analysis we are able to illustrate analytic results of Propositions 6 and 7 under more general functional forms.

To conduct the numerical analysis, we choose specific functional forms and parameter values based on realistic considerations from practice. Our choice of functions and parameters reflects extensive discussions with senior managers responsible for NPD within a business unit of a beverage company (Chao and Kavadias 2006). The business unit that was the subject of this case study operated under an endogenous budget with the cumulative net budget controlled throughout the development cycle (i.e. an organization design mechanism similar to π_{M1}). Optimal solutions are generated using a standard shooting method based on a discrete approximation of the continuous time model (for details see Sethi and Thompson 2000). Appendix C.2 contains a detailed account of all functional forms, base case parameter values, and experiments for the numerical analysis.

5.5.2 p_1^* and p_2^* Under Non-Linear $C_3(\cdot)$

Figure 23 depicts the dynamic behavior of the decision variables for each organization design mechanism in the base case experiment. Proposition 6 is shown to be robust for non-linear functional forms of $C_3(\cdot)$. A manager operating under an endogenous budget optimally front-loads the effort aimed at existing product improvement. The same generalization holds for Proposition 7. When budget control is employed throughout the development cycle, the manager optimally front-loads effort towards developing the new product.

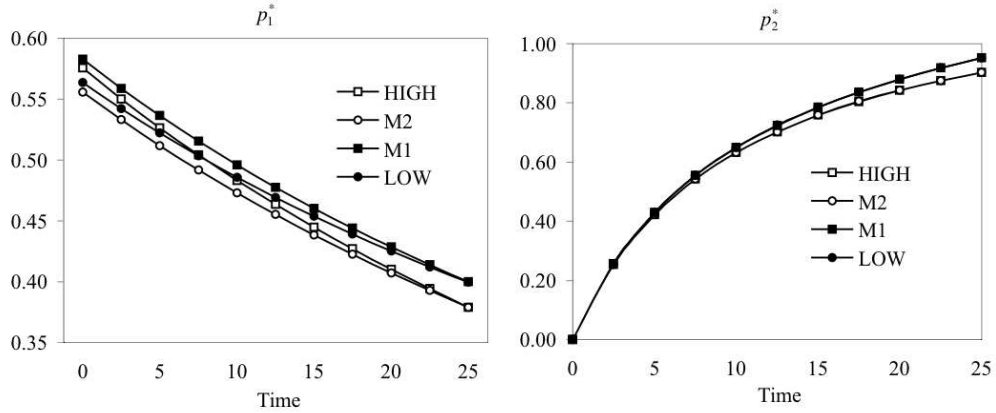


Figure 23: Dynamic behavior of p_1^* and p_2^* based on numerical analysis.

5.5.3 Profit and New Product Launch Time

Managers responsible for resource allocation decisions must consider the competition intensity faced by the business unit and the market potential of the new product. The former embodies an external market threat (e.g. revenue loss due to competitors actions) while the latter embodies a response to that threat (e.g., radical expansion, invasion of new markets, incorporation of new technologies).

Figure 24 depicts the new product launch time and total profit earned by the business unit as a function of the expected market potential for the new product ($\partial V_2 / \partial P_2$).⁵ As

⁵Innovative products often have high market potential and high development uncertainty. Note that we use $\partial V_2 / \partial P_2$ as a proxy for market potential without considering the effects of increased uncertainty. Still, our analysis is valid if we interpret $\partial V_2 / \partial P_2$ as the expected market potential, which suffices given our focus on organization design choices as opposed to the effects of stochastic return on investment.

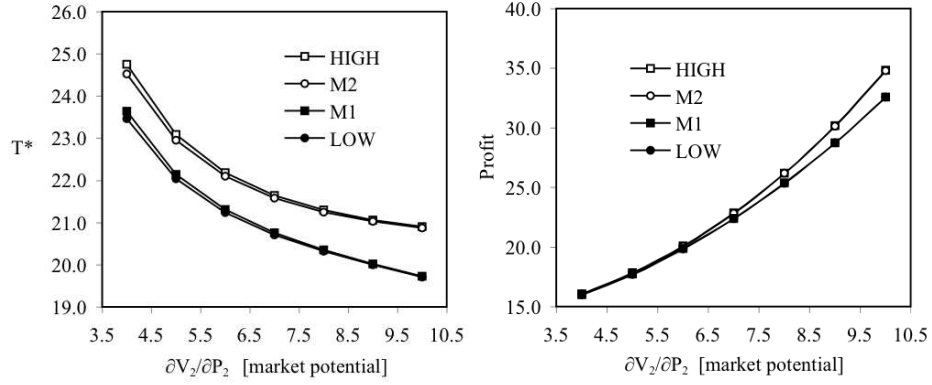


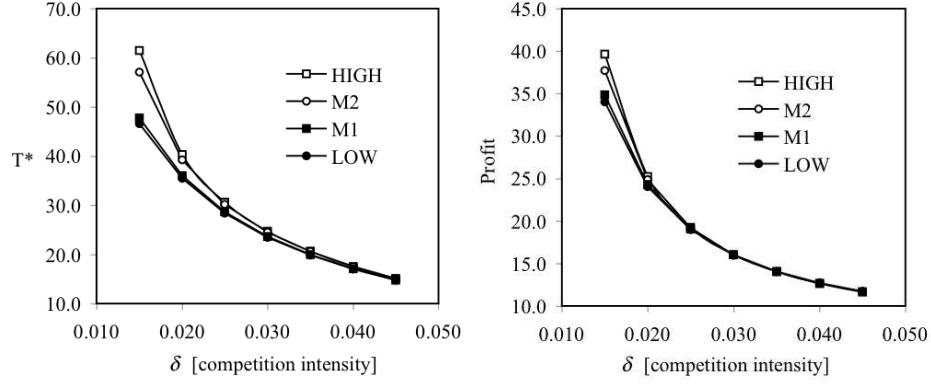
Figure 24: New product launch time and profit as a function of the expected market potential for the new product.

expected, new product launch time is a decreasing function of expected market potential and profit is an increasing function of the expected market potential. The manager optimally accelerates new product launch to capture the expected market potential and reap the rewards in terms of higher profits. More interesting is the fact that, for the entire range of expected market potential, π_{HIGH} and π_{M2} result in a substantially delayed new product launch compared to π_{LOW} and π_{M1} . Recall from Proposition 7 that organization design mechanisms π_{LOW} and π_{M1} drive higher effort towards developing the new product. Based on the numerical results for T^* , we can extend this result and conclude that budget control throughout the development cycle drives a higher rate of effort *for a shorter period of time* compared to budget control only at the end of a development cycle. Thus, tight budget control drives more intense effort towards developing the new product. The results depicted in the right panel of Figure 24 show that the value created by the more intense effort is dominated by the cost of generating that effort. For high values of expected market potential, π_{HIGH} and π_{M2} result in substantially higher profit compared to π_{LOW} and π_{M1} . This is due to the fact that payoffs exhibit diminishing returns to effort while costs are increasing and convex in effort.

For low values of expected market potential, the best organization design choice is clearly one that imposes tight budget control. This strategy ensures a faster new product launch without sacrificing profit. Conversely, for high values of expected market potential the

choice of organization design mechanism is not as simple. High values of expected market potential force senior managers to choose between an accelerated new product launch with lower profit or a delayed launch with higher profit. To maximize profits, high autonomy in terms of budget control is advocated. From this perspective our results support prior studies on organization design and innovation (Christensen 1997, Tatikonda and Rosenthal 2000, Christensen and Raynor 2003). These studies cite high autonomy as the preferred mechanism for business units whose aim is to develop new products that have high market potential. We add to this theory and note that more autonomy is advocated because of rational resource allocation and budget control decisions in addition to the behavioral benefits of creativity and organizational culture. However, managers should be cautioned that the higher profit comes at the expense of a delayed new product launch when business units are granted autonomy in terms of budget control.

Figure 25 presents profit and new product launch time as a function of competition intensity. Competition intensity collectively captures the effects of products introduced by competing firms as well as shifting consumer preferences. Together these forces result in lost value from the existing product and new product. For low values of competition intensity, the profit generated under design mechanisms π_{HIGH} and π_{M2} is approximately 10% greater than the profit under π_{LOW} and π_{M1} . Once again, autonomy in terms of budget control drives the best choice of organization mechanism in terms of profit. The increased profit is accompanied by a delayed new product launch time. The new product launch time under design mechanisms π_{HIGH} and π_{M2} is approximately 25% longer than the new product launch time under design mechanisms π_{LOW} and π_{M1} . As expected, profit and new product launch time decrease in competition intensity. In fact, under extremely high levels of competition intensity the choice of organization design mechanism has a negligible effect on profit and new product launch time. The result stems from the dynamic behavior of the payoff loss: as time passes the loss is decreasing at a decreasing rate. Thus, the manager optimally launches the new product as early as possible to avoid deterioration in the payoff values. Of course, an earlier launch time effectively makes all the organization design mechanisms equivalent. Note that in the limit ($T = 0$), all mechanisms share the



Note: δ determines the shape of the payoff loss for the existing product and the new product. Higher delta implies higher $\partial R/\partial t$, $\partial V_1/\partial T$, and $\partial V_2/\partial T$.

Figure 25: New product launch time and profit as a function of competition intensity.

same values for $P_1(0)$ and $P_2(0)$.

The implication for senior managers is that the choice of organization design mechanism drives two distinct strategies. Autonomy in terms of budget control results in higher profit from less intense development effort and a delayed new product launch. Based on this observation, senior managers should not be surprised when autonomous teams suffer from delayed new product release. On the other hand, budget control throughout the development cycle results in lower profit from more intense development effort and an accelerated new product launch. Christensen (1996) clearly describes these phenomena in a case study of a division of Hewlett Packard. That business unit was given autonomy with respect to budget creation and control. Senior managers pushed for intense development efforts and a short break even time (early product launch) for a radical and unproven innovation (i.e. a 1.3 inch disk drive). The project was abandoned as a failure for not meeting high expectations in terms of profitability. Our results predict that high autonomy *optimally* drives less intense effort towards developing a new product and a delayed product launch. Thus, it appears that HP suffered from misalignment between their NPD strategy and the choice of organization design mechanism.

5.6 *Conclusions and Implications*

The goal of this manuscript is to understand how organization design mechanisms impact resource allocation and NPD portfolio strategy. To address these goals we developed an analytic model of dynamic resource allocation subject to different organization design mechanisms that determine how the NPD budget is created and controlled within a business unit. Our analysis focused on the balance between improving an existing product and developing a fundamentally new product.

5.6.1 Implications for Theory

Although the Operations Research literature provides a rich history of work on resource allocation and NPD portfolio management, most of this research ignores the organizational and behavioral aspects that impact this problem. As a result, managers rarely use the proposed tools to make decisions; rather decisions come about through processes that are not transparent and managers manipulate the tools to provide quantitative support for their decisions (Loch et al. 2001). Recent work in resource allocation and NPD portfolio strategy highlights the need to study organizational and behavioral aspects that impact resource allocation decisions (Chao and Kavadias 2006, Gino and Pisano 2006). We attempt to gain insights into this problem by explicitly modeled an organization design choice and the subsequent effect on resource allocation. Our analysis leads to a number of testable hypotheses that merit empirical validation.

H1: Front-loading for existing product improvement is positively associated with the use of an endogenous budget.

H2: Front-loading for new product development is positively associated with frequent control of the NPD budget.

H3a: Profit is positively associated with expected market potential of a new product.

H3b: Frequency of control of the NPD budget negatively moderates the positive relationship between profit and expected market potential of a new product.

H4a: Profit is negatively associated with competition intensity.

H4b: Frequency of control of the NPD budget negatively moderates the negative relationship between profit and competition intensity.

H5: New product launch time is negatively associated with expected market potential of a new product.

H6a: New product launch time is negatively associated with competition intensity.

H6b: Frequency of control of the NPD budget negatively moderates the negative relationship between new product launch time and competition intensity.

Together these hypotheses allow us to take a necessary step towards understanding important organizational processes that drive innovation and economic growth. Empirical validation of these claims is an open area for future research.

5.6.2 Implications for Practice

Perhaps the most important implications of our research for practicing managers are the specific organization design mechanisms that can be used to drive innovation and profit. This is most clearly evident from the viewpoint of senior managers responsible for making the decision of which organization design mechanism to use.

Our first conclusion is with regard to the NPD portfolio and the balance between improving an existing product and developing a new product. We show that autonomy in terms of how the NPD budget is created drives the manager to remain focused on existing product improvement for a longer period of time relative to cases in which the manager is simply given a fixed NPD budget. Since existing product improvement embodies incremental effort relative to new product development, we conclude that higher autonomy in terms of budget creation leads to a portfolio strategy that is biased towards incremental projects.

A second conclusion focuses on how the NPD budget is controlled and directly impacts profit and new product launch time. For these metrics, we show that budget control drives two distinct strategies. When the manager is held accountable for budget overruns throughout the development cycle the result is lower profit from more intense development effort

and an accelerated new product launch. On the other hand, when the manager is held accountable for budget overruns only at the end of the development cycle the result is higher profit from less intense development efforts and a delayed product launch. Senior managers should be aware that their choice of organization design mechanism will contribute to the innovation and NPD efforts delivered by business unit managers.

Finally, business unit managers must be aware of changes in the marginal cost of capital for NPD. This cost may represent the cost of monitoring NPD activities or the cost for using external sources of funding. If a manager does not have autonomy in terms of budget creation, then the best strategy in response to a higher marginal cost of capital is to reduce efforts towards existing product improvement and new product development. However, when given autonomy in terms of budget creation, the best decision depends on the amount of time remaining the development cycle. Early in a development cycle, the best response to a higher marginal cost of capital is to increase resource expenditure for existing product improvement.

Whether considered from the vantage point of senior managers or business unit managers, alignment between innovation strategy and the choice of organization design mechanism can ensure that resources are effectively allocated to maximize value and competitiveness.

CHAPTER VI

CONCLUSIONS AND OPEN RESEARCH QUESTIONS

Academics and practitioners have proposed a plethora of methods to attack the resource allocation and NPD portfolio problem. A broad literature review suggests that quantitative research efforts are constrained to the tactical or operational level of analysis and have not been widely adopted in practice. Conversely, case-based frameworks and qualitative models are widely used in practice, but lack rigorous theoretical foundations.

The fundamental contribution of this thesis is the explicit treatment of organizational and behavioral elements that impact the resource allocation and NPD portfolio problem. We adopt a hierarchical perspective and posit that the resource allocation and NPD portfolio problem acquires a unique structure depending on the level at which the problem is considered. The hierarchical perspective allows us to provide a rigorous link between strategy (vision) and execution (money). In this final chapter, we draw conclusions from the three studies that comprise this thesis. We then identify a number of open research questions with respect to resource allocation and NPD portfolio management.

6.1 Overarching Insights

Beginning at the firm level, each study in this thesis considers the drivers of effective resource allocation and NPD portfolio decisions at successively more detailed levels of analysis. We begin with an analysis of the firms total R&D investment. Next, we analyze how the R&D investment is partitioned into innovation focused “strategic buckets”. Finally, we analyze how individual NPD programs are funded and how they evolve over time in an organization setting that is defined by more or less autonomy. Below we highlight our primary conclusions and contributions:

- At the highest level of analysis, we discuss how the NPD portfolio impacts the consistency of R&D investment within an industry. This is an important theoretical

contribution as it sheds additional light on a long standing question in the economics of R&D investment. From the practical side, this study opens the door for managers to understand the long-run impact of NPD portfolio strategy. Specifically, firm level data such as cost of sales and overall NPD portfolio composition can be used to estimate an equilibrium R&D intensity, which in turn can be used to estimate whether firms are over or under investing in research and development.

- Having described where the firm’s R&D investment comes from, we analyze how it should be partitioned between incremental and radical initiatives in the portfolio. We establish how interaction complexity and environmental instability impact the value of the innovation initiatives in a strategic bucket. Although environmental complexity and instability both confound managers, we find that they have completely opposite effects on the NPD portfolio balance. Environmental complexity shifts the balance towards radical innovation. Conversely, environmental instability shifts the balance towards incremental innovation.
- Finally, we explicitly account for the hierarchical nature of the resource allocation and NPD portfolio problem through our study of organization design mechanisms and their impact on resource allocation policies. We find that autonomy may lead to a NPD portfolio that is biased towards incremental projects. This insight challenges existing claims regarding autonomy, creativity, and innovation.

6.2 Open Research Questions

The studies in this thesis point to a set of open ended research questions associated with resource allocation and NPD portfolio management. In general, the research community should attempt to acquire a holistic view of the NPD portfolio problem. A holistic view dictates that we recognize that different problem parameters are defined at different levels of the organization hierarchy. In particular:

1. We need to develop methods that can shed light onto the structure of the underlying performance landscape and measure the interactions among profit determinants at a

strategic level. A number of efforts have tried to isolate specific influence factors, but we feel that research here is at an embryonic stage.

2. The research methodologies must identify the notion of organizational hierarchy and its impact on decisions. The infamous quote that, “*resources are allocated to the manager that screams the loudest*” signifies that managers associate their career paths with specific resource allocation and NPD portfolio decisions and that they may attempt to “game” the system. Thus, we need to build additional intuition regarding the incentive and motivation structures associated with NPD portfolio decisions.
3. The theoretical structures that look at isolated decisions in the NPD pipeline should be extended to allow for a holistic process view. As a corollary to this thought, we note that overall NPD portfolio value emerges from individual project outputs. Therefore, we ought to look for new methods that aggregate individual project information into an overall portfolio value. The classic DuPont framework for financial modeling is a good starting point along these lines.
4. Finally, considerable effort should be invested to empirically assess the impact of resource allocation and NPD portfolio strategy. Unfortunately NPD portfolio data are extremely sensitive and often confidential because NPD portfolio decisions are of vital importance to firm competitiveness. Nevertheless, secondary data (R&D investment, key product characteristics, market variables) offer a reasonable starting point for assessing the impact of NPD portfolio decisions.

We believe that the resource allocation and NPD portfolio problem remains largely an open question especially at senior levels of decision making. We echo previous observations from the research community that call for new approaches and methods that shed light on the problem. It is essential that we understand the various steps required to operationalize such a complex decision since the NPD portfolio directly impacts firm competitiveness.

APPENDIX A

In A.1 we provide proofs for Propositions 1, 2, and 3 and in A.2 we provide details of the experimental design for the evolutionary model. We restate equations from the manuscript when necessary to ease exposition. As a convention, we denote the partial derivative of any variable x with respect to its argument as x' when the argument is unambiguous. We denote the time derivative for any variable x as \dot{x} .

A.1 Proofs

The problem stated in Chapter 3 is solved using optimal control theory (Kamien and Schwartz 1991, Sethi and Thompson 2000). Below we state the current value Hamiltonian (H):

$$H = [1 - c(t)]S(t) - r(t) + f[r(t)] \int_t^\infty \lambda(\tau)\omega(\tau - t)d\tau - \lambda(t)\delta S(t) \quad (7)$$

The necessary conditions for optimality are:

$$\frac{\partial H}{\partial r} = 0 \quad (8)$$

$$\dot{\lambda} - \rho\lambda = -\frac{\partial H}{\partial S} \quad (9)$$

Equation 8 is the necessary first-order conditions for the optimal R&D investment (r^*). Equation 9 is the necessary condition for the co-state variable $\lambda(t)$ (marginal value function for sales). To conserve space, we do not reiterate the equations for $\dot{S}(t)$ and $\omega(\cdot)$, which are also necessary conditions. We can now state the proof for Proposition 1:

Proposition 1. *Optimal R&D Investment.* The optimal R&D investment, r^* , is defined implicitly by $\partial f / \partial r^* \int_t^\infty \lambda(\tau)\omega(\tau - t)d\tau = 1$.

Proof of Proposition 1. The proof follows directly from the necessary condition in Equation 8. Differentiating H with respect to r and setting this term equal to zero gives: $\partial f / \partial r^* \int_t^\infty \lambda(\tau)\omega(\tau - t)d\tau = 1$. The left hand side of this expression is the marginal

expected benefit from a dollar invested in R&D . The right hand side of the expression is the marginal cost of investing the dollar in R&D . Note that the marginal expected benefit takes into account all future marginal benefits from the R&D investment (captured in the term $\int_t^\infty \lambda(\tau)\omega(\tau - t)d\tau$). QED.

Based on the result in Proposition 1, we seek long-run equilibrium values for the firm's R&D investment and sales rate. The necessary conditions for a long-run equilibrium are:

$$\dot{\lambda} = 0 \quad (10)$$

$$\dot{S} = 0 \quad (11)$$

Proposition 2. *Equilibrium R&D investment:* $\bar{r} = g^{-1}[(\rho + \delta)/(1 - c)\mu]$ where $g^{-1}(\cdot)$ is a decreasing and convex function defined by $g(r) = \partial f/\partial r$. *Equilibrium Sales Rate:* $\bar{S} = f(\bar{r})\mu/\delta$ where $f(\cdot)$ is an increasing and concave function. *Equilibrium R&D Intensity:* There exists an equilibrium R&D intensity given by: $\bar{\beta} = \bar{r}/\bar{S}$.

Proof of Proposition 2. To prove the first part of Proposition 2 we make use of Equations 9 and 10. These conditions define a long-run equilibrium for the co-state variable (marginal value function): $\bar{\lambda} = (1 - \bar{c})/(\rho + \delta)$. Note that we have assumed that sufficient time has passed so that $\dot{c} = 0$ and the cost of sales has reached its limiting value. We now make use of Proposition 1 and the expression for the optimal R&D investment. We can remove $\lambda(\tau)$ from the integral because it is no longer a function of time. Also, recall that we define $\omega(\cdot)$ such that $\int_t^\infty \omega(\tau - t)d\tau = \mu$. Finally, let $\partial f/\partial r = g(r)$ and note that $g(r)$ is decreasing and convex in r because $f(r)$ is increasing and concave in r . We can now write the complete expression for the equilibrium R&D investment as $\bar{r} = g^{-1}[(\rho + \delta)/(1 - \bar{c})\mu]$.

To prove the second part of Proposition 2 we make use of equation 11 along with the state equation that defines the change in sales. This gives us $\int_{-\infty}^t f[r(\tau)]\omega(t - \tau)d\tau = \delta\bar{S}$. To find the equilibrium sales rate we make use of the equilibrium R&D investment established above and we note that $\int_{-\infty}^t \omega(t - \tau)d\tau \rightarrow \mu$ as $t \rightarrow \infty$. This leaves us with $\bar{S} = f[g^{-1}(1/\bar{\lambda}\mu)]\mu/\delta$.

To prove that there exists an equilibrium R&D intensity given by $\bar{\beta} = \bar{r}/\bar{S}$ we consider the locus of points in (S, λ) space for which the equilibrium conditions in Equations 10 and 11 are satisfied. The curve defined by the points for which $\dot{S} = 0$ is an increasing and

concave function of λ . Using similar logic, the curve defined by the points for which $\dot{\lambda} = 0$ is not a function of S . The point at which these two curves intersect in (S, λ) space defines the long-run equilibrium R&D intensity. QED.

Proposition 3 is a comparative statics analysis for $\bar{\beta}$. The comparative statics allows us to understand the factors that drive lower or higher equilibrium R&D intensity.

Proposition 3. *Comparative Statics Analysis for R&D Intensity:* $\bar{\beta}$ is higher if: (i) δ is higher, (ii) μ is lower, (iii) $f(\cdot)$ is lower, (iv) \bar{c} is lower, (v) ρ is lower.

Proof of Proposition 3. To ease exposition we provide a complete expression for the equilibrium R&D intensity:

$$\bar{\beta} = \frac{\bar{r}}{\bar{S}} = \frac{g^{-1}[\frac{\rho+\delta}{(1-\bar{c})\mu}]\delta}{f[g^{-1}[\frac{\rho+\delta}{(1-\bar{c})\mu}]]\mu} \quad (12)$$

We prove each part of Proposition 3 in succession. (i) $\partial\bar{\beta}/\partial\delta > 0$. (ii) $\partial\bar{\beta}/\partial\mu < 0$. (iii) $\partial\bar{\beta}/\partial f(\cdot) < 0$. (iv) $\partial\bar{\beta}/\partial\bar{c} < 0$. (v) $\partial\bar{\beta}/\partial\rho < 0$. QED.

A.2 Experimental Design for the Evolutionary Model

In this section we detail the functional forms, parameter values, and experimental design for the evolutionary model described in Section 3.4. The functional form of $f(r)$ ensures that R&D productivity is subject to diminishing returns. The functional form of the time lag of R&D effectiveness is a Gamma function with parameters (n_1, n_2) . Note that $\mu \in (0, 1)$ limits the total effectiveness of R&D investment.

$$f(r) = A[1 - e^{-r}] \quad (13)$$

$$\omega(t) = \mu \frac{n_1^{n_2} t^{(n_2-1)} e^{-n_1 t}}{(n_2 - 1)!} \quad (14)$$

Figure 26 depicts the experimental design for the base case experiment as well as each experiment E1-E5. For each experiment, we report the parameter value that changes relative to the base case (all other parameters are the same as the base case experiment). Throughout the simulation there are a number of parameters that remain static. In each

experiment we limit the number of firms to $N = 500$ and we employ 100 replications to account for any initialization bias. We also fix the shape parameter for $\omega(t)$ at $n_1 = 2$. Finally, we hold static the percentage of firms that are killed and the percentage of new firms that enter the population at $x = 0.05$. The convention that population size remains constant is aligned with other work in evolutionary systems and population dynamics.

Simulation of the evolutionary model takes place through a discrete time approximation to the analytic model. The following steps take place in period $t = 0, 1, 2, \dots$ for each firm $i = 1, 2, \dots, N$:

1. Each firm determines its R&D investment: $r_i = \beta_i S_i$
2. The R&D investment has a stochastic outcome on sales, which depends on the time lag in R&D effectiveness: $S_i(t+1) = (1 - \delta)S_i(t) + \sum_{\tau=0}^t f_i[r_i(\tau)]\omega_i(t - \tau)$.
3. Firm profit is calculated: $\Pi_i = [1 - \bar{c}_i]S_i(t) - r_i(t)$. The lowest $x\%$ of firms (in terms of profit) are eliminated from the population.
4. New firms enter the population with random sales (S_i), cost of sales (\bar{c}_i), and per-period sales decline (δ_i). Portfolio strategy $\pi_i = \{f_i(\cdot), \omega_i(\cdot), \mu_i\}$ is copied randomly from one of the top performing firms (top $x\%$ in terms of profit).

The above process of variation, selection, and retention takes place until the system reaches steady state, which we define as the period after which parameter values do not change by more than 0.50% for 100 consecutive periods. Steady state is achieved at or around $t = 100$ for the majority of experiments.

Experiment	S_i	A_i	$n_{2,i}$	μ_i	c_i	δ_i	ρ
Base Case	$U(0,20)$	$U(5,25)$	$U(2,10)$	$U(0.10,0.50)$	$U(0.10,0.20)$	$U(0.20,0.30)$	0.10
E1 (higher \bar{c})	-	-	-	-	$U(0.80,0.90)$	-	-
E2 (lower δ)	-	-	-	-	-	$U(0.05,0.15)$	-
E3 (higher $f(\cdot)$)	-	$U(30,50)$	-	-	-	-	-
E4 (higher μ)	-	-	-	$U(0.50,0.90)$	-	-	-
E5 (higher ρ)	-	-	-	-	-	-	0.25

Note: draws for A_i , $n_{2,i}$, and μ_i are correlated so that the distribution of firm portfolios ranges from high-risk, high reward to low-risk, low reward. Each experiment consists of $N = 500$ firms per replication and 100 replications.

Figure 26: Initial parameter values for the evolutionary model.

APPENDIX B

In B.1 we provide proofs for Propositions 1, 2, and 3. In B.2 and B.3 we provide extensions of the analytic model based on a search for the best possible performance and a classic two-armed bandit. Finally, in B.4 we provide details of the experimental design for the simulation. We restate equations from the manuscript when necessary to ease exposition.

B.1 Proofs

Recall that the expected performance for an m period commitment (considered at $t = 0$) to an NPD initiative of type d was derived as:

$$J_0^d = \left[-c(d) + rp(d)\hat{V}(d) \right] \frac{1 - r^m[1 - p(d)]^m}{1 - r[1 - p(d)]} \quad (15)$$

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

Proof of Proposition 1. We assume that J_0^d is continuous in m and $r = 1$ to ease exposition. To see that J_0^d is increasing and concave in m note that the only term in Equation 15 that is a function of m is $a(m) = 1 - [1 - p(d)]^m$, so it suffices to analyze this term. Differentiating with respect to m gives $da/dm = -[1 - p(d)]^m \ln[1 - p(d)] > 0$ because $p(d) \in (0, 1)$. Similarly, $d^2a/dm^2 = -(\ln[1 - p(d)])^2 [1 - p(d)]^m < 0$. Since $da/dm > 0$ and $d^2a/dm^2 < 0$, $a(m)$ is increasing and concave in m and so is J_0^d .

$J_0^{d_1} > J_0^{d_2}$ for $m = 1$ follows directly by letting $m = 1$ in Equation 15. To see that $J_0^{d_1} < J_0^{d_2}$ as $m \rightarrow \infty$ first note that $m \rightarrow \infty$ implies that $[1 - p(d)]^m \rightarrow 0$. From Equation 15 we are left to show that $[-c(d_1) + p(d_1)\hat{V}(d_1)] \frac{1}{p(d_1)} < [-c(d_2) + p(d_2)\hat{V}(d_2)] \frac{1}{p(d_2)}$. The threshold values \bar{p} and \underline{p} imply that for sufficiently high $p(d_1)$ and sufficiently low $p(d_2)$ this inequality holds. The conditions on $p(d_1)$ and $p(d_2)$ make sense because d_1 represents

incremental innovation and d_2 represents radical innovation. QED.

Having described the structure of the NPD program return curves, we now turn our attention towards a comparative statics analysis for the crossing time. We define the function $f(m)$ as the difference between $J_0^{d_1}$ and $J_0^{d_2}$:

$$\begin{aligned} f(m) &= \left[-c(d_1) + rp(d_1)\hat{V}(d_1) \right] \frac{1 - r^m[1 - p(d_1)]^m}{1 - r[1 - p(d_1)]} \\ &\quad - \left[-c(d_2) + rp(d_2)\hat{V}(d_2) \right] \frac{1 - r^m[1 - p(d_2)]^m}{1 - r[1 - p(d_2)]} \end{aligned} \quad (16)$$

We note the following properties without providing a formal proof: provided a crossing time exists, at \bar{m} we have $J_0^{d_1} = J_0^{d_2}$. For $m < \bar{m}$ we have $J_0^{d_1} > J_0^{d_2} \Rightarrow f(m) > 0$ and for $m > \bar{m}$ we have $J_0^{d_1} < J_0^{d_2} \Rightarrow f(m) < 0$. Proposition 2 is a comparative statics analysis of \bar{m} in order to understand the factors that make incremental or radical innovation more favorable.

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

Proof of Proposition 2. First, note that if an \bar{m} exists it is unique since the individual NPD program return curves are increasing and concave in m , $J_0^{d_1} > J_0^{d_2}$ for $m = 1$, and $J_0^{d_1} < J_0^{d_2}$ as $m \rightarrow \infty$. The differential of \bar{m} with respect to any parameter x is $d\bar{m}/dx = -(\partial f/\partial x)/(\partial f/\partial m)$. Furthermore, we know that $\partial f/\partial m < 0$ at \bar{m} . For notational convenience let $\hat{V}_i = \hat{V}(d_i)$, $p_i = p(d_i)$, and $c_i = c(d_i)$ for $i = 1, 2$ and assume that $r = 1$.

We provide a proof for each part of Proposition 2 in succession. (i) $\partial f/\partial \hat{V}_1 = 1 - [1 - p(d_1)]^m > 0 \Rightarrow d\bar{m}/d\hat{V}_1 > 0$. (ii) $\partial f/\partial p_1 = (-c_1 + p_1\hat{V}_1)\partial/\partial p_1\{[1 - (1 - p_1)^m]/p_1\} + [1 - (1 - p_1)^m]\hat{V}_1/p_1 > 0 \Rightarrow d\bar{m}/dp_1 > 0$. (iii) $\partial f/\partial c_1 = (-1 + [1 - p(d_1)]^m)/p(d_1) < 0 \Rightarrow d\bar{m}/dc_1 < 0$. (iv) $\partial f/\partial \hat{V}_2 = -1 + [1 - p(d_2)]^m < 0 \Rightarrow d\bar{m}/d\hat{V}_2 < 0$. (v) $\partial f/\partial p_2 = -(-c_2 + p_2\hat{V}_2)\partial/\partial p_2\{[1 - (1 - p_2)^m]/p_2\} - [1 - (1 - p_2)^m]\hat{V}_2/p_2 < 0 \Rightarrow d\bar{m}/dp_2 < 0$. (vi) $\partial f/\partial c_2 = (1 - [1 - p(d_2)]^m)/p(d_2) > 0 \Rightarrow d\bar{m}/dc_2 > 0$. QED.

Recall that the difference between incremental and radical NPD program performance

for the renewal process defined by technological and market disruptions is given by

$$\Delta J = \frac{q}{1 - qr^t} f(t) + \frac{1 - q}{1 - qr^t} f(m) \quad (17)$$

Proposition 3. *Technological and Market Disruptions.* For $t < \bar{m} < m$, ΔJ is a increasing function of q . Furthermore, there exists a $\bar{q} \in (0, 1)$ such that $q < \bar{q} \Rightarrow \Delta J < 0$ and $q > \bar{q} \Rightarrow \Delta J > 0$.

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

For $t < \bar{m} < m$, $f(t) > 0$ and $f(m) < 0$. From Equation 17 we can write $\lim_{q \rightarrow 0} \Delta J = f(m) < 0$ and $\lim_{q \rightarrow 1} \Delta J = \frac{1}{1 - r^t} f(t) > 0$. To prove that there exists a unique threshold probability \bar{q} , we are left to show that $\partial \Delta J / \partial q > 0$. After some algebraic manipulation we get $\partial \Delta J / \partial q = \frac{f(t) + f(m)[r^t - 1]}{(1 - qr^t)^2} > 0$. The final inequality follows because $f(t) > 0$, $f(m) < 0$, and $r^t < 1$. QED.

B.2 Maximum Value Extension

In this section we provide an alternative probabilistic structure that shows the robustness of our result. Consider that the two alternative types of innovation can be viewed as draws from an extreme value distribution (Gumbel distribution). The reason for the specific distributional assumption stems from the need to obtain a closed form expression for the distribution of the maximum value (for a more thorough discussion of extreme value theory and the Gumbel distribution see Dahan and Mendelson 2001). Let the expected performance for an m period commitment (considered at $t = 0$) to an NPD program of type d be denoted by J_0^d . If the $F(\cdot)$ are distributed according to a Gumbel distribution, we can state the following:

$$J_0^d = E[\max\{F(\omega_1), \dots, F(\omega_m)\}] = \mu_d + \beta_d \gamma + \beta_d \ln(m) \quad (18)$$

where μ_d represents the *location* parameter of the Gumbel distribution, β_d the *scale* parameter, and γ is the *Euler-Mascheroni* constant.

The NPD program achieves a higher value (on expectation) with each period that passes. It is a straightforward exercise to show that J_0^d is increasing and concave in m . Now, contemplate the equivalence between our theoretical framework and the current structure. For $m = 1$ the result is $J_0^d = \mu_d + \beta_d \gamma$. As before, we assume that incremental innovation delivers higher immediate benefit (similar to our assumption that $-c(d_1) + p(d_1)V(d_1) > -c(d_2) + p(d_2)V(d_2)$). This implies that for $d_1 < d_2$ and $m = 1$ we have $J_0^{d_1} > J_0^{d_2}$. Mathematically, this condition translates to $\mu_{d_1} + \beta_{d_1} \gamma > \mu_{d_2} + \beta_{d_2} \gamma$ for $m = 1$. We assume that variance is higher for the radical innovation efforts because of the widespread search. For the Gumbel distribution this implies that $\beta_{d_2} > \beta_{d_1}$. Under these circumstances we can state the following: *there exists a crossing time, \bar{m} , such that prior to \bar{m} incremental innovation achieves higher expected performance and after \bar{m} radical innovation achieves higher expected performance.*

When NPD program performance is the maximum possible value achieved over a finite horizon (rather than a search for a target value) the intuition is similar to Proposition 1. Note that an underlying assumption here is the independence of the draws, which is consistent with our belief that managers do not have explicit knowledge regarding how the different performance attributes map to the performance function. Still, managers must engage in innovation efforts to improve product performance.

B.3 Multi-Armed Bandit Extension

In this section we provide an alternative formulation of the model. This extension considers a period-by-period decision regarding the type of innovation effort (incremental or radical) to pursue in each period of a finite horizon problem. We will show that the length of the horizon impacts the tradeoff between incremental and radical innovation. Specifically, we will show that for short horizon problems, it does not make sense to pursue radical innovation. Conversely, as the length of the horizon increases, there exists a threshold policy under which radical innovation makes sense. This intuition is similar to the result established in the manuscript.

We build this model using the same definitions established in §4.3 of the thesis. Let

$\hat{V}_i = \hat{V}(d_i)$, $p_i = p(d_i)$, and $c_i = c(d_i)$ for $i = 1, 2$. For any $d_1 < d_2$, recall the following assumptions: $\hat{V}_1 < \hat{V}_2$, $p_1 > p_2$, $c_1 < c_2$, and $p_1\hat{V}_1 > p_2\hat{V}_2$. These assumptions are equivalent to saying that incremental innovation has lower potential value, higher probability of success, and lower cost relative to radical innovation. Also, the expected value of incremental innovation is greater than the expected value of radical innovation ($p_1\hat{V}_1 > p_2\hat{V}_2$). Finally, let $v_1 = -c_1 + p_1\hat{V}_1$ and $v_2 = -c_2 + p_2\hat{V}_2$ be the single period payoff (net of the cost of innovation) for each type of innovative effort. Based on our assumptions, $v_1 > v_2$. Thus, from a standpoint of short term financial metrics, incremental innovation dominates. Consider a firm that attempts to improve product performance over a finite horizon $t = 0, 1, 2, \dots, T$. We can write the firm's decision problem in any period t as:

$$J_t = \max\{v_1 + (1 - p_1)J_{t+1}, v_2 + (1 - p_2)J_{t+1}\} \quad (19)$$

with boundary condition $J_T = 0$. We define a policy as a choice of the type of innovative effort in each period: $\pi = \{k_0^*, k_1^*, k_2^*, \dots, k_{T-1}^*\}$ where $k_t^* \in \{I, R\}$ is the optimal choice between incremental (I) and radical (R) innovation at each decision epoch t .

In the final decision epoch we have $J_{T-1} = \max\{v_1, v_2\}$ and the optimal choice is $k_{T-1}^* = I$. Working backwards, when two periods remain in the decision horizon we have $J_{T-2} = \max\{v_1 + (1 - p_1)v_1, v_2 + (1 - p_2)v_2\}$ and the optimal choice is

$$k_{T-2}^* = \begin{cases} I & \text{if } \frac{v_1 - v_2}{v_1} > p_1 - p_2 \\ R & \text{otherwise} \end{cases} \quad (20)$$

When three periods remain in the decision horizon we have $J_{T-3} = \max\{v_1 + (1 - p_1)J_{T-2}^*, v_2 + (1 - p_2)J_{T-2}^*\}$. Using the information for k_{T-2}^* and k_{T-1}^* the optimal choice at $t = T - 3$ is

$$k_{T-3}^* = \begin{cases} I & \text{if } \frac{v_1 - v_2}{J_{T-2}^*} > p_1 - p_2 \\ R & \text{otherwise} \end{cases} \quad (21)$$

Of the potential sub-policies for the final three decision epochs, we will show that $\{I, R, I\}$ is not a feasible policy. The intuition behind our analysis is that there exists one and only one switch between radical and incremental innovation (once incremental innovation is chosen, it is chosen for the remainder of the horizon). The following condition

is necessary for $\{I, R, I\}$ to be a feasible policy:

$$\frac{v_1 - v_2}{v_2 + (1 - p_2)v_1} > p_1 - p_2 > \frac{v_1 - v_2}{v_1} \quad (22)$$

The left inequality establishes the optimal choice of incremental innovation in period $T - 3$ and the right inequality establishes the optimality condition for $\{k_{T-2}^*, k_{T-1}^*\} = \{R, I\}$. Based on this we can write:

$$\begin{aligned} v_1 - v_2 &> (p_1 - p_2)[v_2 + (1 - p_2)v_1] \\ &> (p_1 - p_2)[v_1 + (1 - p_1)v_1] \\ &= v_1(p_1 - p_2)[1 + (1 - p_1)] \\ &> (v_1 - v_2)[1 + (1 - p_1)] \end{aligned} \quad (23)$$

The final inequality in Equation 23 is a contradiction because $[1 + (1 - p_1)] > 1$. Thus, the sub-policy $\{k_{T-3}^*, k_{T-2}^*, k_{T-1}^*\} = \{I, R, I\}$ is not feasible. Therefore, the only sub-policies that are feasible for the final three decision epochs are $\{I, I, I\}$, $\{R, I, I\}$, and $\{R, R, I\}$. This logic can be repeated for each preceding decision epoch. We state the conditions for a threshold policy in the following Claim.

Claim. There exists a period m after which incremental innovation is always chosen. If $1 + (1 - p_1) + \dots + (1 - p_1)^{m-2} > (v_1 - v_2)/(p_1 - p_2)$, radical innovation is chosen in every period until period m .

Proof of Claim The proof is by induction on m . Assume that $k_{T-m}^* = I$ if $(v_1 - v_2) > [1 + (1 - p_1) + \dots + (1 - p_1)^{m-2}](p_1 - p_2)$ and $k_{T-m+1}^* = I$. We will show that $k_{T-m-1}^* = I$ if $(v_1 - v_2) > [1 + (1 - p_1) + \dots + (1 - p_1)^{m-1}](p_1 - p_2)$. The value function for $t = T - m - 1$ is $J_{T-m-1} = \max\{v_1 + (1 - p_1)J_{T-m}^*, v_2 + (1 - p_2)J_{T-m}^*\}$. This results in

$$k_{T-m-1}^* = \begin{cases} I & \text{if } \frac{v_1 - v_2}{J_{T-m}^*} > p_1 - p_2 \\ R & \text{otherwise} \end{cases} \quad (24)$$

The proof that $k_{T-m-1}^* = I$ if $k_{T-m}^* = I$ and $1 + (1 - p_1) + \dots + (1 - p_1)^{m-1} < (v_1 - v_2)/(p_1 - p_2)$ is straightforward. If instead $k_{T-m}^* = R$ then we have $v_1 + (1 - p_1)J_{T-m}^* > v_2 + (1 - p_2)J_{T-m}^*$. However, an alternate policy would imply $J_{T-m}^* > v_1[1 + (1 - p_1) + \dots + (1 - p_1)^{m-2}]$ and we obtain a contradiction as in Equation 23. QED.

B.4 Simulation Experimental Design

Figure 27 shows the parameters and value used for the simulation experiments in §4.5. The choice of $N = 15$ and $S = 2$ define the size of the technology/market landscape. Because our interest lies in understanding complexity in terms of performance interactions rather than size, we have limited these variables to static values. This assumption is in line with other work in complex performance landscapes and it does not alter the qualitative results of our study. The contribution of each attribute to overall product performance is $U(0, 1)$ to account for the fact that managers cannot infer the performance function. Research on complex performance landscapes has shown that the landscape structure is robust with respect to the choice of distribution for the f_j . In particular, the landscape structure is similar if $f_j \sim N(\mu, \sigma^2)$ or $f_j \sim \exp(\lambda)$. Our full experimental design varies K , d , and s as shown in Figure 27. This results in $15 \times 15 \times 27 = 6075$ experiments. In order to conserve space in the manuscript we cannot show the results for every combination of K , d , and s . Instead, we show results that highlight robust phenomena. A complete data set is available from the author by request.

Parameter and Value	Description
$N = 15$	Number of attributes per product
$S = 2$	Number of states per attribute
$f_j \sim U(0, 1)$	Contribution of each attribute to overall product performance
$K \in \{0, 1, 2, \dots, N - 1\}$	Number of interactions between product attributes
$d \in \{1, 2, \dots, N\}$	Search distance for NPD programs
$s \in \{1.000, 0.9990, 0.9980, \dots, 0.9750\}$	Environmental stability (with probability $1-s$ a disruption will occur in each period)

Figure 27: Parameters and values used for the simulation experiments.

Because our analysis is focused on dynamic phenomena, the standard error for NPD program performance is a function of time. Thus, we provide bounds for the standard error. In our case, $\hat{\sigma}^2 \in (0, 0.004)$ and $n = 500$. This gives a standard error of $SE \in (0, 0.00283)$. In the worst case situation, this results in a 99.0% confidence interval for NPD program performance. In many cases, the confidence interval approaches 99.9% and theoretically, the confidence interval approaches 100% for a number of experiments.

Note that our simulation analysis results in NPD program performance curves that are increasing and concave in time and we do not optimize with respect to commitment time. Assuming that the per-period cost of innovation is constant, such an optimization would result in an optimum commitment time for each type of innovative effort (increasing and concave performance and linear cumulative cost). If the crossing time between incremental and radical NPD program performance occurs before the minimum optimal commitment time, our insights are valid. If the crossing time occurs after the optimal commitment times the problem becomes very complex as a function of the costs. Figure 28 depicts NPD program performance net of per period costs in an environment where $K = 4$ (the dashed line begins at the optimal commitment time). Despite the fact that $K = 4$ in both graphs, the difference in costs results in a different crossing time. Still, we feel that our insights regarding performance (revenue) are robust and contribute to the understanding of how value is created by NPD programs.

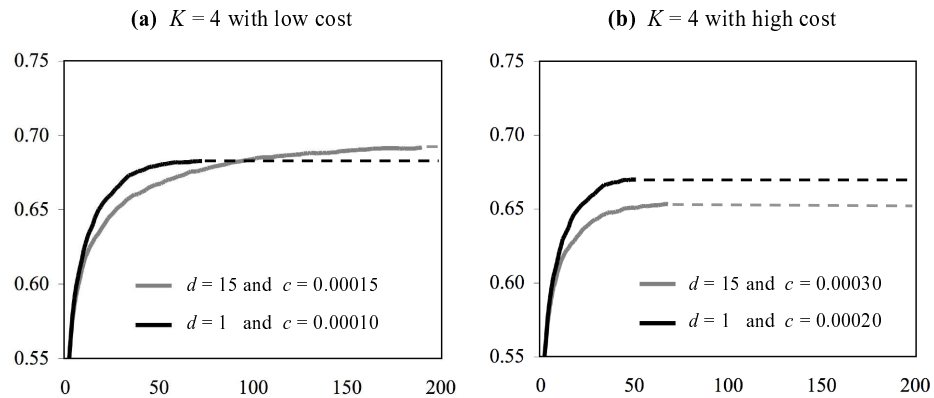


Figure 28: NPD Program performance net of per period costs.

APPENDIX C

In C.1 we provide proofs for Propositions 1-7 and in C.2 we provide details of the experimental design for the numerical analysis. We restate equations from the chapter when necessary to ease exposition.

C.1 Proofs

Each organization design mechanism π_i defines a different structure for the problem stated in equation xxxx on page xxxx of the text. The problem is solved using optimal control theory (Kamien and Schwartz 1991, Sethi and Thompson 2000). Below we state the the Hamiltonian (H) and salvage value function (Φ) for each organization design mechanism.

$$\begin{aligned} \pi_{LOW} : \quad H &= R - C_1 - C_2 + C_3 + \lambda_1 p_1 + \lambda_2(1 - \alpha)p_2 + \lambda_3(B - C_1 - C_2) \quad (25) \\ \Phi &= V_1 + V_2 + Z(T) \end{aligned}$$

$$\begin{aligned} \pi_{M1} : \quad H &= R - C_1 - C_2 + C_3 + \lambda_1 p_1 + \lambda_2(1 - \alpha)p_2 + \lambda_3(\beta R - C_1 - C_2) \quad (26) \\ \Phi &= V_1 + V_2 + Z(T) \end{aligned}$$

$$\begin{aligned} \pi_{M2} : \quad H &= R - C_1 - C_2 + \lambda_1 p_1 + \lambda_2(1 - \alpha)p_2 + \lambda_3(B - C_1 - C_2) \quad (27) \\ \Phi &= V_1 + V_2 + Z(T) + C_3[Z(T)] \end{aligned}$$

$$\begin{aligned} \pi_{HIGH} : \quad H &= R - C_1 - C_2 + \lambda_1 p_1 + \lambda_2(1 - \alpha)p_2 + \lambda_3(\beta R - C_1 - C_2) \quad (28) \\ \Phi &= V_1 + V_2 + Z(T) + C_3[Z(T)] \end{aligned}$$

The necessary conditions for optimality are:

$$\frac{\partial H}{\partial p_1} = 0 \quad (29)$$

$$\frac{\partial H}{\partial p_2} = 0 \quad (30)$$

$$\dot{\lambda}_1 = -\frac{\partial H}{\partial P_1} \quad \text{and} \quad \lambda_1(T) = \frac{\partial \Phi}{\partial P_1} \quad (31)$$

$$\dot{\lambda}_2 = -\frac{\partial H}{\partial P_2} \quad \text{and} \quad \lambda_2(T) = \frac{\partial \Phi}{\partial P_2} \quad (32)$$

$$\dot{\lambda}_3 = -\frac{\partial H}{\partial Z} \quad \text{and} \quad \lambda_3(T) = \frac{\partial \Phi}{\partial Z} \quad (33)$$

$$H(T) + \frac{\partial \Phi}{\partial T} = 0 \quad (34)$$

Equations 29 and 30 are the necessary first-order conditions for the decision variables p_1^* and p_2^* respectively. Equations 31, 32, and 33 are the necessary conditions for the co-state variables (marginal value functions for P_1 , P_2 , and Z respectively). Finally, equation 34 is the necessary transversality condition for T^* (the optimal new product launch date), which is stated in general form here. For the sake of brevity, we do not restate the state equations, which also form part of the necessary conditions.

Proof of Proposition 1. We begin with a proof of part (iii) of Proposition 1. For π_{LOW} and π_{M1} , Equation 33 gives $\lambda_3(T) = 1$ and $\dot{\lambda}_3 = -\partial C_3/\partial Z < 0 \Rightarrow \lambda_3 = 1 + \int_t^T (\partial C_3/\partial Z) dx > 0$. For π_{HIGH} and π_{M2} , Equation 33 gives $\lambda_3(T) = 1 + \partial C_3/\partial Z$ and $\dot{\lambda}_3 = 0 \Rightarrow \lambda_3 = 1 + \partial C_3/\partial Z > 0$. For part (i) of Proposition 1, we provide a proof for π_{M1} (proofs for the other organization design mechanisms follow the same reasoning). For π_{M1} , equation 31 gives $\lambda_1(T) = \partial V_1/\partial P_1 > 0$ and $\dot{\lambda}_1 = -\frac{\partial R}{\partial P_1}[1 + \beta\lambda_3] < 0 \Rightarrow \lambda_1(t) = \partial V_1/\partial P_1 + \int_t^T \frac{\partial R}{\partial P_1}[1 + \beta\lambda_3] dx > 0$. For part (ii) of Proposition 1, note that for any organization design mechanism, π_i , Equation 32 gives $\dot{\lambda}_2 = 0$ and $\lambda_2(T) = \frac{\partial V_2}{\partial P_2} > 0 \Rightarrow \lambda_2(t) = \frac{\partial V_2}{\partial P_2} > 0$. QED.

Proof of Proposition 2. From Equation 29, the necessary condition for p_1^* is $\partial C_1/\partial p_1 = \lambda_1/(1 + \lambda_3)$. Let $f_1(p_1) = \partial C_1/\partial p_1$. Then, by the implicit function theorem: $dp_1/dt = [\partial f_1/\partial p_1]^{-1}[-\lambda_1\dot{\lambda}_3/(1 + \lambda_3)^2 + \dot{\lambda}_1/(1 + \lambda_3)]$ where $\partial f_1/\partial p_1 = \partial^2 C_1/\partial p_1^2 > 0$. To prove part (i) of Proposition 2, note that for π_{HIGH} and π_{M2} , $\dot{\lambda}_3 = 0$, $\lambda_3 > 0$, and $\dot{\lambda}_1 < 0 \Rightarrow dp_1/dt < 0$. To see that p_1^* is convex for π_{HIGH} and π_{M2} , note that $d^2 p_1/dt^2 =$

$[\partial f_1/\partial p_1]^{-1}[\ddot{\lambda}_1/(1+\lambda_3)] > 0$ where the final inequality follows from the fact that $\ddot{\lambda}_1 = -(1+\beta\lambda_3)[(\partial g/\partial P_1)(dP_1/dt) + \partial g/\partial t] > 0$ for π_{HIGH} and $\ddot{\lambda}_1 = -[(\partial g/\partial P_1)(dP_1/dt) + \partial g/\partial t] > 0$ for π_{M2} where $g[P_1(t), t] = \partial R/\partial P_1$. Part (ii) of Proposition 2 follows the same reasoning and the conclusion is that p_1^* is convex-decreasing if $E_{\lambda_1} = \dot{\lambda}_1\lambda_3/\dot{\lambda}_3\lambda_1 > 1$ and p_1^* is convex-increasing if $E_{\lambda_1} = \dot{\lambda}_1\lambda_3/\dot{\lambda}_3\lambda_1 < 1$. Part (iii) of Proposition 2 follows from Equation 30. The necessary condition for p_2^* is $\partial C_2/\partial p_2 = \lambda_2(1-\alpha)/(1+\lambda_3)$. Let $f_2(p_2) = \partial C_2/\partial p_2$. Note that $\partial f_2/\partial p_2 = \partial^2 C_2/\partial p_2^2 > 0$ because C_2 is convex-increasing. Again, by the implicit function theorem: $dp_2/dt = [\partial f_2/\partial p_2]^{-1}[-\lambda_2(1-\alpha)\dot{\lambda}_3/(1+\lambda_3)^2 - \lambda_2\dot{\alpha}/(1+\lambda_3)] > 0$. Careful examination of dp_2/dt shows that for any organization design mechanism, $dp_2/dt > 0$. QED.

Proof of Proposition 3. At any time t during the development cycle, Equation 29 gives $p_1^* = f_1^{-1}[\lambda_1/(1+\lambda_3)]$ where $f(p_1) = \partial C_1/\partial p_1$. Note that $f_1^{-1}(\cdot)$ is an increasing function of its argument given our assumption that $C_1[p_1(t)]$ is convex-increasing in $p_1(t)$. We prove each part of Proposition 3 in succession: (i) $\partial p_1^*/\partial \bar{c}_1 < 0$ where $\bar{c}_1 = \partial^2 C_1/\partial p_1^2$. This follows directly from the definition of $f_1(\cdot)$. (ii) $\partial p_1^*/\partial \bar{r} = (\partial \lambda_1/\partial \bar{r})(1+\lambda_3)^{-1} > 0$ where $\bar{r} = \partial R/\partial P_1$. (iii) $\partial p_1^*/\partial \delta_R = (\partial \lambda_1/\partial \delta_R)(1+\lambda_3)^{-1} < 0$ where $\delta_R = \partial R/\partial t$. (iv) $\partial p_1^*/\partial \bar{v}_1 = (\partial \lambda_1/\partial \bar{v}_1)(1+\lambda_3)^{-1} > 0$ where $\bar{v}_1 = \partial V_1/\partial P_1$. (v) $\partial p_1^*/\partial \delta_{V1} = (\partial \lambda_1/\partial \delta_{V1})(1+\lambda_3)^{-1} < 0$ where $\delta_{V1} = \partial V_1/\partial T$. (vi) $\partial p_1^*/\partial \beta = (\partial \lambda_1/\partial \beta)(1+\lambda_3)^{-1} > 0$. (vii) For organization design mechanisms π_{LOW} and π_{M2} , $\partial p_1^*/\partial C_3 = -\lambda_1(1+\lambda_3)^{-2}(\partial \lambda_3/\partial \bar{c}_3) < 0$ where $\bar{c}_3 = \partial C_3/\partial Z$. For organization design mechanisms π_{HIGH} and π_{M1} :

$$\partial p_1^*/\partial \bar{c}_3 = \frac{-\lambda_1\partial \lambda_3/\partial \bar{c}_3 + (1+\lambda_3)\partial \lambda_1/\partial \bar{c}_3}{(1+\lambda_3)^2} \quad (35)$$

The fact that the numerator of 35 may be positive or negative leads to the existence of threshold times t_{HIGH}^c and t_{M1}^c . A relationship between the threshold times can be established by noting the effects of a unit increase in \bar{c}_3 . For π_{HIGH} a unit increase in \bar{c}_3 implies that the numerator of Equation 35 is $-\lambda_1 + (1+\lambda_3)\beta \int_t^T \bar{r} dx$. A little algebra leads to the following condition: $\partial p_1^*/\partial \bar{c}_3 > 0$ if $\beta \int_t^T \bar{r} dx / (\partial C_1/\partial p_1^*) > 1$. For π_{M1} the same reasoning leads to the following condition: $\partial p_1^*/\partial \bar{c}_3 > 0$ if $\beta \int_t^T \bar{r}(T-x)(T-t)^{-1} dx / (\partial C_1/\partial p_1^*) > 1$. Both of these expressions represent a trade off for $Z(T)$ in terms of instantaneous cost of effort p_1^* versus the ability of that effort to create NPD budget over the remainder of the

development cycle. To see that $t_{HIGH}^c \geq t_{M1}^c$ note that $(T-x)(T-t)^{-1} \leq 1$. Therefore, for a given p_1^* , the inequality for π_{M1} would become equality at a smaller value of t , which leads us to $t_{HIGH}^c \geq t_{M1}^c$. QED.

Proof of Proposition 4. The proof for Proposition 4 follows exactly the same reasoning as that of Proposition 3. To conserve space, we omit the proof for Proposition 4.

Proof of Proposition 5. Recall that we define a crossing time, t^* , as the time during the development cycle when $p_1^* = p_2^*$. In what follows we have assumed a quadratic cost functional for $C_1[p_1(t)]$ and $C_2[p_2(t)]$. The proof for general convex-increasing cost functions follows the same reasoning but is more tedious. From Equations 29 and 30, $p_1^* = \lambda_1/\bar{c}_1(1 + \lambda_3)$ and $p_2^* = \lambda_2(1 - \alpha)/\bar{c}_1(1 + \lambda_3)$ where $\bar{c}_1 = \partial^2 C_1/\partial p_1^2$ and $\bar{c}_2 = \partial^2 C_2/\partial p_2^2$. We can then write $p_1^* = p_2^*$ for each organization design mechanism and t_i^* is defined implicitly as follows:

$$\pi_{LOW} : \int_{t_{LOW}^*}^T \bar{r} dx = \bar{c}_1 \bar{v}_2 (1 - \alpha) / \bar{c}_2 - \bar{v}_1 \quad (36)$$

$$\pi_{M1} : \int_{t_{M1}^*}^T \bar{r} \left[1 + \beta \int_x^T \frac{\partial C_3}{\partial Z} d\tau \right] dx = \bar{c}_1 \bar{v}_2 (1 - \alpha) / \bar{c}_2 - \bar{v}_1 \quad (37)$$

$$\pi_{M2} : \int_{t_{M2}^*}^T \bar{r} dx = \bar{c}_1 \bar{v}_2 (1 - \alpha) / \bar{c}_2 - \bar{v}_1 \quad (38)$$

$$\pi_{HIGH} : \int_{t_{HIGH}^*}^T \bar{r} \left[1 + \beta \frac{\partial C_3}{\partial Z} \right] dx = \bar{c}_1 \bar{v}_2 (1 - \alpha) / \bar{c}_2 - \bar{v}_1 \quad (39)$$

Where $\bar{r} = \partial R/\partial P_1$, $\bar{v}_1 = \partial V_1/\partial P_1$, and $\bar{v}_2 = \partial V_2/\partial P_2$. Note that the right hand sides of Equations 36 - 39 are equal. Therefore, it suffices to compare the integrand for each expression to determine the relative order of the crossing times. For π_{LOW} and π_{M2} the integrands are equal and $t_{LOW}^* = t_{M2}^*$ to ensure that the right hand sides remain equal. For π_{HIGH} and π_{M1} , there is an additional non-negative term inside the integrand, which implies that $t_{LOW}^* = t_{M2}^* \leq t_{HIGH}^*$ and $t_{LOW}^* = t_{M2}^* \leq t_{M1}^*$ to ensure that the right hand sides remain equal.

In order to compare t_{HIGH}^* and t_{M1}^* we make the additional assumption that $C_3[Z(T)] = \bar{c}_3 Z(T)$ for π_{HIGH} and $C_3[Z(T)] = (\bar{c}_3/T)Z(t)$ for π_{M1} . Under these assumptions of linear $C_3(\cdot)$, the left hand side of Equation 37 reduces to $\int_{t_{M1}^*}^T \bar{r} [1 + \beta \bar{c}_3 (T - x) T^{-1} \frac{T-x}{T}] dx$ and

the left hand side of Equation 39 reduces to $\int_{t_{HIGH}^*}^T \bar{r}[1 + \beta\bar{c}_3]dx$. Since $(T - x)/T \leq 1$ we can conclude that $t_{M1}^* \leq t_{HIGH}^*$ to ensure that the right hand sides remain equal. QED.

Proof of Proposition 6. The proof for Proposition 6 relies on the assumption of a linear functional form for $C_3(\cdot)$. In particular, we let $C_3[Z(T)] = \bar{c}_3 Z(T)$ and $C_3[Z(t)] = (\bar{c}_3/T)Z(t)$. Note that we scale the cost parameter \bar{c}_3 to account for the length of the development cycle. This ensures that any difference in p_1^* across organization design mechanisms is due to the method of control rather than the absolute cost of control. Given the form of $C_3(\cdot)$, we can write p_1^* for each organization design mechanism as follows:

$$\pi_{LOW} : p_1^* = \frac{\bar{v}_1 + \int_t^T \bar{r}dx}{\bar{c}_1[2 + \bar{c}_3(T - t)/T]} \quad (40)$$

$$\pi_{M1} : p_1^* = \frac{\bar{v}_1 + \int_t^T \bar{r}[1 + \beta(1 + \bar{c}_3(T - t)/T)]dx}{\bar{c}_1[2 + \bar{c}_3(T - t)/T]} \quad (41)$$

$$\pi_{M2} : p_1^* = \frac{\bar{v}_1 + \int_t^T \bar{r}dx}{\bar{c}_1[2 + \bar{c}_3]} \quad (42)$$

$$\pi_{HIGH} : p_1^* = \frac{\bar{v}_1 + \int_t^T \bar{r}[1 + \beta(1 + \bar{c}_3)]dx}{\bar{c}_1[2 + \bar{c}_3]} \quad (43)$$

Where $\bar{r} = \partial R/\partial P_1$, $\bar{v}_1 = \partial V_1/\partial P_1$, $\bar{c}_1 = \partial^2 C_1/\partial p_1^2$, and $\bar{c}_3 = \partial C_3/\partial Z$. Let $p_{1,i}^*$ denote the optimal rate of effort towards improving the existing product under design mechanism π_i . Comparing these expressions at $t = 0$ it is apparent that $p_{1,LOW}^* = p_{1,M2}^* < p_{1,M1}^* < p_{1,HIGH}^*$. Likewise comparing the expressions at $t = T$ it is apparent that $p_{1,LOW}^* = p_{1,M1}^*$ and $p_{1,HIGH}^* = p_{1,M2}^*$. For $t \in (0, T)$, we have $p_{1,M2}^* = p_{1,LOW}^*$ because the numerators for these expressions are equal and $\bar{c}_1[2 + \bar{c}_3] > \bar{c}_1[2 + \bar{c}_3(T - t)/T]$. Similarly, for $t \in (0, T)$ $p_{1,LOW}^* < p_{1,M1}^*$ because the denominators for these expressions are equal and $\beta[1 + \bar{c}_3(T - t)/T] > 0$. QED.

Proof of Proposition 7. The proof for Proposition 7 relies on the assumption of a linear functional form for $C_3(\cdot)$. As before, we let $C_3[Z(T)] = \bar{c}_3 Z(T)$ and $C_3[Z(t)] = (\bar{c}_3/T)Z(t)$. Note that we scale the cost parameter \bar{c}_3 to account for the length of the development cycle. This ensures that any difference in p_2^* across organization design mechanisms is due to the method of control rather than the absolute cost of control. Given the form of $C_3(\cdot)$, we can

write p_2^* for each organization design mechanism as follows:

$$\pi_{LOW} : p_2^* = \frac{\bar{v}_2(1 - \alpha)}{\bar{c}_2[2 + \bar{c}_3(T - t)/T]} \quad (44)$$

$$\pi_{M1} : p_2^* = \frac{\bar{v}_2(1 - \alpha)}{\bar{c}_2[2 + \bar{c}_3(T - t)/T]} \quad (45)$$

$$\pi_{M2} : p_2^* = \frac{\bar{v}_2(1 - \alpha)}{\bar{c}_2[2 + \bar{c}_3]} \quad (46)$$

$$\pi_{HIGH} : p_2^* = \frac{\bar{v}_2(1 - \alpha)}{\bar{c}_2[2 + \bar{c}_3]} \quad (47)$$

Where $\bar{v}_2 = \partial V_2 / \partial P_2$, $\bar{c}_2 = \partial^2 C_2 / \partial p_2^2$, and $\bar{c}_3 = \partial C_3 / \partial Z$. Let $p_{2,i}^*$ denote the optimal rate of effort towards developing the new product under design mechanism π_i . Comparing these expressions at $t = 0$ it is apparent that $p_{2,LOW}^* = p_{2,M1}^* = p_{2,M2}^* = p_{2,HIGH}^*$. Furthermore, for $t \in (0, T]$ we have $p_{2,LOW}^* = p_{2,M1}^* > p_{2,M2}^* = p_{2,HIGH}^*$ because $(T - t)/T < 1$ for all $t \in (0, T]$. QED.

C.2 Numerical Analysis and Experimental Design

A complete experimental design is provided below. The functional forms employed in the numerical analysis are as follows:

$$R[P_1(t), t] = \frac{\bar{r}P_1(t)}{1 + \bar{\delta}_R t} \quad \alpha(t) = \frac{1}{1 + \bar{\alpha}t} \quad C_1[p_1(t)] = \frac{1}{2}\bar{c}_1 p_1^2(t) \quad C_2[p_2(t)] = \frac{1}{2}\bar{c}_2 p_2^2(t)$$

$$C_3(\cdot) = \bar{c}_3[1 - \exp(-\bar{c}_3 Z(t))] \text{ for } \pi_{LOW} \text{ and } \pi_{M1}$$

$$C_3(\cdot) = \bar{c}_3 T[1 - \exp(-\bar{c}_3 Z(T))] \text{ for } \pi_{M2} \text{ and } \pi_{HIGH}$$

$$V_1[P_1(T), T] = \frac{\bar{v}_1 P_1(T)}{1 + \bar{\delta}_{V1} T} \quad V_2[P_2(T), T] = \frac{\bar{v}_2 P_2(T)}{1 + \bar{\delta}_{V2} T}$$

The parameter values for the base case experiment are as follows:

$$\begin{aligned} \bar{r} &= 0.025 & \bar{\delta}_R &= 0.03 & \bar{\alpha} &= 0.10 & \bar{c}_1 &= 1.25 & \bar{c}_2 &= 1.50 & \bar{c}_3 &= 0.05 \\ B_{LOW} &= 0.025 & \beta_{M1} &= 0.10 & B_{M2} &= 0.025 & \beta_{HIGH} &= 0.10 & \bar{v}_1 &= 1.0 \\ \bar{v}_2 &= 4.0 & \bar{\delta}_{V1} &= 0.03 & \bar{\delta}_{V2} &= 0.03 & P_1(0) &= 10 & P_2(0) &= 0 & Z(0) &= 0 \end{aligned}$$

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