THREE ESSAYS ON THE ROLE OF INFORMATION STRUCTURES ON NEW PRODUCT DEVELOPMENT STRATEGIES

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THREE ESSAYS ON THE ROLE OF INFORMATION STRUCTURES ON NEW PRODUCT DEVELOPMENT STRATEGIES

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To my parents Konstantinos and Sophia

and my brother Andreas.

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SUMMARY

The new product development (NPD) process has been long conceptualized as an intense information processing task, yet several questions about the role of information in shaping NPD decisions remain open. For instance, the persistent representation of NPD decisions as a single decision-maker outcome in existing theory; it limits our understanding of decisions that involve multiple and heterogeneous organizational stakeholders (persons or units), and it appears distant from the managerial realities. This dissertation focuses on managerial decisions where information acquisition, ownership and interpretation exhibit heterogeneity. The first essay (Chapter 2) examines the role of informational asymmetries (e.g., varying degrees of uncertainty) that competing firms face when investing in R&D. The study underlines the strong path dependency that informational spillovers cause to R&D decisions. The second essay (Chapter 3) reveals the detrimental effects of interpretive diversity (i.e., different people may interpret differently the same information) on project termination decisions. Interestingly, the detrimental impact of such interpretive diversity is higher when the project progress information is deemed to be, on average, reliable by the team members. The third essay (Chapter 4) examines how consumers' information regarding future market conditions can affect a firm's strategy on striking a balance between its primary and secondary markets. The analysis shows that, in the presence of such information, seemingly competing companies (e.g., an Original Equipment Manufacturer and a third-party entrant) could develop synergies that benefit both of them.

CHAPTER I

INTRODUCTION

Information economics has had a tremendous impact on economic theory and policy. As Stiglitz (2002, p.461) highlights: "even a small amount of information imperfection could have a profound effect on the nature of the market equilibrium". To date, the literature on new product development provides us with a good understanding regarding the different sources of uncertainty (e.g., technical or market) and potential sources of information that could mitigate such risks (e.g., testing and prototypes, focus groups, lead users). In the majority of these studies, however, the analysis implicitly assumes a single-decision maker setting. For instance, in models of optimal project termination times, the decision is based on a single objective function. Yet, in reality, such decisions are taken by cross-functional team whose members rarely have the same perception regarding the project progress. Such information asymmetries are emerging as a very promising field in NPD (Sosa et al. 2004, Mihm et al. 2003). In addition, very few studies have examined how information asymmetries across firms affect their R&D search strategies. This dissertation focuses on managerial decisions where information acquisition, ownership and interpretation exhibit heterogeneity.

The first essay, presented in Chapter 2, examines the role of informational asymmetries (e.g. varying degrees of uncertainty) that competing firms face when investing in R&D. Such informational asymmetries are generated in collaborative R&D environments where knowledge disseminates across the various member firms. Consider the case of the Georgia Electronic Design Center (GEDC), a leading university research center at Georgia Tech. A major objective of the center has been to showcase existing technological developments generated from recent research projects. Through those exhibition fairs, formally called industry review, firms gain a better understanding of the underlying technological potential of different scientific domains. Thus, although the pioneering firm faces a considerable amount of uncertainty, follower firms (potentially competitors) obtain additional information and therefore could make a more informed decision about their future investments.

Such information is critical for the member firms because it is often used to direct their future R&D investments. According to our field study, senior R&D executives and research scientists attend presentations and prototype exhibitions that facilitate the identification of areas for future investments. Benefiting from this information though is not straightforward. R&D managers who observe past outcomes realized by a rival's R&D projects need to address the following question: should future R&D focus on the domain already explored by rivals or should it pursue unexplored scientific domains?

The study presented in Chapter 2 develops a model that views R&D as a process of iterative exploration trials for new technological improvements that may emerge from the same or different scientific domains. Firms compete within similar market segments and therefore they need to account for strategic interactions when assessing the direction of their R&D efforts. Our analysis shows that the R&D search choices are strongly path dependent, and that future decisions rely on a threshold policy. Major technological breakthroughs prompt search within the same scientific domain, a herding-like behavior. Yet, moderately significant improvements (i.e. the case in most of the projects in mature fields of engineering) may direct firms to explore new areas. The study further explores the properties of the threshold policy with respect to the structure of the technological landscape and the parameters of commercialization. A limited ability to infer the remaining potential of a scientific domain from past outcomes prompts firms to diversify their R&D efforts. At the same time, an increased ability to learn from different scientific domains due to strong similarities in their underlying knowledge base renders diversification preferable.

The third Chapter looks at information asymmetries within a new product development team. Consider one of the most challenging decisions that NPD teams are faced with: the decision on whether to continue or terminate an underperforming project. A vast literature has examined the rich mathematical properties of optimal stopping problems (typically formulated as dynamic programming models) as well as the role of different types of uncertainty (market payoff, technical performance, budget variability). While those studies have enriched our understanding about the structure of the problem, it is still remains hard to implement them in practice. While there are many reasons as to why a theoretical model could not be applied to practice, in the case of optimal termination decisions, a fundamental one seems to be the mere fact that different people may have a very different understanding of what constitutes negative information. Numerous case studies have shown that the same information (e.g., the most recent market research report) is interpreted entirely differently by different team members (e.g., an engineer versus a marketer).

The study presented in Chapter 3 develops a theoretical model to understand how such an interpretive diversity affects project termination decisions. The study builds a model around the concept of information *fidelity*, i.e. the degree of accuracy that the decision-maker assigns to the new information. We account for the potential interpretive diversity across team members by allowing each team member to assign his/her own fidelity on the incoming information. Then, I examine the stopping behavior of different team structures (e.g., light-weight versus heavy-weight project manager team). Our analysis reveals the complex role of diversity. Depending on the underlying project uncertainty, diversity might either become a source of conservatism, causing the team to stop projects earlier than necessary, or a source of escalation, leading to costly delays in project termination decisions. Thus, the existence of distinct "thought worlds" within an organization gives rise to systematic biases, even when the decision-makers are perfectly rational. Our results are robust across different team hierarchical structures, and they are magnified in the presence of social conformity. Interestingly, seemingly opposing managerial strategies, namely the diversification of the team composition and the pressure to conform to a target, may complement each other in amplifying escalation phenomena.

Chapter 4 takes an entirely different perspective on the information structure by focusing on the information that consumers have regarding a firm's future strategy. The study was motivated by discussions with managers from a global supplier of refurbished Information Technology (IT) equipment (e.g., servers, networking, IP telephony). The profitability, and often the viability, of such companies are strongly affected by the policies imposed by the Original Equipment Manufacturers (OEMs) such as IBM, Sun, and HP. One would expect that such OEMs would have similar strategies on how they balance their primary markets (i.e., markets for their new products) and secondary markets (i.e., markets where refurbished equipment is traded). In practice, however, we observe radically different strategies. Some OEMs are actively supporting the existence of IT refurbishers while others are, even more actively, trying to eliminate them. The theoretical model studies the drivers behind those diametrically opposite strategies. One of the key findings is that consumers' awareness of the potential resale value has significant implications for the OEM's strategy. Such strategic information is deemed highly critical. In fact, there exist a large number of industry analyst firms who specialize in forecasting the resale value of IT equipment and who offer comprehensive cost/benefit analyses over the life cycle of the IT equipment.

CHAPTER II

THE ROLE OF INFORMATIONAL SPILLOVERS ON COMPETITIVE R&D SEARCH

2.1 Introduction

Few topics have received as much attention, from academics and practitioners alike, as the management of innovation. Although early studies center on issues of timing (for a review see Reinganum 1989), more recent studies argue that assimilating new information and, more importantly, interpreting it correctly, plays a key role on the success of innovation efforts.[1]

Early on, economists identify knowledge spillovers as a critical determinant of R&D investments (Arrow 1962). More recently, Romer (1990) characterizes such spillovers as a central driver of economic growth. Several empirical studies (Griliches 1979, 1992, Jaffe 1986) demonstrate the existence and beneficial role of such information dissemination and cross-pollination mechanisms, while others examine how they shape the incentives to innovate (for a review see Veugelers 1998). However, the majority of these studies focuses on only one dimension of innovative activity: the total amount of resources invested in R&D (i.e., the R&D intensity). As a result, we know very little about the operational implications of informational spillovers on the *direction* of R&D efforts.

Motivating example: the Georgia Electronic Design Center (GEDC)

The following example describes a mechanism through which informational spillovers are generated and illustrates their importance in shaping future R&D decisions. The

[1] DeBondt (1997) highlights the relevance: *"The challenge may not always be to be among the first to produce the new information, but may instead be how to recognize, obtain, employ and complement the relevant innovative information."* (DeBondt (1997), p.2)

Georgia Electronic Design Center (GEDC) was established by the State of Georgia and the Georgia Institute of Technology in 2002 to develop and test advanced new technologies that enhance the performance of microelectronics devices, such as Micro-Electro-Mechanical Systems (MEMS). Research is conducted across several technological domains of specialization, such as Wireless Sensors, Cognitive Radio, Agile Optical/Photonic, Multi-Gigabit Wireless, and has led to several break-through technologies.[2]

Like most university research centers of this type, GEDC draws the largest amount of funding from close collaborations with industry partners. Member companies include prominent high-tech industry players, such as Intel, AMD, Microsoft, Samsung, Nokia, etc. Companies typically initiate Directed Research (DR) projects that involve a respectable amount of investment. These projects rest upon exclusive licensing and detailed legal contracts that determine the ownership of the intellectual property (IP) (Thursby and Thursby 2003).

An event of particular interest for our study is the GEDC *industry review*. During this biannual event, member companies are invited to view the progress of the center across the different scientific domains. Senior R&D executives and research scientists attend presentations and prototype exhibitions that present findings from recent DR projects. Thus, although the sponsor firm holds the IP rights of the specific technology developed, other members of GEDC can still observe the technology and interpret it as a signal for the potential of a scientific domain. In fact, those prototype exhibitions can be very influential for the member firms since most of the new DR initiatives emerge from the discussions that take place during the industry review.

The GEDC's modus operandi is not unique. In fact, the majority of university

[2]A GEDC team recently established a new world record for the highest data rate transmitted wirelessly at 60GHz.

research centers seems to operate under similar "business models" for technology development and transfer. As Corey (1997) points out "[consortium] members may choose from the consortium's bundle of product offerings those that meet their particular needs. They have the option of allocating their annual fees to particular R&D areas and forgoing participation in others" (Corey 1997, p.85).

The GEDC example highlights a robust feature of modern R&D strategies. Firms seem to hold a steady presence in several university research centers, to achieve a two-fold objective: i) To mitigate the significant risks and expenditures associated with research through collaborative or targeted funding efforts; and (ii) To ensure access to state-of-the-art technological trends when planning their future R&D efforts. An extensive literature in economics studies collaborative R&D efforts driven by cost-sharing reasons (e.g., R&D consortia) where firms agree to split the total cost and share the benefits. Much less is understood though for indirect forms of collaborative structures, which are based on information sharing and learning mechanisms. For instance, in GEDC, member firms develop individual projects and thus there is no direct benefit due to cost sharing. Yet, the industry review allows firms to observe their rivals' findings, which, in turn, allows for more informed future decisions.[3] Clearly, one of the most challenging managerial tasks is how to correctly interpret and act upon observing these past findings.

The focus of this paper is the critical decision that senior R&D management faces concerning the direction of search: Should an investment be made to domains already explored by rival firms or towards completely new avenues? In making this decision, a firm needs to balance two opposing forces. The first is the so-called "neighborhood effect". In his seminal study, Jaffe (1986) demonstrates the existence of R&D spillovers

[3]Cohen and Levinthal (1994) characterize such channels as "windows on new technologies" that allow companies to better assess the potential of recent scientific developments. University research centers are only one instance of such channels. Others include practitioner and academic conferences, or the turnover of R&D labor where fresh university graduates disseminate knowledge.

by showing that firm-level R&D productivity is positively associated with the R&D investment of "technological neighbors" (Jaffe 1986, p.986). That is, firms experience higher returns on R&D investments when they undertake projects technologically similar to their rivals'. On the other hand, Furman et al. (2006) point out that competition might discourage follow-up investments in the same scientific domains since the pioneering firm might have already seized the most profitable opportunities from the field (the so-called "fish out the pool" effect).

We approach the above question by developing a two-stage game of two competing firms that sequentially decide where to direct their investments for future technological developments. Investing in a scientific domain leads to technology improvements which translate to a competitive advantage in the market. We account for the inherent uncertainty of R&D by modeling the realization of a technology improvement as a random draw from a probability distribution that describes the technological potential of a scientific domain. Such a realization also provides an imperfect signal about the future potential of the particular domain. It may also be informative about the potential of related scientific domains.[4] Once firms observe the realization, they can refine their understanding about each scientific domain, and make a more-informed decision regarding their future investments.

Our results suggest that a firm's optimal R&D search strategy exhibits a threshold policy. Depending on the realized technology improvement, the firm chooses to pursue search within an unexplored scientific domain (exploration strategy), to follow-up on the competitor's path (exploitation strategy), or to forego R&D search altogether. The technological distance between the alternative domains moderates the shape and order in which these strategies become preferred across the past technology realization spectrum.

[4]The concept of "related domains" is formalized in our model setup section and it corresponds to Jaffe's (1986) technological distance.

Once we outline the general conditions that determine the optimal search strategy, we focus on the most insightful case where a threshold between exploration and exploitation exists. For past outcomes above a technological improvement threshold, a firm benefits from exploiting the same scientific domain. For lower outcomes, exploration of alternative domains renders higher expected benefits. We show that this threshold value always lies strictly above the a priori expected potential of the explored scientific domain. Thus, a firm may divert its R&D efforts towards exploration even when the past findings led to significant (i.e., better than average) improvement. The result is robust even when the different domains are mutually exclusive options (i.e., a low outcome in one domain indicates a higher likelihood for a high outcome in the other).

We study the properties of the above threshold with respect to the *technological distance* (Jaffe 1986) of the scientific domains and the informational value of past outcomes. As the scientific domains become less distant (i.e., the distributions of their technological potentials exhibit higher correlation), a firm learns more about alternative domains from prior R&D efforts, and exploration of a new domain becomes preferable. In contrast, as past outcomes become more informative of the explored domain, they allow for faster learning, and exploitation of the same domain is more promising. Note that both higher correlation and higher precision render past findings more informative for a firm; yet, their impact on the direction of the search effort is diametrically opposite, highlighting the managerial value of identifying the different sources of learning.

The competitive dynamics also play a critical role on the R&D search path. Fiercer market competition prompts exploration of alternative domains, driving diversification upstream at the R&D stage. With respect to the firm's incentives to innovate, we show that the potential of a follow-up exploitation by rival firms diminishes the search incentives (i.e., firms only invest for sufficiently low search costs). However, competition intensity may have a non-monotonic impact on these incentives. A firm may invest under a very competitive environment, but forego investment in a milder one. Our analysis also reveals the dual role of learning from past outcomes by showing that more informative outcomes may not always be more beneficial to the firm. In contrast, in light of a moderate past outcome, a firm is better off when this outcome carries limited information about the potential of the domain.

Our study contributes to the extant literature along three dimensions. First, we outline a comprehensive mechanism to describe the realization of R&D spillovers at an operational level. The past literature predominantly conceptualizes them as a fixed and costless benefit. We take an operational perspective and we conceptualize the effect of R&D spillovers as the actionable strategy implications due to information generated from other firms' efforts. Second, our approach illustrates the strong path dependency of the R&D spillover effects. The commonly held view of a fixed effect might be accurate at the overall economy level, but it does not translate into straightforward effects at the senior R&D management level. The insight is important since it highlights the need to provide managers with a deeper understanding regarding the role of specific parameters (e.g., the different sources of learning). Finally, we add further insights on the new product development literature, as the latter focuses extensively on a single firm's decisions. We analyze a competitive setting and we outline contingency actions regarding the direction of search among rival firms.

The remainder of this paper is organized as follows. After reviewing the related literature in Section 2, we present our key model assumptions (Section 3). Section 4 describes the optimal search strategy contingent on the past realized technology improvements. In Section 5, we discuss the a priori (i.e., before the realization of the technology improvement) incentives to innovate and a member firm's average profitability when both rivals are equally likely to initiate R&D search. Finally, Section 6 concludes by providing practical implications of our work.

2.2 Literature Review

Our research question draws upon three streams of literature. We begin by briefly presenting the literature on R&D spillovers. The central question is how the incentives to invest in innovation vary due to spillover effects. Next we summarize the rather few papers that focus on the R&D path decision by accounting for the different options that firms have when pursuing R&D initiatives. Finally, we discuss recent work on new product development (NPD) that highlights the role of imperfect learning during the experimentation stage.

Arrow (1962) pioneered the idea that a firm's incentives to innovate decrease when knowledge generated by its innovation efforts gets involuntarily transmitted to competitors. In another early study, Schmookler (1966) articulated that a firm's technological progress may not solely be the outcome of its own research efforts but also of other firms' research results. Since then, economists expressed a great interest in understanding the impact of such knowledge diffusions, a concept known as R&D spillovers (Griliches 1979,1992, Jaffe 1986).

The first normative treatment of R&D spillovers dates back to Ruff (1969). He considers an oligopoly setting where the "effective" research effort per firm (X_i) is a weighted sum of the its own effort (x_i) and the effort carried out by its rivals (x_j): $X_i = x_i + n\beta x_j$, where n is the number of firms and β is an exogenously set parameter that represents the impact of spillovers. In his words: "β is the transmission coefficient and measures the ease with which research results are transmitted among firms." (Ruff 1969, p.402) He concludes that the incentives to innovate decrease for higher spillover levels.

Two of the most influential studies in the R&D spillovers literature come from Katz (1986) and d'Aspremont and Jacquemin (1988). Their novelty lies in recognizing that firms are seldom of a wholly cooperative or non-cooperative type. Instead, they argue that firms may cooperate during an initial stage (i.e., cost reduction process innovation efforts), and compete in a subsequent stage (i.e., capacity competition). Their analysis highlights that the effectiveness of any collaborative structure depends on the spillover parameter: Low values of β prompt non-cooperative behaviors and higher amounts of R&D investments because firms view each other as fierce competitors. As β increases cooperative efforts become more profitable since they allow firms to exploit the involuntary transmitted knowledge. Since then, a remarkably extensive literature has extended the d'Aspremont and Jacquemin (1988) framework by examining the firms' incentives to innovate under different collaborative structures. Surveys on this literature are provided by DeBondt (1997) and Veugelers (1998).

We depart from the standard approach in the past literature in three ways. First, instead of modeling R&D spillovers as an exogenous cost reduction process we focus on a fundamental driver for the creation of R&D spillovers: The dissemination of knowledge through specialized labs, university research centers, scientific publications, conference presentations, and consortia meetings. Thus, the benefits from spillovers arise endogenously through the dissemination of new information generated by prior R&D efforts.[5] Second, we allow firms to pursue diverse scientific domains rather than examining the R&D intensity for a single one. By doing so, we develop an understanding about the evolution of the equilibrium search path. Third, we recognize that the highly uncertain nature of R&D calls for a stochastic, instead of a deterministic formulation of the R&D spillover effect. We therefore, incorporate a concise conceptualization of the impact of past research on the search process.

The second stream of work that pertains to our work focuses on the direction instead of the intensity of the R&D search. In a pioneering paper Dasgupta and Stiglitz (1980) argue that firms need to decide both on their R&D spending as well as the direction of their efforts. They capture the latter by enabling firms to pursue projects

[5]To our knowledge, the only other paper that used this novel approach is Cohen and Levinthal (1994) who study the incentives of a firm to build its absorptive capacity in the context of uncertainty and competition.

with different risk profiles. In their formulation, market power increases in the cost advantage over rivals, therefore, competitive markets encourage firms to undertake risky R&D projects. Bhattacharya and Mookherjee (1986) also examine whether firms choose to invest in similar (i.e., highly correlated) or diverse R&D projects. They find that firms benefit from diverse projects since the reward from innovation is higher as the likelihood of the rival succeeding is lower. On the other hand, Dasgupta and Maskin (1987) recognize that diversification is costly, and for that reason, firms have an incentive to deviate from the socially optimal diversity by choosing excessively correlated projects. Fershtman and Rubinstein (1997) echo the previous observation by showing that competition prevents the firms from exploring different sets of "boxes" (alternatives). Cardon and Sasaki (1998) drop the "winner-take-all" assumption implied in previous R&D search models. They show that firms invest in the same research project ("cluster") when the project outcomes are highly correlated but decide to follow a different path ("separate") when the project outcomes are less or negatively correlated with each other. Finally, Cabral (2003) considers an infinite-period R&D race where firms choose between low- and high-variance strategies. He shows that the firm's optimal choice is to pursue safe R&D projects when ahead in the race and risky ones when lagging behind.

Our study differs from this stream in two important aspects. First, no prior work addresses the role of the informational spillovers that emerge from past research efforts. We focus on how those spillovers affect the R&D search path. Second, we demonstrate the strong path dependency of the phenomenon. With the exception of Cabral, past research has considered only simultaneous games, and as a result it is focused on static R&D search models.

Finally, our research touches upon a central question of the NPD literature: The role of learning during the experimentation search process. Weitzman (1979) sparked a voluminous literature on the optimal search problem. In the context of NPD, testing and experimentation grant a better understanding of the design space. Thus, the designers converge to a concept when the benefits from further exploration do not outweigh the costs associated with it (Clark and Fujimoto 1989, Thomke 1998, 2003). Loch et. al (2001) compare the two basic approaches of experimentation, sequential versus parallel. They characterize the conditions under which it is optimal to pursue one or the other and they recognize that the sequential approach bears the fruit of learning. Erat and Kavadias (2008) examine the role of the design space structure on learning and on the optimal number of experimentation stages. They recognize that different design configurations may share common features and therefore exhibit correlated performances. We build on this literature by conceptualizing spillovers as the knowledge generated upon completion of a research endeavor. We extend this literature by examining how learning from past outcomes affects the optimal strategy of a rival firm rather than the strategy of the firm that originally initiated the experimentation process.

2.3 Model Setup

Consider two firms that contemplate the same set of scientific domains and future applications associated with them. As in our case study, this could happen due to a close collaboration with a research center. An investment to a specific domain yields some technological improvement that could subsequently improve the firm's product performance and profitability. As we discussed earlier, industry events like the one organized by the GEDC allow senior R&D managers and engineers to observe past technology improvements from domains that rival firms already explored. At that point, a critical decision needs to be taken: Should a member firm direct R&D effort on an already explored domain, or invest in alternative unexplored ones.

The main goal of this paper is to understand how the R&D search path of rival firms evolves contingent on past outcomes. To that end, we assume that firms search the scientific landscape sequentially, rather than simultaneously. By doing so, we focus on the role of informational spillovers since the latter are generated through past findings. Prior literature on technology diffusion has identified various reasons (e.g, firm's size, existing capital, past experience with related technologies, extend of diversification) as to why some firms may choose to experiment with a technological domain earlier than others (for a review see Hoppe 2002 and the references therein).

We envision the following sequence of events. Initially (i.e., in the first-period) firm A (hereafter the *leader*) pursues search within a scientific domain. The search leads to a technology improvement, owned by the leader, which in turn, translates to better product performance and a competitive advantage. Through the information channel, firm B (hereafter the *follower*) can observe the technology improvement achieved by the leader and use the outcome as an indication of the potential that the particular domain exhibits. In the second period, the follower decides whether to invest in the same scientific domain (hereafter called the *explored*), an alternative domain (hereafter called the *unexplored*), or to not invest at all. Firms are profit-maximizers, and therefore, their decisions reflect their assessment of which scientific domain yields higher technology improvement. If the follower pursues R&D, he obtains a technology improvement, otherwise he competes with the leader with his current technology. The above sequence of events is illustrated in Figure 1. Next, we describe how the informational spillovers are realized and the nature of market competition between the firms.

Technological Potential and Informational Spillovers

Unexplored scientific domains exhibit high uncertainty regarding their potential for realizing technology improvements that are commercially viable. In that light, we assume that the potential for technological improvement (hereafter technological potential) of each scientific domain can be represented by a normally distributed random

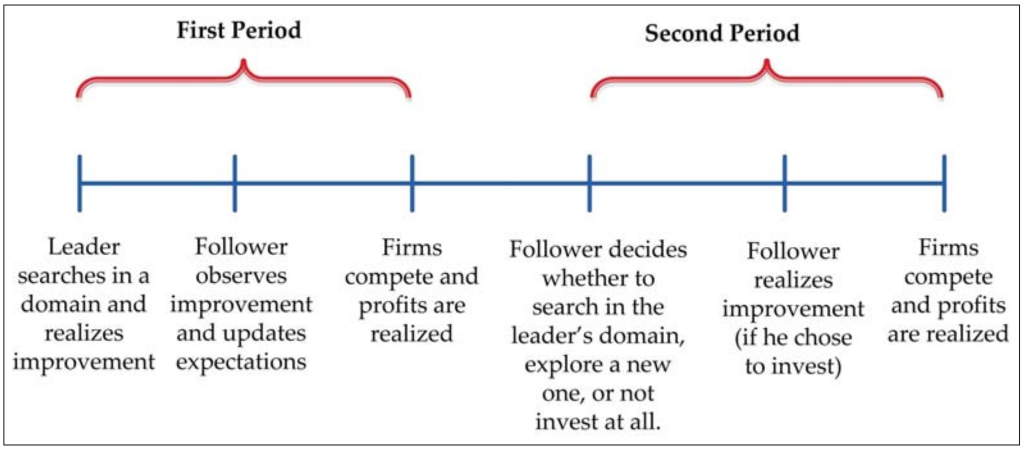


Figure 1: Sequence of Events.

variable. Then, a technology improvement realized from a search in a scientific domain is a draw from this distribution. The normal distribution allows us to separate the expected potential (mean value) from the uncertainty (standard deviation) of the technological potential, while it enables Bayesian updating in a mathematically tractable fashion. Moreover, the assumption of a continuous distribution can better approximate the reality of "invent arounds" that take place when a follower firm conducts research within the same scientific domain as the leader. Thus, although a specific improvement cannot be replicated by other rival firms (IP protection), it may be still possible to achieve further improvement by investing in that domain. Similar assumptions regarding the underlying probability distribution of projects with uncertain performance can be found in March (1991) and Cohen and Levinthal (1994).

We consider a scientific landscape that comprises multiple scientific domains to reflect the potentially different technological alternatives that firms can pursue to improve product performance. For example, in the case of GEDC some efforts explored the use of thin film materials for imprinting and creating very light Radio Frequency Identification (RFID) tags, while others looked into imprinting a specialized type of conducting ink on normal paper. For ease of exposition we assume that two such scientific domains are relevant to the firms' technological needs. A parameter of particular interest in the R&D spillovers literature is the *technological distance* between two scientific domains (Griliches 1979, Jaffe 1986). This concept aims to capture the degree to which knowledge from one field is transferable to the other. We proxy this concept by allowing the probability distributions of the two scientific domains to be correlated. For instance, in the RFID example, despite the major differences with respect to the materials that the two alternatives exhibit, they still rely on the same wave propagation electromagnetic principles. Therefore, findings from one alternative could improve the understanding for the other. Finally, we assume that the two scientific domains have the same *a priori* technological potential (i.e., same probability distribution function) which is common knowledge among the firms. This assumption, albeit restrictive, allows us to isolate the effect of informational spillovers on the direction of search from other exogenous factors such as potential asymmetries between the two scientific fields.

In summary of our previous discussion, let μ_1 and σ_1 denote the *a priori* mean and standard deviation, respectively, of the two technological potential distributions. Let T_1 denote the technological potential of the first scientific area. We assume that T_1 is normally distributed $T_1 \sim N(\mu_1, \sigma_1^2)$. Let t_A be the outcome of the leader's R&D search that the follower observes upon completion of the leader's project. We assume that t_A is a noisy signal of the underlying distribution of T_1 such that $t_A = T_1 + \epsilon$ where ϵ represents the noise term that is independent of T_1 and normally distributed $\epsilon \sim N(0, \sigma^2)$. Let θ_0 denote the correlation between the distributions of the two scientific domains. The following two Lemmas describe how the underlying probability distribution of each scientific domain evolves contingent on the realization of the leader's project.

Lemma 1 *The posterior distribution for the technological potential of the explored domain is normal $N(\mu_1', \sigma_1'^2)$ with $\mu_1' = kt_A + (1-k)\,\mu_1$ and $\sigma_1' = \sqrt{\frac{\sigma_1^2\sigma^2}{\sigma_1^2+\sigma^2}}$ where*

$k = \frac{\sigma_1^2}{\sigma_1^2+\sigma^2}$.

Proof All proofs are provided in the technical appendix A for ease of readability.

An important element of our model is the variance σ^2 of the noise term. It reflects the extent to which the leader's R&D outcome, t_A, is informative of the underlying distribution function of the scientific domain potential. In fact, the posterior mean of the technological potential distribution is a weighted average of the realized outcome, t_A, and the prior expectation μ_1. The weights depend on the *noise-to-signal ratio* (NSR) in an intuitive fashion. When the variance of the noise term, σ^2 tends to zero (or respectively its precision tends to infinity), the signal's weight k tends to one and shifts the ex-post potential of the scientific domain to a small neighborhood of values around t_A. In contrast, high values of σ^2, render k almost zero, thus the search outcome does not reduce significantly the uncertainty associated with the specific domain.

From a managerial standpoint, the variance σ^2 reflects the fact that the technological potential of a scientific domain is not exhausted based on a single research trial. Literature in technology management and industrial dynamics (see Schilling (2002) for an overview) shows that novel technologies start off with very high performance uncertainty, and as our understanding increases the potential improvement reduces (decreasing returns on the R&D investment). In similar vein, Gino and Pisano (2005) use the term "information regime" to describe the relationship between research effort and the rate of uncertainty resolution over the development cycle. They distinguish between *information rich* technologies, in which experimentation generates a significant amount of high quality (predictive) information early in the development process, and *information poor* technologies, in which information accumulates slowly. Similarly, in our model, a high variance σ^2 represents an information poor experimentation process (low learning rate) while as σ^2 decreases, more knowledge is accumulated from a single trial and we shift to information rich regimes (high learning rate).

Lemma 2 *The posterior distribution for the technological potential of the unexplored domain is normal* $N(\mu_2, \sigma_2^2)$ *with* $\mu_2 = \mu_1 + \frac{\sigma_1}{\sqrt{\sigma_1^2+\sigma^2}}\theta(t_A - \mu_1)$ *and* $\sigma_2 = \sigma_1\sqrt{1-\theta^2}$.

Lemma 2 illustrates the role of correlation between the different scientific domains, and thus, the extent to which the outcome of a search effort in one field translates to reliable indications about the other. For example, the updated mean value μ_2 is higher than the prior mean μ_1 when the outcome is above the prior mean and the distributions are positively correlated with each other. On the contrary, for negatively correlated distributions, the updated mean is lower than the prior mean. Moreover, the magnitude of this impact depends on the precision of the signal. In particular, the absolute distance $|\mu_2 - \mu_1|$ from the prior mean monotonically increases in the signal's precision, reflecting the higher informational value of a precise signal.

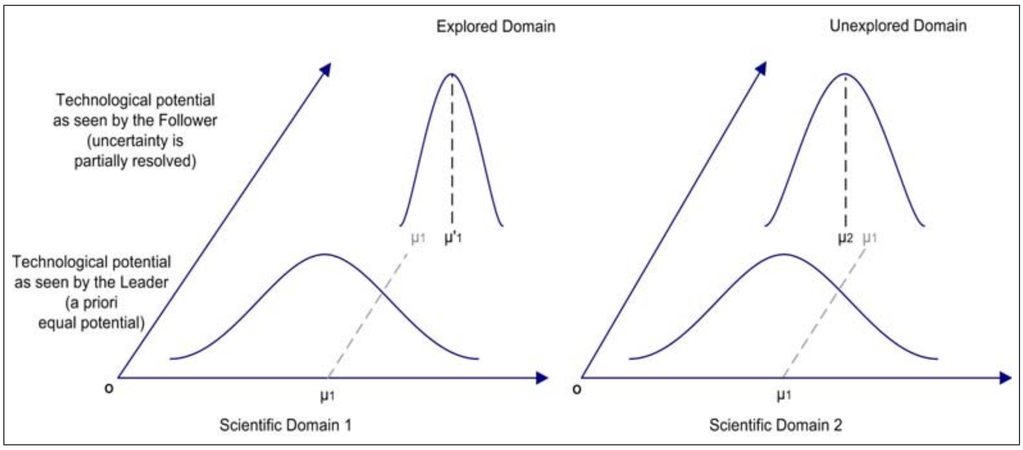


Figure 2: Scientific Domains as seen by the Leader (first period) and the Follower (second period).

Market Competition

A technology improvement allows a firm to charge a price premium for its end-product. Such premium may emerge from new product features (e.g., built-in wireless capabilities for laptops or lighter materials). Our assumption captures two features that we have systematically observed in our motivating GEDC case study: (i) higher underlying technologies translate into higher performance along a competitive dimension, and (ii) a milder form of competition - as opposed to the traditional "winner-takes-all" - where technology superiority implies better performance, but not monopoly profits. Similar demand models have often been used in the extant literature (Levinthal and Purohit 1989, Padmanabhan and Png 1997, Plambeck and Taylor 2005).

Let A be the current market size, c the per unit production cost and e the degree of competition between the two firms' products (hereafter competition intensity). Also, let q_{1A} and q_{1B} be the respective first-period capacity decisions for each firm. These capacity decisions represent the end-product sales under a market clearing mechanism, and they allow us to consider the fact that the participating firms also account for pricing considerations when competing. Thus, in the first period period the corresponding prices are: $p_{1A} = A + bt_A - q_{1A} - eq_{1B}$ and $p_{1B} = A - eq_{1A} - q_{1B}$. These equations capture the technological advantage of the leader in the first period. In the second period, the leader competes with his existing technology improvement, t_A, while the follower has the option to pursue search either in the explored or the unexplored domain. Let t_B denote the technology outcome resulting from the follower's R&D effort. Contingent on this realized performance, the second-period prices will be $p_{2A} = A + bt_A - q_{2A} - eq_{2B}$ and $p_{2B} = A + bt_B - eq_{2A} - q_{2B}$ with corresponding profits $\Pi_{2A}(q_{2A}, q_{2B}) = (p_{2A} - c)\, q_{2A}$ and $\Pi_{2B}(q_{2A}, q_{2B}) = (p_{2B} - c)\, q_{2B}$.

2.4 The Path Dependent Nature of Search under Spillovers

In this section we characterize the follower's search strategy contingent on past R&D outcomes (i.e., the technological improvement generated by the leader's search). Recall that the leader's outcome, t_A, is a noisy signal of the underlying potential for both the explored and the unexplored scientific domain. Let $\Pi^E_{2B}(t_A)$ and $\Pi^U_{2B}(t_A)$ denote the follower's second-period expected profits from searching in the explored and unexplored scientific domain, respectively. That is, $\Pi_{2B}^{E}(t_A) = E[\Pi_{2B}(\mu_1', \sigma_1' \mid t_A)]$ and $\Pi_{2B}^{U}(t_A) = E[\Pi_{2B}(\mu_2, \sigma_2 \mid t_A)]$. Lemmas 3 and 4 describe how those profit functions change as a function of the technology improvement achieved by the leader.

Lemma 3 *$\Pi_{2B}^{E}(t_A)$ increases in t_A.*

The follower's expected profits from the explored scientific domain always increase in the past outcome t_A. Interestingly, this is true despite the fact that a higher t_A expands the market share of the leader and shrinks the market for the follower since their products are substitutes. The result stems from the informational value of t_A regarding the potential of the explored scientific domain. A higher t_A increases the mean of the posterior distribution (μ_1'), to reflect the higher average potential of the explored domain. Moreover, the variance ($\sigma_1'^2$) decreases to reflect the partial resolution of uncertainty as the knowledge associated with the domains grows. As a result, the higher potential is more likely to be achieved. Therefore, although a higher t_A gives the leader a greater technological leap upfront, it also increases the chances of the follower outperforming him in the future.

Lemma 4 highlights the critical role of the technological distance θ_o on the effect of past technology improvements on the expected profitability of the unexplored domain.

Lemma 4 *There is a unique $\widetilde{\theta}_o > 0$ such that: for $\theta_o > \widetilde{\theta}_o$, $\Pi_{2B}^{U}(t_A)$ increases in t_A while for $\theta_o < \widetilde{\theta}_o$, it decreases in t_A.*

Unlike the case described in Lemma 3, now the trade-off between a less competitive rival (lower t_A) and a signal of high underlying potential (higher t_A) depends on θ_o. It is natural to expect, that when $\theta_o < 0$ the expected profitability from search in the unexplored domain decreases in t_A : not only the leader becomes more competitive but also it signals a very low posterior mean for the distribution of the unexplored domain. The effect of t_A on the leader's competitive advantage (competition effect) also dominates the effect on the higher posterior distribution for for positive but rather low values of θ_o (informational effect). As a result, $\Pi^U_{2B}(t_A)$ decreases in t_A for $0 < \theta_o < \widetilde{\theta_o}$. On the contrary, for highly correlated domains (i.e., $\theta_o > \widetilde{\theta_o}$) the informational value of a high t_A as a signal of a high underlying potential outweighs the competition effect, making $\Pi^U_{2B}(t_A)$ an increasing function of t_A.

Recall that the follower has the choice to search either within the explored domain with expected profits $\Pi^E_{2B}(t_A)$, the unexplored domain with expected profits $\Pi^U_{2B}(t_A)$, or forego any search effort and receive profits $\Pi^N_{2B}(t_A)$. Search in a scientific domain comes at a cost K. In line with prior research in the R&D experimentation process (Cardon and Sasaki 1998, Cabral 2003, Loch et. al 2001, Erat and Kavadias 2008), we assume that domains have equal search costs in order to isolate the effect of remaining potential from other exogenous factors such as asymmetric costs. Therefore the follower's problem can be formulated as $max\{\Pi^E_{2B}(t_A)-K, \Pi^U_{2B}(t_A)-K, \Pi^N_{2B}(t_A)\}$.

Theorems 1 and 2 characterize the follower's optimal R&D search strategy contingent on the past outcome t_A and the search cost K for negatively and positively correlated domains, respectively.

Theorem 1 *When the domains are negatively correlated with each other (i.e., $\theta_o < 0$), for every tuplet (t_A, K) there exist $\widetilde{t}_U(K)$ values $\widetilde{t}_U(K)$ and $\widetilde{t}_E(K)$ such that the optimal R&D search strategy is:*

- *to search the explored scientific domain when $t_A \in (\widetilde{t}_E(K), \infty)$*
- *to search the unexplored scientific domain when $t_A \in (0, \widetilde{t}_U(K))$*
- *to perform no search in all other cases.*

The values $\widetilde{t}_U(K)$ and $\widetilde{t}_E(K)$ are monotonic in K and there exist K_E such that for $K \leq K_E$, $\widetilde{t}_U(K) = \widetilde{t}_E(K)$.

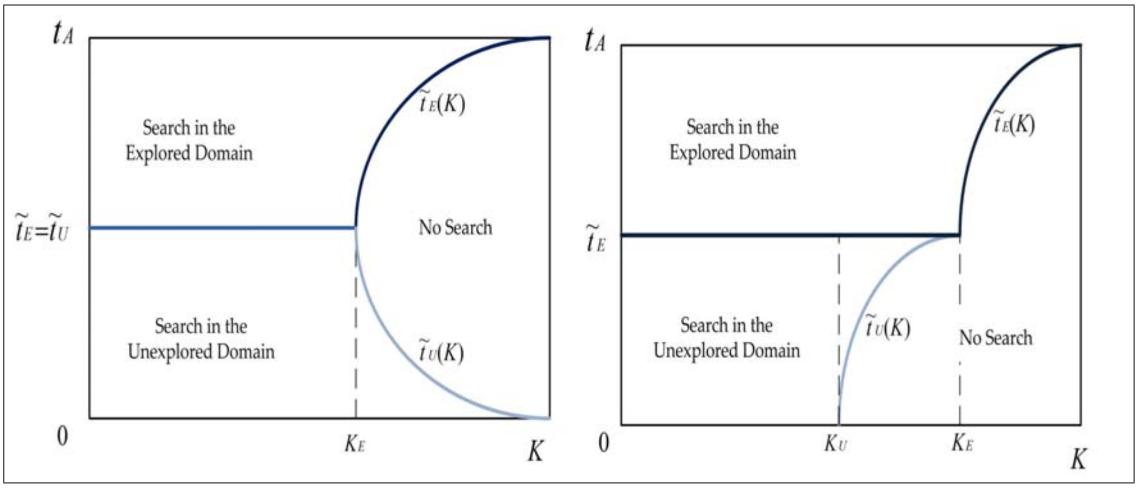


Figure 3: Optimal R&D Search Strategy for negatively (left) and positively (right) correlated domains.

According to Theorem 1, when the search cost is low $K \leq K_E$ even the least promising R&D option dominates the option of not searching. On the contrary, when the search cost is high ($K > K_E$), the follower undertakes search only when the past outcome is very high ($t_A > \widetilde{t}_E(K)$), in which case he searches in the explored domain, or when the past outcome is very low ($t_A < \widetilde{t}_U(K)$), in which case he searches in the unexplored domain. Intuitively, the follower invests only when there is a clear indication on which scientific domain projects the highest potential. For intermediate outcomes, the inconclusive information renders investment in technology improvements a non-profitable avenue and the follower competes with his current technology.

Theorem 2 *When the domains are positively correlated with each other (i.e., $\theta_o > 0$), for every tuplet (t_A, K) there exist values $\widetilde{t}_U(K)$ and $\widetilde{t}_E(K)$ such that the optimal R&D search strategy is:*

- *to search the explored scientific domain when $t_A \in (\widetilde{t}_E(K), \infty)$*
- *to search the unexplored scientific domain when $t_A \in (\widetilde{t}_U(K), \widetilde{t}_E(K))$*
- *to perform no search in all other cases.*

The values $\widetilde{t}_U(K)$ and $\widetilde{t}_E(K)$ are defined such that i) $\widetilde{t}_U(K) = 0$ for $K \leq K_U$, ii) $\widetilde{t}_U(K) = \widetilde{t}_E(K)$ for $K \geq K_E$.

When the search cost is low ($K \leq K_U$), the follower always benefits from search, either in the unexplored or the explored domain, regardless of the realized outcome. At the opposite end, for high search cost ($K \geq K_E$), the unexplored domain is out of consideration as it is regarded too risky. Similarly to Theorem 1, the follower searches only when there is a very clear indication ($t_A > \widetilde{t}_E(K)$), but unlike Theorem 1 the follower only searches in the domain from which this indication is coming from (i.e., the explored domain). Finally, for intermediate search costs ($K_U < K < K_E$), the follower's strategy balances expected rewards (higher mean of the explored) with remaining potential (higher variance of the unexplored). Adjacent technological domains exhibit similar posterior trends regarding their potential for technology improvements. Thus, the expected profitability of both domains increases in the past outcome t_A. Yet, the impact of a marginal increase of t_A on the expected profitability of the explored domain is higher than that of the unexplored domain since the effect on the latter is mitigated by the correlation θ_o. As a result, while intermediate outcomes may prompt the follower to search the unexplored domain, there is always a threshold above which he would rather search in the explored one. Intuitively, in light of a very high past outcome ($t_A > \widetilde{t}_E$) uncertainty is undesirable since the follower wants to ensure that his realized outcome will be close to the leader's. On the contrary, for lower outcomes ($\widetilde{t}_U(K) < t_A < \widetilde{t}_E$) higher uncertainty is desirable because it allows for a higher upside potential. For even, lower outcomes $t_A < \widetilde{t}_U(K)$ neither of the domains exhibit sufficient potential for undertaking search.

Note that for both the case of negatively and positively correlated domains, $\widetilde{t}_E$ denotes the threshold value such that for outcomes above $\widetilde{t}_E$ the follower abandons the unexplored domain and decides to search in the explored one. In the following paragraphs we further analyze the properties of this threshold with respect to our key model parameters. As described previously, there are two additional thresholds

$\widetilde{t}_U(K)$ and $\widetilde{t}_E(K)$. We focus on the properties of $\widetilde{t}_E$ for two reasons. First, the focus of our paper is to examine the circumstances under which the follower builds upon the leader's domain versus exploring alternative ones. This trade-off between between exploitation (search in explored domain) and exploration (search in unexplored domain) is captured by the threshold $\widetilde{t}_E$. Second, the thresholds $\widetilde{t}_U(K)$ and $\widetilde{t}_E(K)$ exhibit non-monotonic properties that depend on the realization of t_A. Those properties (available by the authors) are omitted in the interested of brevity.

Proposition 1 *The threshold value $\widetilde{t}_E$ is strictly higher than the prior expected value μ_1.*

According to proposition 1, despite a good past outcome (i.e., above the prior expectation) the follower might choose to abandon the explored domain and instead search in the unexplored one. What makes this result particularly puzzling is the fact that it holds for even negatively correlated domains. For instance, consider two negatively correlated domains and an outcome t_A in the area $\mu_1 < t_A < \widetilde{t}_E$. Under this scenario the explored scientific area has a higher posterior improvement expectation ($\mu_1' > \mu_1$), while the unexplored area exhibits a lower expected potential ($\mu_2 < \mu_1$). Nonetheless, the follower's optimal policy is to search in the unexplored one.

The result stems from the indirect effect of the posterior variances. Recall that the posterior variance represents the remaining uncertainty regarding the potential of a specific domain for technology improvements. The information acquired through the past R&D finding decreases the posterior variance for both domains. The decrease, however, is larger for the explored domain since the effect on the unexplored is mitigated by the correlation θ_o. For "average" realized outcomes, near the mean μ_1, such an uncertainty resolution is undesirable because it essentially diminishes the remaining potential of the explored domain. On the other hand, the unexplored domain appears to be more promising exactly because the milder uncertainty resolution allows for a higher "upside potential". Figure 4 illustrates the phenomenon.

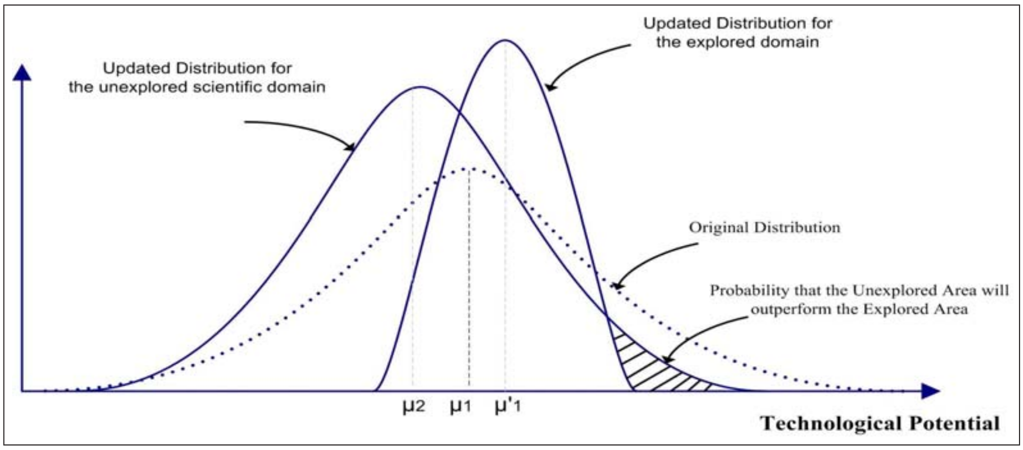


Figure 4: The impact of higher remaining potential on follower's optimal strategy.

Proposition 2 *The threshold value* $\widetilde{t}_E$ *increases in the correlation* θ_o.

Proposition 2 states that the smaller the technological distance (i.e., higher θ_o), the higher the threshold $\widetilde{t}_E$. Therefore, the follower becomes less likely to draw from the explored domain. Note that θ_o has no impact on the posterior distribution of the already explored domain, it only affects the distribution of the unexplored. First consider the case of negatively correlated domains so that a high t_A affects negatively the potential of the unexplored domain. As θ_o increases the realized outcome t_A not only conveys less negative information (μ_2 increases) but also the upside potential increases (higher variance σ_2^2). Thus, the unexplored domain becomes more attractive to the follower. In the case of positively correlated domains a high t_A affects positively the posterior mean μ_2. Thus, as θ_o increases, t_A becomes more informative and μ_2 increases. As a result, despite the decreasing variance σ_2^2, the expected profitability of the unexplored domain increases in θ_o. Essentially, knowledge becomes more reliable (March 1991) and the follower, ceteris paribus, is more likely to search in the unexplored domain.

This result is counter to the analysis of Cardon and Sasaki (1998) who find that firms become more likely to search in the same domain (clustering) as the correlation across different domains increases. The difference stems from the different role that the correlation plays in each model. In Cardon and Sasaki firms search simultaneously and the benefit from clustering is the potential preemption of the rival. When the correlation is high, the likelihood of successful preemption is high, and the incentives to preempt the rival through clustering is higher. We focus on informational spillovers, where correlation reflects higher informational value regarding the distribution of the alternative domain.

Proposition 3 *The threshold value $\widetilde{t}_E$ increases in the competition intensity e.*

As the degree of competition increases, the follower requires a higher technological improvement to overcome the leader's advantage. Put differently, fiercer competition makes exploration a more promising strategy. Intuitively, as competition intensity increases a given technology improvement achieved by the leader becomes more detrimental to the follower's profitability. Thus, the need to outperform the leader becomes even more significant, leading the follower to adopt a more risk-taking strategy. This finding is consistent with March (1991) who argues that firms should increase their exploration efforts in industries with high degrees of competition.

Proposition 4 *The threshold value $\widetilde{t}_E$ increases in the standard deviation of the noise σ.*

Proposition 4 reveals the effect of a noisy informational signal on the follower's optimal R&D search strategy. It states that as the signal becomes less noisy (lower σ), the follower becomes more likely to search in the already explored domain. Intuitively, as σ decreases, the realized outcome t_A becomes more informative for both the explored and the unexplored scientific domain. Yet, the effect is more profound in the explored domain since the effect in the unexplored is mitigated by the correlation θ_o. From a managerial standpoint, our result suggests that high learning rates (low σ) encourage exploitation strategies whereas low learning rates (high σ) promote exploration strategies.

Proposition 5 *When $\theta_o < 0$, there exist $\underline{t_\sigma}$ and $\overline{t_\sigma}$ such that for $\underline{t_\sigma} < t_A < \overline{t_\sigma}$ the follower's second-period expected profits increase in σ and decrease elsewhere. When $\theta_o > 0$, there exists $\overline{t_\sigma}$ such that for $t_A < \overline{t_\sigma}$ the follower's second-period expected profits increase in σ while for $t_A > \overline{t_\sigma}$ they decrease in σ.*

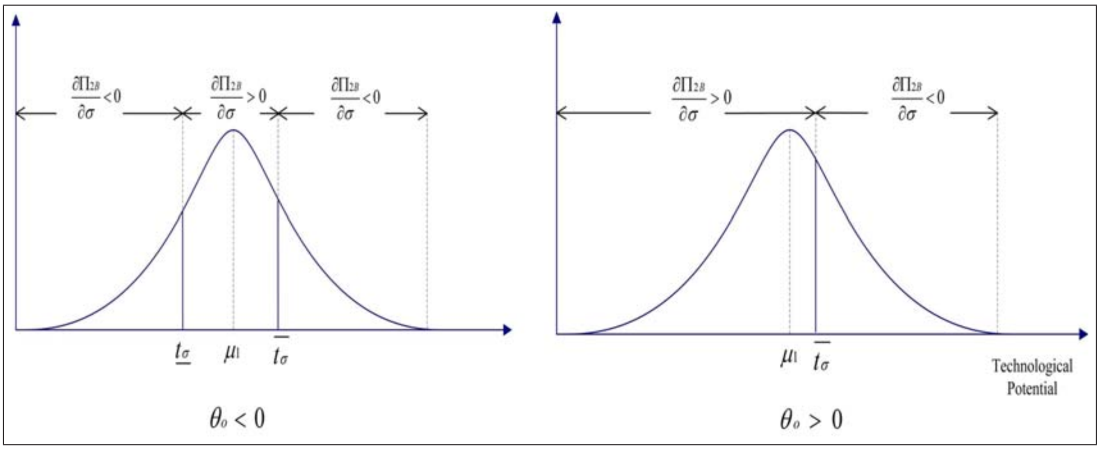


Figure 5: Impact of noise on follower's expected profits.

Proposition 5 allows us to explore the role of learning rate on the follower's profitability. One would expect that faster learning rates (less noisy signals) always benefit the follower. Yet, as Figure 5 illustrates, there are cases where the follower is better off in an environment of a slower learning rate (higher noise levels). The direction of the impact, whether positive or negative, depends on the past outcome t_A and the correlation θ_o between the domains. In the case of negatively correlated domains, the follower benefits from fast learning rates only when the leader's R&D outcome prove sufficient underlying potential ($t_A > \overline{t_\sigma}$) or turn out fruitless ($t_A < \underline{t_\sigma}$). That is, when there is a clear indication as to which scientific area is the most promising. Otherwise, the follower prefers a slower learning rate which corresponds to slower depletion rates, and thus, to a significant remaining upside potential. These contingencies differ under positively correlated domains. In that case, the follower knows that high learning rates indicate future outcomes closer to the leader's output. Therefore, a high t_A makes faster learning desirable ("if the leader succeeded, I will too"). On the contrary, a rather low t_A makes slower learning desirable ("even if the leader failed, there are still chances that I can make it").

Proposition 5 bears managerial significance because it highlights the strong path dependency of R&D spillovers. Typically, the Economics literature considered spillovers as a deterministic effect where firms enjoy a fixed fraction of the competitor's R&D investment. Yet, in reality, findings from past R&D efforts not only provide information about the state of the world but also they determine future performance. We provide intuition regarding the joint effect of past R&D outcomes and the rate of uncertainty resolution on firms' performance.

2.5 Uncertainty Resolution and Innovation Incentives

So far, we focused our analysis on the follower's R&D search strategy. In this section we look at the phenomenon from two different angles. First, we study the role of informational spillovers on the incentives of the leader to initiate R&D search. We find that the potential of a follow-up investment by a rival firm renders any upfront investment less likely. Interestingly though, competition intensity has a non-monotonic effect on the cost threshold. In other words, higher competition intensity might prompt the leader to invest while a milder competitive environment would discourage innovation activity.

Second, we study how the *average* profitability of a firm changes by the presence of informational spillovers. The notion of average profitability aims to reflect a situation often encountered in GEDC and similar research centers: Requests for research projects arrive asynchronously, and firms exhibit little or no control over leading or following in a specific scientific domain. At the outset, we assume that nature draws the leader, and we compute the a priori expected profits (i.e., the profits before any search outcome is realized) as the average of the leader's and follower's profits. The analysis reveals two interesting insights. Regarding the role of the correlation, we find that a member firm is better off when the scientific landscape exhibits high diversity (i.e. scientific domains are negatively correlated). We also show that the learning rate about a scientific domain has a non-monotonic effect on the average profitability.

2.5.1 The leader's incentives

Let $E[\Pi_{1A}]$ and $E[\Pi_{2A}]$ denote the leader's first and second-period profits, respectively. Apparently, there is a $K_L \doteq E[\Pi_{1A}] + E[\Pi_{2A}]$ such that for $K < K_L$, the leader decides to search while for $K \geq K_L$, the cost is too high and no research activity is undertaken. Define K_L^M to be the corresponding threshold value given that the follower does not invest in technology improvements.

Proposition 6 *The potential of a rival firm investing in technology improvements reduces the incentives of the leader to invest in a scientific domain. In particular, the set of search cost values for which the leader initiates investment becomes narrower:* $K_L \leq K_L^M$. *Yet, competition intensity* e *has a non-monotonic impact on the threshold* K_L.

Proposition 6 states that projects that would be profitable in a setting where only the leader would invest (i.e. projects with $K_L < K < K_L^M$) are considered too costly when both firms are likely to invest. It is worth noticing, though, that the impact of competition intensity may have a non-monotonic impact on the leader's incentives to innovate. Figure 6 plots the expected profits of the leader (Π_A) and the follower (Π_B) when both firms invest in technology improvements, and also the leader's profits when the follower chooses to not invest ($\Pi_{AB'}$).

As we see in Figure 6 for $e > e_o$ the follower's expected profits lie below the search cost K. Thus, for $e > e_o$ the leader anticipates that the follower will not pursue search in any domain, and therefore she will hold a greater competitive advantage in the market. As a result, the leader's expected profits jump up at $e = e_o$ and consequently the critical threshold value for which $K_L = E[\Pi_{1A}] + E[\Pi_{2A}]$ jumps up as

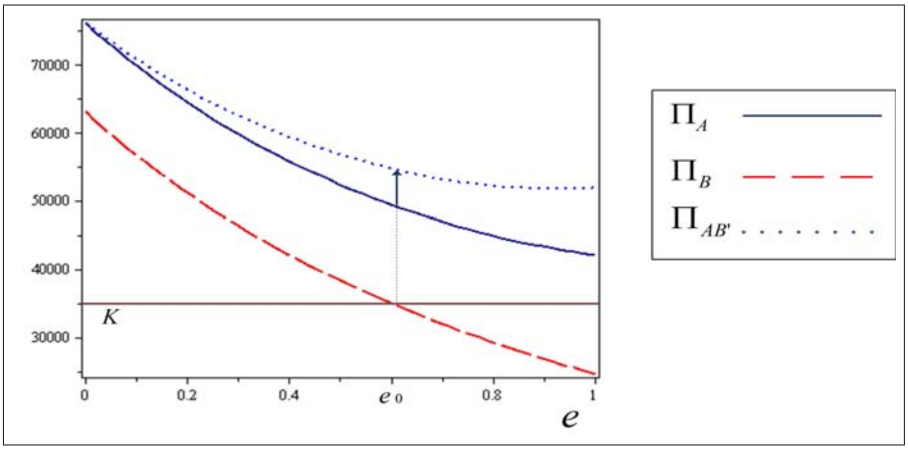


Figure 6: Total Expected Profits for $A = 300, c = 1, b = 0.9, \mu_1 = 100, \sigma_1 = 30, \sigma = 20, \theta_o = -0.5$.

well. Essentially, a fiercer end-product competition acts as a preemption mechanism against the follower who is forced to drop out from the R&D race, while allowing the leader to stay and exploit the benefits of the research efforts.

2.5.2 Firm's average expected profitability

In this section we study the average expected profitability of a firm with respect to the technological distance θ_o and the noise term σ^2. We calculate the average expected profits under the assumption that each firm has an equal chance of being the leader, i.e., $E[\Pi] = \frac{1}{2}(E[\Pi_A] + E[\Pi_B])$ where $E[\Pi_A]$ and $E[\Pi_B]$ denote the sum of first- and second-period profits for the leader and the follower, respectively. As described earlier, the follower's optimal R&D search strategy is contingent on the past search outcomes t_A. As a result, the leader's profit function is a sum of integrations over truncated normal distributions, which renders further analytical derivations intractable. Instead we conduct an extensive numerical analysis through which we derive two insightful observations.

Observation 1: A member firm's average expected profits decrease in θ_o.

Observation 1 states that, all else being equal, firms prefer a scientific landscape with maximum diversification (i.e., $\theta_o = -1$). A more diversified scientific landscape, increases the expected profitability since it provides firms with more flexibility in choosing where to allocate their future R&D budgets. More precisely, it is the follower's profitability that decreases monotonically in θ_o while the leader's monotonically increases in θ_o. Yet, the effect of θ_o is stronger in the former case and that is why we observe the average profitability decreasing in θ_o.

Observation 2: The average expected profitability exhibits a u-shaped relationship with respect to the learning rate σ.

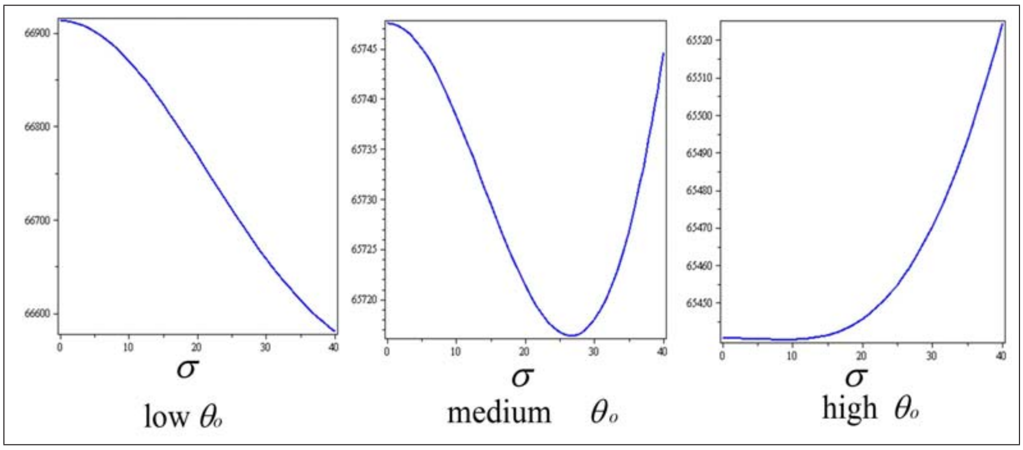


Figure 7: Impact of σ on average expected profitability for $A = 500, c = 1, b = 0.7, \mu_1 = 160, \sigma_1 = 40, \theta_o = \{-0.6, 0.3, 0.6\}, e = 0.4$.

Observation 2 highlights the dual effect of σ in the critical trade-off between uncertainty resolution and remaining potential. As we can see in Figure 7, for low θ_o, the scientific area is more diversified, and information coming from past outcomes can be very valuable since it points to the domain with the highest potential. As a result, the average profitability decreases in the noisiness of the environment. Conversely, for high θ_o, the two domains exhibit close behaviors regarding their potential. Hence, a more precise signal does not add much informational value but it rather narrows the possibility of radical subsequent improvements. Finally, for intermediate values of correlation the impact is non-monotonic. Higher precision (lower σ) increases the profitability only for relatively precise signals (left side of the curve). On the other hand, when the signal is rather vague (high σ) regarding the potential of each domain (right side of the curve) the higher precision reduces the remaining potential without significantly affecting the informational content.

2.6 Conclusions

Our study provides a theoretical framework for R&D search strategies in the context of today's innovation practices where collaborative R&D efforts allow the dissemination of the generated knowledge among rival firms. Drawing upon a case study within a leading university research center, we develop a model to analyze one of the key decisions that R&D managers from participant companies are faced with: To undertake R&D projects in scientific domains already explored by rivals, or to direct their R&D efforts towards unexplored domains. While the model structure is motivated by the specific case, the implications are more general. Scientific knowledge generated from past research efforts can be disseminated through various channels, such as academic conferences, industry trade-shows, or industrial consortia. Economic theory has already accounted for the fact that knowledge generated through company specific R&D efforts *spills over* to the rest of the industry (Arrow 1962). Still, to our knowledge, very few papers have drawn operational implications from such informational spillovers on the direction of R&D search.

The main contribution of this article is to underline the strong path dependency that informational spillovers cause to R&D decisions. Prior work has conceptualized R&D spillovers as direct benefits (e.g., immediate cost reductions) that realize in a deterministic way. While this approach is necessary for developing an intuition about the effects of spillovers on the overall economy, it provides few insights to R&D managers who strive to develop contingency plans and decide on the direction of their future efforts. Our case points to the dynamics stemming from the highly uncertain nature of any R&D effort. Our analysis reveals that the benefits from such knowledge dissemination channels are not straightforward. Management benefits only when delineating carefully crafted alternative plans that depend on the realization of prior R&D search outcomes.

We develop managerial insights along the following dimensions. First, we characterize the optimal R&D search direction contingent on: i) The technological landscape faced by the firms; and ii) The actual realized technological improvements. The optimal choice exhibits a threshold policy. If past outcomes are beyond a technological improvement threshold, then a firm benefits from exploiting the same scientific domain. If not, exploration of alternative domains may render higher benefits, or firms may choose to forego R&D investment. Once we focus on the interesting setting where a threshold between exploration and exploitation exists, we find that the threshold exhibits a striking property: It is optimal to abandon the previously searched domain even for realized improvements that exceeded the a priori expected technology improvement. The result stems from the critical trade-off between the a posteriori expected potential improvement and the posterior upside for the potential improvement (tail of the technological potential distribution). The former is higher for the previously explored domain, but the latter is higher for the unexplored.

Second, we find that, ceteris paribus, highly correlated scientific domains make exploration more promising. At the same time, learning through a more precise signal, prompts for exploitation. From a managerial standpoint, both higher correlation and higher precision allow the follower to assimilate more information from past efforts; yet they prompt different actions. Thus, disentangling the different sources of learning is particularly useful for R&D managers. Third, our study illustrates the role of competition intensity on both the prior and posterior R&D search strategies. Fiercer competition, shifts the ex-post contingency threshold higher, suggesting exploration. In addition, a priori, the threat of the follow-up exploitation by a rival firm reduces the incentives to initiate R&D search. Yet, the relationship between innovation incentives and competition intensity is non-monotonic. Under some circumstances, the leader may initiate search for a fiercer industry environment, but not for a milder one.

Lastly, our analysis also reveals the dual role of learning (uncertainty resolution). One would expect that a follower firm is always better off when past outcomes are as informative as possible (maximum learning). Our results, though, point to the downside of such a high precision: it narrows the upside remaining potential of the distribution, making the follower more likely to realize an improvement only marginally higher than previous improvements. Thus, a higher learning rate may set a tighter upper bound on technology improvements and, consequently, on future profitability.

Our model takes a first step toward enriching the research on informational spillovers by incorporating the operational aspects of the R&D experimentation process. To develop a qualitative understanding of such a complex phenomenon, we rely on specific assumptions about: i) the structure of the scientific landscape (e.g., technological potential normally distributed, a priori symmetric distributions, equal search costs); ii) the nature of competition among the firms (i.e., linear demand functions); and iii) perfect observability of the technology improvement by the follower. Our assumptions aim to capture the first-order effects of informational spillovers, that is, the basic mechanism of knowledge dissemination. In practice, there may exist second-order effects that relate to additional gaming considerations, e.g., the leader might want to signal a distorted outcome to reduce the informational value of past findings, and direct the follower to suboptimal choices. We deem these issues outside the scope of the present model, and we plan to pursue them in future research endeavors. At the same time, we believe that our results could translate into testable hypotheses regarding the direction of the R&D search path. Future empirical research could verify the theoretical results and provide additional insights on the phenomenon.

CHAPTER III

IS DIVERSITY (UN)BIASED? CROSS-FUNCTIONAL TEAMS AND PROJECT TERMINATION DECISIONS

3.1 Introduction

There is a limited number of factors that management can take for granted during new product development (NPD) projects. A rather frequent one is that NPD projects may result in failures, despite the significant amount of resources invested in them. It is true that innovation entails unavoidable risk and failure is lurking around the corner in every risky endeavor. Nonetheless, uncertainty alone does not explain the striking budget overruns or the excessive overtime associated with several NPD projects (Staw and Ross 1987, Wheelwright and Clark 1992).

Examples from a variety of industries abound. Boulding *et al.* (1997) quotes the case of NeXT desktop computers, while Royer (2001) analyzes the Selecta Vision videodisk player introduced by RCA. Both studies highlight a common denominator: despite the strong negative evidence available to the project team, both initiatives resulted in tremendous budget overruns (over \$200M and \$580M, respectively), and they tied up valuable resources for almost 15 years before shutting down. In a follow-up study, Royer (2003) presents two additional case studies at the industry-leading companies Essilor International and Lafarge Group. Again, both firms invested millions of euros in innovation projects which eventually they had to abandon. What makes those cases memorable is not the failure itself, since they were all risky R&D projects. The striking coincidence they share is that the project teams kept pursuing the initially set objectives, despite strong evidence there was no turnaround.

Prior research has long coined a term for such phenomena: *escalation of commitment situations*. First described by Staw (1976), escalation of commitment refers to "the tendency to invest additional resources in an apparently losing proposition" (www.businessdictionary.com). Since then, a number of psychologists, organizational theorists and economists have explored the determinants of such phenomena (see Staw and Ross 1989, Brockner 1992 for excellent reviews).

Among the various reasons cited for such a systematic persistence, a prominent one is the seeming inability of NPD teams to reach a common understanding on what constitutes negative information, and more, importantly, to act upon it[1]. Although previous research (Staw and Ross 1989, March 1994, Gibbons 2003) establishes that the inability to act upon new information is often driven by sociological, psychological, or organizational forces that lie within the group decision process, our understanding on how the existence of diverse perspectives affects escalation is rather limited. Thus, we seek to answer the following research question: Is a team with diverse perspectives more, less, or equally prone to escalation[2] phenomena, compared to a team with homogeneous perspectives?

We focus on the team diversity with respect to the interpretation of new information, given the strikingly consistent finding among the research on escalation phenomena that individuals systematically underestimate feedback that indicates failure (Staw and Ross 1989, Russo and Schoemaker (1989), Boulding *et al.* 1997, Royer 2001). To capture the critical role of such information biasing, we build our model around the concept of information *fidelity* (Loch *et al.* 2001), which refers to the degree of accuracy that the decision-maker assigns to the new information. Prior research in organization theory (Dougherty 1992) and psychology (Carpendale and

[1]It is impressive that in the practitioner lingo, project termination has found expression in strong language content, such as "pulling the plug", "killing the project", or "shutting down the project", indicating the perceived difficulty.

[2]For space preservation, we will be using the terms "escalation" and "escalation of commitment" interchangeably.

Chandler 1996) uses the term *interpretive diversity* to refer to the fact that two individuals exposed to precisely the same stimulus may interpret it in quite different, but equally plausible, ways. Given the cross-functional nature of modern NPD teams, we posit that team members may interpret the same information differently due to different organizational roles and cultures (Griffin and Hauser 1996 and the references therein). We proxy the existence of such interpretive diversity by allowing team members to assign different degrees of fidelity to the new information. In other words, individuals may "read" too much or too little in the new information.

We build our analysis gradually. We start off with the assumption that all team members analyze new information through the same interpretive scheme. This is our baseline case of a homogeneous team and it serves as a benchmark for our subsequent analysis. We establish the existence of a unique threshold with respect to the members' belief about the project success likelihood. Continuation is optimal as long as the current belief lies above the threshold value. Then, we show that the threshold decreases in the information fidelity. Thus, the team members exhibit more risk-taking behavior in the face of more-accurate information.

We relax the assumption of homogeneity and allow the team members to differ with respect to the fidelity they assign to the new information. In this setting, which is referred to as the diverse team, we conduct a detailed numerical experiment that compares the termination decisions of the diverse and the homogeneous teams. Our goal is to assess whether interpretive diversity results in "pulling the plug" earlier or later. Our results reveal that the answer depends on the underlying project uncertainty. In particular, for highly uncertain projects, diversity drives systematic earlier termination. At the opposite end, for less-risky projects, diversity leads to consistent escalation patterns.

Our results are robust across different team structures (Clark and Wheelwright 1992) and in the presence of social conformity (Asch 1951). The former accounts for the influence that certain members of the team may have on shaping the beliefs of their peers. The latter represents the change in a member's belief that happens based on past collective outcomes (Jones 1984). We show that the presence of a dominant team member (e.g., a heavyweight project manager) amplifies the effect of diversity. Similarly, social conformity amplifies escalation, but the magnitude of its impact depends on the project environment. Thus, we complement previous studies that stress the critical role of project team structures on the overall product development performance (Ancona 1990, 1992; Brown and Eisenhardt 1995), and we establish a rigorous link between those structures and the likelihood of observing escalation.

Our findings bear managerial significance because they identify robust patterns of escalation in NPD teams. So far, the joint effects of interpretive diversity and team structure on project metrics have been dealt mainly on a case-by-case observational level. Through our normative study, we quantify specific trade-offs and study the underlying mechanisms of escalation patterns. We depart from prior work that attributes escalation to psychological (e.g., sunk cost fallacy) or organizational issues (e.g., misalignment of incentives) by illustrating how the existence of distinct thought worlds within an organization gives rise to systematic biases in termination decisions, even when the decision-makers are perfectly rational. Such decision biases may emerge directly through the team interpretive diversity, and indirectly through the presence of peer pressure (social conformity). The complex interplay between these two seemingly opposing forces justifies, at a basic level, the difficulty in the decision to kill a bad project.

The remainder of this paper is organized as follows. In §2, we summarize key findings from the relevant literature. We describe our key assumptions and model formulation in §3. §4 presents the structural properties of the termination decisions, with respect to the information fidelity, while §5 examines the effects of dispersion under different team structures. Finally, §6 concludes with a discussion of the managerial implications.

3.2 Literature Review

There are three strands of literature that pertain to our study. The first one discusses the escalation of commitment situations. The second one addresses the impact of various types of team diversity on the performance of a collective task. We particularly focus on studies that examine diverse new product development teams. Finally, we briefly review the literature on the properties of optimal project termination decisions.

3.2.1 Escalation of commitment

Since Staw's (1976) initial study, researchers have shown that the tendency to pursue a deteriorating course of action is not merely coincidental. In a series of studies, Staw and Ross (1987, 1989) identify the drivers of escalation phenomena. They categorize them to project-specific (e.g., high closing costs), psychological (e.g. sunk cost fallacy), sociological (e.g., external justification), and organizational (e.g. incentive misalignment with company objectives[3]) reasons.

In an extensive experimental study, Boulding *et al.* (1997) find a strong resistance to terminate existing projects combined with a *consistent* behavior of distorting negative information. Schmidt and Calantone (1998, 2002) find significant support for the reluctance of project teams to terminate a deteriorating project, and they point out that this reluctance is more pronounced for major innovation initiatives. Royer (2001, 2002, 2003) highlights the emergence and persistence of a *collective belief* not only among specific development groups, but also across entire organizations. Recently, Biyalogorsky *et al.* (2006) argue that biased prior beliefs have a profound impact on maintaining escalation phenomena, while involvement with initial project decisions is

[3]In several instances, managers are rewarded solely on the outcome and never for process success (Kerr 1975, Loch and Tapper 2002).

found to be less detrimental. We contribute to the literature by pointing to a very specific information-related bias that may lead to escalations: the diverse interpretive schemes through which new product development teams internalize new information regarding successful commercialization.

3.2.2 Team diversity and structure

The literature on team diversity is extensive (Williams and O'Reilly 1998, Mannix and Neale 2005, van Knippenberg and Schippers 2007). The central question in this stream is how differences among group members affect group processes and the overall performance. The diversity research has largely been divided in two rather contradictory research paradigms: the information/decision-making perspective, and the social categorization one (Cavarretta 2007). The former dates back to the seminal work on heterogeneity in small groups conducted by Hoffman (1959). Hoffman argues that diverse groups of individuals are expected to have a broader range of knowledge and expertise, and, thus, achieve higher performance. A number of empirical studies support this argument by showing that the expression of alternative perspectives can lead to novel insights and solutions (Nemeth 1986, Gruenfeld *et al.* 1996). At the other end of the spectrum, according to the social categorization perspective, diversity creates social divisions (Pfeffer 1983) which, in turn, create poor social integration and cohesion, which result in negative group outcomes (O'Reilly et al. 1989). As a result of those contradictory perspectives, a unidirectional effect of the team diversity on performance has yet to be reached. Instead, scholars have shifted their efforts on studying the link between diversity and performance in specific contexts. We adopt such an approach by studying the effect of interpretive diversity on a specific performance metric, namely the ability to terminate projects.

In the context of NPD, the critical role of cross-functional teams is indisputable (Wheelwright and Clark 1992, Griffin and Hauser 1996, and references therein). Yet, effectively managing such teams poses considerable challenges. Allen (1977) points out the existence of significant barriers to effective communication within R&D organizations. Ancona and Caldwell (1992) focus on what intra-organization communication patterns determine product success. Sosa *et al.* (2004) examine how the architectural design interfaces map onto communication patterns in complex development efforts. They identify significant misalignments between planned team interactions and the actual organizational communication. Griffin and Hauser (1996) summarize a number of functional differences within an organization regarding the departmental structure, tolerance for ambiguity, preference for projects, etc. Gupta & Wilemon (1998) and Souder (1988) point out the reality of diverse perspectives among R&D engineers and marketing analysts (e.g., R&D staff attributes less emphasis to new market information compared to their marketing colleagues). Ancona and Candwell (1990) stress the importance of conflicting views during the development phase, and highlight that cross-functional teams struggle between opposing objectives. In a study that inspired our model development, Dougherty (1992) discusses the impact of "interpretive schemes" in project decisions. She argues that such schemes may turn into "interpretive barriers," and she finds that departmental *thought worlds* may selectively filter parts of the new information, overestimating or underestimating specific aspects of the incoming information. She concludes that "innovators must [...] develop collaborative mechanisms that deal directly with the interpretive as well as structural barriers to collective action" (Dougherty, 1992, p.195).

The above studies suggest that diversity can have significant implications on the performance of an NPD team. In line with the extant literature, we adopt two important observations for our study: i) Project team members may interpret new information about the project progress with different degrees of fidelity; and ii) Project team members may exhibit communication patterns that reflect different degrees of cross-influence. Both of these properties are central in our effort to analyze how escalation patterns emerge.

3.2.3 Optimal Stopping

Decision theory has long considered the problem of optimally terminating an action based on gradual information resolution, due to its interesting mathematical structure and its numerous applications (see Chow *et al.* 1971 for a relevant discussion). Roberts and Weitzman (1981) conduct one of the first studies with an R&D focus. They conceptualize an R&D project as a sequence of costly stages, with uncertain payoffs that are realized only upon the project completion. At each stage, the decision-maker selects whether to continue or terminate the project based on the available information. Within the numerous models that adopt similar premises, the ones more relevant to our study are Jensen (1982) and McCardle (1985). They both study the problem of adopting a new technology with uncertain potential, which is gradually resolved through a Bayesian updating scheme. Jensen (1982) derives the optimal adoption/rejection rule contingent on the current belief, while McCardle (1985) allows the firm to spend additional resources, in order to improve the understanding of the technology. More recently, Huchzermeier and Loch (2001) develop a stochastic dynamic program to assess the option value of managerial flexibility (e.g. ability to abandon a project). They show that projects with more uncertain market outcomes increase the value of managerial flexibility. Unfortunately, their results are not generalizable for other sources of uncertainty (e.g. technical, scheduling), as attested by Santiago and Vakili (2005). They show that the joint effects of uncertainty and time-to-market on the optimal continuation thresholds are not monotonic, but they yield complex mathematic structures. A similar structure in our setting prevents the closed-form determination of the optimal stopping times.

Our key departure from the above literature is that we relax the assumption of the single decision-maker. Instead, we admit to the fact that project decisions are usually the outcome of a group meeting. Moreover, those individuals may interpret the incoming information through their own interpretive schemes. Our results suggest that this interpretive diversity leads to systematic biases which cannot be directly extrapolated from previous single decision-maker frameworks.

3.3 Model Setup

Consider an NPD project that requires $t = 1, 2, ..., T$ stages for completion. Upon the project kick-off meeting, each of the $i = 1, 2, ..., M$ project team members holds an *a priori* belief about the potential success of the project, say $Prob(x_0 = S; t = T, i) = p_{i,T}$, where x_0 is the final state of the project. Project success is synonymous to successful commercialization of the product developed during the T stages, and x_0 realizes at the last stage. Upon successful commercialization, the project reward is V_0, which is constant and known to the project team.

During the project execution, team members receive information on the venture progress, and commercialization uncertainty is gradually resolved. For example, as additional lab experiments or focus groups are conducted, the team obtains a more-accurate picture about the probability of success. The information realizes through a coarse two-level signal ξ_t that represents "good news" or "bad news" (i.e., $\xi_t = \{s, f\}$). Thus, we view it as "on track" development versus performance deterioration from the planned progress. This information structure is similar to Loch *et al.* (2001). Given that NPD projects are inherently uncertain, it is extremely hard to have precise knowledge about their success. The dual representation of the information content is extendable to multiple levels, at the cost of additional complexity without the benefit of further insights. Such information briefings take place during the milestone meetings. At the end of every stage t, the project team summarizes the new project progress information.

Once the milestone meeting takes place, the decision-making process is as follows.

First, in light of the new information, each team member updates her belief regarding the probability of success. With updated beliefs, the members enter the meeting and participate in extensive discussions and argumentation. Depending on the cross-influence structure of the team, members may adjust their beliefs to accommodate the opinions of their peers. Once the team members finalize their beliefs, i.e., further discussions have no impact, each member forms her final opinion for continuation or termination of the project.

Continuation implies a costly investment, c_t, for at least one more stage. We assume $c_t = c$ for all t stages, in line with the extant literature (Huchzermeier and Loch 2001, Thomke and Bell 2001, Dahan and Mendelson 2001, Erat and Kavadias 2008), and in order to isolate the information assimilation effect. Finally, the overall decision follows a majority rule. The latter is our proxy for the collective belief. In other words, the project continues if, after all the previous steps, the majority of the team members insist it is valuable. In the following paragraphs, we describe each building block of our model setup in further detail.

3.3.1 Assimilating New Information

Drawing upon the insights of Gupta and Wilemon (1988), Souder (1988), and Dougherty (1992), we posit that each team member may evaluate the project progress differently: upon receiving the new information, she internalizes it through her own "filters" (e.g., past experience, functional role within the organization, different cultural perspectives and mental models[4]). From a modeling perspective, we represent the interpretive differences through the fidelity q_i that the member i attributes to the information. In other words, q_i indicates the extent to which member i considers the information as a reliable representation of the actual project situation. Equation (1) describes the

[4] "Departmental thought worlds partition the information and insights. Each has a distinct system of meaning which colors its interpretation of the same information, selectively filters technology-market issues, and produces a qualitatively different understanding of product innovation" (Dougherty 1992, p. 195).

ex-post member i's belief about the successful project commercialization. Thus, at stage t, the member i with prior belief $p_{i,t+1}$ and fidelity q_i revises her belief as follows:

$$p_{i,t}(p_{i,t+1}, q_i, \xi_t) = \begin{cases} \frac{q_i p_{i,t+1}}{q_i p_{i,t+1} + (1-q_j)(1-p_{i,t+1})}, & \text{if } \xi_t = s \\ \frac{(1-q_i) p_{i,t+1}}{(1-q_i) p_{i,t+1} + q_i(1-p_{i,t+1})}, & \text{if } \xi_t = f \end{cases} \tag{1}$$

3.3.2 Social Influence

With revised beliefs $p_{i,t}(p_{i,t+1}, q_i, \xi_t)$, the members participate in the milestone project meeting where opinions regarding the project success are exchanged. Those discussions give rise to peer influences. Such forces of influence offer a surrogate metric for the internal team structure, i.e., communication patterns and hierarchy. We formalize those interactions as follows. Let $\mathbf{p}_t = (p_{1,t}, p_{2,t}, ..., p_{M,t})^T$ be the vector of beliefs prior to the milestone meeting. We model the discussion by the changes recorded in an interior vector $\mathbf{a}_{t,\kappa}$ such that $\mathbf{a}_{t,1} = \mathbf{p}_t$ and $\mathbf{a}_{t,\kappa+1} = \mathbf{T}\mathbf{a}_{t,\kappa}$ where κ indicates the number of iterative discussions that take place; $\mathbf{T}$ is a matrix that summarizes the cross-influences among the team members. Social network theory discusses the implications of this matrix representation, which is often referred to as *structure* or *weight* matrix (French 1956, Leenders 2002). In line with that stream of research, row i represents the relative importance that member i attributes to peers' opinions. Formally, $\mathbf{T} = [w_{ij}]$ with $\sum_{j=1,...,M} w_{ij} = 1$, implies that team member i attributes weight w_{ij} to team member j's belief. The different specifications of $\mathbf{T}$ represent various team structures. With respect to the iterative nature of the discussion, we posit that the internal meeting discussions will cease once a fixed point is reached (Lam, 2002), i.e. there exists $\widetilde{k}$ such that $\mathbf{a}_{t,\widetilde{\kappa}} = \mathbf{T}\mathbf{a}_{t,\widetilde{\kappa}-1}$[5].

[5]Mihm et al. (2003) and Lam (2002) discuss properties of convergence to a fixed point. We assume here that $\mathbf{T}$ adheres to stability properties, that is, we assume away degenerate cases.

3.3.3 Team Decision

Once the discussion ends, members make their proposals regarding the project continuation. They individually assess the project potential by "solving" a stochastic dynamic program with state variable their belief about the likelihood of successful project commercialization. The latter is the outcome of the meeting described above (i.e., $p_{i,t}(= p_{i,t,\widetilde{\kappa}})$). More formally, the value function recursion for the i^{th} member is:

$$V_{i,t}(p_{i,t}; q_i) = \max\{-c + V_{i,t-1}(p_{i,t-1}; q_i)P(\xi_{t-1} = s) + V_{i,t-1}(p_{i,t-1}; q_i)P(\xi_{t-1} = f), 0\} \tag{2}$$

The above dynamic equation rests upon an important assumption concerning the knowledge available to each member. We assume that each member extrapolates the likelihood of success by using her q_i value, but she is not aware of the distribution of the q_j ($j{\neq}i$) values. The assumption is reasonable given our interpretation of q_i: a hardwired interpretive scheme that the member has built over multiple different and not necessarily traceable experiences. An alternative justification for our assumption comes from Madarasz (2008) and the notion that individuals tend to project their information biases on others. In our setting, this translates to member i inherently assuming that $q_j{=}q_i$ for every $j{\neq}i$. In summary, in the dynamic program, members consider only their potential updates given the information progress signals, and they can not factor in potential future influences from their peers.

Based on (2), member i proposes continuation or abandonment at the project team meeting. More formally, if we let $D_{i,t}(p_{i,t}, q_i) = \{0, 1\}$ be member i's proposal at the stage t:

$$D_{i,t}(p_{i,t}; q_i) = \begin{cases} 0, & \text{if } V_{i,t}(p_t, q_i) \leq 0 \\ 1, & \text{if } V_{i,t}(p_t, q_i) > 0 \end{cases} \tag{3}$$

The overall decision follows a majority rule. Termination results from an aggregation of the individual proposals with equal weights:

$$D_t(\mathbf{p}_t) = \frac{1}{M} \sum_{j=1}^{M} D_{i,t}(p_{i,t}, q_i) \tag{4}$$

If $D_t(\mathbf{p}_t) > 0.5$, the team pursues the project further the project. Our majority rule assumption is a formal representation of a fair setting. After all interactions, if most members are in favor of continuation, we posit that it is a fair outcome to pursue the project further. Note that the potential authority-related influences manifest earlier in the decision process through the influence matrix $\mathbf{T}$. For example, during the discussions, dominant members shape the beliefs of their peers.

3.4 Results and Analysis

In this section, we analyze the project team termination decision in a sequential manner. First, in §4.1, we analyze a situation where all team members have the same "interpretive scheme", that is, they assign the same degree of fidelity to new information concerning the project progress. Under this premise, $q_i = q$ for every i and, thus, the structure of the influence matrix does not affect team behavior. Then, in §4.2, we proceed with the more realistic setting where team members exhibit interpretive diversity, and, moreover, where peer influence affects members' beliefs. We examine three distinct influence structures: a decision committee with negligible interactions (i.e., $\mathbf{T} = \mathbf{I}$, where $\mathbf{I}$ is the unity matrix); a heavyweight project manager structure (Wheelwright and Clark 1992), where $w_{1j} = 1$ for every j; and a lightweight project manager structure ($w_{ij} = \frac{1}{M}$ where M is the team size). We recognize that those three structures represent limiting cases[6], but they allow us to highlight the directional effects of interpretive diversity. Finally, in §4.3, we incorporate social conformity effects, where non-majority members may adapt their beliefs ($p_{i,t}$) to align with the majority.

[6]Our results are insensitive to slight deviations from these structures, e.g. a heavyweight team with $w_{1j} = 1 - \delta$ and $w_{ij} = \delta$ ($i \neq 1$) for a small δ.

3.4.1 Homogenous team perspectives

Our benchmark case assumes that team members interpret information in exactly the same way. We can envision such homogeneity in "autonomous" or "tiger" teams structures that are characterized by strong cultural ties (Wheelwright and Clark 1992). Prior literature claims that such teams are essential for the development of breakthrough new technologies (Christensen 1997) because they are set outside the organizational boundaries in an effort to reset their culture without roadblocks from the current organizational structures[7]. Drawing on this argument, we posit that some teams develop their own *culture*, and they establish a (significantly more) homogeneous interpretive scheme among the team members.

Within our modeling context, such a team structure coincides with the situation of a single decision-maker ($q_i = q$ for all i). Also, we assume that all team members share the same initial belief about the likelihood of the project success, i.e $p_{i,T} = p_T$ for all i. This assumption ensures the avoidance of any initialization bias, and allows us to isolate the effects of interpretive diversity. It also implies that all beliefs stay the same $p_{i,t} = p_t$. We derive analytically the structural properties of the optimal termination policy with respect to our key parameters. *Proposition 1* formally states that the team decides based on a *threshold* policy, i.e. the members suggest termination only if their belief about the project successful commercialization lies below a critical value. Then, in *Proposition 2*, we describe how those termination thresholds depend on the timing of the information, i.e., the current stage t. Finally, *Proposition 3* discusses the role of the "interpretive scheme" q on determining those threshold values.

Proposition 1 *At stage t, the team members suggest project termination if and only if their common belief about the project successful completion p_t lies below a threshold*

[7]Especially in large organizations, the existing "routines" may inhibit the pursuit of radical innovations. To avoid such deadlocks, organizational theorists advocate the establishment of independent, autonomous teams as a countermeasure (Russo and Schoemaker 1989).

value. Thus, there exists $\widetilde{p}_{t,q}$ such that $D_t = 0$ if and only if $p_{i,t} \leq \widetilde{p}_{t,q}$

Proof: All proofs are in the Appendix B.

Proposition 1 is a straightforward result in optimal stopping problems. Yet, it confirms that the interpretive diversity has a direct effect on the project continuation decision.

Proposition 2 *The optimal termination thresholds $\widetilde{p}_{t,q}$ are increasing in t.*

Proposition 2 bears managerial relevance. The greater the timely distance from the project completion, the higher the team members' beliefs shall be to support continuation. The insight stems from the fact that with more remaining stages, higher costs lie ahead, and, therefore, team members prefer only "sure" investments. However, one could adopt an alternative perspective. There is an inherent link between escalation situations and high initial beliefs (Royer 2003). If not for such beliefs, large-scale projects would rarely initiate.

Proposition 3 *The optimal termination thresholds $\widetilde{p}_{t,q}$ are decreasing in q.*

Proposition 3 analyzes the termination decision with respect to the interpretive schemes q. Low values of q describe situations where the team members perceive progress information as unreliable and uncertain; naturally, they hedge against the information uncertainty through higher thresholds, i.e., they react more conservatively.

We should underline here that while Proposition 3 describes the impact of q on the termination thresholds, it cannot provide insights on the actual termination time. For example, higher thresholds (associated with low q values) do not necessarily imply an earlier project termination. The reason for that is the direct impact that q has on how the belief for success evolves over time. Higher values of q define lower thresholds, but also drive more drastic changes when updating the current belief, which may result in hitting those critical thresholds earlier. On the other hand, while low q values correspond to higher thresholds, they also correspond to very mild changes in the belief. Put differently, new information is viewed as unreliable and it is overlooked. Due to this interplay between threshold values and impact of the updating scheme on the current belief, closed-form calculation of the termination time becomes intractable[8]. In order to shed light on the relationship between the project duration and the information fidelity, we rely on an extensive numerical analysis. Figure 8 presents the average project duration (from 500 realizations for each q level) as a function of q for two different levels of the initial belief.

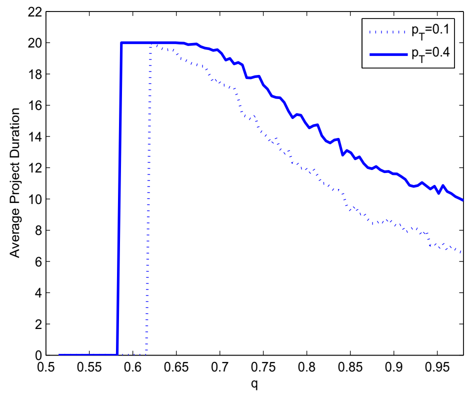


Figure 8: Average project duration for $T = 20$, $V = 100,000$, $c = 1$

Consistent with Proposition 3, for very low values of information fidelity, the optimal thresholds are set so high that the initial belief is too low to initiate the project. As q increases, the threshold decreases and, for a low enough value, project initiation is desirable. Interestingly, the optimal policy switches to the other end of the spectrum, prompting full project completion. For this range of q values, progress information is largely ignored, and "bad news" mildly affects the current belief. We can readily extrapolate from Figure 8 the direct relationship between information fidelity

[8]The underlying mathematical reasons for that echo the intractability challenges outlined by Santiago and Vakili (2005) regarding the shape of the interim value function (Santiago and Vakili 2005, p. 121).

and escalation. If managers assign low q values to negative information, despite its true reliability (Boulding *et al.* 1997), the project termination is suboptimally postponed. Note also that the range of values for which completion is sure increases under a higher initial belief (Royer 2003). For higher q values, the occurrence of negative information drives a drastic decrease in the members' beliefs, and leads to faster termination decisions. Thus, contingent on the initiation of the project, the average project duration is a non-increasing function of information fidelity. Apart from the curve monotonicity result, it is interesting to note its shape: the inverse S-curve graph indicates that the impact of q is not homogenous across the different fidelity levels. The pattern is consistent for a wide range of the parameters T, V, c, and p_T[9].

3.4.2 Diverse team perspectives

In this section, we introduce interpretive diversity: team members assign different fidelity to progress information. We refer to such a team as the diverse team. Common practice dictates that successful NPD teams must include individual members with different functional roles in the organization. Drawing upon research in organization theory (Dougherty 1992), it is reasonable to assume that these individuals may interpret the project progress information differently. For example, engineers may emphasize strict quantitative criteria, as opposed to intangible/qualitative metrics used in consumer semi-structured interviews (Griffin and Hauser 1996). At the same time, marketing executives may downplay technical information as "*simply a matter of putting in the effort*"[10]. These biases tend to be systematic, and they reflect the conflicting priorities and objectives of individuals within an organization. Diverse perspectives may also emerge due to an alternative reason. Potentially, different

[9]For very low p_T values, ($\simeq 0$) the left part of the curve becomes steeper, approaching a linear form, while for very high p_T values, ($\simeq 1$) the drop becomes much smoother.

[10]Anecdotal quote contributed by a participant of an NPD-focused executive seminar at Georgia Tech.

members acquire the new information through different channels, and the latter ones add varying levels of distortion in the information signal[11].

The existence of interpretive diversity raises the following question: *Ceteris paribus*, is a diverse team more likely to terminate a project earlier or later than a homogeneous one? Thus, for the same project characteristics (i.e., same initial beliefs, stages to completion, and development costs), we compare the average number of stages that the project went through before a termination decision is made. To ensure an unbiased and meaningful comparison of the termination times, we set the information fidelity assigned by the homogeneous team to be equal to the true fidelity of the progress information, say q_R. In that light, the termination time of the homogeneous team is the optimal stopping time for the given level of project uncertainty[12]. Hence, for a homogeneous team that assigns fidelity q_R to the progress information, the corresponding diverse team consists of members with differing fidelities that are uniformly distributed around q_R. Formally, for each member i, $q_i \sim U(q_R - \varepsilon, q_R + \varepsilon)$. We refer to ε as the diversity factor since it captures the degree of diversity within the team. Thus, we can claim that in our setting, any deviations in the stopping times observed under a diverse team reflect the effect of diversity. We conduct our analysis through a carefully crafted design of experiments, as discussed below.

3.4.2.1 Design of the numerical experiment

We investigate the effects of diversity through a 3×3 experimental design that accounts for the two major dimensions introduced in our model: (i) the underlying project uncertainty, denoted by the true information fidelity (also viewed by the homogeneous team) q_R; and (ii) the structure of the intra-team influence matrix $\mathbf{T}$. More formally, q_R takes three distinct levels $q_R = \{0.65, 0.75, 0.9\}$ that correspond

[11] One can safely assume that distortion increases in the distance from the actual origin of the information as the infamous *Telephone* (or *Russian Scandal* or *Chinese Whisper*) kids' game shows.

[12] In our setting, the fidelity q_R offers a good proxy for the level of project uncertainty.

to low, medium, and high values, while $\mathbf{T}$ undertakes three possible formats: the independent team structure where $\mathbf{T} = [w_{ij}] = \mathbf{I}$; the heavyweight project manager structure where $w_{1j} = 1, w_{ij}^{j \neq 1} = 0$; and the lightweight project manager team structure where $w_{ij} = \frac{1}{M}$. Then, each set $\{q_R, \mathbf{T}\}$ defines a distinct numerical experiment, and each experiment proceeds as follows:

1. We specify the project environment characterized by the parameters $\mathbf{p}_T, V_0, c, T$ that remain fixed throughout the experiment.

2. For a given diversity factor ε ($\varepsilon \in [0, 0.05]$ discretized in increments of 0.0005), we initialize a vector consisting of the elements $q_i \sim U(q_R - \varepsilon, q_R + \varepsilon)$ with $i = 1, 2, .., M$; it represents the interpretive schemes of the team members and it remains fixed throughout the experiment.

3. At each project stage t, a signal ξ_t is generated, which represents the project progress news. Each team member updates her belief based on the signal realization, her current belief, and her specific fidelity q_i.

4. Each team member enters the milestone meeting and contributes her updated belief into the discussion. During the discussion, the members are influenced by peer beliefs. Those interactions are captured through iterative calculations of $\mathbf{p}_t\mathbf{T}$ until there is convergence to a fixed point (i.e. there is a vector of beliefs $\mathbf{p}$ such that $\mathbf{Tp} = \mathbf{p}$). Note also that since this convergence occurs during the meeting, the length of the interactions (i.e., the number of iterations until convergence is reached) does not affect the overall project duration.

5. Once each member forms a post-discussion belief, she compares it to the corresponding threshold, calculated through the dynamic program assessment described in equation (2). Then, each member advocates continuation(i.e., $D_{i,t} = 1$) or termination (i.e., $D_{i,t} = 0$).

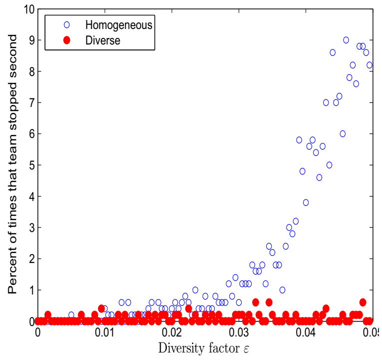
6. The overall team decision depends on the majority, i.e. if $D_t > 0.5$ the team moves to stage $t-1$, otherwise the project is terminated and the total duration (i.e. number of completed stages) is recorded. We denote the project duration for the homogenous and the diverse team, T_H and T_D, respectively.

We replicate each experiment 500 times to provide a reliable estimator of the difference in the the stopping times between the homogenous and the diverse team. We report the difference as the percentage of times (out of this 500 replications) that each team terminated after the other. Across all simulations, we set the project environment parameters as follows: $\mathbf{p}_T = 0.2$, $V_0 = 100,000$, $c = 1$, and $T = 20$. Our results are qualitatively insensitive to the precise choice of those parameters as long as obvious degenerate cases are avoided (e.g., the team immediately terminates or always continues due to very low or very high V_0 values, respectively). Finally, while we report all results for a team of M=5 team members, we discuss the implications of higher team sizes at the end of Section 4.2.1.

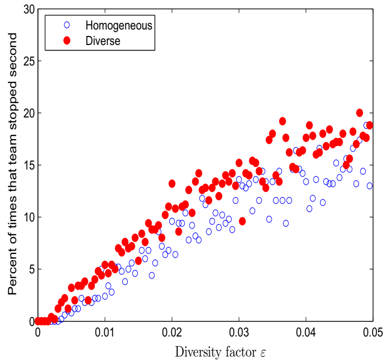
3.4.2.2 Independent team members

In our first set of numerical experiments, we consider a team with completely independent decision-makers. That is, each team member shapes her belief without any peer influence. Mathematically, this setting corresponds to $\mathbf{T} = \mathbf{I}$. Although the above setting is more suitable for a decision committee than a team that manages NPD projects, its analysis offers some key insights that build our intuition for the more complex team structures that follow. Figure 9 illustrates our main result.

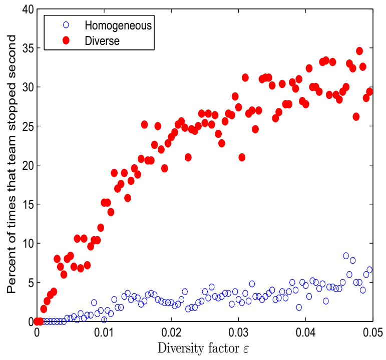
Figure 9 reveals an important managerial insight. There is no uniform answer as to whether a diverse team terminates a project before or after the corresponding homogeneous one. Rather, the answer critically depends on the underlying project uncertainty, as the latter is approximated by the information fidelity q_R. For low q_R values (i.e., high project uncertainty), the diverse team terminates the project before



(a) low q_R



(b) medium q_R



(c) high q_R

Figure 9: Percentage of times that each team stopped second

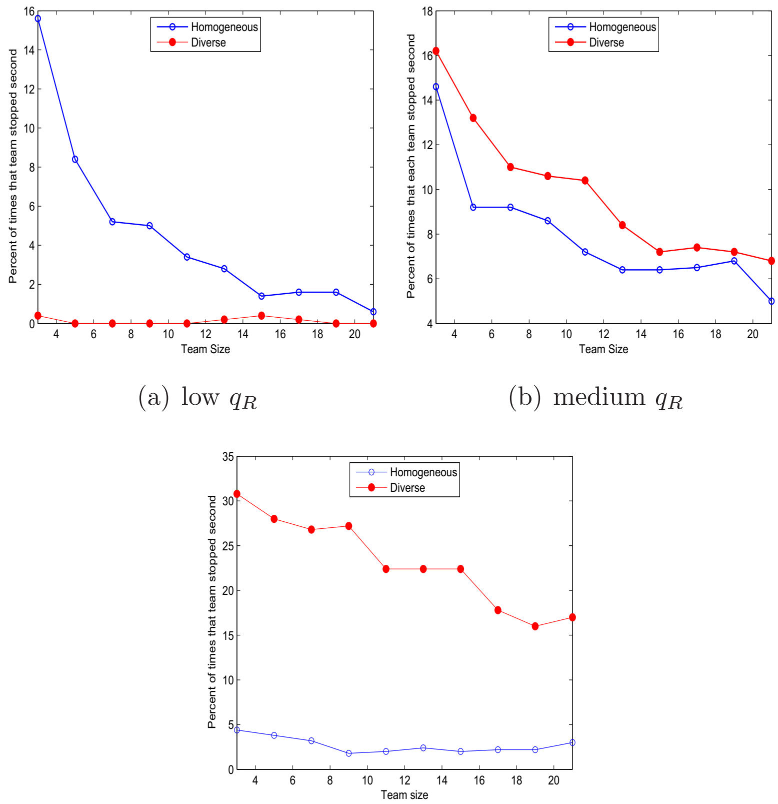
the homogenous one (Figure 9a). What drives this rather conservative behavior of the diverse team? The answer lies in the left part of the S-curve observed in Figure 8. In that region, the homogeneous team continues for a large set of stages as q_R lies at the flat part of the curve. When the majority of the diverse team members are such that $q_i < q_R$ termination does not change, due to the flat part of the curve. But, when the majority of the members place more emphasis on the negative progress information, (i.e. $q_i > q_R$), the diverse team stops earlier than the homogenous one. Note that the implications of this result are not necessarily positive. In contrast, the diverse team might terminate some projects "too early", compared to the homogeneous one that represents the optimal decision, and would probably pursue those projects until completion. Thus, interpretive diversity may hinder innovation by abandoning projects which could eventually turn out to be successful. Interestingly, prior research has argued that in highly uncertain environments, NPD teams may get trapped and terminate a project permanently (Bonabeau *et al.* 2008, p.99). The same literature advocates that homogeneous teams are the only way to break the so-called *corporate conservatism*. We should carefully place the following disclaimer here: the magnitude of the difference between the two team configurations is relatively small (a maximum of 10%). This is driven by the smooth updating effects for such small q_i values. Despite the variance ε, the information is on average unreliable and it does not alter dramatically the team members' beliefs. Hence, the behavior of the diverse team lies close to that of the homogeneous team.

For medium q_R values, there is no clear dominance regarding the termination decisions. Figure 9b illustrates that as ε increases, the likelihood of both teams terminating together decreases. Nonetheless, we cannot infer which team is more likely to delay project termination. This result happens due to the (almost) linearly decreasing part of the S-curve (see Figure 8). The linearity implies that $E_q[T(q)] = T(E[q]) = T(q_R)$ where $T(q)$ represents the stopping time as a function of the information fidelity (see Figure 8).

Finally, for high q_R values (Figure 9c), we observe a systematic escalation behavior of the diverse team, driven by the right part of the S-curve (Figure 8). As the diversity factor ε increases, the diverse team exhibits a persistence to pursue projects that would be terminated under the respective homogenous setting. The result is striking given that a high q_R value represents accurate information (low project uncertainty).

Before discussing the effect of intra-team influences, it is worth mentioning the team size effect on the above results. Figure 10 plots the percentage of times that each team terminated second for different team sizes (M). The graphs show that our main result remains qualitatively robust. Still, as the team size increases, the two team structures appear to converge to similar termination behaviors. In fact, the termination decision of the homogenous team is independent of the team size.

It is the diverse team behavior that changes. The result stems from a standard sampling convergence argument: as the team size increases, the q_i values become more uniformly distributed around the mean, and there are diminishing effects on the team decision from "extremists" (i.e., team members close to $q \pm \varepsilon$ values). Thus, the diverse team aligns more with the homogeneous one. Yet, in the high q_R region, there is visibly less alignment due to the higher impact of the q_i values on the updated beliefs. Hence, small deviations from the q_R still lead to different individual decisions ($D_{i,t}$) despite the larger team sizes.



(a) low q_R

(b) medium q_R

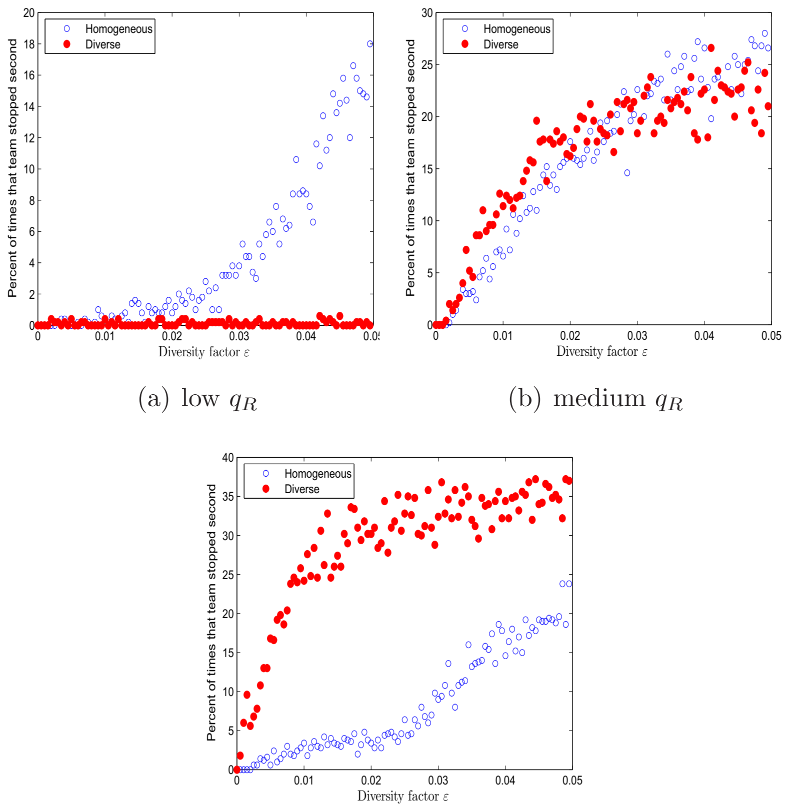
(c) high q_R

Figure 10: Percentage of times that each team stopped second for $\varepsilon = 0.05$

A disclaimer is necessary for Figure 10. The downward trends in the graphs seem to suggest that larger teams are more beneficial, since they diminish the escalation phenomena. Yet, such a conclusion presents only one side of the story, as it ignores the effects of coordinating costs among the team members. In reality, large teams experience severe coordination challenges that outweigh the benefits (Mihm *et al.* 2003). Therefore, the results reported in Figure 10 do not aim to advise the formation of larger NPD teams, but to demonstrate the robustness of our earlier conclusions with respect to the size of the team.

3.4.2.3 Heavyweight project manager

Our next set of experiments investigates the impact of a dominant team member, i.e., a heavyweight project manager (PM), on the termination decisions of the diverse team. We approximate the heavyweight PM team structure (hereafter heavyweight team) as follows: the intra-team influence matrix ($\mathbf{T}$) is such that $w_{1j} = 1$ for every j, while $w_{ij} = 0$ for all other interactions. Thus, during the discussion, one member (without loss of generality, the one with $i = 1$) shapes the beliefs of the rest of team.



(a) low q_R (b) medium q_R

(c) high q_R

Figure 11: Percentage of times that each team stopped second (heavyweight team)

Figure 11 illustrates the key result for a heavyweight team: the effect of diversity is magnified across the q_R values. For example, the percentage of realization where the diverse team stops earlier (low q_R values) doubles compared to the no-interaction case. A similar argument holds for the medium q_R values. Two additional effects arise in the high q_R region. First, escalation occurs even for small deviations from the q_R (e.g., for $\varepsilon = 0.005$). Second, as ε grows higher, the diverse team may increasingly terminate before the homogeneous one, reflecting the high level of outcome variation in this setting. These results stem from the fact that the heavyweight team ends up being a "one-man-show", and the stopping behavior of the diverse team is determined by the perception of a single person. The latter may drive extreme decisions, as there is some likelihood that the person in charge may have a severely skewed interpretation of reality.

3.4.2.4 Lightweight project manager

This set of experiments explores the effect of an influence structure that lies in direct contrast to the heavyweight PM setting. Each team member is influenced equally by all other team members. We term such a team as the lightweight project manager team structure (hereafter lightweight team) to reflect this mild, but nonetheless important form of interaction. Formally, $\mathbf{T}$ is such that $w_{ij} = \frac{1}{M}$ for all i, j values[13]. Figure 12 reveals that under symmetric intra-team influences, the interpretive diversity effect are smoother than the no-interaction case. Thus, for a given level of ε, the percentage of times that the diverse team stopped "too early" or "too late" is lower. However, it is important to note that the effect due to interaction is stronger in the "too early" cases, and rather negligible in the "too late" ones (contrast empty circle points and filled circle points in Figures 11 and 12). In other words, team members

[13] Although this structure might seem unrealistic because of the perfect symmetricity of the interactions, it captures the effects of a team without a significant dominance from any of the team members. Our results are qualitatively insensitive to small deviations in the influence matrix structure, e.g., $w_{ij} = \frac{1}{M} \pm \delta$, with δ small.

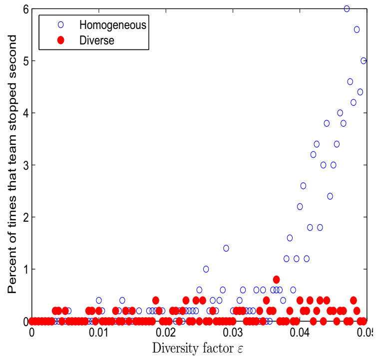
with low beliefs (i.e., the pessimists) are influenced significantly by their peers with high beliefs (i.e., the optimists), but not vice versa.

To understand what drives this unidirectional relationship, one should note that lower beliefs indicate members that assign higher fidelity to the progress information. This higher assigned fidelity has two effects. First, according to Proposition 3, the pessimists have, in general, lower termination thresholds, and a slight modification in their beliefs during the meeting may lead them to "switch" sides. Second, a higher fidelity amplifies the impact of the current belief, $p_{i,t}$, on the optimism of a member (i.e., the probability that the next signal will be positive[14]) and therefore on the likelihood that the member proposes continuation. Combining these effects, we explain how a symmetric influence matrix has an asymmetric impact among the diverse team members. Our observation bears significance as it highlights the limitations of extensive intra-team communication. Communication may hinder understanding of the project status: the optimists use the communication channels to drive the team expectations higher, resulting in more escalation phenomena.

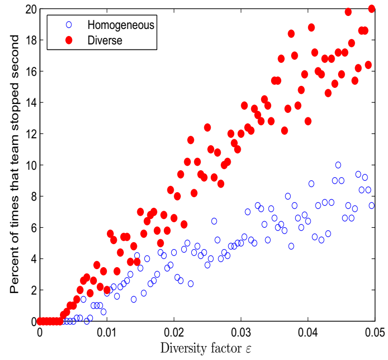
3.4.3 Social conformity

A vast literature in psychology, sociology and economics has established that individual decisions are not only driven by personal considerations (e.g., interpretive schemes), but also by "social" forces, such as the desire for social acceptance. One that has been widely discussed, as it plays an important role in team decision-making, is the issue of *social conformity.* Social conformity represents the act of changing perspective and behavior to match the beliefs of others (Cialdini and Goldstein 2004). Although social conformity was formally demonstrated for the first time in Asch (1951) and Deutsch and Gerard (1955), it has arguably been shaping decision-making for a long time[15]. Of particular interest for our model is the effect of majority on shaping

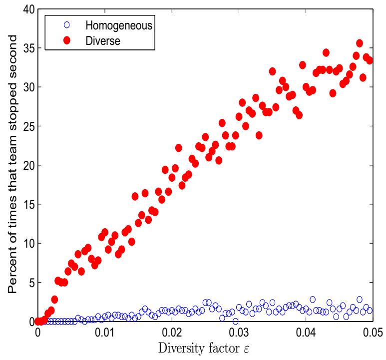
[14]Mathematically, the probability $Pr(\xi_t = s)$ is supermodular in $p_{i,t}$ and q_i.
[15]"To do exactly as your neighbors do is the only sensible rule..." (Emily Post, 1922 Ch. 33)



(a) low q_R



(b) medium q_R



(c) high q_R

Figure 12: Percentage of times that each team stopped second (lightweight team)

the beliefs of the team members (Boyd and Richerson 1985, Hung and Plott 2001). We do not aim to contribute to this extensive literature. Instead, we adopt its basic mechanisms to explore the implications of social conformity on project termination decisions under different information perception structures.

Within the context of our study, conformity manifests as follows: after the t^{th} stage decision has taken place, each member contemplates whether to stick to her belief or to conform with the majority. How does the conformity happen? In the event that the majority of beliefs advocate termination, conforming does not have an effect since the project is abandoned. However, if most of the members' beliefs lie above their respective thresholds, then the project continues, and the team members with beliefs below their thresholds may choose to conform to the majority[16] and

[16]In some organizational contexts, executives that persist on their termination opinions are called

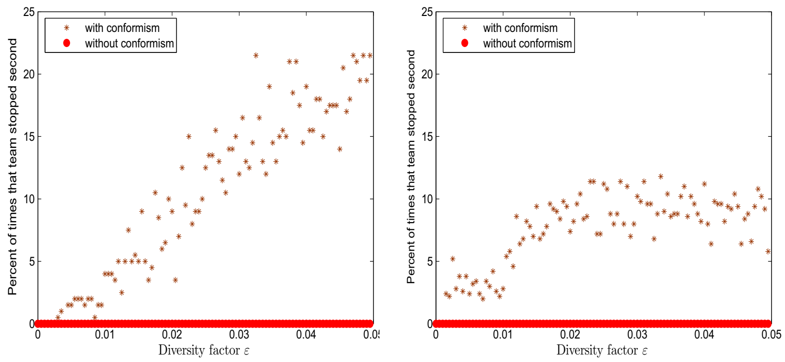
to switch their beliefs to the lowest optimistic belief, that is, $p_{i,t+1} = p_{j,t}$ where $p_{j,t} = min_{k \neq i}\{p_{k,t} : D_{k,t} = 1\}$.

We choose this mild rule because it is the most conservative form of conformism. The members that switch beliefs adopt the belief that lies the closest to their past beliefs (saving face, or inherent difficulty to drastically change). Slight modifications of the proposed mechanism, e.g. the pessimistic members do not conform with certainty but only with an exogenous probability α, do not change our results qualitatively.

We compare a diverse team without intra-team influences ($\mathbf{T} = \mathbf{I}$) and without social conformity with one where social conformity is present[17]. Figure 13 confirms that conformity is an additional driver of escalation. Both for medium and high q_R, conformity delays further the termination decision. Interestingly, the impact of conformity for low q_R values is negligible, reflecting the fact that, in such settings, the team members do not hold radically different opinions (e.g., left part of Figure 8). Note that the delay due to conformity comes in addition to the delay already observed due to the interpretive diversity. The combination of these two effects renders project termination highly challenging, and it offers additional explanatory power to scholars that study escalation phenomena. Our result also highlights the detrimental effects that social conformity contexts impose, since they diminish the "heretic" voices that may challenge common wisdom. Finally, it is interesting to note that, despite the seemingly opposing nature of social conformity and diversity (i.e., conformity suppresses diversity as it pushes everybody towards a common perspective), the former reinforces the effect of the latter, leading to further delays in the project termination decision.

blockers, a nickname that carries a negative connotation. We would like to thank an NPD manager for pointing us to this jargon.

[17]It is noteworthy to highlight the difference between intra-team influences and social conformity. The former represents adjustments in one's beliefs due to input and rational argumentation from another peer. The latter relates more to a behavioral reaction that emerges from the inherent individual need to be aligned with their peers



(a) medium q_R (b) high q_R

Figure 13: Percentage of times that each team stopped second

3.5 Conclusions and Discussion

In this paper, we examine the challenges associated with project termination decisions (Schmidt and Calantone 1998). The extant literature from a variety of research fields, spanning from psychology to operations management reveals that NPD project termination is anything but a simple decision, even for the most capable organizations. Several detailed case studies confirm the often cited claim that "projects get a life of their own," and they illustrate the detrimental effects of *escalation of commitment* situations. In the majority of these studies, escalation is attributed to either psychological or organizational issues. We undertake a different approach, and we try to explain whether such phenomena arise even among perfectly rational decision-makers. We analyze the decision patterns of project teams whose members propose continuation or termination based on their perception of project progress and a dynamic assessment of the likelihood of project success. We depart from the extensive prior literature on optimal stopping problems that implicitly assumes a single decision-maker. On the contrary, we account for the potentially different "interpretive schemes" (Dougherty 1992) that characterize modern cross-functional NPD teams. We approximate such *interpretive* diversity through individual-specific fidelity assigned to new information.

In order to determine the effects of interpretive diversity, we need to isolate its impact. To that end, we first study the optimal termination policy of a benchmark homogeneous team. In that setting, the termination decision is governed by a threshold policy, and continuation is advocated only if the belief about the successful commercialization is above a given value. These threshold values decrease in the information fidelity. Put differently, as the information becomes less reliable, the team raises the threshold values, leading to a more conservative continuation policy. Yet, the above result says nothing about the actual termination time, which is the relevant managerial metric, as it denotes how long it takes before "pulling the plug" of a deteriorating project. Given the path dependency of the phenomenon, we reside on extensive numerical experimentation and we estimate the average number of stages that the project continues. The results reveal an inverse S-shaped relationship between the information fidelity and the project duration. In other words, low emphasis on outside information delays project termination, since evidence is deemed uninformative. For higher levels of fidelity, the impact of information increases, and thus, the project stops faster. Interestingly, for low levels of fidelity, the impact of information is less drastic, only moderately affecting the overall project duration. As we discuss below, this concave-convex relationship has significant implications for the impact of interpretive diversity on termination decisions.

We build intuition gradually and we consider a team structure where members assign different degrees of fidelity to the project progress information. Our main result indicates that the impact of diversity critically depends on the underlying project uncertainty, with the latter being proxied by the average information fidelity. For low levels of information fidelity, the diverse team rushes to stop projects earlier than necessary, a conservative behavior that runs the risk of terminating potentially successful projects. In contrast, for high levels of information fidelity, diversity becomes a systematic source of escalation, and the diverse team continues projects that a homogeneous one would have terminated.

We also incorporate the effects of the intra-team communication web, i.e. the influences that team members exert on their peers. While our results do not change qualitatively across different team structures, two systematic effects emerge. First, the presence of a heavyweight project manager intensifies the escalation effects, and, surprisingly, the results persist even under lightweight team structures. Finally, we account for social conformity effects, i.e. the adaptation of member beliefs to the majority. We illustrate how social conformity leads to additional delays.

Our results develop managerial intuition along three dimensions. First, we highlight the perils of interpretive diversity. Our study draws a cautious message regarding the (often implied) beneficial nature of cross-functional NPD teams. The organizational theory literature has long debated the mixed effects of diversity on team performance (Cavarretta 2007). We show that, regarding a *specific* performance metric (project termination decisions), a *specific* type of diversity (project progress information interpretation) bears different outcomes depending on the underlying project uncertainty. Thus, we admit the limitation of context specificity, but at the benefit of richer and focused operational conclusions. Second, we outline the involved dynamic interplay between the team structure, the interpretive diversity, and the project uncertainty. We show that one needs to pay attention to all three factors together when assessing NPD decisions. Finally, we show that seemingly opposing managerial actions, namely the diversification of the team composition and the pressure to conform to a target, may lead to the same negative outcome regarding termination decisions. Thus, we call for a deeper understanding of the origins and magnitude of each of these factors, a task that senior management must accomplish to meaningfully address the particularly challenging task of terminating ("killing") NPD projects.

Our model is a normative effort to analyze and further examine the admittedly complex phenomenon of escalation of commitment in NPD projects. As a normative effort, it is bound to the limitations that theoretical abstractions exhibit. Thus, we do not provide a decision support system, but rather we establish directional results that build managerial intuition. At a finer level, we have assumed away any strategic considerations from the team members. Recently, the economics literature has placed emphasis on such gaming aspects (Caillaud and Tirole 2007, Bond and Eraslan 2007). We focus on projects where all team members are equally benefiting from a successful completion, a context with less strategizing. In addition, we assume that team members have no information about their peers' interpretive schemes. Future research should extend our setting to account for more-informed decision-makers.

CHAPTER IV

RELICENSING AS A SECONDARY MARKET STRATEGY

4.1 Introduction

Today, Original Equipment Manufacturers (OEMs) in the Information Technology (IT) industry often face difficult decisions when forming strategies involving secondary markets for their products. In the years before the dot-com bubble of the late 1990s, there was a limited secondary IT market. Some reasons for this lack of demand for refurbished IT equipment included: 1) IT OEMs focused on their primary sales channels and discouraged customers from considering refurbished equipment; 2) buyers of IT equipment were leery of the quality level of a refurbished product; and 3) there was a lack of independent secondary market firms to refurbish, resell, and support IT equipment. Shortages of higher-end IT equipment such as servers and routers during the late 1990s however, led to unmet demand that was often satisfied by a new market of third-party IT equipment brokers and refurbishers[1]. In the years following, the dot-com bust resulted in a large surplus of barely used IT equipment for sale from companies who failed when the bubble burst. The availability of so much inexpensive used IT equipment led to significant price discounts compared to the price of new equipment and even more brokers and refurbishers entering the

[1]Third-party refurbishers do not manufacture their own products, but instead rebuild and reconfigure used OEM products that they buy from IT users who upgrade or no longer need those products. Unlike other markets such as the automotive market, potential customers in the used IT equipment market typically expect the equipment to be refurbished before purchasing; thus the vast majority of the sales in the IT secondary market are between refurbishers and the end-users rather than between the end-users themselves. Following industry usage, we will use the terms "refurbished" and "remanufactured" interchangeably in this paper; for a detailed definition of these terms, see Thierry et al. (1995).

secondary market (Berinato 2002).

One of the lasting effects from the dot-com era is that major customers of IT equipment have started accepting refurbished IT equipment as a viable alternative to new equipment and a new body of IT refurbishers has entered the market to meet this demand. According to a 2002 survey of 187 IT executives in CIO magazine, 77 percent said they were purchasing secondary market equipment and 46 percent expected to increase their spending on refurbished equipment in the next year by an average of 15 percent (Berinato 2002). In another article, Computer Business Review highlights that "third-party companies have built $100+ million per year businesses in buying used computer equipment, refurbishing it, and selling or leasing it out to someone else" (CBRonline.com 2005). Given the size and growth of the secondary market, the days of ignoring it and only focusing on the sale of new products are over for all major IT OEMs. OEMs may either embrace the secondary market or try to eliminate it, but one thing is now evident, they must form strategies to respond to it.

Some of the major OEMs in the IT industry have not only embraced the existence of a secondary market, but also deploy it to obtain competitive advantage over their rivals. IBM and Hewlett Packard, for instance, create high resale values for their used equipment by facilitating the resale process and secondary use (e.g. charging small relicensing fees, offering maintenance and inspection) so that the original customers gain a higher net benefit from their new product purchases. Such a proactive, and in a sense cooperative, relationship with third-party brokers and refurbishers, however, is not a standard policy among all IT OEMs. An alternative strategy is to institute policies and fees that attempt to eliminate the secondary market. For example, Sun Microsystems (Sun), one of the leading firms in the IT server business, was "under fire for deliberately attempting to eliminate the secondary market for its machines worldwide through their new pricing and licensing schemes" (Marion 2004). Cisco is another company that requires each buyer of its refurbished equipment to pay high relicensing fees for the proprietary software that makes the equipment run.

The following excerpts, typical of the IT industry, shed some light on how the relicensing mechanism works. "Cisco adopts a policy of non-transferability of its software to protect its intellectual property rights." What this means is that owners of Cisco products are only allowed to transfer, resell, or re-lease used Cisco hardware and not the embedded software that runs on it. This practice, in effect, eliminates the secondary market and creates customer dissatisfaction. Cisco's response to this criticism was to institute relicensing fees, albeit significant: "As Cisco's installed base of equipment has grown to such large numbers over the years, our customers have become more interested in selling and leasing used Cisco equipment on the secondary market. In order to provide our valued customers and partners with this capability, Cisco is now setting up a program where companies who are interested in buying used equipment, may now purchase a new software license to do so" (Cisco.com 2007).

Despite such statements that a relicensing fee mechanism allows reselling refurbished equipment on the secondary market, many industry observers argue that some OEMs use unreasonably high relicensing fees as a means of limiting the secondary market. In the case of Sun, Marion (2004) highlights the fact that the relicensing fee is deliberately set so high that the overall cost of a unit of refurbished equipment, including hardware and software, reaches that of a new one: "In the end, the potential buyer for the refurbished equipment may have no choice but to return to Sun for a new product." He concludes by stressing another interesting facet of the problem: "End users need to know this and take action to adjust the Sun hardware values reflected on their respective balance sheets to account for the impact that Sun's actions, described above, will have on resale and residual values." In other words, users should be aware that Sun's practices result in very low resale values of used equipment and this information should be factored into their original purchase decision.

In fact, many IT consulting companies (e.g. www.computereconomics.com) offer detailed forecasts regarding future resale values of used IT equipment, underlining the critical role of the resale value in the initial IT purchase decision.

From a research perspective, the discussion above raises the fundamental question addressed in this paper. Given the OEM's ability to interfere with the IT secondary market through pricing and relicensing schemes, is limiting this market or, conversely, encouraging its existence, a more profitable strategy? If one strategy is dominant over the other, the winner is currently not clear based on anecdotal evidence alone. Our goal is to understand how the OEM's incentives and optimal strategies are shaped contingent on costs, product characteristics, consumer preferences and the intensity of remanufacturing competition. Motivated by the industry articles concerning Sun, a company that has historically been considered the premium brand in the server market (Sun.com 2007), we also examine whether such a brand premium could justify an aggressive strategy vis-à-vis the secondary market.

We begin our analysis by studying the optimal strategy of an OEM that has a monopoly on the new product market, but faces future competition from a third-party entrant who purchases the used products from the OEM's customers, refurbishes them, and resells them in competition with the OEM's new products. The OEM collects a relicensing fee on every product sold by the entrant; and can effectively "shut down" the secondary market by charging a high enough fee. Our key finding is that it is suboptimal for the OEM to shut down the secondary market when the refurbishing cost is low, even though this means the entrant is more competitive. This seemingly counter-intuitive strategy is driven by the fact that in this cost range, not only can the OEM charge a higher relicensing fee, but she can also benefit from a stronger resale value effect. If customers are not strategic (no resale value effect) or the OEM's second-generation product is technologically superior to the first, however, then the OEM adopts a more aggressive strategy against the secondary market, and may even charge a high enough fee to shut it down completely for any level of refurbishing cost. Similarly, if the OEM decides to enter the secondary market herself (in conjunction with imposing a relicensing fee), she will do so more aggressively when the refurbishing cost is low, exiting the secondary market and benefiting indirectly from its existence at higher values of the refurbishing cost.

We also examine how the OEM's strategy changes as the number of the independent entrants increases, i.e. the secondary market becomes more competitive. We find that both the OEM's profits as well as the size of the secondary market grow with an increase in the number of entrants. Interestingly, the OEM decreases her relicensing fee even as the sales volume of refurbished equipment grows, and the cannibalization of new products increases. This is because an increasing network of resellers strengthens the marginal impact of the relicensing fee on the resale value effect relative to the corresponding impact on the cannibalization effect. As a result, the OEM chooses to lower the relicensing fee, further stimulating the procurement competition among the entrants, and benefits from the higher resale value of her used product.

We conclude by analyzing OEM strategies in a differentiated new product duopoly setting. Our numerical results show the high-end OEM always charges a higher relicensing fee than the low-end OEM, and the difference between relicensing fees can be significant. Thus, a high relicensing fee need not be indicative of an attempt to shut down the secondary market, but rather reflect the brand premium the high-end OEM commands. This result may help explain the significantly different relicensing fees observed in practice. Overall, our research highlights the strategic importance of supporting an active secondary market under a wide range of circumstances, particularly in the presence of strategic consumers and low refurbishing costs.

4.2 Literature Review

A rapidly growing stream of literature on remanufacturing has focused on the competition between the OEM and independent refurbishers/remanufacturers (Majumder and Groenevelt 2001, Debo et al. 2005, Ferguson and Toktay 2006, Ferrer and Swaminathan 2006), or the role of remanufacturing in primary market competition between OEMs (Heese et al. 2005, Atasu et al. 2007). We contribute to this literature in the following ways.

First, although these papers provide a theoretical framework for analyzing the competition between the OEM and potential entrants that refurbish and sell the OEM's product, they do not incorporate the effect of the resale value on the consumers' net utility from purchasing a new product. As a result, they focus only on the cannibalization effect, and therefore, the existence of independent remanufacturers is always detrimental for the OEM's profit. Two exceptions that account for the resale value effect are Heese et al. (2005) and Debo et al. (2005). Heese et al. (2005) examine the profitability of product take-back strategies incorporating the resale value effect into consumer strategies. The resale value, though, is set exogenously while in our paper is determined by the competitive dynamics of the secondary market. Moreover, the relicensing fee mechanism, introduced in our paper, reverses some of the results presented in Debo et al. (2005). We contribute to this literature by endogenizing the resale value, and more importantly, by linking it to the consumers' willingness to pay for a new product. Thus, competition from an independent refurbisher has both a positive (resale value effect) and a negative (cannibalization of new product sales) impact on the OEM's profit. We show that the resale value effect can dominate and the OEM can benefit from the existence of an entrant.

Second, in their extension capturing the resale value effect, Debo et al. (2005) find that as the number of remanufacturers increases (cannibalization increases), the OEM's profit decreases despite the positive resale value effect. With the relicensing fee mechanism, we show that a higher competitive intensity in the secondary market can benefit the OEM. This happens because the relicensing fee allows the OEM to directly impact the secondary market: The OEM increases her profits by reducing the relicensing fee and increasing the product's resale value as remanufacturing competition increases.

Third, we show that if the OEM decides to refurbish her own products in conjunction with a relicensing fee mechanism, she will dominate the secondary market at low refurbishing costs, while leaving the secondary market to the entrant at higher levels of refurbishing cost. This is consistent with Ferrer and Swaminathan (2006), who show that a higher remanufacturing cost savings means higher participation by the OEM in the secondary market, and Ferguson and Toktay (2006), who find that as the entrant becomes more competitive and the cannibalization threat increases, the OEM should increase her efforts to deter the secondary market. If the OEM makes a strategic determination not to participate in the refurbished product market, however, then she should pursue the diametrically opposed strategy of supporting the secondary market at low levels of the refurbishing cost to exploit the strong resale value effect in this cost range.

While the idea that a secondary market can benefit the OEM is relatively new in the remanufacturing literature, it is well established in the durable goods literature, a thorough review of which can be found in Waldman (2003). Until the early 1970s, the main conclusion regarding the impact of secondary markets on a monopolist's profitability was due to the cannibalization effect between new and used products. In the words of Gaskins (1974), "conventional economic wisdom... contends that the existence of a competitive secondhand market constitutes a major long-run restraint on monopoly power in a primary market." Motivated by the market for diamonds, however, Miller (1974) argues that "the buyer of a newly produced diamond pays a price consistent with what the diamond can be sold for to others including members of later generations" and thus "the initial price captures the present value of all subsequent transactions." In essence, he points out the "resale value effect," arguing that a secondary market might increase the value derived by the consumer, and in turn, the price that the monopolist can charge for it. This argument is also stressed by Benjamin and Kormendi (1974), Liebowitz (1982), Rust (1986), and Levinthal and Purohit (1989), who all argue that whether or not a monopolist has the incentive to eliminate the secondary market is not clear-cut. A limitation of these papers is the assumption that the demand side is modeled by a representative consumer (homogeneous consumer preferences). Anderson and Ginsburgh (1994) argue that in those models, the size of the second-hand market is indeterminate since the representative consumer buys both new goods and used goods each period and essentially sells the used good to herself. By introducing a model in which consumers have heterogeneous tastes, they show that the existence of a secondary market enables the monopolist to achieve price discrimination between high and low valuation consumers who buy new and used products, respectively.

Models allowing consumers to have heterogeneous tastes are refined in further research by Waldman (1996, 1997), Desai and Purohit (1998), Hendel and Lizzeri (1999) and Desai et al. (2004, 2007). Waldman (1996) employs the seminal Mussa and Rosen (1978) analysis of market segmentation and product-line pricing to allow consumers to vary in their valuations of quality. His main result is that because of the substitution effect between new and used products, the price at which old units trade on the secondary market constrains the price that the monopolist can charge for the new units. Therefore, he demonstrates that the monopolist may have an incentive to "shut down" the market by reducing durability to "sufficiently low" values. In a follow-up paper, Waldman (1997) demonstrates that leasing versus selling can be used to eliminate the secondary market, and argues that this motivation might have been the primary reason for many prominent anti-trust leasing cases (United Shoe, IBM, Xerox). Hendel and Lizzeri (1999) study leasing and selling strategies under secondary markets when durability is endogenous and the OEM can either allow a fully functioning secondary market (perfectly competitive with no restrictions) or shut down the secondary market completely. They show conditions where the OEM would not want to shut down the secondary market but prefers reducing the durability instead. Finally, Desai and Purohit (1998) and Desai et al. (2004, 2007) include the discounted resale price (resulting from perfect competition in the second period) in the consumer's first-period valuation of the new product, but their primary focus is on evaluating leasing versus selling, solving the time-consistency problem, or evaluating the impact of demand uncertainty, respectively.

We contribute to the literature on interfering with the secondary market along the following dimensions. First, we introduce one more mechanism to this literature – imposing a relicensing fee – and are the first to capture the strategic implications of this widespread mechanism. Unlike previously explored mechanisms that require the OEM to make modifications to her product or market strategies, the relicensing fee mechanism is "costless" in that the OEM can set the fee as high as needed to deter the entrants without any direct repercussions. We show that nevertheless, the OEM should not shut down the secondary market under a wide range of conditions. By treating the relicensing fee as a continuous decision variable, we avoid restricting the OEM to either fully supporting or completely shutting down the secondary market (e.g. as in Hendel and Lizzeri 1999).

Second, we analyze the relicensing fee strategy in depth, by modeling operational elements such as production cost and refurbishing cost, by making a distinction between the inherent durability of the product and the value to the customer after refurbishing, by varying the level of competitive intensity on the secondary market, and by allowing competition in the primary market. We highlight some of these elements below:

We relax the common assumption of perfect competition in the secondary market and allow for a profit-maximizing entrant to collect and refurbish the used products (in the durable goods literature, consumers are allowed to sell the used product to each other, creating a perfectly competitive secondary market, and refurbishing cost is not modeled). The value offered to the consumers for the used product by the entrant is determined as his optimal response to the OEM's decisions. Thus, the purchase price for used units and the prices charged to consumers for new and refurbished products arise as the Nash equilibrium of the game between the OEM and the entrant. This allows us to examine the impact of the production and refurbishing costs on the OEM's strategy. We also study how the relicensing fee strategy changes with respect to the number of entrants.

We also relax the assumption of a monopolist OEM by allowing vertically differentiated new products to compete in the primary market. To our knowledge, we are the first to model differentiated new and refurbished products competing in both the primary and secondary markets. We find that the high-end OEM always charges a higher relicensing fee than the low-end OEM and that the difference between relicensing fees can be significant. Yet, whether a high-end or a low-end OEM has a greater secondary market depends on the market conditions and the relative brand differential between the two OEMs. Our results indicate that even with competition in the primary market, it remains rare for either OEM to eliminate the secondary market, although the total size of the secondary market decreases as the brand premium of the high-end OEM decreases.

We conclude by highlighting a contribution at the intersection of the remanufacturing and durable goods literatures. Prior work on durable goods theory assumes consumers trade among each other, selling the (depreciated) used product as is. In contrast, prior work on remanufacturing assumes that a used product provides no utility unless it is refurbished. Our model captures both aspects, where the product depreciates with use, but it can be refurbished by an entrant to offer a higher utility than if used as is. We are thus able to separate the effect of inherent product durability from the effect of the remanufacturing process. As our analysis reveals, although both effects reduce the demand for new products in the second period, their role on the relicensing strategy is diametrically opposite. In particular, the optimal relicensing fee decreases in the durability of the product, but increases in the value that the customer obtains from the refurbished product. As explained in detail later, the difference stems from the way in which these two features affect the resale value of the product.

4.3 Key Assumptions and Notation

Our baseline analysis assumes the OEM holds a monopoly in the new product market. We develop a two-period model. In the first period, the OEM sells new products. In the second period, the OEM may again sell new products, and there is a third-party entrant who may refurbish and resell used products bought from the OEM's first-period customers. Thus, in the second period, the OEM's new product sales face competition from the refurbished products offered by the entrant. At the same time, the OEM generates relicensing fee revenues from the refurbished products. Our goal is to examine the OEM's relicensing fee strategy in the face of future competition from refurbished products. We make the following assumptions:

Assumption 1. *Consumer willingness-to-pay is heterogeneous and uniformly distributed in the interval* $[0, 1]$.

We assume that consumer types are distributed uniformly in the interval $[0, 1]$, where a consumer of type $\theta \in [0, 1]$ has a willingness-to-pay of θ for a new product. In any period, each consumer uses at most one unit. The market size is normalized to 1. With this representation, in a single-period problem with only the new product, consumer θ's utility function would be $U_1(\theta) = \theta - p_1$, where U_1 represents consumer utility and p_1 is the price paid for the new product. This would lead to the familiar inverse demand function $p_1 = 1 - q_1$, where q_1 is the quantity of new product sold in the first period. Demand functions for our two-period model are developed in the Analysis section.

Assumption 2. *The product depreciates with use.*

The rate of depreciation of a product depends on its durability, which we parametrize by δ_o. Thus, if the consumer type θ who bought a new product in the first period continues to use that product in the second period, the utility he obtains in that period is $\delta_o\theta$. If $\delta_o = 0$, consumers obtain no utility from their used product in the second period. In this case, the product's useful life (in the absence of being refurbished by the entrant) is effectively only one period. Therefore, all first-period customers re-enter the market in the second period, and can buy another new product or a refurbished product. The majority of remanufacturing papers make this one-period useful product life assumption (Majumder and Groenevelt 2001, Ray et al. 2005, Ferrer and Swaminathan 2006, Ferguson and Toktay 2006, and Atasu et al. 2007).

Assumption 3. *Consumers do not sell their used products directly to each other.*

Used IT equipment, before it can be reused by another party, typically requires some costly refurbishing effort (e.g., updating software, replacing hardware components, testing the equipment). Thus, we assume that consumers cannot sell their used products directly to each other. Instead, a third-party refurbisher buys used products from first-period consumers (return volume depends on the price offered by the entrant), and enters the market in the second period by refurbishing and reselling these products. This assumption reflects the current practice in the used IT market where most used equipment, before it can be resold, requires software updates and the replacement of wearable parts that the consumers do not have the technical capability to perform.

Assumption 4. *Each consumer's willingness-to-pay for the refurbished product is a* *fraction δ of their willingness-to pay for the new product, where $\delta_o < \delta < 1$.*

Under this assumption, a consumer with a willingness-to-pay θ for the new product has a willingness-to-pay $\delta\theta$ for the refurbished one. The nature of competition between new and refurbished units is thus one of vertical differentiation. That is, for the same price, consumers prefer a new product to a refurbished one. This assumption is driven by the evidence that consumers are concerned about the quality of a refurbished product and this is reflected in their willingness to pay for it. Empirical evidence for lower valuation of remanufactured products is offered in Guide and Li (2007), and Subramanian and Subramanyam (2007). This perspective is also reflected in a number of articles in the practitioner and academic literature (Lund and Skeels 1983, Hauser and Lund 2003, Kandra 2002, Debo et al. 2005, Vorasayan and Ryan 2006, Jin et al. 2007). Since refurbishing involves software updates, the replacement of wearable parts, cleaning and testing, the relative utility that a customer would obtain from using a refurbished product is higher than if he just kept using his now-used product that he had purchased in the first period. We capture this by assuming $\delta_o < \delta$.

Assumption 5. *The disutility to a consumer of reselling a used product is a fraction of his original willingness-to-pay for the new product.*

The entrant offers a resale value (denoted by s) to first-period customers to purchase their used products at the end of the first period. We assume that a consumer with a willingness-to-pay θ for a new product will incur a perceived transactional disutility (hereafter disutility) of $\gamma\theta$ (where $0 < \gamma < \delta$) to sell his used product to the entrant (e.g. perceived disutility of searching for IT resellers, removing sensitive data, etc.). Hence, a higher incentive is needed to induce a higher willingness-to-pay consumer to resell his used product. This is consistent with consumer search theory which states that consumers are diversified with respect to how much disutility they perceive from such searching, with wealthy consumers experiencing the greatest loss (Phlips 1983, Mehta et al. 2003). This behavioral characteristic also forms the basis behind the common use of product rebates that allow price discrimination between consumers who will take the time to send in the rebate and those who will not. For example, Gerstner and Hess (1991) argue that "there is a positive association between willingness-to-pay and redemption costs" (Gerstner and Hess 1991, p. 875) since "high-end customers have higher time costs for the activities required to take advantage of the discount" (Gerstner et al. 1994, p. 1438). Obviously, the higher the rebate, the higher the percentage of customers that claim it. Similarly, with this assumption, the higher the price offered by the entrant, the higher the percentage of customers who will sell their used product to the entrant. In line with previous research on reverse logistics and remanufacturing, this assumption ensures that the average cost of acquisition increases in the quantity of the products collected (Guide 2000, Guide and Van Wassenhove 2001, Galbreth and Blackburn 2006, Ferguson and Toktay 2006).

Assumption 6. *Consumers are strategic.*

There is empirical evidence that IT consumers are strategic in their purchasing behavior (Song and Chintagunta 2003, Nair 2004, Plambeck and Wang 2006). Accordingly, we assume that consumers take into account the future resale value s of the product in making their purchase decisions. This is facilitated in practice by the existence of IT consulting companies that offer resale value forecasts.

Assumption 7. *The OEM charges a relicensing fee h in the second period to any consumer who purchases a refurbished product.*

The establishment of a relicensing fee, typically called a Digital License Agreement (DLA), has been widely employed by OEMs as a means of protecting their intellectual property rights. A DLA allows a consumer to re-install the necessary software for the equipment to operate and thus, a refurbished product is of no use without it. OEMs publish list prices for new equipment (that implicitly includes both hardware and software cost) and most publish a separate list where their relicensing policies are explicitly laid out. The relicensing fee, declared in the first period, constitutes an important element of our model, since it affects the resale value offered by the entrant, which is taken into account by strategic consumers of new products. In particular, the utility that each consumer derives from purchasing a refurbished product is given by the difference of their willingness-to-pay and the price plus the relicensing fee.

Assumption 8. *In the second period, the OEM introduces new products technologically equivalent or superior to the ones introduced in the first period.*

The IT industry is characterized by rapid technological change. It is typical for an OEM to introduce an improved version of her existing product not long after the original product introduction. For instance, an upgraded version might have a faster Central Process Unit (CPU) or bigger memory. To capture the increased consumer willingness-to-pay due to this technology improvement, we assume that a consumer with a willingness-to-pay θ for the new product in the first-period has a willingness-to-pay $\alpha\theta$, where $\alpha \geq 1$, for a new second-period product.

4.4 Analysis: Monopoly in the New Product Market

In this section, we analyze the model with a single OEM who sells a new product in both periods and charges a relicensing fee for refurbished products that are acquired, refurbished and resold by entrants in the second period.

In this competitive setting, the OEM has a significant advantage over the entrants: She controls the relicensing fee that consumers of refurbished products need to pay on top of the purchase price charged by the entrants. As the relicensing fee increases, the cost to consumers of the refurbished product increases, which in turn reduces demand and shifts consumers to the new product. At first sight, a high value for the relicensing fee may seem like a good idea for the OEM, since it eliminates the competition from the refurbished product. Eliminating the secondary market, however, has an important impact on first-period profits. Since consumers can no longer sell their used products to an entrant, the net utility they obtain from the new product decreases. Consequently, the price charged by the monopolist OEM, along with her first-period profits, is lower than it would have been had the consumers foreseen a positive resale value for their used products. Hence, the OEM needs to balance the impact of two opposite forces: A lower relicensing fee leads to competition in the second period, but allows the OEM to charge a premium in the first period that reflects the consumer's ability to resell the product in the second period.

To analyze this trade-off systematically and delineate the impact of various drivers, we start with a baseline model where $\delta_o = 0$ and there is a single entrant. Then we explore the following extensions that shed light on the role of the resale value effect, competition and durability: non-strategic consumers, N entrants, OEM participation in the secondary market and $\delta_o > 0$.

4.4.1 Analysis of the Baseline Model

With the baseline model assumption that the used product offers no utility in the second period ($\delta_o = 0$), two-period consumer strategies decompose into two independent single-period decisions: In period 1, the consumer choices are to buy new or to not buy, and in period 2, the consumer choices are to buy new or refurbished or nothing, regardless of their first-period decision. In addition, first-period buyers decide to sell their product to the entrant or not (depending on the value of s relative to their disutility $\gamma\theta$), which impacts their net first-period utility, but has no impact on their second-period choices.

Derivation of Demand Functions. As discussed above, the two periods decouple in the consumer strategy space. Let us start with the first-period decision of the consumer, to buy a new product or not. The resale value of the product, since it is a consequence of selling the product bought in the first period, needs to be included in the net utility obtained from that product's purchase. Consumer θ will sell the used product to the entrant for a price s only if this value is greater than his disutility $\gamma\theta$. Therefore, a strategic consumer of type θ derives a net utility of $U_1(\theta) = \theta - p_1 + (s - \gamma\theta)I_{(s \geq \gamma\theta)}$ from purchasing a new product in period 1, where $I_{(s \geq \gamma\theta)} = 1$ when $s \geq \gamma\theta$ and 0 otherwise.

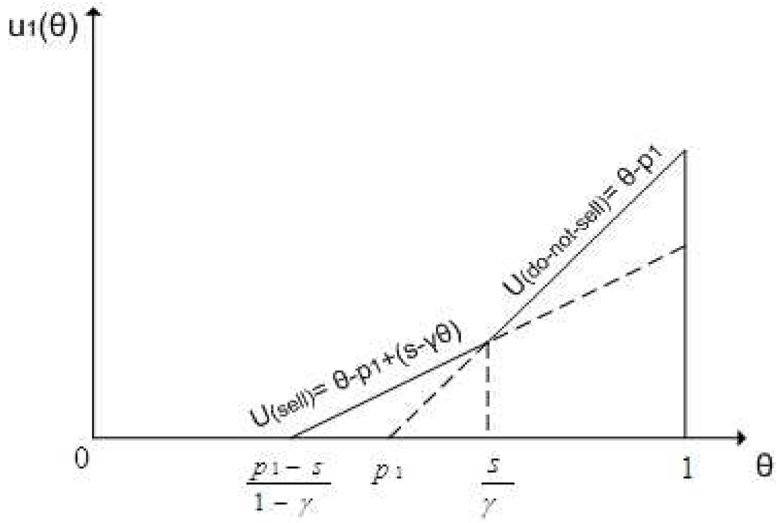


Figure 14: Consumer state space and corresponding utilities from selling versus not selling the used product.

As shown in Figure 14, contingent on their type, first-period consumers fall in one of three segments. If $\theta \leq \frac{p_1 - s}{1-\gamma}$, consumers do not purchase the new product, while for $\frac{p_1 - s}{1-\gamma} < \theta \leq \frac{s}{\gamma}$, consumers purchase the new product and subsequently resell it. Finally, for $\frac{s}{\gamma} < \theta \leq 1$, consumers purchase the new product and do not resell it. Therefore, the total sales quantity in period 1 is $q_1 = 1 - \frac{p_1 - s}{1-\gamma}$, or, $p_1 = (1-\gamma)(1-q_1) + s$, and the total number of units acquired by the entrant is given by $q_u = \frac{s}{\gamma} - \frac{p_1 - s}{1-\gamma}$. Note that the entrant would never set $s > \gamma$, as $s = \gamma$ is sufficient to ensure all consumers sell their used products ($q_u = q_1$).

We now turn to the second period. Let p_2 and p_r denote the second-period prices of new and refurbished products, respectively. Following our previous discussion, the corresponding consumer utilities obtained by consumer type θ from purchasing each type of product in the second-period are $U_2(\theta) = \alpha\theta - p_2$ for the new product and $U_r(\theta) = \delta\theta - p_r - h$ for the refurbished product. From these utility functions, and letting q_2 and q_r represent the second-period quantities of new and refurbished product respectively, the inverse demand functions are

$$p_2 = \alpha(1 - q_2) - \delta q_r$$
$$p_r = \delta(1 - q_r - q_2) - h.$$

Analysis of the Second-Period OEM-Entrant Competition. We solve the problem by backward induction, starting with the second period. Let Π_2 and Π_e denote the OEM's and the entrant's second-period profit, respectively. At this stage, the OEM decides the quantity of new products that she will sell in the market, while the entrant decides the price s that he will offer to the consumers to obtain their used products, as well as the quantity of refurbished products that he will make available in the market, denoted by q_r. We assume that the unit production cost is $c < 1$, and the unit refurbishing cost is $c_r < c$.

The OEM's second-period objective given the entrant's choice of q_r is

$$Max_{q_2}\ \Pi_2(q_2|q_r) = (p_2 - c)q_2 + hq_r = (\alpha - \alpha q_2 - \delta q_r - c)\, q_2 + hq_r \quad s.t.\ q_2 \geq 0. \quad (5)$$

The first part of (5) captures the profit obtained from selling q_2 units of new products while the second part represents the profit from the relicensing fee (h), obtained from the q_r customers who purchase the refurbished units from the entrant. The quantity of new products to sell is the only decision variable for the OEM in the second period as the relicensing fee is set in the first period.

The entrant's corresponding objective given the OEM's choice of q_2 is

$$Max_{q_r,s}\ \Pi_e(q_r, s|q_2) = (p_r - c_r)q_r - sq_u \qquad s.t.\ 0 \leq q_r \leq q_u \quad (6)$$

$$\text{where } q_u = \frac{s}{\gamma} - \frac{p_1 - s}{1 - \gamma}.$$

The constraint in (6) ensures the quantity of refurbished product is no greater than the number of units collected from the consumers at a resale price of s, given by

$q_u = \frac{s}{\gamma} - \frac{p_1 - s}{1-\gamma}$ (see Figure 14). In practice, the amount collected falls far short of the volume of existing used products, so we do not explicitly model the constraint $q_u \le q_1$ and limit the analysis to parameters where $q_u^* < q_1^*$ in equilibrium. Where appropriate, the potential effect of this constraint is discussed. The following lemmas characterize the price the entrant will pay for the used units.

Lemma 1 *At optimality, the entrant has no incentive to collect more units than the ones he intends to sell in the market. That is, the constraint $q_r \le q_u$ is binding and the optimal resale price offered by the entrant satisfies*

$$s^*(q_r) = \gamma(1-\gamma)q_r + \gamma p_1. \tag{7}$$

All proofs are provided in the Appendix C.

Lemma 2 *For equilibria where both new and refurbished products co-exist, the equilibrium resale value is given by $s^*(q_1, h) = \gamma \frac{[2\gamma\alpha(\gamma-1)+\delta(\delta-4\alpha)]q_1+[5\delta+2\gamma(1-\gamma)-2(h+c_r)]\alpha+\delta c-\delta^2}{2\gamma\alpha(2-\gamma)+\delta(4\alpha-\delta)}$ while the corresponding second-period quantities are $q_2^*(q_1, h) = \frac{\delta h-\gamma\delta q_1-\delta(\delta-\gamma)+\delta c_r-(\alpha-c)[\gamma(\gamma-2)-2\delta]}{2\gamma\alpha(2-\gamma)+\delta(4\alpha-\delta)}$ and $q_r^*(q_1, h) = \frac{2\alpha(\gamma q_1-h-\gamma-c_r)+\delta(\alpha+c)}{2\gamma\alpha(2-\gamma)+\delta(4\alpha-\delta)}$.*

The second lemma reveals two interesting properties of the equilibrium resale value. First, s^* decreases in the quantity of new products sold in the first period. This observation is consistent with the resale values we observe in practice: Whenever a large supply of a specific used model becomes available, its resale value drops dramatically. Second, s^* increases as the relicensing fee h decreases: A low value of h means a higher profit potential from the secondary market, thus the entrant is willing to offer a higher resale price to first-period consumers. In addition, the entrant's decision of whether to enter the market or not is directly related to the relicensing fee h, since the latter affects the profitability of refurbished products. Therefore, the OEM acts as a Stackelberg leader who decides between allowing the existence of a secondary market or not by her choice of h. To characterize the optimal OEM strategy, we need to examine the total profit across both periods. Thus, we now move to the OEM's first-period decisions.

Analysis of the OEM's First-Period Strategy. In the first period, the OEM's decisions include the quantity of new units to sell as well as the relicensing fee. More specifically, the OEM's problem is

$$Max_{q_1,h}\ \Pi(q_1,h) = \Pi_1(q_1,h) + \Pi_2^*(q_1,h) \quad s.t.\ q_1 \geq 0,\ h \geq 0, \tag{8}$$

where $\Pi_1(q_1,h)$ denotes the profit from the sales of new products in the first period. Thus,

$$\Pi_1(q_1,h) = [p_1(q_1,h) - c]\, q_1 = [(1-\gamma)(1-q_1) + s^*(q_1,h) - c]\, q_1,$$

where $s^*(q_1,h)$ is characterized in Lemma 2. Although we ignore discounting in our formulation, the addition of a discount factor to the second-period profit does not fundamentally change our results, but reinforces the resale value effect, as the OEM cares more about first-period profits.

We are now ready to state our main result for the baseline model. The following proposition states that as long as the refurbishing cost is below a threshold value, the OEM is always better off by maintaining a secondary market for her products.

Proposition 1 *For $c_r < c\frac{(\delta-\alpha\gamma)}{\alpha}$, it is not optimal for the OEM to eliminate the secondary market ($q_r^* > 0$). The OEM charges a positive relicensing fee $h^* > 0$, which is decreasing in c and c_r but increasing in α. For $c\frac{(\delta-\alpha\gamma)}{\alpha} \leq c_r < \frac{1}{2}[\delta(1+\frac{c}{\alpha}) - \gamma(1+c)]$, the OEM charges a positive relicensing fee so as to eliminate the secondary market ($q_r^* = 0$). For $c_r \geq \frac{1}{2}[\delta(1+\frac{c}{\alpha}) - \gamma(1+c)]$, $h^* = 0$ and $q_r^* = 0$.*

Proposition 1 may appear counter-intuitive at first glance: As the entrant becomes more competitive in relation to the OEM (c_r decreases in relation to c), the OEM chooses not to eliminate the secondary market. The result is driven by the double benefit that the OEM obtains from the secondary market: the resale value effect and relicensing fee revenues. At low values of refurbishing cost, these benefits outweigh the negative impact of cannibalization even though this is where the entrant poses the most competition to the OEM. But it is precisely because entry is more desirable for the third-party refurbisher that he offers a high resale value to first-period customers, which benefits the OEM. When consumers have a higher willingness-to-pay for the refurbished product or when their transactional disutility is lower, this makes entering the secondary market more attractive, captured in an increasing threshold value below which the OEM allows the secondary market to exist. These results warn against the common perception of many OEMs that competition from an outside firm through the secondary market is always detrimental to their profits. It is possible for the OEM to co-opt the third party into her business strategy by using the relicensing fee strategically.

As the technology improvement parameter α increases, the threshold value $c\frac{(\delta - \alpha\gamma)}{\alpha}$ decreases. For radical technology improvements ($\alpha \geq \frac{\delta}{\gamma}$), the OEM shuts down the secondary market regardless of the refurbishing cost. Intuitively, a higher technology improvement leads to a higher profit margin from the new product in the second period, and thus, the OEM adopts a more aggressive strategy against the secondary market. For this reason, we also observe that the optimal relicensing fee increases in α. On the other hand, when the refurbishing cost c_r increases, the OEM lowers the relicensing fee. Note that both higher α and higher c_r make the new product more competitive against a refurbished product, yet they have the opposite effect on the relicensing fee. A higher α gives the OEM an incentive to change the balance between the primary and secondary market to exploit the additional profit margins from the new products. In contrast, a higher c_r limits the ability of the entrant to maintain a secondary market and distorts the balance the OEM considers optimal. As a result, the OEM attempts to strengthen the secondary market by lowering the relicensing fee. Finally, when the production cost c increases, the OEM lowers the relicensing fee and the quantity of refurbished units increases. In this case, the OEM prefers to produce fewer new units in the second period and exploit the resulting increase in the resale value by charging a higher price for the new product in the first period.

In the range $c\frac{(\delta-\alpha\gamma)}{\alpha} \leq c_r \leq \frac{1}{2}[\delta(1+\frac{c}{\alpha})-\gamma(1+c)]$, the OEM sets $h^* > 0$ so as to eliminate the secondary market ($q_r^* = 0$) since the high refurbishing cost prevents the entrant from offering a high enough resale price. Hence, the resale value benefit from maintaining an active secondary market does not outweigh the detrimental effect of cannibalization. For even higher values of the refurbishing cost, $c_r > \frac{1}{2}[\delta(1+\frac{c}{\alpha}) - \gamma(1+c)]$, the secondary market is not viable: $q_r^* = 0$ even if the relicensing fee were set to zero. Thus, $h^* = 0$ and $q_r^* = 0$.

4.4.2 The Role of the Resale Value Effect

We attributed the OEM's choice to "live and let live" for low enough refurbishing cost to the resale value effect and the relicensing fee. To separate out the impact of these two factors, we can analyze the same problem, but with non-strategic consumers who do not take the resale value into account when they purchase a new product. In this case, there is no resale value effect by definition. It can be shown that Proposition 1 holds in this setting, with the first threshold changing to $\frac{c\delta-\frac{1}{2}\alpha\gamma(1+c)}{\alpha} < c\frac{(\delta-\alpha\gamma)}{\alpha}$ (see Oraiopoulos et al. 2007 for the derivation of this result when $\alpha = 1$). Thus, when consumers are non-strategic, and the OEM only benefits from the relicensing fee revenue, it is optimal for the OEM to eliminate the secondary market under a much wider range of conditions. For example, the OEM may prefer to eliminate the secondary market even when the refurbishing cost is zero and there is no technology improvement (this happens when the threshold $c\delta - \frac{1}{2}\gamma(1+c)$ is negative).

This finding demonstrates that a forward-looking consumer base can influence the OEM's secondary market strategy. The common perception in the IT industry is that historically, consumers of IT products did not take into account the future resale value in their initial purchases. This could explain why some IT OEMs have historically deployed policies to deter the secondary market for their products. As mentioned in the introduction however, there are indications that consumers of IT equipment are becoming increasingly concerned about resale values during their initial purchase decisions. Our results suggest that this is not necessarily a bad trend for the OEM, but her secondary market strategies need to evolve with the market.

4.4.3 The Role of Competition

As discussed above, Proposition 1 reveals a somewhat counterintuitive finding about the role of third-party competition. To explore the impact of competition on the OEM's strategy further, we take a two-pronged approach: i) We analyze the effect of the competitive intensity of the secondary market on the OEM strategy and profit, and ii) We allow the OEM to interfere with the secondary market directly by refurbishing herself.

Competitive Intensity of the Secondary Market. The significant profit opportunity in the secondary market has given rise to a number of firms founded with the sole purpose of buying and refurbishing used IT equipment (CBRonline.com 2005). According to the United Network Equipment Dealer Association (uneda.com), there are over 300 certified refurbishers today and many more who are not yet certified. To capture this phenomenon, we increase the competitive intensity within the secondary market by allowing N symmetric third-party entrants to compete in acquiring, refurbishing and reselling the used products (this model is similar to Debo et al. 2005).

One may expect that as the number of entrants increases, the OEM employs a more aggressive strategy vis-à-vis the secondary market and her profit decreases. Interestingly, however, we show the OEM's relicensing fee is decreasing and her profit is concave increasing in the number of entrants. (The analysis for the case $\alpha = 1$ can be found in Oraiopoulos et al. 2007.) Consistent with standard economic theory, as the number of entrants increases, internal competition drives the prices of the refurbished units down and the secondary market attracts more consumers (the overall quantity of refurbished products increases). This leads to higher cannibalization of new units in the second period, but also to a higher resale value. In fact, adding an additional entrant increases the marginal impact of the relicensing fee on the resale value more than it increases the detrimental cannibalization effect. As a result, the OEM charges a lower relicensing fee, providing greater support to the secondary market. This result differs from Debo et al. (2005) who find that an increase in the competitive intensity of the secondary market reduces both the OEM's incentive to invest in remanufacturability and her profit. This difference can be explained through the strategic as well as the economic role of the relicensing fee: The OEM not only has a more powerful mechanism of controlling the demand for refurbished products, she also derives revenues from the relicensed equipment.

The OEM Participates in the Secondary Market. At first sight, our conclusion that the OEM welcomes competition in the secondary market seems counter to the previous results in the remanufacturing literature. For example, Ferrer and Swaminathan (2006) show a higher remanufacturing cost savings means higher participation by the OEM in the secondary market. Ferguson and Toktay (2006) find that as the entrant becomes more competitive (c_r becomes lower) and the cannibalization threat increases, the OEM should increase her efforts to deter the secondary market.

The difference in these findings is driven by how the OEM interferes with the secondary market. Remanufacturing is a direct approach, while imposing a relicensing fee is an indirect approach. In practice, some OEMs adopt a strategy of not participating in the secondary market, while others enter the refurbishing business. To investigate the impact of the latter approach, we extend our baseline model to allow refurbishing by the OEM. Our analysis yields the following results:

At low levels of the refurbishing cost, the OEM charges a high relicensing fee and places a much larger volume of refurbished product on the market compared to the entrant. This is because the OEM's margin on the refurbished product is $h + p_r - c_r - s$, while the entrant's margin is only $p_r - c_r - s$. In addition, the OEM benefits from the resale value effect. As the refurbishing cost increases, the margins from refurbished products drop, and the capacity to charge a high relicensing fee decreases, so the quantity refurbished by the OEM drops significantly. This allows the entrant to increase his quantity, but not enough to compensate the decrease in the OEM's quantity. Thus, similar to our baseline model, the overall size of the secondary market decreases in the refurbishing cost. As the refurbishing cost increases further, the OEM completely exits the secondary market, and in this range, the results are qualitatively the same as in the model where the OEM is not allowed to refurbish.

In summary, the OEM exploits the market for refurbished products herself when the profit margin is high, but leaves the entrant to do so when the margin is low, capturing value only via the relicensing fee and the resale value effect.

This analysis enriches our understanding of the role of competition: At low levels of refurbishing cost, it is optimal for the OEM to remanufacture in conjunction with imposing relicensing fees, a result consistent with previous models (Debo et al. 2005, Ferrer and Swaminathan 2006, Ferguson and Toktay 2006, etc.). This strategy limits the participation of third-party entrants in the market. If the OEM makes a strategic determination not to participate in the refurbished product market (e.g. Sun) for other reasons (brand equity worries, resistance from sales department, etc.), however, then she should pursue the diametrically opposed strategy of supporting the secondary market at low refurbishing cost to exploit the strong resale value effect in this cost range.

4.4.4 The Role of Durability

A key assumption in our baseline model is the one-period product lifetime assumption ($\delta_o = 0$). That is, a product bought in the first period provides no utility in the second period, unless it is refurbished by the entrant. This assumption reflects the fact that for IT equipment where relicensing fees are common such as servers and networking equipment, most users upgrade to the newest generation when it is introduced because of performance requirements and software compatibility issues. There is however, a portion of the IT market where these issues are of lower concern, such as mainframes and workstations. For these products, consumers may decide to "hold on to" their used products despite the reduced functionality they provide, and abstain from the market in the second period. We explore the implications of such a consumer segment by letting $\delta_o > 0$; the higher the δ_o, the more "durable" the product. To maintain tractability, we focus on the special case of $\alpha = 1$ (i.e., no technological improvement) and $\gamma = 0$ (no transactional disutility). With the assumption $\gamma = 0$, the consumer's decision about whether to return or keep a product boils down to a comparison of the utility the used product affords versus the sum of the resale value and the net utility from buying a new product. Since the utility of keeping the product is $\delta_o\theta$, consumers are heterogeneous in their utility from replacing the product, and the volume returned increases in s as in the baseline model even though $\gamma = 0$. The derivation of the demand functions based on two-period consumer strategies, and the supporting analysis leading up to the main result in Proposition 2 below are presented in Appendix B.

Proposition 2 *There exists $\widetilde{c_r}$ such that for $c_r < \widetilde{c_r}$, it is not optimal for the OEM to eliminate the secondary market: $q_r^* > 0$. Moreover, for $c_r < \widetilde{c_r'} < \widetilde{c_r}$, the OEM charges a positive relicensing fee h^* which decreases in c_r, but increases in c. For $\widetilde{c_r'} < c_r < \widetilde{c_r}$, the OEM sets the relicensing fee to zero ($h^* = 0$).*

Proposition 2 states that the OEM allows for a secondary market to exist when the refurbishing cost in low enough. In addition, the optimal relicensing fee decreases in the refurbishing cost c_r. These results are structurally the same as our findings in Proposition 1. Thus, the fundamental conclusions about when the OEM should allow the secondary market to exist and how she should deploy the relicensing fee do not depend on the level of durability of the product. A set of numerical experiments (available from the authors) show that the impact of α and γ in this model is also consistent with their impact described in the baseline model.

There is one difference however, in the role the production cost c plays: The relicensing fee h^* increases in the production cost c, whereas it decreases in the production cost when $\delta_o = 0$. This difference stems from how production cost impacts the resale value effect. When $\delta_o > 0$, as the production cost increases, fewer new products are sold in the second period, and thus, fewer first-period consumers decide to replace their used product with a new one. In other words, fewer first-period consumers benefit from the resale value effect. Consequently, the resale value effect is weakened as the production cost increases, and the OEM increases the relicensing fee. In contrast, when $\delta_o = 0$, the number of customers who decide to return their products is independent of the production cost. In fact, a higher production cost has only the direct effect of reducing the OEM's margin. As a result, the entrant is more competitive, and willing to pay a higher resale value to a larger number of customers. Hence, the resale value effect is strengthened as the production cost increases and the OEM lowers the relicensing fee.

Corollary 1 *The relicensing fee h^* decreases in δ_o, but increases in δ.*

The fact that h^* decreases in δ_o is particularly interesting if we contrast it with the impact of the production cost c. Higher durability expands the market segment that chooses to keep using the product, and shrinks the segment of consumers who decide to sell their used products and buy a new one in the second-period. This is similar to the effect of a higher production cost. However, higher durability generates higher consumer utility, and therefore, higher demand for new products in the first period. The increased volume amplifies the value captured from the resale value effect, since more consumers can be charged the price premium stemming from it. Consequently, the OEM finds it profitable to drop the relicensing fee as durability increases.

Corollary 1 allows us to disentangle the effect of inherent product durability from the effect of the remanufacturing operation. Prior work on durable goods theory assumes that consumers trade among each other, selling the (depreciated) used product, which offers relative utility δ_0, as is. In contrast, prior work on remanufacturing assumes that a product is of no value ($\delta_0 = 0$) unless it is refurbished, in which case it offers relative utility $\delta(> \delta_0)$. One might expect δ and δ_o to have the same impact on h^*, since as they increase, they both reduce the demand for the new product in the second period. Interestingly, Corollary 1 shows that they have opposite effects on the OEM's relicensing fee. A higher δ_o means that consumers obtain more utility from the product over its life-cycle and the size of the new product market increases. As discussed above, this results in the OEM decreasing h^* as the durability δ_o increases. In contrast, a higher δ generates a higher willingness-to-pay for a refurbished product that the entrant exploits and increases the threat of cannibalization. Consequently, as δ increases, the OEM increases the relicensing fee, both to exploit the additional value that consumers place on the refurbished product and to keep cannibalization in check. This is similar to the effect of decreasing c_r on the relicensing fee.

4.5 Analysis: Differentiated Duopoly in the Primary Market

Thus far, we have assumed a monopolist setting in the primary market with the competition being restricted to the secondary market. In practice, the IT primary market is characterized by competition. Industry experts stress performance, efficiency, flexibility, longevity, reliability, and maintenance as factors of primary importance (ServerWatch 2008, SearchServerVirtualization 2008). According to a recent market research report regarding the selection criteria for IT servers, quality and reliability were found to be the most important ones (IDC 2006). These are dimensions of vertical differentiation: For the same price, higher reliability, efficiency etc. are preferred to lower reliability, efficiency, etc. To capture this characteristic of the IT market, we relax the monopolistic primary market assumption and develop a vertically differentiated duopoly model where consumers place a higher value on firm A's product than on firm B's product. This assumption allows us to address two critical questions: What are the pricing and relicensing strategies of each OEM and how do they differ? What is the impact of the quality (performance, reliability, etc.) differential on those strategies?

We capture the difference in the perceived quality between firms as follows: A consumer who derives utility θ from a new product by firm A derives utility $(1-\beta)\theta$ from a new product by firm B. Without loss of generality, we assume that $\beta > 0$ so that firm B represents the low-end firm. The relative difference in consumers' valuations, β, is called the brand differential or the brand premium of the high-end OEM. We also assume an equal rate of perceived utility depreciation for both firms. That is, a consumer derives utility $\delta\theta$ from firm A's refurbished product, while he derives utility $(1-\beta)\delta\theta$ from firm B's. This assumption allows us to maintain the same relative brand differential between OEMs on the secondary market. We assume that $\delta < 1-\beta$ so that a given consumer values the low-end firm's new product strictly more than the high-end firm's refurbished product. This is a reasonable assumption based on observations of the current state of the IT industry and eliminates the trivial case where one firm dominates both the primary and secondary markets. In addition, we normalize the cost of refurbishing to zero for both products. This rules out refurbishing cost disparity from explaining the differences in the OEMs' strategies and corresponds to the more interesting cases in Proposition 1 where the existence of a secondary market is beneficial for the OEM. Finally, we assume a perfectly competitive secondary markets for each type of refurbished product. This implies that for any given used product purchase prices, s^A and s^B, $p^A_{2,r} = s^A$ and $p^B_{2,r} = s^B$. While we do this for tractability, the analysis of the competitive secondary market case suggests that the structure of the optimal policy is essentially the same for any level of competitive intensity on the secondary market.

Similar to our baseline model, we solve the problem by backward induction, starting with the second period (Appendix C). Unlike our previous analysis, however, deriving the Nash equilibrium $(q^*_{1A,} h^*_A, q^*_{1B,} h^*_B)$ for any arbitrary set of parameters is much more complex because the profit expressions are long and do not allow easy algebraic handling. Rather, our approach is to solve the unconstrained game and subsequently identify the range of parameter values in which the results are meaningful (e.g. Desai 2001). Therefore, hereafter, we focus on those parameter values for which all non-negativity constraints are satisfied, namely, all market segments have positive quantities in equilibrium. For those parameters, we conduct an extensive numerical investigation and explore how the optimal OEM strategies (relicensing fee and quantity decisions) change as a function of the brand premium. In the numerical study, we calculate the equilibrium quantity and relicensing fee decisions for every combination of the parameter values $\delta \in [0.3, 0.8]$, $\gamma \in [0.01, 0.15]$, and $c \in [0.01, 0.5]$ (discretized in increments of 0.1, 0.03, and 0.05, respectively). We find that as long as all non-negativity constraints are satisfied, the insights remain the same across all the parameter combinations. These insights are described in Observations 1-3 below. Figure 15 provides an illustrative example while Table 1 summarizes the impact of δ, γ, c on the equilibrium decisions.

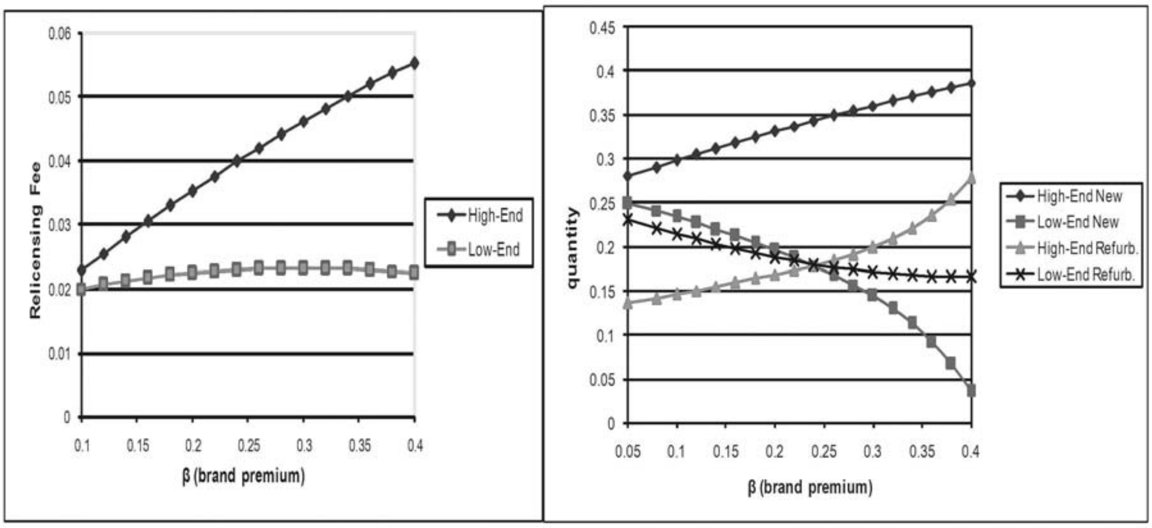


Figure 15: Relicensing Fees (left) and Equilibrium Quantities in Second Period (right) as a function of β for δ=0.5, γ=0.05, and c=0.15,

	h_A^*	h_B^*	q_{2A}^*	q_{2B}^*	q_{UA}^*	q_{UB}^*
$\delta \nearrow$	$\nearrow$	$\nearrow$	$\searrow$	$\searrow$	$\nearrow$	$\nearrow$
$\gamma \nearrow$	$\searrow$	$\searrow$	$\nearrow$	$\nearrow$	$\searrow$	$\searrow$
$c \nearrow$	$\searrow$	$\searrow$	$\searrow$	$\searrow$	$\nearrow$	$\nearrow$

Table 1: Comparative Statics when all Market Segments Exist.

Observation 1: *The high-end OEM always charges a higher relicensing fee than the low-end OEM and the difference between the relicensing fees can be large.*

This is because the high-end OEM's relative brand premium exists in the secondary market as well, which she capitalizes on by charging a higher relicensing fee. Note that despite the higher relicensing fee h_A^*, the high-end OEM maintains an active secondary market. Thus, a high relicensing fee need not be indicative of an attempt to shut down the secondary market, but rather reflect the brand premium a particular OEM commands. As reported in Table 1, our comparative statics analysis suggests that for a fixed brand premium between the two OEMs, both relicensing fees increase in δ, and decrease in γ and c.

Observation 2: *The high-end OEM's relicensing fee increases in the brand premium (β). For the low-end OEM, there is a non-monotonic relationship between the relicensing fee and the brand premium: h_B^* first increases and then decreases in β.*

To understand this relationship, we must look at how a marginal change in the brand premium affects the equilibrium decisions of each OEM. A marginal increase in β increases both the primary and the secondary markets for the high-end OEM's products. An increase in the brand premium β is translated to a higher relicensing fee at any β value since consumers have higher willingness-to-pay for her refurbished products. In contrast, the low-end OEM increases h_B^* only at low values of β. For low values of β, the low-end OEM has a considerable presence in both the primary and secondary markets. An increase in the brand premium hurts both the primary and secondary markets, the former to a larger extent. The low-end OEM attempts to maintain her primary market presence by increasing her relicensing fee and limiting the cannibalization effect. On the contrary, for high values of β where the high-end OEM dominates, the low-end OEM's primary market has significantly shrunk, and the impact of a marginal increase in β on cannibalization is much less significant. As a result, we observe a decrease in the relicensing fee as an attempt to strengthen the resale value effect.

The effect of δ, γ and c on the equilibrium quantities can be observed in Table 1. A higher δ makes the secondary market more profitable, so the secondary market grows at the expense of the primary. A higher γ makes the secondary market less profitable, so the opposite effect is seen. Finally, a higher c lowers the profitability of new products, so the primary market shrinks and the secondary market grows.

Observation 3: *There is a threshold value for the brand premium β below which the low-end OEM's product makes up a larger share of the secondary market. This threshold increases as δ decreases, γ* increases, or *c decreases.*

Observation 3 suggests that although a positive brand premium always translates to a larger market share in the primary market (under symmetric production costs), the same is not true for the corresponding secondary markets. This result could explain the strategy of some high-end OEMs who choose not to have large secondary markets for their refurbished products despite the brand premium they command. Note also that a lower c makes the primary market more profitable, while a lower δ or a higher γ reduces the margins of the secondary market. Thus, the above conditions make the primary market more attractive to the high-end OEM, who has a leadership advantage, leaving the low-end OEM to focus on the secondary market (via relicensing fees).

In our analysis, we assume an equal unit production cost for both the high-end and low-end OEM; thus the differentiation is along the brand premium dimension. This is a reasonable assumption for many IT products since they can be characterized as development-intensive-products, i.e. products whose fixed costs of development far outweigh the unit variable costs (Krishnan and Zhu 2006). Because our focus is on a firm's decisions for a given product line, we do not consider these initial fixed costs. If the assumption of equal production costs is relaxed and the high-end OEM has a higher production cost, we expect her to decrease her relicensing fee to increase the resale value of her primary product.

4.6 Conclusions

Secondary markets in the IT industry have grown steadily, forcing OEMs to form strategies to respond to them. For products such as servers and storage devices, OEMs have a powerful mechanism at their disposal: instituting a software relicensing fee charged to secondary users. A high relicensing fee can virtually shut down the secondary market, while a low relicensing fee can allow it to thrive. The optimal strategy is not obvious: An active secondary market not only generates relicensing revenues for the OEM but also has an indirect positive benefit by increasing the

OEM's new product's resale value, which in turn, increases the price that can be charged for the new product (resale value effect). At the same time, it also has a direct detrimental effect as the refurbished product competes with the OEM's new product (cannibalization effect) in future periods. In practice, comparable OEMs have surprisingly different relicensing fee strategies. The existing literature on secondary markets does not provide guidance concerning this widespread mechanism. Our paper fills this gap by contributing to the theory of secondary markets and by providing managerial guidelines on the use of relicensing fees.

Our research makes several theoretical contributions to the literature on how OEMs should balance their primary and secondary markets. First, we explicitly model the role of the relicensing fee. Though widespread, the relicensing fee mechanism has not been studied in the literature to date. Our paper is the first to examine both the economic (i.e., direct revenues) and the strategic (i.e., interference mechanism) implications of this mechanism. Second, unlike prior research that assumes that used products are traded among consumers in a perfectly competitive market, we model the incentive of independent entrants to purchase, refurbish, and resell those used products. By doing so, we account for the operational realities of maintaining a secondary market, that is, the refurbishing process. In practice, reselling an IT product worth several thousand dollars requires a number of procedures (e.g., replacing hardware components, testing performance, etc.) that are not costless. As our analysis reveals, the effect of such procedures, proxied by the magnitude of the refurbishing cost, is a key determinant of the OEM's strategy vis-à-vis the secondary market. In addition, by explicitly modeling the independent entrants, we are able to examine how an increase in the competitive intensity in the secondary market (i.e., higher number of entrants) affects the OEM's strategy. Third, current theoretical frameworks that consider a monopolist OEM have limited power in explaining the adoption of different secondary market strategies by competing OEMs. In our duopoly model, we capture the equilibrium relicensing fee strategies of competing OEMs and compare how they evolve as the brand premium between them increases. To our knowledge, our paper is the first to study differentiated new and refurbished products competing in both the primary and secondary markets.

In parallel, we complement the rapidly growing literature on remanufacturing by linking the consumers' willingness-to-pay for a new product to the potential resale value of the product at the end of use. By doing so, we show that a market for refurbished products can benefit the OEM even if it is operated by independent entrants. Finally, our comprehensive model allows us to disentangle the effect of inherent product durability from the effect of the remanufacturing process. Prior work on remanufacturing assumes that after one period of use, the product has zero utility for the consumer unless it is refurbished, in which case it offers a fraction of the utility offered by a new product. In contrast, the literature on durable goods assumes that a product can be used in subsequent periods as is, offering the consumer a fraction of its original utility. Our model is the first to integrate these two effects, namely, the inherent durability of the product and the value added by the refurbishing process. We show that although they both imply that the used or refurbished product is a closer substitute to the new product, their effect on the OEM's relicensing fee strategy is diametrically opposite.

Our results help IT OEMs to identify critical tradeoffs involving the relicensing fee along the dimensions of technology improvement, refurbishing cost, and competitive dynamics. We find that in the presence of radical technology improvements, the OEM should increase the relicensing fee to make the refurbished product less affordable and to increase the market share of her second-generation new product. A second critical factor in the OEM's decision is the refurbishing cost. If the OEM chooses to enter the refurbishing business herself, then she should do so aggressively at low refurbishing cost. Interestingly, if the OEM chooses not to undertake refurbishing, a low refurbishing cost should make the OEM willing to support a secondary market, even though this market is operated by third-party entrants who are becoming more competitive as the refurbishing cost decreases. This happens because the OEM can then exploit the secondary market through the resale value effect and the relicensing fee revenues. This is especially important for an OEM with high production costs: The right combination of price and relicensing fee allows the OEM to mitigate the low margin of her new product by producing fewer units but charging a price premium for them due to the resale value effect. Our experience is that OEMs are very concerned with cannibalization and tend to overlook the resale value effect. When using the relicensing fee mechanism only, it is precisely in cases where cannibalization is a strong threat that the OEMs should embrace the secondary market. This requires a strategic shift in the OEM's approach relative to the case where she refurbishes her own products. The above results hold even when the OEM faces competition from multiple third-party entrants. In fact, the strategic and economic value of an active secondary market for the OEM are amplified as the number of entrants increases. Therefore, the OEM should actually lower the relicensing fee to strengthen the resale value effect as the competitive intensity increases, despite the stronger threat of cannibalization.

Finally, our differentiated duopoly model offers insights regarding the different relicensing fee strategies observed in practice. As we would expect, the high-end OEM always charges a higher relicensing fee since her brand premium is maintained in the secondary market. In fact, the high-end OEM should monotonically increase her relicensing fee as her brand premium is strengthened. Interestingly, however, although a brand premium always translates to a larger market share in the primary market, the same is not true for the corresponding secondary market. This result could explain the strategy of some high-end OEMs who choose not to have large secondary markets for their refurbished units despite the brand premium they command. Thus, it is possible that certain conditions make the primary market more attractive to the high-end OEM, who has a leadership advantage, leaving the low-end OEM to focus on the secondary market (via her relicensing fees).

To conclude, our paper highlights the strategic importance of supporting an active secondary market under a wide range of circumstances, particularly in the presence of strategic consumers and a low refurbishing cost. These conditions are valid in the IT industry today: There exist a large number of industry analyst firms who specialize in forecasting the resale value of IT equipment and who offer comprehensive cost/benefit analysis over the life-cycle of the IT equipment while the modularity of IT solutions makes refurbishment a cost-effective proposition for many products. Thus, charging very high relicensing fees with the purpose of shutting down the secondary market, a strategy attributed to some IT OEMs, appears to be myopic and suboptimal in the presence of strategic consumers. At the same time, we demonstrate that charging higher relicensing fees than lower end competitors need not mean an OEM is doing so with the sole purpose of eliminating the secondary market, but rather that she is capitalizing on her brand premium.

Appendix A

Lemma 1 *The posterior distribution for the technological potential of the explored domain is normal* $N(\mu_1', \sigma_1'^2)$ *with* $\mu_1' = kt_A + (1-k)\,\mu_1$ *and* $\sigma_1' = \sqrt{\frac{\sigma_1^2\sigma^2}{\sigma_1^2+\sigma^2}}$ *where* $k = \frac{\sigma_1^2}{\sigma_1^2+\sigma^2}$.

Proof: From Bayes' rule we derive the updated distribution:

$$f(T_1 \mid t_A) = \frac{f(t_A|T_1)f(T_1)}{f(t_A)} = \frac{\frac{1}{\sigma\sqrt{2\pi}}e^{(-\frac{(T_1-t_A)^2}{2\sigma^2})}\frac{1}{\sigma_1\sqrt{2\pi}}e^{(-\frac{(T_1-\mu_1)^2}{2\sigma_1^2})}}{\frac{1}{\sqrt{\sigma_1^2+\sigma^2}\sqrt{2\pi}}e^{(-\frac{(t_A-\mu_1)^2}{2(\sigma_1^2+\sigma^2)})}}$$

which after some algebraic manipulation gives :

$$f(T_1 \mid t_A) = \frac{1}{\sigma_1'\sqrt{2\pi}}e^{(-\frac{(T_1-\mu_1')^2}{2\sigma_1'^2})}$$

where $\mu_1' = kt_A + (1-k)\,\mu_1$ with $k = \frac{\sigma_1^2}{\sigma_1^2+\sigma^2}$and $\sigma_1' = \sqrt{\frac{\sigma_1^2\sigma^2}{\sigma_1^2+\sigma^2}}$

Lemma 2 *The posterior distribution for the technological potential of the unexplored domain is normal* $N(\mu_2, \sigma_2)$ *with* $\mu_2 = \theta t_A + (1-\theta)\,\mu_1$ *and* $\sigma_2 = \sigma_1\sqrt{1-\theta^2}$ *where* $\theta = \frac{\theta_o\sigma_1}{\sqrt{\sigma_1^2+\sigma^2}}$

Proof By definition, $\rho(t_A, T_2) = \frac{E[t_AT_2]-E[t_A]E[T_2]}{\sqrt{Var(t_A)}\sqrt{Var(T_2)}} = \frac{E[(T_1T_2+\varepsilon T_2]-E[T_1+\varepsilon]E[T_2]}{\sqrt{\sigma_1^2+\sigma^2}\sigma_1} =$ $= \frac{E[T_1T_2]-E[T_1]E[T_2]}{\sqrt{\sigma_1^2+\sigma^2}\sigma_1}$ since $E[\varepsilon] = 0$. But, $\frac{E[T_1T_2]-E[T_1]E[T_2]}{\sigma_1^2} = \theta_o$. So, $\theta = \rho(t_A, T_2) = \theta_o\ \frac{\sigma_1}{\sqrt{\sigma_1^2+\sigma^2}}$. Thus, from the properties of the bivariate normal distribution (Rencher 2002), we know that the updated distribution for the second scientific is normal $N(\mu_2, \sigma_2^2)$ with $\mu_2 = \theta t_A + \frac{\sigma_1}{\sqrt{\sigma_1^2+\sigma^2}}\,(1-\theta)\,\mu_1$ and $\sigma_2 = \sigma_1\sqrt{1-\theta^2}$ where $\theta = \frac{\theta_o\sigma_1}{\sqrt{\sigma_1^2+\sigma^2}}$

Second Period Analysis

Solving for the Nash equilibrium in the second period, we can easily derive the leader's profit function as $\Pi_{2A}(\,t_B \mid t_A) = \frac{1}{(e^2-4)^2}[(2-e)(A-c)+2bt_A-ebt_B]^2$ and the follower's as

$\Pi_{2B}\,(\,t_B \mid t_A) = \frac{1}{(e^2-4)^2}[(2-e)(A-c) - ebt_A + 2bt_B]^2$

In order to choose the scientific domain, the follower perceives t_B as a random variable which follows the normal distribution $\widetilde{t_B} \sim N(\mu_B, \sigma_B)$. Therefore, the exploration target domain (new versus already explored) stems from the comparison of the expected profits in each case. Note that the profit functions are second degree polynomials in t_B, and therefore we can derive the expected profits for each firm by using the following property: $E[\widetilde{t_B}^2] = E[\widetilde{t_B}]^2 + \sigma_B^2 = \mu_B^2 + \sigma_B^2$. Thus, the second-period expected profits can be written as:

$E[\Pi_{2B}(\mu_B, \sigma_B)] = \frac{1}{(e^2-4)^2}\{[(2-e)(A-c) - ebt_A]^2 + 2[(2-e)(A-c) - ebt_A](2b\mu_B) + 4b^2(\mu_B^2 + \sigma_B^2)\}$

At this point, the follower can either draw from the explored domain (that the leader has drawn), draw from the unexplored one, or forego investment in technology improvements.

According to Lemma 1, if the follower draws from the explored domain $\mu_B = \mu_1' = kt_A + (1-k)\,\mu_1$ and $\sigma_B = \sqrt{\sigma_1'^2 + \sigma^2} = \sqrt{\frac{\sigma_1^2\sigma^2}{\sigma_1^2+\sigma^2} + \sigma^2}$ where $k = \frac{\sigma_1^2}{\sigma_1^2+\sigma^2}$ On the other hand, if the follower draws from the explored domain (Lemma 2) $\mu_B = \mu_2 = \mu_1 + \frac{\sigma_1}{\sqrt{\sigma_1^2+\sigma^2}}\theta(t_A - \mu_1)$ and $\sigma_B = \sqrt{\sigma_2^2 + \sigma^2} = \sqrt{\sigma_1^2(1-\theta^2) + \sigma^2}$ where $\theta = \frac{\theta_o\sigma_1}{\sqrt{\sigma_1^2+\sigma^2}}$.

Let $\Pi_{2B}^E(t_A)$ and $\Pi_{2B}^U(t_A)$ denote the follower's second-period expected profits when investing in the explored and unexplored scientific domain, respectively. That is, $\Pi_{2B}^E(t_A) = E[\Pi_{2B}(\mu_1', \sigma_1' \mid t_A)]$ and $\Pi_{2B}^U(t_A) = E[\Pi_{2B}(\mu_2, \sigma_2 \mid t_A)]$. Also let $\Pi_{2B}^N(t_A)$ denote the second-period profits if no investment is undertaken. Essentially, this corresponds to setting $t_B = 0$. Investment in a scientific domain comes at a cost K, and therefore the follower's search problem can be described as $max\{\Pi_{2B}^E(t_A) - K, \Pi_{2B}^U(t_A) - K, \Pi_{2B}^N(t_A)\}$

Lemma 3 $\Pi_{2B}^E(t_A)$ *increases in* t_A.

Proof: $\frac{\partial^2\Pi_{2B}^E(t_A)}{\partial t_A^2} = \frac{2b^2(-2\sigma_1^2+e((\sigma_1^2+\sigma^2))^2}{(\sigma_1^2+\sigma^2)^2(e^2-4)^2} > 0$ so $\Pi_{2B}^E(t_A)$ is convex.

Moreover, $\left.\frac{\partial\Pi_{2B}^E(t_A)}{\partial t_A}\right|_{t_A=0} = \frac{2b(2\sigma_1^2-e((\sigma_1^2+\sigma^2))}{(\sigma_1^2+\sigma^2)^2(e^2-4)^2}[(2-e)(A-c) + 2b\mu_1\sigma^2] > 0$ for $\sigma < \sigma_1$. Thus, $\frac{\partial\Pi_{2B}^E(t_A)}{\partial t_A} > 0$ for every $t_A > 0$.

Lemma 4 *There is a unique $\widetilde{\theta_o} > 0$ such that for $\theta_o > \widetilde{\theta_o}$, $\Pi^U_{2B}(t_A)$ increases in t_A, while for $\theta_o < \widetilde{\theta_o}$, it decreases in t_A.*

Proof:

First note that for $\theta_o < 0$, $\frac{\partial \mu_2}{\partial t_A} = \frac{\theta_o \sigma_1}{\sqrt{\sigma_1^2+\sigma^2}} < 0$ when $\theta_o < 0$, $\frac{\partial \sigma_2}{\partial t_A} = 0$, and $\frac{\partial \Pi^U_{2B}(t_A)}{\partial t_A} < 0$. Thus, $\frac{\partial \Pi^U_{2B}(t_A)}{\partial t_A} = \frac{\partial \Pi^U_{2B}(t_A)}{\partial t_A} = \frac{\partial \Pi^U_{2B}(t_A)}{\partial \mu_2}\frac{\partial \mu_2}{\partial t_A} + \frac{\partial \Pi^U_{2B}(t_A)}{\partial \sigma_2}\frac{\partial \sigma_2}{\partial t_A} + \frac{\partial \Pi^U_{2B}(t_A)}{\partial t_A} < 0$ and $\Pi^U_{2B}(t_A)$ is always decreasing in t_A. Also note that for $\theta_o = 1$, $\Pi^U_{2B}(t_A) = \Pi^E_{2B}(t_A)$ for every t_A and therefore, according to Lemma 3, $\frac{\partial \Pi^U_{2B}(t_A)}{\partial t_A} > 0$. Thus, there is at least one $\widetilde{\theta_o} \in (0,1)$ such that $\left.\frac{\partial \Pi^E_{2B}(t_A)}{\partial t_A}\right|_{\theta_o=\widetilde{\theta_o}} = 0$. For $\theta_o < \widetilde{\theta_o}$, $\frac{\partial \Pi^U_{2B}(t_A)}{\partial t_A} < 0$ while for $\theta_o > \widetilde{\theta_o}$ $\frac{\partial \Pi^U_{2B}(t_A)}{\partial t_A} > 0$. To see that $\widetilde{\theta_o}$ is unique notice that if $\frac{\partial \Pi^U_{2B}(t_A)}{\partial t_A}$ had another root, say $\widetilde{\theta_o}' \in (\widetilde{\theta_o}, 1)$ then it would have a third one since at $\left.\frac{\partial \Pi^E_{2B}(t_A)}{\partial t_A}\right|_{\theta_o=1} > 0$. The latter is impossible since $\frac{\partial \Pi^U_{2B}(t_A)}{\partial t_A}$ is quadratic in θ_o and therefore it can have at most two roots.

Lemma 5 *Let $G(t_A) = \Pi^E_{2B}(t_A) - \Pi^U_{2B}(t_A)$ denote the difference of the expected profits between drawing from the explored versus drawing from the unexplored one. Then $G(t_A)$ always increases in t_A.*

Proof: First note that, for $t_A = \mu_1$, $G(\mu_1) = \frac{4b^2\sigma_1^4}{(\sigma_1^2+\sigma^2)(e^2-4)^2}(\theta_o^2 - 1) < 0$ for $-1 < \theta_o < 1$. Also note that for $t_A < \mu_1$, $\mu_1' - \mu_2 = \frac{\sigma_1^2(1-\theta_o)(t_A-\mu_1)}{\sigma_1^2+\sigma^2} < 0$ and this difference is increasing in t_A. Since σ_1' and σ_2 do not depend on t_A, $G(t_A)$ will also be increasing in t_A. We will now show that $G(t_A)$ is also increasing in t_A for $t_A > \mu_1$. For $t_A > \mu_1$, note that $\frac{\partial^3 G(t_A,\theta_o)}{\partial t_A \partial \theta_o^2} = -\frac{16b^2\sigma_1^4(t_A-\mu_1)}{(\sigma_1^2+\sigma^2)^2(e^2-4)^2} < 0$. Moreover, the maximum of $\frac{\partial G(t_A,\theta_o)}{\partial t_A}$ occurs for $\overline{\theta_o} = -\frac{(\sigma_1^2+\sigma^2)[(2-e)(A-c)-2ebt_A+(e+2)b\mu_1]}{4b\sigma_1^2(t_A-\mu_1)} < 0$. Also, $\left.\frac{\partial G(t_A,\theta_o)}{\partial t_A}\right|_{\theta_o=1} = 0$. Since $\frac{\partial G(t_A,\theta_o)}{\partial t_A}$ is quadratic(concave) in θ_o, it will be symmetric with respect to the unique maximum $\overline{\theta_o}$. Therefore, $\frac{\partial G(t_A,\theta_o)}{\partial t_A} > 0$ for $-1 + 2\overline{\theta_o} < \theta_o < 1$ and since $\overline{\theta_o} < 0$, $\frac{\partial G(t_A,\theta_o)}{\partial t_A} > 0$ for $-1 < \theta_o < 1$.

Lemma 6 *For $\theta_o < 0$, $\Pi^U_{2B}(t_A)$ is decreasing in t_A faster than what $\Pi^N_{2B}(t_A)$ does*

$(\frac{d\Pi^U_{2B}(t_A)}{dt_A} < \frac{d\Pi^N_{2B}(t_A)}{dt_A})$. *On the contrary, for* $0 < \theta_o < \widetilde{\theta}_o$: $\Pi^U_{2B}(t_A)$ *is decreasing in* t_A *slower than what* $\Pi^N_{2B}(t_A)$ *does* $(\frac{d\Pi^U_{2B}(t_A)}{dt_A} > \frac{d\Pi^N_{2B}(t_A)}{dt_A})$.

Proof: By definition $\frac{d\Pi^U_{2B}(t_A)}{dt_A} = \frac{\partial\Pi^U_{2B}(t_A)}{\partial\mu_2}\frac{\partial\mu_2}{\partial t_A} + \frac{\partial\Pi^U_{2B}(t_A)}{\partial t_A}$ (since $\frac{\partial\sigma_2}{\partial t_A} = 0$) and $\frac{d\Pi^N_{2B}(t_A)}{dt_A} = \frac{\partial\Pi^N_{2B}(t_A)}{\partial t_A}$. Also for $\theta_o = 0$, $\frac{d\Pi^U_{2B}(t_A)}{dt_A} = \frac{d\Pi^N_{2B}(t_A)}{dt_A}$. Finally, note that when $\theta_o < 0$, $\frac{\partial\mu_2}{\partial t_A} < 0$ while for $0 < \theta_o < \widetilde{\theta}_o$, $\frac{\partial\mu_2}{\partial t_A} > 0$. Thus, for $\theta_o < 0$, $\frac{d\Pi^U_{2B}(t_A)}{dt_A} < \frac{d\Pi^N_{2B}(t_A)}{dt_A}$ while for $0 < \theta_o < \widetilde{\theta}_o$, $\frac{d\Pi^U_{2B}(t_A)}{dt_A} > \frac{d\Pi^N_{2B}(t_A)}{dt_A}$.

Theorem 1 *When the domains are negatively correlated with each other (i.e.,* $\theta_o < 0$*), for every tuplet* (t_A, K) *there exist values* $\widetilde{t}_U(K)$ *and* $\widetilde{t}_E(K)$ *such that the optimal R&D search strategy is:*

- *to search the explored scientific domain when* $t_A \in (\widetilde{t}_E(K), \infty)$
- *to search the unexplored scientific domain when* $t_A \in (0, \widetilde{t}_U(K))$
- *to perform no search in all other cases.*

The values $\widetilde{t}_U(K)$ *and* $\widetilde{t}_E(K)$ *are monotonic in* K *and there exist* K_E *such that for* $K \leq K_E$, $\widetilde{t}_U(K) = \widetilde{t}_E(K)$.

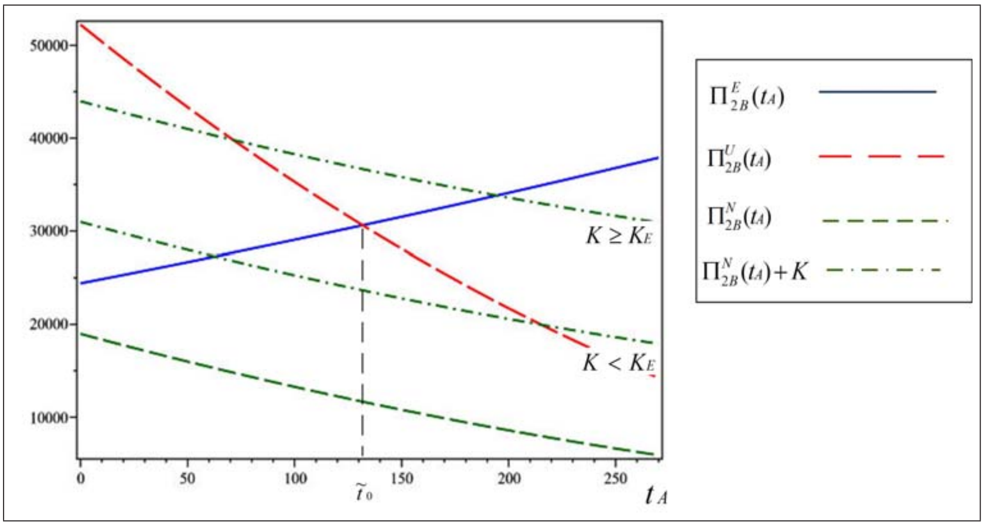


Figure 16: Follower's second-period expected profits for $A = 400, c = 0.7, b = 0.8, \mu_1 = 120, \sigma_1 = 50, \sigma = 30, e = 0.9, \theta_0 = -0.5$

Proof: Note that according to Lemma 3 and 4, when $\theta_o < 0$, $\Pi^E_{2B}(t_A)$ is increasing in t_A while $\Pi^U_{2B}(t_A)$ is decreasing in t_A. Also note that $\Pi^N_{2B}(t_A)$ is decreasing in t_A but at a faster rate compared to $\Pi^U_{2B}(t_A)$. Let $H(t_A) = \Pi^N_{2B}(t_A) + K$.

Let $\widetilde{t_0}$ be the unique intersection point of $\Pi^E_{2B}(t_A)$ and $\Pi^U_{2B}(t_A)$ and $K_E \doteq \Pi^E_{2B}(\widetilde{t_0}) - \Pi^N_{2B}(\widetilde{t_0})$. Now note that if $H(\widetilde{t_0}) < \Pi^E_{2B}(\widetilde{t_0}) = \Pi^U_{2B}(\widetilde{t_0}) \Leftrightarrow \Pi^N_{2B}(\widetilde{t_0}) < \Pi^E_{2B}(\widetilde{t_0}) - K = \Pi^U_{2B}(\widetilde{t_0}) - K \Leftrightarrow K < \Pi^E_{2B}(\widetilde{t_0}) - \Pi^N_{2B}(\widetilde{t_0})$ then the follower always invests since for $t_A > \widetilde{t_0}$, $\Pi^N_{2B}(t_A) < \Pi^E_{2B}(\widetilde{t_0}) - K$ and for $t_A < \widetilde{t_0}$, $\Pi^N_{2B}(t_A) < \Pi^U_{2B}(\widetilde{t_0}) - K$ (Lemma 6). Thus, there is a unique threshold $\widetilde{t}_E \doteq \widetilde{t_0}$ such that for $t_A < \widetilde{t}_E$ the follower searches in the unexplored domain, while for $t_A > \widetilde{t}_E$ the follower invests in the explored one.

Now consider the case where $H(\widetilde{t_0}) > \Pi^E_{2B}(\widetilde{t_0}) \Leftrightarrow K > K_E$ .Since $\Pi^E_{2B}(t_A)$ is increasing in t_A and $H(t_A)$ is decreasing in t_A there is unique threshold $\widetilde{t}_E(K)$ such that $\Pi^E_{2B}(\widetilde{t}_E) = H(\widetilde{t}_E)$. Thus, for $t_A > \widetilde{t}_E(K)$ the follower searches in the explored domain. Similarly, since $\Pi^U_{2B}(t_A)$ is decreasing in t_A faster than $H(t_A)$, there is unique threshold $\widetilde{t}_U(K)$ such that $\Pi^U_{2B}(\widetilde{t}_U(K)) = H(\widetilde{t}_U(K))$. Thus, for $t_A < \widetilde{t}_U(K)$ the follower searches in the unexplored domain. Finally, when $\widetilde{t}_U(K) < t_A < \widetilde{t}_E(K)$, $\Pi^U_{2B}(t_A) < H(t_A)$ and $\Pi^E_{2B}(t_A) < H(t_A)$ and the follower does not invest.

Theorem 2 *When the domains are positively correlated with each other (i.e., $\theta_o > 0$), for every tuplet (t_A, K) there exist values $\widetilde{t}_U(K)$ and $\widetilde{t}_E(K)$ such that the optimal R&D search strategy is:*

- *to search the explored scientific domain when $t_A \in (\widetilde{t}_E(K), \infty)$*
- *to search the unexplored scientific domain when $t_A \in (\widetilde{t}_U(K), \widetilde{t}_E(K))$*
- *to perform no search in all other cases.*

The values $\widetilde{t}_U(K)$ and $\widetilde{t}_E(K)$ are defined such that i) $\widetilde{t}_U(K) = 0$ for $K \leq K_U$, ii) $\widetilde{t}_U(K) = \widetilde{t}_E(K) = \widetilde{t}$ for $K \geq K_E$

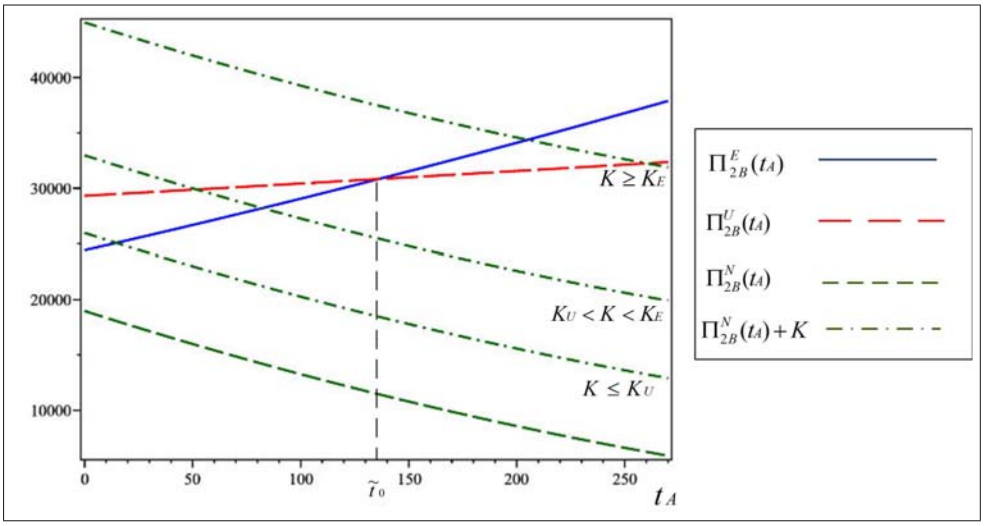


Figure 17: Follower's second-period expected profits for $A = 400, c = 0.7, b = 0.8, \mu_1 = 120, \sigma_1 = 50, \sigma = 30, e = 0.9, \theta_0 = 0.5$

Proof: First consider the case where $\theta_o > \widetilde{\theta}_o$. Note that according to Lemma 3 and 4, when $\widetilde{\theta}_o < \theta_o$, both $\Pi^E_{2B}(t_A)$ and $\Pi^U_{2B}(t_A)$ are increasing in t_A. Let $H(t_A) = \Pi^N_{2B}(t_A) + K$. The optimal policy for the follower is $\max\{\Pi^E_{2B}(t_A) - K, \Pi^U_{2B}(t_A) - K, \Pi^N_{2B}(t_A)\} = \max\{\Pi^E_{2B}(t_A), \Pi^E_{2B}(t_A), H(t_A)\}$. Let $\widetilde{t_0}$ be the unique intersection point of $\Pi^E_{2B}(t_A)$ and $\Pi^U_{2B}(t_A)$.

Note that if $H(\widetilde{t_0}) > \Pi^U_{2B}(\widetilde{t_0})$ then the option of not investing in either domain dominates the option of investing in the unexplored domain for $t_A < \widetilde{t_0}$. We also know that $\Pi^E_{2B}(t_A)$ is increasing faster than $\Pi^U_{2B}(t_A)$ (Lemma 5) so for $t_A > \widetilde{t_0}$ the option of investing the explored domain always dominates the option of investing in the unexplored one. Also note that although $H(\widetilde{t_0}) > \Pi^E_{2B}(\widetilde{t_0})$, $\Pi^E_{2B}(t_A)$ is increasing in t_A while $H(t_A)$ is decreasing in t_A and therefore, there will be a unique threshold $\widetilde{t}_E(K)$ such that for $t_A < \widetilde{t}_E(K)$ the follower does not invest in any domain while for $t_A > \widetilde{t}_E(K)$ the follower invests in the explored one.

Now consider the case where $H(\widetilde{t_0}) < \Pi^U_{2B}(\widetilde{t_0})$. Since $H(t_A)$ is decreasing in t_A and $\Pi^U_{2B}(t_A)$ increasing in t_A there will be an area $(\widetilde{t}_U(K), \widetilde{t_0})$ such that for $t_A \in (\widetilde{t}_U(K), \widetilde{t_0})$, $\Pi^U_{2B}(t_A) > H(t_A)$, that is, the option of investing in the unexplored domain dominates the option of not investing. Moreover, for sufficiently low K values,

$K < K_U \doteq \Pi^U_{2B}(0) - \Pi^N_{2B}(0)$ the option of investing in the unexplored domain will always dominate the option of not investing. Finally, for $t_A > \widetilde{t}_0$ the follower will always invests in the explored domain.

To summarize, when $\theta_o > \widetilde{\theta}_o$, there are three subcases: i) when $K > K_E$ a unique threshold $\widetilde{t}_E$ such that for $t_A < \widetilde{t}_E(K)$ the follower does not invest in any domain while for $t_A > \widetilde{t}_E(K)$ the follower invests in the explored one; ii) when $K_U < K < K_E$, there are two threshold values $\widetilde{t}_U(K)$ and $\widetilde{t}_E$ such that: for $t_A < \widetilde{t}_U(K)$ the follower does not invest in either domain, for $\widetilde{t}_U(K) < t_A < \widetilde{t}_E$ the follower invests in the unexplored domain, while for $t_A > \widetilde{t}_E$ the follower invests in the explored domain; iii) when $K < K_U$ there is a unique threshold $\widetilde{t}_E$ such that for $t_A < \widetilde{t}_E$ the follower searches in the unexplored domain while for $t_A > \widetilde{t}_E$ the follower invests in the explored one.

Now consider the case where $0 < \theta_o < \widetilde{\theta}_o$. Note that according to Lemmas 3 and 4, when $\theta_o < 0$, $\Pi^E_{2B}(t_A)$ is increasing in t_A while $\Pi^U_{2B}(t_A)$ is decreasing in t_A. Also note that according to Lemma 6, $\Pi^N_{2B}(t_A)$ is decreasing in t_A but at a slower rate compared to $\Pi^U_{2B}(t_A)$. Let $H(t_A) = \Pi^N_{2B}(t_A) + K$. The optimal policy for the follower is $\max\{\Pi^E_{2B}(t_A) - K, \Pi^U_{2B}(t_A) - K, \Pi^N_{2B}(t_A)\} = \max\{\Pi^E_{2B}(t_A), \Pi^E_{2B}(t_A), H(t_A)\}$.

Let $\widetilde{t}_0$ be the unique intersection point of $\Pi^E_{2B}(t_A)$ and $\Pi^U_{2B}(t_A)$.

Note that if $H(\widetilde{t}_0) > \Pi^U_{2B}(\widetilde{t}_0)$ then the option of not investing in either domain dominates the option of investing in the unexplored domain for $t_A < \widetilde{t}_0$ while for $t_A > \widetilde{t}_0$ the option of investing in the explored domain dominates the other two. Also the condition $H(\widetilde{t}_0) > \Pi^U_{2B}(\widetilde{t}_0)$ can be equivalently written as $\Pi^N_{2B}(\widetilde{t}_0) > \Pi^E_{2B}(\widetilde{t}_0) - K = \Pi^U_{2B}(\widetilde{t}_0) - K \Leftrightarrow K > \Pi^E_{2B}(\widetilde{t}_0) - \Pi^N_{2B}(\widetilde{t}_0)$. Let $K_E \doteq \Pi^E_{2B}(\widetilde{t}_0) - \Pi^N_{2B}(\widetilde{t}_0)$. Then, when $K > K_E$, the follower either draws from the explored domain with profits $\Pi^E_{2B}(t_A) - K$ or does not draw at all and receives profits $\Pi^N_{2B}(t_A)$. But since $\Pi^E_{2B}(t_A)$ is increasing in t_A there must be a unique threshold $\widetilde{t}_E(K)$ such that for $t_A < \widetilde{t}_E(K)$ the follower does not invest in any domain while for $t_A > \widetilde{t}_E$ the follower invests in the explored one.

Now consider the case where $H(\widetilde{t_0}) < \Pi_{2B}^U(\widetilde{t_0})$. Since $H(\widetilde{t_0})$ is decreasing faster than $\Pi_{2B}^U(\widetilde{t_0})$ then there will be an area $(\widetilde{t}_U(K), \widetilde{t_0})$ such that for $t_A \in (\widetilde{t}_U(K), \widetilde{t_0})$, $\Pi_{2B}^U(t_A) > H(t_A)$, that is, the option of investing in the unexplored domain dominates the option of not investing. Moreover, for sufficiently low K values, $K < K_U \doteq \Pi_{2B}^U(0) - \Pi_{2B}^N(0)$ the option of investing in the unexplored domain will always dominate the option of not investing. Finally, for $t_A > \widetilde{t_0}$ the follower will always invests in the explored domain.

In short, when $0 < \theta_o < \widetilde{\theta}_o$, there are three subcases: i) when $K > K_E$ a unique threshold $\widetilde{t}_E(K)$ such that for $t_A < \widetilde{t}_E(K)$ the follower does not invest in any domain while for $t_A > \widetilde{t}_E(K)$ the follower invests in the explored one; ii) when $K_U < K < K_E$, there are two threshold values $\widetilde{t}_U(K)$ and $\widetilde{t}_E$ such that: for $t_A < \widetilde{t}_U(K)$ the follower does not invest in either domain, for $\widetilde{t}_U(K) < t_A < \widetilde{t}_E$ the follower invests in the unexplored domain, while for $t_A > \widetilde{t}_E$ the follower invests in the explored domain; iii) when $K < K_U$ there is a unique threshold $\widetilde{t}_E$ such that for $t_A < \widetilde{t}_E$ the follower searches in the unexplored domain while for $t_A > \widetilde{t}_E$ the follower invests in the explored one.

Note that the structure of the optimal strategy is identical with the structure for the case of $\theta_o > \widetilde{\theta}_o$.

Finally, to see why both threshold values $\widetilde{t}_U(K)$ and $\widetilde{t}_E(K)$ are concave increasing in K, consider the a generic profit function $\Pi(t_A) = R(t_A) - K$. The threshold values $\widetilde{t}_U(K)$ and $\widetilde{t}_E(K)$ are defined as the t_A values that solve the above equation for $R(t_A) = \Pi_{2B}^U(t_A)$ and $R(t_A) = \Pi_{2B}^E(t_A)$, respectively. But $R(t_A)$ is convex in t_A and K is linear, thus the thresholds will be concave increasing.

Proposition 1 *The threshold value $\widetilde{t}_E$ is strictly higher than the prior expected value μ_1.*

Proof: Recall that $\widetilde{t}_E$ is the unique root of $G(t_A)$, the difference between the expected profits from searching in the explored and the unexplored domain. Since

$G(\mu_1)=\frac{4b^2\sigma_1^4}{(\sigma_1^2+\sigma^2)(e^2-4)^2}(\theta_o^2-1)<0$ and $G(t_A)$ is increasing in t_A (Lemma 5), the unique threshold for which the follower invests in the explored domain always lies above the prior mean of the distribution: $\widetilde{t}_E>\mu_1$.

Lemma 7 *For every* θ_o, $\frac{\partial G(\widetilde{t}_E,\theta_o)}{\partial\theta_o}<0$.

Proof: For $-1<\theta_o<0$, $\frac{\partial\mu_2}{\partial\theta_o}=\frac{\sigma_1^2(t_A-\mu_1)}{\sigma_1^2+\sigma^2}>0$ and $\frac{\partial\sigma_2}{\partial\theta_o}=-\frac{\sigma_1^3\theta_o}{\sqrt{\sigma_1^2+\sigma^2}\sqrt{(1-\theta_o^2)\sigma_1^2+\sigma^2}}>0$ for $t_A>\mu_1$.

Also, $\frac{\partial E[\Pi_{2B}(\mu_2,\sigma_2|t_A)]}{\partial\mu_2}=4b[(2-e)(A-c)+2b\mu_2-ebt_A]>0$ and $\frac{\partial E[\Pi_{2B}(\mu_2,\sigma_2|t_A)]}{\partial\sigma_2}=\frac{8b^2\sigma_2}{(e^2-4)^2}>0$.

Therefore, $\frac{\partial\Pi_{2B}^U}{\partial\theta_o}=\frac{\partial\Pi_{2B}^U(t_A)}{\partial\theta_o}=\frac{\partial\Pi_{2B}^U(t_A)}{\partial\mu_2}\frac{\partial\mu_2}{\partial\theta_o}+\frac{\partial\Pi_{2B}^U(t_A)}{\partial\sigma_2}\frac{\partial\sigma_2}{\partial\theta_o}>0$. Also, $\frac{\partial G(t_A,\theta_o)}{\partial\theta_o}=\frac{\partial\Pi_{2B}^E(t_A)}{\partial\theta_o}-\frac{\partial\Pi_{2B}^U(t_A)}{\partial\theta_o}=-\frac{\partial\Pi_{2B}^U(t_A)}{\partial\theta_o}<0$ for $-1<\theta_o<0$. For a given t_A, $G(t_A,\theta_o)$ is quadratic in θ_o. To see that, note that $\Pi_{2B}^E(t_A)$ does not depend on θ_o while

$\Pi_{2B}^U(t_A)=\frac{1}{(e^2-4)^2}\{[(2-e)(A-c)-ebt_A]^2+2[(2-e)(A-c)-ebt_A](2b\mu_B)+4b^2(\mu_B^2+\sigma_B^2)\}$ with μ_B being linear in θ_o and σ_B^2 being quadratic in θ_o.

We proceed by the method of proof by contradiction. Assume there are $\widetilde{t}_E$ and $\widetilde{\theta}_o>0$ such that $G(\widetilde{t}_E,\widetilde{\theta}_o)=0$ and $\left.\frac{\partial G(\widetilde{t}_E,\theta_o)}{\partial\theta_o}\right|_{\theta_o=\widetilde{\theta}_o}>0$. Note that for a fixed $\widetilde{t}_E$, $G(\widetilde{t}_E,\theta_o)$ is either concave or convex in θ_o.

If $G(\widetilde{t}_E,\theta_o)$ is concave, then since $\frac{\partial G(\widetilde{t}_E,\theta_o)}{\partial\theta_o}<0$ for $-1<\theta_o<0$, $\frac{\partial G(\widetilde{t}_E,\theta_o)}{\partial\theta_o}<0$ also for $0<\theta_o<1$ and therefore $\left.\frac{\partial G(\widetilde{t}_E,\theta_o)}{\partial\theta_o}\right|_{\theta_o=\widetilde{\theta}_o}>0$ cannot be true.

If $G(\widetilde{t}_E,\theta_o)$ is convex, then it has two roots at $\widetilde{\theta}_o$ and 1. Therefore, in a neighborhood near $\widetilde{\theta}_o$, $G(\widetilde{t}_E,\theta_o)$ changes sign, from positive to negative and therefore, $\left.\frac{\partial G(\widetilde{t}_E,\theta_o)}{\partial\theta_o}\right|_{\theta_o=\widetilde{\theta}_o}<0$. Since we cannot have $\widetilde{t}_E$ and $\widetilde{\theta}_o$ such that $G(\widetilde{t}_E,\widetilde{\theta}_o)=0$ and $\left.\frac{\partial G(\widetilde{t}_E,\theta_o)}{\partial\theta_o}\right|_{\theta_o=\widetilde{\theta}_o}>0$, we conclude that $\frac{\partial G(\widetilde{t}_E,\theta_o)}{\partial\theta_o}<0$ for every $\theta_o\in(-1,1)$.

Proposition 2 *The threshold* $\widetilde{t}_E$ *increases in* θ_o.

Proof: Applying the Implicit Function Theorem (IFT) at the threshold $\widetilde{t}_E$ we get : $\frac{d\widetilde{t}_E(\theta_o)}{d\theta_o}=-\frac{\frac{\partial G(\widetilde{t}_E,\theta_o)}{\partial\theta_o}}{\frac{\partial G(\widetilde{t}_E,\theta_o)}{\partial t_A}}$. From Lemma 5 we know that $\frac{\partial G(\widetilde{t}_E,\theta_o)}{\partial t_A}>0$ and from Lemma

7 we get $\frac{\partial G(\widetilde{t}_E,\theta_o)}{\partial\theta_o} < 0$. Therefore $\frac{d\widetilde{t}_E(\theta_o)}{d\theta_o} > 0$. Intuitively, a higher θ_o makes $\Pi^U_{2B}(t_A)$ to increase faster in t_A (or decrease slower when it is decreasing) and therefore the threshold in Figure 16 (Figure 17) shifts to higher values.

Lemma 8 *The profit functions $\Pi^E_{2B}(t_A)$ are $\Pi^U_{2B}(t_A)$ are decreasing in e.*

Proof: Consider the generic profit function for the follower's second-period profits (e.g., the function valid for both scientific domains) $\Pi_{2B}\left(t_B \mid t_A\right) = \frac{1}{(e^2-4)^2}[(2-e)(A-c)-ebt_A+2bt_B]^2$ and note that $\frac{d\Pi_{2B}\,(e)}{de} = -2\frac{[(2-e)(A-c)-ebt_A+2bt_B][(e^2-4)^2(A-c)-4ebt_B+bt_Ae^2+4bt_A]}{(e^2-4)^3}$ < 0. Since, the distribution from which t_B is drawn does not depend on e, both $\Pi^E_{2B}(t_A)$ are $\Pi^U_{2B}(t_A)$ are decreasing in e.

Proposition 3 *The threshold $\widetilde{t}_E$ increases in e*

Proof:

Applying the IFT : $\frac{d\widetilde{t}_E(e)}{de} = -\frac{\frac{\partial G(\widetilde{t}_E,e)}{\partial e}}{\frac{\partial G(\widetilde{t}_E,e)}{\partial t_A}}$. According to proposition 1,$\frac{\partial G(\widetilde{t}_E,e)}{\partial t_A} > 0$. We will also prove that $\frac{\partial G(\widetilde{t}_E,e)}{\partial e} < 0$ and therefore $\frac{d\widetilde{t}_E(e)}{de} > 0$. First we will show that $\frac{\partial G(t_A,e)}{\partial e} < 0$ when $e \to 0^+$.

$\left.\frac{\partial^2 G(t_A,e)}{\partial e\partial t_A}\right|_{e\to 0^+} =$

$\lim_{e\to 0^+} \frac{1}{(e^2-4)^3}\{\frac{\sigma_1^2}{\sigma_1^2+\sigma^2}[(3e^2-8e+4)(A-c)(1+4bt_A+3be^2t_A)(1-\theta_o)-8eb(\mu_1'-\theta_o\mu_2)]+4b^2(4+3e^2)(\mu_1'-\mu_2)\} = -\frac{1}{64}[4(A-c)(1+4bt_A)(1-\theta_o)+16b^2(\mu_1'-\mu_2)] < 0.$

So, $\left.\frac{\partial^2 G(t_A,e)}{\partial e\partial t_A}\right|_{e\to 0^+} < 0$ and $\frac{\partial G(t_A,e)}{\partial e}$ is decreasing in t_A when $e \to 0^+$. Also, $\left.\frac{\partial G(t_A,e)}{\partial e}\right|_{t_A=\mu_1} < 0$.

Thus, when $e \to 0^+$, for $t_A > \mu_1$, $\left.\frac{\partial G(t_A,e)}{\partial e}\right|_{t_A} < \left.\frac{\partial G(t_A,e)}{\partial e}\right|_{t_A=\mu_1} < 0$.

We can rewrite $G(t_A,e)$ as $G(t_A,e) = \frac{1}{(\sigma_1^2+\sigma^2)^3(e^2-4)^2}(B_1(t_A)e+B_2(t_A))$ (1)

with $G'(t_A,e) = \frac{1}{(\sigma_1^2+\sigma^2)^3(e^2-4)^4}[B_1(t_A)(e^2-4)^2-4e(e^2-4)(B_1(t_A)e+B_2(t_A))]$

so that when $G'(t_A,e\to 0^+) = \frac{1}{16(\sigma_1^2+\sigma^2)^3}B_1(t_A)$

We proved before that $G'(t_A,e\to 0^+) < 0$, and therefore from (1), $B_1(t_A) < 0$ (2).

Thus, from (1) and (2) $\lim_{e\to 2^-} G(t_A, e) = -\infty$.

Assume that there is $\widetilde{t}_E$ and e_o such that $G(\widetilde{t}_E, e_o) = 0$ and $\left.\frac{\partial G(\widetilde{t}_E,e)}{\partial e}\right|_{e=e_o} > 0$.

Since, $\lim_{e\to 2^-} G(t_A, e) = -\infty$, there must be $e'_o \in (e_o, 2)$ such that $G(\widetilde{t}_E, e'_o) = 0$.

This, however, is impossible since according to (1) $G(t_A, e)$ has at most one real root.

Therefore, $\left.\frac{\partial G(\widetilde{t}_E,e)}{\partial e}\right|_{e=e_o} < 0$ at every threshold such that $G(\widetilde{t}_E, e_o) = 0$.

Thus, $\frac{\partial G(\widetilde{t}_E,e)}{\partial e} < 0$, and $\frac{d\widetilde{t}_E(e)}{de} > 0$.

Proposition 4 *The threshold $\widetilde{t}_E$ increases in σ.*

Proof: Applying the IFT at the threshold value we get : $\frac{d\widetilde{t}_E(\sigma)}{d\sigma} = -\frac{\frac{\partial G(\widetilde{t}_E,\sigma)}{\partial \sigma}}{\frac{\partial G(\widetilde{t}_E,\sigma)}{\partial t_A}}$

According to proposition 1,$\frac{\partial G(\widetilde{t}_E,\sigma)}{\partial t_A} > 0$. We will also prove that $\frac{\partial G(\widetilde{t}_E,\sigma)}{\partial \sigma} < 0$ and therefore $\frac{d\widetilde{t}_E(\sigma)}{d\sigma} > 0$.

We can rewrite $\frac{\partial G(t_A,\sigma)}{\partial \sigma}$ as follows: $\frac{\partial G(t_A,\sigma)}{\partial \sigma} = \frac{8b\sigma_1^2\sigma}{(\sigma_1^2+\sigma^2)^3(e^2-4)^2}(\Gamma_1(t_A)\sigma^2 + \Gamma_2(t_A))$ (3)

We will prove that $\frac{\partial G(\widetilde{t}_E,\sigma)}{\partial \sigma} < 0$ by the method of contradiction.

Assume there are $\widetilde{t}_E$ and σ_o such that $G(\widetilde{t}_E, \sigma_o) = 0$ and $\left.\frac{\partial G(\widetilde{t}_E,\sigma)}{\partial \sigma}\right|_{\sigma=\sigma_o} > 0$.

For the latter to be true, and given (3), the are three possible cases:

CASE I: $\Gamma_1(\widetilde{t}_E) > 0$ and $\Gamma_2(\widetilde{t}_E) > 0$

Under this case, however, $\frac{\partial G(\widetilde{t}_E,\sigma)}{\partial \sigma} > 0$ for every σ which is not possible given that $\lim_{\sigma\to\infty} G(t_A, \sigma) = 0$. To see why the latter is true, note that for $\sigma \to \infty$, $\mu'_1 = \mu_2$ and $\sigma'_1 = \sigma_2$, and therefore $G(t_A, \sigma) = 0$.

CASE II: $\Gamma_1(\widetilde{t}_E) > 0$ and $\Gamma_2(\widetilde{t}_E) < 0$

Note that $\left.\frac{\partial G(\widetilde{t}_E,\sigma)}{\partial \sigma}\right|_{\sigma=\sigma_o} > 0$ and since $\lim_{\sigma\to\infty} G(\widetilde{t}_E, \sigma) = 0$ there must be at least one $\sigma'_o > \sigma_o$ such that $\left.\frac{\partial G(\widetilde{t}_E,\sigma)}{\partial \sigma}\right|_{\sigma=\sigma'_o} = 0$ otherwise $G(t_A, \sigma)$ would be increasing in σ. Also, from (3) note that $\left.\frac{\partial G(\widetilde{t}_E,\sigma)}{\partial \sigma}\right|_{\sigma\to 0^+} < 0$ since $\Gamma_2(\widetilde{t}_E) < 0$. Since, $\left.\frac{\partial G(\widetilde{t}_E,\sigma)}{\partial \sigma}\right|_{\sigma=\sigma_o} > 0$ there must be at least one σ''_o with $0 < \sigma''_o < \sigma_o$ such that $\left.\frac{\partial G(\widetilde{t}_E,\sigma_o)}{\partial \sigma}\right|_{\sigma=\sigma''_o} = 0$. We showed that if there were $\widetilde{t}_E$ and σ_o such that $G(\widetilde{t}_E, \sigma_o) = 0$ and $\left.\frac{\partial G(\widetilde{t}_E,\sigma)}{\partial \sigma}\right|_{\sigma=\sigma_o} > 0$, then $\frac{\partial G(\widetilde{t}_E,\sigma)}{\partial\sigma}$ would have at least two positive roots. The latter though, is impossible according to (3). Therefore, $\left.\frac{\partial G(\widetilde{t}_E,\sigma)}{\partial\sigma}\right|_{\sigma=\sigma_o} < 0$ at every threshold such that $G(\widetilde{t}_E,\sigma_o)=0$.

CASE III: $\Gamma_1(\widetilde{t}_E)<0$ and $\Gamma_2(\widetilde{t}_E)>0$.

Integrating (3), we get that $G(\widetilde{t}_E,\sigma)=\frac{8b\sigma_1^2}{(e^2-4)^2}[-\frac{1}{2}\frac{\Gamma_1(\widetilde{t}_E)}{(\sigma_1^2+\sigma^2)}-\frac{1}{4}\frac{-\sigma_1^2\Gamma_1(\widetilde{t}_E)+\Gamma_2(\widetilde{t}_E)}{(\sigma_1^2+\sigma^2)^2}+c_o]=$ $=\frac{8b\sigma_1^2}{(e^2-4)^2}[-\frac{1}{4}\frac{\sigma_1^2\Gamma_1(\widetilde{t}_E)+\Gamma_2(\widetilde{t}_E)+2\sigma^2\Gamma_1(\widetilde{t}_E)-4c_o\sigma_1^4-8c_o\sigma_1^2\sigma^2-4c_o\sigma^4}{(\sigma_1^2+\sigma^2)^2}]$. However, from the full expression of $G(\widetilde{t}_E,\sigma)$ (omitted for brevity) we see that there is no σ^4 term, thus, $c_o=0$, and $G(\widetilde{t}_E,\sigma)=\frac{8b\sigma_1^2}{(e^2-4)^2}[-\frac{1}{4}\frac{(\sigma_1^2+2\sigma^2)\Gamma_1(\widetilde{t}_E)+\Gamma_2(\widetilde{t}_E)}{(\sigma_1^2+\sigma^2)^2}]$. The only positive root of $G(\widetilde{t}_E,\sigma)$ is $\sigma^*=-\frac{1}{2}\frac{\sqrt{-2\Gamma_1(\widetilde{t}_E)[\sigma_1^2\Gamma_1(\widetilde{t}_E)+\Gamma_2(\widetilde{t}_E)]}}{\Gamma_1(\widetilde{t}_E)}$. If $\sigma_1^2\Gamma_1(\widetilde{t}_E)+\Gamma_2(\widetilde{t}_E)<0$ then $G(\widetilde{t}_E,\sigma)$ has no positive root. This is impossible since we assumed that are $\widetilde{t}_E$ and σ_o such that $G(\widetilde{t}_E,\sigma_o)=0$. If $\sigma_1^2\Gamma_1(\widetilde{t}_E)+\Gamma_2(\widetilde{t}_E)>0$ then σ^* is the only positive root and since $G(\widetilde{t}_E,\sigma)$ is increasing-decreasing for $\sigma>\sigma^*$, the unique root of $\frac{\partial G(\widetilde{t}_E,\sigma)}{\partial\sigma}$ has to be greater than σ^*. Let , σ^{**} be the root of $\frac{\partial G(t_A,\sigma)}{\partial\sigma}$, then $\sigma^{**}=-\frac{\sqrt{-\Gamma_1(\widetilde{t}_E)\Gamma_2(\widetilde{t}_E)}}{\Gamma_1(\widetilde{t}_E)}$. We need $\sigma^{**}>\sigma^*$, or equivalently, $-\frac{\sqrt{-\Gamma_1(\widetilde{t}_E)\Gamma_2(\widetilde{t}_E)}}{\Gamma_1(\widetilde{t}_E)}>-\frac{1}{2}\frac{\sqrt{-2\Gamma_1(\widetilde{t}_E)[\sigma_1^2\Gamma_1(\widetilde{t}_E)+\Gamma_2(\widetilde{t}_E)]}}{\Gamma_1(\widetilde{t}_E)}$, or $2\Gamma_1(\widetilde{t}_E)\Gamma_2(\widetilde{t}_E)>-\Gamma_1(\widetilde{t}_E)[\sigma_1^2\Gamma_1(\widetilde{t}_E)+\Gamma_2(\widetilde{t}_E)]$ which is impossible since $\Gamma_1(\widetilde{t}_E)\Gamma_2(\widetilde{t}_E)<0$ and $-\Gamma_1(\widetilde{t}_E)[\sigma_1^2\Gamma_1(\widetilde{t}_E)+\Gamma_2(\widetilde{t}_E)]>0$. Thus the case $\Gamma_1(\widetilde{t}_E)<0$ and $\Gamma_2(\widetilde{t}_E)>0$ is not possible.

Since none of the cases I,II, and III is possible, there cannot be $\widetilde{t}_E$ and σ_o such that $G(\widetilde{t}_E,\sigma_o)=0$ and $\left.\frac{\partial G(\widetilde{t}_E,\sigma)}{\partial\sigma}\right|_{\sigma=\sigma_o}>0$. Thus, $\left.\frac{\partial G(\widetilde{t}_E,\sigma)}{\partial\sigma}\right|_{\sigma=\sigma_o}<0$.

Proposition 5 *When $\theta_o<0$, there are $\underline{t_\sigma}$ and $\overline{t_\sigma}$ such that for $\underline{t_\sigma}<t_A<\overline{t_\sigma}$ the follower's second-period expected profits increase in σ and decrease elsewhere. When $\theta_o>0$, there is $\overline{t_\sigma}$ such that for $t_A<\overline{t_\sigma}$ the follower's second-period expected profits increase in σ while for $t_A>\overline{t_\sigma}$ they decrease in σ.*

Proof:

First consider the case where $t_A<\widetilde{t}_E$ and note that

$\left.\frac{\partial\Pi_{2B}^U(t_A,\sigma)}{\partial\sigma}\right|_{t_A=\mu_1}=\frac{8b^2\sigma\sigma_1^4\theta_o^2}{(e^2-4)^2(\sigma_1^2+\sigma^2)^2}>0.$

$\frac{\partial^2 \Pi^U_{2B}(t_A,\sigma)}{\partial\sigma\partial t_A} = -\frac{8\theta_o b\sigma\sigma_1^2}{(e^2-4)^2(\sigma_1^2+\sigma^2)^3}\{\sigma^2[(2-e)(A-c)-2ebt_A+(2-e)b\mu_1]+\sigma_1^2[(2-e)(A-c)+2(2\theta_o-e)bt_A+(2+e-4\theta_o)b\mu_1]\}$. For $\theta_o < 0$, $\frac{\partial^2 \Pi^U_{2B}(t_A,\sigma)}{\partial\sigma\partial t_A} > 0$, $\frac{\partial \Pi^U_{2B}(t_A,\sigma)}{\partial\sigma}$ increases in t_A and therefore there will be a unique threshold ($\underline{t_\sigma} < \mu_1$) below which it will become negative. On the contrary, for $\theta_o > 0$, $\frac{\partial^2 \Pi^U_{2B}(t_A,\sigma)}{\partial\sigma\partial t_A} < 0$, $\frac{\partial \Pi^U_{2B}(t_A,\sigma)}{\partial\sigma}$ decreases in t_A and therefore there will be a unique threshold ($\mu_1 < \underline{t_\sigma}$) above which it will become negative. When $t_A > \widetilde{t}_E$, and the follower invests in the explored domain $\frac{\partial \Pi^E_{2B}(t_A,\sigma)}{\partial\sigma}$ is decreasing in t_A since

$\frac{\partial^2 \Pi^E_{2B}(t_A,\sigma)}{\partial\sigma\partial t_A} = \frac{-8b^2\sigma\sigma_1^2}{(e^2-4)^2(\sigma_1^2+\sigma^2)^3}\{\sigma^2[(2-e)(A-c)+2ebt_A-(2+e)b\mu_1]+\sigma_1^2[(2-e)(A-c)+2(e-2)bt_A+(2-e)b\mu_1]\} < 0$

For $\theta_o < 0$ and for a fixed $\widetilde{t}_E$, $\frac{\partial \Pi^E_{2B}(\widetilde{t}_E,\sigma)}{\partial\sigma} = \frac{\partial \Pi^U_{2B}(\widetilde{t}_E,\sigma)}{\partial\sigma} > 0$. But since $\frac{\partial \Pi^E_{2B}(t_A,\sigma)}{\partial\sigma}$ is decreasing in t_A there will be unique threshold ($\overline{t_\sigma} > \mu_1$) below which it will become negative. For $\theta_o > 0$ and $\widetilde{t}_E < \underline{t_\sigma}$, $\frac{\partial \Pi^E_{2B}(\widetilde{t}_E,\sigma)}{\partial\sigma} = \frac{\partial \Pi^U_{2B}(\widetilde{t}_E,\sigma)}{\partial\sigma} > 0$, and since $\frac{\partial \Pi^E_{2B}(t_A,\sigma)}{\partial\sigma}$ is decreasing in t_A there will be unique threshold ($\overline{t_\sigma} > \mu_1$) below which it will become negative. For $\theta_o > 0$ and $\widetilde{t}_E > \underline{t_\sigma}$, $\frac{\partial \Pi^E_{2B}(\widetilde{t}_E,\sigma)}{\partial\sigma} = \frac{\partial \Pi^U_{2B}(\widetilde{t}_E,\sigma)}{\partial\sigma} < 0$, and since $\frac{\partial \Pi^E_{2B}(t_A,\sigma)}{\partial\sigma}$ is decreasing in t_A, $\frac{\partial \Pi^E_{2B}(t_A,\sigma)}{\partial\sigma} < 0$ for $t_A > \widetilde{t}_E$. In the latter case, $\overline{t_\sigma} = \widetilde{t}_E$.

Proposition 6 *The potential of a rival firm investing in technology improvements reduces the incentives of the leader to invest in a scientific domain. In particular, the set of search cost values for which the leader initiates investment becomes narrower:* $K_L \leq K_L^M$*. Yet, competition intensity (e) has a non-monotonic impact on the threshold* K_L*.*

Proof: In a duopoly setting, $K_L = E[\Pi_{1A}] + E[\Pi_{2A}]$. Note here that $E[\Pi_{2A}]$ depends on the follower's strategy while $E[\Pi_{1A}]$ does not. Also, $K_L^M = 2E[\Pi_{1A}]$ and therefore, $K_L - K_L^M = E[\Pi_{2A}] - E[\Pi_{1A}] \leq 0$. The latter inequality is true since the leader's second-period profits are decreasing in t_B : $\Pi_{2A}(t_B \mid t_A) = \frac{1}{(e^2-4)^2}[(2-e)(A-c)+2bt_A - ebt_B]^2$ and the first-period profits $E[\Pi_{1A}]$ correspond to $t_B = 0$.

Appendix B

Proposition 1 : The value function $V_t(p_t)$ is non-decreasing in p_t.

Proof: For $t = 1$, $V_1(p_1) = \max\{p_1 V_0 - c, 0\}$ which is apparently non-decreasing in p_1. Let p_t^s denote the updated belief upon arrival of a successful indication (s) starting with an initial belief p_{t+1}. Then $p_t^s \doteq p_t(p_{t+1}|\xi_t = s) = \frac{qp_{t+1}}{qp_{t+1}+(1-q)(1-p_{t+1})}$. Similarly, we can define p_t^f as the updated belief upon arrival of an indication for failure (f). Then $p_t^f \doteq p_1(p_{t+1}|\xi_t = f) = \frac{(1-q)p_{t+1}}{(1-q)p_{t+1}+q(1-p_{t+1})}$.

We will proceed by induction. For $t = 2$, $V_2(p_2) = \max\{V_1(p_1^s)P(\xi_1 = s) + V_1(p_1^f)P(\xi_1 = f) - c, 0\}$.

Taking the first derivative, $\frac{\partial V_2(p_2)}{\partial p_2} = \frac{\partial P(\xi_1=s)}{\partial p_2} V_1(p_1^s)$

$P(\xi_1 = s)\frac{\partial V_1(p_1^s)}{\partial p_2} + \frac{\partial P(\xi_1=f)}{\partial p_2} V_1(p_1^f) + P(\xi_1 = f)\frac{\partial V_1(p_1^f)}{\partial p_2}$ $=(2q-1)V_1(p_1^s) + P(\xi_1 = s)\frac{\partial V_1(p_1^s)}{\partial (p_1^s)}\frac{\partial (p_1^s)}{\partial p_2} + (1-2q)V_1(p_1^f) + P(\xi_1 = f)\frac{\partial V_1(p_1^f)}{\partial (p_1^f)}\frac{\partial (p_1^f)}{\partial p_2}$

which through some algebraic manipulation results in $\frac{\partial V_2(p_2,q)}{\partial p_2} = (2q-1)[V_1(p_1^s) - V_1(p_1^f)] + \frac{q(1-q)}{P(\xi_1=s)}\frac{\partial V_1(p_1^s)}{\partial (p_1^s)} + \frac{q(1-q)}{P(\xi_1=f)}\frac{\partial V_1(p_1^f)}{\partial (p_1^f)}$

All three terms are non-negative for $q > \frac{1}{2}$ and $V_2(p_2)$ is non-decreasing in p_2. Assume that $V_t(p_t) = \max\{V_t(p_{t-1}^s)P(\xi_{t-1} = s) + V_t(p_{t-1}^f)P(\xi_{t-1} = f) - c, 0\}$ is non-decreasing in p_t. We will show that $V_{t+1}(p_{t+1}) = \max\{V_t(p_t^s)P(\xi_t = s) + V_t(p_t^f)P(\xi_t = f) - c, 0\}$ is also non-decreasing in p_{t+1}.

$\frac{\partial V_{t+1}(p_{t+1},q)}{\partial p_{t+1}} = \frac{\partial P(\xi_t=s)}{\partial p_{t+1}} V_t(p_t^s) + P(\xi_t = s)\frac{\partial V_t(p_t^s)}{\partial p_{t+1}} + \frac{\partial P(\xi_t=f)}{\partial p_{t+1}} V_t(p_t^f) + P(\xi_t = f)\frac{\partial V_t(p_t^f)}{\partial p_{t+1}} =$. But $= (2q-1)[V_t(p_t^s) - V_t(p_t^f)] + \frac{q(1-q)}{P(\xi_t=s)}\frac{\partial V_t(p_t^s)}{\partial (p_t^s)} + \frac{q(1-q)}{P(\xi_t=f)}\frac{\partial V_t(p_t^f)}{\partial (p_t^f)} > 0$ since $V_t(p_t)$ is non-decreasing in p_t.

Hence, the function $V_t(p_t)$ non-decreasing in p_t.

Region-Based Analysis

We proceed through an approach that we tag "region-based analysis". Essentially, for each stage t, we define two values $\underline{p_t}$ and $\overline{p_t}$ such that: for $p_t \leq \underline{p_t}$ you decide to terminate and for $p_t \geq \overline{p_t}$ you continue, regardless of the outcome of the next test.

Mathematically, $\underline{p_t}$ is defined as the highest belief such that even under a successful test in the next stage you would be indifferent between terminating or continuing the project ($V_{t-1}(p^s_{t-1}) = 0$ where $p^s_{t-1} = \frac{q\underline{p_t}}{q\underline{p_t}+(1-q)(1-\underline{p_t})}$). Similarly, $\overline{p_t}$ is defined as the lowest belief such that even if the next test indicates a failure, you would be indifferent between continuing and terminating the project.($V_{t-1}(p^f_{t-1}) = 0$ where $p^f_{t-1} = \frac{(1-q)\overline{p_t}}{(1-q)\overline{p_t}+q(1-\overline{p_t})}$). Our region based approach essentially means that to derive the unique threshold (Proposition 1) for each stage it is sufficient to focus on the middle region in which $\underline{p_t} \leq p_t \leq \overline{p_t}$ since for $p_t < \underline{p_t}$ you always terminate, while for $p_t > \overline{p_t}$ you always continue to the next stage.

Lemma 1: For $\underline{p_t} \leq p_t \leq \overline{p_t}$, $V_t(p_t) = \max\{V_{t-1}(p^s_{t-1})P(\xi_t = s) - c, 0\}$

Proof: It is sufficient to prove that $V_{t-1}(p^f_{t-1}) = 0$. Since, $p_t \leq \overline{p_t}$, $p^f_{t-1} = \frac{(1-q)p_t}{(1-q)p_t+q(1-p_t)} \leq \frac{(1-q)\overline{p_t}}{(1-q)\overline{p_t}+q(1-\overline{p_t})} = \overline{p}^f_{t-1}$ and from Proposition 1, we get $V_{t-1}(p^f_{t-1}) \leq V_{t-1}(\overline{p}^f_{t-1}) = 0$. Therefore, $V_{t-1}(p^f_{t-1}) = 0$ for $p_t \leq \overline{p_t}$.

Lemma 2: The value function $V_t(p_t)$ of every threshold region ($\underline{p_t} \leq p_t \leq \overline{p_t}$) can be written as follows: $V_t(p_t) = A_{t,q}p_t - C_{t,q}$ where the functions $A_{t,q}$ and $C_{t,q}$ are defined by the following recursive relationships: $A_{t+1,q} = qA_{t,q} + (1-2q)C_{t,q}$ and $C_{t+1,q} = (1-q)C_{t,q} + c$

Proof: We proceed by induction. First, we prove that it holds for $t = 2$. In particular, $V_2(p_2) = P(\xi_2 = s)V_1(p_1|\xi_1 = s) - c =$ (since $V_1(p_1|\xi_1 = f) = 0$)

$=[qp_2 + (1-q)(1-p_2)][\frac{qp_2}{qp_2+(1-q)(1-p_2)}V_0 - c] - c = [qV_0 + (1-2q)c]p_2 - (2-q)c$

We assume that it holds for $t = k$ so that : $V_k(p_k) = A_{k,q}p_k - C_{k,q}$.

We will prove that it holds for $t = k+1$.

$V_{k+1}(p_{k+1}) = P(\xi_k = s)V_k(p_k|\xi_k = s) - c =$

$= [qp_{k+1} + (1-q)(1-p_{k+1})][A_{k,q}\frac{qp_{k+1}}{qp_{k+1}+(1-q)(1-p_{k+1})} - C_{k,q}] - c$

$= qA_{k,q}p_{k+1} - [qp_{k+1} + (1-q)(1-p_{k+1})]C_{k,q} - c =$

$= [qA_{k,q} + (1-2q)C_{k,q}]p_{k+1} - (1-q)C_{k,q} - c = A_{k+1,q}p_{k+1} - C_{k+1,q}$

Therefore, $V_t(p_t) = A_{t,q}p_t - C_{t,q}\ \forall\ t = 1, 2, ..., N$

Proposition 2: The optimal threshold values $\widetilde{p_{t,q}}$ are increasing in t

Proof: From Lemma 2 we know that $\widetilde{p}_{t,q} = \frac{C_{t,q}}{A_{t,q}}$ and $\widetilde{p}_{t+1,q} = \frac{C_{t+1,q}}{A_{t+1,q}} = \frac{(1-q)C_{t,q}+c}{qA_{t,q}+(1-2q)C_{t,q}}$

We need to show that $\widetilde{p}_{t+1,q} > \widetilde{p}_{t,q}$, or equivalently, $\frac{(1-q)C_{t,q}+c}{qA_{t,q}+(1-2q)C_{t,q}} > \frac{C_{t,q}}{A_{t,q}}$, or, $(1-2q)[A_{t,q} - C_{t,q}]C_{t,q} + cA_{t,q} > 0$.

Since $C_{t,q} \geq c$, it is sufficient to show that $(1-2q)[A_{t,q} - C_{t,q}] + A_{t,q} > 0$, or, $\frac{A_{t,q}}{C_{t,q}} > \frac{1-2q}{2(1-q)}$. But $\frac{A_{t,q}}{C_{t,q}} > 1$ (otherwise $\widetilde{p}_{t,q} > 1$ and the project would have been terminated at the previous stage) and $\frac{1-2q}{2(1-q)} < 1$ since $1-2q < 2(1-q)$. Therefore, $\frac{A_{t,q}}{C_{t,q}} > \frac{1-2q}{2(1-q)}$ and $\widetilde{p}_{t+1,q} > \widetilde{p}_{t,q}$.

Lemma 3: The function $C_t(q)$ is decreasing in q.

Proof: We will prove it by induction. For $t = 2 : C_2'(q) = -c < 0$. Since $C_{t+1,q} = (1-q)C_{t,q} + c$, $C'_{t+1,q} = (1-q)C'_{t,q} - C_{t,q}$. Assuming that it holds for $t = k$, that is, $C'_{k,q} < 0$. It is easy to see that it also holds for $t = k+1$. So $C_{t,q}$ is decreasing in q $\forall$ $t = 1, 2, ..., N$

Proposition 3: The threshold values $\widetilde{p}_{t,q}$ are decreasing in q.

Proof: The optimal threshold will satisfy the equation $A_{t,q}\widetilde{p}_{t,q} = C_{t,q}$.

Differentiating with respect to q : $A_{t,q}\widetilde{p}'_{t,q} + A'_{t,q}\widetilde{p}_{t,q} = C'_{t,q} \Leftrightarrow \widetilde{p}_{t,q} = \frac{C'_{t,q} - A_{t,q}\widetilde{p}'_{t,q}}{A'_{t,q}}$ since $A'_{t,q} \neq 0$ (if there is q_0 such that $A'_{t,q_0} = 0$, then A_{t,q_0}) $\widetilde{p}'_{t,q_0} = C'_{t,q_0} < 0$ and $\widetilde{p}'_{t,q_0} < 0$ since $A_{t,q_0} > 0$). Also, $0 \leq \widetilde{p}_{t,q} \leq 1$ $\Leftrightarrow 0 \leq C'_{t,q} - A_{t,q}\widetilde{p}'_{t,q}$.However $C'_{t,q} < 0$ (Lemma 3) and $A_{t,q} > 0$, so $\widetilde{p}'_{t,q} < 0$.

Appendix C

Proof of Lemma 1. The entrant's optimization problem given the OEM's choice of q_2 is

$$Max_{q_r,s}\Pi_e(q_r,s|q_2)=[\delta(1-q_r-q_2)-h-c_r]\,q_r-s(\frac{s}{\gamma}-\frac{p_1-s}{1-\gamma})$$
$$\text{s.t.}\quad 0\le q_r\le\frac{s}{\gamma}-\frac{p_1-s}{1-\gamma}. \tag{1}$$

The Lagrangian for the entrant's problem is $L(q_r,s,\lambda_1,\lambda_2)=[\delta(1-q_r-q_2)-h-c_r]\,q_r-s(\frac{s}{\gamma}-\frac{p_1-s}{1-\gamma})+\lambda_1(\frac{s}{\gamma}-\frac{p_1-s}{1-\gamma}-q_r)+\mu_1 q_r$.

The Kuhn-Tucker conditions for optimality are $\frac{\partial L}{\partial q_r}=0$, $\frac{\partial L}{\partial s}=0$, $\lambda_1(\frac{s}{\gamma}-\frac{p_1-s}{1-\gamma}-q_r)=0$ and $\mu_1 q_r=0$, with $0\le q_r\le\frac{s}{\gamma}-\frac{p_1-s}{1-\gamma}$, $\lambda_1\ge0$, $\mu_1\ge0$.

Assume $\frac{s}{\gamma}-\frac{p_1-s}{1-\gamma}-q_r>0$. Then, at optimality, $\lambda_1=0$. Solving $\frac{\partial L}{\partial s}=0$, we get $s^*=\frac{\gamma p_1}{2}$, which gives $\frac{s^*}{\gamma}-\frac{p_1-s^*}{1-\gamma}=-\frac{p_1}{2(1-\gamma)}<0$, which violates the original condition $\frac{s}{\gamma}-\frac{p_1-s}{1-\gamma}-q_r>0$.

Since this case cannot meet the KT conditions, we hereafter assume that the right constraint in (1) is binding. Intuitively, the entrant would not be willing to acquire more used units than the quantity she would sell in the secondary market. Rewriting this equality, we obtain $s^*(q_r)=\gamma(1-\gamma)q_r+\gamma p_1$, where we suppress dependence on p_1 determined in period 1.

Proof of Lemma 2. Based on Lemma 1 we can reduce the entrant's problem to a single decision variable optimization problem in q_r:

$$Max_{q_r}\Pi_e=[p_r-s^*(q_r)-c_r]\,q_r=[p_r-\gamma(1-\gamma)q_r-\gamma p_1-c_r]\,q_r\qquad s.t.\;\; q_r\ge0. \tag{2}$$

We also know the profit function of the OEM

$$Max_{q_2}\Pi_2(q_2|q_r)=(p_2-c)q_2+hq_r=(\alpha-\alpha q_2-\delta q_r-c)\,q_2+hq_r\qquad s.t.\; q_2\ge0. \tag{3}$$

Here, Π_e and Π_2 are concave in q_r and q_2, respectively. By solving the first-order conditions simultaneously, we can obtain the following Nash equilibrium:

$$q_2^*(p_1,h) = \frac{2(\delta+\gamma-\gamma^2)(\alpha-c)-\delta^2+\delta h+\delta\gamma p_1+\delta c_r}{4\gamma\alpha(1-\gamma)+\delta(4\alpha-\delta)} \tag{4}$$

$$q_r^*(p_1,h) = \frac{\alpha(\delta-2c_r-2h-2\gamma p_1)+\delta c}{4\gamma\alpha(1-\gamma)+\delta(4\alpha-\delta)}. \tag{5}$$

Substituting q_r^* from (5) into the expression derived in Lemma 1 gives

$$s^*(p_1,h) = \frac{\gamma[(2\alpha\,\gamma(1-\gamma)p_1+\delta\,(4\alpha-\delta)p_1-2\alpha(1-\gamma)(h-c_r)+\delta(1-\gamma)c]}{4\gamma\alpha(1-\gamma)+\delta(4\alpha-\delta)}. \tag{6}$$

Recall that the quantity of new units sold in the first period by the OEM can be expressed as

$$q_1 = 1-\frac{p_1-s}{1-\gamma}, \text{ or, } p_1=(1-\gamma)(1-q_1)+s. \tag{7}$$

Substituting p_1 from (7) into (6), we obtain the equilibrium price s^* that the entrant pays the first-period consumers to collect used products as a function of q_1 and h:

$$s^*(q_1,h) = \gamma\frac{[2\gamma\alpha(\gamma-1)+\delta(\delta-4\alpha)]q_1+[5\delta+2\gamma(1-\gamma)-2(h+c_r)]\alpha+\delta c-\delta^2}{2\gamma\alpha(2-\gamma)+\delta(4\alpha-\delta)}. \tag{8}$$

Moreover, from (6) and (7) we can rewrite (4) and (5) in terms of q_1 and h:

$$q_2^*(q_1,h) = \frac{\delta h-\gamma\delta q_1-\delta(\delta-\gamma)+\delta c_r-(\alpha-c)[\gamma(\gamma-2)-2\delta]}{2\gamma\alpha(2-\gamma)+\delta(4\alpha-\delta)} \tag{9}$$

$$q_r^*(q_1,h) = \frac{2\alpha(\gamma q_1-h-\gamma-c_r)+\delta(\alpha+c)}{2\gamma\alpha(2-\gamma)+\delta(4\alpha-\delta)}. \tag{10}$$

This Nash equilibrium is valid as long as the right-hand sides of (9) and (10) are non-negative, respectively, which can be written as $h-\gamma q_1 \geq A$ and $h-\gamma q_1 \leq B$, where $A \doteq (\delta-\gamma)-c_r+\frac{(\alpha-c)\gamma(\gamma-2)}{\delta}-2(\alpha-c)$ and $B \doteq \frac{1}{2\alpha}\delta(\alpha+c)-(\gamma+c_r)$.

Proof of Proposition 1. In period 1, the OEM chooses $q_1 \geq 0$ and $h \geq 0$ so as to maximize the sum of first- and second-period profits. The OEM's second-period profit can be obtained using (9 - 10) as long as q_1 and h satisfy $h-\gamma q_1 \geq A$ and $h-\gamma q_1 \leq B$. For completeness, we need to characterize the OEM's second-period profit outside this range, or argue that the optimal solution will satisfy the two conditions. For a given

q_1, it is in fact sufficient to restrict the domain of h to values yielding a non-negative quantity in (10), $h - \gamma q_1 \leq B$, since once the secondary market has been eliminated, increasing h does not improve the OEM's profits. The same need not be true however for (9); even when the OEM abstains from the primary market in the second period, he can improve his profits by decreasing h and increasing first-period resale value, and we cannot use the expressions in Lemma 2 to calculate second-period profits in this range ($h - \gamma q_1 < A$). We proceed by enforcing $h - \gamma q_1 \leq B$, but determining the optimal OEM strategy for those values of q_1 and h yielding $h - \gamma q_1 \geq A$ (Case A) and $h - \gamma q_1 \leq A$ (Case B), separately, and then combining the results.

Case A ($h - \gamma q_1 \geq A$). The OEM's optimization problem is

$$Max_{q_1,h}\ \Pi(q_1,h) = \Pi_1(q_1,h) + \Pi_2^*(q_1,h)$$

$$\text{s.t.} \quad A \leq h - \gamma q_1 \leq B$$

$$q_1 \geq 0, \quad h \geq 0,$$

where $\Pi_1(q_1,h) = (p_1(q_1,h) - c)q_1$ denotes the profit from the sales of new products in the first period and $\Pi_2^*(q_1,h)$ is calculated using (9) and (10). The determinant of the Hessian of the objective function $\Pi(q_1,h)$ is $\frac{4\alpha(8\delta\alpha - 3\delta^2 + 8\gamma\alpha(1-\gamma)}{[2\gamma\alpha(\gamma-2)+\delta(\delta-4\alpha)]^2} > 0$ with $\frac{\partial^2\Pi(q_1,h)}{\partial q_1^2} < 0$. Thus, the Hessian is negative definite and the profit function is concave in (q_1,h). Define the Lagrangian $L(q_1,h,\lambda_1,\lambda_2) = \Pi(q_1,h) + \lambda_1(h - \gamma q_1 - A) + \lambda_2(B - h + \gamma q_1) + \mu_1 h$. The Kuhn-Tucker conditions for optimality are:

$$\frac{\partial L}{\partial q_1} = 0 \tag{11}$$

$$\frac{\partial L}{\partial h} = 0 \tag{12}$$

$$\lambda_1(h - \gamma q_1 - A) = 0 \tag{13}$$

$$\lambda_2(B - h + \gamma q_1) = 0 \tag{14}$$

$$\mu_1 h = 0 \tag{15}$$

and $\lambda_1 \geq 0$, $\lambda_2 \geq 0$, $\mu_1 \geq 0$. The constraint $q_1 \geq 0$ will be checked separately. Note that $\lambda_1\lambda_2 = 0$, since otherwise both constraints (13) and (14) would be binding, which is not possible.

Case A.I : $\lambda_1 = 0$, $\lambda_2 \neq 0$, $\mu_1 = 0$.

$\lambda_2 \neq 0$ implies $B - h^* + \gamma q_1^* = 0$. Solving the KT conditions, we obtain $h^* = \frac{1}{2}[\delta(1+\frac{c}{\alpha}) - \gamma(1+c)] - c_r$, $q_1^* = \frac{1}{2}(1-c) > 0$, $q_2^* = \frac{1}{2}(1-\frac{c}{\alpha}) > 0$ and $\lambda_2 = 2\,\frac{c(\delta-\alpha\gamma)-\alpha c_r}{2\gamma\alpha(\gamma-2)+\delta(\delta-4\alpha)}$ with corresponding profit $\frac{(1-c)^2}{2}$. Case I is valid for $\lambda_2 > 0$ and $h^* \geq 0$, or, $\frac{c(\delta-\alpha\gamma)}{\alpha} < c_r \leq \frac{1}{2}[\delta(1+\frac{c}{\alpha}) - \gamma(1+c)]$ and represents the case of having no refurbished products in the second period due to the high remanufacturing cost and the positive relicensing fee.

Case A.II : $\lambda_1 = 0$, $\lambda_2 \neq 0$, $\mu_1 \neq 0$.

$\lambda_2 \neq 0$ implies $B - h^* + \gamma q_1^* = 0$. Moreover, $\mu_1 \neq 0$ implies $h^* = 0$. Solving the KT conditions, we obtain $q_1^* = \frac{1}{2}\,\frac{2(\alpha\gamma+c_r)-\delta(\alpha+c)}{\alpha\gamma}$ and $\mu_1 = \frac{(1+c)\alpha\gamma-\delta(\alpha+c)+2\alpha c_r}{\alpha\gamma^2}$.

We need $\mu_1 > 0$, which is true for $c_r > c_{r,\mu_1} \doteq \frac{1}{2}[\delta(1+\frac{c}{\alpha}) - \gamma(1+c)]$. We also need $\lambda_2 > 0$. From the expression for λ_2 (omitted for brevity), we have $\dfrac{\partial\lambda_2}{\partial c_r} = \frac{2(\delta^2-4\alpha\delta+3\alpha\gamma^2-4\alpha\gamma)}{(2\alpha\gamma^2-4\alpha\gamma-4\alpha\delta+\delta^2)\gamma^2} > 0$, so λ_2 is increasing in c_r. Therefore it is sufficient to show that $\lambda_2(c_r = c_{r,\mu_1}) > 0$. But $\lambda_2(c_r = c_{r,\mu_1}) = -\frac{(\alpha\gamma-\delta)c+(\delta-\gamma)\alpha}{(2\alpha\gamma^2-4\alpha\gamma-4\alpha\delta+\delta^2)} > 0$, so $\lambda_2 > 0$.

Therefore, this case is valid for $c_r > \frac{1}{2}[\delta(1+\frac{c}{\alpha}) - \gamma(1+c)]$ and represents the case of having no refurbished products in the second period due to the high remanufacturing cost even if the OEM sets the relicensing fee to zero. This condition also ensures that $q_1^* > 0$.

Case A.III : $\lambda_1 \neq 0, \lambda_2 = 0$, $\mu_1 = 0$.

$\lambda_1 \neq 0$ implies $h^* - \gamma q_1^* = A$. Solving the KT conditions, we obtain $q_1^* = \frac{1}{2}\,\frac{(1-c)(\delta+2\alpha\gamma)}{\delta} > 0$, $h^* = \frac{1}{2}\,\frac{[4\gamma(1-\gamma)+\delta\,(4-\gamma]c+4\gamma\alpha(\gamma-1)+2\,\delta(\delta-c_r)-\delta(4\alpha+\gamma)}{\delta}$, and $\lambda_1 = \frac{[\delta\,(\delta-8\alpha+2\alpha\gamma)+8\gamma\alpha(\gamma-1)]c+\delta(8\alpha^2-3\delta\alpha+2\alpha c_r)+8\gamma(1-\gamma)\alpha^2}{\delta(2\alpha\gamma^2-4\alpha\gamma-4\alpha\delta+\delta^2)}$. Case III is valid for $\lambda_1 > 0$ and $h^* \geq 0$ or, $c \geq \max\{c_{\lambda_1}, c_{h^*}\}$, where $c_{\lambda_1} = \frac{\alpha[\delta(8\alpha-3\delta+2c_r)+8\gamma\alpha(1-\gamma)]}{\delta\,(8\alpha-\delta-2\gamma\alpha)+8\alpha\gamma(1-\gamma)}$ and $c_{h^*} =$

$\frac{4\alpha\gamma(\gamma-1)+2\,\delta(\delta-c_r)-\delta(4\alpha+\gamma)}{4\,\gamma(\gamma-1)+\delta\,(\gamma-4]}$ are the values of c that satisfy $\lambda_1(c) = 0$ and $h^*(c) = 0$, respectively. Let $\overline{c} \doteq c_{\lambda_1} - c_{h^*}$. Note that $\frac{d\overline{c}}{d\alpha} = \frac{\delta^3[(8\gamma^2-8\gamma-8\delta+2\delta\gamma)c_r-8\gamma^2\delta+8\gamma\delta+8\delta^2-3\delta^2\gamma}{(8\alpha\gamma^2-8\alpha\,\gamma-8\alpha\delta+2\delta\gamma\alpha+\delta^2)^2(-2\gamma^2+4\,\gamma+4\,\delta-\delta^2)} > 0$ because the denominator is always positive, while the numerator is decreasing in c_r and is positive for $c_r = \delta - \gamma > \frac{(\delta-\alpha\gamma)}{\alpha} > \frac{c(\delta-\alpha\gamma)}{\alpha}$. Thus $\frac{d\overline{c}}{d\alpha} > 0$ for $c_r < \delta - \gamma$. Also $\overline{c}(\alpha = 1) = -\frac{2\delta(4\gamma^2-4\gamma+\delta\,\gamma-4\,\delta+\delta^2)(\delta-\gamma-c_r)}{(8\,\gamma^2-8\,\gamma+2\delta\,\gamma-8\,\delta+\delta^2)(4\,\gamma^2-4\,\gamma-4\,\delta+\delta\gamma)} > 0$ because $c(\delta-\gamma) > c_r$ (for if we assume that $c(\delta-\gamma) \leq c_r$, $\lambda_1 < 0$ and this case becomes impossible) and $c < 1$. Therefore, $\max\{c_{\lambda_1}, c_{h^*}\} = c_{\lambda_1}$ and $h^* > 0$.

Case III represents the case of having no new products in the second period due to the high unit production cost, but charging a positive relicensing fee, and is valid for $c > \frac{\alpha[\delta(8\alpha-3\delta+2c_r)+8\gamma\alpha(1-\gamma)]}{\delta\,(8\alpha-\delta-2\gamma\alpha)+8\alpha\gamma(1-\gamma)}$.

Case A.IV : $\lambda_1 \neq 0, \lambda_2 = 0, \mu_1 \neq 0$.

$\lambda_1 \neq 0$ implies $h^* - \gamma q_1^* = A$. Case IV is valid for $\lambda_1 > 0$, $\mu_1 > 0$ and $q_r^* > 0$. The latter is positive when $c_r < \delta - \frac{1}{2}\gamma(1+\alpha)$. However, μ_1 is linearly decreasing in c, λ_1 is linearly increasing in c, and $c_{\mu_1} < c_{\lambda_1}$because $\lambda_1(c_{\mu_1}) < 0$. To prove the latter note that $\dfrac{\partial\lambda_1(c_{\mu_1})}{\partial c_r} = \frac{\delta\,(-8\alpha+2\delta+2\gamma\alpha)-8\alpha\gamma(1-\gamma)}{\delta(4\,\gamma^2-4\,\gamma-4\,\delta+\delta\gamma)} > 0$ and also that for $c_r = \delta - \frac{1}{2}\gamma(1+\alpha)$, $\lambda_1(c_{\mu_1}) = \frac{\alpha\gamma(1-\alpha)}{\delta} \leq 0$ since $\alpha \geq 1$. Therefore, λ_1 and μ_1 can never be positive at the same time, and this case is impossible.

Case A.V : $\lambda_1 = 0, \lambda_2 = 0, \mu_1 = 0$. Solving the KT conditions we obtain

$h^* = \frac{1}{2}\frac{(-8\delta\gamma^2+8\delta^2+8\gamma^3-8\gamma^2-8\gamma c_r+8\gamma^2 c_r-8\delta c_r)\alpha^2+(3\gamma\delta^2-3\delta^3+\gamma\delta^2 c+4c_r\delta^2)\alpha-\delta^3 c}{\alpha[8\,\gamma(1-\gamma)\alpha+8\delta\alpha-3\delta^2]}$,

$q_1^* = \frac{1}{2}\frac{(8\gamma+4c\gamma^2-8\gamma^2-8\delta c-4\gamma c_r-8c\gamma+8\delta^2)\alpha-3\delta^2(1+c)+4\gamma\delta c}{8\,\gamma(1-\gamma)\alpha+8\delta\alpha-3\delta^2}$,

$q_2^* = \frac{1}{2}\frac{(8\gamma^2-8\gamma-8\delta)\alpha^2+(8c\gamma+3\delta^2-8c\gamma^2-2\delta c_r-2\gamma\delta c+8\delta c)\alpha-\delta^2 c}{\alpha[8\,\gamma(\gamma-1)\alpha+3\,\delta^2-8\delta\alpha]}$, and $q_r^* = \frac{2(\alpha c_r-c(\delta-\alpha\gamma))}{8\,\gamma(\gamma-1)\alpha+3\,\delta^2-8\delta\alpha}$.

We can see that $q_2^* \geq 0$ for $c \leq c_{q_2^*} = \frac{\alpha[\delta(8\alpha-3\delta+2c_r)+8\gamma\alpha(1-\gamma)]}{\delta\,(8\alpha-\delta-2\gamma\alpha)+8\alpha\gamma(1-\gamma)}$, while $q_r^* \geq 0$ for $c_r \leq \frac{c(\delta-\alpha\gamma)}{\alpha}$.

Moreover, $h^* \geq 0$ for $c \leq c_{h^*} \doteq -\frac{(3\gamma\delta^2-8\delta\alpha\gamma^2+8\delta^2\alpha+8\gamma^3\alpha-8\gamma^2\alpha-8c_r\delta\alpha-3\delta^3-8c_r\gamma\alpha+8c_r\gamma^2\alpha+4c_r\delta^2)\alpha}{\delta^2(-\delta+\gamma\alpha)}$. But $c_{h^*} - c_{q_2^*} > 0$ and therefore this case is valid for $c \leq \frac{\alpha[\delta(8\alpha-3\delta+2c_r)+8\gamma\alpha(1-\gamma)]}{\delta\,(8\alpha-\delta-2\gamma\alpha)+8\alpha\gamma(1-\gamma)}$.

Case V represents the case where both new and refurbished products exist in the second period with a positive relicensing fee.

Case A.VI : $\lambda_1 = 0, \lambda_2 = 0, \mu_1 \neq 0$.

Here $q_2^* > 0$ and $h^* = 0$. This case was also found to be impossible because $q_2^* \mu_1 < 0$. Another of way of seeing this is to note that both q_2^* and h^* decrease in c, but as c increases, it is always q_2^* that becomes zero first ($c_{h^*} > c_{q_2^*}$). Therefore the case of $q_2^* > 0$ and $h^* = 0$ is not possible.

Case B ($h - \gamma q_1 \leq A$). Solving for the Nash equilibrium in the second period under this condition, we obtain $q_2^*(q_1, h) = 0$ and $q_r^*(q_1, h) = \frac{\gamma q_1 - h + \delta - \gamma - c_r}{2(\delta+\gamma)-\gamma^2}$. The OEM's optimization problem is:

$$Max_{q_1,h}\ \Pi(q_1,h) = \Pi_1(q_1,h) + h q_r^*(q_1,h) = (p_1(q_1,h) - c)q_1 + h\frac{\gamma q_1 - h + \delta - \gamma - c_r}{2(\delta+\gamma) - \gamma^2} \tag{16}$$

$$\text{s.t.} \quad h - \gamma q_1 \leq A \tag{17}$$

$$h - \gamma q_1 \leq B \tag{18}$$

$$q_1 \geq 0, \quad h \geq 0.$$

Note that since $A < B$, constraint (18) will never be binding at the optimal solution, and therefore can be eliminated. Solving the constrained maximization problem, we have the following cases:

Case B.I : For $c \geq \frac{\alpha[\delta(8\alpha-3\delta+2c_r)+8\gamma\alpha(1-\gamma)]}{\delta\,(8\alpha-\delta-2\gamma\alpha)+8\alpha\gamma(1-\gamma)}$, constraint (17) is non-binding and the optimal values are $q_1^* = \frac{1}{4}\frac{\delta(2+\gamma)+2\gamma(1-\gamma)-\gamma c_r-(2\gamma+2\delta-\gamma^2)c}{\delta+\gamma-\gamma^2}$ and $h^* = \frac{1}{2}(\delta-\gamma-c_r)$, yielding $q_r^* = \frac{1}{4}\frac{\delta-\gamma c-c_r}{\delta+\gamma-\gamma^2}$. In this parameter range, $c_r < c(\delta-\gamma)$, which is in turn less than $\delta-\gamma$, so $h^* > 0$, $q_r^* > 0$ and $q_1^* > 0$.

Case B.II : For $c \leq \frac{\alpha[\delta(8\alpha-3\delta+2c_r)+8\gamma\alpha(1-\gamma)]}{\delta\,(8\alpha-\delta-2\gamma\alpha)+8\alpha\gamma(1-\gamma)}$, constraint (17) is binding and the optimal values are $q_1^* = \frac{1}{2}\frac{(1-c)(\delta+2\alpha\gamma)}{\delta} > 0$, $h^* = \frac{1}{2}\frac{[4\gamma(1-\gamma)+\delta\,(4-\gamma]c+4\gamma\alpha(\gamma-1)+2\,\delta(\delta-c_r)-\delta(4\alpha+\gamma)}{\delta}$, yielding $q_r^* = \frac{\alpha-c}{\delta}$. Note that this case yields the same optimal solution and objective function value with Case A.III.

We illustrate the structure of the optimal solution subject to the conditions of Cases A and B in Figure 18, where we use the observation that $c \geq \tilde{c}(\delta,\gamma,c_r)$ implies

$c \geq \frac{\alpha c_r}{\delta - \alpha\gamma}$, or, $c_r \leq \frac{c(\delta - \alpha\gamma)}{\alpha}$.

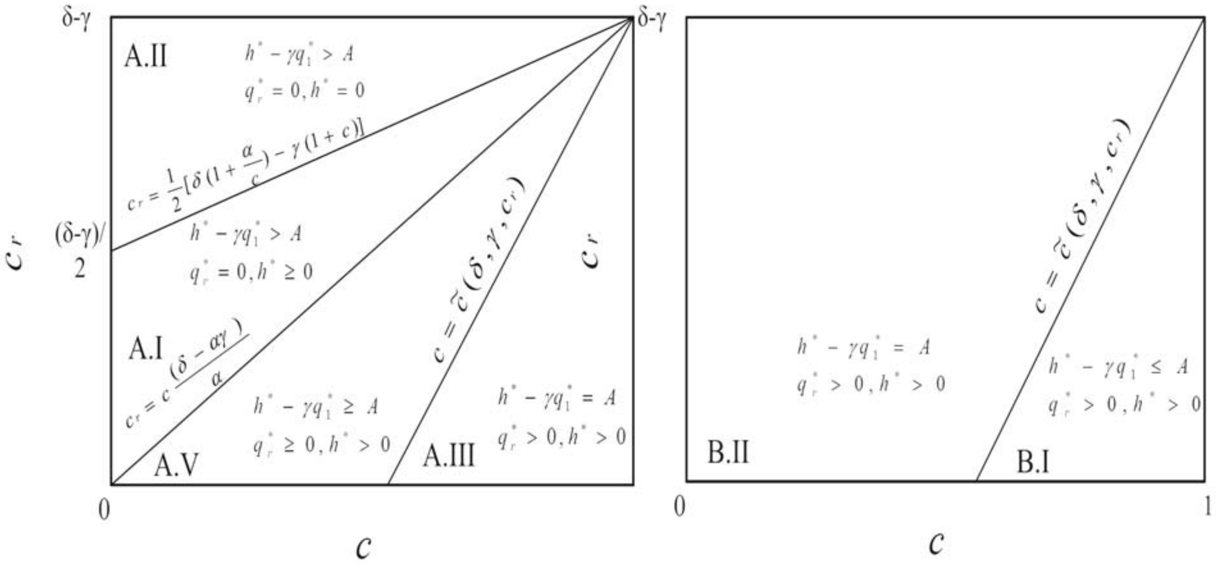


Figure 18: Structure of Optimal Solution subject to constraints $h - \gamma q_1 \geq A$ (left panel) and $h - \gamma q_1 \leq A$ (right panel).

We now compare the optimal constrained solutions of cases A and B to find the global optimal solution structure.

For $c \geq \widetilde{c}(\delta, \gamma, c_r) \doteq \frac{\alpha[\delta(8\alpha - 3\delta + 2c_r) + 8\gamma\alpha(1-\gamma)]}{\delta(8\alpha - \delta - 2\gamma\alpha) + 8\alpha\gamma(1-\gamma)}$, Cases A.III and Case B.I need to be compared to find q_1^* and h^* in this parameter range. Since both cases A and B include the boundary $h - \gamma q_1 = A$, but the optimal solution in case B satisfies $h^* - \gamma q_1^* < A$, while that in case A.III satisfies $h^* - \gamma q_1^* = A$, we conclude that case B.I gives the global optimum in this range.

For $c < \widetilde{c}(\delta, \gamma, c_r)$, Case B.II needs to be compared with Cases A.I, A.II and A.V to find q_1^* and h^* in their respective parameter ranges. Since both cases A and B include the boundary $h - \gamma q_1 = A$, but the optimal solutions in case A satisfy $h^* - \gamma q_1^* > A$, while that in case B.II satisfies $h^* - \gamma q_1^* = A$, we conclude that cases A.I, A.II and A.V give the global optimum in their respective parameter ranges. The structure of the optimal solution is summarized in the following table.

Condition	Equilibrium Outcome in the Second Period
$c > \tilde{c}(\delta, \gamma, c_r) \doteq \frac{\alpha[\delta(8\alpha-3\delta+2c_r)+8\gamma\alpha(1-\gamma)]}{\delta(8\alpha-\delta-2\gamma\alpha)+8\alpha\gamma(1-\gamma)}$	Only refurbished products
$c \le \tilde{c}(\delta, \gamma, c_r)$ and $c_r \le \frac{c(\delta-\alpha\gamma)}{\alpha}$	Both new and refurbished products
$c \le \tilde{c}(\delta, \gamma, c_r)$ and $\frac{c(\delta-\alpha\gamma)}{\alpha} < c_r \le \frac{1}{2}[\delta(1+\frac{c}{\alpha}) - \gamma(1+c)]$	Only new products. ($q_r^* = 0$ due to $h^* > 0$)
$c \le \tilde{c}(\delta, \gamma, c_r)$ and $c_r > \frac{1}{2}[\delta(1+\frac{c}{\alpha}) - \gamma(1+c)]$	Only new products. ($q_r^* = 0$ even if $h^* = 0$)

We now examine the impact of c, c_r, and α on h^* for the more interesting case where both new and refurbished products exist in the second period (Case V). The expression for h^* is given by $h^* = \frac{1}{2}\frac{(-8\gamma^2-8\gamma c_r-8\delta c_r+8\gamma^3-8\delta\gamma^2+8\delta^2+8\gamma^2 c_r)\alpha^2+(4\delta^2 c_r-3\delta^3+3\delta^2\gamma+\delta^2\gamma c)\alpha-\delta^3 c}{\alpha(8\alpha\delta-3\delta^2+8\alpha(1-\gamma))}$. First note that $\dfrac{\partial h^*}{\partial c} = -\frac{1}{2}\frac{\delta^2(\delta-\alpha\gamma)}{\alpha(8\alpha\delta-3\delta^2+8\alpha(1-\gamma))} < 0$ and also that $\dfrac{\partial h^*}{\partial c_r} = -2\frac{(2\alpha\gamma+2\alpha\delta-2\alpha\gamma^2-\delta^2)}{(8\alpha\delta-3\delta^2+8\alpha(1-\gamma))} < 0$. We will now show that $\dfrac{\partial h^*}{\partial \alpha} > 0$. $\dfrac{\partial h^*}{\partial \alpha} = \frac{1}{2}\frac{\Pi(\alpha)}{\alpha^2(8\alpha\delta-3\delta^2+8\alpha(1-\gamma))^2}$ where $\Pi(\alpha) = (-8\gamma\delta c - 8c\gamma^2 + 8\gamma^2 c_r - 8c_r\gamma + 8c\gamma^3 - 8\delta c_r)\alpha^2 + (16\delta^2 c - 16\delta^2\gamma^2 c + 16\gamma\delta c)\alpha^2 - 3\delta^2 c$ but $\dfrac{\partial \Pi(\alpha)}{\partial c_r} = 8(\gamma^2 - \gamma - \delta)\alpha^2 < 0$ and $\Pi(\alpha, c_r = \frac{c(\delta-\alpha\gamma)}{\alpha}) = \delta c(8\alpha\delta - 3\delta^2 + 8\alpha(1-\gamma)) > 0$, thus $\Pi(\alpha) > 0$ and $\dfrac{\partial h^*}{\partial \alpha} > 0$.

Two-period useful lifetime model.

We assume that a consumer who bought a new product in the first period will either return the product to get a new one or hold onto it. In other words, a consumer will not return a used product to get a refurbished one. This assumption is valid in situations where the willingness-to-pay for a refurbished product is not significantly higher from the utility offered by a used product, and therefore consumers are not willing to engage into the reselling process and pay the additional relicensing fee associated with it. To maintain tractability, we focus on the special case of $\alpha = 1$ (i.e., no technological improvement) and $\gamma = 0$ (no transactional disutility).

Under the above assumptions, the consumer state space is divided into the following segments illustrated in Fig. 19. Consumers who buy a new product in the first period, resell it, and again buy a new one in the second period, with total utility $U_{NSN}(\theta) = \theta - p_1 + s + \theta - p_2$. Consumers who buy a new product in the first period and continue using it in the second period, with total utility $U_{NK}(\theta) = \theta - p_1 + \delta_o\theta$. Consumers who do not buy in the first period, but buy a new product in the second period, with total utility $U_{ON}(\theta) = \theta - p_2$. And finally, consumers who do not buy in the first period, but buy a refurbished product in the second one, with total utility $U_{OR}(\theta) = \delta\theta - p_r - h$. We focus our analysis on those sets of parameters for which all four segments exist in equilibrium. Although this analysis does not address the optimal strategy for the entire range of parameter values, it does capture the effect of product durability on the OEM's relicensing policy and it identifies the region where a secondary market exists.

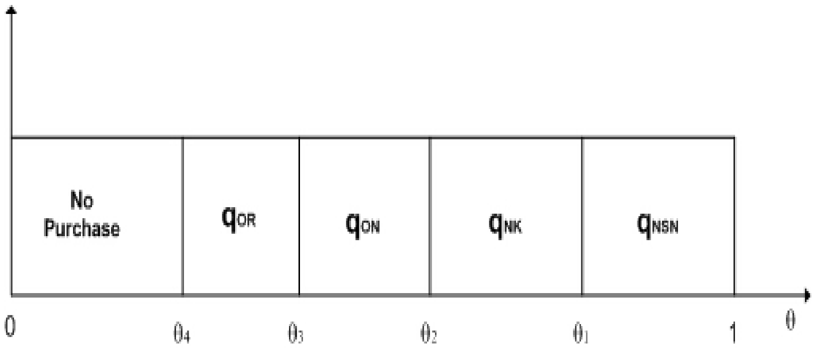


Figure 19: Consumer state space over the two-period horizon.

Solving for the indifferent consumers we get $\theta_1 = \frac{p_2 - s}{1-\delta_o}$, $\theta_2 = \frac{p_1 - p_2}{\delta_o}$, $\theta_3 = \frac{p_2 - p_r - h}{1-\delta}$, $\theta_4 = \frac{p_r + h}{\delta}$, and the corresponding demand for each segment, $q_{nsn} = 1 - \theta_1$, $q_{nk} = \theta_1 - \theta_2$, $q_{on} = \theta_2 - \theta_3$, $q_r = \theta_3 - \theta_4$. Moreover, $q_1 = q_{nsn} + q_{nk}$ and $q_2 = q_{nsn} + q_{on}$, while the number of units returned to the entrant will be $q_u = 1 - \theta_1$. To find the prices that correspond to the market sizes q_2 and q_r we solve the following system:

$$q_2 = q_{nsn} + q_{on} = 1 - \theta_1 + \theta_2 - \theta_3$$
$$q_r = \theta_3 - \theta_4,$$

from which we get

$$p_2 = \frac{(1 - q_r\delta - q_2)\delta_o{}^2 + (q_r\,\delta - s - 1 + q_2 + p_1)\delta_o - p_1}{-1 - \delta_o + \delta_o^2}$$
$$p_r = -\frac{(-\delta + q_2\delta + q_r\delta + h)\delta_o^2 + [\delta(1 + s - p_1 - q_2 - q_r) - h]\delta_o + \delta(\delta q_r - q_r + p_1) - h}{-1 - \delta + \delta^2}.$$

As in the baseline model, in the second-period the OEM sets the quantity q_2, while the entrant sets the quantity q_r and the resale price s offered to first-period consumers. The OEM's second-period objective given the entrant's choice of q_r is

$$Max_{q_2}\ \Pi_2(q_2|q_r)\ = (p_2 - c)q_2 + hq_r \quad \text{s.t.} \quad q_2 \geq 0$$

while the entrant's objective function is given by

$$\begin{aligned} Max_{q_r,s}\ \Pi_e(q_r, s|q_2) =& (p_r - c_r)q_r - sq_u \\ &\text{s.t. } q_r \leq q_u \\ &q_r \geq 0, s \geq 0. \end{aligned}$$

Let $q_2^*(q_1, h), q_r^*(q_1, h)$, and $s^*(q_1, h)$ denote the equilibrium of the above game. Then, the first-period OEM's problem is:

$$Max_{q_1,h}\ \Pi_1(q_1, h) + \Pi_2(q_2^*(q_1, h)) \quad \text{s.t. } q_1 \geq 0,\ h \geq 0.$$

Lemma 9 *At optimality, the entrant has no incentive to collect more units than the ones he intends to sell in the market. That is, the constraint* $q_r \leq q_u$ *is binding and the optimal resale price offered by the entrant satisfies* $s^*(q_r) = (2 - \delta - \delta_o)q_r + \delta - q_1 - q_2$. *Moreover, the equilibrium resale value is decreasing in* q_1 *and* h.

Proof of Lemma 9 We will show that for a given q_2, the entrant will always set q_r and s such that $q_r^* = q_u(s^*)$. Assume that there exist q_r^* and s^* such that $q_r^* < q_u(s^*)$. The FOC with respect to q_r and s give $\frac{\partial \Pi_e}{\partial q_r} = 0$ and $\frac{\partial \Pi_e}{\partial s} = 0$, or equivalently, $s^* = \frac{1}{2}(\delta_o - q_1 - q_2)$ and $q_r^* = \frac{1}{2}\frac{(q_1+q_2-2)(\delta_o-1)\delta+(h+c_r)(\delta_o-2)}{\delta(\delta-2+\delta_o)}$. After substituting s^*, we get $q_u(s^*) = \frac{1}{2}\frac{(q_1+q_2-1)\delta+(h+c_r)+\delta_o-q_1-q_2}{\delta-2+\delta_o}$ and the inequality $q_r^* < q_u(s^*)$ can be rewritten as $\frac{1}{2}\frac{(q_1+q_2-1)\delta+(h+c_r)}{\delta} > 0$. However, if $q_u(s^*) > 0$, then $(q_1 + q_2 - 1)\delta + (h + c_r) + \delta_o - q_1 - q_2 < 0$, and since $\frac{1}{2}\frac{(q_1+q_2-1)\delta+(h+c_r)}{\delta} > 0$, we need $\delta_o - q_1 - q_2 < 0$. Recall that $s^* = \frac{1}{2}(\delta_o - q_1 - q_2)$, and therefore, that would lead to $s^* < 0$ which cannot be true. Therefore, we cannot have non-binding solutions, and therefore, $q_r^* = q_u(s^*)$.

Proof of Proposition 2.

The entrant's first-period problem is

$$Max_{q_1,h}\ \Pi_1(q_1,h) + \Pi_2^*(q_1,h)$$
$$\text{s.t. } q_1 \geq 0$$
$$h \geq 0.$$

Define the Lagrangian $L(q_1, h, \lambda_1, \lambda_2)$ $=\Pi(q_1, h)+\mu_1 h$. The Kuhn-Tucker conditions for optimality are:

$$\frac{\partial L}{\partial q_1} = 0 \tag{19}$$
$$\frac{\partial L}{\partial h} = 0 \tag{20}$$
$$\mu_1 h = 0 \tag{21}$$

with $\mu_1 \geq 0$.

Case I : $\mu_1 = 0$. Solving the KT conditions, we obtain
$h^* = \frac{1}{2}\frac{(-8\delta_o^3+(-4\delta^2-8c_r+12+6\delta)\delta_o^2+(-3\delta^2c-4\delta^2c_r+\delta^3c+3\delta c+3\delta^2-c-10\delta+10c_r+2\delta^3+1)\delta_o-\delta^2c_r+\delta^3+3c_r-3\delta}{8\delta_o^2+(2\delta+3\delta^2-11)\delta_o+\delta^2-3}$
and $q_{or}^* = -\frac{1}{2}\frac{-4\delta_o^2+(4+4\delta c-4c-4c_r-\delta)\delta_o+1-c-c_r+\delta c}{8\delta_o^2+(2\delta+3\delta^2-11)\delta_o+\delta^2-3}$. Case I is valid for $q_{nsn}^* = q_{or}^* \geq 0$, $q_{nk}^* \geq 0$, $q_{on}^* \geq 0$ and $h^* \geq 0$. The above conditions are satisfied in the area $\underline{c_r^I} \leq c_r \leq \widetilde{c_r'}$ where $\underline{c_r^I} = \frac{(2-8c-2\delta)\delta_o^2+(-\delta^2c-2\delta c+2\delta^2+9c-3+3\delta)\delta_o+2(1+c)\delta-\delta^2(c-1)-2}{1+(2\delta+2)\delta_o}$ and $\widetilde{c_r'} = \frac{(-8\delta_o^3+(6\delta+12-4\delta^2)\delta_o^2+(\delta^3c+3\delta c+3\delta^2-10\delta+2\delta^3-3\delta^2c+1-c)\delta_o+\delta^3-3\delta)}{(4\delta_o+1)(2\delta_o+\delta^2-3)}$. This case represents the setting of having all market segments positive as well as a positive relicensing fee.

To see that h^* is decreasing in c_r and increasing in c, note that $\frac{\partial h^*}{\partial c_r} = -\frac{1}{2}\frac{(4\delta_o+1)(2\delta_o+\delta^2-3)}{8\delta_o^2+(2\delta+3\delta^2-11)\delta_o+\delta^2-3} < 0$ and $\frac{\partial h^*}{\partial c} = \frac{1}{2}\frac{\delta_o(\delta-1)^3}{8\delta_o^2+(2\delta+3\delta^2-11)\delta_o+\delta^2-3} > 0$ since $8\delta_o^2 + (2\delta + 3\delta^2 - 11)\delta_o + \delta^2 - 3 < 0$.

Note that the lower bound $\underline{c_r^I}$ corresponds to the c_r value such that $q_{on}^*(c_r) = 0$. For lower values of c_r, there will exist an even larger secondary market. To see that this secondary market exists, note that when $q_{on} = 0$, $q_2 = q_{nsn} = q_{or}$ and therefore, assuming that $q_{or} = 0$ would mean that neither new nor refurbished products are sold in the second period. Since q_{on} and q_{or} cannot be simultaneously zero, $q_{or}^* > 0$ for $c_r < \underline{c_r^I}$.

Case II : $\mu_1 \neq 0$. Case II is valid for $q^*_{nsn} = q^*_{or} \geq 0$, $q^*_{nk} \geq 0$, $q^*_{on} \geq 0$ and $h^* = 0$. The above conditions are satisfied in the area $\widetilde{c'_r} \leq c_r \leq \widetilde{c_r}$, where $\widetilde{c'_r}$ is defined in Case I and $\widetilde{c_r} = \frac{(-16\delta_o^3+(8\delta c+36-4\delta(1+\delta)-8c)\delta_o^2+(-\delta+12c+4\delta^2+2\delta^2c+\delta^3-16\delta c-12+2\delta^3c)\delta_o+\delta^3-\delta+4(c-1)-6\delta c+2\delta^2c}{(4\delta_o+1)(4\delta_o-7+\delta^2+2\delta)}$. This case represents the setting of having all market segments positive but a relicensing fee equal to zero.

To summarize, when $0 \leq c_r < \widetilde{c'_r}$ $q^*_r > 0$ and $h^* > 0$, while for $\widetilde{c'_r} \leq c_r < \widetilde{c_r}$, $q^*_r > 0$ and $h^* = 0$.

Proof of Corollary 1.

To show that $\frac{\partial h^*}{\partial \delta_o} < 0$, note that $\frac{\partial h^*}{\partial \delta_o}$ can be written as $\frac{\partial h^*}{\partial \delta_o} = -\frac{1}{2}\frac{\Phi_1(\delta,\delta_o,c_r,c)}{[\Phi_2(\delta,\delta_o)]^2}$ where Φ_1 and Φ_2 are defined as follows: $\Phi_1 \doteq 3+72\delta_o+3\delta+68\delta_o^2-4\delta^3+2\delta^2-176\delta_o^3+64\delta_o^4+\delta^5-\delta^4-3c_r-3c+8\delta^3c\delta_o^2-8c_r\delta_o^2\delta^2+16c_r\delta_o^2\delta-12\delta_o\delta-c\delta^5-48\delta_o\delta^2-8c\delta_o^2-8c_r\delta_o^2+32\delta_o^3\delta+c_r\delta^4-38\delta_o^2\delta+6c_r\delta+6\delta_o^2\delta^3+9c\delta-8c\delta^2+12\delta_o^2\delta^4-44\delta_o^2\delta^2-2\delta^2c_r+4\delta^3\delta_o+3c\delta^4-2\delta^3c_r-24c\delta^2\delta_o^2+24\delta_o^2c\delta+8\delta_o\delta^4+48\delta_o^3\delta^2$ and $\Phi_2 \doteq 8\delta_o^2+2\delta_o\delta+3\delta_o\delta^2-11\delta_o-3+\delta^2$. Therefore, it is sufficient to show that $\Phi_1(\delta,\delta_o,c_r,c) > 0$. But $\frac{\partial \Phi_1}{\partial c_r} = -(\delta-1)^2(8\delta_o^2+3-\delta^2) < 0$ and $\frac{\partial \Phi_1}{\partial c} = (\delta-1)^3(8\delta_o^2+3-\delta^2) < 0$ and thus, it is sufficient to show that $\Phi_1(\delta,\delta_o,c_r = 1, c = 1) > 0$. The latter is a function of only δ and δ_o, and by plotting the function for all possible values $0 < \delta_o < \delta < 1$, it can be readily seen that it is always positive. Thus, $\frac{\partial h^*}{\partial \delta_o} < 0$.

Similarly, to show that $\frac{\partial h^*}{\partial \delta} > 0$, we can rewrite $\frac{\partial h^*}{\partial \delta}$ as $\frac{\partial h^*}{\partial \delta} = \frac{1}{2}\frac{\Phi_3(\delta,\delta_o,c_r,c)}{[\Phi_2(\delta,\delta_o)]^2}$ where $\Phi_3 \doteq 9+\delta_o\delta^4c+24\delta_o^3\delta^2c-16\delta_o^3c_r\delta+20c\delta_o\delta+8c_r\delta_o\delta-48c\delta_o^3\delta+63\delta_o+66\delta_o^2-6\delta^2-170\delta_o^3+64\delta_o^4+\delta^4+4\delta^3c\delta_o^2-8c_r\delta_o^2\delta^2+28c_r\delta_o^2\delta-2\delta^2c_r\delta_o-20\delta_o\delta-32\delta_o\delta^2-31c\delta_o^2-20c_r\delta_o^2+80\delta_o^3\delta-72\delta_o^2\delta+8\delta_o^2\delta^3+6\delta_o^2\delta^4-12\delta_o^2\delta^2+4\delta^3\delta_o-48c\delta^2\delta_o^2+72c\delta_o^2\delta+5\delta_o\delta^4+22\delta_o^3\delta^2-12\delta_o\delta^2c+3\delta_o^2\delta^4c+24c\delta_o^3-16\delta_o^4\delta-6c_r\delta_o-9c\delta_o+16c_r\delta_o^3$ and Φ_2 is defined above. Therefore, it is sufficient to show that $\Phi_3(\delta,\delta_o,c_r,c) > 0$. But $\frac{\partial \Phi_3}{\partial c_r} = -2\delta_o(\delta-1)(1+4\delta_o)(\delta-3+2\delta_o) < 0$ and $\frac{\partial \Phi_3}{\partial c} = \delta_o(\delta-1)^2(3\delta_o\delta^2+\delta^2+10\delta_o\delta+2\delta-9-31\delta_o+24\delta_o^2) < 0$ (for all $0 < \delta_o < \delta < 1$), and thus, it is sufficient to show that $\Phi_1(\delta,\delta_o,c_r = 1, c = 1) > 0$. The latter is a function of only δ and δ_o, and by plotting the function for all possible values $0 < \delta_o < \delta < 1$, it can be readily seen that it is always positive. Thus, $\frac{\partial h^*}{\partial \delta} < 0$.

Competition in both the primary and secondary markets with brand differentiation.

Second-Period Analysis

The net utility consumer θ derives from purchasing firm A's new product is $U_2^A(\theta) = \theta - p_2^A$, firm B's new product $U_2^B(\theta) = (1-\beta)\theta - p_2^B$, firm A's refurbished product $U_{2,r}^A(\theta) = \delta\theta - p_{2,r}^A - h^A$, and firm B's refurbished product $U_{2,r}^B(\theta) = (1-\beta)\delta\theta - p_{2,r}^B - h^B$. Solving for the marginal consumers, we get

$$\theta_1 = \frac{p_2^A - p_2^B}{\beta}, \theta_2 = \frac{p_2^B - p_{2,r}^A - h^A}{1-\beta-\delta}, \theta_3 = \frac{p_{2,r}^A - p_{2,r}^B + h^A - h^B}{\beta\delta}, \theta_4 = \frac{p_{2,r}^B + h^B}{(1-\beta)\delta}$$

with respective demand for each product of $q_2^A = 1 - \theta_1$, $q_2^B = \theta_1 - \theta_2$, $q_{2,r}^A = \theta_2 - \theta_3$, and $q_{2,r}^A = \theta_3 - \theta_4$. Figure 20 illustrates the four market segments.

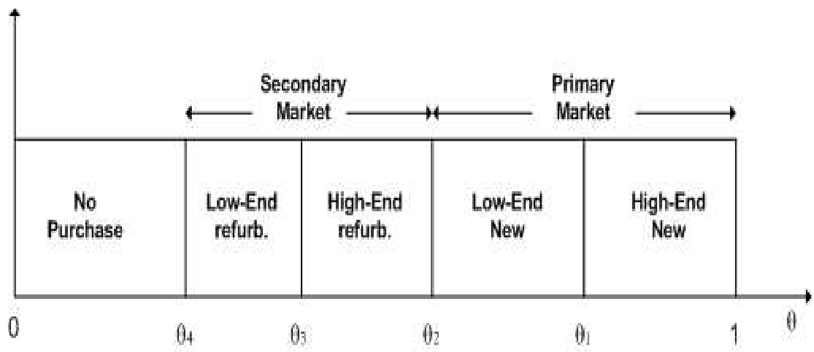


Figure 20: Consumer State Space in the Second Period

Under perfect competition in the secondary markets and no refurbishing cost, the refurbished products are available at a price equal to the resale value of used products ($p_{2,r}^A = s^A$ and $p_{2,r}^B = s^B$) with corresponding inverse demand functions

$$p_2^A = (\delta - 1 + \beta)q_2^B + h^A - (1-\delta)q_2^A + 1 - \delta + s^A$$
$$p_2^B = (\delta - 1 + \beta)q_2^A + h^A - (1-\beta-\delta)q_2^B + 1 - \beta - \delta + s^A.$$

Finally, the second-stage optimization problems for firms A and B are

$$Max_{q_2^A}\Pi_2^A(q_2^A|q_2^B) = (p_2^A - c)q_2^A + h^A q_{2,r}^A$$
$$Max_{q_2^B}\Pi_2^B(q_2^B|q_2^A) = (p_2^B - c)q_2^B + h^B q_{2,r}^B.$$

By solving the first-order conditions simultaneously, we derive the N.E. of this game, $q_2^{A*}(h^A, h^B, s^A, s^B)$ and $q_2^{B*}(h^A, h^B, s^A, s^B)$, and subsequently the quantities $q_{2,r}^{A*}(h^A, h^B, s^A, s^B)$ and $q_{2,r}^{B*}(h^A, h^B, s^A, s^B)$, from the demand equations corresponding to the market segmentation presented in Figure 20.

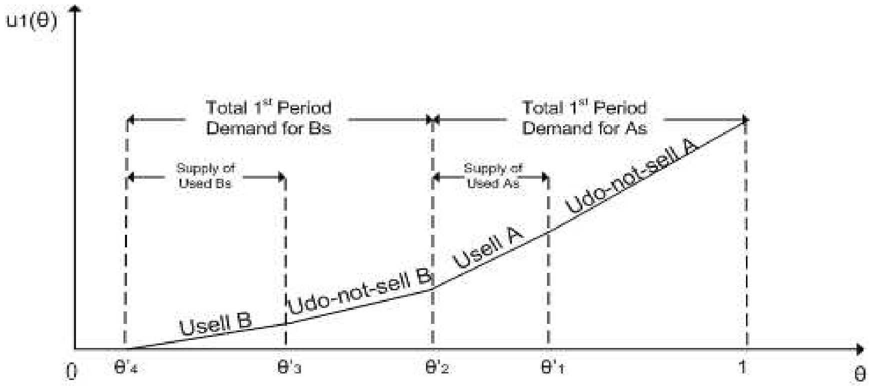


Figure 21: Consumer State Space in the First Period

First-period analysis

Similar to our analysis for the monopolistic OEM, if s^j denotes the resale value of firm j's new product ($j = A, B$) at the end of period 1, then consumers of firms A and B will derive the corresponding utilities in period 1:

$$U_1^A(\theta) = \theta - p_1^A + (s^A - \gamma\theta)I_{(s^A \geq \gamma\theta)}$$
$$U_1^B(\theta) = (1-\beta)\theta - p_1^B + (s^B - (1-\beta)\gamma\theta)I_{(s^B \geq (1-\beta)\gamma\theta)}.$$

Figure 21 illustrates the total demand in the first period as well as the segment of consumers who decide to sell their used products.The marginal consumers are $\theta_1' = \frac{s^A}{\gamma}$, $\theta'_2 = \frac{p_1^A - p_1^B - s^A}{\beta - \gamma}$, $\theta_3' = \frac{s^B}{(1-\beta)\gamma}$ and $\theta'_4 = \frac{p_1^B - s^B}{(1-\beta)(1-\gamma)}$, with respective demand for new products of $q_1^A = 1 - \theta_2'$, and $q_1^B = \theta_2' - \theta'_4$, and respective supply of used products of $q_{1,r}^A = \theta_1' - \theta'_2$ and $q_{1,r}^B = \theta_3' - \theta'_4$. By setting these quantities equal to the equilibrium secondary market sizes of the second period $q_{2,r}^{A*}(h^A, h^B, s^A, s^B)$ and $q_{2,r}^{B*}(h^A, h^B, s^A, s^B)$, we can express the resale values in terms of the prices of new products and the relicensing fees: $s^A(h^A, h^B, p_1^A, p_1^B)$ and $s^B(h^A, h^B, p_1^A, p_1^B)$. The first-period profits are given by $\Pi_1^A(q_1^A|q_1^B) = (p_1^A - c)q_1^A$ and $\Pi_1^B(q_1^B|q_1^A) = (p_1^B - c)q_1^B$, while the total optimal profits over the two-period horizon are:

$$
\begin{aligned}
Max_{q_1^A, h^A} \Pi_A(q_1^A, h^A|q_1^B, h^B) &= (p_{1A} - c)q_1^A + \Pi_{2A}^*(q_1^A, h^A|q_1^B, h^B) \\
Max_{q_1^B, h^B} \Pi_B(q_1^B, h^B|q_1^A, h^A) &= (p_{1B} - c)q_1^B + \Pi_{2B}^*(q_1^B, h^B|q_1^A, h^A)
\end{aligned}
$$

We verify that the conditions for a unique unconstrained Nash Equilibrium are met (convex strategy set, Hessian negative definite) and solve the first-order conditions simultaneously for all the decision variables to derive the values $q_1^{A*}, h^{A*}, q_1^{B*}, h^{B*}$. The equilibrium is valid only for parameters yielding positive quantities, thus, the analysis in the paper is reflective of this set. For example, Figure 15 in the paper is plotted for $\beta \in [0.1, 0.4]$. The upper threshold $\overline{\beta}$ is the highest value of $\beta \in (0, 1 - \delta)$ for which the low-end OEM produces new products in the second period. That is, for values of β above that point, the low-end OEM is priced out of the primary market in the second period (this constraint is always the first to be violated). On the other hand, the lower threshold $\underline{\beta} = \gamma$ denotes the lowest value of β for which the ordering of the consumer state space in Figure 21 is valid (low-end OEM's new product above high-end OEM's refurbished product).

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