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An Empirical Analysis of Environmental Uncertainty, Realoptions Decision Patterns and Firm Performance

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AN EMPIRICAL ANALYSIS OF ENVIRONMENTAL UNCERTAINTY, REAL OPTIONS DECISION PATTERNS AND FIRM PERFORMANCE

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by

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ABSTRACT

AN EMPIRICAL ANALYSIS OF ENVIRONMENTAL UNCERTAINTY, REAL OPTIONS DECISION PATTERNS AND FIRM PERFORMANCE

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Real options theory has become an influential explanatory and normative framework for making resource allocation decisions. Despite a growing body of strategy research regarding real options, however, there is as of yet little empirical confirmation (1) that firm resource allocation behavior conforms with real options theory, or (2) that employing real options principles has a positive impact on firm performance.

This research examines these questions. Using a survey instrument designed to measure a range of real options-theoretic decision patterns, data has been collected from a sample of 173 U.S. manufacturing firms. This data set has been used to test two central premises.

The first is that, in contrast to much of the real options literature, there is no inherently superior real options decision pattern. Instead, real options-optimal investment decisions depend on the magnitude and source of the uncertainties that firms encounter in their task environments. This premise is tested by measuring two important sources of uncertainty in the external environment: uncertainty regarding the level and composition

of demand (market uncertainty) and uncertainty regarding the intentions and actions of competitors (competitive uncertainty). I develop the theoretical foundation for expecting that patterns of real options behavior vary with these two sources of uncertainty, and that different sources of uncertainty frequently promote competing real options-theoretic decision behavior. The research tests these hypothesized relationships empirically. The principal contribution of this analysis has been to develop a more fine-grained appreciation of the relationship between real options theory and a multidimensional conceptualization of uncertainty.

The second premise of the research is that making investment decisions based on real options principles has a positive effect on firm performance. There is ample theoretical foundation for the superiority of real options theory as a framework for making resource commitment decisions. The research examines this expectation empirically by testing whether the fit or congruence between real options decision patterns and environmental uncertainty is positively related to firm profitability, market value and growth.

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CHAPTER 1

INTRODUCTION

Real options theory is a relatively new explanatory and prescriptive conceptual framework for firm-level resource allocation decision-making. Though initially developed as an asset pricing and project evaluation methodology, principally in the realm of finance, real options theory has, in the last two decades, become influential in the study of strategy. It has been applied to explain a range of strategic behavior, including joint ventures (Chi, 2000; Chi & McGuire, 1996; Kogut, 1991), research and development (Faulkner, 1996; McGrath, 1997; Miller & Arikan, 2004; Mitchell & Hamilton, 1988), the multinational corporation (Kogut, 1985; Kogut and Kulatilaka, 1994a), investment in capabilities and competencies (Kogut & Kulatilaka, 2001), entrepreneurship (McGrath, 1999), venture capital (Hackett & Dilts, 2004; Hurry, Miller & Bowman, 1992), innovation (Reiss, 1998; Wu, 2005), market entry and exit (Dixit, 1989; Folta & O'Brien, 2004; Miller & Folta, 2002; O'Brien, Folta & Johnson, 2003), acquisitions (Smith & Triantis, 1994), and restructuring (Hurry, 1993). Real options theory has been used to shed light on long-standing issues in the field – including governance (Leiblein, 2003; Santoro & McGill, 2005), vertical integration (Leiblein & Miller, 2003; Sutcliffe & Zaheer, 1998), and diversification (Kogut & Kulatilaka, 2001) – and has been examined in relation to other important theoretical traditions such as the resource-based and knowledge-based views (Bowman & Hurry, 1993; Coff & Laverty, 2001; Kogut & Kulatilaka, 1994b and 2001; Miller, 2002; Vassolo, Anand & Folta, 2004), transaction cost economics (Leiblein, 2003; Sanchez, 2003) and game theory (Grenadier, 2002; Smit & Ankum, 1993).

Not least, real options theory has provided an alternate explanatory framework for the real asset investment behavior of firms. Pindyck (1991) observed that neoclassical investment theory has failed to provide a good empirical model of capital investment behavior. Companies demonstrably do not allocate resources in accordance with its precepts (Bower, 1972). In establishing a conceptual foundation for investment behavior that deviates from strict adherence to the expected net present value (ENPV) decision rubrics of neoclassical finance, real options theory better explains how managers actually think and act (Teach, 2003). It also ameliorates a long standing divide between strategy and finance by providing a formal economic foundation for long-term strategic resource allocation decisions that have often proved difficult to justify using conventional financial decision standards (Allessandri et al., 2004; Chen, Kensington & Conover, 1998; Kester, 1984; Lander & Pinches, 1998; McGrath & Nerkar, 2004; Miller & Waller, 2003; Nichols, 1994; Triantis & Borison, 2001).

Finally, real options theory has been advanced as an overarching, integrating lens for strategy as a whole. Bowman & Hurry (1993) view real options as the choice mechanism that underlies the temporal unfolding of strategy, and conceptualize organizations as generators and repositories of real options for strategic choice. McGrath, Ferrier & Mendelow (2004) see real options as "poised to occupy a central conceptual position in the development of theory that offers guidance for strategic decision-making under uncertainty" (86).

In summary, considerable progress has been made in establishing real options as a prominent strategic construct. Despite these advances, however, several important dimensions of real options as strategic theory warrant additional work. A review of the growing real options literature suggests three deficiencies in particular that merit further attention and that have motivated the present research.

First, the base of empirical study supporting the role of real options in strategic management remains relatively small. Theoretical and modeling research greatly outweighs empirical studies. Such empirical research as has been conducted does not provide definitive support for real options theory. Many of the specific strategic phenomena that have been examined from a real options perspective can also be explained by other theoretical frames. Joint ventures, for example, have been examined from the perspective of the knowledge-based view, which interprets them as mechanisms for acquiring knowledge (Hamel, 1991) and from a transaction cost perspective, which explains joint ventures as a hybrid form of economic organization combining selective advantages of market and hierarchy (Hennart, 1988; Mowrey, Oxley & Silverman, 1996). Similarly, management behavior that departs from neoclassical investment standards has been explained as a reflection of the agency problems of public corporations (Jensen & Meckling, 1976).

In addition, real options-theoretic studies of specific strategic phenomena do not demonstrate that real options principles inform decision-making more broadly within firms. Folta & Miller (2002) and Trigeorgis (1993), among others, emphasize the importance of empirical studies that examine the extent to which managerial behavior actually conforms to real options principles. Yet I know of no published studies that examine the extent of real options decision-making at the firm level.[1]

[1] There has been some empirical study of investment decisions and real options principles at the industry or sector level. Harchaoui & Lasserre (1996), for example, examined capacity additions in the Canadian copper mining sector in relation to "trigger" copper prices calculated under a real options model, and found a significant relationship between them. Similarly, Moel & Tufano (2002) examined the pattern of North

A second notable characteristic of the real options literature is that the relationship between uncertainty and real options decision-making has been only modestly examined. Nuanced managerial response to uncertainty is at the heart of the real options perspective. Real options theory maintains that resource allocation decisions are shaped in response to the uncertainty surrounding those decisions, rather than solely in response to the expected cash flow value of decisions as measured by traditional financial decision rubrics. The theory suggests that firms will act rationally to maximize the total value of resource commitments, taking into account both the expected cash flow value and the option value of those commitments. Option value is a complex function with respect to uncertainty, such that it is not possible to specify optimal action without an explicit recognition of the magnitude, source and type of uncertainty. Despite the importance of the uncertainty construct in real options theory, there has been very limited research, either empirical or theoretical, into the relationship between either the magnitude or source of uncertainty and real options resource allocation behavior. Most of the real options literature treats uncertainty as omnipresent and unitary.

Finally, there has been virtually no empirical study of real options in relation to performance. As described in detail in Chapter 3, real options-based decision-making has been widely advanced as superior to the conventional financial decision-making standards used by most firms. Implicit in this view is that firms employing real options principles (either formally, using real options-based evaluation tools, or informally, as a judgmental heuristic), will achieve superior sustained performance relative to firms that do not employ those principles. The absence of empirical confirmation that real options

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American gold mine openings and closings over a 20-year period and found them to be consistent with real options principles. These studies, however, are economic rather than strategic in their orientation and do not focus on the behavior of individual firms.

decision-making has a positive impact on performance is an important research opportunity (Triantis & Borison, 2001).

The present research makes an empirical contribution to the growing literature regarding real options and strategy along each of these three dimensions. First, it measures and analyzes real options behavior at the level of the firm for a large multi-industry sample, encompassing multiple real options decision patterns. Second, in place of a uni-dimensional conceptualization of uncertainty, it explores theoretically the relationships between different kinds of uncertainty and different patterns of real options decision-making, and tests those relationships empirically. In this regard, the study represents an initial effort to derive a more fine-grained specification of real options theory in relation to uncertainty, in the hope that further efforts along these lines will receive future research attention. Finally, the research breaks new ground in exploring whether application of real options decision-making is reflected in differential performance at the level of the firm.

The remainder of this thesis consists of five chapters. Chapter 2 reviews the conceptual foundations of real options theory as a strategic decision framework and identifies the principal resource allocation decision patterns consistent with the theory. It also lays the conceptual foundation regarding uncertainty as it relates to real options decision-making. Chapter 3 develops the theoretical basis for the research and presents a suite of hypotheses derived from that theoretical analysis. Chapter 4 describes the data sources and methodology employed in the study, both as regards the survey instrument and its administration, and the analytical techniques used in hypothesis testing. Chapter 5 describes the results of the analysis and provides an interpretive discussion of those results. Chapter 6 explores the implications of the research for both academics and practitioners, describes the limitations of the study and concludes by suggesting priorities for future research.

CHAPTER 2

LITERATURE REVIEW

This chapter establishes the conceptual foundations regarding real options and uncertainty on which the research rests. This is accomplished under three broad headings. First is a summary of the real options theoretical framework, identifying its principal features and its differences from conventional decision-making standards. The second section describes specific decision patterns that have been discussed in the real options literature, and that formed the basis for measuring real options behavior, as discussed in Chapter 4. The third section briefly summarizes the relevant literature on uncertainty, establishing the conceptual framework for incorporating environmental uncertainty into the research.

2.1 Summary of Real Options Theory

Real options theory rests on the insight that real (that is, non-financial) assets are in many ways analogous to financial options (Myers, 1977). Like puts and calls in the financial markets – which, at a cost, confer the right but not the obligation to sell or buy respectively an underlying security in the future – investments in real assets similarly represent the acquisition of non-obligatory rights to future choices and opportunities (Dixit & Pindyck, 1995; Kester, 1984). All assets and resource commitments contain such choice possibilities. A manufacturing facility, for example, is a nexus of options, including the right to produce, to expand the plant, to shut it down temporarily if at any point market conditions make it desirable to do so, to alter its inputs and outputs, or to abandon it entirely (Kulatilaka, 1995; McDonald & Siegel, 1985). A wide variety of assets have been interpreted within the real options perspective, including inventory, organizational slack (Bowman & Hurry, 1993), unused debt capacity (Trigeorgis, 1993), and cash reserves (Cossin & Hricko, 2004).

Were firms endowed with perfect foreknowledge of future events affecting their activities, such possibilities to make future choices would be of no value, since firms could value and make optimal decisions for the future a priori. Similarly, if all investments were perfectly and costlessly reversible, real options would have no value, since firms could easily undo any investment that proved unwise. Capital investment decisions are, however, inherently uncertain and hard to undo (Carruth, Dickerson & Henley, 2000; Pindyck, 1991).[2] In the presence of uncertainty and irreversibility, future choice possibilities – real options – have economic value, since they permit firms to act on or "exercise" choice possibilities under favorable future conditions ("in the money" options) but to delay or forego action under unfavorable conditions ("out of the money" options) (Dixit & Pindyck, 1995).

Underlying real options theory, therefore, are two central concepts. The first is *asymmetrical response to uncertainty*. The distinctive characteristic of the options approach lies in making limited cost, incremental investments that confer or preserve the ability to make more substantial commitments only if outcomes are favorable (Kogut, 1991; Kogut & Kulatilaka, 2001; McGrath et al., 2004; Trigeorgis & Mason, 1987). This asymmetry can be achieved only to the extent that firms can avoid or delay making large irreversible commitments (McGrath, 1999). The second core concept is the *value of management flexibility*. Real options theory incorporates into resource decisions ex ante

[2] Some non-company-specific investments may be partially reversible by liquidation or sale. Even in such cases, however, reversibility is typically limited. Salvage values rarely recover full investment. Further, market values are likely to be well below original outlays for investments which have fallen short of expectations. In other words, investments are likely to be least reversible in those circumstances when firms are most interested to reverse them (Dixit & Pindyck, 1995; Pindyck, 1991).

the discretion that informed management has to adapt to future developments ex post (Trigeorgis, 1993). The theory anticipates that firms will act to maximize the value of assets as uncertain events unfold, and the latitude for such action has economic value. In the illustrative manufacturing facility, management will make the appropriate decisions to operate, expand, switch inputs and products, or abandon the facility, as warranted by market conditions. Real options theory reflects therefore a very activist managerial approach in which uncertainty is partially endogenized through agency.

Implicit in real options theory is a conceptualization of firm response to uncertainty that is different from that embodied in much strategic and organizational theory, in which uncertainty is viewed as an undesirable source of variance that firms attempt to reduce or eliminate (Thompson, 1967). Real options theory, by contrast, encourages firms to exploit rather than avoid uncertainty (Coy, 1999; Garud, Kumaraswamy & Nayyar, 1998; Kogut, 1991; Kogut & Kulatilaka, 1994b & 2001; McGrath, 1999; McGrath et al., 2004; Morris, Teisberg & Kolbe, 1991; Sanchez, 1991). As long as exposure to downside risk can be limited by the prudent use of options, uncertainty is a source of opportunity and can be beneficial to the firm.

2.2 Real Options Decision Patterns

The real options literature identifies a number of decision patterns that are consistent with the real options principles described above. I here summarize these patterns of action, in effect constructing from the literature a taxonomy of real options-theoretic decision behaviors. Table 2.1 identifies five core dimensions of the real options construct and the decision patterns associated with each. I describe below the foundation for each pattern from the perspective of real options theory.[3]

2.2.1 Timing

A central element of the real options construct is its implications for the optimal timing of resource commitments. Real options theory puts when to invest, as much as whether to invest, at the center of attention in capital budgeting (Dixit & Pindyck, 1995). Further, the theory provides economic justification for timing decisions that deviate from the standard financial metrics for project valuation specified by neoclassical financial theory and embodied in the discounted cash flow investment evaluation processes used by most companies in capital budgeting.[4] Under neoclassical investment theory, investments should be undertaken when they demonstrate an expected net present value (ENPV) equal to or greater than zero.[5] Real options theory, by contrast, dictates that optimal timing may deviate from the ENPV standard under conditions of uncertainty if there are substantial option values associated with the deviation decision.[6]

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[3] The boundaries of real options theory as a strategic construct are not clearly defined, as witnessed by the exchange of views in the *Academy of Management Review*, 29 (1): 2004. Adner & Levinthal (2004a and b) maintain that a clear abandonment test is an essential element of the construct, limiting the applicability of real options in strategy to investments aimed at specific, definable opportunities and characterized by clear abandonment criteria. Other authors argue instead for a broader conceptualization of real options as a guiding managerial heuristic that incorporates resource commitments for which neither specific target opportunities nor clear abandonment conditions can be specified ex ante (Kogut & Kulatilaka, 2004; McGrath et al., 2004a and b; Pandza et al., 2003; Zardkoohi, 2004). In the interests of comprehensiveness, this research will adopt the broader of these two framings, thus including real options decision patterns which would not meet more restrictive specifications of the construct's boundaries.

[4] A number of surveys and studies have shown that net present value and related standards are by the far the most widely used capital budgeting methods (Busby & Pitts, 1997; Graham & Harvey, 2001; Teach, 2003).

[5] Within this broad theoretical frame there are a number of alternate formulations. For example, various specific metrics are used, including net present value (NPV), internal rate of return (IRR) and net present value index (NPVI). Some formulations substitute the broader concept of "utility" for cash flow, thus allowing for varying risk preferences. There are also various bases for determining appropriate discount rates. From the perspective of this research, however, all these variations represent second order differences within the ENPV standard.

[6] Properly speaking, there is no fundamental conceptual incompatibility between discounted cash flow net present value and real options approaches to investment evaluation. If option values and project

Table 2.1

Real Options-Theoretic Decision Patterns

Construct Dimension	Associated Decision Patterns
Timing	Deviation from the neoclassical investment theory timing rubric (invest when ENPV $\geq$ 0): - Deferral - Early action/acceleration
Staging	Breaking real asset investment into components and making incremental decisions at each stage
Operating Flexibility	Making real asset investments specifically designed to create or preserve operational flexibility: - Incremental versus large-scale capacity additions - Flexible producing assets versus highly specific assets
Partial Commitment	Making initial investments, short of full commitment, which can later be expanded or discontinued/reversed based on subsequent developments: - Joint ventures - Minority equity positions - Small acquisitions - "Toehold" positions
Platform Investments	Making non-revenue generating investments to create preferential access to future opportunities that cannot be currently defined in detail - Technology positioning - Capabilities and competencies - Knowledge

interrelationships were incorporated in NPV calculations, the results would be consistent with real options principles (Kester, 1984; Luehrman, 1998b). ENPV, however, promotes investment decision-making based on expected values, and does not, as typically employed, either consider or value real options. As described in Section 3.3 of this proposal, the omission of real options considerations leads to systematic distortions in investment decisions.

By far the most studied of these timing deviations is deferral or delay. Deferral represents a deliberate decision to postpone undertaking an investment even when the ENPV standard would justify immediate pursuit, in the interest of waiting for total or partial uncertainty resolution (McDonald & Siegel, 1986).[7] It is a central tenet of real options theory that there can often be considerable option value in delaying resource commitments. All investment projects have a deferral value. Real option theory specifies that every resource commitment made forgoes an option to take the same action at a later time, when key uncertainties may be partially or fully resolved, thus reducing downside risk or clarifying the best basis on which to proceed (McDonald & Siegel, 1986). In effect, every project competes with itself over time (Ingersoll & Ross, 1992). Conceptually, real options theory recognizes that the option of waiting always has a value where uncertainty is present, and if that value is greater than the foregone benefits of acting now (for example, through the loss or postponement of dividends), then deferral is the economically maximizing course of action. McDonald & Siegel (1986) demonstrate that the present value loss from suboptimal timing can be substantial, easily on the order of 10-20% (See also Teisberg, 1994). Kester (1984) maintains that companies routinely commit before they need to.

Although deferral is the most widely discussed real options timing pattern, real options theory also supports timing decisions to accelerate investment. It may, for example, be optimal from a real options perspective to invest even when stand-alone project economics do not meet ENPV standards. Such early action may be justified when there is potential to gain valuable information, to capture future growth opportunities or

[7] The real options concept of deferral is independent of capital availability issues, that is, it does not encompass postponing investments due to capital constraints.

to achieve first mover advantage (Dixit & Pindyck, 1995; Kester, 1984; Kulatilaka, 1995). Under such circumstances, firms may also justifiably take action to accelerate the implementation of investments by minimizing "time to build," even when there is an incremental cost to doing so (Kulatilaka, 1995).

In summary, real options theory provides a theoretical foundation for systematically making investment timing decisions that deviate from conventional financial standards. Further, such deviations are not unidirectional. In the presence of uncertainty, both delay and acceleration have option value and either may, in the specific instance, represent optimal investment timing.

2.2.2 Staging

The second broad real options-theoretic pattern of action entails the time ordering of resource commitments. The principal options-theoretic decision pattern applicable to temporal ordering is staging (Majd & Pindyck, 1987; Trigeorgis & Mason, 1987). Real options theory conceptualizes resource commitments within an overall project as a series of sequential options, such that it is both possible and desirable to decompose projects into their component parts and to make decisions regarding continuation, discontinuation or revision after each step has been taken (Majd & Pindyck, 1987). Hence, as an example, a plant construction project may, from a decision-making perspective, be decomposed into distinct design/engineering, site development and construction phases, with "go-no go" decisions made at each stage on an incremental or "money forward" basis. In real options terms, pursuit of each stage represents an option to continue to the next stage, and the entire project consists of a series of compound options (Trigeorgis & Mason, 1987). Staging also permits revision of the scope and scale of the commitment at each decision point in response to experience gained or information received to that point.

Many authors maintain that encouraging management to frame projects in this way is the single most important benefit of real options theory to management practice (Alessandri et al., 2004; Faulkner, 1996; Kemna, 1993; Kogut & Kulatilaka, 1994a; Luehrman, 1998b; Miller & Park, 2002; Triantis & Borison, 2001). Smith & McArdle (1999) point out that the compound-option character of investments is often overlooked in the formulation and evaluation of project decisions. Bowman & Moscowitz (2001) maintain that the real options perspective is more important in project design than evaluation, encouraging firms to identify the hidden options structure in their projects.

As in the case of timing, however, real options prescriptions regarding project staging are not unidirectional. Concurrent or parallel pursuit of project elements rather than staged or sequenced ordering may also be justified in real options terms. I explain the conditions under which this is so in Chapter 3.

2.2.3 Operating Flexibility

As described earlier, real options theory recognizes and ascribes value to management's scope to adjust future action in response to future events. All assets contain flexibility options to the extent that there is latitude for making such adjustments. Further, firms can and do make investments in producing assets in such a way as to maximize management's future scope of action in the face of uncertainty (Dixit & Pindyck, 1995). Considerations of operating flexibility influence both the decision to add producing assets and decisions regarding the character of those additions. Capacity expansion decisions frequently entail a tradeoff between adding capacity in modest increments so as to preserve future flexibility and committing to large capacity increments so as to achieve the maximum benefits of efficiency and scale economies (Dixit & Pindyck, 1995).[8] Furthermore, firms may make deliberate investments in flexible producing assets – assets that can be redeployed or adapted to a range of operating conditions. Flexible assets include, for example, manufacturing facilities designed to allow for easy changes in production levels, product mix, or feedstock qualities (Kulatilaka, 1988 & 1995; Sanchez, 2003) and cross-training of employees (Leiblein & Miller, 2003). Investments in regional diversification also constitute flexible operating assets. Kogut & Kulatilaka (1994a) interpret the multinational enterprise as in part a complex network of operating flexibility options that allow for continuing optimization of exchange rates and input costs across countries.

Investing in operational flexibility usually entails an incremental cost relative to more specialized, inflexible assets. Adding capacity in modest increments forgoes the scale economies of large-scale additions, in effect incurring as an opportunity cost the lost efficiencies of size (Dixit & Pindyck, 1995). Similarly, flexible manufacturing facilities typically require higher capital outlays per unit of production than dedicated, inflexible plant (Triantias & Hodder, 1990). Employee cross-training incurs an explicit additional training cost relative to specialized training. The multinational enterprise requires incremental management and coordination costs relative to regionally focused firms. In each case, such incremental costs represent the cost of acquiring and

[8] It is important to distinguish decisions to add capacity incrementally from the concept of project staging as described earlier. Project staging refers to the steps within a single investment project, each of which must be undertaken before the project can generate revenue. Incremental capacity decisions, by contrast, relate to how capacity expansion projects are defined. Each increment represents an investment which is expected to generate revenue in and of itself, and is not a necessary precondition to making later capacity additions.

maintaining the operating flexibility option. Real options theory maintains that the higher cost of flexible assets is justified when the option value of the operating flexibility thereby created exceeds the associated incremental cost.

2.2.4 Partial Commitment

The three real options decision patterns discussed above relate to two central elements of real options theory: timing and flexibility. Other decision patterns focus on a third core dimension of the theory: growth. Real options theory maintains that virtually all resource commitments create a "right" or preferential access to future growth opportunities that would not otherwise exist (Kester, 1984). Existing assets are typically rich in opportunities for future growth, and most companies are endowed with extensive growth options (Kasanen, 1993). The difference between market value and book value has been interpreted as reflecting the unrealized value of these embedded growth options (Bowman & Hurry, 1993; Herath & Park, 1999; Kester, 1984; Pindyck, 1991).

Investments in new assets also create future growth options. New plant investment, for example, typically creates an option on future incremental low-cost capacity additions (Myers, 1977; Trigeorgis & Mason, 1987). Entry into a new market brings with it the option of future expansion in that or related markets (Kogut & Kulatilaka, 1994a). Similarly, investment in brand creates future growth opportunities in new products and markets (Dias & Ryals, 2002).

Several real options decision patterns are designed to capture growth options. The first of these is partial commitment. Consistent with the real options principle of asymmetric response to uncertainty, firms using real options decision principles seek continuously to reduce their exposure to the downside risks of uncertainty while maintaining access to its upside potential. Partial commitment constitutes one broad pattern of action that serves this objective. Such investments represent a subset of commitment in which the focal firm makes an investment at a level below optimal or ultimate target scale as an initial step toward a market position of strategic interest. "Toehold" and "foothold" diversification investments are one common form of partial commitment (Zardkoohi, 2004). Joint ventures and minority equity positions are others. Kogut's (1991) interpretation of joint ventures as real options characterizes them as partial commitments, designed to test the waters of a new product or market at less than full commitment. In this reading, joint ventures provide a vehicle for expansion in the target market through acquisition of the joint venture, while delaying the cost of full entry until uncertainties are clarified and providing reversibility through pre-contemplated sale to the joint venture partner if future market developments are unfavorable.

A defining characteristic of partial commitments is that they are temporizing investments, an intermediate position on the road to larger, more permanent investments rather than goals in themselves. Hence, as reported by Kogut (1991), most joint ventures are ultimately terminated through buyout by one of the partners and structured from inception with ultimate termination in mind. Similarly, minority equity investments are often preludes to full acquisition.

Based on these characteristics, partial commitment constitutes a decision pattern distinct from those described earlier. Since it entails current investment, it is different from deferral, the essence of which is to forego current action. It is also different from project staging, in that partial commitments are not inherently necessary steps to the conclusion of a revenue-generating project, but intermediate actions undertaken to reach a larger strategic objective. Though they often lead to further subsequent commitments, they are undertaken as investments expected to generate revenues in and of themselves.

2.2.5 Platform Investments

The second growth capture decision pattern is platform or positioning investment. Several types of platform investments have been examined at the conceptual level from a real options perspective. Kogut & Kulatilaka (1994b & 2001) define the platform concept as any investment in physical or human assets that provides the opportunity to respond to future contingent events and enter into a wide range of future possibilities.[9] Where flexible producing assets provide operational flexibility, platform investments create strategic flexibility. An important distinguishing characteristic of such investments is that they are often pure options, that is, they generate no dividends, as, for example, investments in knowledge, capabilities and basic research.

Platform investments may be technical or organizational. McGrath (1997) and others explicitly interpret technology positioning investments as platform investments that enable the firm to reduce technology-related uncertainty for itself idiosyncratically, without reducing it for others. Kogut & Kulatilaka (1994b & 2001) maintain that the most important platform investments are the distinctive competencies of the firm. Such competencies represent the choice of capabilities that permit the firm to make the best response to future market opportunities. Since they apply over a broad range of possible opportunities, capabilities and competencies are especially rich in growth option potential. Kogut & Kulatilaka point out that capabilities are explicitly convergent with

[9] As used here, platform investments denote investments made principally or exclusively to confer access to future opportunities, as distinct from dividend-generating investments which have the additional effect of doing so.

three aspects of real options: asymmetric response to uncertainty, managerial discretion and irreversibility. Other classes of platform investments include brand (Dias & Ryals, 2002) and knowledge acquisition (Bowman & Hurry, 1993).

It is notable that the deviation of real options decision-making from that prescribed by expected net present value may be especially marked for platform investments, which, if they have a directly associated revenue stream at all, often do not meet traditional investment standards on a stand-alone basis. In this connection, Kogut & Kulatilaka (1994a) cite the “iron law” that initial entry moves into overseas markets invariably fail to make money, but do create growth options. Kemna (1993) reports, based on her work with Shell Oil on several real options evaluation pilot projects, that it is often economically justifiable in real options terms to extend options on projects that are not currently economic (such as oil leases), and that pursuit of projects with poor stand-alone economics may similarly be warranted if there are substantial growth options to be gained.

The central contention of this research is that each of the real options-theoretic decision patterns described above constitutes a differentiated response to both the extent and nature of the uncertainties in the task environment. Before reviewing the literature that examines their relationship to uncertainty, I first briefly review the substantial literature on uncertainty in order to establish the conceptual foundation regarding uncertainty that has been used in this research.

2.3 Uncertainty

This section addresses three aspects of uncertainty as it relates to the present research. First, I review the importance of the uncertainty construct in organization and strategy research generally and its central role in real options theory. Second, I identify the varying conceptualizations of uncertainty that have been employed in previous organizational and strategy research, and relate these conceptualizations to real options theory. Finally, I lay the foundation for disaggregating uncertainty into component sources, and for focusing in this research on two sources of uncertainty – market-related and competition-related – as particularly relevant for the study of real options.

2.3.1 Importance of the Uncertainty Construct in Real Options Theory

Uncertainty is a central concept in both strategic and organizational studies, and a large literature has developed on the subject. In organizational research, uncertainty figures prominently in the structural adaptation or "fit" model of contingency theory. In this theoretical tradition, uncertainty is the key construct that explains the relationship between organizations and their environments (Downey, Hellriegal & Slocum, 1975; Milliken, 1987). Thompson (1967), for example, viewed uncertainty as the central organizational and managerial problem and interpreted organization structure principally as a mechanism for buffering the firm from its effects. In contingency theory, uncertainty became the driving consideration in organizational design (Burns & Stalker, 1961; Lawrence & Lorsch, 1967; Woodward, 1965).

Uncertainty has been prominent in other theoretical traditions as well. The transaction cost framework for explaining economic organization is based in part on uncertainty as a contributing element in making market versus hierarchy decisions

(Williamson, 1975 & 1985). Uncertainty is also prominent in evolutionary perspectives on organization, which emphasize complexity, rapid change, and environmental turbulence (Emery & Trist, 1965; Loasby, 2002; Terreberry, 1968).

The uncertainty construct is also fundamental in the field of strategy. It is central to choice theory, which maintains that the firm's response to environment has a significant impact on performance (Aldrich, 1979; Child, 1972). This theme is extended in the work of Miles & Snow (1978), whose prospector-defender-analyzer-reactor strategic types are based in part on firms' differential responses to uncertainty. In addition, a number of studies have suggested that uncertainty is or should be influential in the selection of strategic processes and practices (Boulton et al., 1982; Courtney, Kirkland & Vigurie, 1997; Javidan, 1984; Lindsay & Rue, 1980). Finally, uncertainty is fundamental in those schools of strategic thought that emphasize the incremental and emergent nature of the strategy task (Helmer, 2003; Lindblom, 1959; Mintzberg, 1987 & 1990; Quinn, 1980).

That uncertainty is a central construct in the real options approach to resource allocation and asset management is well established in the literature. Uncertainty is fundamental to both the theory and practice of capital budgeting (Carruth et al., 2000; Dixit, 1989; Pindyck, 1991). The essence of capital budgeting is making optimal resource dedication decisions in the face of unknown future outcomes. As described earlier, managerial response to uncertainty is at the core of real options theory, which is defined by asymmetrical response to uncertainty and management flexibility to respond to uncertain future conditions.

2.3.2 Definition of Uncertainty

Despite the importance of uncertainty in strategy research, there are substantial issues in both the conceptualization and measurement of the uncertainty construct that affect the present research (Milliken, 1987). In this section, I review the principal conceptual issues, reserving discussion of measurement questions for Chapter 4. On the conceptual level, a number of authors have expressed concern about the clarity and consistency of the uncertainty construct (Boyd, Dess & Rasheed, 1993; Downey & Slocum, 1975; Downey et al., 1975; Duncan, 1972; Milliken, 1987; Tosi, Aldag & Storey, 1973). They note in particular the lack of agreement regarding the definition of the uncertainty construct. What is meant by uncertainty has varied among authors. Information theorists, for example, have generally conceptualized uncertainty as the difference between the amount of information required to perform a task and the amount of information that has already been obtained (Daft, Sormunen & Parks, 1988; Galbraith, 1977). Decision theorists, by contrast, have tended to define uncertainty as the inability to confidently assign probabilities to events (Pfeffer & Salancik, 1978). Implicit in this conceptualization is that the set of future possibilities can be identified, but the probability distribution across that set is unknown (Conrath, 1967; Knight, 1921; Loasby, 2002).

Other authors have by contrast placed the broader concept of unpredictability at the heart of environmental uncertainty (Buchko, 1994; Downey & Slocum, 1975; Miles & Snow, 1978; Milliken, 1987; Tosi, Aldag & Storey, 1973; Wholey & Brittain, 1989). In this view, decision-makers may not know the boundaries of possible future events (Conrath, 1967). Firms are affected by events from outside their historical set

(Terreberry, 1968) and thus the potential for surprise is ever-present (Loasby, 2002). This broader framing of uncertainty as boundary-less unpredictability has the advantage of encompassing highly unstable, discontinuous and turbulent environments. In such environments, uncertainty is less a matter of acquiring information or assigning probabilities than one of irresolvable unpredictability resulting from the dynamic interaction of multiple variables (Kogut & Kulatilaka, 2001).

Real options theory implicitly defines uncertainty in the broadest of these conceptualizations, placing primary emphasis on the unpredictability of the future as the source of option values and the economic rationale for real options decision-making. The theory does not require a choice among the uncertainty dimensions described above, but encompasses them all. Some real options decision patterns, for example, are designed specifically to acquire information (Roberts & Weitzman, 1981). The acquisition of seismic information by oil companies prior to drilling wells and the consumer research and test marketing activities of consumer products companies represent such information gathering options. Real options behavior is also induced by uncertainties in which the variable of interest is clear and the range of possible outcomes can be specified, but their probabilities are not known. Deferring the expansion of a plant until demand levels are clearer or delaying investment until an important regulatory issue is resolved represent real options-theoretic behaviors that respond to unknown probabilities. Finally, real options theory applies in those environments in which instability and discontinuity make the acquisition of strategically useful information impractical and where the variables of interest cannot be fully specified (Loasby, 2002). Investments in technology, knowledge and capability platforms are real options-theoretic responses to such environments (Kogut & Kulatilaka, 2001).

2.3.3 Market and Competitive Uncertainty

As discussed above, uncertainty is fundamental to real options theory. In much of the real options literature, however, uncertainty is implicitly treated as a unitary omnipresent construct, rather than as a feature of the environment that varies in magnitude and source. In this section I establish the conceptual basis for how uncertainty has been incorporated in the research, focusing on the relevance of market and competitive uncertainty as the two most influential sources of environment uncertainty from the perspective of real options theory.

A number of authors have argued that the breadth of uncertainty as a construct requires a multidimensional approach to conceptualizing and measuring it (Milliken, 1987; Sharfman & Dean, 1991; Sutcliffe & Zaheer, 1998; Tosi & Slocum, 1984; Yasai-Arkedani, 1986). Consistent with this view, differentiating among sources of uncertainty in the environment is an established practice in both organizational and strategy research. Dill's (1958) four-component formulation – consisting of customer, supplier, competitor and regulatory uncertainties – has been repeated, modified and used extensively in both organizational and strategic research. Subsequent authors have introduced technology uncertainty into this typology, but in other respects have generally remained faithful to Dill's breakdown (Daft et al., 1988; Duncan, 1972; Elenkov, 1997; Kumar & Seth, 1998; Miles & Snow, 1978). There is therefore ample theoretical support and precedent in the literature for analyzing strategic variables in relation to multiple dimensions of environmental uncertainty.

Determining which sources of environmental uncertainty are most relevant in the context of the present research, however, required careful consideration of the relationship between environmental and investment uncertainty. From the perspective of real options theory, environmental uncertainty affects investment decisions in two ways. The first is financial. Environmental uncertainty creates uncertainty regarding the cash flows associated with identifiable projects. Numerous sources in the finance-related real options literature make it clear that the uncertainty directly relevant to real options decision-making is that associated with investment cash flows and project values. The second is strategic. Environmental uncertainty makes it difficult to anticipate the opportunities that will be strategically attractive in the future. The literature regarding platform and capabilities investments as real options emphasize this second aspect. Kogut & Kulatilaka (1994b and 2001), for example, specifically describe investment in platforms and capabilities as positioning the firm to take advantage of emerging future opportunities not clearly identifiable at the time such investments are made.

Accordingly, the appropriate sources of environmental uncertainty for this research are those that most directly influence (1) the cash flows and therefore the value of identifiable investment possibilities and (2) the ability of firms to anticipate the kind of investment opportunities that will emerge in the future. Two sources of environmental uncertainty are directly relevant to both of these dimensions. The first of these is market demand uncertainty, broadly defined as uncertainty related to aggregate customer actions and choices (Kumar & Seth, 1998; Sutcliffe & Zaheer, 1998). In making current investment decisions, companies face uncertainty regarding the volume of total market demand, the composition of demand by product and the prices that can be realized at different levels of demand, all of which directly affect project revenues. To the extent that there are non-variable costs in the production system, these uncertainties also affect aggregate operating margins and therefore project value. Market-related uncertainties are characteristic of a wide range of investment decisions, including, for example, plant construction/expansion, new product development and entry into new markets. Market uncertainty is also a potent determinant of future opportunities. Shifts in customer tastes, needs, preferences, and demographics create uncertainty regarding the kinds of products and businesses that will be strategically attractive in the future (DeSarbo et al., 2005).

The second dimension of the environment influential in determining real options decision patterns is competitive uncertainty, encompassing uncertainty regarding the population of firms whose products compete with or can be substituted for those of the focal firm; the strategies, plans, and tactical actions of those competitive firms; and how they may respond to the actions of the focal firm and other competitors. Competitive uncertainty directly affects the cash flows of current investment projects. Competitor actions, for example, affect market shares and therefore that portion of aggregate demand that will accrue to the focal firm, critically influencing both revenues and unit costs (Bergh, 1998). Competitor investment actions influence the industry supply-demand balance and therefore prices. Competitor actions may also influence input costs and therefore margins. Furthermore, the timing of competitor actions may affect both the feasibility and cost of investment by the focal firm. Except in perfectly competitive markets, competitor actions may create first mover advantage or preemptive effects that influence the profitability of investments (Kulatilaka & Perotti, 1998; Lieberman & Montgomery, 1988; Smit & Ankum, 1993).

Competitive uncertainty is also influential in determining the landscape of future opportunities. Competitor innovation creates new and unforeseen product categories and markets. Competitors introduce new technologies that threaten to render obsolete existing technology platforms, raise product performance standards or change industry cost structure. Uncertainty regarding the intentions and actions of competitors is, therefore, a prominent source of uncertainty regarding both investment cash flows and the nature of future investment opportunities.

In conclusion, there is a solid conceptual foundation for regarding market and competitive uncertainty as two distinct and highly influential sources of uncertainty that affect real options decision patterns, and both are well-supported in the real options and uncertainty literatures. It is noted also that these uncertainty sources are well suited to the present research from several other perspectives. First, both market and competitive uncertainty influence a wide range of real option decision patterns. As will be discussed in detail in Chapter 3, both are linked theoretically with all five classes of real options decision patterns described earlier. Market and competitive uncertainty therefore comprise a robust basis for generating hypotheses across the full range of real options-theoretic decision patterns.

Second, as will also be evident from the theoretical development presented in Chapter 3, market and competitive uncertainty tend to promote different and sometimes directly competing real options decision patterns. As described earlier, for example, market uncertainty frequently encourages deferral behavior, while competitive uncertainty often argues for acceleration (Kester, 1984; Smit & Ankum, 1993; Trigeorgis, 1991). In combination, therefore, these two sources of uncertainty provide a basis for generating analytically useful variance in real options decision patterns.

CHAPTER 3

THEORETICAL DEVELOPMENT AND HYPOTHESES

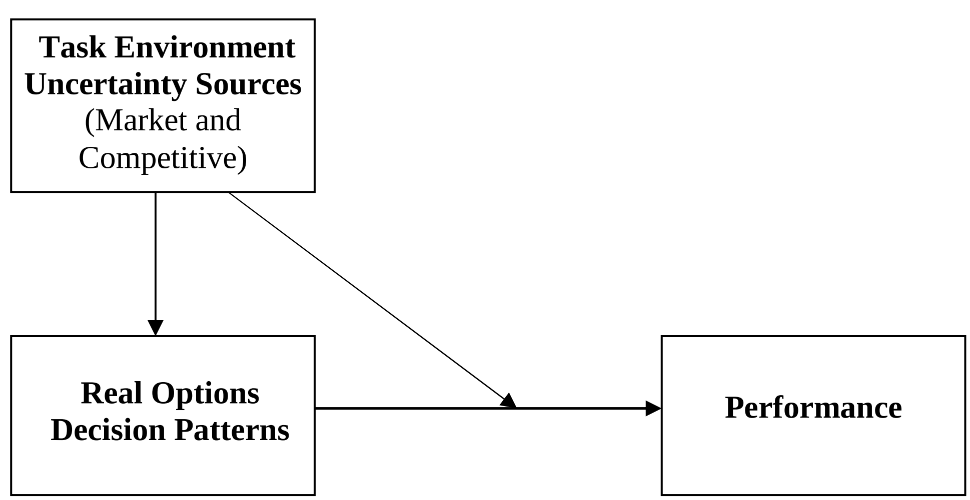
This chapter integrates the theoretical foundation laid in Chapter 2 in an overall conceptual model for the proposed research and presents a group of hypotheses which state expected relationships (1) between market and competitive uncertainty as independent variables and various real options decision patterns as dependent variables, and (2) between real options decision patterns and uncertainty as independent variables and firm performance as the dependent variable.

3.1 General Model

Figure 3.1 presents the overall conceptual model on which the proposed research rests. The model indicates that real options-based decision-making patterns are

Figure 3.1

General Real Options Model



conditioned by the uncertainty characteristics of the environment in which decisions are made. The model treats uncertainty as a multidimensional construct in which sources of uncertainty are influential. Different patterns of real options decision-making are more likely to emerge in response to different sources of uncertainty, specifically market and competitive uncertainty as defined in Chapter 2.

The model further anticipates that the fit between uncertainty and real options decision patterns will influence firm performance. Real options theory represents a normative as well as an explanatory framework for strategic resource allocation decisions. Implicitly, therefore, application of real options principles in decision-making should produce positive differential performance effects. Since, however, appropriate real options decision patterns are a function of the sources of environmental uncertainty, it is the degree of fit or consistency between the two that influences performance, rather than any inherently superior decision pattern.

3.2 Hypotheses Regarding Uncertainty and Real Options Decision Patterns

As described in the earlier literature review and the general model presented above, it is a central premise of this research that optimal real options decision patterns vary based on the magnitude and source of uncertainty encountered in the external environment. Patterns of real options behavior that are appropriate under one set of conditions as regards market and competitive uncertainty may be inappropriate under another. Further, different sources of uncertainty may lead to competing real options decision patterns, requiring that firms strike a balance between offsetting options. These relationships between uncertainty and real options behavior are elaborated below, examining in turn each of the five classes of real options decision patterns described in

Chapter 2. In the interest of clarity in developing theory and hypotheses, I first consider the relationships between market uncertainty and real options decision patterns in the absence of competitive uncertainty. I then introduce competitive uncertainty. This protocol has been adopted purely for expository purposes and implies no judgment regarding the primacy, either conceptually or empirically, of the two uncertainty sources.

3.2.1 Timing

Real options theory suggests that market uncertainty provides a strong incentive for firms to defer investment commitments. The option to defer has considerable value in the presence of uncertainty regarding market demand, since market factors are an important determinant of investment cash flows. This option value derives from the opportunity to proceed with the investment later if additional information indicates favorable market conditions, but not to proceed under an unfavorable market evolution. The option to defer entails an opportunity cost in the form of a postponement or reduction of project dividends.[10] When the value of the deferral option exceeds its cost, real options theory suggests that firms as rational actors will delay investment pending uncertainty resolution. The incentive to defer increases with market uncertainty, since the value of the deferral option increases with variability in investment cash flow.

There is a large theoretical literature linking deferral and market uncertainty, consisting principally of formal economic and financial models of deferral option values in relation to project-specific cash flow uncertainty resulting from exogenous market factors (for example, Dixit, 1989; McDonald & Siegel, 1986; Smit & Ankum, 1993). It

[10] For investments characterized by indefinite cash flow streams, the relevant option cost is that of postponed cash flow. Where cash flow is time limited (for example, investments involving patents), deferral may result in an aggregate loss of dividends (Reiss, 1998).

is implicit in these studies that the incentive to defer increases with market uncertainty. The greater the market uncertainty surrounding an investment, the more uncertain is its cash flow, and the more valuable therefore is the associated deferral option.

Several empirical studies of market entry support the expectation that firms delay investment in response to market uncertainty. O'Brien et al. (2003), for example, conducted a multi-industry archival study of new entrepreneurial entry in relation to industry uncertainty. They found a significant negative relationship between levels of entry and market uncertainty. They concluded, consistent with real options theory, that entrepreneurs delay entry when market uncertainty is high. Folta & O'Brien (2004) also examined the relationship between uncertainty and entry in real options-theoretic terms, with a particular emphasis on the tradeoff between deferral and growth options. The authors maintained that deferral options have dominated thinking about real options, suggesting a unilaterally negative relationship between investment and uncertainty. They instead proposed that deferral and growth represent "dueling" options, the former encouraging delay, and the latter generally favoring early action. They hypothesized that the timing effect of uncertainty is not monotonic but curvilinear. Market uncertainty deters entry only when the growth options associated with entry are modest, but encourages entry when the associated growth options are substantial. They found support for this formulation, but they also found that the option to defer appears to dominate the duel, coming into play over 93% of the range of market uncertainty. Folta & O'Brien's study therefore provides partial empirical support for deferral in response to market uncertainty.

Folta & O'Brien's contrary finding that at very high levels of market uncertainty firms forego deferral in order to capture growth options is ambiguous. Though their study did not incorporate competition as a variable, other literature clearly suggests that competitive uncertainty strongly promotes growth capture actions, as discussed in the next section. I therefore conclude that, because their analysis did not account for competitive uncertainty, the growth capture behavior observed in the Folta & O'Brien study is indeterminate as regards the effects of market uncertainty purely on investment timing. I consider this issue in greater detail subsequently in the discussion of growth options.

In summary, both theory and empirical evidence argue that deferral option values increase with market uncertainty, and that, absent other considerations, as market uncertainty rises firms have a progressively stronger incentive to defer investment until clarifying market information is available.

Deferral may not, however, represent optimal investment timing in the presence of competitive uncertainty. As the level of competitive uncertainty increases, the danger of preemptive action by a competitor increases as well. Except in perfectly competitive markets, preemptive action by competitors may create first mover advantage, making later action by the focal firm less rewarding and/or more costly.[11] At the extreme, if such preemptive effects are severe, deferral can lead to total loss of the investment opportunity to a quicker-moving competitor whose actions have the effect of forestalling subsequent

[11] As used here, first mover advantage is broadly defined as the ability of early movers to earn economic rents based on achieving a favorable competitive position deriving from the timing of their investments. First mover advantage may consist of (1) technology leadership through learning curve effects or patents, (2) preemption of scarce factors, including product positions or scale economies, and (3) switching costs, broadly defined to include both financial costs and the psychological costs associated with brand loyalty (Liebermen & Montgomery, 1988).

entrants. In real options terms, competitive uncertainty introduces an additional cost to the option to defer beyond the postponement of dividends. This cost consists of the potential reduction in the value of the investment opportunity resulting from ceding first mover advantage. Once a position is established by a competitor, it may be more costly for the focal firm to act, and the benefits from doing so may be smaller. Where complete preemption is possible, deferral may surrender the entire value of the investment to a competitor. As competitive uncertainty increases, these competition-related costs of deferral loom progressively larger.

That competitive uncertainty may lead to different investment timing decisions than market uncertainty has strong theoretical support in both the finance and strategy literatures. Grenadier (2002), for example, modeled the relationship between competitive uncertainty and deferral from a game-theoretic perspective. He noted that the typical modeling of option values in the financial literature is unrepresentative of many real world situations in that it assumes competitive isolation. In particular, high deferral option values, and therefore the attractiveness of deferral as a course of action, depend on the lack of strategic interaction among option holders. Grenadier's model demonstrates that the presence of competition greatly erodes deferral option values, due to the danger of preemption, such that the real options-theoretic decision rule converges with conventional ENPV decision standards as competitive uncertainty increases. In Grenadier's analysis, this effect is pronounced even in the presence of relatively few competitors. In summary, Grenadier established a theoretical foundation for expecting that uncertainty regarding the actions of competitors greatly reduces the attractiveness of deferral and constitutes a disincentive to delay.

Other authors maintain that competitive uncertainty not only reduces the value of deferral, but may make early action and acceleration optimal from a real options perspective (Kogut & Kulatilaka, 2001; Kulatilaka & Perotti, 1998; Smit & Ankum, 1993). Acting early on an investment, even when it does not promise a positive expected net present value, may be justified if such early action (1) creates or consolidates first mover advantage for the focal firm, (2) preempts competitors from acting, or (3) protects valuable growth options.

In conclusion, real options theory strongly suggests that market and competitive uncertainty induce different and competing patterns of real options-optimal investment timing. High competitive uncertainty undermines the value of deferral and may, depending on the competitive structure of the industry, create incentives to commit even when ENPV standards would indicate that such commitment is premature. When market uncertainty is low but competitive uncertainty high, the incentive for prompt or early commitment is likely to dominate the offsetting incentive to delay, since the option value of deferral under those conditions is low and its cost high. When both are high, however, market and competitive uncertainty create competing incentives, since both the value and the cost of deferral are high. In either case, investment decisions in environments characterized by high competitive uncertainty are likely to demonstrate a time pattern different from that which would result from market uncertainty alone. Based on these considerations, it is hypothesized that:

H1a: Competitive uncertainty will negatively moderate the relationship between market uncertainty and deferral.

H1b: Competitive uncertainty will positively moderate the relationship between market uncertainty and acceleration.

3.2.2 Staging

In addition to deferral, real options theory argues for specific project sequencing patterns in response to market uncertainty. Where important market factors are unclear, staging or phasing of investment represents a directionally optimal real options decision pattern. Following Roberts & Weitzman (1981), I here distinguish between “one-sided” projects and “two-sided” projects. One-sided projects are those in which all project steps must be undertaken to reach project conclusion. R&D is illustrative of such projects: basic research must precede development, and development must precede commercialization. Two-sided projects are those where it is possible to proceed at any point to project conclusion but in which discretionary steps may be added to clarify uncertainty. The introduction of a new product, which may either be undertaken immediately upon development or clarified by such additional steps as market research or test marketing, is a representative two-sided investment situation.

For one-sided projects, breaking required project elements down into stages for purposes of decision-making encourages close monitoring of market developments as commitment levels increase, permitting appropriate mid-course corrections, changes in project timing and even discontinuation if conditions warrant. Staging maximizes the potential to continuously review project status based on the most recent uncertainty-clarifying market information. Such information may result from the firm’s learning from previous stages, or simply from the passage of time (Roberts & Weitzman, 1981). Implicit in staging is an active stage-gate or milestone review process in which the firm carefully and rigorously monitors project fundamentals and makes appropriate decisions in response to developments (Kogut & Kulatilaka, 2004; Kumaraswamy, 1996; McGrath et al., 2004; Zardkoohi, 2004).

As described in Chapter 2, real options reasoning conceptualizes investment in each project stage as the purchase of an option to proceed to the next stage. The value of these compound sequential options increases with the variance in project outcomes. Since market uncertainty directly influences project variance, the value of the staging option increases with market uncertainty.

In two-sided projects, firms have the discretion to add uncertainty-resolving steps to investment projects, as in the case of test marketing by consumer product firms or the acquisition of seismic data by petroleum companies prior to drilling exploration wells. Such discretionary actions also constitute investments in real options. The value of such information options increases with project variance, but their cost (consisting of their explicit cost and any delay they may introduce into the project) does not. Accordingly, the incentive to undertake discretionary uncertainty-resolving project steps increases with market uncertainty. Hence, the attractiveness of undertaking market research or test marketing programs increases to the extent that market acceptance is unclear.

As in the case of deferral, however, competitive uncertainty introduces additional and competing considerations into staging decisions. The danger of preemptive action by a competitor makes staging within projects less attractive from a real options perspective. Similarly, the option value of market uncertainty reduction through information acquisition is offset by the increased option cost of degradation in project benefits or the loss of the underlying opportunity due to competitor action (Childs & Triantis, 1999). In response to competitive uncertainty, firms are therefore more likely to pursue the components of individual investment projects concurrently rather than in stages and to forego efforts to collect uncertainty-clarifying information before full commitment. Hence, it is hypothesized that:

H2: Competitive uncertainty will negatively moderate the relationship between market uncertainty and project staging.

3.2.3 Operating Flexibility

It is also consistent with real options theory to expect that investments in operating flexibility will increase with market uncertainty. Increments in market uncertainty increase the option value of flexible producing assets, while the incremental cost of such assets remains fixed. Flexible assets therefore become increasingly attractive from a real options perspective as market uncertainty rises. Conversely, as market uncertainty falls, the option value of flexibility declines toward or below the cost of the option, making flexibility decreasingly attractive.

By this logic, companies are more likely to add capacity incrementally than in large periodic expansions to the extent that they are uncertain about market demand. A pattern of multiple small additions maximizes management's flexibility to make optimal future capacity decisions as market uncertainty is clarified (Dixit & Pindyck, 1995). Firms are also more likely to invest in producing assets that maximize their flexibility to vary easily the level and mix of production and to make such changes with minimal adverse impact on profitability. In effect, both incrementalism in capacity expansion and flexible producing assets provide buffers between market demand uncertainty and variance in investment cash flow.

There is a strong conceptual foundation for linking flexible assets with market uncertainty. Sanchez (2003), for example, attempts a theoretical integration of real options theory and transaction cost economics perspectives on asset investment preferences. He notes that the two theoretical perspectives suggest seemingly contradictory prescriptions for making asset decisions, with transaction cost economics generally favoring internalization of highly specific assets and real options theory instead arguing for investing in flexible assets and avoiding the commitment of internalization. He proposes a contingent application of the two theoretical frames depending on the source of uncertainty. His conceptual model distinguishes between asset characteristics (flexible or highly specific) and governance (market or hierarchy) as separate dimensions of the production decision, with transaction cost considerations of opportunism driving governance choices and real options considerations of market uncertainty driving the choice between flexible or highly specific assets. Sanchez notes that flexible producing assets provide multiple benefits in the face of market uncertainty. They typically entail lower fixed costs relative to highly specific assets, thus alleviating the profitability consequences of variability in demand, and they allow for easier adaptation to such variability. Sanchez thus lays the real options-theoretic foundation for interpreting investments in flexible operating assets as significantly conditioned by market uncertainty.

While the above discussion points to the existence of theoretical work, I am aware of no empirical studies that examine the relationship between market uncertainty and operational flexibility. There is, however, considerable anecdotal evidence that flexible producing assets are common in industries characterized by high market demand variability. Petroleum refineries and chemical plants, for example, have traditionally invested extensively in process flexibility to adapt to variations in overall demand levels, product mix and the availability and cost of feedstock (Chen et al., 1998). Despite the potent scale economies of large coal-fired power generation facilities, electric utilities commonly invest in smaller, fuel-flexible plants to accommodate to demand variations, even though the unit production cost of such facilities is considerably higher (Dixit & Pindyck, 1995).

None of the literature examined in the course of this research provides direct theoretical foundation for considering the impact of competitive uncertainty on operating flexibility decision patterns. I therefore seek to extend theory by suggesting that competitive uncertainty counteracts the real options-based incentives to maximize operating flexibility in response to market uncertainty. As regards the pattern of capacity additions, competitive uncertainty creates contrary incentives to market uncertainty, directionally encouraging companies to make large-scale rather than incremental capacity additions. These contrary incentives are two-fold. First, large-scale additions can have an important preemptive effect (Lieberman & Montgomery, 1988). By adding capacity in excess of clearly visible market demand, the firm discourages competitor capacity additions and therefore maximizes its ability to capture future growth in demand. Conversely, incremental capacity addition may encourage more aggressive competitors to add capacity, and positions competitors who do so to take advantage of upside demand evolution.

Expressed in real options terms, the value of the flexibility option created by incremental capacity addition is dominant in the capacity planning decision only so long as the growth option to meet future demand is preserved. Competitive uncertainty puts that growth option at risk by permitting competitors to make the next increment of capacity addition. Competitive uncertainty therefore introduces a tradeoff between competing flexibility and growth options, and directionally argues for adding capacity in large preemptive chunks rather than in multiple smaller increments.

The second disincentive to investing in asset flexibility associated with competitive uncertainty is cost related. As noted earlier, both incremental capacity additions and flexible producing assets sacrifice the competitive benefits of scale, which include both lower average unit costs and lower marginal costs. In industries where cost leadership is an important basis of competition, asset flexibility may thus reduce competitive position by ceding cost leadership to competitors. It is well established that scale economies are an important source of competitive advantage (Ghemawat, 1991; Lieberman & Montgomery, 1988; Porter, 1985), and preserving them becomes an increasingly important consideration in investment decisions as competitive uncertainty increases. Based on these considerations, it is hypothesized that:

> H3: Competitive uncertainty will negatively moderate the relationship between market uncertainty and investments in operating flexibility.

3.2.4 Partial Commitment

Real options theory specifies that market uncertainty creates growth options, and that the value of these growth options increase with the level of market uncertainty. When the variability of future market conditions is high, the potential for a very favorable evolution is also high, leading to new opportunities not currently identifiable. In short, industry environments characterized by large market-related uncertainties give rise to valuable growth options associated with upside market potential. Conversely, stable, predictable markets present little downside risk, but offer little growth potential as well. As market uncertainty rises, therefore, firms have increasing incentives to take action to capture growth options (Folta & O'Brien, 2004; Kulatilaka & Perotti, 1998). At the same time, however, as noted in section 3.2.1 above, market uncertainty encourages deferral of commitments in order to minimize exposure to the downside potential inherent in market variance. Hence, as market-related uncertainty increases, firms are faced with the progressively more difficult challenge of optimizing the competing benefits of restraint and aggressive action in resource allocation decisions.

Consistent with real options theory, therefore, firms operating in task environments characterized by large market-related uncertainties have strong incentives to seek investment alternatives that simultaneously capture future growth options but avoid full and immediate commitment. As described in Chapter 2, partial commitment is a decision pattern for doing so. Through partial commitment the firm makes a sufficient investment to preserve access to the growth opportunities of interest, but one that represents less than full-scale commitment. Such actions include small acquisitions, minority equity interests and joint ventures (Kogut, 1991; Smith & Triantis, 1994). Kogut's previously described real options theoretic interpretation of joint ventures (1991) explicitly describes them in these terms. Joint ventures simultaneously provide discretion to expand under favorable conditions, but limit downside exposure to unfavorable ones by limiting commitment and preserving some degree of reversibility.

As for other real options decision-patterns, however, competitive uncertainty reduces the incentive to make partial commitments. In the presence of competition, there is a strong incentive to avoid loss of growth options through competitor preemption (Kester, 1984; Trigeorgis, 1993; Trigeorgis & Mason, 1987). There is strong theoretical foundation for this expectation in the real options literature. Kulatilaka & Perotti (1998), for example, modeled the impact of competition on real options decisions, focusing in particular on the relative value of deferral and growth options. In their analysis of growth options and competition, Kulatilaka & Perotti found two important effects. First, the presence of competition alters the relative value of the deferral and growth options associated with strategic investment. When the focal firm enjoys exclusive access to an opportunity or a monopolistic position in the target market, the growth options associated with the focal investment are not at risk competitively and deferral is directionally the better strategy in response to market uncertainty. When, however, both the opportunity and the focal market are exposed to competition, the potential for partial or total preemption reduces the value of deferral. Deferral runs the risk of losing growth options due to competition, while early action enhances the value of growth options by preserving access to them and by reducing the "exercise" price of pursuing them.

Second, the presence of competitive uncertainty changes the relative sensitivity of deferral and growth option values to market uncertainty. When an investment produces little or no competitive advantage, the value of the deferral option associated with it increases more steeply than that of its growth options with increases in market uncertainty. Conversely, when an investment has a strong preemptive effect, the growth option value of early action increases more steeply with market uncertainty than the value of waiting to invest. The implication that market uncertainty does not constitute a universal disincentive to invest is consistent with Folta & O'Brien's (2004) empirical finding discussed earlier, but clarifies their result by suggesting that market uncertainty may selectively encourage growth capture over deferral behaviors because of competitive uncertainty. On the strength of market uncertainty alone, the outcome of the deferral-growth capture duel is indeterminate.

The clear implication of Kulatilaka & Perotti's analysis is that competitive uncertainty constitutes a powerful incentive to take action to avoid the loss of growth opportunities through preemption or, conversely, to achieve the competitive benefits of preemption by the focal firm. As applied to growth options decision patterns, their work suggests that increasing competitive uncertainty will undermine the attractiveness of partial commitment as a growth capture strategy. To the extent that partial commitment is an intermediate or temporizing decision pattern (Kogut, 1991), the competitive benefits of early action are likely to increasingly offset the benefits of limited commitment as competitive uncertainty increases.

In short, high market uncertainty creates a "duel" between deferral and growth options (Folta & O'Brien, 2004). Which one dominates real options decision-making depends on the level of competitive uncertainty. As competitive uncertainty increases, real options reasoning increasingly favors growth capture over deferral. Hence, partial commitment becomes decreasingly optimal versus full commitment as competitive uncertainty increases.

There is some empirical evidence supporting this expectation in Folta's (1998) and Folta & Miller's (2002) studies of joint venture formation and buyouts in the biotechnology industry. These studies, however, examine a single industry, and are therefore of limited generalizability. The proposed research will seek broader confirmation of their findings by testing the hypothesis that:

H4: Competitive uncertainty will negatively moderate the relationship between market uncertainty and partial commitment investments.

3.2.5 Platform Investments

For most of the real options decision patterns described above – deferral, staging, operating flexibility and partial commitments – market uncertainty has been seen to be the principal driving force motivating each behavior. For each, I have described how competitive uncertainty creates countervailing incentives that moderate or reverse them. I submit that platform investments entail a substantially different relationship between market and competitive uncertainty, one in which market uncertainty constitutes an incentive for platform investments, but only in the presence of competitive uncertainty. Put in other terms, market uncertainty is a necessary but not sufficient real options basis for justifying platform investments.

There is ample theoretical foundation for viewing platform investments as real options-based responses to market uncertainty. Since they apply over a broad range of future conditions, platform investments preserve future growth opportunities when market uncertainty precludes immediate identification of the products and markets that will be most rewarding in the future. For this reason, platform investments are especially well-suited to discontinuous, high uncertainty environments (Kogut & Kulatilaka, 2001).

Platform investments do not, however, represent an optimal response to market uncertainty in the absence of competitive uncertainty. Kulatilaka and Perotti's (1998) previously cited theoretical discussion of competition and growth options supports this contention. They pointed out that where growth options are insulated from competition, the incentive to act on them is greatly reduced. Only when there is the potential for the competitive preemption of growth options does it become real options-optimal to capture them by making platform investments. Kulatilaka and Perotti's reasoning can be extended and clarified by considering the hypothetical case of complete competitive isolation, that is, when the focal firm enjoys exclusive access to growth options. In this case, the firm gains little from investing in readiness for unknown future market developments. With no exposure to preemption or first mover advantage, waiting to see what happens is arguably the optimal strategy, since it entails no platform costs and does not compromise access to future opportunities when they arise.

Competitive uncertainty, however, alters the decision dynamics of platform investments by exposing future growth opportunities to preemption. Competitive uncertainty creates a race toward future, presently invisible opportunities, and provides the driving force behind platform investments. That competitive uncertainty is the mainspring of platform investing is well-supported by the real options literature. McGrath (1987), for example, described technology platforms not simply as preparing for unknown future products/markets, but achieving an advantaged competitive position in them. Technology platforms allow the focal firm to idiosyncratically reduce uncertainty for itself and not for other firms, thereby becoming better prepared for the future than its competitors.

The central position of competitive uncertainty in platform investing is even more evident in the case of capabilities and competencies. Creating and maintaining capabilities are direct investments in competitive advantage. They constitute the early acquisition of strategic factors that are valuable, non-tradable and difficult to imitate (Kogut & Kulatilaka, 1994b & 2001). They also permit the firm to move more quickly as market developments unfold. The essence of platform investments is the creation of competitive isolation and timing advantage (Kogut & Kulatilaka, 1994b & 2001).

Based on these considerations, I conclude that there is little incentive to undertake platform investments on the strength of market uncertainty alone, but that the combination of market and competitive uncertainty makes platform investment a real options-optimal decision pattern. Hence:

> H5: Competitive uncertainty will positively moderate the relationship between market uncertainty and platform investments.

3.3 Hypotheses Regarding Real Options Decision Patterns and Performance

The second part of the research examines the relationships between real options decision patterns and firm performance. The theoretical foundation for expecting that adherence to real options decision-making principles contributes to firm performance is strong. That how a firm responds to uncertainty has a significant effect on performance is a long-standing premise in strategy research (Aldrich, 1979; Child, 1972; Miles & Snow, 1978). Further, real options reasoning has been widely advanced as a better basis for making investment decisions under uncertainty than the expected net present value framework as it is typically employed, implying that real options decision making enhances performance.

There is an extensive literature that describes the limitations and weaknesses of ENPV and lays the theoretical foundation for the superiority of real options-based decision-making. This literature identifies four ways in which real options theory leads to better investment decisions. First, the ENPV rubric is “static,” in that it does not consider alternate possible timings to the present (Dixit & Pindyck, 1995; Luehrman, 1998a; Miller & Park, 2002). Second, expected value does not value management discretion (Bowman & Moscowitz, 2001; Brennan & Schwartz, 1985; Chen et al., 1998; Miller & Park, 2002; Triantis & Hodder, 1990; Trigeorgis & Mason, 1987). It implicitly assumes that, once taken, decisions will not be modified and that management does not take action to ameliorate unfavorable developments or to capitalize on favorable ones (Luehrman, 1998b). It therefore assumes a passive response to the future that is inconsistent with the foundations of strategy as a field of study (Yeo, 2003). Third, ENPV values investments on a stand-alone basis, failing to take project interrelationships into account or to optimize their sequencing (Childs et al., 1998; Trigeorgis & Mason, 1987). Finally, ENPV does not incorporate the value of growth options (Dixit & Pindyck, 1995). It has been argued that as a result of these shortcomings ENPV distorts investment decision-making, systematically underestimating the value of those option-rich investments that are important to long-term strategic success (Hayes & Abernathy, 1980; Hayes & Garvin, 1982; Kemna, 1993; Lewis, Enke & Spurlock, 2004; Trigeorgis & Mason, 1987). By focusing attention on optimal timing, by partially endogenizing project performance, by optimizing the relationships among projects and by explicitly addressing growth options, real options reasoning represents a conceptually superior basis for making strategic resource allocation decisions.

There has, however, been very minimal study of the relationship between real options-based decision-making and performance, and virtually no empirical research. I am aware of only three studies that address real options and performance in any way.

Miller & Arikan (2004) conducted a simulation analysis of the comparative performance of evolutionary, formal real options pricing and informal real options reasoning approaches to resource allocation. They found that real options reasoning did not emerge as a clearly superior basis for decision-making. Reuer & Leibling (2000) conducted an empirical study to test Kogut & Kulatilaka's (1994a) interpretation of the multinational corporation as a network of real options designed to provide operational flexibility. They analyzed whether multinationality, as predicted by Kogut & Kultatilaka's real options interpretation, reduces downside risk, which they measured by inter-period comparisons of return on assets and equity. They found no evidence that multinational companies achieve reduction in downside risk versus comparable domestic companies. Kumaraswamy (1996) studied the extent to which high-technology companies adopted a real options perspective in their R&D activities and further explored the relationship between adoption and various measures of performance. While his study did not directly test the impact of real options R&D management on financial performance, it did find strong relationships between a real options approach to the management of R&D and a several measures of R&D performance. In summary, empirical research regarding real options and performance is meager, and as such provides little support for real options reasoning as an avenue to differential performance.

As a normative framework for decision-making, however, it is implicit that consistent application of real options principles to resource allocation decisions will lead to superior aggregate outcomes at the level of the firm. To the extent that firms using those principles are able to (1) achieve asymmetrical exposure to uncertainty, selectively benefiting from upside potential while reducing downside risk; (2) maximize the value of managerial flexibility; and (3) capitalize on growth options, they can be expected to make investment decisions of superior average quality in comparison with firms not using those principles. Superior investment decision quality should, in turn, positively affect relative performance.

Mere adoption of real options decision patterns is not, however, sufficient to achieve improved performance. Consistent with the central contention of this research, not all real options decision patterns are optimal in all task environments. Only those decision patterns that are consistent with the underlying sources of environmental uncertainty are likely to have positive performance effects. Further, real options decision patterns often compete with each other, and must be balanced by firms, considering the specific magnitude and source of the uncertainties they face. Therefore, the appropriate conceptual framework for examining the performance impacts of real options as a basis for resource allocation decision-making is to examine the fit between real options decision patterns and the sources of uncertainty in the environment.

Accordingly, hypotheses were developed to express the expected relationships between the uncertainty/decision pattern fit and performance. As described earlier, market and competitive uncertainty frequently represent countervailing incentive and disincentive for employing specific decision patterns. To facilitate exposition and interpretation, hypotheses for each decision pattern were structured to isolate the effect of the disincentive uncertainty source on the relationship between the incentive uncertainty source and performance. Hence, for deferral, market uncertainty is the primary incentive for the decision pattern and competitive uncertainty the countervailing disincentive. Accordingly, it is hypothesized that:

H6a: When competitive uncertainty is low, a positive relationship will exist between deferral and performance as market uncertainty increases.

H6b: When competitive uncertainty is high, a negative relationship will exist between deferral and performance as market uncertainty increases.

In the case of acceleration, competitive uncertainty represents the principal real options rationale for the decision pattern and market uncertainty the offsetting disincentive. Hence, it is hypothesized that:

H6c: When market uncertainty is low, a positive relationship will exist between acceleration and performance as competitive uncertainty increases.

H6d: When market uncertainty is high, a negative relationship will exist between acceleration and performance as competitive uncertainty increases.

Staging, operating flexibility and partial commitment all share in the same theoretical structure as deferral, with market uncertainty promoting those decision patterns and competitive uncertainty discouraging them. Accordingly it is hypothesized that:

H7a: When competitive uncertainty is low, a positive relationship will exist between staging and performance as market uncertainty increases.

H7b: When competitive uncertainty is high, a negative relationship will exist between staging and performance as market uncertainty increases.

H8a: When competitive uncertainty is low, a positive relationship will exist between operating flexibility and performance as market uncertainty increases.

H8b: When competitive uncertainty is high, a negative relationship will exist between operating flexibility and performance as market uncertainty increases.

H9a: When competitive uncertainty is low, a positive relationship will exist between partial commitment and performance as market uncertainty increases.

H9b: When competitive uncertainty is high, a negative relationship will exist between partial commitment and performance as market uncertainty increases.

Finally, for the platform decision pattern, the expected relationships entail a different theoretical structure, with market and competitive uncertainty acting as mutually reinforcing incentives, both of which are required to make platform a performance-enhancing decision pattern. Accordingly it is hypothesized that:

H10a: When competitive uncertainty is low, a negative relationship will exist between platform and performance as market uncertainty increases.

H10b: When competitive uncertainty is high, a positive relationship will exist between platform and performance as market uncertainty increases.

CHAPTER 4

DATA AND ANALYSIS METHODS

In this chapter, I describe (1) the sample of firms included in the research, (2) the measures used for each of the independent and dependent variables and the data sources for these measures, and (3) the analysis methods that were used to test the hypotheses presented in Chapter 3.

4.1 Research Sample

The survey population was drawn from domestic public companies in the manufacturing sector (2-digit NAICS codes of 31, 32 and 33). Only manufacturing companies were included since the archival measures of uncertainty used in the analysis are available only for such companies in the Census Bureau's *Annual Survey of Manufacturers.* Manufacturing companies represent a suitable research population since they are typically capital asset-intensive and therefore susceptible to real options logic. Further, the manufacturing sector contains a broad range of industries, creating variance in both the dependent and independent variables and increasing the generalizability of the results. The population included only publicly-held companies in order to assure the availability of secondary performance data for testing the relationships between real options decision patterns and firm performance.

Two additional constraints were placed on the selection of companies for the survey population. First, only companies with annual revenues of $50 million or more were included. Applying a minimum size requirement was deemed necessary to assure that the sample included only companies with sufficient scale to provide meaningful data on the broad range of investment behavior that the survey was intended to tap. While there is no clear basis from previous literature for setting an appropriate minimum size criterion, the $50 million annual revenue test used was considered a conservative one for this purpose.

The survey population was further confined to firms with an identifiable dominant business line, using a minimum requirement of 70% of revenue accounted for by a single 3-digit NAICS code as a diversification cut-off standard. Limiting the sample to substantially undiversified companies was necessary to maintain correspondence between the survey data and industry-level uncertainty and performance data from secondary sources. The 70% standard has extensive support in the literature (Rumelt, 1974, 1982 & 1991) and is considered conservative. Diversification levels at or below 30% of total revenues was judged unlikely to distort the results of the analysis. There is strong support in the literature for expecting that firms, even those with a significant level of diversification, make decisions based on the frame of reference derived from their dominant business (Keats & Hitt, 1988; Porter, 1985; Pralahad & Bettis, 1986).

Using these criteria, screening of the *Compustat* database identified 1375 companies for inclusion in the survey population.[12]

4.2 Measurement of the Research Variables

The proposed research required measurement of four primary groups of variables, as follows:

- Real options decisions patterns exhibited at the level of the firm (dependent variables);

[12] Included in this total are 29 publishing companies categorized as manufacturing in the NAICS coding system at the time the survey population was established, but which have since been reclassified to other codes. Since these companies were included in the survey and yielded 6 responses, they have been retained in the analysis sample.

- Market and competitive uncertainty (independent variables);
- Firm performance (dependent variable);
- Control variables.

The purpose of this section is to describe how each of these variables was measured and the methods used for data collection.

4.2.1 Real Options Decision Patterns

4.2.1.1 Survey Development

Specific real options decision patterns are extensively described in the theoretical literature, as reviewed in Chapter 2. Review of this literature, however, identified no scales for measuring these patterns individually or for combining them into an overall, comprehensive instrument that incorporates multiple decision patterns. The research therefore required the development of such an instrument.

Spector (1992) emphasizes the importance of careful theoretical grounding in developing scales. The first step, therefore, in constructing a survey instrument for this research was to derive a preliminary specification of real options-theoretic decision patterns, and to categorize those patterns into conceptually distinct groups representing different dimensions of the real options construct. Based on a review of the real options literature in both the strategy and finance domains, five real options constructs and specific decision patterns associated with each were identified, as described in Chapter 2. An initial item pool was then developed, including items reflecting each of the five constructs and specific decision patterns within each. In addition to real options decision patterns, the survey was used to collect data regarding (1) perceived market and competitive uncertainty, and (2) firm strategic orientation. The sources for these scales and the analysis undertaken to establish their construct validity and reliability are described later in this section.

The initial survey instrument was subjected to detailed critical review by a panel of experts with experience in survey design and/or knowledge of real options. In addition to the members of the committee supervising this research, each of whom provided review and commentary, the expert panel consisted of five academics at four institutions, including a professor of finance knowledgeable about real options, one professor of organization studies with extensive survey research experience, and three professors in strategic management, one of whom has published extensively on the subject of real options. Panel members conducted a broad review of the draft survey instrument, including the conceptual coherence of the constructs, the clarity and appropriateness of the individual items and the design of the instrument as a whole.

A pilot test of the survey was then conducted with a group of executives similar in profile to the survey target population. A complement of 12 executives was enlisted to take the survey and to provide feedback on (1) the clarity of the individual items, (2) survey completion time, and (3) the overall format and structure of the survey. All were CEO’s or COO’s of their respective companies. Each of the firms was in a different industry. The companies represented a broad spread of firm size, ranging from approximately $30 million to $50 billion in annual revenue. In addition to taking the survey, participants in the pilot test responded to additional questions regarding the survey itself. Follow-up conversations were undertaken with approximately half of the pilot test respondents, either by telephone or in person. None of the pilot test respondents or their firms were included in the survey sample itself.

The pilot test resulted in substantial revisions to the survey instrument. These changes had the net effect of shortening the survey, eliminating specific items that the respondents found confusing, and clarifying ambiguous items. The pilot test also confirmed that the survey generated substantial variance across the 12 companies.

The final survey instrument resulting from these steps is contained in Appendix A.

4.2.1.2 Survey Administration

Limiting the survey to the most senior general managers in each company was considered crucial since only such executives could confidently be expected to be aware of the firm's overall resource allocation decision patterns. Extensive effort was required both to identify appropriate target respondents for each company in the research sample and to secure an adequate volume of responses to support the research. Target respondents for the survey were members of the top management team (TMT), typically the Chairman, CEO, President/COO or CFO. TMT members were identified from Dun and Bradstreet's *Million Dollar* and S&P's *Net Advantage* databases. The accuracy and currency of the data from these sources was checked for most companies by reference to company websites. In some cases, executives in other positions than those listed above were included in the survey (for example, senior group executives, chief planning and development officers, and chief technology officers) but only in those cases where company websites confirmed that these executives were members of the top management team. In a few cases, former or retired Chairman and CEO's were surveyed, but only in those cases where their departures were recent (2007 or later).

A multi-stage process was used to administer the survey over a period of five months. Two survey mailings were undertaken to CEO's and CFO's respectively. Response rates for both mailings were on the order of 2%. Additional efforts were undertaken to increase overall response rates, including (1) online and mail administration of the survey to members of various alumni networks (the Harvard Graduate School of Business Administration, the Smeal College of Business at Penn State University, the Amos Tuck School of Business at Dartmouth College and the University of Massachusetts Alumni Association), (2) direct contacts with specific executives based on prior relationships or other associations, and (3) a large-scale email campaign covering approximately 3000 executives in those firms that had not responded to previous survey rounds. After the initial survey mailings, data collection relied heavily on online administration of the survey, using the Qualtrics survey software. Where online administration was employed, multiple follow-ups to the initial approach were used to increase response rates (Dillman, 2007).

These data collection efforts yielded 173 usable unique company responses, representing a response rate of 12.6%. While this response rate is low in comparison with those generally considered desirable, it reflects the difficulty of securing research participation from top management in public companies and is consistent with response rates in other recent research entailing surveys of similar target respondents (Skaggs & Huffman, 2003; Skaggs & Youndt, 2004). Respondents included a very high proportion of the most senior executives in each of the firms. Table 4.1 summarizes respondents by position. Further, the respondent sample represents a broad range of industries. Table

4.2 summarizes the industry composition of both the survey population and the respondent sample, based on three-digit NAICS codes.

Table 4.1

Survey Respondents by Position

Position	Responses
Chairman/CEO	71
Chief Financial Officer	44
President/Chief Operating Officer	22
Group Executive	15
Senior Strategy/Corporate Development Officer	9
Chief Marketing Officer	3
Chief Technology Officer	1
Other TMT Members (Senior and Executive VP)	8
TOTAL	173

4.2.1.3 Scale Validation and Reliability

The survey data was factor analyzed to test the construct validity of the five real options decision patterns and to identify those survey items constituting scales of sufficient reliability. Both exploratory and confirmatory factor analyses were conducted. Exploratory factor analysis was deemed advisable given the newness of the survey instrument, the absence of previous scales for measuring real options-related constructs and the tentativeness of some of the constructs themselves. Stevens (1996) and Gorsuch (1983), however, stress that confirmatory factor analysis is an appropriate approach for validating measurement models when there is a pre-existing theoretical basis for

Table 4.2

Survey Population and Respondents by Industry

NAICS Code	Industry	Survey Population	Respondent Sample
311	Food Mfg	60	6
312	Beverage & Tobacco	18	3
313	Textile Mills	9	1
314	Textile Product Mills	4	0
315	Apparel Mfg	41	3
316	Leather & Allied Products	22	2
321	Wood Products	17	1
322	Paper Mfg	34	5
323	Printing & Related	18	3
324	Petroleum & Coal	20	4
325	Chemicals	197	20
326	Plastics & Rubber Products	39	2
327	Non-Metallic Minerals	19	1
331	Primary Metals	47	6
332	Fabricated Metal Products	50	11
333	Machinery Mfg	127	21
334	Computers & Electronics	373	38
335	Electrical Equipment	51	10
336	Transport Equipment	93	10
337	Furniture & Related	22	2
339	Miscellaneous Mfg	85	18
511	Publishing	29	6
	TOTAL	1375	173

specifying factor structure. Since this research was guided by a predefined theoretical framework, confirmatory factor analysis was also performed.

In the exploratory analysis, factors were extracted using the principal components method based on eigenvalues over 1. The resulting factors were then subjected to varimax rotation to derive a final factor structure. In the rotated factor results, only loadings of .600 or greater were considered significant. Reliability analysis was performed on the resulting scales, using Cronbach's alpha, with a minimum target reliability of .7 (Nunnally, 1978). Each scale was item-analyzed to maximize the internal consistency of the items, and items were removed as necessary to achieve acceptable alpha (Spector, 1992). The results of this analysis are described below. For reference, Appendix B contains the rotated factor solution and scale reliabilities for the real options decision patterns.

Factor analysis strongly supported three of the five real options constructs defined in the theory development underlying this research: staging, operating flexibility and platform investments. For staging, four of the six survey items designed to test the construct loaded heavily on a single factor. Further, the absence of significant cross-loadings for these items indicated that they were factorially pure and divergent from the other real options constructs. Two of the original staging items did not load significantly on this factor, and were eliminated from the scale. Review of the conceptual foundation for these items in light of the factor analysis suggests that they in fact relate more to project discontinuation than to staging per se. As discussed further below, these items suggest the presence of an additional real options construct, not incorporated in this research, relating to project discontinuation. Based on the factor analysis results, a four item scale was retained for staging. The items are displayed in Table 4.3. Alpha for this scale is .742, and cannot be improved by further item reduction.

Similarly strong support was found for the operating flexibility construct. Four of the six survey items designed to measure operating flexibility showed loadings in excess of .600 on a single factor, again with no significant cross-loadings. The remaining two

Table 4.3

Real Options Decision Patterns Scale Items

Timing - Deferral	1. Our investment decisions take into account whether delaying a project may improve its attractiveness. 2. We postpone projects which meet our standard investment criteria in order to further monitor market developments.
Timing - Acceleration	1. If a project looks sound, we proceed with it rather than invest time and money to gather further information regarding its potential success. 2. In executing strategic investment projects, getting them done quickly is the most important consideration to us.
Staging	1. We break investment projects down into stages and evaluate whether or not to proceed at the end of each stage. 2. We revise project features (for example, capacity level or technology used) throughout the project. 3. We revise project schedules and implementation timing throughout the project. 4. We set project milestones and continuously evaluate progress toward them.
Operating Flexibility	When making investments in productive capacity, our company typically: 1. Invests in facilities that allow for easy changes in production levels. 2. Invests in facilities that allow for easy changes in product/service mix. 3. Invests in facilities that allow for easy changes in feedstocks or raw materials. 4. Places primary emphasis on the ability to easily change operating parameters.

(Continued Next Page)

Table 4.3 (Continued)

Real Options Decision Patterns Scale Items

Partial Commitment	In making investments in new activities, our company typically: 1. Acquires minority equity positions in other companies in the target product/service/market which can later lead to full acquisition. 2. Establishes joint ventures, partnerships or alliances.
Platform	Our company invests in projects that do not meet our standard financial criteria when they: 1. Offer future growth opportunities not captured in the project financial projections. 2. Generate important knowledge or experience. 3. Contribute to important competencies and capabilities. 4. Establish and early position in an attractive product or market. 5. Have the potential to yield multiple products/services rather than a single product/service.

survey items did not load significantly and were dropped from the scale. Conceptual review of these two items clarified this result, since both items relate to the pattern of capacity additions, rather than to operating flexibility per se. Accordingly, operating flexibility has been measured on the basis of four items (Table 4.3). Alpha for the scale is .721, and cannot be improved by further item reduction.

Five items were included in the survey to measure investments and resource commitments which do not provide immediately attractive financial rewards but which provide a platform for future growth opportunities (Table 4.3). All the items loaded heavily on a single factor, with no significant cross loadings on other factors. These results indicated that the original platform scale was both internally consistent and sharply distinct from other real options sub-constructs. Alpha for the resulting five-item scale is .839, and cannot be improved by item reduction.

The remaining two real options constructs – timing and partial commitment – did not show the same degree of support from the factor analysis, and the scales for measuring them are of lower reliability than those discussed above. For the timing construct, five items were included in the survey. These items were intended to incorporate two competing aspects of timing in a single scale – deferral (three items) and acceleration (three items). The acceleration items were reverse coded for purposes of factor analysis. Contrary to expectations, however, the factor analysis separated these two aspects of timing into distinct constructs. The deferral items loaded heavily together, as did the acceleration items. There were no significant cross-loadings between the deferral and acceleration items. Interpreting these results, it was concluded that deferral and acceleration in fact represent distinct sub-constructs, and both have been employed in the subsequent analysis. Deferral has been measured by a two item scale (Table 4.3). The three acceleration items loaded together. However, reliability analysis indicated that alpha was materially improved by the elimination of one item, which was therefore dropped, resulting in a two item scale (Table 4.3). Reliabilities for these scales – alpha of .584 for deferral and .621 for acceleration – are lower than is desirable, but are considered minimally acceptable for use in the analysis.

The factor analysis similarly indicated that the six survey items designed to measure the partial commitment real options decision pattern do not constitute a single construct. Only two of the items loaded significantly together, with the other four spread over other factors. The resulting partial commitment scale (Table 4.3) is not strong, consisting of only two items with low reliability (alpha of .540) and not fully tapping the intended conceptual boundaries of the construct.

Exploratory factor analysis suggested the presence of two additional real options constructs not contemplated in this research that are worthy of further consideration. First, three items relating to project discontinuation or reversal loaded significantly on a single factor. Since discontinuation is widely regarded as an important element of real options theory (Adner & Levinthal, 2004a & 2004b), an abandonment construct is conceptually appealing. Second, three items relating to gradualism or small scale, reversible entry decision patterns loaded significantly on a single factor, suggesting that "toehold" may represent an additional construct of interest. In neither case, however, did the items constitute reliable scales and have therefore not been further developed in this research.

Table 4.4 summarizes the characteristics of the final scales for measuring real options decision patterns.

Confirmatory factor analysis was conducted on the scales derived from exploratory factor analysis and reliability testing, using LISREL 8.8. Confirmatory factor analysis of the real options decision patterns was complicated by the limited number of items associated with some of the real options constructs. Three of the constructs (deferral, acceleration and partial commitment) are measured by two-item scales. Since LISREL does not permit latent variables with fewer than three observed variables, it was not possible to directly test these scales in LISREL. Two analyses were performed

Table 4.4

Scale Characteristics – Real Options Decision Patterns

Decision Pattern	Number of Items	Cronbach's Alpha
Timing (Deferral)	2	.584
Timing (Acceleration)	2	.621
Staging	4	.742
Operating Flexibility	4	.721
Partial Commitment	2	.540
Platform	5	.839

in order to derive as representative a picture of overall model fit as possible given this constraint.

First, LISREL was run including only the three real options constructs with three or more items (staging, operating flexibility and platform). Table 4.5 displays the resultant goodness of fit statistics. The four fit indicators shown are those recommended by Kline (2005), including (1) normed chi-square (minimum fit chi-square divided by degrees of freedom), (2) comparative fit index (CFI), (3) the 90% confidence interval for the root mean square error of approximation (RMSEA), and (4) the standardized root mean square residual (SRMR). For each indicator the table displays Kline's (2005) suggested guidelines for goodness of fit.

The analysis shows good fit for the three-construct analysis (Column 1 of Table 4.5). Normed chi-square, CFI and RMSEA are all well within generally accepted guidelines. Further, the path diagram indicates that all item/construct paths are significant to the .001 level. Hence, this partial analysis demonstrates good fit for that portion of the real options decision pattern model that can be directly evaluated in LISREL.

Table 4.5

Summary of Real Option Decision Pattern Fit Statistics

	Guideline (Kline, 2005)	Column 1: Excluding 2-Item Constructs	Column 2: Expanded Items
Normed Chi-Square	< 3*	1.894	1.814
Comparative Fit Index	≥ .9**	.933	.856
Root Mean Square Error Of Approximation (Upper Bound)	≤ .08**	.092	.074
Standardized Root Mean Square Residual	≤ .10**	.085	.102

Additional LISREL analysis was undertaken to estimate indirectly the fit of the other three real options constructs. In this second analysis, one additional item was included for each of the two-item constructs. These additional items were drawn from the initial item pool for each of the constructs. However, these items are extraneous in the sense that they did not survive exploratory factor analysis and reliability testing and were not therefore among the items included in the final scales. Hence, the added items were included in the analysis solely to permit evaluation on a basis as close as possible to the optimal two-item measurement scale. The rationale for this procedure was as follows: If the resultant sub-optimal model demonstrates acceptable goodness of fit, it would provide indirect but relevant evidence that the fit of the optimal model was at least as good.

The results are displayed in Column 2 of the table, indicating what appears to be marginally acceptable fit. Normed chi-square and RMSEA are well within guidelines, while SRMR and CFI are slightly outside them. While not definitive, these results provide a reasonable basis for expecting that the optimal measurement model incorporating two-item scales would demonstrate good fit.

4.2.2 Market and Competitive Uncertainty

4.2.2.1 Objective versus Perceived Environmental Uncertainty

Whether uncertainty is best measured based on objective metrics or perceptions has been a subject of long-standing and continuing discussion in the uncertainty literature.[13] Proponents of perceived environmental uncertainty measures point out that uncertainty, properly speaking, is not an attribute of the external environment but a psychological or cognitive state (Downey et al., 1975; Downey & Slocum, 1975; Miles, Snow & Pfeffer, 1974; Milliken, 1987). Organizations come to know environments only through perceptions, and therefore objective attributes have no inherent meaning until structured by a perceiver (Downey et al., 1975; Weick, 1969). Firms in the same industry can and do perceive uncertainly differently (Bourgeois, 1985; Downey & Slocum, 1975; Miles, Snow & Pfeffer, 1974).

Proponents of objective measures argue that industry attributes inherently affect the ability of firms to predict the future, independent of the perceiver (Hrebiniak & Snow,

[13] Both perceived and objective approaches have been extensively used. Several long-standing and much used scales have been developed to measure perceived environmental uncertainty (Lawrence & Lorsch, 1967; Duncan, 1972; Miles &Snow, 1978). Similarly, a large body of empirical work has been based on objective uncertainty metrics, most notably that developed by Dess & Beard (1984).

1980; Jauch & Kraft, 1986; Tinker, 1976; Yasai-Arkedani, 1986). This objectivist view emphasizes the correspondence of perceived uncertainty to objective measures as important to successful management. Bourgeois (1978 & 1985), for example, studied the degree of correlation between perceived and objective uncertainty measures in relation to performance, and found that consistency between them was significantly and strongly correlated with firm financial performance.

Objectivists also point out several conceptual and methodological problems associated with using perceived uncertainty measures in strategic and organizational research. Perceived uncertainty measures, for example, are by definition based on individual perceptions and may not be representative of the larger organizational units in which individuals reside (Boyd et al., 1993; Buchko, 1994; Duncan, 1972). Such perceptions may be significantly affected by individual cognitive processes, behavioral response repertoires, social expectations and prior experiences, and may not therefore be consistent across individuals (Bourgeois, 1980; Downey & Slocum, 1975). Further, individual perceptions are conditioned by organizational factors such as level and position in the firm (Boyd et al., 1993; Yasai-Arkedani, 1986). Reliance on perceptual measures in the study of organizational behavior therefore raises issues regarding the correspondence between uncertainty as perceived by any one individual and the aggregate perceptions on which firm actions are based. Finally, there is some evidence that perceived measures of uncertainty are less stable over time than objective ones. Buchko (1994) reports poor test-retest reliability of perceived uncertainty scales, suggesting the time dependence of such measures. In the context of strategic research, time-stable measures of uncertainty are desirable.

Several notable attempts have been made to integrate or reconcile the perceived and objective approaches to conceptualizing and measuring uncertainty (Bourgeois, 1980; Boyd et al., 1993; Sharfman & Dean, 1991; Yasai-Arkedani, 1986). The general consensus of this literature has been to recognize that both approaches are relevant, depending on the research context in which they are used, and to emphasize the importance of selecting a measurement basis appropriate to the underlying research purpose. Perceived environmental uncertainty is generally regarded as best-suited in studying behavior, action and decision-making processes, while objective measures are appropriate for studying strategy content, constraints and outcomes (Bourgeois, 1980; Boyd et al., 1993; Snyder & Glueck, 1982). Insofar as the proposed research entails both relationships between uncertainty and behavior and relationships between uncertainty, behavior and performance, there is therefore support in the literature for using either perceived or objective measures for operationalizing uncertainty in this case.

In summary, an extensive review of the literature did not clearly establish the superiority of either approach in the specific context of this research. It was therefore decided to use both objective and perceived measures of uncertainty. Since the research examines the relationship between decision patterns and performance, objective measures were considered appropriate. At the same time, perceived uncertainty is a direct reflection of the bases on which decisions are made, which arguably makes it relevant for studying the relationships between uncertainty and real options decision patterns.

4.2.2.2 Perceived Market (PMU) and Competitive Uncertainty (PCU)

Data regarding perceived environmental uncertainty was collected in the survey instrument. A number of perceived uncertainty scales have been developed by other researchers, some of which are structured on the basis of specific sources of uncertainty, as required by the present research (Buchko, 1994; Daft et al. 1988; Desarbo et al, 2005; Kumar & Seth, 1998; Miles & Snow, 1978; Sutcliffe & Zaheer, 1998). After reviewing the relevant scales, I selected that developed by Desarbo et al. (2005) as the basis for the survey items because of the compactness of the scale and the conceptual proximity of the items to the market and competitive uncertainty constructs as defined in this research. The items were adapted to make the scale more compact, to shorten the items, and to link them more directly to the market and competitive uncertainty constructs. Three items were used to measure perceived market uncertainty (PMU) and five for perceived competitive uncertainty (PCU). The items were structured on a seven-point Lickert scale measuring perceived degree of predictability.

The perceived uncertainty items were factor-analyzed, using the same procedures described earlier for the real options decision patterns. Rotated factor results and reliabilities are displayed in Appendix B for reference. The results support the construct validity of both PMU and PCU. In each case, all the survey items loaded significantly and exclusively on a single factor. For PCU, one item with a marginally significant loading of .539 was retained because of its theoretical importance in the construct. Alphas of the resulting scales are .630 for PMU and .756 for PCU. Scale items are displayed in Table 4.6.

Confirmatory factor analysis indicated a reasonably good measurement model fit for the perceived market and competitive uncertainty constructs. Normed chi-square (2.91) and SRMR (.067) were within guidelines and CFI (.894) close to the > .9

Table 4.6

Perceived Uncertainty Scale Items

Market Uncertainty	1. Customer demand for existing products/services is predictable/unpredictable. 2. Customer demand for new products/services is predictable/unpredictable. 3. Customer needs and desires are predictable/unpredictable.
Competitive Uncertainty	1. Competitor price actions are predictable/unpredictable. 2. Competitor changes in product/service quality are predictable/unpredictable. 3. Competitor changes in product/service technology are predictable/unpredictable. 4. Competitor introductions of new products/services are predictable/unpredictable. 5. The entry of new competitors is predictable/unpredictable.

guideline. However, the 90% confidence interval for RMSEA (.133) was clearly outside guideline, indicating poor fit for this measure. Item/construct paths were found to be significant to the .01 level for all three perceived market uncertainty items and to the .001 level for all four perceived competitive uncertainty items.

4.2.2.3 Objective Uncertainty Measures

The objective measures of uncertainty used in the research are rooted in the objective measurements of task environments developed by Dess & Beard (1984), with adjustments based on improvements and refinements introduced by subsequent authors. Drawing on prior work by Aldrich (1979) and others, Dess & Beard developed a scale for measuring task environment characteristics consisting of three dimensions: munificence, dynamism and complexity. Of these, the latter two are conceptually related to uncertainty (Castrogiovanni, 2002). In Dess & Beard's formulation, dynamism reflects the instability, lack of pattern and unpredictability of the task environment. They operationalized dynamism for 460 industry groups based on 4-digit SIC codes using measures of the variability (volatility) of sales, margins, employment and value-added over a ten-year period based on data from the U.S. Department of Commerce *Census of Manufacturers*. Since it reflects unpredictable variability in industry-level demand and margins, Dess & Beard's dynamism measure, with adjustments as described below, formed the basis for the objective measure of market uncertainty used in this research.

Dess & Beard's complexity dimension captures the degree of heterogeneity in the task environment, representing the range of external environment factors that must be monitored by the firm and to which it must respond. Managers facing complex, non-homogeneous environments will perceive greater uncertainty and experience greater difficulty in anticipating future developments than managers facing simple environments. Dess & Beard operationalized the complexity construct by a series of concentration measures, including sales, value-added, employment and number of establishments. Since their complexity measure is primarily related to industry structure, it approximates the competitive uncertainty construct required for this research.

Dess & Beard conducted extensive item and factor analysis to establish the reliability and construct validity of their scale. Other authors have confirmed their findings (Castrogiovanni, 2002; Rasheed & Prescott, 1987). Their task environment measures of uncertainty have been extensively used by other researchers in a variety of contexts (Bergh, 1998; Bergh & Lawless, 1998; Boyd, 1990; Carpenter & Fredrickson, 2001; Castrogiovanni, 2002; Keats & Hitt, 1988; Lawless & Finch, 1989; Sharfman & Dean, 1991; Subramaniam & Youndt, 2005).

4.2.2.3.1 Objective Market Uncertainty (OMU)

Following Dess and Beard, this research uses a volatility-based measure to operationalize market uncertainty. Conceptually, volatility measures enjoy strong legitimacy in the study of uncertainty. Tosi et al. (1973) maintain that volatility is a good proxy for uncertainty, since a high degree of variability implies low ability to predict and is thus convergent with the core uncertainty dimension of unpredictability. Downey et al. (1975) also regard volatility as a valid indicator of unpredictable and dynamic market conditions.

Volatility measures have been the most frequently used objective measures of uncertainty in strategic and organizational research. David & Han (2004), in their review of the empirical evidence for transaction cost economics, documented 23 different uncertainty metrics, the large majority of which were based on volatility measures. Volatility measures have also been used extensively in the real options empirical literature as measures of uncertainty. A number of real options studies use the volatility of stock price indices (Folta, 1998; Folta & Miller, 2002; Miller & Folta, 2002; Vassolo et al., 2004) or unit demand (Leiblein &Miller, 2003) as a measure of uncertainty for specific industries. Several multi-industry real options studies have used the volatility in industry gross domestic product as a measure of market uncertainty (Folta & O'Brien, 2004; O'Brien et al., 2003).

Following these authors, I have used the variability in the value of shipments as reported in the Department of Commerce *Annual Survey of Manufacturers* as the basis for operationalizing market uncertainty. The *Survey* reports annual shipment data by NAICS code. Data from the *Survey* was collected on the basis of six-digit NAICS codes, representing the finest level of industry disaggregation in the NAICS coding system.

Considerable effort was taken to select the appropriate time period for this measure. Since the real options survey implicitly measures current and recent decision behavior, a relatively contemporaneous measure of uncertainty is appropriate. At the same time, however, a larger number of data points yields a more stable measure. After careful consideration, I selected a five-year time horizon ending with the most recent year for which data was available in the *Annual Survey of Manufacturers* (2002-2006). Previous research provides support for this choice. While some studies focusing on long-term trends in environments have examined longer time periods (Castrogiovanni, 2002; Wholey & Britain, 1989), five years has been the most widely used analysis period in research that relates uncertainty to a current/recent dependent variable (Bergh, 1998; Bergh & Lawless, 1998; Bourgeois, 1978 & 1985; Boyd, 1990; Carpenter & Frederickson, 2001; Keats & Hitt, 1988; Leiblein & Miller, 2003).

Selection of the appropriate procedure for using the data as a measure of market uncertainty is a subject of importance to the research. A number of authors have pointed out that simple measures of variability do not equate with unpredictability (Bourgeois, 1978; Buchko, 1994; Downey & Slocum, 1975; Milliken, 1987; Yasai-Arkedani, 1986). To the extent that variance includes a systematic component, such as cyclical variation or trend, total volatility may include a predictable component that is not convergent with the uncertainty construct as it is defined in this research. Accordingly, a metric which de-trends the data is required. Bourgeois (1978 & 1985) argues for using the coefficient of variation of first differences, a procedure that measures variations in the year-to-year rate of change. A high coefficient of first differences indicates unpredictability. Dess & Beard (1984) calculated their dynamism items as the standard error of the regression coefficient divided by the mean value of the data. Others have used the same procedure (Bergh, 1998; Bergh & Lawless, 1998; Boyd, 1990; Carpenter & Frederickson, 2001; Sharfman & Dean, 1991). Following the bulk of previous research, I have used the Dess & Beard metric. Thus, for each 6-digit NAICS code, a least-squares regression line was fitted to the annual value of shipments data, and the ratio of the standard error of the regression slope coefficient to the mean value of the data was derived. The resulting ratios were used as measures of market uncertainty, with a high ratio indicating greater variability around the base trend and therefore high market uncertainty.

4.2.2.3.2 Objective Competitive Uncertainty (OCU)

There is a substantial literature supporting industry competitive structure as an appropriate basis for measuring competitive uncertainty. As described earlier, Dess & Beard's (1984) scale for task environment uncertainty defined the complexity dimension of the task environment primarily in terms of concentration measures. In their conceptualization, low concentration increases heterogeneity and increases the range of factors that contribute to unpredictability. Other authors, however, drawing on industrial organization theory and metrics, have argued that concentration alone is only a partial measure of competitive uncertainty. Boyd (1990), for example, maintains that both the number of competitors and the distribution of their market shares are important contributing factors. Relatively few competitors with highly concentrated shares make it easier to monitor and anticipate competitor actions. Such industry structures also increase the likelihood of coordinated action among firms, thereby increasing predictability. At the extreme, complete monopoly entails no competitive uncertainty.[14] By contrast, industries characterized by a large number of competitors have greater potential for unexpected or disruptive action by one or several firms. Where market shares are widely distributed, there is less potential for a few dominant firms to exert oligopolisitic market control. Furthermore, industries with dispersed market share structures are frequently characterized by intense competitive rivalry, increasing the potential for unpredictable competitor actions (Porter, 1980 and 1985).

Based on this theoretical foundation and the supporting literature, I have used a measure of competitive structure that encompasses both the number of competitors and dispersion in market shares as the basis for operationalizing competitive uncertainty. There is substantial agreement that the Herfindahl/Hirschman (H-index) is the best composite measure of these two dimensions of industry structure (Boyd, 1990; Porter, 1980; Schmalensee, 1977). The H-index is the sum of the squared market shares of all firms in an industry group. Normalized, it varies between zero (representing perfect competition) and one (representing total monopoly). Hence a low H-index indicates a competitive structure consisting of numerous competitors and highly dispersed market shares. In the context of this research, H-index is therefore inversely related to competitive uncertainty. H-index has become increasingly prominent in strategy research (Acar & Sankaran, 1999). A number of studies have used H-index or related measures to represent competitive uncertainty (Boyd, 1990; Subramaniam & Youndt, 2005).

[14] A number of authors have suggested that the relationship between industry structure and competitive uncertainty is not linear (see Boyd, 1990 for relevant citations). In this view, competitive uncertainty does not increase monotonically with number of competitors, but instead declines as industry structure approaches perfect competition. Given the rarity of perfectly competitive industries, however, the practical importance of this effect is unclear.

H-index data was collected from the Department of Commerce *Census of Manufacturers*, which reports H-Index data by NAICS code at five year intervals. The most recent available year (2002) was used. Data was collected on the basis of 6-digit NAICS codes so as to be consistent with the operationalization of market uncertainty as described earlier. Since a low H-index reflects a large number of competitors and therefore high competitive uncertainty, the H-index data was reversed (1 – H-Index) to derive the objective measure of competitive uncertainty employed in the analysis.

4.2.3 Firm Performance

The research includes multiple measures of firm performance, consistent with the recognition that performance is a multi-dimensional construct, with individual measures reflecting different aspects of performance (Chakravarthy, 1986; Venkatraman & Ramanujam, 1986). All the measures employed are objective and were derived from secondary sources so as to avoid the danger of self-report and common methods bias associated with survey based, perceptual performance data.

Performance measures have been selected so as to maintain the strongest possible conceptual linkage to the real options construct. Real options theory suggests, for example, that making decisions on the basis of options reasoning will improve the efficiency of capital use by selectively limiting exposure to downside risk and taking advantage of upside potential. I have selected return on assets (ROA) as the best widely available aggregate measure of capital efficiency. ROA is widely used in performance analysis in strategy research (see Bowman & Helfat, 2001, for a review of ROA in strategy research). ROA was calculated as net income divided by average total assets.

The average of the most recent three year ROA data (2005-2007) was used in order to reduce the potential for anomalous effects in any single year.

Measures of capital efficiency do not, however, capture the growth dimension of firm performance, which is also central to the real options construct. As described in Chapter 2, emphasis on identifying and capturing options for future growth is one of the conceptual foundations of real options theory, suggesting that firms that make decisions consistent with the theory can achieve higher sustained levels of growth than other firms in the same industry that do not. To capture the growth dimension of firm performance, compound annual revenue growth rate over five years (2003-2007) has been selected as a second performance indicator (GR).

Finally, real options theory is explicitly a framework for maximizing firm value, making the inclusion of a value-based performance measurement appropriate in this research. To capture the value enhancement dimension of real options theory, the research includes a measure of market value relative to book value for fiscal year 2007 as a third measure of performance. Metrics that relate market value to accounting book value are well-established in both the real options and broader strategy literatures (Folta & O'Brien, 2004; Hambrick & Cannella, 2004; Hawawini et al., 2003; Nayyar, 1993; O'Brien, 2003; Tuschke & Sanders, 2003). As noted earlier, many authors have cited the excess of market value over book value as in indicator of option values (Folta & O'Brien, 2004; Myers, 1977).

The specific measure employed to quantify the relationship between market value and book value is an adaptation of the traditional market value to book value ratio. Approximately 5% of the companies in the research population were found to have negative book net worth, such that the ratio of market value to book value yields an uninterpretable negative result. Further, for companies with very small book net worth, the calculation yields a deceptively high apparent performance result due entirely to the small denominator. For these reasons, a variant of the market-to-book ratio (MTB) was developed which relates the difference between market value and book value to market value. The specific formula for this adapted ratio is as follows:

$$\frac{\text{Market Value of Equity} - \text{Book Value of Equity}}{\text{Market Value of Equity}}$$

This specification is conceptually equivalent to the traditional market-to-book ratio, but avoids negative numbers and the artificially high results associated with small book net worth.

The most recent fiscal year was used for the MTB variable in lieu of a multi-year average. Unlike profitability measures, which are inherently periodic in character, market-to-book is a cumulative measure of performance, and the most recent available data best reflects the cumulative impact on firm value of the resource allocation decisions made in previous years.

Data for all three performance indicators was obtained from the *Mergent* and *Compustat* databases, which are the principal sources of individual company financial data.

Although each of the three performance measures represents a conceptually distinct dimension of performance, it is possible that they together represent a single construct. To test this possibility, an exploratory factor analysis was performed to test for the existence of an overall performance construct. This analysis clearly confirmed growth as a distinct performance dimension. ROA and MTB emerged as one factor. However, reliability for the combined measure was unacceptably low (alpha = .17). Accordingly, the three performance measures have been retained as separate dimensions of firm performance in the analysis.

4.2.4 Control Variables

In addition to the main research variables described above, four control variables have been included in the analysis.

The first is firm size. Studies have shown that firm size can systematically affect a range of strategic and performance variables (Huselid, 1995; Keats & Hitt, 1988). While there is no empirical evidence that firm size influences real options decision patterns, it is plausible to expect that size may be correlated with the sophistication of resource allocation decision processes in general and with the incidence of specific patterns of decision making. For these reasons, firm size, as measured by the natural log of fiscal year 2007 total assets, has been used as a control variable. Measuring size on the basis of assets, rather than other bases such as revenues or employment, was considered appropriate in research regarding capital investment decisions.

A second control variable was incorporated to capture differences among companies in capital intensity. It is well-established in the literature that real options decision-making is particularly relevant in industries/firms characterized by large fixed asset investment requirements (Merton, 1998; Triantis & Borison, 2001). Variations among companies in capital intensity may therefore be influential in real options decision patterns. For this reason capital intensity at the company level has been incorporated in the analysis, using the ratio of fixed assets (net property, plant and equipment) to total revenues for fiscal year 2007 as a suitable measure.

A third control variable was used to incorporate strategic differences among companies. Not all companies respond to uncertainty in the same way. Firm-specific strategic factors are likely to influence the relative emphasis placed on the various real options decision patterns examined in this research. Jauch & Kraft (1986) point out that some companies adopt a strategic posture aimed to reduce environmental uncertainty while others seek to capitalize on it as a source of opportunities. Miles & Snow (1978) identified four distinct strategic types, each of which is characterized by a different pattern of strategic response to environmental uncertainty. Recognizing that strategy may represent an intervening variable between environmental uncertainty and real options decision patterns, a measure of strategic orientation has been incorporated as a control variable in the analysis.

Data on strategic orientation was collected in the real options survey instrument. Conceptualization of strategic orientation was based heavily on the Miles & Snow (1978) strategic typology, since many of the dimensions of their typology are convergent with real options theory, including breadth of product domain, degree of orientation to growth opportunities, extent of innovation leadership, receptiveness to change, flexibility and technology diversity. A number of existing scales for quantifying the Miles & Snow strategic types were identified (Conant et al., 1990; DeSarbo et al., 2005; Segev, 1987; Thomas & McDaniel, 1990). After careful consideration, the Segev (1987) scale was selected as the basis for this analysis for three reasons: (1) the scale is more compact than others examined; (2) it is structured in the Lickert-scale format used in the real options survey; and (3) it displayed good reliability (alpha = .82). The scale was adapted for purposes of this research. The principal adaptation was to limit the scale to the "prospector" strategic type. Whereas previous operationalizations of the Miles & Snow typology were designed to categorize companies by type, the analysis process used in this research required a continuous variable reflecting strategic orientation. Using a single type as the basis for the scale resulted in such a measurement, in effect reflecting degree of similarity with the prospector type. Segev's scale was also reduced in item count to meet the space limitations of the survey and to focus the items on real options decision patterns.

Exploratory factor analysis was conducted on the resulting items. All but one of the prospector items loaded significantly as a single factor. The final five item scale (Table 4.7) displays good reliability (alpha = .759). The rotated factor solution and reliability analysis for strategic orientation is displayed in Appendix B for reference.

Table 4.7

Strategic Orientation Scale Items

1. Our firm leads the industry in innovation.
2. Our firm's product domain is periodically redefined.
3. Our firm believes in being "first-in" in the industry in the development of new products.
4. Our firm responds rapidly to early signals of opportunity in the environment.
5. Our firm quickly adopts promising innovations.

Finally, control variables have been incorporated reflecting industry-level performance. There is substantial evidence of significant performance differences among industries, based on different economic structures and industry conditions (Hansen & Wernerfelt, 1989; Hawawini, Subramanian & Verdin, 2003; McGahan & Porter, 1997; Powell, 1996; Rumelt, 1991; Schmalensee, 1985). For this reason, industry-level controls on performance are common in strategy research. Since the proposed research entails comparative performance analysis of companies in a wide range of industries, controlling for industry-level effects is necessary in testing the relationship between real options behavior and performance. Accordingly, data for the three performance measures described above were derived for each industry represented in the survey population and incorporated as a control variable.

Since industry level data is not directly available for all three performance indicators used in this research, the required data was developed specifically for this study based on the total population of 1375 companies included in the survey. Sixty-two of the companies were excluded from this analysis for one of the following reasons: (1) the company has ceased to exist since the time the population was first established, typically because of acquisition, and performance data was unavailable in the source databases; (2) the company's NAICS code has been changed, such that it is no longer in the manufacturing sector; or (3) data for the company was too old (defined as no data more recent than fiscal year 2005). Excluding these companies, 1313 firms were included in developing performance control data. Each of the three performance metrics were calculated for each company in the population, using the same data sources, calculation procedure and time periods described earlier for the survey sample. Data for the individual companies were then aggregated based on 3-digit NAICS code, and simple average performance data calculated for each code. Extreme outliers (defined as data lying more than two inter-quartile ranges outside the upper and lower quartiles) were eliminated in developing these averages.

Table 4.8 presents descriptive statistics and correlations for all variables used in the analysis of uncertainty and real options decision patterns. Table 4.9 displays the same data for all variables used in the analysis of real options decision patterns and performance.

4.3 Threats to Validity

4.3.1 Common Methods Bias

This research relied partially on perceptual data collected via survey. Real options decision patterns, which constitute the dependent variables in the first stage of the research (the relationships between environmental uncertainty and real options behavior) and independent variables in the second stage (the relationships between real options behavior and performance) were derived from perceptual measures. Perceptual measures were also used as one approach to measuring market and competitive uncertainty, which are the key independent variables in the first stage of the analysis, and for the strategic orientation control variable. Although the survey respondents consisted of senior executives with presumably a thorough understanding of their firms and the business environments in which they operate, the use of perceptual measures raises the concern that common methods bias is present in the analysis (Pedhazur & Schmelkin, 1991). Recognizing this danger, a number of design techniques were employed to ensure that artificial methods-related variance did not influence the results of the research.

Table 4.8: Stage 1 Analysis Descriptive Statistics and Correlations

	Mean	Std Dev	Deferral	Accel	Staging	OpFlex	PartCom	Platform	PerMU	PerCU	ObjMU	ObjCU	PMUxCU	OMUxCU	LogAss	CI Index
Deferral (DEF)	4.857	1.106														
Acceleration (ACC)	3.581	1.445	-.212(**)													
Staging (ST)	5.138	1.090	.251(**)	-.237(**)												
OpFlex (OF)	4.464	1.026	0.045	.207(**)	0.101											
PartCom (PC)	3.599	1.435	-0.033	0.013	-0.027	-0.028										
Platform (PLAT)	4.143	1.254	0.115	0.079	0.050	.213(**)	.181(*)									
PerMU (PMU)	3.513	0.984	-0.074	-0.020	.151(*)	0.059	0.007	-0.087								
PerCU (PCU)	3.802	1.012	-.202(**)	-0.046	0.014	-0.032	0.039	-0.116	0.088							
ObjMU (OMU)	0.017	0.011	-0.011	0.055	0.003	0.034	-0.138	-0.011	0.068	0.142						
ObjCU (OCU)	0.927	0.062	-0.114	0.025	-0.074	0.041	-0.023	-0.084	-0.020	0.051	-.292(**)					
PerMUXCU	0.094	1.008	0.013	0.137	-.207(**)	-0.025	0.063	0.083	-0.088	-0.137	-0.072	-0.035				
ObjMUXCU	-0.291	1.274	-0.032	-0.026	-.163(*)	-0.013	-0.060	-0.070	-0.028	0.022	-.355(**)	.198(*)	-0.005			
LOG Assets (Size)	7.106	1.848	0.049	-.201(**)	0.121	0.050	-0.008	0.019	-.198(**)	-0.053	0.048	-.252(**)	0.107	0.009		
CI Index (CI)	0.213	0.197	0.025	-0.112	0.123	-0.128	0.147	-0.143	0.026	-0.121	0.079	-.157(*)	-0.016	-.226(**)	.370(**)	
Strategy (SO)	4.697	1.006	.171(*)	0.015	.275(**)	.227(**)	0.052	.322(**)	-0.082	-0.017	0.024	0.022	-0.038	-0.012	.168(*)	-0.019

** Correlation significant at the 0.01 level (2-tailed).
*Correlation significant at the 0.05 level (2-tailed).

Table 4.9: Stage 2 Analysis Descriptive Statistics and Correlations (Continued on next page)

	Mean	Std Dev	Defer	Accel	Staging	OpFlex	PartCom	Platform	PerMU	PerCU	ObjMU	ObjCU	ROA	MTB	Growth
Deferral (DEF)	4.857	1.106													
Accleration (ACC)	3.581	1.445	-.212(**)												
Staging (ST)	5.138	1.090	.251(**)	-.237(**)											
OpFlex (OF)	4.464	1.026	0.045	.207(**)	0.101										
PartCom (PC)	3.599	1.435	-0.033	0.013	-0.027	-0.028									
Platform (PLAT)	4.143	1.254	0.115	0.079	0.050	.213(**)	.181(*)								
PerMU (PMU)	3.513	0.984	-0.074	-0.020	.151(*)	0.059	0.007	-0.087							
PerCU (PCU)	3.802	1.012	-.202(**)	-0.046	0.014	-0.032	0.039	-0.116	0.088						
ObjMU (OMU)	0.017	0.011	-0.011	0.055	0.003	0.034	-0.138	-0.011	0.068	0.142					
ObjCU (OCU)	0.927	0.062	-0.114	0.025	-0.074	0.041	-0.023	-0.084	-0.020	0.051	-.292(**)				
ROA	5.319	9.138	0.033	-0.032	0.021	0.065	-0.067	0.021	-.163(*)	0.028	0.087	0.092			
Mkt-To-Bk (MTB)	0.558	0.417	0.030	-0.072	-0.025	0.074	0.024	0.023	-0.011	-0.005	-0.001	-0.122	0.095		
Growth (GR)	11.623	16.835	0.044	0.042	0.068	0.006	.183(*)	0.073	-0.061	0.023	0.011	0.066	0.087	0.111	
PCUxDef	-0.202	1.062	0.078	0.004	0.011	-.177(*)	0.047	-0.075	0.012	0.017	-0.035	-0.022	-.166(*)	-0.014	-0.137
PCUxAcc	-0.046	1.123	0.002	0.032	-0.094	-0.108	-0.048	0.129	0.119	-0.107	-0.027	-0.013	0.034	0.023	-0.073
PCUxStag	0.014	1.088	0.009	-0.098	0.133	0.120	0.050	-0.123	-.195(*)	0.075	-.188(*)	0.116	-0.006	-0.064	-0.033
PCUxOpFl	-0.032	1.116	-.171(*)	-0.110	0.118	0.057	-0.018	0.047	-0.028	0.129	0.006	-0.081	0.053	.189(*)	-0.056
PCUxPartCom	0.039	0.939	0.052	-0.057	0.057	-0.021	0.082	0.036	0.071	0.039	-0.014	-0.077	-0.027	0.136	0.051
PCUxPlatform	-0.116	1.097	-0.068	0.134	-0.122	0.051	0.028	0.122	0.078	-.180(*)	0.007	-0.051	-0.076	0.083	-0.083
OCUxDef	-0.115	0.869	0.151	-0.120	0.084	0.110	0.055	-0.077	-0.062	-0.024	-0.046	.323(**)	0.053	-0.023	0.052
OCUxAcc	0.025	0.876	-0.117	0.139	-0.088	-0.008	-0.087	-0.060	0.018	-0.016	-0.037	.287(**)	-0.125	-0.118	0.001
OCUxStag-	0.074	0.923	0.077	-0.083	.244(**)	0.010	0.103	0.033	0.100	0.137	-.232(**)	0.146	-0.022	.266(**)	0.003
OCUxOpFl	0.041	0.873	0.109	-0.010	0.010	0.085	-0.017	-0.018	-0.115	-0.104	-0.017	-0.064	0.033	-0.121	-0.027
OCUxPartCom	-0.023	0.969	0.049	-0.079	0.098	-0.015	0.071	0.076	0.068	-0.075	-0.074	0.141	-0.070	-.281(**)	-0.008
OCUxPlatform	-0.084	0.862	-0.073	-0.062	0.037	-0.018	0.084	0.100	0.027	-0.063	-0.100	.255(**)	0.065	-.319(**)	0.022
LOG Assets	7.106	1.848	0.049	-.201(**)	0.121	0.050	-0.008	0.019	-.198(**)	-0.053	0.048	-.252(**)	.167(*)	.264(**)	0.042
Control ROA	4.403	2.596	-0.088	-0.101	-0.135	-0.057	0.042	-0.031	-0.101	-0.050	0.095	-0.049	0.142	-0.013	0.064
Control MTB	0.470	0.182	0.061	0.037	0.087	0.034	0.052	0.016	-0.060	0.012	-0.115	-0.016	0.042	0.109	0.105
Control GR	11.948	4.273	0.015	-0.003	.152(*)	0.037	0.043	-0.127	-0.040	0.063	.236(**)	0.087	0.033	0.044	.242(**)

**Correlation significant at the .01 level (2-tailed)
*Correlation significant at the .05 level (2-tailed)

Table 4.9 (Continued): Stage 2 Analysis Descriptive Statistics and Correlations

	PCUxDef	PCUxAcc	PCUxSt	PCUxOF	PCUxPC	PCUxPla	OCUxDef	OCUxAcc	OCUxSt	OCUxOF	OCUxPC	OCUxPla	LOGAss	ConROA	ConMTB
Deferral (DEF)															
Accleration (ACC)															
Staging (ST)															
OpFlex (OF)															
PartCom (PC)															
Platform (PLAT)															
PerMU (PMU)															
PerCU (PCU)															
ObjMU (OMU)															
ObjCU (OCU)															
ROA															
Mkt-To-Bk (MTB)															
Growth (GR)															
PCUxDef															
PCUxAcc	-.156(*)														
PCUxStag	0.122	-.317(**)													
PCUxOpFl	-0.129	0.027	0.066												
PCUxPartCom	0.057	0.067	0.078	0.002											
PCUxPlatform	0.128	0.136	-.158(*)	.259(**)	.275(**)										
OCUxDef	0.018	0.012	0.035	-0.109	-0.042	-0.021									
OCUxAcc	0.024	0.074	0.020	-0.091	-0.113	0.013	-0.016								
OCUxStag	0.020	0.015	0.007	0.058	0.143	0.055	.306(**)	-0.022							
OCUxOpFl	-0.100	-0.088	0.064	-0.018	-0.084	-0.088	-0.033	.225(**)	0.073						
OCUxPartCom	-0.045	-0.085	0.114	-0.062	0.076	-0.073	-0.055	0.068	-.189(*)	0.084					
OCUxPlatform	-0.028	0.004	0.069	-0.097	-0.085	0.106	.236(**)	.241(**)	0.098	.193(*)	0.141				
LOG Assets	-0.054	-0.151	0.082	.200(*)	-0.005	-0.088	0.022	-0.093	0.030	-0.058	-0.129	-0.118			
Control ROA	-0.046	-0.099	0.083	0.101	-0.033	-0.032	-0.089	-0.131	-0.045	.191(*)	-0.071	0.061	.283(**)		
Control MTB	0.048	-0.088	-0.068	0.093	-0.011	-0.002	-0.044	-0.030	0.058	0.110	0.027	-0.048	0.041	-.239(**)	
Control GR	0.020	-.188(*)	-0.004	0.130	-0.039	-0.021	0.037	0.023	-0.068	-0.064	0.056	-0.043	0.040	0.080	.407(**)

**Correlation significant at the .01 level (2-tailed)
*Correlation significant at the .05 level (2-tailed)

The threat posed by common methods bias can be reduced by gathering data from a variety of sources (Kerlinger, 1996). Accordingly, I used objective data wherever possible. This includes all performance data, which is exclusively objective, and measures of market and competitive uncertainty, which were developed on the basis of both perceived and objective data.

Where it was not possible to base variables on objective data, a number of design techniques were employed to minimize the potential for methods bias. Following Podsakoff et al. (2003), these techniques relate to both survey design and data collection. First, the specific purpose of the research was carefully excluded from both the presentation of the survey and the individual survey items. Neither the terminology nor the concept of real options appeared in the survey itself or the accompanying materials sent to respondents. This complete masking of real options as the subject of the research reduced the danger of methods bias in several ways. First, it avoided the priming effects which could influence the pattern of responses if the subject domain were known and reduced the potential for respondents to bias their responses in order to appear consistent with real options theory. Further, cloaking the specific relationships under study minimized the potential for percept-percept bias, by which respondents anticipate the relationships under study and respond in accordance with their preconceptions regarding those relationships.

Second, every effort was made create physical and psychological separation between different classes of variables in the survey instrument. Survey items regarding market and competitive uncertainty were placed in a separate section of the survey from the real options decision patterns. A different response pattern was used for real options decision patterns (agree/disagree) and uncertainty (predictable/unpredictable). Reverse-scored items were incorporated in the survey to protect against acquiescence effects whereby respondents answer equally and positively to all items.

In addition, the strong assurances of confidentiality given to respondents minimized the potential for response bias. The survey did not request any information regarding the identity of the respondent or the firm, thus creating a strong aura of anonymity for respondents and reducing the potential for desirability-biased responses (Podsakoff et al., 2003).

Complex or ambiguous constructs are especially susceptible to methods bias (Podsakoff et al., 2003). Accordingly, considerable care was taken to derive items which were (1) free of emotive or cuing language, (2) concise and simply-worded, (3) unambiguous, and (4) free of specialized terms not familiar to respondents. Both the expert panel review and executive pilot test described earlier assisted in this item clarification process, resulting in extensive improvement to the instrument along these lines.

Finally, the underlying design of the research project as a whole reduced the danger of percept-percept bias, which can occur when both dependent and independent variables are based on respondent perceptions (Kerlinger, 1986; Subramaniam & Venkatraman, 1998). In such cases, there is the danger that respondents will anticipate the hypothesized relationships that the researcher seeks to test and respond in a manner consistent with those relationships. The potential for such bias is deemed low in this research given the relatively large number of variables and the interactive nature of the research hypotheses, making it highly unlikely that respondents could intuit the nature of the relationships under study.

4.3.2 Sample Bias

The validity of the study results depends on having an unbiased sample of the total research population. In the present research, two potential sources of sampling bias merit attention. The first is the possibility that the respondent companies are systematically different in the primary study variables from the research population as a whole. Even when the sampling procedure is ideally random, such differences may exist if certain classes of companies (for example, based on size, industry or performance) are more likely to respond than others. The second potential source of bias derives from the methods used in the data collection process. The use of multiple data collection strategies, especially convenience sampling on the basis of affiliation, raises the possibility that responses received as a result of these strategies introduced bias in the resulting sample. In particular, graduates of the Harvard Business School (HBS) account for 93, or approximately 54% of the total 173 respondent companies. Accordingly, analysis was conducted to determine if there was significant bias in the sample from either of these two sources.

To test for the presence of sample bias, the study sample was compared to the total survey population of 1375 companies on the basis of (1) company size (total assets), (2) industry composition, based on three-digit NAICS code, and (3) each of the three performance measures (ROA, MTB and GR). In each case a chi-squared test was performed to determine if there were significant differences between the population and sample distributions. Table 4.10 summarizes the results.

Table 4.10

Comparison of Sample and Population Distributions (Chi-Squared Significance)

Company Size (Total Assets)	.093 (.399)*
Industry	.312
Performance	
ROA	.466
MTB	.401
GR	.209

* Excluding companies with total assets in excess of $100 billion.

In no case did the analysis reveal significant differences. Only for company size did the differences between population and sample approach significance. Examination of the company size data indicated that total assets are lognormally distributed in the total population of companies surveyed, such that there is a relatively small group of very large companies. This “tail” of large firms is disproportionately represented in the respondent sample; of the seven companies with total assets of $100 billion or more in the survey population, five are included among the respondent companies. Further analysis revealed that these five companies had a potent effect on the chi-squared results. A revised analysis excluding the largest size class changed the chi-squared test results from $p = .093$ to $p = .399$. Based on this analysis I concluded that company size bias did not threaten the validity of the study results. This conclusion is reinforced by the use of company size (as measured by total assets) as a control variable in all the regression analyses, thus accounting explicitly for variance associated with company size.

Additional analysis was conducted within the respondent sample to further test for the presence of sampling bias between HBS graduates and other respondents. Using

ANOVA, means for the HBS and non-HBS sub-samples were compared for (1) market and competitive uncertainty, both perceived and objective, (2) capital intensity and (3) strategic orientation. The ANOVA results in all cases indicate no significant mean differences between the HBS and non-HBS sub-samples (Table 4.11). Based on both the chi-squared and ANOVA analyses, I concluded that the reliance on HBS graduates in the data collection process, while a departure from ideal standards of randomness, did not introduce significant bias into the study.

Table 4.11

ANOVA Analysis of HBS and Non-HBS Sub-Samples (P Value)

Main Independent Variables	
Perceived Market Uncertainty	.303
Perceived Competitive Uncertainty	.365
Objective Market Uncertainty	.971
Objective Competitive Uncertainty	.787
Control Variables	
Strategic Orientation	.931
Capital Intensity	.892

4.4 Analysis Methods

The hypothesized relationships were tested using hierarchical linear regression methods (Aiken & West, 1991). Separate analyses were performed for evaluating (1) the relationships between uncertainty and real options decision patterns and (2) the relationships between decision patterns, uncertainty and firm performance.

For the first analysis, an initial model was evaluated for each real option decision pattern individually, incorporating market and competitive uncertainty and three control variables (total assets, capital intensity and strategic orientation) as independent variables and the real options decision patterns as the dependent variable. A second model was analyzed in which the uncertainty/decision pattern interaction terms were added in order to test Hypotheses 1 through 5 by difference from the first model. Significant interactions were graphed to facilitate interpretation and presentation (Aiken & West, 1991). This analysis procedure was executed separately for perceived and objective measures of market and competitive uncertainty. An F-statistic of .05 or less was considered significant. However, given that the relationships examined in this research have not been previously studied empirically, findings which approach significance ($p > .05$ but $\leq .10$) have been noted and interpreted.

In the performance analysis, which entails a number of three way interactions between market uncertainty, competitive uncertainty and decision patterns, a three-step hierarchical regression procedure was used. The first step incorporated the six real options decision patterns, competitive and market uncertainty and two control variables (total assets and industry performance) as the independent variables and firm performance as the dependent variable. This model tested for the presence of significant main effect relationships between decision patterns and performance. A second model then introduced two-way interactions between market uncertainty and decision patterns and competitive uncertainty and decision patterns. Model 3 introduced the three-way interactions between market uncertainty, competitive uncertainty and decision patterns required to test the performance hypotheses. To facilitate interpretation, significant interactions were graphed using the procedures suggested by Aiken & West (1991) for three-way interactions.

This procedure was repeated for each of the three performance measures (ROA, MTB and GR). Further, the entire performance analysis was conducted for both perceived and objective uncertainty measures.

In both stages of the analysis, survey data was centered to facilitate the calculation and interpretation of interactions. Further, since the objective data for market and competitive uncertainty were expressed in different units, Z-scores were used for these variables in the regressions.

CHAPTER 5

RESULTS AND DISCUSSION

5.1 Relationships between Uncertainty and Real Options Decision Patterns

In the first stage of the analysis, I sought to establish that employment of six specific real options-theoretic decision patterns is systematically related to the relative presence of uncertainty regarding the level and composition of demand (market uncertainty) and uncertainty regarding the intentions and actions of competitors (competitive uncertainty). Table 5.1 summarizes the regression analysis results for this phase of the project, highlighting those instances where the change between model 1 and model 2 was found to be significant. The individual regression analyses are contained in Appendix C for reference. The results are reviewed below for each real options decision pattern.

Table 5.1

Summary of Model Results – Analysis of Uncertainty and Real Options Decision Patterns

		Model 1 P Value	Model 2 P Value	Model 2 ΔR^2	P Value ΔR^2
Deferral	Perceived	.033	.060	.000	.871
	Objective	.170	.253	.000	.799
Acceleration	Perceived	.146	.060	.022	.050
	Objective	.158	.241	.000	.897
Staging	Perceived	.000	.000	.035	.009
	Objective	.005	.002	.021	.049
Operating Flexibility	Perceived	.018	.032	.001	.709
	Objective	.033	.054	.002	.596
Partial Commitment	Perceived	.325	.315	.007	.263
	Objective	.081	.101	.005	.365
Platform	Perceived	.000	.000	.005	.327
	Objective	.000	.000	.010	.176

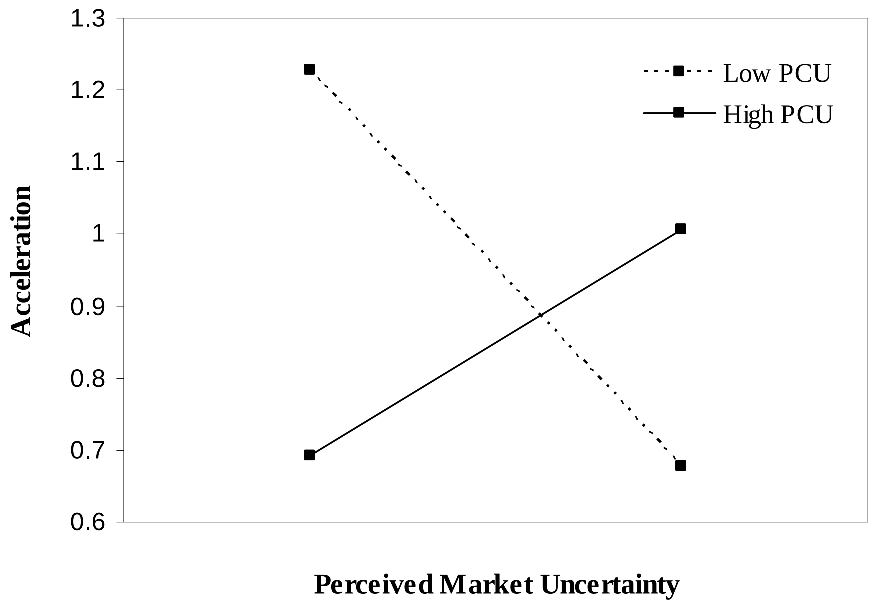
5.1.1 Timing

As described earlier, the real options timing construct was divided into two sub-constructs – deferral and acceleration – based on the results of factor analysis. Separate regression analyses were therefore performed for each of the sub-constructs.

Analysis of deferral using perceived uncertainty data revealed a significant ($b = -.213$, $p =.011$) negative main effect relationship between competitive uncertainty and deferral. This finding is consistent with theory, which suggests that competitive uncertainty discourages deferral, and therefore provides general support to the theory underlying H1a. However, no significant interaction between market and competitive uncertainty was found. Hence H1a is not supported on the basis of perceived uncertainty data. Replicating the deferral analysis using objective uncertainty data yielded no significant results for either model 1 or model 2 and therefore no support for H1a.

The analysis did find support for the hypothesized relationships between MU, CU and acceleration. Based on perceived uncertainty data, model 1 was not significant. Model 2, however, did find a significant relationship ($b = .217$, $p =.050$) between the MUxCU interaction and acceleration. To facilitate interpretation of this finding, the interaction was graphed. Following Aiken & West (1991), the regression equation was used to calculate values for acceleration at intervals of one standard deviation above and below the mean for both MU and CU. The plotted results are displayed in Figure 5.1, revealing a disordinal interaction between PMU and PCU in relation to acceleration. When PCU is low, acceleration shows a strong negative correlation with PMU. High PCU, however, changes the direction of the PMU/acceleration relationship. Thus H1b is supported on the basis of perceived uncertainty.

Figure 5.1: Acceleration PMUxPCU Interaction

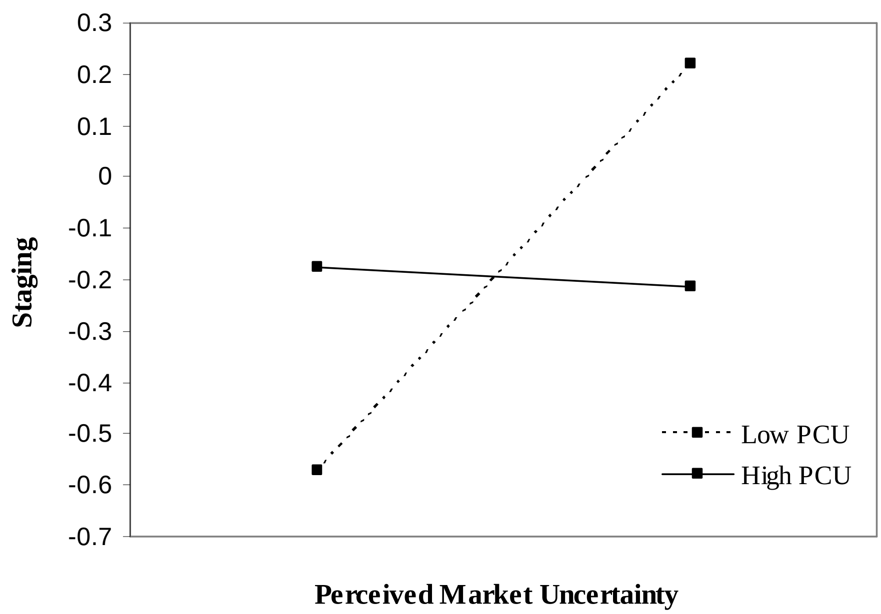


Evaluation of the same relationships using objective uncertainty measures did not detect any significant main effect or interaction relationships between MU or CU and acceleration. Hence, on the basis of objective uncertainty data, H1b is not supported.

5.1.2 Staging

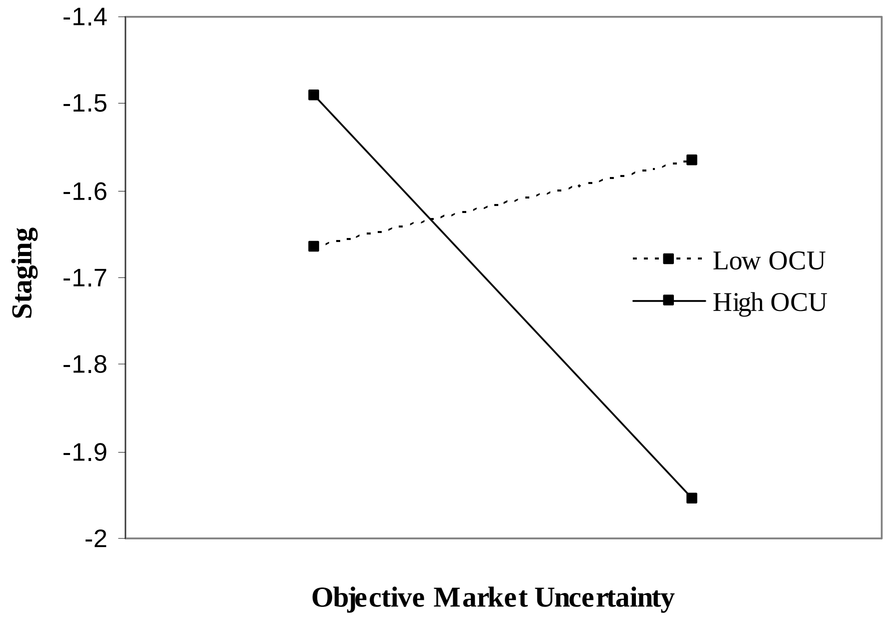
The analysis provided strong support for the hypothesized relationships between uncertainty and staging, both on the basis of perceived and objective uncertainty measures. Using perceived uncertainty data, model 1 revealed a significant ($b = .203$, $p =.015$) positive main effect relationship between market uncertainty and staging. More important, there is a highly significant ($b = -.208$, $p =.009$) relationship between the PMU/PCU interaction and staging in model 2. Graphic analysis of this interaction is consistent with the hypothesized relationships (Figure 5.2). When PCU is low, staging displays a strong positive relationship with PMU. This is consistent with theory, which anticipates that MU will induce staging in the absence of CU. When PCU is high, however, the PMU/staging relationship disappears. This result supports the expectation that competitive uncertainty will negatively moderate the relationship between market uncertainty and staging. Thus the analysis supports H2 based on perceived uncertainty.

Figure 5.2: Staging PMUxPCU Interaction



Analysis of staging using objective uncertainty data also supports H2. Model 1 detected no OMU or OCU main effects, but model 2 revealed a significant (b = -.140, p =.049) OMU/OCU interaction. A plot of this interaction (Figure 5.3) reflects the same relationship structure as did the perceived uncertainty regression. Thus the hypothesized moderating relationship between market uncertainty, competitive uncertainty and staging is supported on the basis of both perceived and objective uncertainty measures.

Figure 5.3: Staging OMUxOCU Interaction



5.1.3 Operating Flexibility

The regression analysis did not support the hypothesized relationship between MU, CU and operating flexibility. Using perceived uncertainty data, model 1 revealed no main effects linking operating flexibility to either PMU or PCU. The only significant main effects detected were a negative relationship between operating flexibility and the capital intensity control variable (b = -.839, p =.047) and a positive relationship with the strategic orientation control variable (b =.212. p =.006). Further, the hypothesized interaction between PMU and PCU was not significant. Hence, the analysis indicated no relationship, either direct or moderated, between PMU, PCU and operating flexibility. Replication of this analysis using objective uncertainty data also failed to reveal significant MU or CU main effects or interactions. Hence H3 is not supported either on the basis of perceived or objective uncertainty data.

5.1.4 Partial Commitment

As a result of the factor analysis, the partial commitment construct was more narrowly defined than in its original conception, and relates primarily to joint ventures, minority investments and alliances. The regression analysis did not provide support for the hypothesized relationship between partial commitments so defined and either MU or CU. Using perceived uncertainty measures, no significant PMU or PCU main effects were found, nor was the PMU/PCU interaction significant. Regression using objective uncertainty data produced the same result. As in the perceived uncertainty analysis, the OMU/OCU interaction was not significant. Hence there is no support for H4 from either the perceived or objective uncertainty regressions.

5.1.5 Platform Investments

As for partial commitments, regression analysis using perceived uncertainty measures revealed no significant main effect or interaction relationships between environmental uncertainty and platform investments. Thus H5 is not supported on the basis of perceived uncertainty. The regression did detect a near-significant ($b = -.155$, $p = .089$) negative main effect relationship between competitive uncertainty and platform, a result directionally contrary to H5, which anticipates that competitive uncertainty will promote platform investment. The comparable analysis using objective uncertainty data also detected a near-significant ($b = -.162$, $p = .103$) negative main effect relationship between CU and platform, but the MUxCU interaction was not significant, indicating no support for H5 based on objective uncertainty.

5.2 Relationships between Uncertainty, Real Options Decision Patterns and Performance

As described earlier, analysis of the relationships between uncertainty, real options decision patterns and performance was conducted using a hierarchical regression analysis procedure consisting of three steps, which permitted identification of main effects (Model 1), two-way interactions between real options decision patterns and market and competitive uncertainty individually in relation to performance (Model 2), and three-way interactions between real options decision patterns and market and competitive uncertainty jointly in relation to performance (Model 3). The last of these three steps tests the relationships specified in Hypotheses 6 through 10. Separate analyses were conducted for each of the three performance measures, using both perceived and objective uncertainty data. Hence, six analyses were conducted for each of the real options decision patterns. The regression analyses are displayed in Appendix D for reference.

Table 5.2 summarizes the results for each of the models evaluated, highlighting significant results. In each case, Model 3 reflects the three-way interactions between market uncertainty, competitive uncertainty and the six real options decision patterns which constitute the basis for the performance hypotheses. In two cases (perceived growth and perceived MTB), the change in R^2 associated with Model 3 is significant ($p = .000$ and .025 respectively), indicating that the MUxCUxRODP interactions are significant factors in explaining performance in these cases. The incremental R^2 values (.155 and .078 respectively) indicate that the additional variance explained by these interactions is material. No significance was found for either GR or MTB using objective uncertainty data. Further, no significant relationships were found for the return on assets performance metric in any of the regressions. Hence, none of the performance hypotheses are supported for this indicator. Table 5.3 summarizes the analysis results for each of the real options decision patterns individually. These results are discussed below for each of the real options decision patterns in turn.

Table 5.2

Performance Analysis Summary of Model Results

	Model 1 P Value	Model 2 P Value	Model 3 P Value	Model 3 ΔR^2	P Value ΔR^2
ROA – Perceived	.314	.619	.576	.038	.374
Objective	.205	.126	.068	.055	.122
Growth – Perceived	.065	.149	.000	.155	.000
Objective	.053	.344	.427	.028	.576
MTB – Perceived	.092	.109	.021	.078	.025
Objective	.089	.000	.000	.048	.105

Table 5.3

Performance Analysis Summary of Results by Real Options Decision Pattern (Three-Way Interaction P Values)

	Growth (Perceived)	MTB (Perceived)
Deferral	.021	--
Acceleration	.047	.015
Staging	--	.011
Operating Flexibility	--	.048
Partial Commitment	--	--
Platform	.000	--

5.2.1 Timing

As before, separate analyses were conducted for the deferral and acceleration dimensions of timing. For deferral, Hypotheses 6a and 6b are based on the expectation that the value of deferral is high when market uncertainty is great, but that this value is offset by the threat of preemption associated with competitive uncertainty. Based on that theory I hypothesized that under conditions of low competitive uncertainty, a positive relationship will exist between deferral and performance as market uncertainty increases (H6a), but that under conditions of high competitive uncertainty, the same relationship would be negatively associated with performance (H6b). The analysis revealed a significant three-way deferral interaction ($b = -3.100$, $p = .021$) for the growth performance measure, based on perceived uncertainty data. To facilitate interpretation of this and subsequent three-way interactions, I have adopted the procedure recommended by Aiken & West (1991) for interpretation of three-way interactions, which allows for two-dimensional display of the interaction by employing separate graphs for high and low conditions for one of the interaction terms. On this basis the deferral interaction was graphed separately for high and low competitive uncertainty (Figures 5.4a and 5.4b respectively). The results are consistent with the deferral hypotheses. When competitive uncertainty is low (Figure 5.4a) deferral shows a positive relationship to growth at both high and low market uncertainty conditions, but more so when market uncertainty is high. Thus H6a is supported for the growth metric, based on perceived uncertainty. When competitive uncertainty is high (Figure 5.4b), the hypothesized negative relationship between deferral, performance and market uncertainty is strongly in evidence. Hence, H6b is also supported.

Figure 5.4a: Deferral/Growth, LCU (Perceived)

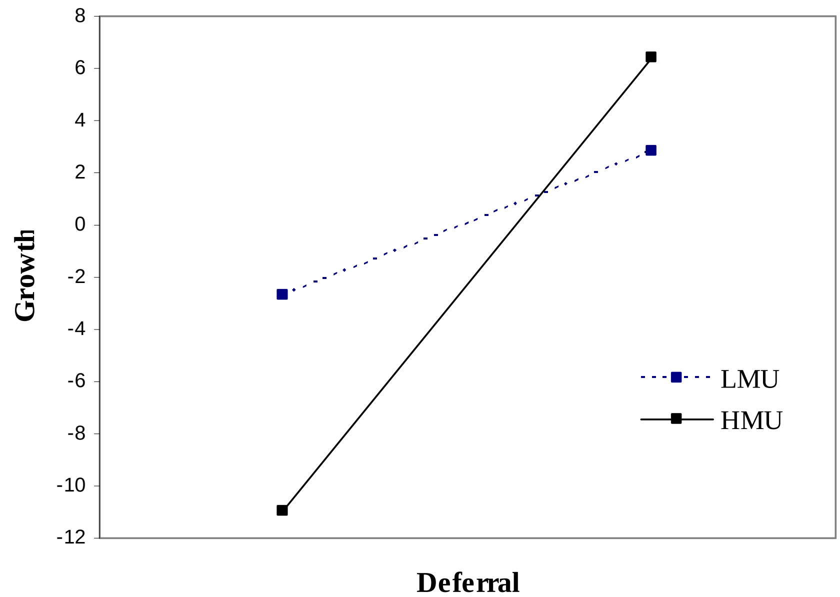
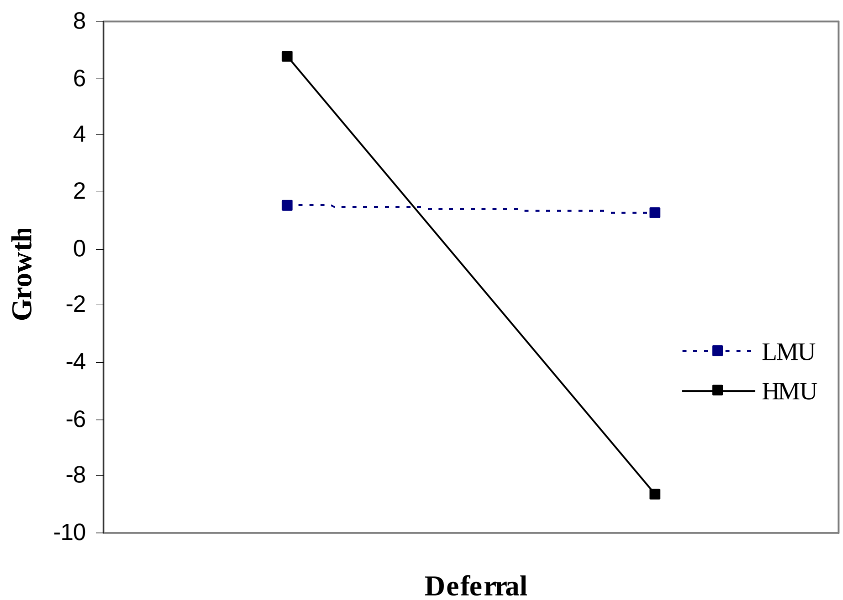


Figure 5.4b: Deferral/Growth, HCU (Perceived)



No comparable significant relationships were detected for deferral and growth using objective uncertainty measures, and no significant relationships were found between deferral and the market-to-book performance metric.

As regards acceleration, the theoretical basis for the hypothesized performance effects (H6c and H6d) is conceptually the reverse of that for deferral. When there is little market uncertainty, acceleration is a valuable response to competitive uncertainty. Hence I hypothesized that when market uncertainty is low, a positive relationship will exist between acceleration and performance as competitive uncertainty increases (H6c). When market uncertainty is high, however, acceleration has negative performance value, such that a negative relationship between acceleration and performance should be in evidence as competitive uncertainty increases (H6d).

Significant three-way interactions were detected for the acceleration/performance relationship for both MTB ($b = -.061$, $p = .015$) and growth ($b = -1.892$, $p = .047$), in both cases based on perceived uncertainty data. Graphing these interactions indicated support for the acceleration hypotheses. Figures 5.5a and 5.5b display the interactions for MTB, which support the hypothesized relationships. When market uncertainty is low (Figure 5.5a), acceleration is positively related to performance when competitive uncertainty is high, but negatively related when competitive uncertainty is low, as predicted by H6c. When market uncertainty is high, these relationships are reversed, as anticipated by H6d. Hence, H6C and H6d are supported for the MTB metric using perceived uncertainty.

In the case of the growth metric, the interaction graphs (Figures 5.6a and 5.6b) show consistent relationships. In the high market uncertainty case (Figure 5.6b), the

Figure 5.5a: Acceleration/Market-to-Book, LMU (Perceived)

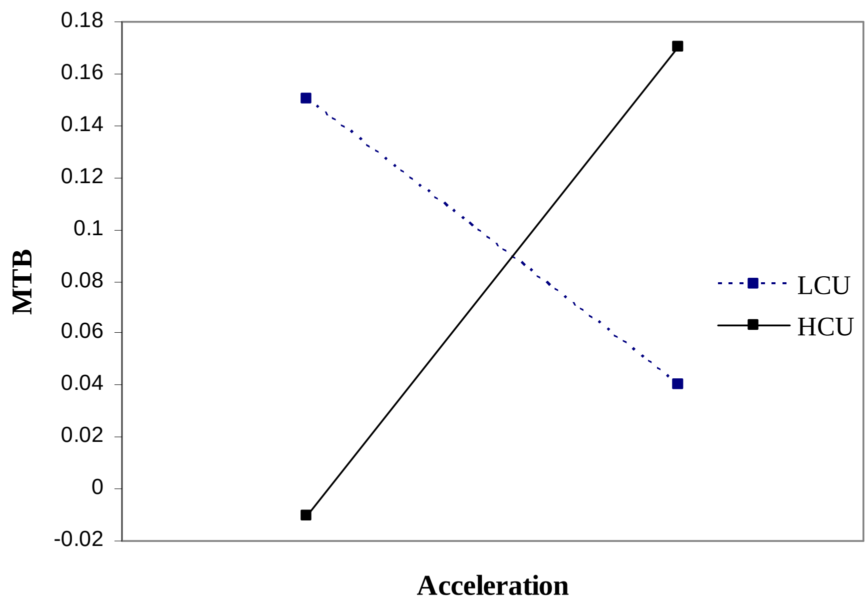
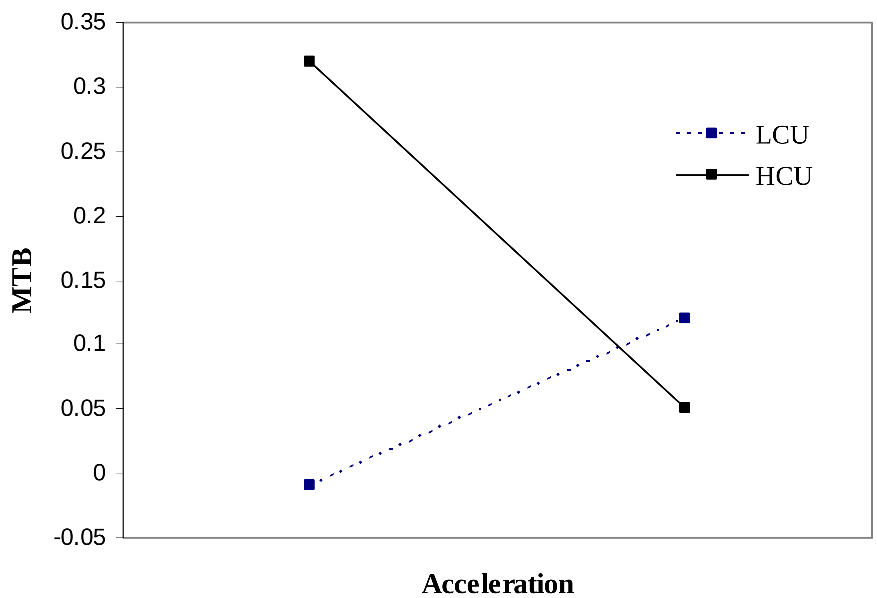


Figure 5.5b: Acceleration/Market-to-Book, HMU (Perceived)



predicted relationships are strongly evident, supporting H6d. In the low market uncertainty case, the expected disordinal interaction is not present. Acceleration is positively related to growth for both high and low competitive uncertainty conditions, albeit slightly more so when competitive uncertainty is high. This is consistent with theory, since, in the absence of market uncertainty, acceleration may well be a growth-producing strategy at all levels of competitive uncertainty. Hence H6c and H6d are supported for the growth metric using perceived uncertainty data.

In summary, the analysis provides support for H6c and H6d for both growth and MTB performance metrics, based on perceived data. No comparable significant relationships were detected using objective uncertainty data.

5.2.2 Staging

The theoretical foundation for developing hypotheses regarding the relationship between staging and performance is comparable to that for deferral. Staging is a valuable and therefore performance-enhancing strategy for responding to market uncertainty, but its value is reduced by competitive uncertainty. On this basis, H7a anticipates that when competitive uncertainty is low, a positive relationship will exist between staging and performance as market uncertainty increases, while H7b anticipates a negative staging/performance/market uncertainty relationship when competitive uncertainty is high. A significant ($b = -.088$, $p = .011$) staging interaction was found for the MTB performance indicator, using perceived uncertainty data. Graphical analysis of this interaction (Figures 5.7a and 5.7b) indicates support for both staging hypotheses. When competitive uncertainty is high (Figure 5.7b), staging is negatively related to performance when market uncertainty is high, but not so when it is low, as predicted. When

Figure 5.6a: Acceleration/Growth, LMU (Perceived)

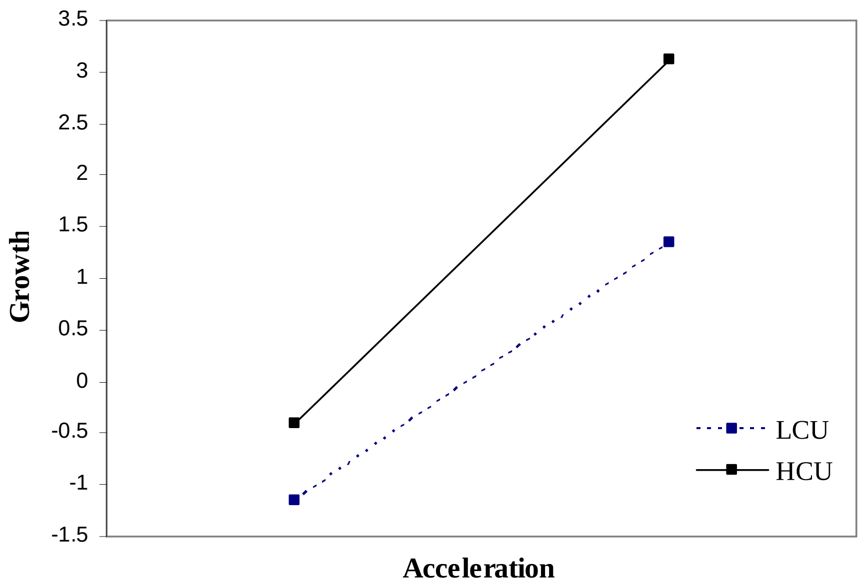


Figure 5.6b: Acceleration/Growth, HMU (Perceived)

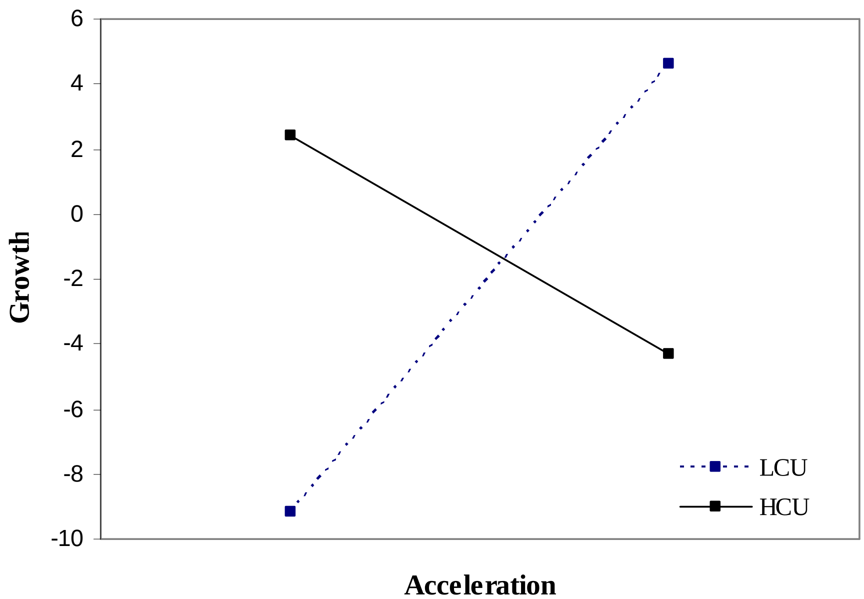


Figure 5.7a: Staging/Market-to-Book, LCU (Perceived)

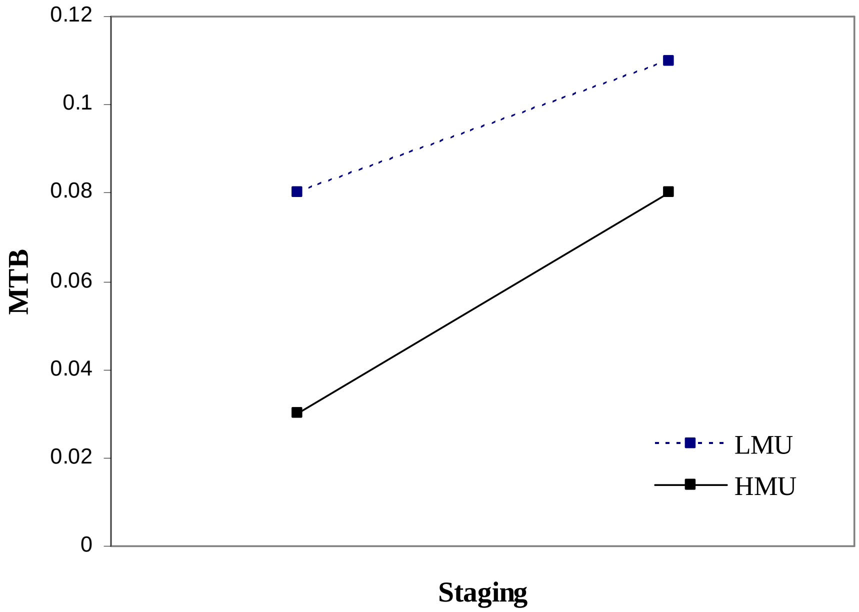
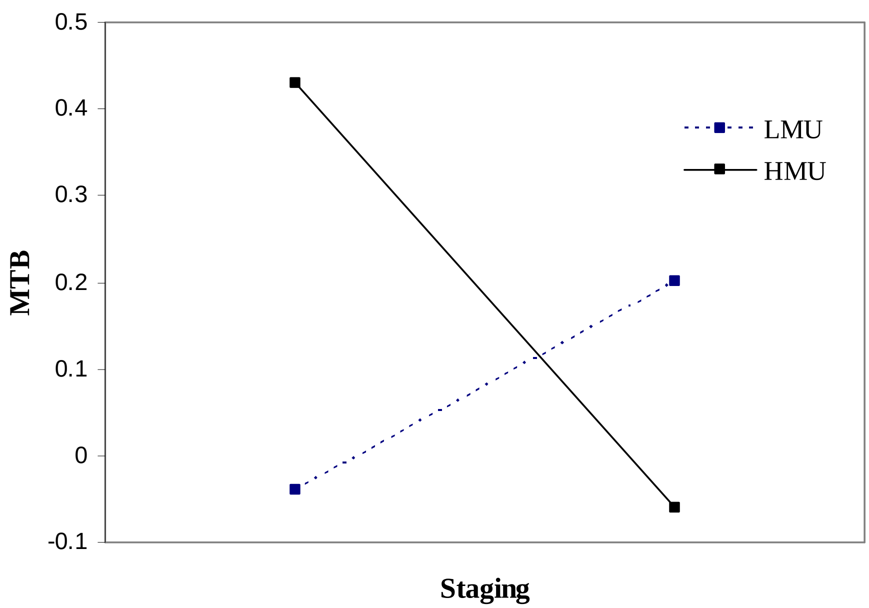


Figure 5.7b: Staging/Market-to-Book, HCU (Perceived)



competitive uncertainty is low (Figure 5.7a), staging is positively associated with performance at all levels of market uncertainty, but again slightly more so when market uncertainty is high than when it is low. This is consistent with theory, which suggests that, absent competitive uncertainty, staging is a performance-improving response to market uncertainty generally. Thus, H7a and H7b are supported for the MTB metric, based on perceived uncertainty data. No significant staging/performance relationships were found using objective data, and none for the growth performance metric.

5.2.3 Operating Flexibility

The hypothesized relationships between operating flexibility and performance are based on the theoretical foundation that such flexibility is a valuable strategy for accommodating to market uncertainty, but that its value is reduced or eliminated with increasing competitive uncertainty. On this basis I hypothesized that when competitive uncertainty is low, a positive relationship will exist between operating flexibility and performance as market uncertainty increases (H8a), but the reverse would obtain when competitive uncertainty is high (H8b).

A significant three-way interaction ($b = .074$, $p=.048$) was found in the MTB analysis using perceived uncertainty data. A graph of the interaction (Figure 5.8a and 5.8b) does not, however, support the hypothesized relationships. When competitive uncertainty is low (Figure 5.8a), the relationship between operating flexibility and performance is negative when market uncertainty is high and positive when it is low, contrary to H8a. Further, when competitive uncertainty is high (Figure 5.8b), operating flexibility is positively related to performance when market uncertainty is high and

Figure 5.8a: Operating Flexibility/Market-to-Book, LCU (Perceived)

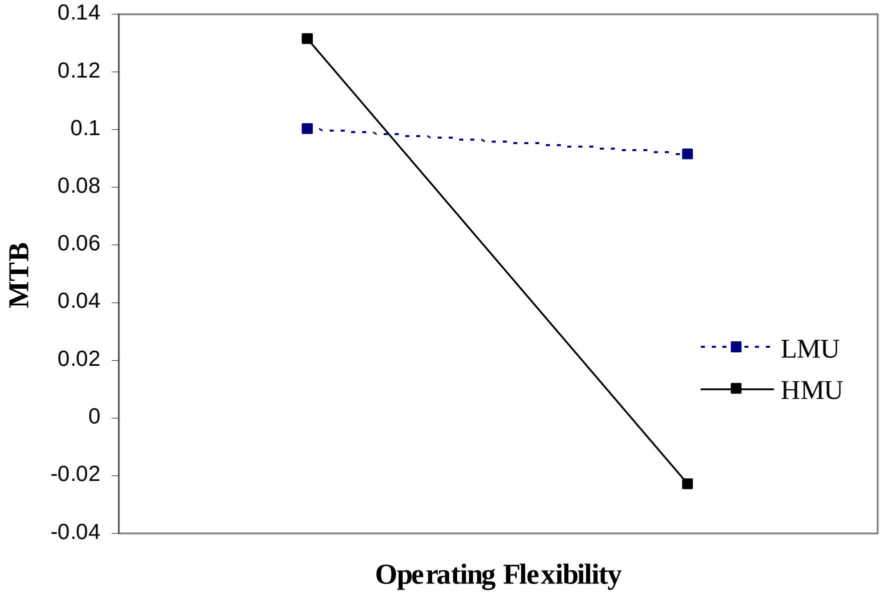
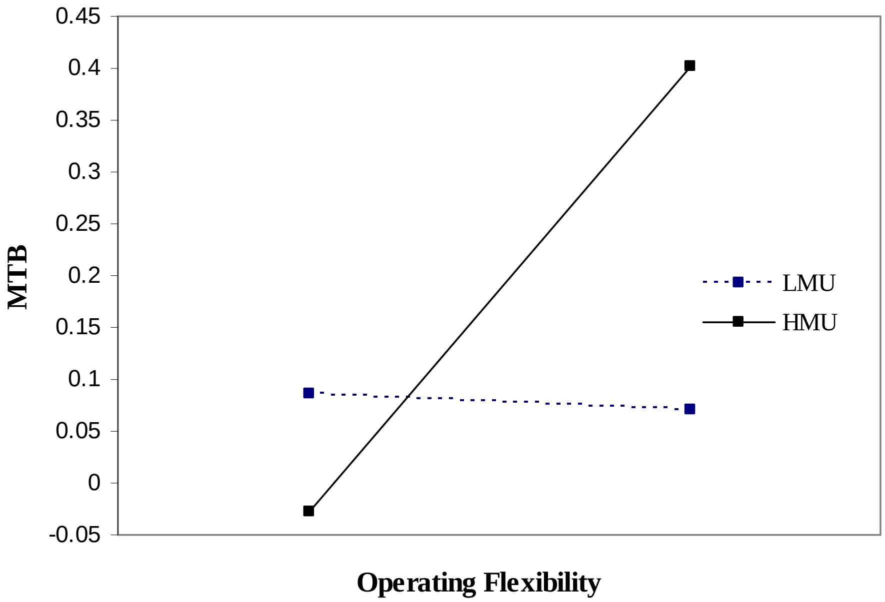


Figure 5.8b: Operating Flexibility/Market-to-Book, HCU (Perceived)



negatively when it is low, again in direct contradiction to the hypothesized relationship. Thus neither H8a nor H8b is supported. I consider explanations for this unexpected finding in the discussion section below. No significant relationship was found between operating flexibility and growth using perceived uncertainty data, and no significant relationship with any of the performance indicators using objective uncertainty data.

5.2.4 Partial Commitment

Theory for partial commitment is similar to that for deferral and staging. I hypothesized that making limited scale commitments was a performance-enhancing response to market uncertainty, but that its value is reduced when competitive uncertainty is high. No significant three-way interactions were found for the partial commitment real options decision pattern and performance. Hence, H9a and H9b received no support for any of the performance metrics, either on the basis of perceived or objective data.

5.2.5 Platform Investments

Theory development for platform investments suggests that market uncertainty alone does not make such investments a valuable strategy from a real options perspective. Only when market uncertainty is accompanied by competitive uncertainty does the platform decision pattern become valuable, in that it establishes resource positions which can provide competitive advantage in responding to market uncertainty. On this basis, I hypothesized that when competitive uncertainty is low, platform would display a negative relationship to performance as market uncertainty increases (H10a), but that the reverse would be true when competitive uncertainty is high (H10b).

The highly significant three-way platform interaction ($b = -.4.089$, $p \leq .000$) detected for the growth metric using perceived data was graphed to determine if it

Figure 5.9a: Platform/Growth, LCU (Perceived)

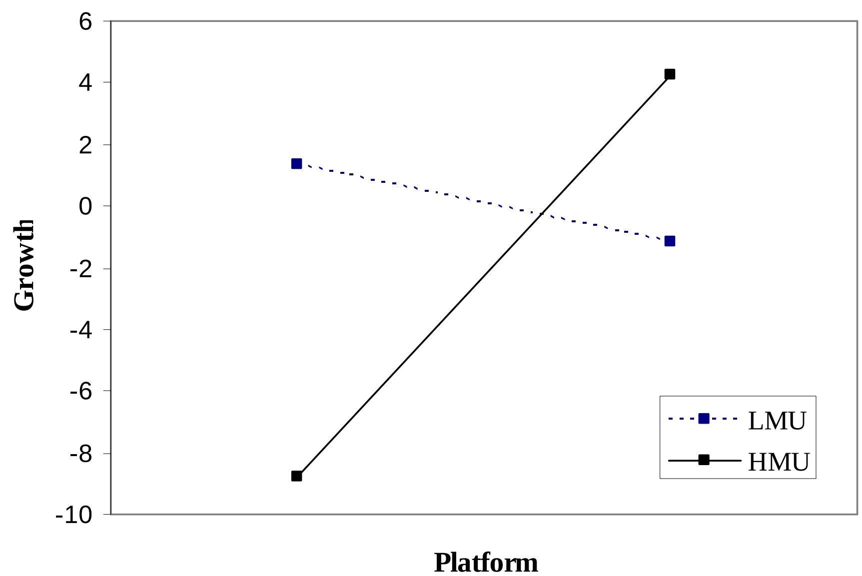
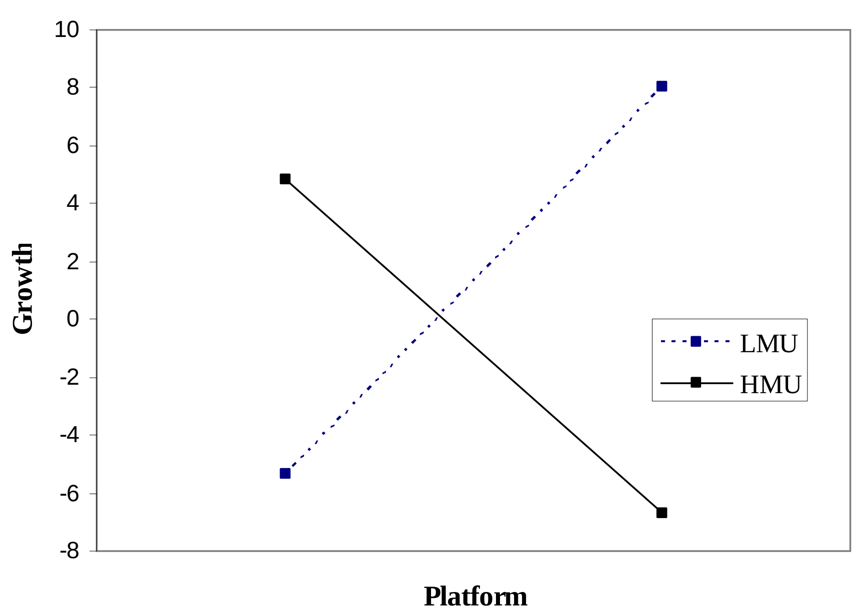


Figure 5.9b: Platform/Growth, HCU (Perceived)



supported the hypothesized relationships (Figures 5.9a and 5.9b). The results are contrary to those expected. When competitive uncertainty is low, platform is positively related to performance at high market uncertainty, contrary to H10a. When competitive uncertainty is high, platform is negatively related to performance at high market uncertainty, contradicting H10b. Hence, H10a and H10b are not supported. I consider the possible explanations for these contrary findings in the subsequent discussion of results.

No significant relationships were found for the impact of platform investments on growth using objective uncertainty data, or on the MTB performance metric on any basis.

5.3 Discussion – Relationships between Uncertainty and Real Options Decision Patterns

In the first stage of the research, I hypothesized that uncertainty regarding demand factors (market uncertainty) and uncertainty regarding competitor actions (competitive uncertainty) would separately and differentially affect the incidence of six specific types of real options-theoretic decision patterns. Regression analysis found strong support for some of the hypothesized relationships and no support for others. In what follows, I discuss and interpret these findings.

Two hypotheses (H1a and H1b) addressed real options decision patterns affecting the timing of resource commitments – deferral (delay) and acceleration. As regards deferral, I theorized that companies would tend to delay resource commitments in order to await clarification of market uncertainty, but that competitive uncertainty would introduce a countervailing disincentive to defer lest delay lead to competitive preemption. H1a therefore anticipated that competitive uncertainty would negatively moderate the relationship between market uncertainty and deferral. No support was found for this hypothesis, using either perceived or objective measures of uncertainty. Given the extensive theoretical support for H1a from the real options literature, this finding is surprising and bears further consideration.

Two explanations for this result are possible. First, the factors that drive deferral behavior may be different from those identified in this study, perhaps factors outside the domain of real options theory. Companies, for example, may defer resource commitments as a result of capital constraints or as a function of strategy, a possibility discussed in greater detail subsequently. This explanation does not, however, resolve the fundamental theoretical dilemma that deferral is one of the earliest and most-discussed real options behaviors in the literature, and that the weight of that literature supports the hypothesized relationship.

The second and more likely explanation is that competitive uncertainty as a disincentive to defer greatly outweighs market uncertainty as an incentive to do so. In this interpretation, the presence of even modest levels of competitive uncertainty undermines deferral as a resource allocation strategy. If this is so, only in an environment in which there is no little or no competitive uncertainty (that is, oligopoly or monopoly) would deferral emerge in response to market uncertainty. In analytical terms, this interpretation suggests a step or threshold function in the relationship, where the step function occurs at relatively low levels of competitive uncertainty. Such a function would not necessarily be detectable by the linear regression techniques used in this study.

There is theoretical support for this interpretation. Grenadier's (2002) previously-cited game-theoretic modeling of the deferral decision found that the presence of relatively few competitors was sufficient to discourage deferral. Further, some of the findings in this research provide directional support for this interpretation. In the deferral analysis, for example, no main effect relationship between market uncertainty and deferral was found, but a significant negative main effect relationship ($b = -.213$, $p = .011$) was detected between competitive uncertainty and deferral. This finding is consistent with the interpretation that a little competitive uncertainty can undo a lot of market uncertainty as a determinant for decisions to delay, and suggests the following proposition:

> P1: Market uncertainty will be correlated with deferral only in the total or near-total absence of competitive uncertainty.

Given the prominence of deferral as a real options-theoretic response to market uncertainty in the literature, further study of the construct is warranted, particularly in settings where there is little or no competitive uncertainty. A particularly fruitful approach would be to study timing decisions for "proprietary" options, that is, options available only to the focal company and therefore not exposed to competitive threat. Studies of specific industries rich in proprietary options may be the best approach for isolating the effects of market uncertainty on deferral. Industries in which patents, copyrights and long-term leases are common may be especially fruitful for this purpose, including, for example, pharmaceuticals, publishing and the exploration and production sector of the petroleum industry.

Results for the second timing dimension examined in the study – acceleration – also directionally lend support to the preeminence of competitive uncertainty in timing decisions. The theoretical relationships here are the direct inverse of deferral. Faced with market uncertainty alone, companies would have no incentive to accelerate resource commitments, but competitive uncertainty creates a countervailing incentive to move quickly in order to gain the benefits of preemption. Thus H1b anticipates that competitive uncertainty will positively moderate the relationship between market uncertainty and acceleration. H1b was supported on the basis of perceived data. No main effects were found for either market or competitive uncertainty, but the predicted interaction was present.

Notable in the interaction is the strength of the moderating relationship (Figure 5.1). When competitive uncertainty is low, acceleration is sharply reduced as market uncertainty increases. This result is intuitive; companies have little incentive to rush when they face no competitive threat. But a high level of competitive uncertainty does not simply dampen the negative effect of market uncertainty. It appears to eliminate it completely. Put in other terms, when competitive uncertainty is high, the relationship between market uncertainty and acceleration is positive.

There is both theoretical and empirical foundation for this result. As discussed by Folta & O'Brien (2004) in their analysis of timing, when market uncertainty is high, the value of deferral is high but there is also a growth option associated with future market uncertainty. The value of that growth option also increases with market uncertainty, thus creating a "duel" between simultaneous deferral and growth options. In their empirical analysis, Folta & O'Brien found that market uncertainty did indeed induce deferral, but only up to a point, beyond which the relationship reversed, as the value of the growth option increases relative to that of the deferral option.

The results of the present research regarding market uncertainty, competitive uncertainty and acceleration are consistent with Folta & O'Brien's findings regarding deferral. A re-examination of Figure 5.1 in light of their work suggests a more nuanced interpretation. When market uncertainty is high, the value of the associated growth option is also high. As long as competitive uncertainty is low, that growth option is not at risk, such that there is little incentive to accelerate. In that case, the downside of market uncertainty increasingly discourages acceleration. When competitive uncertainty is high, however, the incentive to accelerate increases with market uncertainty, since the value of the underlying growth option and therefore the potential loss due to possible preemption increase with market uncertainty. This interpretation supports Folta & O'Brien's finding, and clarifies it by isolating the influence of competitive uncertainty in the market uncertainty/timing relationship. Specifically, the interaction found here suggests that the "duel" detected by Folta & O'Brien exists only in the presence of competitive uncertainty.

Taken together, the research results for the two timing sub-constructs studied suggest that competitive uncertainty has a more potent role than market uncertainty in resource allocation timing decisions. Put in other terms, companies may on average be more determined to avoid preemption (or to seek its benefits for themselves) than to protect themselves against uncertain demand evolutions. If this is so, it has implications for both real options research and for management practice. As regards research, it argues for a greater emphasis on the study of real options under competitive conditions. For example, there is a substantial theoretical and methodological literature on the economic attractiveness of deferral which may not reflect the competitive consequences of delaying resource commitments and which may not square with what companies actually do, as the present research implies.

There is an additional interpretive perspective on the research findings regarding investment timing that is related to cognition and decision psychology. It may be that timing decisions are especially susceptible to decision biases and information processing defects. Houghton et al. (2000), for example, studied the presence of such biases in the context of a notional first mover decision. They found significant bias in favor of first mover decisions, resulting from salience (undue reliance on a small sample of success stories in comparable decisions), illusion of control (overestimation of the role of skill versus chance in determining outcomes), and overconfidence (underestimation of risk). They found further that these effects were if anything more prevalent in group decisions than decisions by individuals. Their findings suggest that there may be a general bias in favor of action versus deferral in timing decisions.

These observations raise broader questions regarding the interplay between real options theory and the cognitive and social psychology of decision-making. Although there has been extensive growth in our understanding of decision-making patterns at both the individual and group levels, there has relatively little study of how real options decisions are affected by them, making research in this area an important future priority.

From the perspective of practice, the timing of resource commitments appears to contain an inherent dilemma. One either exercises due caution by delaying action until market uncertainties become clear, at the risk of losing competitive position, or acts immediately to maximize competitive position at the risk of making bad commitments. It is a management challenge to find ways to balance these competing incentives.

The third real options construct examined – staging – may in fact represent such a balancing decision pattern. Theory suggests that breaking projects into individual sequential components and establishing multiple decision points along the way provides a basis for adapting to market conditions as they become clearer and "learning as you go." By this reasoning, staging is likely to be positively related to market uncertainty. At the same time, staging, like deferral, risks competitive preemption to the extent that it introduces multiple decision points and serial versus concurrent action. It was therefore hypothesized in H2 that competitive uncertainty would negatively moderate the relationship between market uncertainty and staging. This expectation was strongly supported using both perceived and objective measures of uncertainty. In addition, a significant positive main effect relationship ($b = .203$, $p =.015$) was found between perceived market uncertainty and staging.

The analysis results for staging are especially notable in relation to those discussed above for deferral. Although separate constructs, the underlying theory for both staging and deferral is essentially the same, as are the expected relationships to market and competitive uncertainty. Yet the regression results indicate that company behavior is quite different for the two constructs. The analysis for deferral suggests that market uncertainty does not drive deferral, and that whatever does drive it is heavily offset by competitive uncertainty. For staging, by contrast, market uncertainty appears as predicted to be an influential factor, although moderated as also predicted by competitive uncertainty.

This difference between two related constructs suggests the possibility that staging is the preferred of the two behavior patterns for responding to the presence of both market and competitive uncertainty. Deferral is a binary choice: one either waits or does not. In other terms, the decision to defer or not is a choice between protecting against market uncertainty or competitive uncertainty, but not both. Staging, by contrast, may be viewed as a middle ground, a way of not deferring which offers some protection against both market and competitive uncertainty. Staging means getting started, but doing so cautiously and in incremental steps. It allows learning and adaptation, and therefore does in part what deferral does. But it also moves forward and thus reduces the risk of competitive preemption. In short, staging may be a directionally optimal timing response to task environments characterized by both market and competitive uncertainty. This interpretation is consistent with the analysis results for the two constructs.

For the remaining real options constructs evaluated – operating flexibility, partial commitment and platform – the analysis provided no support for the hypothesized relationships, using either perceived or objective data. Further, the analysis revealed no significant main effect relationships between these decision patterns and either market or competitive uncertainty which were directionally supportive. Since all three of the constructs have substantial theoretical support as responses to uncertainty in the real options and strategy literatures, this lack of empirical confirmation needs to be understood.

In the case of operational flexibility, I hypothesized (H3) that competitive uncertainty would negatively moderate the relationship between market uncertainty and investment in maximizing the flexibility of producing assets. H3 was not supported in either the perceived or objective analyses. Further, no main effect relationships between the construct and either market or competitive uncertainty were found. A significant or near-significant negative main effect relationship ($b = -.839$, $p = .047$ based on perceived data and $b = -.753$, $p = .073$ based on objective data) between operating flexibility and the capital intensity control variable was however found. This result is counter-intuitive and can only be explained by the greater difficulty and cost of maintaining operating flexibility encountered by fixed-asset intensive firms in general.

I interpret the absence of a significant relationship between competitive uncertainty and operational flexibility as stemming in part from the operating flexibility scale, which as originally designed intended to capture two aspects of the operating flexibility construct: (1) the pattern of capacity additions and, (2) the flexibility of producing facilities to alter operating parameters such as feedstock, product mix and production level. The items related to the pattern of capacity additions did not, however, survive factor analysis and reliability testing, and were eliminated in the final scale. At the same time, the theoretical basis for expecting that competitive uncertainty would moderate a firm's tendency to invest in flexibility is based heavily on the deleted capacity addition aspect of the construct. Hence I regard the test of competitive uncertainty's effect on operating flexibility as inconclusive.

More perplexing is the lack of any significant main effect relationship between operating flexibility and market uncertainty. The theoretical basis for expecting a positive relationship is compelling: operating flexibility makes sense only if one is not sure about the level or product composition of demand, and its attractiveness should increase with that uncertainty. I offer two explanations for the absence of empirical support for this expectation. First is the possibility that very little market uncertainty is required to justify investments in operational flexibility. As in the case of deferral and competitive uncertainty, there may be a threshold effect in the market uncertainty/operating flexibility relationship that makes the linear relationship assumed in the regression analysis an inadequate basis for testing. In short, it may take very little market uncertainty to induce operating flexibility.

Second, the operating flexibility decision pattern may be heavily influenced by strategic factors rather than uncertainty. This possibility is supported by a very significant main effect relationship between operating flexibility and the strategic orientation control variable ($b = .212$, $p = .006$ based on perceived data and $b = .204$, $p = .009$ based on objective data). Since similar relationships were found for other real options decision patterns, this interpretation is discussed in more detail later in this section.

In the case of partial commitment, H4 anticipated that pursuit of joint ventures, minority interests and alliances would be positively related to market uncertainty, since such investments provide the opportunity to clarify and adapt to market uncertainty, but that the relationship would be negatively moderated by competitive uncertainty, which encourages full and immediate commitment. This expectation has strong support in the literature. The absence of support for H4 suggests that factors other than market and competitive uncertainty account for why companies undertake joint ventures, minority investments and strategic alliances. For example, the analysis revealed a significant positive main effect relationship between partial commitments and capital intensity ($b = 1.372$, $p = .026$ using perceived uncertainty measures and $b = 1.364$, $p = .023$ using objective measures). This suggests that minimizing capital requirements may be a more important explanatory factor than uncertainty in decisions to enter into alliances and joint ventures. Other explanatory factors – such as the desire to access the knowledge and capabilities of partners/allies – have been advanced to explain the strategic appeal of such investments, and may also have more explanatory value than the uncertainty variables examined here.

Also, as noted earlier, the partial commitment construct as operationalized in this research emphasizes specific investment vehicles such as joint ventures, minority interests and alliances, and does not fully reflect the boundaries of the construct as originally conceived. The factor analysis suggests the existence of a construct which may better tap the intended real options decision pattern of taking actions to create small initial positions that may later be expanded or divested/discontinued, depending on market evolution. Research into a “toe in the water” or “reversibility” construct may better establish the role of market and competitive uncertainty in such action patterns.

Finally, as regards platform investments, theory indicates that committing resources to developing platforms is a real options-theoretic response to market and competitive uncertainty in combination. Accordingly, I hypothesized that competitive uncertainty positively moderates the relationship between market uncertainty and platform. H5 received no support in the regression analysis. The only notable analysis result detected was a marginally significant negative main effect relationship ($b = -.155$, $p = .089$) between platform and competitive uncertainty in the perceived data analysis, further casting doubt on platform as a response to competitive uncertainty. As for partial commitments, the absence of any significant positive relationships between the platform decision pattern and either market or competitive uncertainty, individually or in concert, runs counter to a substantial and persuasive theoretical literature which interprets positioning investments which offer no direct financial reward – such as investments in

R&D, knowledge and capabilities – as options to gain access to future opportunities in the face of uncertainty about market and competitive developments.

There are several potential explanations for this counter-intuitive outcome. First, the relationship between platform and uncertainty may be different from that hypothesized in this research. For example, platform investments may be more heavily influenced by technology uncertainty, a variable not included in the present research, than market and competitive uncertainty. Much of the theoretical literature regarding platform investments is technology-oriented, making this interpretation plausible. Alternately, platform may be related to the aggregate level of uncertainty rather than to specific sources of uncertainty, as hypothesized in the present research. There is general recognition in the literature that platform investing is especially applicable in highly turbulent environments in which specific sources of uncertainty are less relevant than a broad lack of predictability generally resulting from the combined effect of multiple sources of uncertainty acting jointly. Additional empirical study of platform-type resource commitments in the context of real options theory is needed to clarify these possibilities, focusing on other formulations of uncertainty which incorporate technology uncertainty and total uncertainty as possibly having more explanatory value than the concepts of market and competitive uncertainty as operationalized in the present research. Finally, the highly significant main effect relationship found in the regressions between strategic orientation and platform ($b = .388$, $p < .000$ using perceived data and $b = .403$, $p < .000$ using objective data) indicates that strategy plays a substantial role in decisions to invest in platforms.

In fact, a striking result of the regression analysis generally is the prominence of strategic considerations as an explanatory factor in real options decision patterns. Four of the six real options constructs examined demonstrated a significant positive relationship to the strategic orientation control variable, as shown in Table 5.4.

Table 5.4

Significant Regression Analysis Results for Strategic Orientation and Real Options Decision Patterns (P Value)

	Perceived Uncertainty Measures	Objective Uncertainty Measures
Deferral	.035	.024
Staging	.000	.000
Operating Flexibility	.006	.009
Platform	.000	.000

Two aspects of these results are notable. First is the high degree of significance of the relationships, indicating that strategic orientation is strongly correlated with real options behavior in general. Comparing these results to those for the environmental uncertainty variables which are the principal focus of this research suggests that strategic response to uncertainty is as much or more influential in determining real options behavior than uncertainty itself.

Second is the specific nature of the relationships revealed. Some are readily interpretable. For example, the close relationship between strategic orientation and platform investing is unsurprising, given that the strategic orientation variable reflects the characteristics of the Miles & Snow (1978) prospector strategic type. Companies oriented toward innovation, responsiveness to change, product/market leadership and expansion of their business domain are arguably likely to pursue platform-creating resource commitments. Similarly, the strong relationship between strategic orientation and operating flexibility makes sense, since maintaining such flexibility would arguably be attractive for companies oriented toward new products and markets and that emphasize the ability to adapt to change.

Less intuitive are the relationships between strategic orientation and the deferral and staging real options decision patterns. Both these decision patterns are “protective” in character in that companies employ them in order to learn more and adapt before committing (in the case of deferral) or committing wholly (in the case of staging). It is not immediately apparent that such patterns would be common among companies oriented to growth, expansion and product/market leadership. Yet this research strongly suggests that they are. Prominent by its absence is the lack of any significant relationship between strategic orientation and acceleration. These results seem to indicate that companies oriented to growth and leadership do invest aggressively in growth (platform) and flexibility (operating flexibility), but that they also rely on cautious timing (deferral and staging) in pursuing growth, and are not prone to rushing ahead by accelerating. In short, prospector-like firms appear to employ a wide range of real options decision patterns, suggesting that one of the implicit characteristics of prospectors is that they are active users of real options decision principles generally.

5.4 Discussion – Relationships between Uncertainty, Real Options Decision Patterns and Performance

In the second stage of the research, I explored empirically the relationships between uncertainty, real options decision patterns and performance. The finding of significant support for the hypothesized performance relationships for three of the six real options decision patterns (deferral, acceleration and staging) lends empirical evidence to three basic contentions of this research: (1) that real options decision-making is systematically related to firm performance, (2) that there is no inherently or universally optimal decision pattern but instead (3) that the relationship between decision patterns and performance is mediated by the relative presence of market and competitive uncertainty. The impact of each decision pattern on performance depends on its appropriateness to the uncertainty characteristics of the environment in which it is undertaken, where different types of uncertainty often represent competing incentives and disincentives for the same action.

Market uncertainty, for example, constitutes an incentive to defer and to stage, since both provide opportunity to clarify and adapt to that uncertainty. In both cases, however, competitive uncertainty creates an offsetting disincentive to do so since delay and serial progress expose the focal firm to partial or total preemption. Similarly, competitive uncertainty provides an incentive to accelerate resource commitments in order to "get out in front" of competitors, but market uncertainty provides a competing disincentive to do so since acceleration creates the risk of premature commitment when the magnitude and composition of demand are not clear. Only when these decision patterns are aligned with the relative weight of the two dimensions of uncertainty do they contribute to performance.

The performance analysis did not however support the hypothesized relationships for three of the real options decision patterns. In the case of operating flexibility, for example, the analysis did find a significant three-way interaction relationship, but one contrary to that expected. I hypothesized that operating flexibility in response to market uncertainty would enhance performance, while the analysis suggests it in fact detracts from performance (Figure 5.8a). Conversely, I hypothesized that operating flexibility in conditions of high competitive uncertainty would detract from performance, while the analysis indicates that it is positively associated with performance in that case (Figure 5.8b). These results warrant a reconsideration of theory associated with operating flexibility. Closer examination of the results suggests that operating flexibility does not respond to market and competitive uncertainty in the same way as the other real options decision patterns. Specifically, it appears that a combination of market and competitive uncertainty rather than market uncertainty alone makes operating flexibility a performance-enhancing strategy.

A matrix summary of the four MU/CU conditions drawn from Figures 5.8a and 5.8b highlights this interpretation (Figure 5.10). When both MU and CU are low, operating flexibility has a slightly negative relationship to performance (quadrant I). This finding is plausible, indicating that the value of operating flexibility is low when there is little uncertainty generally. The same is true when MU is low but CU is high (quadrant II), confirming that operating flexibility does not improve performance in the absence of market uncertainty. However, when CU is low but MU is high (quadrant III), the effect of operating flexibility on performance is strongly negative, suggesting that market uncertainty alone does not make operating flexibility a performance-enhancing strategy. It is only when both MU and CU are high (quadrant IV) that operating flexibility has a positive performance effect.

Although contrary to the hypothesized relationships, this result is theoretically plausible. The ability to change operating levels, inputs and product mix easily and at low cost is arguably valuable in responding to unpredictable competitor actions as well as to demand-related uncertainties. These considerations suggest the following proposition:

P2: Operating flexibility will be positively correlated with performance when aggregate environmental uncertainty is high, and negatively correlated when aggregate uncertainty is low.

Figure 5.10

Operating Flexibility Interaction Summary
(Relationship to Performance)

	LMU	**HMU**
LCU	I Slightly Negative (H8a Not Supported)	III Sharply Negative (H8a Not Supported)
HCU	II Slightly Negative (H8b Not Supported)	IV Sharply Positive (H8b Not Supported)

In the case of partial commitment, it alone among the six real options decision patterns showed no significant performance-related interactive relationships with market or competitive uncertainty. Further, it is the only decision pattern for which a main effect relationship to performance was found. The analysis revealed a significant (b = 1.846, p =.038) positive main effect relationship between partial commitment and growth, based on perceived uncertainty data.

I interpret these results as due in large measure to the narrowness of the partial commitment scale. As noted earlier, the scale was considerably reduced in scope as a result of the factor analysis to include specific deal structures (joint ventures, minority investments and alliances), rather than the broader concept of reversible, toehold resource commitments originally intended. That such specific transaction types appear directly related to growth is plausible, but may be more a reflection of strategy than uncertainty, to the extent that companies pursuing growth strategies are arguably more likely to engage in them than other firms. Based on these considerations, I conclude that the analysis has produced no conclusive result as regards those resource commitments designed to establish limited, reversible or expandable positions in areas of interest.

Finally, as regards platform investments, the unexpected analysis results merit closer examination, particularly given the high significance level of the three-way interaction found for the growth performance metric ($b = -4.089$, $p \leq .000$) and the prominence of the platform construct in the literature regarding real options and strategy. I hypothesized that market uncertainty would not make platform a performance-enhancing real options strategy in the absence of competitive uncertainty, since without competitive uncertainty there would be no incentive to "get a jump on" the future and that therefore the costs associated with creating platforms would reduce performance. Firms could instead simply wait and adapt to the future as it emerged. The presence of competitive uncertainty, however, makes platform desirable by creating competitive advantage and/or avoiding preemption. By this reasoning too, absent market uncertainty, there would be little value in platform investments, regardless of the level of competitive uncertainty, since platform makes little sense when future market evolution is clear.

Accordingly H10a and 10b predict that platform would be positively associated with performance only when both market and competitive uncertainty are high.

The contrary analysis results suggest a different dynamic underlying the relationship between platform and performance. A matrix summary drawn from Figures 5.9a and 5.9b assists in explaining these results (Figure 5.11). When both MU and CU are low (quadrant I), platform is negatively associated with performance, in this case growth, consistent with H10a. In other terms, when there is low uncertainty generally, there is little rationale to invest in platforms. However, when MU is high and CU low (quadrant III), platform is positively related to the growth metric. While contrary to H10a, this result is not entirely counter-intuitive, suggesting that when market uncertainty is high, platform produces growth even when competitive uncertainty is low. Put in other words, being prepared for unknown future market conditions contributes to growth, and that contribution increases with market uncertainty.

When MU is low and CU high (quadrant II), platform is positively associated with performance. Though contrary to expectation, this result is, again, theoretically plausible. It suggests that even when market uncertainty is low, platform investments can create preferential access to opportunities, resulting in growth. In this respect, platform is analogous to acceleration, which is also positively associated with performance when MU is low and CU high (Figure 5.6a). In effect, platform may be viewed as akin to acceleration, with the key differences that (1) platform is not just early action but *very* early action and (2) the specific future opportunities to which platform creates access are not known when the investment is made, as they are in the case of acceleration.

Figure 5.11

Platform Interaction Summary
(Relationship to Performance)

	LMU	**HMU**
LCU	I Slightly Negative (H10a Supported)	III Sharply Positive (H10a Not Supported)
HCU	II Sharply Positive (H10b Not Supported)	IV Sharply Negative (H10b Not Supported)

More troublesome are the results when both market and competitive uncertainty are high (quadrant IV). In this case, platform is negatively associated with performance, and strongly so. Contrary to my expectation that platform would be positively related to performance only when both CU and MU are high, quadrants II and III indicate in effect that platform is a growth-enhancing real options strategy when *either* market or competitive uncertainty is high, but not both.

In short, the results indicate that platform is a poor real options strategy in exactly those uncertainty conditions – both high CU and MU – where theory suggests it is most valuable. There are several possible explanations for this finding. The first relates to technology uncertainty. Since, as noted earlier, platform is closely associated with technology investments, inclusion of technology uncertainty in the analysis may be necessary to fully understand its performance impact. Since the present study does not include technology uncertainty as a variable, the results arguably represent an incomplete examination of the construct.

A second interpretation is that, while investment in knowledge, technology or capability platforms may be a theoretically appropriate response to very high uncertainty environments, it is not effective in practice, for one or both of two possible reasons. The first is that platform investments may be a zero-sum game in environments characterized by both high MU and CU. If all firms facing high competitive and market uncertainty invest in creating platforms for capitalizing on future opportunities, some may succeed, but not all can, and the effort in the aggregate may reduce performance for all competitors as a group. This would explain the differences between quadrants III and IV in Figure 5.11. If true, this reading has worrisome implications for the substantial literature that gives prominence to platform as a productive competitive strategy.

The second reason is that firms may not on the whole employ the platform strategy effectively. Platform investing by definition entails substantial resource commitments which do not yield identifiable performance rewards. Inappropriate or excessive commitments of this type can therefore hurt performance. This interpretation is not without foundation in both the academic and practitioner domains. For example, the dangers of overinvestment in R&D, coupled with the difficulty of assessing the productivity of R&D efforts, have been a persistent concern among senior managers. Further, platform investing is especially vulnerable to ineffectiveness in abandonment decisions, resulting from such effects as escalation of commitment and sunk cost bias

(Staw, 1981). The emphasis placed by some authors the importance of abandonment in real options decision-making (Adner & Levinthal, 2004a) provides foundation for the possibility that platform investing as actually implemented by firms is susceptible to the performance-reducing effects of overinvestment and undue persistence in the management of real options.

A final consideration in interpreting these results is the long lead times which may obtain between investment and positive performance outcomes. Platform investments especially are long-term in nature. They are undertaken with the knowledge that they are unlikely to produce positive performance effects in the short term – in fact they may have negative short-term performance consequences to the extent that they incur costs – but will do so over the long haul. Their ultimate performance impacts may therefore elude detection in a cross-sectional study such as the present one. I note, however, that this interpretation implies an aggregate change over time among companies in their investment in platforms. Absent such a change, performance in the time frame analyzed would reflect the benefits of platform investments made in the past. There is no foundation for believing that there has been such a change.

None of these interpretations is in my view conclusive. Nevertheless, the absence of a finding in this research that platform investment is positively associated with growth or any other performance metric in high uncertainty environments runs contrary to a substantial theoretical literature and raises questions about the value of platform as a performance-enhancing strategy. More focused empirical analysis of platform investing in relation to performance therefore seems an important future research priority, as discussed further in Chapter 6.

Apart from the specific regression results, an additional aspect of the performance analysis merits discussion, namely the absence of any significant relationships between real options decision patterns and the return on assets performance indicator (see Table 5.2). All the significant relationships found relate to the growth and MTB performance metrics. I propose as an explanation for this outcome the fact that return on assets, like other profitability indicators, is heavily conditioned by asset choices and resource commitments from the past. To the extent that the real options decision patterns as a group relate to incremental asset choices, their effect on profit performance may be masked by the effect of legacy assets. The other performance metrics used, by contrast, are more direct measures of current/recent resource allocation choices. Growth, for example, is inherently incremental, relating directly to such action patterns as acceleration, partial commitment and platform investments. The market-to-book metric conceptually incorporates the impact of profitability on firm value, but also encompasses investor expectations regarding future performance as a function of the asset choices the firm has made recently or is making currently. Such outcomes may not be reflected in profit measures for some time into the future.

This interpretation has implications for future research into real options theory and performance. As described in Chapter 2, there has been virtually no research into the relationship between real options theory and firm performance, and work in this area is an important direction for future research. The performance results of this study argue that such future research efforts should emphasize those performance indicators most suitable conceptually to real options theory. Specifically, the results presented here suggest performance metrics that isolate to the maximum extent possible performance outcomes from recent/current resource allocation decisions in relation to real options theory in preference to metrics which aggregate such outcomes with those deriving from historical assets and positions. Further, to the extent that real options theory is heavily oriented toward creating growth and value rather than maximizing near-term profitability, it would appear that metrics which directly address those dimensions of performance are more suitable than historical profitability for measuring the performance impacts of real options management of the firm.

5.5 General Discussion

In this section I discuss two notable aspects of the research which relate to both stages of the project. First, why support was found for the hypothesized relationships for only some of the real options decision patterns and not others is an important point for discussion. Table 5.5 summarizes by decision pattern the hypothesized relationships that received support and those that did not. In both stages of the analysis significant relationships were found only for the first three decision patterns (deferral, acceleration and staging).

Table 5.5

Summary of Supported Relationships

	Stage 1 Analysis (Uncertainty and RODP)	Stage 2 Analysis (RODP and Performance)
Deferral	Not Supported	Supported
Acceleration	Supported	Supported
Staging	Supported	Supported
Operating Flexibility	Not Supported	Not Supported
Partial Commitment	Not Supported	Not Supported
Platform	Not Supported	Not Supported

I believe that this result can be cogently explained with reference to the nature of the individual real options constructs themselves. There is a conceptual distinction among them that corresponds to the pattern of analysis results as shown in the table. The first three decision patterns – deferral, acceleration and staging – address the temporal aspects of resource commitments, that is, when things are done. The remaining three – operating flexibility, partial commitment and platform – relate to what kind of resource commitments are made, independent of timing considerations. The hypotheses supported in both stages of the study relate exclusively to the "when" real options constructs. None of the hypotheses regarding the "what" constructs received support.

This explanation directs attention to timing decisions as the most central aspect of real options theory as a response to environmental uncertainty. Such a re-focusing represents a return to the earliest research interest in real options, which emphasized timing decisions as the primary application of real options thinking in resource allocation. There is a substantial literature dating from the 1980's and early 1990's, largely in the finance and management science domains, that addresses deferral and staging in particular as responses to environmental uncertainty. By contrast, the present study suggests that other real options decision patterns affecting the kinds of resource commitments made do not appear significantly influenced by the level of market and competitive uncertainty, but are driven by other factors, including capital constraints, strategy and possibly technological uncertainty.

That both stages of the analysis reflect the same clear difference in results between the timing and non-timing decision patterns makes this interpretation especially compelling.

A further notable feature of this research has been the parallel use of both perceived and objective data for the main independent variables – market and competitive uncertainty. This aspect of the project has provided a rare opportunity to examine the relationship between two approaches, both of which have substantial support in the fields of organization and strategy, and whose relative merits, as described in Chapter 4, have been extensively debated. Although not the principal focus of the research, this dual approach yielded analysis results and insights which merit discussion. Three issues in particular deserve comment.

First, the perceived and objective data developed to represent market and competitive uncertainty are not convergent. Table 5.6 displays the Pearson correlations for all measures of the uncertainty variables developed in the study. For market uncertainty, the table shows the perceived measure based on survey data (PMU) and four alternate objective measures (COV5, COV10, SE/M5 and SE/M10). All are based on the same underlying data on the value of shipments by industry drawn from the *Annual Survey of Manufacturers.* The four variations represent two time periods (five and ten years) and two commonly-used metrics for measuring the variability in the year-to-year data (the coefficient of variation of first differences and the standard error of the regression coefficient divided by the mean of the data). As described in Chapter 4, all four variations have support in the literature as appropriate for research projects such as this one. Also shown are both perceived and objective measures of competitive uncertainty (PCU and OCU respectively). The table shows that there is no significant relationship between (1) perceived and objective competitive uncertainty, or (2) perceived market uncertainty and any of the four variants for objective market

Table 5.6

Pearson Correlations for Perceived and Objective Uncertainty Measures

	PMU	COV5	COV10	SE/M5	SE/M10	PCU
PMU						
COV-5 Yrs	-.001					
COV-10 Yrs	.069	.514**				
SE/Mean-5 Yrs	.068	.222**	.362**			
SE/Mean – 10 Yrs	.001	.139	.492**	.731**		
PCU	.088	.072	.028	.142	.110	
OCU	-.020	-.104	-.190*	-.292**	-.249**	.051

** Significant at the .01 level
*Significant at the .05 level

uncertainty. In effect, the perceived and objective operationalizations of environmental uncertainty do not appear to be related.

Second, the four variants for objective market uncertainty are only imperfectly correlated to each other. While in most cases there is a significant correlation among them, that is not true in all cases, and the degree of correlation is uniformly well below 1.0, surprising given that all are based on the same underlying data series. That these differences between alternate ways of measuring the variability in the same times series is analytically important is demonstrated by the regression analysis results. Table 5.7 displays the results of the uncertainty/real options decision pattern regression analysis using each of the four variants for objective market uncertainty. The table notes all main effects and interactions significant to the level of $P \leq .10$. Each of the four variants produced substantially different results, with numerous instances when using one variant detected relationships that did not emerge using the others.

Table 5.7

Summary of Regression Results for Objective Measures of Uncertainty – Main Effects and Interactions (P Value)

	C of Var – 5 Years			C of Var – 10 Years			SE/Mean – 5 Years			SE/Mean - 10 Years		
	MU	CU	MxC	MU	CU	MxC	MU	CU	MxC	MU	CU	MxC
Deferral	--	--	.087	--	--	--	--	.100	--	.090	.063	--
Acceleration	--	--	--	--	--	--	--	--	--	--	--	--
Staging	--	--		--	--	--	--	--	.049	--	--	.077
Operating Flexibility	--	--	.052	.069	--	.071	--	--	--	.059	--	--
Partial Commitment	--	--	--	.064	--	--	.034	--	--	--	--	--
Platform	--	.088	--	--	.073	--	--	.103	--	--	.058	--

effects and interactions significant to the level of $P \leq .10$. Each of the four variants produced substantially different results, with numerous instances when using one variant detected relationships that did not emerge using the others.

Third, there was only limited consistency in the regression analysis results between the perceived and objective data. In the analysis of the relationship between uncertainty and real options decision patterns, only one of the two significant interactions detected (staging) was present using both perceived and objective measures. The other (acceleration) was found only with perceived data. In the performance regressions, none of the six significant interactions revealed using perceived uncertainty data were replicated using objective data. These results are consistent with the divergence in perceived and objective uncertainty measures noted earlier, and dramatize the impact of that divergence on the regression analysis. Finally, it is notable that perceived uncertainty measures proved much more fertile overall than objective measures in generating significant results in both stages of the analysis.

In short, at least in this project, the fundamental research findings proved highly sensitive to both the selection of basic method (perceived versus objective data) and, within objective data, to alternate procedures for using the same underlying time series. It was not the purpose of this research to draw conclusions about the relative merits of perceived and objective data. However, the project did reveal several aspects about the use of objective data which may contribute to that discussion. First, I found that alternate protocols for measuring the variability of the same data – neither demonstrably superior to the other – produced substantially different results. The use of two different time horizons, again neither of which is inherently the better choice, also produced material differences in results. Here the researcher is faced with an irresolvable tradeoff. The shorter of the two horizons has the benefit of greater contemporaneity, while the longer has the benefit of more stable measurement results. Neither is conceptually superior to the other, nor is there a definitive basis for concluding that one is inherently a better measure of the relevant uncertainty for decision-making.

As described in Chapter 4, the literature regarding the relative merits of perceived and objective uncertainty measures focuses principally on the theoretical suitability of the two approaches. In this research, I found that more mundane procedural issues associated with objective data have a significant bearing on the relative usefulness of the two approaches. Despite the aura of precision and factuality that surrounds objective data, the high sensitivity of measurements to alternate methods for selecting and utilizing it gives to the resulting metrics an indeterminate quality for which there is no clear basis for resolution. Based on the present research, it is the conclusion of this author that perceived measurements represent the more appropriate choice for operationalizing the uncertainty construct in empirical analysis of real options theory.

CHAPTER 6

CONCLUSION

This project has established, for certain classes of real options-theoretic decision patterns, that two central premises regarding real options as strategic theory are empirically justified. First, there is no inherently or universally optimal real options decision pattern. The appropriateness of any decision pattern depends on the relative presence of different sources of uncertainty, and those different sources of uncertainty frequently comprise countervailing incentives and disincentives for the same decision pattern. Second, the project represents the first empirical confirmation that real options principles are positively associated with firm performance, and has further clarified that those performance impacts are also mediated by the relative presence of different sources of uncertainty. These results have significant implications for both practice and research, which I examine here. I conclude with a discussion of the limitations of this investigation and suggestions for future research.

6.1 Implications for Practice

This research has several implications for management practice. First and most prominently, the finding that real options decision patterns have a measurable and systematic influence on performance indicates that real options theory is in fact relevant to practice. In this respect, the research provides empirical justification for decisions that depart from the traditional decision rule that firms should act on opportunities when and only when the expected net present value of doing so is equal to or greater than zero. The study suggests that making decisions consistent with real options principles can contribute to company performance, and warrants efforts by companies to align their decision-making with those principles. In short, real options are real world.

The research also indicates, however, that achieving such alignment is not easy or straightforward. In demonstrating that no decision pattern is inherently superior, it lays the foundation for a contingent view of real options decision-making: firms need to carefully and realistically assess the suitability of specific decision patterns in light of the level of market and competitive uncertainty surrounding those decisions. That task is complicated by the fact that different sources of uncertainty frequently create competing incentives and disincentives to act in certain ways. In the case of deferral, for example, market uncertainty makes it a valuable strategy but competitive uncertainty argues against it. How to act is clear in the absence of one or the other source of uncertainty. However, circumstances in which there is some degree of both are arguably more representative of the conditions under which most decisions are actually made. In such cases, there is no clear normative basis for assessing the net effect of the contest between market and competitive uncertainty. Hence considerable management judgment is required to employ real options principles effectively in practice.

These considerations suggest that, from the perspective of practice, real options decision-making may best be thought of as a firm capability rather than a decision strategy. Real options principles are relatively easy to understand; it is implementing them well that is hard. Realistic appraisal of uncertainty and balancing competing sources of uncertainty in making decisions is one dimension of this capability directly highlighted by this research. Others touched on less directly include the ability to learn from and reshape resource commitments as they proceed (staging) and effectiveness in recognizing when resource commitments no longer justify pursuit and abandoning them in a timely manner in that circumstance. In summary, enhancing performance through real options reasoning is more a function of creating organizational processes, practices and skills that make the firm effective at managing real options than adopting a specific decision pattern.

A final managerial implication is that firms in general may be systematically underutilizing deferral as a decision strategy for responding to market uncertainty. In this respect the results of this research hearken back to a number of early real options authors who maintained that firms do not optimally time resource commitments and that the performance loss associated with such mis-timing can be substantial (McDonald & Siegel, 1986; Tiesberg, 1994). Firms, Kester said, routinely commit before they need to (1984).

Comparison of the research results for deferral in the two analysis stages of the present research lends credence to this view. The analysis of uncertainty and real options decision patterns failed to establish any significant relationships, either as a main effect or interaction, between deferral and market uncertainty, but did reveal a negative main effect relationship between deferral and competitive uncertainty. As discussed in Chapter 5, this result suggests that competitive uncertainty overwhelms market uncertainty as a determinant of deferral behavior. The performance analysis, however, suggests that this heavy emphasis on competitive uncertainty in deferral decisions has negative performance consequences. There I found that a positive relationship between deferral and market uncertainty was associated with better performance (as measured by growth) when competitive uncertainty is low, indicating that deferral is a performance-enhancing decision strategy under those conditions.

Taken together, these results imply a general bias against deferral. Put in other terms, companies appear to overweight competitive uncertainty and underweight market uncertainty in evaluating deferral decisions. As noted in Chapter 5, there is evidence from the domain of decision psychology that such a bias may exist. From the perspective of practice, these considerations suggest that firms should more carefully and objectively appraise the merits of deferral as a decision strategy when there is material market uncertainty to avoid the negative performance consequences of premature commitment.

6.2 Implications for Research

The idea of real options as a corporate capability also has implications for the study of real options in the strategy field. Much of the real options-related strategy literature has focused on real options as a broad reasoning pattern or heuristic that explains why firms make certain kinds of resource commitments. Framed in this way, real options provides theoretical foundation for a range of strategic actions, and has been used primarily as an explanatory framework for certain strategic behaviors. The present research suggests that a richer understanding of real options and strategy may be derived from closer study of real options as a competence that makes some firms more effective than others as managers of real options.

Reframing research efforts around real options as a capability opens the door to connecting real options theory with a number of other strands in strategy research, including the resource-based and knowledge-based views of the firm, both of which have so far been only peripherally visible in the real options literature. Several specific areas of investigation suggest themselves here. Are some firms, for example, better at creating value through a real options-based approach to strategic management? If so, what are the elements that contribute to differences in real options effectiveness? How can real options effectiveness be measured in the first place? How do the components of real options effectiveness relate to other conceptually affiliated strategic constructs such as organizational learning and knowledge management?

An additional implication of this study is that real options research would benefit from a more articulated view of uncertainty in relation to real options. It is non-controversial that real options theory is explicitly a framework for making decisions under conditions of uncertainty. However, the real options literature has for the most part assumed that uncertainty is uniform and omnipresent, implicitly making real options theory relevant in the same way for all firms under all conditions. The present study has demonstrated, by contrast, that both real options behavior and its performance consequences vary with the magnitude and source of uncertainty. The findings presented here open the door to research efforts aimed at achieving a better understanding of the relationships between uncertainty, real options-theoretic decisions and performance. The concepts of market and competitive uncertainty that have been examined here do not exhaust the opportunities to connect the real options and uncertainty literatures. Other uncertainty sources of interest in this regard include technological uncertainty (about which I will say more below), uncertainty in turbulent and emergent environments, and macroeconomic uncertainty (such as interest rates, inflation and economic cycles).

Differentiating by source of uncertainty, however, is not the only opportunity to link the study of real options to a multidimensional conceptualization of uncertainty.

There is, for example, an important stream in the uncertainty literature that examines different *types* of uncertainty. Milliken (1987) distinguished between three types of uncertainty: (1) state uncertainty (uncertainty about the state of the environment and/or the interrelationships among elements within it); (2) effect uncertainty (uncertainty about the impact that the environment will have on the organization); and (3) response uncertainty (uncertainty regarding the range of available responses and their outcomes). Conant (1967) proposed a similar taxonomy, but added the further conceptual distinction between bounded uncertainty (uncertainty about specific variables with clear metrics and a definable range of outcomes) and unbounded uncertainty (where neither all relevant variables nor their range of possible outcomes can be defined). Other authors have differentiated between uncertainties that are subject to resolution with time (such as the cost of producing a new product) versus those which are continuous (such as changes in customer tastes).

These variations in the type of uncertainty encountered are evocative from the perspective of real options, but have not yet been explored in that context. Specifically, real options decision making patterns are likely to vary systematically based on the type of uncertainty encountered. Real options theory, for example, suggests that deferral is a directionally optimal decision strategy in response to uncertainties that are state and effect related, bounded and resolvable. For such uncertainties, waiting can yield a high degree of uncertainty resolution, and therefore has a high option value. When, however, uncertainties are unbounded and/or continuous, deferral yields limited benefits, making it directionally an inferior strategy. Waiting in this case can become paralysis. Similarly, deferral is arguably not the optimal strategy for dealing with response uncertainty, since simply waiting does little to identify and test action possibilities and consequences. In these cases, alternative real options decision patterns seem appropriate. Investment in platforms and operating flexibility, for example, appear better strategies for unbounded and continuous uncertainty. Similarly, partial commitment and platform are likely to prove more productive decision strategies when response uncertainty predominates, since they entail exploration of alternate courses of action. These considerations suggest the following propositions:

P3: Different types of uncertainty (state/effect/response, bounded/unbounded, resolvable/continuous) are associated with different real options decision patterns.

P4: Consistency between the type of uncertainty and real options decision patterns are positively associated with performance.

An additional uncertainty dimension that has the potential to shed light on real options behavior is controllability. A number of authors have observed that some uncertainties are more amenable to control or influence by the firm than others (Buchko, 1994; Sutcliffe & Huber, 1998). Companies, for example, can have some degree of control over demand uncertainty through advertising, promotion and pricing. They may directly influence technology uncertainty through R&D. Large companies in particular may enjoy the resources needed to exert such influence. But no firms exert control over uncertainties associated, for example, with the economy as a whole, or with geopolitical developments.

The controllability dimension of uncertainty is especially relevant to the study of real options since real options theory rests explicitly on the insight that management action has the effect of partially endogenizing uncertainty. As described in Chapter 2, the theory ascribes value to management's ability to maximize value by acting flexibly and wisely in response to unforeseen events. Consistent with this aspect of the theory, it is plausible to expect that firms will employ different real options decision patterns depending on the degree of influence they have (or perceive that they have) over future events. High levels of control/influence suggest acceleration and investment in platforms, while deferral and staging appear more suitable in the face of uncertainties which are entirely beyond the firm's control. I suggest therefore the following proposition:

> P5: Real options decision patterns will vary systematically with the degree of control (perceived or actual) that the firm has over uncertainty.

In summary, in the author's opinion, more concerted effort to connect the study of real options with the large literature on uncertainty represents one of the most prominent and potentially fruitful avenues for future real options research.

Finally, the very different findings in this research for the timing and non-timing real options decision patterns have implications for future research. As described earlier, this project failed to find any significant relationships between uncertainty and behavior in the case of operating flexibility, partial commitments and platform investments, or between those decision patterns and performance. This outcome does not square well with the substantial theoretical literature that interprets these types of resource commitments in real options terms and that implies that they are performance-enhancing decision strategies for dealing with uncertainty. This study does not so much disprove these interpretations as suggest that more concerted empirical study is required to connect the non-timing real options decision patterns more conclusively to real options theory.

The issue is most pressing in the case of platform investments, which include a broad range of resource commitments – including technology, knowledge, and capabilities – that are closely connected to other influential strategy theory such as the resource-based and knowledge-based views of the firm, but for which the present study has failed to find any confirmatory empirical relationships to either uncertainty or performance. Given the prominence of the platform construct in strategy theory, empirical research is needed to test whether platform investments in fact contribute to firm performance and if so, what kinds of platforms and under what circumstances.

6.3 Limitations and Future Directions

One limitation of the present study is its exclusive focus on manufacturing companies. The manufacturing sector represents a large portion of the economy and includes a broad spectrum of industries, making the results of the study highly generalizable. The research leaves unanswered, however, what role real options decision patterns play in other sectors of the economy, for example services and natural resources. The service sector seems especially ripe for real options research attention. Given the structural and strategic differences between services and manufacturing, the relationships examined here may prove different for service companies (Heskett, 1986; Mills & Moburg, 1982). The present research, for example, has identified capital intensity as an important determinant of some real options decision patterns. Service firms may be characterized by lower and less irreversible capital requirements, and may not therefore show comparable relationships. At the same time, however, real options theory is not sector specific, and it is reasonable to anticipate that companies in other sectors would demonstrate similar relationships between market and competitive uncertainty and real options decision patterns to those found here. Empirical study of real options in other industrial sectors than manufacturing is therefore warranted, and constitutes an important opportunity for future research. Specific questions of interest include: What constitutes real options-theoretic decision patterns in service industries? Are they different from those applicable to manufacturing? Are there systematic relationships between market and competitive uncertainty and those decision patterns? Are they different from manufacturing?

As noted earlier, a further limitation of the present research is that it does not incorporate an analysis of technological uncertainty in relation to real options resource allocation practices. In the interest of analytical tractability, I have focused on two important sources of uncertainty with clear theoretical linkages to real options. Unpredictable future technological developments and costs, however, arguably constitute a third source of uncertainty which in theory should induce real options-theoretic resource allocation decisions. Technology investments were one of the earliest domains to attract research attention in the real options literature, and there is a considerable body of both theoretical and normative research that elaborates on option-like practices in technology development. Platform investments and staging represent two such behavior patterns. I am , however, aware of no empirical literature that examines the relationship between technological uncertainty and real options decision patterns, making this an especially fertile area for future research. Specific research questions that appear of particular interest include the following: How can technological uncertainty be measured? What technology development and management practices represent real options-theoretic ways of responding to that uncertainty? How does technology uncertainty interact with other sources of uncertainty to condition real options decision patterns? Finally, does the management of technology development along real options lines contribute to firm performance?

A further limitation is that the present research has not included all the dimensions of the real options construct that are of research interest. This study represents a first attempt to draw together the many strands of the real options literature and translate them into measurable behaviors/decision patterns. It does not, however, pretend to have exhausted the boundaries of what is a large and multifaceted construct. A more comprehensive specification of the dimensions of the real options construct in terms amenable to empirical analysis should have high priority on the research agenda.

Several specific dimensions of the construct not included in the present research appear especially worthy of attention. One is the concept of reversibility. Real options theory suggests that companies would, in the face of uncertainty, seek to maximize their ability to undo resource commitments. At the same time, commitment theory (Ghemawat, 1991) argues contrarily that only irreversible commitments can produce lasting competitive advantage. Empirical research aimed at operationalizing the reversibility construct and examining its relationship to uncertainty and performance would be of considerable interest both in the real options and broader strategy literatures.

Similarly, the present research does not directly address the concept of abandonment in relation to real options. Discontinuation of projects (in real options terms, letting options expire) is implicit in real options theory (Adner & Levinthal, 2004a & 2004b). Knowing when real options no longer have value and acting promptly to cease investing in those that do not is arguably a crucial aspect of effective management of real options. Yet there has been little theoretical work on the abandonment dimension of the real options construct and no empirical research. The literature on real options as a strategic framework is asymmetrical in that it addresses almost exclusively the creation and preservation of options as a factor in strategy. Research into the abandonment dimension of the real options construct is overdue. Questions of interest include the following: Do companies differ in their willingness/ability to divest or abandon "expired" options at the appropriate time? If so, what factors make for those differences? Do the differences have any relationship to performance? Such research will be methodologically challenging. It will require appropriate metrics for operationalizing abandonment, and some methodology for determining what constitutes timely versus premature or overdue abandonment. Nevertheless, I believe that having a better understanding of option abandonment is critical to fully understanding the relationships between real options theory, strategy and performance.

A final limitation of the present study is that the entire analysis has been conducted at the level of the firm. In this study, real options decision patterns have been operationalized by survey data reflecting typical or customary practice at each respondent company. Correspondingly, both perceived and objective measures of market and competitive uncertainty have been developed at the level of the firm, in effect assuming that all resource allocation decisions within the firm share in the same level of uncertainty. This analysis basis was selected to permit a large sample cross-sectional study, with the associated benefit of good external validity. It nevertheless masks considerable potential variation in decision patterns within firms. It is entirely plausible that individual companies employ different decision patterns for different kinds of decisions, based, for example, on variations in products, markets or businesses. Companies may be more prone to specific decision patterns in their existing core business than in entering into new ones. Different decision patterns are likely to be employed for proprietary options not exposed to competitive preemption than for non-proprietary ones. In effect, to the extent that market and competitive uncertainty can vary widely across resource allocation decisions within any firm, even largely undiversified ones, it follows from the central premises of this research as a whole that the decision patterns pursued will also vary. Accordingly, the conceptually appropriate unit of analysis may be the decision rather than the collection of decisions comprising the firm.

Similarly, the cross-sectional character of the study masks variation over time in both market and competitive uncertainty and presumably therefore real options decision patterns. Product technology, customer preferences, unit demand and product mix, and the number and behavior of competitors are subject to continuous change, and should, given the conceptual premises of the project, produce corresponding changes in decision pattern, once again arguing for the individual decision as a relevant unit of analysis.

While I believe that the company basis of analysis is an appropriate choice for an initial examination of uncertainty/real options/performance relationships, study of real options will ultimately need to progress to the level of the individual decision in order to fully understand whether and how well companies employ real options principles. In addition to large-sample cross-sectional research, which has been the staple of real options research in the strategy field, more focused study of multiple decisions over time will be required. A model for such research is Bower's (1972) study of capital budgeting practices within a single large firm over a multi-year period, which broke ground in demonstrating that the processes and dynamics actually surrounding capital commitment decisions depart dramatically from idealized normative capital budgeting standards. A similar small-sample study, conducted from a real options perspective, would provide a deeper and more fine-grained understanding of how companies use or do not use real options principles across multiple decisions over time.

Beyond these specific limitations, the present study suggests two additional priorities for future real options research. One is the study of real options behavior in relation to strategy variables. As described in Chapter 2, real options theory has been applied generically to a number of strategic phenomena. However, there has been little study of real options in relation to *strategic variation*. The significant relationships found in the present research between strategic orientation and real options decision patterns invite a series of research questions. Do certain kinds of strategies require or typically entail specific kinds of real options decision-making? Are some strategies inherently more option-like than others? Do variations in strategic type correlate with variations in real options decision patterns? This research has incorporated as a control variable a strategic profile similar to the Miles & Snow (1978) prospector type. Study of other strategic types would reveal if there are systematic relationships between them and real options decision patterns as well. Such study would advance the field beyond the concept of real options as a broad strategic heuristic toward a more articulated understanding of the role of real options in strategy.

Research along these lines would also shed light on the relative prominence of environmental and strategic variables in determining real options decision patterns. The present research has been based on the premise that variations in the level and source of task environment uncertainty induce consistent real options decision patterns, independent of strategy. That premise has been borne out by the analysis in those decision patterns relating to the timing of resource allocations, but notably not as regards those affecting the kind of resource allocations made. In the latter case, this research indicates that strategy is clearly more influential than uncertainty as a predictor of behavior.

A second broad research opportunity is the study of organizational factors as they relate to real options decision making. As discussed earlier, the absence of significant relationships between uncertainty, real options decision behavior and performance for certain real options decision patterns suggests that the performance consequences of real options decision-making may have as much or more to do with how effectively firms implement real options principles than with the specific decision patterns they follow. If this is so, inquiry into the organizational characteristics that make for real options effectiveness is appropriate. There has been little research attention paid to the intersection of real options and organization. Some authors have commented broadly on organizational factors in the context of real options, including organization structure, decision processes, control and incentive systems, knowledge management practices and communications. There has however, been no empirical analysis linking these organizational factors to real options. More broadly, real options theory has direct relationships to major streams in the organizational literature in a number of areas, each of which suggests research opportunities. For example, real options theory is explicitly about learning and acquiring uncertainty-clarifying information. What is known about organizational learning and knowledge management that is relevant to the study of real options? Is there, for example, a relationship between “absorptive capacity” and real options effectiveness? Similarly, the real options literature recognizes that options management is potentially vulnerable to cognitive imperfections and biases such as escalation of commitment, illusion of control and systematic mis-estimation of probabilities. How do companies deal with these effects? Do they differ in their ability to do so, and do those differences affect how well they manage their portfolio of real options?

In conclusion, McGrath et al. (2004) observed that real options theory is in a preparadigmatic stage of development, “poised to occupy a central conceptual position” in the strategy field, but still preoccupied with the need to clearly establish its first principles (86). The questions they posed nearly five years ago regarding the fundamentals of the theory are still open today. Full exploitation of the potential of real options as a strategic framework will require more empirically rigorous and fine-grained study. It is hoped that the present research will contribute to that future body of work.

APPENDIX A

SURVEY OF CAPITAL INVESTMENT DECISION-MAKING PATTERNS

Survey of Capital Investment Decision-Making Patterns

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Purpose of the Survey and General Instructions

This survey is part of a research project that examines company strategic investment decisions in relation to features of the external environment. The survey focuses on strategically important investments and projects, such as new plant investments, R&D, development of new products and services, acquisitions and related diversifications.

The survey asks for information regarding typical or usual decision-patterns, recognizing that not all decisions will necessarily follow the same pattern. Please note that the data of interest is what your company typically does, rather than its stated principles for making capital investment decisions.

If your company has more than one line of business, please answer the survey questions in the context of your principal business.

This survey is intended to be completed by the CEO, President or other senior general executive conversant with the company's practices in making strategic investment and project commitments. It should take approximately 10-15 minutes to complete. Please return the completed survey within two weeks in the enclosed postage paid reply envelope.

We guarantee complete confidentiality to all participating firms. We will use only aggregated results, and will under no circumstances reveal the identity of the respondents or their companies.

We believe that the results of the study will be of direct interest to executives. In recognition of your contribution to the research, we will provide you with executive summary of our findings, and will happy to discuss them with you.

If you have any questions about the survey or the study of which it is a part, please contact either of the two co-investigators on this project: Mr. Al Boccia at (978) 857-0325 (aboccia@som.umass.edu) or Dr. Bruce Skaggs at (413) 545-5684 (bskaggs@som.umass.edu).

We very much appreciate your help in making this research a success.
THANK YOU!

Survey of Capital Investment Decision-Making Patterns

I. Capital Investment Decision Patterns: This section of the survey assesses specific aspects of your company's decisions regarding strategic investments and projects. In each section, please indicate by circling the appropriate number the extent to which you agree or disagree with the statements regarding your company's typical way of making such decisions.

A. The following items address how timing considerations typically affect your company's decisions regarding strategic investments and projects.

	Strongly Disagree						Strongly Agree
1. Our investment decisions take into account whether delaying a project may improve its attractiveness.	1	2	3	4	5	6	7
2. We postpone projects which meet our standard investment criteria in order to further monitor market developments.	1	2	3	4	5	6	7
3. If a project looks sound, we proceed with it rather than invest time and money to gather further information regarding its potential success.	1	2	3	4	5	6	7
4. In executing strategic investment projects, getting them done quickly is the consideration most important to us.	1	2	3	4	5	6	7
5. We frequently move ahead with projects even when we are not sure of their ultimate success.	1	2	3	4	5	6	7

B. The following items assess the extent to which your company typically takes a staged approach to strategic investments and projects.

	Strongly Disagree						Strongly Agree
1. We break investment projects down into stages and evaluate whether or not to proceed at the end of each stage.	1	2	3	4	5	6	7
2. We revise project features (for example, capacity level or technology used) throughout the project.	1	2	3	4	5	6	7
3. We revise project schedules and implementation timing throughout the project.	1	2	3	4	5	6	7
4. We set project milestones and continuously evaluate progress toward them.	1	2	3	4	5	6	7
5. We discontinue projects that do not meet expectations once we begin to implement them.	1	2	3	4	5	6	7
6. Our decisions about whether or not to continue projects are heavily influenced by how much we have already invested in them.	1	2	3	4	5	6	7

C. The following items address how interdependencies among projects are typically incorporated in your firm's strategic investment decisions.

	Strongly Disagree						Strongly Agree
1. Our decisions to invest in projects take into account the benefits that these investments create for other projects.	1	2	3	4	5	6	7
2. When choosing among related projects, we give greatest priority to those projects from which we can learn the most.	1	2	3	4	5	6	7
3. When choosing among related projects, we give greatest priority to those projects which offer the highest immediate financial rewards.	1	2	3	4	5	6	7
4. When there are several different approaches to the same product/service opportunity, we pursue several approaches until the best one becomes clear.	1	2	3	4	5	6	7
5. In choosing among related projects, we favor those with a wide range of potential outcomes.	1	2	3	4	5	6	7
6. In choosing among related projects, we favor those with a narrow range of potential outcomes.	1	2	3	4	5	6	7

D. The following items relate to the emphasis your firm places on the ability to make future operational changes.

When making investments in productive capacity, our company typically:	Strongly Disagree						Strongly Agree
1. adds capacity in continuous increments rather than large periodic additions.	1	2	3	4	5	6	7
2. invests in facilities that allow for easy changes in production levels.	1	2	3	4	5	6	7
3. invests in facilities that allow for easy changes in product/service mix.	1	2	3	4	5	6	7
4. invests in facilities that allow for easy changes in feedstock or raw materials.	1	2	3	4	5	6	7
5. invests in capacity in response to demand growth rather than ahead of it.	1	2	3	4	5	6	7
6. places primary emphasis on the ability to easily change operating parameters.	1	2	3	4	5	6	7

E. The following items assess how your company typically approaches investing in new activities, such as new products/services, new markets for existing products/services, and related diversifications.

	Strongly Disagree						Strongly Agree
In making investments in new activities, our company typically:							
1. makes modest initial investments that can later be expanded.	1	2	3	4	5	6	7
2. acquires companies smaller than itself as a foothold in the target product/service/market.	1	2	3	4	5	6	7
3. acquires minority equity positions in other companies in the target product/service/market which can later lead to full acquisition.	1	2	3	4	5	6	7
4. establishes joint ventures, partnerships or alliances.	1	2	3	4	5	6	7
5. seeks out entry options which have a clear exit strategy in case they don't work out.	1	2	3	4	5	6	7
6. makes acquisitions that are significant with respect to its own size in order to gain a large early position in the target product/service/market.	1	2	3	4	5	6	7

F. The following statements assess the extent to which your firm makes investments that do not meet its usual standards of financial performance and in what circumstances it typically does so.

	Strongly Disagree						Strongly Agree
Our company invests in projects that do not meet our standard financial criteria when they:							
1. offer future growth opportunities not captured in the project financial projections.	1	2	3	4	5	6	7
2. generate important knowledge or experience.	1	2	3	4	5	6	7
3. contribute to important competencies and capabilities.	1	2	3	4	5	6	7
4. establish an early position in an attractive product or market.	1	2	3	4	5	6	7
5. have the potential to yield multiple products/services rather than a single product/service.	1	2	3	4	5	6	7

II. External Environment: This section assesses your perceptions of your company's external environment as well as the degree of influence or control the company has over external environment factors.

A. Please rate the predictability of the following dimensions of your company's business environment.

	Unpredictable						Predictable
1. Customer demand for existing products/services is....	1	2	3	4	5	6	7
2. Customer demand for new products/services is....	1	2	3	4	5	6	7
3. Customer needs and desires are...	1	2	3	4	5	6	7
4. Competitor price actions are.......	1	2	3	4	5	6	7
5. Competitor changes in product/service quality are.....	1	2	3	4	5	6	7
6. Competitor changes in product/service technology are....	1	2	3	4	5	6	7
7. Competitor introductions of new products/services are....	1	2	3	4	5	6	7
8. The entry of new competitors is...	1	2	3	4	5	6	7
9. Changes in product/service technology are...	1	2	3	4	5	6	7
10. Changes in production process technology are...	1	2	3	4	5	6	7
11. Changes in materials and component technology are...	1	2	3	4	5	6	7

B. The following items assess how much control your company generally has over unexpected or exceptional situations affecting its strategic investments. Please indicate how strongly you agree or disagree with the following statements.

	Strongly Disagree						Strongly Agree
1. The firm has the resources to resolve most situations.	1	2	3	4	5	6	7
2. The firm has the competencies to address most situations.	1	2	3	4	5	6	7
3. Most situations can be contained.	1	2	3	4	5	6	7
4. The firm manages situations instead of situations managing it.	1	2	3	4	5	6	7
5. The firm's responses to situations are heavily constrained by other organizations, groups or individuals.	1	2	3	4	5	6	7

III. Firm Strategy: This section assesses your firm's overall strategic orientation. Please rate how strongly you agree or disagree with the following statements.

	Strongly Disagree						Strongly Agree
1. The firm tries to maintain a safe niche in a relatively stable products domain.	1	2	3	4	5	6	7
2. The firm tries to protect the domain in which it operates by stressing higher quality than its competitors.	1	2	3	4	5	6	7
3. The firm tries to protect the domain in which it operates by stressing lower prices than its competitors.	1	2	3	4	5	6	7
4. The firm concentrates on trying to achieve the best performance in a relatively narrow product market domain.	1	2	3	4	5	6	7
5. The firm places less stress on the examination of changes in the industry that are not directly relevant to the firm.	1	2	3	4	5	6	7
6. The firm leads in innovation in its industry.	1	2	3	4	5	6	7
7. The firm operates in a broad product domain.	1	2	3	4	5	6	7
8. The firm's product domain is periodically redefined.	1	2	3	4	5	6	7
9. The firm believes in being "first-in" in the industry in the development of new products.	1	2	3	4	5	6	7
10. The firm responds rapidly to early signals of opportunities in the environment.	1	2	3	4	5	6	7
11. The firm quickly adopts promising innovations in the industry.	1	2	3	4	5	6	7
12. The innovations which are chosen by the firm are carefully examined.	1	2	3	4	5	6	7
13. The firm often reacts to innovations in the industry by offering similar, lower-cost products.	1	2	3	4	5	6	7
14. The firm carefully monitors competitors' actions in the industry.	1	2	3	4	5	6	7
15. The firm seldom leads in developing new products in the industry.	1	2	3	4	5	6	7

Thank you for your participation in this research!

APPENDIX B

FACTOR AND RELIABILITY ANALYSIS

Factor Analysis: Real Options Decision Patterns

Rotated Component Matrix[a]

	Component											
	1	2	3	4	5	6	7	8	9	10	11	12
IA1	-.098	.295	.047	.066	.712	-.051	-.030	.151	.032	.119	-.188	-.187
IA2	.057	.006	-.016	-.080	.770	.085	-.137	-.120	-.117	-.148	.133	.075
IA3	.161	-.363	.094	.247	-.206	.002	.403	-.052	.410	.153	-.195	-.092
IA4	-.085	-.160	.215	.114	-.177	.156	.627	.050	.298	.083	-.103	.143
IA5	.103	.205	.001	.009	-.052	-.028	.752	.093	-.147	-.105	.080	-.176
IB1	.052	.730	.023	.083	-.053	.095	-.040	-.019	-.076	.010	-.082	.252
IB2	-.003	.793	-.005	.115	.020	.054	.175	-.080	-.056	.049	.031	-.056
IB3	.031	.746	.040	-.028	.275	-.091	.110	-.070	.073	.021	.047	-.154
IB4	-.028	.655	.137	-.054	.029	.050	-.265	.184	-.009	.186	-.115	.001
IB5	-.044	.247	.176	-.131	.048	.490	.228	-.220	-.119	-.148	-.069	.075
IB6	.084	.086	-.110	-.049	.048	-.240	.057	.036	.728	-.272	.349	.019
IC1	.247	.029	.093	.120	.552	.025	-.016	-.043	.076	.274	-.056	.143
IC2	.347	-.114	.043	.344	.195	.266	.302	.001	-.136	.000	.121	.180
IC3	-.181	-.097	.107	-.041	-.027	.181	-.056	-.108	.719	.209	.013	.051
IC4	.015	.013	.016	.186	.103	.683	.126	-.003	.054	.028	.207	.083
IC5	.077	.051	.100	.843	-.005	.175	.089	-.042	.088	-.151	.097	-.023
IC6	.143	-.084	.143	-.813	-.043	.132	-.017	.050	.095	-.014	.021	-.056
ID1	.028	.104	.274	.122	-.082	-.120	.010	-.124	-.137	.506	.447	.079
ID2	.068	.099	.780	.023	.025	-.009	.093	-.066	-.026	.081	-.190	.058
ID3	.135	-.016	.761	-.036	.147	.059	.120	-.069	.111	.138	-.061	-.040
ID4	.058	.043	.680	-.055	.149	.022	-.018	.106	.006	-.117	.151	.076
ID5	-.189	-.111	-.040	.054	-.034	.030	-.002	.038	.189	.063	.775	-.090
ID6	.051	.014	.656	.051	-.315	.062	-.052	-.020	-.028	-.023	.093	.041
IE1	.094	.254	-.142	-.085	.099	.217	-.106	-.006	.124	.656	.161	-.154
IE2	.097	.003	.094	-.183	.085	-.247	.053	.139	.020	.609	-.126	.282
IE3	.245	-.036	-.015	.011	-.019	-.124	.043	.756	.026	-.018	.027	.283
IE4	-.065	.008	-.030	-.087	-.016	.191	.062	.806	-.101	.041	-.008	-.121
IE5	.086	.005	.023	-.063	-.080	.681	-.154	.213	.039	.000	-.195	-.052
IE6	.059	.036	.099	.039	.024	.063	-.065	.063	.043	.066	-.049	.833
IF1	.712	.008	-.044	-.093	.011	-.049	.044	-.083	.118	-.006	-.227	.036
IF2	.799	-.019	.005	-.123	.169	.023	.122	.043	-.046	-.047	.026	.017
IF3	.811	-.018	.172	-.036	.118	.081	.091	.020	-.131	.056	.089	.160
IF4	.835	.090	.115	.094	-.091	-.004	-.089	.095	-.020	.134	-.104	-.068
IF5	.642	-.010	.237	.377	-.165	.051	-.229	.208	-.041	.089	.001	-.085

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 25 iterations.

Shadings indicate items included in final scales

Item orientations are as follows: **IA – Timing**
IB – Staging
IC – Project Interdependence (Not Used)
ID – Operating Flexibility
IE – Partial Commitment
IF – Platform

Scale Reliability: Staging

Case Processing Summary

		N	%
Cases	Valid	172	99.4
	Excluded[a]	1	.6
	Total	173	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.742	.747	4

Inter-Item Correlation Matrix

	IB1	IB2	IB3	IB4
IB1	1.000	.471	.358	.411
IB2	.471	1.000	.561	.381
IB3	.358	.561	1.000	.366
IB4	.411	.381	.366	1.000

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
IB1	15.95	10.728	.518	.289	.700
IB2	15.70	10.891	.624	.408	.632
IB3	15.42	11.146	.546	.346	.678
IB4	14.59	13.706	.484	.237	.717

Scale Reliability: Operating Flexibility

Case Processing Summary

		N	%
Cases	Valid	167	96.5
	Excluded[a]	6	3.5
	Total	173	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.721	.724	4

Inter-Item Correlation Matrix

	ID2	ID3	ID4	ID6
ID2	1.000	.610	.357	.377
ID3	.610	1.000	.449	.285
ID4	.357	.449	1.000	.296
ID6	.377	.285	.296	1.000

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
ID2	12.86	10.003	.590	.420	.611
ID3	12.95	10.034	.599	.434	.607
ID4	13.86	9.951	.468	.236	.689
ID6	13.90	11.478	.397	.172	.721

Scale Reliability: Platform

Case Processing Summary

		N	%
Cases	Valid	172	99.4
	Excluded[a]	1	.6
	Total	173	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.839	.840	5

Inter-Item Correlation Matrix

	IF1	IF2	IF3	IF4	IF5
IF1	1.000	.500	.445	.534	.275
IF2	.500	1.000	.689	.520	.364
IF3	.445	.689	1.000	.657	.480
IF4	.534	.520	.657	1.000	.658
IF5	.275	.364	.480	.658	1.000

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
IF1	16.64	27.051	.536	.365	.836
IF2	17.04	26.472	.650	.521	.804
IF3	16.53	25.724	.726	.599	.784
IF4	16.20	23.937	.769	.642	.769
IF5	16.45	27.618	.544	.447	.832

Scale Reliability: Deferral

Case Processing Summary

		N	%
Cases	Valid	172	99.4
	Excluded[a]	1	.6
	Total	173	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.584	.585	2

Inter-Item Correlation Matrix

	IA1	IA2
IA1	1.000	.413
IA2	.413	1.000

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
IA1	4.30	2.561	.413	.171	.
IA2	4.97	2.356	.413	.171	.

Scale Reliability: Acceleration

Case Processing Summary

		N	%
Cases	Valid	172	99.4
	Excluded[a]	1	.6
	Total	173	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.621	.621	2

Inter-Item Correlation Matrix

	IA3	IA4
IA3	1.000	.451
IA4	.451	1.000

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
IA3	3.41	2.899	.451	.203	.
IA4	3.75	2.855	.451	.203	.

Scale Reliability: Partial Commitment

Case Processing Summary

		N	%
Cases	Valid	172	99.4
	Excluded[a]	1	.6
	Total	173	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.540	.542	2

Inter-Item Correlation Matrix

	IE3	IE4
IE3	1.000	.371
IE4	.371	1.000

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
IE3	4.12	2.786	.371	.138	.
IE4	3.08	3.228	.371	.138	.

Factor Analysis: Perceived Uncertainty

Rotated Component Matrix[a]

	Component	
	1	2
IIA1	.038	.823
IIA2	.088	.747
IIA3	-.029	.693
IIA4	.539	.040
IIA5	.829	-.004
IIA6	.762	.141
IIA7	.805	-.039
IIA8	.635	.008

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 3 iterations.

Shadings indicate items included in final scales

Item orientations are as follows:

IIA1-IIA3 – Perceived Market Uncertainty

IIA14-IIA8 – Perceived Competitive Uncertainty

Scale Reliability: Perceived Market Uncertainty

Case Processing Summary

		N	%
Cases	Valid	173	100.0
	Excluded[a]	0	.0
	Total	173	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.630	.627	3

Inter-Item Correlation Matrix

	IIA1	IIA2	IIA3
IIA1	1.000	.463	.363
IIA2	.463	1.000	.250
IIA3	.363	.250	1.000

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
IIA1	7.39	3.948	.525	.279	.399
IIA2	6.31	4.528	.440	.222	.529
IIA3	7.38	5.295	.360	.140	.632

Scale Reliability: Perceived Competitive Uncertainty

Case Processing Summary

		N	%
Cases	Valid	170	98.3
	Excluded[a]	3	1.7
	Total	173	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.756	.765	5

Inter-Item Correlation Matrix

	IIA4	IIA5	IIA6	IIA7	IIA8
IIA4	1.000	.413	.234	.324	.151
IIA5	.413	1.000	.651	.489	.361
IIA6	.234	.651	1.000	.498	.298
IIA7	.324	.489	.498	1.000	.523
IIA8	.151	.361	.298	.523	1.000

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
IIA4	15.28	19.186	.352	.202	.771
IIA5	15.38	16.841	.668	.524	.665
IIA6	15.19	17.270	.563	.472	.699
IIA7	14.99	16.615	.647	.440	.669
IIA8	15.20	17.072	.437	.292	.751

Factor Analysis: Strategic Orientation

Rotated Component Matrix[a]

	Component				
	1	2	3	4	5
III1	-.132	.027	-.101	-.072	.771
III2	.162	-.182	.250	.022	.718
III3	-.093	.773	.037	-.041	-.281
III4	.180	.152	-.069	-.789	.178
III5	-.043	.222	-.623	-.151	.215
III6	.737	-.370	.095	-.067	.082
III7	.309	.108	.031	.782	.096
III8	.473	.055	-.051	.377	.011
III9	.687	-.350	.098	-.080	-.069
III10	.716	.034	.218	.158	.119
III11	.802	.103	.094	.098	-.010
III12	.265	.075	.566	-.142	.288
III13	-.075	.718	-.052	-.012	.072
III14	.120	.045	.771	.038	.097
III15	-.559	.392	-.257	.134	.203

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.

a. Rotation converged in 10 iterations.

Shadings indicate items included in final scale

Item orientations are as follows:

III1-III5 – Defender strategic type

III6-III11 – Prospector strategic type

III12-III15 – Analyzer strategic type

Scale Reliability: Strategic Orientation

Case Processing Summary

		N	%
Cases	Valid	170	98.3
	Excluded[a]	3	1.7
	Total	173	100.0

a. Listwise deletion based on all variables in the procedure.

Reliability Statistics

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.759	.764	5

Inter-Item Correlation Matrix

	III6	III8	III9	III10	III11
III6	1.000	.185	.618	.438	.508
III8	.185	1.000	.191	.293	.266
III9	.618	.191	1.000	.405	.412
III10	.438	.293	.405	1.000	.620
III11	.508	.266	.412	.620	1.000

Item-Total Statistics

	Scale Mean if Item Deleted	Scale Variance if Item Deleted	Corrected Item-Total Correlation	Squared Multiple Correlation	Cronbach's Alpha if Item Deleted
III6	18.77	17.267	.608	.463	.685
III8	19.65	20.536	.292	.101	.798
III9	19.26	17.057	.555	.408	.706
III10	19.25	18.317	.601	.429	.692
III11	19.33	17.855	.619	.459	.685

APPENDIX C

REGRESSION ANALYSES – UNCERTAINTY AND REAL OPTIONS DECISION PATTERNS

Deferral - Perceived Uncertainty

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.263[a]	.069	.042	1.07952	.069	2.491	5	167	.033
2	.264[b]	.070	.036	1.08268	.000	.027	1	166	.871

a. Predictors: (Constant), RStratOrient, CPerCU, CPerMU, CIIndex, LOGTA

b. Predictors: (Constant), RStratOrient, CPerCU, CPerMU, CIIndex, LOGTA, PerMxCInt

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-.849	.481		-1.764	.080
	CPerMU	-.049	.086	-.044	-.574	.567
	CPerCU	-.213	.083	-.194	-2.564	.011
	LOGTA	.001	.050	.001	.012	.990
	CIIndex	.027	.461	.005	.060	.953
	RStratOrient	.178	.084	.161	2.122	.035
2	(Constant)	-.849	.483		-1.759	.080
	CPerMU	-.050	.087	-.045	-.580	.562
	CPerCU	-.215	.084	-.195	-2.555	.012
	LOGTA	.002	.051	.003	.030	.976
	CIIndex	.022	.463	.004	.048	.962
	RStratOrient	.177	.084	.160	2.101	.037
	PerMxCInt	-.014	.084	-.012	-.163	.871

a. Dependent Variable: CDefer

Deferral - Objective Uncertainty

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.212[a]	.045	.016	1.09359	.045	1.573	5	167	.170
2	.213[b]	.045	.011	1.09666	.000	.065	1	166	.799

a. Predictors: (Constant), ZRHINDEX, RStratOrient, CIIndex, ZSEMean5, LOGTA

b. Predictors: (Constant), ZRHINDEX, RStratOrient, CIIndex, ZSEMean5, LOGTA, SMUxCU5

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-.853	.485		-1.760	.080
	LOGTA	-.011	.051	-.019	-.221	.826
	CIIndex	.100	.462	.018	.216	.830
	RStratOrient	.194	.085	.175	2.276	.024
	ZSEMean5	-.061	.089	-.054	-.686	.494
	ZRHINDEX	-.151	.092	-.135	-1.653	.100
2	(Constant)	-.862	.487		-1.769	.079
	LOGTA	-.009	.052	-.016	-.182	.856
	CIIndex	.071	.477	.013	.149	.882
	RStratOrient	.193	.086	.175	2.258	.025
	ZSEMean5	-.069	.094	-.061	-.730	.467
	ZRHINDEX	-.149	.092	-.133	-1.611	.109
	SMUxCU5	-.019	.074	-.021	-.255	.799

a. Dependent Variable: CDefer

Acceleration - Perceived Uncertainty

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.218[a]	.047	.019	1.42668	.047	1.665	5	167	.146
2	.263[b]	.069	.036	1.41446	.022	3.898	1	166	.050

a. Predictors: (Constant), RStratOrient, CPerCU, CPerMU, CIIndex, LOGTA

b. Predictors: (Constant), RStratOrient, CPerCU, CPerMU, CIIndex, LOGTA, PerMxCInt

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.900	.636		1.414	.159
	CPerMU	-.071	.114	-.049	-.626	.532
	CPerCU	-.080	.110	-.056	-.730	.466
	LOGTA	-.156	.066	-.199	-2.356	.020
	CIIndex	-.302	.609	-.041	-.496	.621
	RStratOrient	.059	.111	.041	.529	.597
2	(Constant)	.900	.631		1.426	.156
	CPerMU	-.059	.113	-.040	-.522	.602
	CPerCU	-.051	.110	-.035	-.461	.646
	LOGTA	-.171	.066	-.218	-2.584	.011
	CIIndex	-.216	.605	-.029	-.357	.721
	RStratOrient	.073	.110	.051	.662	.509
	PerMxCInt	.217	.110	.151	1.974	.050

a. Dependent Variable: CAccel

Acceleration - Objective Uncertainty

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.215[a]	.046	.018	1.42768	.046	1.616	5	167	.158
2	.215[b]	.046	.012	1.43190	.000	.017	1	166	.897

a. Predictors: (Constant), ZRHINDEX, RStratOrient, CIIndex, ZSEMean5, LOGTA

b. Predictors: (Constant), ZRHINDEX, RStratOrient, CIIndex, ZSEMean5, LOGTA, SMUxCU5

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.850	.633		1.344	.181
	LOGTA	-.151	.067	-.192	-2.262	.025
	CIIndex	-.332	.604	-.045	-.550	.583
	RStratOrient	.062	.111	.043	.560	.576
	ZSEMean5	.091	.116	.062	.787	.432
	ZRHINDEX	-.019	.120	-.013	-.159	.874
2	(Constant)	.844	.636		1.328	.186
	LOGTA	-.150	.068	-.190	-2.215	.028
	CIIndex	-.351	.623	-.048	-.563	.574
	RStratOrient	.062	.112	.043	.553	.581
	ZSEMean5	.086	.123	.059	.705	.482
	ZRHINDEX	-.017	.121	-.012	-.144	.886
	SMUxCU5	-.013	.097	-.011	-.130	.897

a. Dependent Variable: CAccel

Staging - Perceived Uncertainty

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.351[a]	.123	.097	1.03318	.123	4.687	5	167	.000
2	.398[b]	.158	.128	1.01537	.035	6.910	1	166	.009

a. Predictors: (Constant), RStratOrient, CPerCU, CPerMU, CIIndex, LOGTA

b. Predictors: (Constant), RStratOrient, CPerCU, CPerMU, CIIndex, LOGTA, PerMxCInt

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-1.842	.461		-3.998	.000
	CPerMU	.203	.082	.184	2.460	.015
	CPerCU	.019	.079	.017	.235	.815
	LOGTA	.044	.048	.075	.924	.357
	CIIndex	.534	.441	.096	1.210	.228
	RStratOrient	.301	.080	.276	3.740	.000
2	(Constant)	-1.842	.453		-4.068	.000
	CPerMU	.191	.081	.173	2.355	.020
	CPerCU	-.010	.079	-.009	-.121	.904
	LOGTA	.059	.048	.099	1.231	.220
	CIIndex	.452	.434	.081	1.040	.300
	RStratOrient	.287	.079	.263	3.626	.000
	PerMxCInt	-.208	.079	-.191	-2.629	.009

a. Dependent Variable: CStaging

Staging - Objective Uncertainty

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change
1	.307[a]	.094	.067	1.05012	.094	3.468	5	167	.005
2	.339[b]	.115	.083	1.04098	.021	3.948	1	166	.049

a. Predictors: (Constant), ZRHINDEX, RStratOrient, CIIndex, ZSEMean5, LOGTA

b. Predictors: (Constant), ZRHINDEX, RStratOrient, CIIndex, ZSEMean5, LOGTA, SMUxCU5

Coefficients[a]

Model		Unstandardized Coefficients: B	Std. Error	Standardized Coefficients: Beta	t	Sig.
1	(Constant)	-1.604	.465		-3.448	.001
	LOGTA	.011	.049	.019	.225	.823
	CIIndex	.621	.444	.112	1.397	.164
	RStratOrient	.297	.082	.272	3.624	.000
	ZSEMean5	-.036	.085	-.032	-.416	.678
	ZRHINDEX	-.073	.088	-.066	-.825	.411
2	(Constant)	-1.669	.462		-3.609	.000
	LOGTA	.025	.049	.042	.504	.615
	CIIndex	.409	.453	.074	.904	.367
	RStratOrient	.291	.081	.267	3.579	.000
	ZSEMean5	-.091	.089	-.082	-1.021	.309
	ZRHINDEX	-.054	.088	-.049	-.612	.542
	SMUxCU5	-.140	.070	-.161	-1.987	.049

a. Dependent Variable: CStaging

Operating Flexibility - Perceived Uncertainty

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.279[a]	.078	.050	.98271	.078	2.823	5	167	.018
2	.281[b]	.079	.045	.98525	.001	.140	1	166	.709

a. Predictors: (Constant), RStratOrient, CPerCU, CPerMU, CIIndex, LOGTA

b. Predictors: (Constant), RStratOrient, CPerCU, CPerMU, CIIndex, LOGTA, PerMxCInt

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-1.173	.438		-2.677	.008
	CPerMU	.104	.078	.101	1.326	.187
	CPerCU	-.052	.076	-.052	-.685	.494
	LOGTA	.050	.046	.092	1.103	.272
	CIIndex	-.839	.419	-.163	-2.001	.047
	RStratOrient	.212	.077	.209	2.765	.006
2	(Constant)	-1.173	.439		-2.670	.008
	CPerMU	.102	.079	.100	1.300	.195
	CPerCU	-.056	.076	-.055	-.728	.467
	LOGTA	.052	.046	.095	1.135	.258
	CIIndex	-.850	.421	-.165	-2.018	.045
	RStratOrient	.210	.077	.207	2.727	.007
	PerMxCInt	-.029	.077	-.028	-.374	.709

a. Dependent Variable: COpflex

Operating Flexibility - Objective Uncertainty

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.264[a]	.070	.042	.98715	.070	2.498	5	167	.033
2	.267[b]	.071	.038	.98928	.002	.282	1	166	.596

a. Predictors: (Constant), ZRHINDEX, RStratOrient, CIIndex, ZSEMean5, LOGTA

b. Predictors: (Constant), ZRHINDEX, RStratOrient, CIIndex, ZSEMean5, LOGTA, SMUxCU5

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-1.109	.437		-2.535	.012
	LOGTA	.044	.046	.079	.948	.345
	CIIndex	-.753	.417	-.146	-1.804	.073
	RStratOrient	.204	.077	.202	2.653	.009
	ZSEMean5	.050	.080	.048	.617	.538
	ZRHINDEX	.048	.083	.047	.585	.559
2	(Constant)	-1.126	.439		-2.561	.011
	LOGTA	.047	.047	.086	1.011	.313
	CIIndex	-.807	.430	-.156	-1.874	.063
	RStratOrient	.203	.077	.200	2.626	.009
	ZSEMean5	.035	.085	.035	.419	.676
	ZRHINDEX	.053	.083	.052	.638	.524
	SMUxCU5	-.035	.067	-.044	-.531	.596

a. Dependent Variable: COpflex

Partial Commitment - Perceived Uncertainty

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.184[a]	.034	.005	1.42766	.034	1.171	5	167	.325
2	.203[b]	.041	.007	1.42654	.007	1.262	1	166	.263

a. Predictors: (Constant), RStratOrient, CPerCU, CPerMU, CIIndex, LOGTA

b. Predictors: (Constant), RStratOrient, CPerCU, CPerMU, CIIndex, LOGTA, PerMxCInt

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-.272	.637		-.428	.669
	CPerMU	-.021	.114	-.015	-.186	.853
	CPerCU	.085	.110	.059	.770	.442
	LOGTA	-.069	.066	-.088	-1.033	.303
	CIIndex	1.372	.609	.187	2.253	.026
	RStratOrient	.099	.111	.069	.895	.372
2	(Constant)	-.273	.636		-.428	.669
	CPerMU	-.014	.114	-.010	-.124	.901
	CPerCU	.101	.111	.071	.917	.361
	LOGTA	-.077	.067	-.099	-1.154	.250
	CIIndex	1.421	.610	.194	2.329	.021
	RStratOrient	.108	.111	.075	.967	.335
	PerMxCInt	.125	.111	.087	1.124	.263

a. Dependent Variable: CPartCom

Partial Commitment - Objective Uncertainty

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.238[a]	.057	.028	1.41083	.057	2.001	5	167	.081
2	.247[b]	.061	.027	1.41156	.005	.827	1	166	.365

a. Predictors: (Constant), ZRHINDEX, RStratOrient, CIIndex, ZSEMean5, LOGTA

b. Predictors: (Constant), ZRHINDEX, RStratOrient, CIIndex, ZSEMean5, LOGTA, SMUxCU5

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-.262	.625		-.419	.676
	LOGTA	-.077	.066	-.098	-1.165	.246
	CIIndex	1.364	.597	.186	2.287	.023
	RStratOrient	.110	.110	.077	.999	.319
	ZSEMean5	-.245	.115	-.168	-2.137	.034
	ZRHINDEX	-.101	.118	-.070	-.855	.394
2	(Constant)	-.302	.627		-.482	.630
	LOGTA	-.068	.067	-.087	-1.025	.307
	CIIndex	1.233	.614	.168	2.008	.046
	RStratOrient	.106	.110	.074	.964	.336
	ZSEMean5	-.280	.121	-.192	-2.313	.022
	ZRHINDEX	-.089	.119	-.061	-.751	.454
	SMUxCU5	-.087	.095	-.076	-.909	.365

a. Dependent Variable: CPartCom

Platform - Perceived Uncertainty

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.372[a]	.138	.113	1.17751	.138	5.368	5	167	.000
2	.379[b]	.143	.112	1.17762	.005	.968	1	166	.327

a. Predictors: (Constant), RStratOrient, CPerCU, CPerMU, CIIndex, LOGTA

b. Predictors: (Constant), RStratOrient, CPerCU, CPerMU, CIIndex, LOGTA, PerMxCInt

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-1.667	.525		-3.175	.002
	CPerMU	-.057	.094	-.045	-.604	.547
	CPerCU	-.155	.091	-.124	-1.709	.089
	LOGTA	.007	.055	.011	.131	.896
	CIIndex	-.971	.502	-.152	-1.933	.055
	RStratOrient	.388	.092	.309	4.231	.000
2	(Constant)	-1.668	.525		-3.175	.002
	CPerMU	-.052	.094	-.041	-.549	.584
	CPerCU	-.142	.091	-.114	-1.559	.121
	LOGTA	.001	.055	.002	.019	.985
	CIIndex	-.935	.504	-.146	-1.857	.065
	RStratOrient	.394	.092	.314	4.285	.000
	PerMxCInt	.090	.092	.072	.984	.327

a. Dependent Variable: CPlat

Platform - Objective Uncertainty

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.367[a]	.134	.108	1.18032	.134	5.183	5	167	.000
2	.379[b]	.144	.113	1.17732	.010	1.850	1	166	.176

a. Predictors: (Constant), ZRHINDEX, RStratOrient, CIIndex, ZSEMean5, LOGTA

b. Predictors: (Constant), ZRHINDEX, RStratOrient, CIIndex, ZSEMean5, LOGTA, SMUxCU5

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-1.656	.523		-3.166	.002
	LOGTA	-.005	.055	-.008	-.097	.923
	CIIndex	-.943	.499	-.148	-1.890	.060
	RStratOrient	.403	.092	.322	4.382	.000
	ZSEMean5	-.055	.096	-.044	-.577	.565
	ZRHINDEX	-.162	.099	-.128	-1.637	.103
2	(Constant)	-1.706	.523		-3.262	.001
	LOGTA	.005	.056	.008	.094	.925
	CIIndex	-1.107	.512	-.173	-2.161	.032
	RStratOrient	.399	.092	.318	4.340	.000
	ZSEMean5	-.098	.101	-.077	-.975	.331
	ZRHINDEX	-.147	.099	-.116	-1.484	.140
	SMUxCU5	-.108	.080	-.108	-1.360	.176

a. Dependent Variable: CPlat

APPENDIX D

REGRESSION ANALYSES – PERFORMANCE

Growth - Perceived Uncertainty

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.316[a]	.100	.044	16.168	.100	1.798	10	162	.065
2	.415[b]	.172	.044	16.171	.072	.996	13	149	.458
3	.572[c]	.327	.190	14.880	.155	5.494	6	143	.000

a. Predictors: (Constant), ConGr5, CAccel, CPerMU, CPartCom, CPerCU, COpflex, LOGTA, CDefer, CPlat, CStaging

b. Predictors: (Constant), ConGr5, CAccel, CPerMU, CPartCom, CPerCU, COpflex, LOGTA, CDefer, CPlat, CStaging, PMUxOpFl, PMUxPartC, PMUxAcc, PMUxDef, PCUxPartC, PCUxDef, PMUxPlat, PCUxOpFl, PCUxAcc, PCUxStag, PMUxStag, PMUxPCU, PCUxPlat

c. Predictors: (Constant), ConGr5, CAccel, CPerMU, CPartCom, CPerCU, COpflex, LOGTA, CDefer, CPlat, CStaging, PMUxOpFl, PMUxPartC, PMUxAcc, PMUxDef, PCUxPartC, PCUxDef, PMUxPlat, PCUxOpFl, PCUxAcc, PCUxStag, PMUxStag, PMUxPCU, PCUxPlat, PMUxPCUxPlat, PMUxPCUxStag, PMUxPCUxPartC, PMUxPCUxOpFl, PMUxPCUxAcc, PMUxPCUxDef

ANOVA (d)

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	4698.733	10	469.873	1.798	.065
	Residual	42346.500	162	261.398		
	Total	47045.234	172			
2	Regression	8083.143	23	351.441	1.344	.149
	Residual	38962.091	149	261.491		
	Total	47045.234	172			
3	Regression	15381.965	29	530.413	2.395	.000
	Residual	31663.269	143	221.421		
	Total	47045.234	172			

d Dependent Variable: Growth5Yr

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	-1.226	6.259		-.196	.845
	CDefer	.619	1.215	.041	.509	.611
	CAccel	.748	.943	.065	.794	.429
	CStaging	.663	1.248	.044	.531	.596
	COpflex	-.471	1.300	-.029	-.362	.717
	CPartCom	1.846	.883	.160	2.090	.038
	CPlat	.840	1.059	.064	.794	.428
	CPerMU	-.705	1.322	-.042	-.534	.594
	CPerCU	.406	1.273	.025	.319	.750
	LOGTA	.299	.709	.033	.421	.674
	ConGr5	.898	.300	.230	2.994	.003
2	(Constant)	-2.461	6.645		-.370	.712
	CDefer	-.012	1.281	-.001	-.009	.993
	CAccel	.651	.977	.057	.667	.506
	CStaging	1.205	1.335	.079	.902	.368
	COpflex	-.587	1.394	-.036	-.421	.674
	CPartCom	1.664	.908	.144	1.834	.069
	CPlat	.793	1.110	.060	.714	.476
	CPerMU	-.844	1.406	-.050	-.600	.549
	CPerCU	.803	1.384	.049	.581	.562
	LOGTA	.241	.751	.027	.320	.749
	ConGr5	.944	.311	.242	3.030	.003
	PCUxDef	-2.081	1.188	-.148	-1.752	.082
	PCUxAcc	-.536	.882	-.053	-.608	.544
	PCUxStag	-1.132	1.349	-.081	-.839	.403
	PCUxOpFl	-1.086	1.339	-.074	-.811	.419
	PCUxPartC	.798	1.059	.065	.754	.452
	PCUxPlat	-.748	1.128	-.062	-.663	.509
	PMUxDef	-.504	1.323	-.033	-.381	.704
	PMUxAcc	-.911	.992	-.076	-.918	.360
	PMUxStag	1.607	1.381	.106	1.164	.246
	PMUxOpFl	.107	1.386	.007	.077	.938
	PMUxPartC	1.156	.944	.103	1.224	.223
	PMUxPlat	.282	1.167	.021	.242	.809
	PMUxPCU	1.233	1.548	.074	.796	.427
3	(Constant)	-.441	6.267		-.070	.944
	CDefer	.809	1.242	.054	.652	.516
	CAccel	1.127	.934	.098	1.207	.229
	CStaging	1.104	1.314	.073	.840	.402
	COpflex	-.545	1.322	-.033	-.412	.681
	CPartCom	1.571	.876	.136	1.793	.075
	CPlat	1.226	1.044	.093	1.174	.242
	CPerMU	-1.186	1.412	-.071	-.840	.403
	CPerCU	.636	1.397	.039	.456	.649
	LOGTA	.538	.712	.060	.756	.451
	ConGr5	.632	.293	.162	2.159	.033
	PCUxDef	-4.355	1.253	-.309	-3.476	.001
	PCUxAcc	-1.689	.887	-.166	-1.903	.059
	PCUxStag	-.009	1.291	-.001	-.007	.995
	PCUxOpFl	-.913	1.307	-.062	-.698	.486
	PCUxPartC	.565	1.017	.046	.555	.580
	PCUxPlat	-.873	1.043	-.073	-.837	.404
	PMUxDef	-.390	1.306	-.025	-.299	.765
	PMUxAcc	.083	.946	.007	.087	.930
	PMUxStag	.474	1.321	.031	.359	.720
	PMUxOpFl	1.249	1.410	.077	.886	.377
	PMUxPartC	.930	.876	.083	1.062	.290
	PMUxPlat	-.960	1.102	-.070	-.871	.385
	PMUxPCU	.016	1.497	.001	.011	.991
	PMUxPCUxDef	-3.100	1.329	-.218	-2.332	.021
	PMUxPCUxAcc	-1.892	.946	-.181	-2.000	.047
	PMUxPCUxStag	.325	1.310	.022	.248	.805
	PMUxPCUxOpFl	1.226	1.421	.080	.863	.389
	PMUxPCUxPartC	.778	1.029	.067	.756	.451
	PMUxPCUxPlat	-4.089	1.115	-.329	-3.666	.000

a. Dependent Variable: Growth5Yr

Growth - Objective Uncertainty

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.322[a]	.104	.048	16.135	.104	1.871	10	162	.053
2	.382[b]	.146	.014	16.421	.042	.570	13	149	.875
3	.417[c]	.174	.006	16.489	.028	.794	6	143	.576

a. Predictors: (Constant), ConGr5, CAccel, CPartCom, CRHINDEX, COpflex, CDefer, LOGTA, CPlat, CStaging, CSEMean5

b. Predictors: (Constant), ConGr5, CAccel, CPartCom, CRHINDEX, COpflex, CDefer, LOGTA, CPlat, CStaging, CSEMean5, OMUxAcc, OCUxOpFl, OMUxPartC, OMUxPlat, OMUxOpFl, OCUxStag, OMUxDef, OCUxAcc, OCUxPartC, OCUxDef, OMUxStag, OCUxPlat, OMUxOCU

c. Predictors: (Constant), ConGr5, CAccel, CPartCom, CRHINDEX, COpflex, CDefer, LOGTA, CPlat, CStaging, CSEMean5, OMUxAcc, OCUxOpFl, OMUxPartC, OMUxPlat, OMUxOpFl, OCUxStag, OMUxDef, OCUxAcc, OCUxPartC, OCUxDef, OMUxStag, OCUxPlat, OMUxOCU, OMUxOCUxDef, OMUxOCUxOpFl, OMUxOCUxAcc, OMUxOCUxPartC, OMUxOCUxPlat, OMUxOCUxStag

ANOVA (d)

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	4871.133	10	487.113	1.871	.053
	Residual	42174.100	162	260.334		
	Total	47045.234	172			
2	Regression	6868.123	23	298.614	1.107	.344
	Residual	40177.110	149	269.645		
	Total	47045.234	172			
3	Regression	8163.947	29	281.515	1.035	.427
	Residual	38881.286	143	271.897		
	Total	47045.234	172			

d Dependent Variable: Growth5Yr

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	-2.913	6.228		-.468	.641
	CDefer	.731	1.186	.049	.616	.539
	CAccel	.814	.940	.071	.866	.388
	CStaging	.617	1.224	.041	.504	.615
	COpflex	-.639	1.297	-.039	-.493	.623
	CPartCom	1.858	.894	.161	2.079	.039
	CPlat	.937	1.049	.071	.893	.373
	LOGTA	.553	.714	.061	.775	.439
	CRHINDEX	21.406	22.542	.079	.950	.344
	CSEMean5	-3.300	123.837	-.002	-.027	.979
	ConGr5	.888	.313	.227	2.838	.005
2	(Constant)	-5.744	6.615		-.868	.387
	CDefer	.947	1.266	.063	.748	.456
	CAccel	.846	.986	.074	.858	.392
	CStaging	.683	1.387	.045	.493	.623
	COpflex	-.562	1.373	-.034	-.410	.683
	CPartCom	1.690	.936	.146	1.806	.073
	CPlat	.878	1.131	.066	.776	.439
	LOGTA	.864	.758	.096	1.140	.256
	CRHINDEX	23.461	26.867	.086	.873	.384
	CSEMean5	-58.808	134.096	-.039	-.439	.662
	ConGr5	.910	.327	.233	2.779	.006
	OCUxDef	6.895	26.481	.024	.260	.795
	OCUxAcc	-.348	18.982	-.002	-.018	.985
	OCUxStag	-13.627	25.748	-.050	-.529	.597
	OCUxOpFl	6.452	25.978	.021	.248	.804
	OCUxPartC	-18.116	17.517	-.093	-1.034	.303
	OCUxPlat	17.855	23.644	.071	.755	.451
	OMUxDef	235.114	137.523	.152	1.710	.089
	OMUxAcc	75.736	92.347	.074	.820	.413
	OMUxStag	-148.444	143.484	-.102	-1.035	.303
	OMUxOpFl	55.010	150.665	.031	.365	.716
	OMUxPartC	-14.790	97.718	-.013	-.151	.880
	OMUxPlat	133.709	106.135	.108	1.260	.210
	OMUxOCU	-1693.865	1953.754	-.089	-.867	.387
3	(Constant)	-5.180	6.866		-.755	.452
	CDefer	.688	1.321	.046	.521	.603
	CAccel	1.005	1.009	.087	.996	.321
	CStaging	.556	1.454	.037	.382	.703
	COpflex	-1.112	1.427	-.068	-.779	.437
	CPartCom	1.730	1.033	.150	1.676	.096
	CPlat	1.065	1.183	.081	.900	.370
	LOGTA	.837	.783	.093	1.069	.287
	CRHINDEX	35.356	29.095	.130	1.215	.226
	CSEMean5	-62.851	147.077	-.042	-.427	.670
	ConGr5	.878	.341	.225	2.577	.011
	OCUxDef	12.660	27.397	.045	.462	.645
	OCUxAcc	-1.356	19.629	-.006	-.069	.945
	OCUxStag	-18.668	26.955	-.069	-.693	.490
	OCUxOpFl	2.546	30.183	.008	.084	.933
	OCUxPartC	-5.818	19.423	-.030	-.300	.765
	OCUxPlat	-1.318	27.440	-.005	-.048	.962
	OMUxDef	217.435	146.016	.141	1.489	.139
	OMUxAcc	100.691	95.625	.098	1.053	.294
	OMUxStag	-164.711	168.082	-.113	-.980	.329
	OMUxOpFl	-3.547	162.143	-.002	-.022	.983
	OMUxPartC	5.143	105.209	.005	.049	.961
	OMUxPlat	139.602	112.495	.112	1.241	.217
	OMUxOCU	117.178	3326.313	.006	.035	.972
	OMUxOCUxDef	629.506	3319.760	.022	.190	.850
	OMUxOCUxAcc	1155.262	1731.368	.067	.667	.506
	OMUxOCUxStag	-2481.411	2746.150	-.138	-.904	.368
	OMUxOCUxOpFl	-4563.691	3019.995	-.161	-1.511	.133
	OMUxOCUxPartC	256.234	1988.785	.017	.129	.898
	OMUxOCUxPlat	337.922	2356.571	.020	.143	.886

a. Dependent Variable: Growth5Yr

Market-to-Book - Perceived Uncertainty

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.306[a]	.094	.038	.40164	.094	1.671	10	162	.092
2	.424[b]	.180	.053	.39833	.086	1.208	13	149	.279
3	.508[c]	.258	.107	.38681	.078	2.501	6	143	.025

a. Predictors: (Constant), ConMTB, CPerCU, COpflex, CPartCom, LOGTA, CStaging, CPerMU, CPlat, CDefer, CAccel

b. Predictors: (Constant), ConMTB, CPerCU, COpflex, CPartCom, LOGTA, CStaging, CPerMU, CPlat, CDefer, CAccel, PMUxOpFl, PMUxPlat, PMUxAcc, PCUxPartC, PCUxDef, PMUxPartC, PCUxOpFl, PMUxDef, PCUxAcc, PMUxPCU, PMUxStag, PCUxPlat, PCUxSta

c. Predictors: (Constant), ConMTB, CPerCU, COpflex, CPartCom, LOGTA, CStaging, CPerMU, CPlat, CDefer, CAccel, PMUxOpFl, PMUxPlat, PMUxAcc, PCUxPartC, PCUxDef, PMUxPartC, PCUxOpFl, PMUxDef, PCUxAcc, PMUxPCU, PMUxStag, PCUxPlat, PCUxSta PMUxPCUxPlat, PMUxPCUxStag, PMUxPCUxPartC, PMUxPCUxOpFl, PMUxPCUxAcc, PMUxPCUxDef

ANOVA (d)

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2.696	10	.270	1.671	.092
	Residual	26.133	162	.161		
	Total	28.829	172			
2	Regression	5.188	23	.226	1.422	.109
	Residual	23.641	149	.159		
	Total	28.829	172			
3	Regression	7.434	29	.256	1.713	.021
	Residual	21.396	143	.150		
	Total	28.829	172			

d Dependent Variable: MktToBk

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	.019	.150		.125	.901
	CDefer	.010	.030	.027	.332	.740
	CAccel	-.015	.023	-.052	-.631	.529
	CStaging	-.038	.031	-.100	-1.225	.222
	COpflex	.027	.032	.067	.847	.398
	CPartCom	.005	.022	.018	.235	.815
	CPlat	.003	.026	.011	.134	.893
	CPerMU	.025	.033	.059	.752	.453
	CPerCU	.004	.032	.009	.119	.905
	LOGTA	.060	.018	.268	3.396	.001
	ConMTB	.242	.172	.106	1.407	.161
2	(Constant)	.139	.158		.880	.380
	CDefer	.023	.032	.062	.724	.470
	CAccel	-.013	.024	-.046	-.541	.589
	CStaging	-.042	.033	-.111	-1.272	.205
	COpflex	.039	.034	.095	1.123	.263
	CPartCom	.005	.022	.017	.219	.827
	CPlat	-.013	.027	-.041	-.499	.619
	CPerMU	.015	.035	.036	.434	.665
	CPerCU	-.015	.034	-.036	-.426	.671
	LOGTA	.049	.019	.220	2.662	.009
	ConMTB	.177	.174	.078	1.021	.309
	PCUxDef	.004	.029	.010	.124	.902
	PCUxAcc	.006	.022	.022	.258	.797
	PCUxStag	-.023	.033	-.067	-.691	.491
	PCUxOpFl	.049	.033	.134	1.475	.142
	PCUxPartC	.032	.026	.107	1.240	.217
	PCUxPlat	.006	.028	.019	.201	.841
	PMUxDef	.018	.033	.047	.543	.588
	PMUxAcc	-.024	.024	-.081	-.984	.327
	PMUxStag	-.077	.034	-.206	-2.274	.024
	PMUxOpFl	.027	.034	.068	.802	.424
	PMUxPartC	.016	.023	.058	.700	.485
	PMUxPlat	.025	.028	.072	.862	.390
	PMUxPCU	.012	.038	.029	.308	.759
3	(Constant)	.104	.157		.660	.511
	CDefer	.011	.032	.030	.341	.734
	CAccel	-.008	.024	-.028	-.332	.741
	CStaging	-.021	.034	-.057	-.628	.531
	COpflex	.031	.034	.077	.912	.363
	CPartCom	-.007	.023	-.026	-.322	.748
	CPlat	-.004	.027	-.013	-.163	.871
	CPerMU	.017	.037	.040	.452	.652
	CPerCU	.029	.036	.071	.793	.429
	LOGTA	.054	.019	.240	2.899	.004
	ConMTB	.174	.170	.077	1.025	.307
	PCUxDef	.025	.033	.072	.768	.444
	PCUxAcc	-.009	.023	-.035	-.381	.704
	PCUxStag	-.038	.034	-.109	-1.115	.267
	PCUxOpFl	.071	.034	.196	2.089	.038
	PCUxPartC	.018	.026	.060	.683	.496
	PCUxPlat	.009	.027	.030	.327	.744
	PMUxDef	.007	.034	.018	.206	.837
	PMUxAcc	-.019	.025	-.063	-.761	.448
	PMUxStag	-.083	.034	-.222	-2.418	.017
	PMUxOpFl	.038	.037	.094	1.029	.305
	PMUxPartC	.013	.023	.048	.587	.558
	PMUxPlat	.029	.028	.085	1.020	.309
	PMUxPCU	.038	.039	.093	.979	.329
	PMUxPCUxDef	.024	.034	.069	.708	.480
	PMUxPCUxAcc	-.061	.025	-.235	-2.470	.015
	PMUxPCUxStag	-.088	.034	-.245	-2.591	.011
	PMUxPCUxOpFl	.074	.037	.195	1.996	.048
	PMUxPCUxPartC	.027	.027	.093	1.012	.313
	PMUxPCUxPlat	.009	.029	.030	.319	.751

a. Dependent Variable: MktToBk

Market-to-Book - Objective Uncertainty

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.307[a]	.094	.038	.40151	.094	1.683	10	162	.089
2	.557[b]	.310	.204	.36527	.216	3.596	13	149	.000
3	.599[c]	.359	.229	.35959	.048	1.790	6	143	.105

a. Predictors: (Constant), ConMTB, CRHINDEX, CAccel, CPartCom, COpflex, CDefer, CPlat, LOGTA, CSEMean5, CStaging

b. Predictors: (Constant), ConMTB, CRHINDEX, CAccel, CPartCom, COpflex, CDefer, CPlat, LOGTA, CSEMean5, CStaging, OMUxAcc, OCUxOpFl, OMUxPartC, OMUxPlat, OMUxOpFl, OCUxStag, OMUxDef, OCUxAcc, OCUxPartC, OCUxDef, OMUxStag, OCUxPlat, OMUxOCU

c. Predictors: (Constant), ConMTB, CRHINDEX, CAccel, CPartCom, COpflex, CDefer, CPlat, LOGTA, CSEMean5, CStaging, OMUxAcc, OCUxOpFl, OMUxPartC, OMUxPlat, OMUxOpFl, OCUxStag, OMUxDef, OCUxAcc, OCUxPartC, OCUxDef, OMUxStag, OCUxPlat, OMUxOCU, OMUxOCUxDef, OMUxOCUxOpFl, OMUxOCUxAcc, OMUxOCUxPartC, OMUxOCUxPlat, OMUxOCUxStag

ANOVA (d)

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2.713	10	.271	1.683	.089
	Residual	26.116	162	.161		
	Total	28.829	172			
2	Regression	8.950	23	.389	2.916	.000
	Residual	19.879	149	.133		
	Total	28.829	172			
3	Regression	10.338	29	.356	2.757	.000
	Residual	18.491	143	.129		
	Total	28.829	172			

d Dependent Variable: MktToBk

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	.071	.150		.472	.638
	CDefer	.004	.030	.011	.142	.887
	CAccel	-.017	.023	-.059	-.715	.476
	CStaging	-.034	.030	-.090	-1.127	.261
	COpflex	.032	.032	.079	.993	.322
	CPartCom	.005	.022	.017	.216	.830
	CPlat	.000	.026	-.001	-.015	.988
	LOGTA	.053	.018	.238	2.995	.003
	CRHINDEX	-.460	.551	-.068	-.834	.406
	CSEMean5	-.758	2.959	-.020	-.256	.798
	ConMTB	.232	.172	.102	1.351	.179
2	(Constant)	.167	.141		1.180	.240
	CDefer	.003	.028	.009	.113	.910
	CAccel	-.029	.022	-.103	-1.333	.185
	CStaging	-.039	.031	-.102	-1.262	.209
	COpflex	.044	.031	.107	1.426	.156
	CPartCom	.006	.021	.020	.280	.780
	CPlat	.015	.025	.047	.620	.536
	LOGTA	.039	.017	.177	2.339	.021
	CRHINDEX	-.068	.589	-.010	-.116	.908
	CSEMean5	1.498	2.889	.040	.518	.605
	ConMTB	.198	.159	.087	1.247	.214
	OCUxDef	-.426	.589	-.061	-.723	.471
	OCUxAcc	.262	.422	.049	.620	.536
	OCUxStag	1.858	.572	.277	3.247	.001
	OCUxOpFl	-.545	.580	-.071	-.938	.350
	OCUxPartC	-.977	.390	-.202	-2.507	.013
	OCUxPlat	-1.577	.525	-.253	-3.006	.003
	OMUxDef	1.858	3.061	.049	.607	.545
	OMUxAcc	3.981	2.054	.156	1.938	.054
	OMUxStag	.920	3.200	.026	.288	.774
	OMUxOpFl	2.628	3.344	.059	.786	.433
	OMUxPartC	-3.556	2.178	-.126	-1.632	.105
	OMUxPlat	-.815	2.338	-.027	-.349	.728
	OMUxOCU	3.318	43.338	.007	.077	.939
3	(Constant)	.187	.144		1.299	.196
	CDefer	.005	.029	.014	.183	.855
	CAccel	-.026	.022	-.091	-1.173	.243
	CStaging	-.061	.031	-.163	-1.964	.051
	COpflex	.045	.031	.111	1.450	.149
	CPartCom	.007	.022	.024	.312	.755
	CPlat	.006	.026	.020	.251	.802
	LOGTA	.036	.017	.159	2.081	.039
	CRHINDEX	-.003	.630	.000	-.005	.996
	CSEMean5	-.379	3.050	-.010	-.124	.901
	ConMTB	.212	.158	.093	1.340	.183
	OCUxDef	-.550	.598	-.078	-.921	.359
	OCUxAcc	.335	.428	.063	.784	.434
	OCUxStag	2.052	.584	.306	3.512	.001
	OCUxOpFl	-.952	.657	-.125	-1.449	.150
	OCUxPartC	-.854	.424	-.176	-2.015	.046
	OCUxPlat	-1.215	.596	-.195	-2.040	.043
	OMUxDef	-.542	3.179	-.014	-.170	.865
	OMUxAcc	5.063	2.085	.199	2.428	.016
	OMUxStag	1.445	3.630	.040	.398	.691
	OMUxOpFl	-.238	3.508	-.005	-.068	.946
	OMUxPartC	-2.258	2.283	-.080	-.989	.324
	OMUxPlat	-1.636	2.429	-.053	-.673	.502
	OMUxOCU	40.970	71.783	.087	.571	.569
	OMUxOCUxDef	-4.285	72.012	-.006	-.060	.953
	OMUxOCUxAcc	54.208	37.756	.127	1.436	.153
	OMUxOCUxStag	-118.291	59.153	-.265	-2.000	.047
	OMUxOCUxOpFl	40.226	65.760	.057	.612	.542
	OMUxOCUxPartC	28.608	43.122	.074	.663	.508
	OMUxOCUxPlat	-.668	50.801	-.002	-.013	.990

a. Dependent Variable: MktToBk

Return on Assets - Perceived Uncertainty

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.260[a]	.067	.010	9.0133	.067	1.171	10	162	.314
2	.347[b]	.120	-.016	9.1290	.053	.686	13	149	.775
3	.398[c]	.158	-.012	9.1134	.038	1.085	6	143	.374

a. Predictors: (Constant), ConROA, CPlat, CAccel, CPerCU, CPerMU, CPartCom, COpflex, CStaging, CDefer, LOGTA

b. Predictors: (Constant), ConROA, CPlat, CAccel, CPerCU, CPerMU, CPartCom, COpflex, CStaging, CDefer, LOGTA, PMUxOpFl, PMUxPlat, PMUxAcc, PCUxPartC, PCUxDef, PMUxPartC, PCUxOpFl, PMUxDef, PCUxAcc, PCUxStag, PMUxStag, PMUxPCU, PCUxPlat

c. Predictors: (Constant), ConROA, CPlat, CAccel, CPerCU, CPerMU, CPartCom, COpflex, CStaging, CDefer, LOGTA, PMUxOpFl, PMUxPlat, PMUxAcc, PCUxPartC, PCUxDef, PMUxPartC, PCUxOpFl, PMUxDef, PCUxAcc, PCUxStag, PMUxStag, PMUxPCU, PCUxPlat, PMUxPCUxPlat, PMUxPCUxStag, PMUxPCUxPartC, PMUxPCUxOpFl, PMUxPCUxAcc, PMUxPCUxDef

ANOVA (d)

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	951.131	10	95.113	1.171	.314
	Residual	13160.699	162	81.239		
	Total	14111.830	172			
2	Regression	1694.477	23	73.673	.884	.619
	Residual	12417.353	149	83.338		
	Total	14111.830	172			
3	Regression	2235.083	29	77.072	.928	.576
	Residual	11876.747	143	83.054		
	Total	14111.830	172			

d Dependent Variable: AvgROA3

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	-.075	2.927		-.026	.980
	CDefer	.206	.680	.025	.303	.762
	CAccel	-.006	.528	-.001	-.012	.990
	CStaging	.234	.695	.028	.337	.736
	COpflex	.582	.724	.065	.804	.423
	CPartCom	-.447	.491	-.071	-.910	.364
	CPlat	.086	.583	.012	.148	.882
	CPerMU	-1.268	.735	-.138	-1.726	.086
	CPerCU	.552	.710	.061	.778	.438
	LOGTA	.510	.411	.103	1.241	.217
	ConROA	.402	.286	.114	1.407	.161
2	(Constant)	.365	3.114		.117	.907
	CDefer	.290	.725	.035	.400	.690
	CAccel	.036	.552	.006	.065	.948
	CStaging	.318	.760	.038	.418	.677
	COpflex	.570	.788	.063	.723	.471
	CPartCom	-.428	.512	-.068	-.837	.404
	CPlat	-.102	.620	-.014	-.164	.870
	CPerMU	-1.414	.792	-.154	-1.786	.076
	CPerCU	.414	.783	.046	.529	.598
	LOGTA	.394	.442	.080	.891	.374
	ConROA	.479	.296	.136	1.618	.108
	PCUxDef	-1.071	.671	-.139	-1.596	.113
	PCUxAcc	.254	.493	.045	.514	.608
	PCUxStag	.013	.761	.002	.018	.986
	PCUxOpFl	-.386	.751	-.048	-.513	.609
	PCUxPartC	-.370	.598	-.055	-.619	.537
	PCUxPlat	.111	.638	.017	.173	.863
	PMUxDef	.611	.750	.073	.815	.416
	PMUxAcc	.165	.562	.025	.295	.769
	PMUxStag	-.954	.781	-.115	-1.222	.224
	PMUxOpFl	.474	.783	.053	.605	.546
	PMUxPartC	.916	.535	.149	1.714	.089
	PMUxPlat	-.086	.653	-.011	-.132	.895
	PMUxPCU	.068	.878	.008	.078	.938
3	(Constant)	-.436	3.189		-.137	.891
	CDefer	.272	.761	.033	.357	.722
	CAccel	.060	.572	.010	.105	.916
	CStaging	.493	.815	.059	.606	.546
	COpflex	.681	.810	.076	.841	.402
	CPartCom	-.337	.537	-.053	-.627	.532
	CPlat	.039	.634	.005	.062	.951
	CPerMU	-1.674	.861	-.182	-1.945	.054
	CPerCU	.610	.861	.068	.709	.479
	LOGTA	.469	.454	.095	1.035	.302
	ConROA	.515	.298	.146	1.728	.086
	PCUxDef	-1.253	.768	-.163	-1.633	.105
	PCUxAcc	.147	.537	.026	.274	.784
	PCUxStag	-.053	.792	-.007	-.066	.947
	PCUxOpFl	-.717	.795	-.090	-.902	.369
	PCUxPartC	-.361	.623	-.054	-.580	.563
	PCUxPlat	.124	.639	.019	.194	.847
	PMUxDef	.302	.801	.036	.377	.707
	PMUxAcc	.114	.580	.017	.197	.844
	PMUxStag	-.853	.811	-.103	-1.052	.295
	PMUxOpFl	.832	.864	.094	.963	.337
	PMUxPartC	.963	.538	.156	1.788	.076
	PMUxPlat	-.169	.666	-.022	-.254	.800
	PMUxPCU	-.099	.920	-.011	-.108	.914
	PMUxPCUxDef	-.293	.811	-.038	-.362	.718
	PMUxPCUxAcc	.017	.580	.003	.030	.976
	PMUxPCUxStag	-.591	.806	-.074	-.734	.464
	PMUxPCUxOpFl	-.322	.871	-.038	-.370	.712
	PMUxPCUxPartC	-.568	.630	-.089	-.901	.369
	PMUxPCUxPlat	-.915	.678	-.134	-1.350	.179

a. Dependent Variable: AvgROA3

Return on Assets - Objective Uncertainty

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.278[a]	.077	.020	8.9657	.077	1.356	10	162	.205
2	.420[b]	.176	.049	8.8323	.099	1.379	13	149	.176
3	.481[c]	.232	.076	8.7080	.055	1.714	6	143	.122

a. Predictors: (Constant), CSEMean5, CStaging, CPlat, LOGTA, CPartCom, COpflex, CDefer, ConROA, CRHINDEX, CAccel

b. Predictors: (Constant), CSEMean5, CStaging, CPlat, LOGTA, CPartCom, COpflex, CDefer, ConROA, CRHINDEX, CAccel, OMUxAcc, OMUxPartC, OMUxPlat, OCUxOpFl, OMUxOpFl, OCUxStag, OMUxDef, OCUxAcc, OCUxPartC, OMUxStag, OCUxDef, OCUxPlat, OMUxOCU

c. Predictors: (Constant), CSEMean5, CStaging, CPlat, LOGTA, CPartCom, COpflex, CDefer, ConROA, CRHINDEX, CAccel, OMUxAcc, OMUxPartC, OMUxPlat, OCUxOpFl, OMUxOpFl, OCUxStag, OMUxDef, OCUxAcc, OCUxPartC, OMUxStag, OCUxDef, OCUxPlat, OMUxOCU, OMUxOCUxDef, OMUxOCUxOpFl, OMUxOCUxAcc, OMUxOCUxPartC, OMUxOCUxPlat, OMUxOCUxStag

ANOVA(d)

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1089.723	10	108.972	1.356	.205
	Residual	13022.107	162	80.383		
	Total	14111.830	172			
2	Regression	2488.450	23	108.193	1.387	.126
	Residual	11623.381	149	78.009		
	Total	14111.830	172			
3	Regression	3268.325	29	112.701	1.486	.068
	Residual	10843.505	143	75.829		
	Total	14111.830	172			

d Dependent Variable: AvgROA3

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	-2.316	2.924		-.792	.430
	CDefer	.374	.661	.045	.566	.572
	CAccel	.028	.524	.004	.053	.958
	CStaging	.078	.680	.009	.115	.909
	COpflex	.326	.721	.036	.453	.651
	CPartCom	-.334	.494	-.053	-.677	.499
	CPlat	.232	.576	.032	.402	.688
	LOGTA	.853	.413	.173	2.064	.041
	ConROA	.357	.285	.102	1.254	.212
	CRHINDEX	26.409	12.322	.178	2.143	.034
	CSEMean5	93.504	66.185	.114	1.413	.160
2	(Constant)	-2.461	3.027		-.813	.418
	CDefer	.261	.683	.032	.382	.703
	CAccel	.212	.531	.034	.400	.690
	CStaging	.142	.743	.017	.191	.849
	COpflex	.267	.738	.030	.362	.718
	CPartCom	-.514	.500	-.081	-1.026	.306
	CPlat	.285	.604	.039	.471	.638
	LOGTA	1.050	.426	.212	2.462	.015
	ConROA	.120	.300	.034	.399	.690
	CRHINDEX	42.491	14.383	.286	2.954	.004
	CSEMean5	83.021	70.272	.101	1.181	.239
	OCUxDef	-4.627	14.330	-.030	-.323	.747
	OCUxAcc	-30.255	10.448	-.257	-2.896	.004
	OCUxStag	-4.071	13.829	-.027	-.294	.769
	OCUxOpFl	21.038	14.394	.125	1.462	.146
	OCUxPartC	-3.324	9.435	-.031	-.352	.725
	OCUxPlat	11.317	12.717	.082	.890	.375
	OMUxDef	54.703	74.017	.065	.739	.461
	OMUxAcc	-38.654	49.767	-.069	-.777	.439
	OMUxStag	25.823	77.196	.032	.335	.738
	OMUxOpFl	152.328	81.339	.154	1.873	.063
	OMUxPartC	109.839	52.585	.176	2.089	.038
	OMUxPlat	-11.708	56.605	-.017	-.207	.836
	OMUxOCU	-219.817	1047.690	-.021	-.210	.834
3	(Constant)	-1.101	3.096		-.355	.723
	CDefer	.005	.700	.001	.008	.994
	CAccel	.075	.534	.012	.140	.889
	CStaging	.503	.757	.060	.665	.507
	COpflex	.070	.754	.008	.093	.926
	CPartCom	-.089	.541	-.014	-.165	.869
	CPlat	.011	.624	.002	.018	.985
	LOGTA	.963	.429	.195	2.245	.026
	ConROA	-.009	.299	-.003	-.031	.975
	CRHINDEX	50.776	15.453	.341	3.286	.001
	CSEMean5	120.930	74.385	.147	1.626	.106
	OCUxDef	-1.405	14.538	-.009	-.097	.923
	OCUxAcc	-33.105	10.596	-.281	-3.124	.002
	OCUxStag	-12.325	14.154	-.083	-.871	.385
	OCUxOpFl	8.955	16.152	.053	.554	.580
	OCUxPartC	-8.979	10.277	-.084	-.874	.384
	OCUxPlat	10.398	14.429	.075	.721	.472
	OMUxDef	48.300	77.049	.057	.627	.532
	OMUxAcc	-46.568	50.609	-.083	-.920	.359
	OMUxStag	20.372	87.958	.026	.232	.817
	OMUxOpFl	208.044	85.542	.211	2.432	.016
	OMUxPartC	124.076	55.277	.199	2.245	.026
	OMUxPlat	-27.148	58.911	-.040	-.461	.646
	OMUxOCU	1153.098	1733.804	.110	.665	.507
	OMUxOCUxDef	-1008.319	1740.206	-.065	-.579	.563
	OMUxOCUxAcc	-1085.245	915.093	-.115	-1.186	.238
	OMUxOCUxStag	578.829	1427.680	.059	.405	.686
	OMUxOCUxOpFl	-4210.215	1604.960	-.271	-2.623	.010
	OMUxOCUxPartC	590.001	1043.287	.069	.566	.573
	OMUxOCUxPlat	-1929.753	1220.595	-.210	-1.581	.116

a. Dependent Variable: AvgROA3

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