Strategic Ambidexterity and Sales Growth:

A Longitudinal Test in the Software Sector

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Summary

We test the impact of strategic ambidexterity on firm performance in a sample of software firms over a twelve-year period. By incorporating time into the conceptualization of ambidexterity, we distinguish between simultaneous and sequential forms of ambidexterity as an organizational capability to balance exploration and exploitation. We operationalize both forms using time-paced patterns of product sales in different product markets. Using a sample of 1005 software firms, we find that sequential ambidexterity significantly predicts sales growth as main effect, as well as jointly with a set of contingency effects. Finally, we develop specific implications for further examining the concept of ambidexterity in strategic management research.

Key words:
Simultaneous ambidexterity
Sequential ambidexterity
Packaged software sector
Exploration-exploitation

Introduction

A fundamental assertion in strategic management and organization theory literature is that successful firms balance conflicting demands of today's operations while preparing for tomorrow's opportunities and challenges. This assertion has pervaded many ideas such as Penrose's (1959) growth trajectories, Thompson's (1967) paradox of administration, Cyert and March's (1963) behavioral theory of the firm and March's views on organizational learning (1991) and adaptation (2003). The inherent tension between balancing long-term adaptation and short-term alignment is central to system adaptation (Holland, 1995), competition between incumbents and new entrants (Henderson and Clark, 1990) and concepts such as competency traps (Levitt and March, 1988), core rigidities (Leonard-Barton, 1992), and ambidextrous organization architectures (Tushman and O'Reilly, 1996). Within this stream of work over the last several decades, March's (1991) discourse on balancing exploration and exploitation has caught the imagination of researchers in framing theoretical propositions and guiding empirical research across multiple analysis levels (Gupta, Smith and Shalley, 2006).

A goal of this paper is to contribute theoretically and empirically to the general stream of exploration-exploitation research and in particular to the concept of ambidexterity. Firstly, we conceptualize ambidexterity as an organizational-level capability — namely, collections of routines "that confer upon an organization's management a set of decision options for producing significant outputs of a particular type" (Winter, 2003: p. 991). Secondly, in contrast to prior research that has not explicitly dealt with the issue of time in the conceptualization and operationalization of ambidexterity, we differentiate between simultaneous and sequential forms of ambidexterity. The former reflects routines that drive contemporaneous balancing of exploration and exploitation while the latter reflects dynamic, temporal sequencing of routines for exploration and exploitation. Thirdly, we add to prior measurement approaches that have predominantly focused on management perceptions of ambidexterity by introducing a scheme that reflect the outputs of dynamic capabilities. Specifically, we develop a measure of ambidexterity that is derived from similarities and differences in the sales of products across different product markets. Fourth, in contrast to cross-sectional, single time-period studies, we examine ambidexterity patterns over a 13-year period in the packaged software sector during 1990-2002.

Our paper is organized as follows. We first develop the theoretical perspectives — especially the framing of ambidexterity as a dynamic organizational capability that recognizes the inherent tension in routines that support exploitation and those that shape exploration activities. Then, we incorporate time into the conceptualization of ambidexterity to derive two functional ambidexterity forms (i.e., simultaneous and sequential) and develop a set of hypotheses on their effects on firm performance (as main effects and additional contingency effects). In the methods section, we describe our research setting (the packaged software sector) and discuss our approach to operationalizing, and measuring ambidexterity based on sales profiles of similarities and differences in product markets served. We estimate a series of eleven models to test the hypotheses and rule out plausible alternative explanations. Finally, we discuss our results and develop implications for theoretical and methodological issues in further incorporating ambidexterity within strategic management research.

Theoretical Perspectives

Ambidexterity as Dynamic Organizational Capability

Following Thompson (1967), Duncan (1972) proposed the ideas of dual-structures as a way to deal with the conflicting demands of efficiency and effectiveness. In a similar vein, Tushman and O'Reilly proposed that ambidextrous organizations possess "the ability to simultaneously pursue both incremental and discontinuous innovation and change" and called for organizational architectures that host "multiple contradictory structures, processes and cultures within the same firm" (1996; p. 24). Using case studies from a set of companies that have successfully adapted over time, they offered normative prescriptions for designing ambidextrous organizations and the critical requirement of developing ambidextrous managers who have the ability to proactively cannibalize their current business models to create new business models and overcome competency traps. O'Reilly and Tushman (2004), through their detailed case studies of fifteen business units, found that ambidextrous organizations with structurally independent units that remained integrated into their senior management hierarchy were significantly more successful than other types of organizational architectures. Tushman, Smith, Wood, Westerman, and O'Reilly (2005) concluded that ambidextrous organization designs permit business units to simultaneously explore and exploit, using data on 36 innovation episodes in fifteen business units. What we do not know from these studies is whether these ambidextrous designs permit the development of coherent organizational routines.

Although Tushman and colleagues have focused on structural and organizational characteristics to delve into the visible manifestation of ambidexterity, the core ideas of ambidexterity deal with an organization's capability to manage contradictions and multiple tensions in dealing with today and tomorrow, efficiency and effectiveness, alignment and adaptation, and optimization and innovation. We believe that considerable progress can be made in our understanding of ambidexterity if we position it within the broader research stream on resource-based views (RBV), and more specifically those that focus on dynamic capability. Teece, Pisano, and Shuen (1997) define dynamic capabilities as "the firm's ability to integrate, build, and reconfigure internal and external competences to address rapidly changing environments" (p. 517). Dynamic capabilities are also "organizational and strategic routines by which firms achieve new resource configurations as markets emerge, collide, split, evolve and die" (Eisenhardt and Martin, 2000; p. 1107). Zollo and Winter (2002) view dynamic capabilities as "a learned and stable pattern of collective activity through which the organization systematically generates and modifies its operating routines in pursuit of improved effectiveness" (p. 340). Shared by these three different conceptualizations is the central requirement of organizational routines that permit firms to efficiently transform inputs into outputs (Collis, 1994) in the short term while modifying routines to overcome core rigidities (Leonard-Barton, 1992).

The Fundamental Tension. The fundamental tension between efficiency in the short-term and effectiveness in the long-term is common to the dynamic capability stream and March's (1991) proposition of balancing exploitation and exploration. Exploitation includes "such things as refinement, choices, production, efficiency, selection, implementation and execution," while exploration includes things "such as search, variation, risk-taking, experimentation, play, flexibility, discovery, and innovation" (March, 1991; p. 71). Successful organizations maintain an appropriate balance between exploration and exploitation in the face of scarce resources and limited management attention (Cyert and March, 1963; March, 1991). Organizations that engage in exploration to the exclusion of exploitation are likely to find that they suffer the costs of experimentation without gaining any of the benefits. Similarly, those that engage in exploitation to the exclusion of exploration are likely to find themselves trapped in suboptimal equilibrium.

Moreover, because “returns to exploitation are systematically more certain and sooner, exploitation has a fairly general advantage within adaptive processes” (March, 2003; p. 5).

The dynamic capabilities view echoes a similar tension. Kogut and Zander (1992) remarked that: “Switching to new capabilities is difficult, as neither the knowledge embedded in the current relationships is well understood, nor the social fabric required to support the new learning known. It is the stability of these relationships that generates the characteristics of inertia in a firm’s capabilities” (p. 396). Teece et al. (1997) observed that “where a firm can go is a function of its current position and the paths ahead. It is of course shaped by the path behind. The notion of path dependencies recognizes that ‘history matters.’ . . . Thus, a firm’s previous investments and its repertoires of routines (‘its history’) constrain future behavior” (p. 522). Sorensen and Stuart (2000) noted that “organizational change is seen as the product of searches for new practices in the neighborhood of an organization’s existing routines … They limit their flexibility by restricting the range of organizational actions” (p. 86). This tension is well illustrated by Burgelman’s study of Intel. According to him: “In 1997, Craig Barrett, then Intel’s chief operating officer (COO), observed that Intel’s core microprocessor business had begun to resemble a creosote bush, a desert plant that poisons the ground around it, preventing other plants from growing nearby. The creosote bush metaphor raised potentially interesting questions about the strategic consequences of Intel’s ability to dominate in the PC market segment. It drew attention to the phenomenon of co-evolutionary lock-in: a positive feedback process that increasingly ties the previous success of a company’s strategy to that of its existing product-market environment, thereby making it difficult to change direction” (2002; p. 326).

Empirical results provide preliminary support for this tension. Mitchell and Singh (1993) found that incumbents who do not expand into new subfields fared poorly even in their established business lines. Benner and Tushman (2002) studied process routines through ISO 9000 certification programs and found that such routines favor incremental innovations that build upon current competencies and management activities rather than ones that create new competencies. Using patents in the photography industry, they found that an increase in process management routines allowed exploitation patents to have a much higher share of the patenting activities. Going beyond single industry study, He and Wong (2004) studied a sample of 206 manufacturing firms in Malaysia and Singapore and found that the interaction between explorative and exploitative innovation strategies significantly predicted sales growth and that the relative imbalance between explorative and exploitative innovation strategies negatively impacted sales growth.

These scattered findings call for more systematic understanding of the tension between exploration and exploitation. Specifically, we need to (1) understand the concept of ambidexterity as an organizational-level dynamic capability and (2) empirically examine its impact on firm performance.

Incorporating Time in the Conceptualization of Ambidexterity

The importance of time is recognized in the research streams on organizational learning and dynamic capabilities, but only implicitly. The following two quotes represent this implicit acknowledgement of time. Levinthal and March (1993) observed that: "the basic problem confronting an organization is to engage in sufficient exploitation to ensure its current viability and, at the same time to devote enough energy to exploration to ensure its future viability" (p. 105); and March (2003) observed that: "a fundamental requirement for intelligent adaptation is to maintain a balance between exploitation of things already known and the exploration of things that might come to be known" (p. 3). However, empirical examinations do need to be more explicit in conceptualizing and operationalizing ambidexterity that incorporates time despite the paucity of theoretical understanding about time lags, feedback loops and durations in organizational research (Ancona, Goodman, Lawrence, and Tushman, 2001).

Gupta, Smith, and Shalley (2006), in their introduction to a special research forum on 'the interplay between exploration and exploitation,' differentiated between ambidexterity (as the synchronous pursuit of both exploration and exploitation via loosely coupled and differentiated specialized entities) and punctuated equilibrium (cycling through periods of exploration and exploitation). They go on to ask: "Are the two mechanisms equal substitutes, or is the appropriateness of each mechanism a function of environmental and organizational context?" (p. 698). Lavie and Rosenkopf (2006), through studying how firms balance exploration and exploitation in alliance formation, refute the assumption that firms simultaneously balance exploration and exploitation within each domain, but show how the balance is achieved across domains and over time.

In this vein, we distinguish between simultaneous ambidexterity and sequential ambidexterity. The former reflects contemporaneous routines that balance exploration and exploitation in one specific time period (i.e., time *t*) while the latter reflects temporal sequence of routines that balance exploration (i.e., time *t-1*) and exploitation (i.e., time *t*) in two successive time periods. More specifically, we define sequential ambidexterity as reflecting the joint effects of exploration at (time *t-1*) and exploitation at (time *t*). By distinguishing between these two ambidexterity forms, we advance our theoretical understanding of the temporal nature of how firms balance the conflicting requirements of balancing exploration for tomorrow while optimally competing for today under conditions of limited resources.

Simultaneous Ambidexterity. Following Tushman and O'Reilly (1996) and Tushman et al. (2004), we define simultaneous ambidexterity as the 'synchronous pursuit of exploration and exploitation at the same time period.' This could be accomplished through several mechanisms, among them dual structures or subsystems that are independently tasked for exploitation and exploration (cf. Christensen, 1997). Empirically, this form of ambidexterity is consistent with studies that conceptualize and operationalize ambidexterity as the joint effects of alignment and adaptability concurrently (Gibson and Birkinshaw, 2004) or the joint effects of explorative and exploitative innovations (He and Wong, 2005; Jansen, Van den Bosch, and Volberda, 2005).

Sequential Ambidexterity. Following Brown and Eisenhardt (1997) and Zollo and Winter (2002), we define sequential ambidexterity as 'time-paced sequence of exploration and exploitation.' This definition is consistent with the dynamic capabilities view that requires an organization to have two temporal orientations — the present and the future (Brown and Eisenhardt, 1997). Zollo and Winter (2002) view dynamic capabilities as routines developed through generative variation (exploration) and replication (exploitation). They suggested that exploitation can prime exploration and that in addition to the familiar trade-off between exploration and exploitation, there can be a recursive and co-evolutionary relationship between them.

This form of ambidexterity is a special case of punctuated equilibrium (Tushman and Romanelli, 1985; Burgelman, 2002; Gupta et al., 2006) in the sense of time-lagged sequence of exploration and exploitation; it is viewed as a joint effect of exploration at time *t-1* and exploitation at time *t*. It is also consistent with Smith and Tushman's discussions of the tensions inherent in managing strategic contradictions (2005; Figure 3, p. 528). This follows Lavie and Rosenkopf (2006) who argue that "at any time within a given domain, a firm may emphasize either exploration or exploitation, yet across domains and over time, balance is maintained" (p. 815) Thus, this form of ambidexterity recognizes time periods of continuous adaptation (Brown and Eisenhardt, 1997). Sequential ambidexterity as a general form of ambidexterity has been empirically tested in the context of alliances. For example, Rothaermel and Deeds (2004) represented a sequence of ambidextrous moves as [Exploration Alliances → Products in Development → Exploitation Alliances → Products on Market] and provided empirical support for this sequence using biotechnology firms. However, the general role and performance impact of the functional form of sequential ambidexterity has not been empirically tested.

We now turn to developing a set of hypotheses on how ambidexterity impacts firm sales growth, both as a main effect and in combination with a set of contingency variables.

Our Hypotheses

Ambidexterity's Impact on Sales Growth

Our first hypothesis is that ambidexterity has a positive effect on firm performance, viewed here as sales growth. This hypothesis rests on the impressive body of research on organizational learning and dynamic capabilities discussed earlier, work that asserts the need to balance exploration and exploitation. Specifically, March (2003) observed that: "It is clear that a strategy of exploitation without exploration is a route to obsolescence. It is equally clear that a strategy of exploration without exploitation is a route to elimination. But, it is not clear where the optimum lies between these two extremes" (p. 4). Thus, it is worthwhile to empirically test the theoretical assertion that ambidexterity leads to firm performance growth. We do so by focusing on the two different functional forms of ambidexterity— simultaneous and sequential.

Simultaneous Ambidexterity and Firm Growth. Following Tushman and O'Reilly (1996), Tushman et al. (2005), and He and Wong (2004), we expect that simultaneous ambidexterity to have a positive and significant effect on firm sales growth. Our rationale is that those firms that manage the conflicting demands of efficiency and effectiveness by designing appropriate organizational architectures (Tushman and O'Reilly, 1996) or engaging in the design of dual subsystems to overcome disruptions (Christensen, 1997) and competency traps (Levitt and March, 1988) will achieve a superior growth rate relative to other firms in the industry, even firms that may pursue successfully either exploration or exploitation alone.

It is important to note that despite the intuitively appealing nature of March's (1991) proposition, and O'Reilly and Tushman (2004) and Tushman and O'Reilly's (1996) normative prescriptions, there is limited robust empirical evidence to prove them. He and Wong (2004) are one of the first researchers to test the simultaneous ambidexterity hypothesis; they realized the inherent limitation of relying on one functional specification of ambidexterity, namely, the interaction effects of exploration and exploitation hence adopted an additional specification of matching. They found that that both moderation and matching as alternative specifications of the simultaneous ambidexterity hypothesis supported the expected performance effects.

In addition to He and Wong (2004), we can draw on indirect support for this hypothesis from Katila and Ahuja's (2002) work on patenting activity. They used search scope (propensity to cite different patents) and search depth (propensity to cite certain patents repeatedly) as proxies for exploration of new avenues and exploitation of familiar avenues. Empirically, they demonstrated that the interaction effect (search scope and search depth—indicating ambidexterity, although they never explicitly term it as such) predicted new product development (but they did not examine firm performance). However, there is considerable evidence that new product development is a strong determinant of firm success. Thus, we hypothesize:

H1a: Simultaneous ambidexterity will have a positive effect on firm sales growth.

Sequential Ambidexterity and Firm Growth. While the previous hypothesis was built on the preliminary empirical results offered by He and Wong (2004) who used Asian manufacturers, no direct empirical test of sequential ambidexterity's impact on firm performance exists in the literature. However, findings from related areas and persuasive theoretical arguments can be marshaled to motivate the need to empirically test this hypothesis.

The central thesis is that adaptation occurs over time when there is synchronization between internal capabilities and external requirements. This synchronized adaptation depends upon an organization's absorptive capacity (Cohen and Levinthal, 1990) to create co-evolutionary relationship between exploration and exploitation (Zollo and Winter, 2002). This is also consistent with Brown and Eisenhardt's (1997) notions of time-pacing new product introductions and Helfat and Raubitschek (2000) on product sequencing as strategies for competing in fast-changing and unpredictable markets. This type of time-based pacing of products is based on sequenced organizational routines that allow for an introduction of products that synchronize with market requirements and simultaneously modify and adapt the underlying core capabilities of the firm in the spirit of dynamic capabilities.

Simulation studies provide preliminary support for the assertion that exploration followed by gradual refinements that dislodge firms from their preordained trajectories of evolution enable firms to avoid competency traps (Siggelkow and Levinthal, 2003). The broader implication is that exploring at a certain point in time and then diligently shifting toward exploitation and vice versa is a requirement for long term success. In the context of time-paced evolution of requisite capabilities, partnering with external alliances is an effective way to balance exploration and exploitation (Rothaermel and Deeds, 2004). Thus, empirical examination of time-paced balancing of exploration and exploitation is a worthwhile research contribution (Lavie and Rosenkopf, 2006). Thus, we expect firms who have developed the routines to balance exploration and exploitation across time to have higher sales growth. Thus:

$H1_b$: Sequential ambidexterity will have a positive effect on firm sales growth.

Contingency Effects

In addition to the main effects of the two forms of ambidexterity on firm growth, we examine the possible role of three contingency effects— age, market dominance (share), and the degree of multi-market competition. These three variables reflect possible firm and market characteristics that could influence ambidexterity's impact on firm performance. In addition to limited direct empirical evidence on ambidexterity's impact on firm performance (cf. He and Wong, 2004 for an exception), there has been limited theorizing of possible contingency effects of the role and impact of ambidexterity. So, in deriving hypotheses on contingency effects, we do not distinguish between these contingency impacts on the specific functional form of ambidexterity—namely, simultaneous versus sequential. The contingency hypotheses are offered in the spirit of exploratory examinations in order to delve deeper into understanding the role and effects of ambidexterity.

Age. Are younger firms more able to balance exploration and exploitation because they have not been subjected to core rigidities and competency traps? Or are older firms better able to learn and time-pace their evolution? Age has been recognized in prior organization research through 'liability of newness,' which could result in lack of adequate resources to pursue both exploration and exploitation, as well as in 'liability of senescence,' which could result in ossification and rigidity. Studies have shown that as organizations age, they become more institutionalized with their established set of routines and consequently explore less (Hannan and Freeman, 1984). In contrast, younger firms may have limited endowment of resources, which may be inadequate to balance between exploration and exploitation. In contrast, Sorensen and Stuart (2000) show that an organization's age is positively related to innovation (seen through patents) and that these innovations build on refinement of older technologies, emphasizing exploitation over exploration. Thus, it is worthwhile to examine the possible role of age in moderating the relationship between ambidexterity and sales growth.

$H2_a$: Firm age moderates the impact of simultaneous ambidexterity on firm sales growth.

$H2_b$: Firm age moderates the impact of sequential ambidexterity on firm sales growth.

Market dominance (share). Do market leaders leverage ambidexterity because of their market share and associated scale? Although market share has been an important variable in strategy research, there is limited prior theorizing on whether market dominance impedes or enhances adaptation. Anecdotal evidence based on in-depth analyses of cases involving market leaders such as NCR (Rosenbloom, 2000), Polaroid (Tripsas and Gavetti, 2000) and Firestone Tire (Sull, 1999) shows that market dominance plays an important role in how firms recognize and respond to major shifts. In addition, in the personal computer software industry, historical analyses show the rise and fall of leaders in different segments, such as word processors, spreadsheets, database, personal finance software and operating systems during 1979-1997 (Evans, Nichols, and Reddy, 1999). Thus, market dominance is not sustained over a period of time in software, despite possibilities of lock-in, implying that this could act as a moderator in ambidexterity—performance relationship. Thus, our second moderator is firm dominance and the way it impacts the relationship between ambidexterity and sales growth.

$H3_a$: Firm dominance moderates the impact of simultaneous ambidexterity on firm sales growth.

$H3_b$: Firm dominance moderates the impact of sequential ambidexterity on firm sales growth.

Degree of Multi-Market Competition. While the above two variables have longstanding history in management research, this next variable is new and critical to strategy research dealing with market structure and firm performance. Ambidexterity as a capability linked to performance should be framed in the competitive context that calls for product streams to maximize performance. Multi-market competition is defined as the extent to which a firm's product markets corresponds to that of other firms' product markets (Baum and Korn, 1996; Greve and Baum, 2001). When firms find themselves in similar markets, the possibility of collusion and 'mutual forbearance' (Edwards, 1955, Li and Greenwood, 2004) blunts the intensity of competition and enhancing firm performance (Karnani and Wernerfelt, 1985). Exploitation and exploration occur in response to market structure shifts and shaped by competitive interactions. Furthermore, exploration – namely entry into new product markets – has the potential to perturb the existing intensity of rivalry among firms (Porter, 1985). Empirical evidence from longitudinal studies suggest that multi-market contact between firms impacts not only product market entry but also firm performance (e.g., Baum and Korn, 1996; Gimeno and Woo, 1999). Thus, we expect that multi-market competition to moderate the relationship between ambidexterity and firm performance.

$H4_a$: The degree of multi-market competition moderates the impact of simultaneous ambidexterity on firm sales growth.

$H4_b$: The degree of multi-market competition moderates the impact of sequential ambidexterity on firm sales growth.

Methods

Research Setting: Packaged Software Industry, 1990-2002

We selected the packaged software industry because it is in the midst of profound transitions (Campbell-Kelly, 2003). These transitions call for successful companies to optimize by selling their current products while also designing and launching new products for new product markets. Thus, both exploitation and exploration are requisite routines for long-term success. New product introductions in the high technology sector are critical for successful adaptation (Eisenhardt and Tabrizi, 1995) and new product launches are central to the evolution and growth of the software sector as different software firms launch products to interoperate with other software products across different platform architectures (Bresnahan and Greenstein, 1999). We focus time-sequenced product market moves by software firms over a 13-year period, 1990-2002.

Operationalization of Ambidexterity

Prior approaches to operationalization of ambidexterity fall into three different categories. First is a categorization scheme of structural archetypes with ambidextrous form as one distinct type (Tushman et al., 2005). The second is calibration of the organizational characteristics that underlie ambidexterity through management perceptions of organizational characteristics (Gibson and Birkinshaw, 2004; He and Wong, 2004). The third is objective surrogates using patenting activities to calibrate organizational search and problem solving routines (Katila and Ahuja, 2002). Each scheme has its advantages and disadvantages with varying measurement properties.

To this list, we introduce a measurement scheme of exploitation and exploration routines as a derived metric based on a firm's participation in product markets with differing degree of similarities and differences. Our variables are time-varying outcome measures reflecting *realized* exploration and exploitation; they are based on product launches across distinct within industry product markets over time. Instead of using coarse measures of similarities in product markets using SIC codes, we adopt refined measures based on recent developments in operationalizing within-industry relatedness (Li and Greenwood, 2004) and consistent with studies on networks of competition (Burt, 1988). For example, Burt and Carlson (1989) analyzed the network boundaries of 77 markets and found that they could be grouped into seven classes based on their similarity. Product launches within a class reflect exploitation routines rather than exploration routines. Viewed this way, homogeneous sales patterns across different markets not only indicate market similarities but also indirectly reflect the importance of these markets to the firm. This importance most probably has some effect on the allocation of future resources to these product markets. As White (1981) noted, "Pressures from the buyer side creates a mirror in which producers see themselves, not consumers" (p. 543) and they attempt to create "synergies or scope economies due to the shared underlying capabilities or know-how" (Robins and

Wiersema, 1995, p. 283). As firms repeatedly interact with other firms and customers over time, firms exploit existing capabilities and explore new resources and capabilities to create competitive advantage because "to the extent that the producers of one commodity and producers of another have identical consumers, they are competitors" (Burt, 1988, p. 358).

We adopt the logic of product market relatedness to measure exploitation and exploration routines and operationalize ambidexterity based on similarities and differences in product-markets served by software firms over time. In doing so, we measure ambidexterity as a time-varying characteristic of the organization. We follow recent operationalization of relatedness of market niche (Li and Greenwood, 2004), which builds on Sohn's (2001) operationalization of niche overlap. The main advantage of this index is that it is calculated based on the sales of all firms in the market niches, reflecting strategic choices made by the set of competitors in the industry (choices which are reflections of their heterogeneous capabilities).

Our computation of ambidexterity involves four steps and is depicted schematically in Figure 1. In step 1, we compute the similarities of the software product markets by computing the similarity metric for every product pairs for every year that we examine. We follow Sohn (2001), which is a refinement of niche width similarity adopted in technology niche studies (Jaffe, Trajtenberg, and Henderson 1993). In step 2, we focus on measuring exploitation routines that are captured by looking at how firms use their existing routines to serve current customers. For a given firm, we determine the list of products that were sold by the firm that year and in a prior year. Based on the degree of similarities in product pairs that we described in step 1, we assess the corresponding degree of similarity in resource requirements for this set of products. We also reflect the relative importance for the different product markets to derive a weighted measure of exploitation routines. In step 3, we perform a similar set of calculations for exploration routines. In this context, high levels of exploration mean offering products in those product markets that are highly dissimilar to those that have been offered in the past years. For a given firm, we create a list of products that are new for that year. We then compare the list of new products to the list of products that the firm supported in a previous year. Just as before (in step 2), we compute the importance of the new products relative to the older products based on the sales levels to compute a weighted index. If the new products are very different from existing products (i.e., from those in the previous year), then the degree of exploration is high.

In step 4, we create a measure for ambidexterity as a cross product of exploration and exploitation routines. We specifically operationalize simultaneous ambidexterity as the cross product of exploration and exploitation in time *t*. We operationalize sequential ambidexterity as the cross product of exploration in time *t-1* and exploitation in time *t*. Thus, our approach allows us to derive precise yearly measurements of exploration and exploitation routines and ambidexterity by treating the outputs (sales) as observed effects of organizational routines and resource allocations. A technical appendix (Appendix B) provides additional details on the computation of ambidexterity. Figure 2 graphically represents the two functional ambidexterity forms.

-- Put Figures 1 and 2 about here --

Data

We assembled a database by combining the data from International Data Corporation (IDC) with other secondary sources. IDC employs over 700 analysts in 50 countries to collect and codify data on the global computer industry and the product sales of major companies. IDC is widely considered to be the best source on computer software and hardware; its data has been used in the US DOJ case against Microsoft (Liebowitz and Margolis, 1999) and in academic research (e.g., Stern and Henderson, 2004). Our database therefore contains the global revenues (in millions of dollars) generated by software companies from the sale of its software products at the level of distinct market segments.

Specifically, IDC tracks revenues by: (1) company (e.g., IBM, PeopleSoft, and SAP) with approximately 1200 software firms, (2) product markets (e.g., database, payroll, and website design and development tools) with approximately 90 distinct segments, and (3) time period, spanning from 1990 to 2002. Our database contains over 16,000 unique company – product market – year revenue observations. It also captures firm entry or exit, and new product markets (e.g., middleware and XML), thus allowing for fine-grained computation of exploration and exploitation behaviors by software companies. We supplemented the IDC database with other secondary data sources such as CompuStat.

Table 1 summarizes the data in terms of the number of distinct firms and product markets in each year of the study sample. It is important to note that there is a 14-fold increase in the number of firms in the software sector and a 4-fold increase in the number of products-markets served, reflecting a vibrant, dynamic sector to study exploration and exploitation practices using a longitudinal approach. To address censoring in the data and to accommodate the design of our study, we exclude firms or panels for which we do not have at least three contiguous observation years (i.e., *t-1*, *t*, and *t+1*). The range of year *t* for this study is 1991 to 2001, inclusive. The total number of firm – year observations used in this study is 4153 with 1005 panels or 4.5 years per panel.

Operationalization of Constructs

Firm Growth$_{i,t+1}$. We measure the dependent variable, Firm growth$_{i,t+1}$, as the one-year lagged log of the total revenues in year *t+1* divided by total revenues in year *t* (Carroll and Hannan, 2000). Let $x_{ij,t}$ and $x_{ij,t+1}$ denote firm *i*'s sales in product market *j* in years *t* and *t+1*, respectively. Each observation in the IDC database is a unique company – product – year combination. As such, $x_{i,t} = \sum_{j \in N_t^{Market}} x_{ij,t}$ where $x_{ij,t}$ is firm *i*'s sales in product market *j* in year *t*. Firm growth$_{i,t+1}$ equals $\ln(\Sigma_j x_{ij,t+1} / \Sigma_j x_{ij,t})$.

Although accounting return values (e.g. ROI and ROA) are often used as firm performance measures, we use firm growth because many of the firms in the sample (e.g., IBM and Compaq) offer both hardware and software products, in addition to services. Also, firms often do not separate sales from software from the firm's other sales. Moreover, sales growth is critical to the success of software sector firms (Campbell-Kelly, 2003).

Exploitation$_{i,t}$. We measure firm *i*'s exploitation in year *t* as the sum of the similarity between each pair of product markets common to the firm in years *t* and *t-1* multiplied by the portion of the firm's sales in the product market. We use a two-step process for determining firm exploitation that has been used in prior studies (e.g. Li and Greenwood, 2004, Robins and Wiersema, 1995). Firstly, we compute the similarity between all pairs of product markets offered by all firms in the industry in year *t*. Secondly, we use these weights to calculate firm specific exploitation levels.

We compute the similarity between two product markets in year *t* using Sohn's (2001) specification. This similarity specification has been used in prior within industry multi-market similarity and competition studies (e.g. Li and Greenwood, 2004). Let N_t^{firm} and N_t^{market} denote the sets of all firms and product markets, respectively, in year *t.* Also, let $x_{ij,t}$ denote firm *i*'s sales in product market *j* in year *t*. The term $x_{ij,t}$ is an element of a rectangular matrix with $|N_t^{firm}|$ rows and $|N_t^{market}|$. The similarity index $\omega_{jk,t}$ between two product markets *j* and *k* in year *t* is $\omega_{jk,t} = \frac{\sum_{i \in N_t^{firm}} x_{ij,t} \min(x_{ij,t}, x_{ik,t})}{\sum_{i \in N_t^{firm}} (x_{ij,t})^2}$ (Sohn, 2001). The range of the similarity metric is [0, 1] with 0 and 1 denoting perfect dissimilarity and similarity, respectively, between two product markets. A high similarity between two product markets implies similar resources and routines necessary for the two product markets (Li and Greenwood, 2004; Robins and Wiersema, 1995). The similarity metric is asymmetric or $\omega_{jk,t}$ is does not usually equal $\omega_{kj,t}$ for different product markets *k* and *j*.

The similarity index $\omega_{ij,t}$ measures the similarity among all pairs of product markets in year *t*, some of those products may not be offered by firm *i*. To calculate firm exploitation in year *t* for a particular firm, let $N_{i,t}^{old}$ denote product markets common to firm *i* in the years *t-1* ***and*** *t*. We compute firm *i*'s exploitation in year *t* as $\sum_{j \in N_{i,t}^{old}} \sum_{k \in N_{i,t}^{old} | j \neq k} p_{ij,t}\omega_{jk,t}$ where $p_{ij,t}$ is the proportion of firm *i*'s sales in product market *j* in year *t*. A larger number denotes higher levels of firm exploitation. Figure B1 schematically depicts this computation.

Exploration$_{i,t-1}$. We measure firm *i*'s exploration in year *t-1* as the sum of the similarity between each pair of product markets new to the firm in year *t* with the "old" product markets in years *t-1* (i.e. cartesian product between the new and old product market sets) multiplied by the portion of the firm's sales in the new product market. The degree of exploration is realized once a new software product is launched. However, a firm's new product market in year *t* (i.e., the observation "appearing" in our database) connotes the firm exploring in the previous year because the development and launch of a new software product takes time (Messerschmitt and Szyperski, 2003). Empirical studies measure the degree of exploration using new citations (Katila and Ahuja, 2002) and new product launches (He and Wong, 2004). Recall that the set $N_{i,t}^{old}$ denotes product markets common to firm *i* in the years *t-1* and *t* (i.e., "old"). Let the set $N_{i,t}^{new}$ denote the firm's product markets that found in year *t* and not in year *t-1* (i.e., "new"). The set $N_{i,t}^{new}$ may be empty (i.e., no new product markets in year *t*).

We again use the similarity index $\omega_{ij,t}$ to compute firm exploration. We compute firm *i*'s exploration in year *t-1* as $\sum_{j \in N_{i,t}^{new}} \sum_{k \in N_{i,t}^{old}} p_{ij,t}\left(1.0 - \omega_{jk,t}\right) + p_{ik,t-1}\left(1.0 - \omega_{kj,t}\right)$ where $p_{ij,t}$ and $p_{kj,t}$ are the proportions of firm *i*'s sales in products *j* and *k*, respectively in year *t*. The similarity metric is subtracted from 1.0 because exploration denotes difference instead of similarity (i.e., exploitation). In other words, a high value of the exploration measure suggests that in year *t-1*, the new products if any, are dissimilar from the products that a firm has offered. Figure B2 schematically depicts this computation.

$\mathbf{Exploration_{i,t}}$. We measure firm *i*'s exploration in time t by replacing the appropriate time indices used in the calculation of **$\mathbf{Exploration_{i,t-1}}$**. A firm's new product markets in year *t+1* denotes the firm exploring in year *t*.

$\mathbf{Simultaneous\ Ambidexterity_{i,t}}$. Like prior studies, we measure ambidexterity as the interaction between exploitation and exploration (He and Wong, 2004, Katila and Ahuja, 2002, Gibson and Birkinshaw, 2004). We measure a firm *i*'s simultaneous ambidexterity in year *t* as the interaction of **$\mathbf{Exploitation_{i,t}}$** and **$\mathbf{Exploration_{i,t}}$.**

$\mathbf{Sequential\ Ambidexterity_{i,t}}$. We measure a firm *i*'s sequential ambidexterity in year *t* as the interaction of **$\mathbf{Exploitation_{i,t}}$** and **$\mathbf{Exploration_{i,t-1}}$.**

$\mathbf{Dominance_{i,t}}$. We measure firm *i*'s dominance in year *t* as the weighted sum of a firm's share in each market. Specifically, we multiply a firm's share of market *j* with the proportion of firm *i*'s sales from market *j*.

$\mathbf{ln(Age_{i,t})}$. We measure firm *i*'s age in year *t*, as the difference between year *t* and the first year in which the firm generated sales. We determined the first year that a firm generated sales from the full IDC database that spans the years 1990 to 2002. For those firms that existed prior to 1990, we consulted the Mergent Online™ database and used the natural logarithm of the difference between year *t* and the firm's year of incorporation. Prior studies (e.g. Cottrell and Nault, 2004; Stern and Henderson, 2004) include firm size and age as controls to address their potential impact on firm performance (Hannan and Freeman, 1989).

$\mathbf{Multi\text{-}market\ competition\ (MMC)_{i,t}}$. Per Li and Greenwood (2004) and Baum and Korn (1996), we measure firm *i*'s multi-market competition (MMC) per rival in year *t* as the average, over the number of firms that share at least one product market with firm *i*, of the sum of the number of markets shared by firm *i* and another firm i' in each pair of product markets.

We include in the analysis a set of controls used in prior studies. Full details can be seen in Appendix A. The means, standard deviations, and zero-order correlations are presented in Table 2. Some empirical observations relating to the correlations are worth highlighting. One, the relatively low and negative correlations between $\text{exploitation}_{i,t}$ and $\text{exploration}_{i,t}$ (-0.223), and $\text{exploitation}_{i,t}$ and $\text{exploration}_{i,t-1}$(-0.295), suggest that the three measures (exploration at time *t-1* and *t*, and exploitation at time *t*) are distinct. Two, the negative sign empirically reflects the inherent tension between exploration and exploitation, providing further support for the measures that we develop and use. In contrast, when operationalized through informant-based questionnaire items, Gibson and Birkinshaw (2004) found an empirical correlation of the two dimensions that underlie ambidexterity (alignment and adaptation) to be 0.485. He and Wong (2004) extracted the two dimensions based on principal component analysis to arrive at independent dimensions, but they do not report the empirically observed correlations between the two dimensions. Three, the low correlation between simultaneous and sequential ambidexterity (0.162) suggests that the two measures are distinct, lending support to the use of two different functional forms of ambidexterity. These provide support for the validity of the measures used here.

-- Put Table 2 about here --

Model Specification and Testing

We test the hypotheses using a cross-sectional time series or panel design. The sample contains 1,005 distinct firms with approximately 4.5 years of observations per firm. The design repeatedly measures firm performance and covariates, which includes a lagged performance measure. Under these conditions, ordinary least squares (OLS) may be inefficient and result in biased estimates.

We use the generalized estimating equations (GEE) approach (Liang and Zeger, 1986; Zeger, Liang, and Albert, 1988) that has been used in prior studies (e.g., Bae and Gargiulo, 2004; Katila and Ahuja, 2002). GEE is a flexible estimation procedure that incorporates within firm correlation and heterogeneity and thus results in more efficient and unbiased parameters than

OLS. We triangulated the results obtained from GEE estimation with results obtained from feasible generalized least squares (FGLS) estimation (Greene, 2003) with panel-specific first order autocorrelation and panel-specific heteroskedastic error structure corrections. Results are qualitatively similar. Specifically, GEE estimators are asymptotically normal and consistent given an arbitrary correlation among observations (Liang and Zeger, 1986; Zeger et al., 1988). Because of its flexibility, a set of options must be specified prior to performing estimations. We use a Gaussian distribution for the dependent variable, an identity link function, and an unstructured working correlation matrix. We also performed estimations using an exchangeable working correlation matrix, which denotes an equal correlation model and is equivalent to random effects estimation with consistent results. We also use a sandwich variance estimator for correcting standard errors.

We estimate eleven separate models. Model 1 adds the control variables to provide a base model for estimation. Model 2 adds the three contingency effects. Model 3 adds $\text{exploitation}_{i,t}$, $\text{exploration}_{i,t-1}$, and $\text{exploration}_{i,t}$ as three separate independent constructs while Model 4 includes the two ambidexterity constructs — simultaneous and sequential ambidexterity. Model 5 is the full model with the sets of moderator effects. Models 6—11 test the specific effects of control variables to assess robustness of results. All models are estimated using Stata. Model 5 is used to test the hypotheses.

Results

Tables 3 and 4 summarize the Stata estimations of the eleven models. Adding controls, as well as variables of interest, significantly add to the model at levels better than $p<.001$ (i.e., Models 1-3). The control covariates, even in the presence of theoretical variables of interest—namely, exploitation, exploration, and two forms of ambidexterity – significantly improve model fit, suggesting the importance of the control variables in the models (i.e., Model 4). Comparing models 3 with 2, we see a significant improvement ($\Delta\chi^2 = 58.57$, df = 3, $p<.001$), providing support for the inclusion of variables for exploration (*t* and *t-1*) and exploitation (*t*). When we add two forms of ambidexterity in model 4, there is further improvement in model fit ($\Delta\chi^2 = 45.57$, df = 2, $p<.001$), with significance for the coefficient for sequential ambidexterity (coefficient: 0.083, $p <.001$). Model 5 includes three contingency effects for two forms of ambidexterity. Model 5 is significant (χ^2 of 963.21, $p<.001$), and when we compare model 5 with model 4, we see model 5 is a significant improvement over the main effects model ($\Delta\chi^2$ = 45.38, df = 6, p<.001). We use the coefficients from this model for examining the degree of empirical tests for our hypothesis.

The estimates for the control variables are significant and consistent with prior studies. For example, prior year growth positively impacts next period growth (0.163, p<.001), supporting the need to use it as a control. Furthermore, in line with the broad set of prior studies, firm size (-0.045, p<.001) and age (-0.055,p<.001) both have a negative impact on firm growth. The coefficient for market growth is positive and significant (0.98, p<.01), consistent with the expectation that operating in growing product markets positively impacts performance growth. Exiting from product markets have an insignificant effect on firm performance (.013, p>.10).

-- Put Tables 3 and 4 about here --

Our main hypothesis (H_1) is a test of the positive impact of strategic ambidexterity on firm growth, using two functional specifications. Comparing model (4) with model (3), we find that the addition of the two functional forms of ambidexterity adds significantly to predicting firm growth ($\Delta\chi^2$ = 45.57, df = 2, p<.001). But for testing the set of hypotheses, we use model 5. $H1_a$ – which hypothesized a positive effect of simultaneous ambidexterity on firm growth — did not receive empirical support (coefficient: 0.085, p>.10). However, $H1_b$ – which specified a positive effect of sequential ambidexterity — received empirical support (coefficient: 0.183, p<.05). The estimate for the ambidexterity coefficient is derived after controlling for the main effects of exploitation and exploration. Including the main effects enhances the confidence in the interpretation of the interaction variable, namely ambidexterity (cf. Arnold, 1982; Venkatraman, 1989).

The other hypotheses (H_2-H_4) deal with moderating effects. Looking at coefficients for Model 5 in Table 3, we find support for the three moderating effects with sequential ambidexterity. The coefficient for the moderating effect of market dominance is significant (0.423, p<.10), the coefficient for the moderating effects of firm age is significant (0.057, p<.05) and the coefficient for the moderating effect of multi market competition is negative and significant (-0.157, p<.01). In contrast, only the moderating effect of market dominance is significant and negative for simultaneous ambidexterity (-.859, p<.001).

Exploration-exploitation tension reflects a fundamental trade-off, but it has been most commonly considered in the literature on organization design (Tushman and O'Reilly, 1996; Tushman et al., 2004) and organizational adaptation (March, 1991; 2003). We sought to expand the scope of treatment of this trade-off by treating ambidexterity as an organizational-level capability that drives critical organizational output (namely product launches), which impacts organizational performance (namely sales growth). We developed a systematic basis to conceptualize and operationalize ambidexterity by looking at the patterns of sales in the different market niches served by a software firm.

Our measurement approach based on similarities in product-markets (Li and Greenwood, 2004) is a powerful and novel approach to specify and test the veracity of ambidexterity as an organizational capability. Empirically, our measures show strong properties evidenced by small and negative correlation between exploration and exploitation as well as discriminant validity between simultaneous and sequential ambidexterity. Our results add to the nascent but growing body of research on the value and importance of ambidexterity as a central concept in strategy and organizational analysis (Katila and Ahuja, 2002; Gibson and Birkinshaw, 2004; He and Wong, 2004; Tushman et al, 2005). We believe that the measurement scheme that we introduced here is a robust way to capture how firms successfully navigate at the frontier of exploitation—exploration tradeoff over time.

Discussions

March's (1991) proposition on exploration-exploitation balance at a general level is well accepted, intuitively appealing and generally not falsifiable. Researchers have tried to better understand how this trade-off occurs within organizations (Benner and Tushman, 2002; Gibson and Birkinshaw, 2004; He and Wong, 2004) and across organizations through inter-organizational alliances (Lavie and Rosenkopf, 2006). In doing so, these initial studies have made attempts to deal with the challenges of defining and measuring the concepts of exploration, exploitation and ambidexterity and inter-temporal trade-off (Gupta et al., 2006).

In this vein, we theorized that ambidexterity is a critical organizational-level capability that drives organizational actions and performance. We positioned ambidexterity as a dynamic capability embodied in routines for exploration and exploitation over time. Using new product launches in the software industry over a thirteen year period as realized results of the trade-off between exploration and exploitation, we measured ambidexterity using a fine-grained approach and dealt with inter-temporal issues central to dynamic capability (Eisenhardt and Martin, 2000). Our main result is that when firms are able to successfully operate at the frontier of exploration-exploitation tradeoffs, they do so by time-pacing exploration and exploitation to achieve year-to-year sales growth. Sequential ambidexterity emerged as a more significant predictor than simultaneous ambidexterity of firm growth, thus providing the first empirical evidence of how time plays a part in this fundamental trade-off.

Our testing involved a system of eleven models to rule out alternative explanations. Had we adopted just one model to test a general assertion of ambidexterity's impact on firm growth, we might have erroneously concluded that simultaneous ambidexterity has significant performance effects. Looking at only model 7,which specified main effects of exploration and exploitation at time *t* and the joint effects at time *t*, we would have concluded that ambidexterity is significant at $p<.05$. Indeed, such a result would have been consistent with He and Wong (2004) and in line with the general proposition on the value of ambidexterity. By incorporating time into the conceptualization of two functional forms of ambidexterity and including relevant contingency effects in Model 5, we teased out the specific role of time-paced balancing of exploration and exploitation and advance our understanding of the core proposition in March (1991; 2003). We urge future researchers to continue to examine the possible differential effects of simultaneous versus sequential ambidexterity on form performance under different conditions.

Is ambidexterity a valuable core capability for all software firms? We used a battery of market- and firm- level controls before estimating the impact of ambidexterity. The use of eleven models provided robust support for the main effects of sequential ambidexterity as well as the contingency effects of dominance, age and multi-market competition. Our results provide evidence that this is a valuable organization capability for superior performance growth in the software sector. Sequential ambidexterity is a core management requirement in high-velocity markets, where firms balance paying attention to current markets and customers with recognizing new opportunities and market segments. Managing multiple products requires organizational adjustments that may constrain, contradict or interface with one other, resulting in coordination uncertainty (Camerer and Weber, 1998) that is exacerbated during product launches (Barnett and Freeman, 2001; Iansiti, 1997). Indeed, coordination uncertainty inhibits organizations to achieve exploration-exploitation balance calling for distinct structural alternatives that operate in distinct 'time zones' (Tushman and O'Reilly, 1996) and rhythmic, time-paced transition processes (Brown and Eisenhardt, 1997). While we do not have data on the specific mechanisms that software firms adopted to mitigate problems of coordination uncertainty, our empirical evidence is that those that do so achieve higher levels of performance growth. Clearly, a promising area of inquiry would be to uncover specific structures and processes that allow for sequential ambidexterity to be created and sustained over time.

The roles of three contingency variables are worthy of attention. As highlighted earlier, all three moderating variables emerged significantly in relation to sequential ambidexterity, while market dominance turned out to have a significant negative contingency effect for simultaneous ambidexterity. Looking at market dominance first, we find that it acts negatively for simultaneous ambidexterity (-0.859, $p<.001$) and positively for sequential ambidexterity (0.423, $p<.10$). When dominant firms try to balance exploring new avenues with maintaining their dominant position in their current product-markets, both within the same time period, they find themselves more constrained to achieve firm growth. In contrast, when they balance it across two different time periods, market dominance plays a catalytic role in achieving firm growth. It could be that market leadership traps a firm into allocating resources and management attention in order to defend its current market position (Levinthal and March, 1993), thereby rendering them unable to balance exploration and exploitation concurrently. In contrast, performance is enhanced when firms better align the resources over time to balance exploration and exploitation, a fact which is evidenced by the positive result for the contingency effect of dominance for sequential ambidexterity. Our results of the negative contingency effects of market dominance provide empirical support to case studies that highlight the challenges faced by market leaders in trying to proactively adapt to overcome co-evolutionary lock-in (Burgelman, 2002). Our results of positive contingency effects of dominance on sequential ambidexterity lend support to Brown and Eisenhardt (1997) on the importance of dynamic capability across different time-periods as distinguishing characteristics to achieve sustained growth. Clearly, our empirical results for hypotheses $H3_a$ and $H3_b$ reinforce widely-held notions of market dominance as a two-edged sword under fast-changing conditions with inherent contradictions to be actively managed (Smith and Tushman, 2005).

Our empirical findings on the contingency role of age add to the longstanding research stream on the role of age on innovation and organizational adaptation. The positive contingency effect of age and sequential ambidexterity on firm performance (0.057, $p<.05$) and the non-significant effect when tested for simultaneous ambidexterity reinforce the role of absorptive capacity in assimilating the new information and competences required for succeeding with new innovations (Cohen and Levinthal, 1990). As firms age, they accumulate experience that helps to develop routines to manage strategic contradictions (Smith and Tushman, 2005) and overcome liabilities of newness (Stinchcombe, 1965). Older software firms exploit sequential ambidexterity to achieve firm growth better than younger firms, consistent with writings on dynamic capability and organizational learning (March, 1991).

We introduced multi-market competition as the third moderator since mutual forbearance could create collusion amongst software firms that might inhibit exploration-exploitation tradeoff. The degree of multi-market competition as a control variable did not emerge as significant, while its interaction effect with sequential ambidexterity had a negative effect on firm growth. Contrary to collusion, we find that firms strive to balance their exploration-exploitation tradeoff, recognizing the possible high degree of overlap amongst products within software markets, and that these two jointly inhibit, rather than enhance, firm performance. In adding this variable to have a possible interaction with ambidexterity, we have made an initial foray into linking ambidexterity as an organizational capability to a specific competitive, network structure characteristic. The negative result signals network structure conditions should be considered part of the broader exploration-exploitation balance since some conditions may hinder while others may enhance ambidexterity's impact on firm performance. We believe that considerable progress could be made by linking ambidexterity as an organizational capability to market and network structure characteristics to examine the multiplicity of links to firm performance.

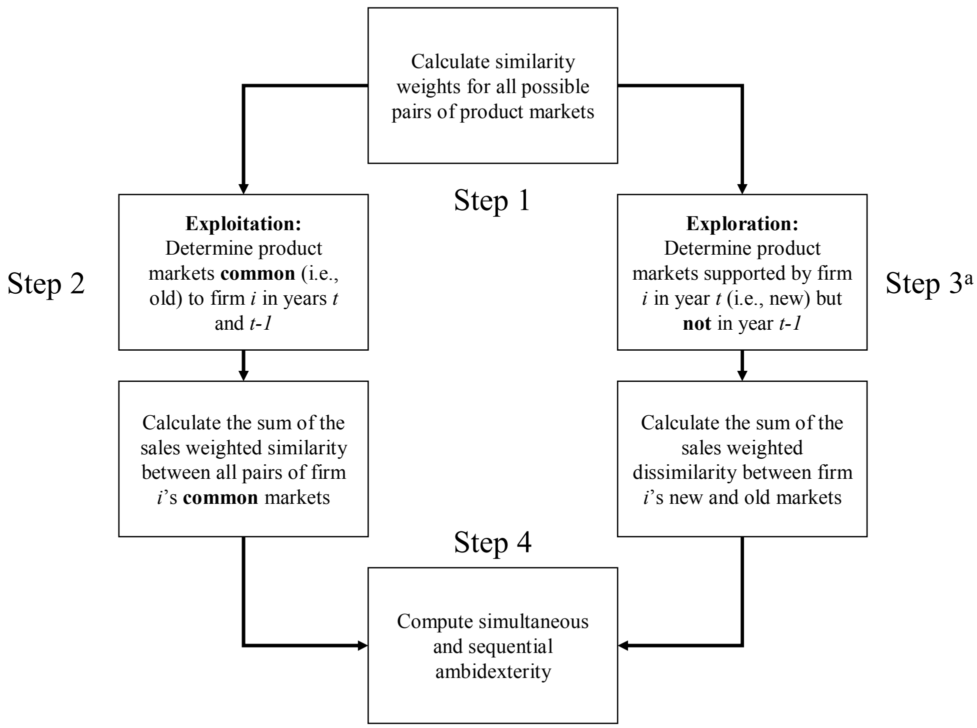
One promising avenue for extension is to consider the antecedents of ambidexterity along the lines of Gibson and Birkinshaw (2004). Since we found ambidexterity to be valuable as organizational-level capability, we need to better understand the drivers of these two forms of ambidexterity? What makes some firms better manage the inter-temporal trade-off between exploration and exploitation? What mechanisms are in place to manage the inherent contradiction between scope and depth (Katila and Ahuja, 2002)? What roles do acquisitions and alliances play to infuse new thinking and complement internal development? Anecdotal evidence hints at how Microsoft, Cisco, SAP, Oracle, IBM and others balance internal R&D and external alliances and relationships to infuse new ideas and adapt their product offerings over time. Such case-based evidence could be formalized into propositions on different mechanisms adopted to balance exploration-exploitation tradeoff.

Our design, which relied on secondary data, could be complemented by primary data that captures organizational characteristics that give rise to different levels and forms of ambidexterity. In the software context, we could examine how companies leverage design operators suggested by Baldwin and Clark (2000)—namely splitting, augmenting, inverting, excluding, substituting and porting—as ways to develop software design and development routines that permit superior ambidexterity. By integrating concepts from product and organizational architectures, we may uncover approaches followed by companies for effective trade-offs across exploitation and exploration. In addition to the structural form (Tushman et al, 2004), we could examine how design moves through the deployment of modular operators such as substitution and porting (Baldwin and Clark, 2000) as well as alliances (Rothaermel and Deeds, 2004; Lavie and Rosenkopf, 2006) help firms to balance exploitation and exploration over time.

Ambidexterity is a powerful concept but one with problems of inadequate correspondence between theoretical statements and analytical approaches to operationalize and test them. Following He and Wong (2004) and Gibson and Birkinshaw (2004), we specified linear effects of ambidexterity on performance with ambidexterity specified as an interaction term of exploration and exploitation. However, March (1991; 2003) observed that excessive exploitation leads to competency trap and excessive exploration without exploitation is a route to failure. Barnett and Freeman (2001) empirically show that excessive simultaneous introduction of new products increased the mortality rates in semiconductor industries. These arguments hint at potentially non-linear effects and confounding signs of predictions depending on the relative emphasis to one set of routines over another. Katila and Ahuja (2002) recognize non-linearity effects of search scope and depth but do not invoke possible dysfunctional effects of excessive depth that may inhibit new product launches. Just as contingency research studies have become clearer in their conceptualization, operationalization and statistical tests of the concept of fit (e.g., Venkatraman, 1989), we believe that progress could be achieved if we develop a robust typology on conceptualizations of ambidexterity with corresponding analytical schemes. Such a typology will go a long way towards cumulative understanding of the dynamics of ambidexterity's role in organizational innovation and success.

In conclusion, our study is the first to examine the main effects of two different forms of ambidexterity on firm growth over time. In addition to establishing that sequential temporal balancing of exploration and exploitation has a superior effect on firm performance, relative to concurrent attempts at this trade-off, we found that sequential ambidexterity has strong moderating effects through firm age, market dominance and the degree of multi-market competition. Beyond providing general empirical support to a widely accepted proposition that ambidexterity influences firm success over time—albeit in a new context, we delved deeper in to the specific conditions that enhance ambidexterity—performance link. We hope that this study stimulates other researchers to frame exploration-exploitation tradeoffs that recognize the roles of time as well as critical internal and external contingencies.

FIGURE 1: Computation of Ambidexterity Constructs



[a]Repeat this step for the next two consecutive years

FIGURE 2: Schematic of Simultaneous and Sequential Ambidexterity

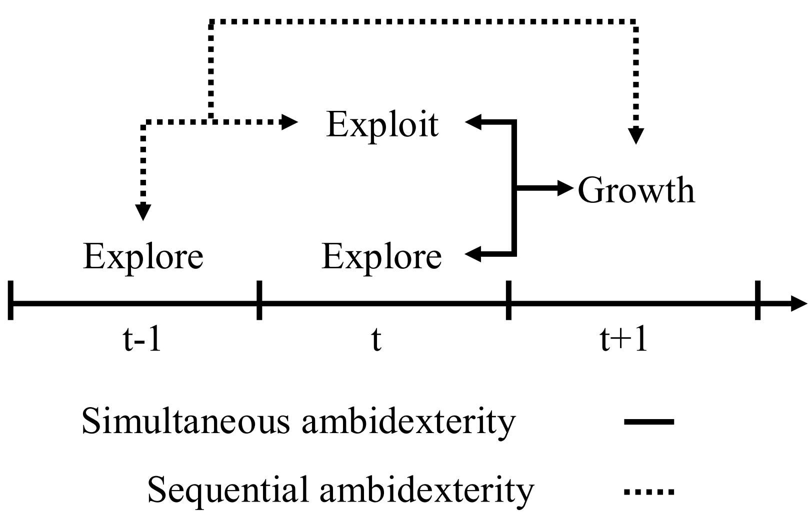


TABLE 1: Basic Description of the Data

Year	Firms	Product Markets
1991	1.00	1.00
1992	1.14	1.11
1993	1.86	1.95
1994	2.57	2.42
1995	3.14	2.79
1996	4.09	3.26
1997	5.69	3.74
1998	7.96	4.11
1999	10.34	4.26
2000	12.64	4.53
2001	14.04	4.53

All numbers have been scaled with respect to 1991 to protect the confidentiality of IDC data. The total number of distinct firms or panels is 1005 with 4513 firm-year observations or 4.5 observations per panel.

TABLE 2: Sample means, standard deviations, and zero-order correlations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
1. Simultaneous ambidexterity$_t$														
2. Sequential ambidexterity$_t$	0.162													
3. Explore$_{t-1}$	0.135	0.540												
4. Exploit$_t$	0.029	0.017	-0.295											
5. Explore$_t$	0.595	0.179	0.368	-0.223										
6. Firm dominance$_t$	0.075	0.107	0.245	-0.233	0.208									
7. Market exit$_t$	0.039	0.143	0.333	-0.240	0.142	0.156								
8. Market diversity$_t$	0.123	0.337	0.420	-0.485	0.384	0.199	0.256							
9. Market growth$_t$	0.061	0.094	0.097	-0.054	0.049	0.145	0.048	0.023						
10. Market concentration$_t$	0.024	0.054	0.133	-0.163	0.099	0.379	0.122	0.147	0.096					
11. Multimarket competition$_t$	-0.098	-0.202	-0.245	0.424	-0.200	-0.450	-0.158	-0.397	-0.058	-0.129				
12. ln(Firm age$_t$)	0.106	0.129	0.272	-0.353	0.266	0.179	0.193	0.472	-0.084	0.109	-0.339			
13. ln(Firm size$_t$)	0.176	0.231	0.395	-0.468	0.360	0.498	0.215	0.488	0.039	0.149	-0.569	0.424		
14. Firm growth$_t$	0.022	0.041	0.064	0.042	0.003	0.065	0.039	-0.067	0.279	0.020	-0.018	-0.241	-0.004	
Mean	0.110	0.097	0.285	0.684	0.270	0.034	0.144	0.400	0.180	0.420	0.553	1.603	3.200	0.246
SD	0.339	0.293	0.847	0.394	0.842	0.073	0.535	0.562	0.297	0.198	0.271	0.813	1.787	0.476

Subscripts *i* omitted; N=4513 with 1005 firms

Table 3: GEE regression results

	Model 1		Model 2		Model 3		Model 4		Model 5	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Simultaneous ambidexterity$_t$							0.039	0.025	0.085	0.057
Simultaneous ambidexterity$_t$ X Dominance$_t$									-0.859***	0.199
Simultaneous ambidexterity$_t$ X Age$_t$									-0.008	0.023
Simultaneous ambidexterity$_t$ X MMC$_t$									-0.022	0.041
Sequential ambidexterity$_t$							0.083**	0.030	0.183*	0.080
Sequential ambidexterity$_t$ X Dominance$_t$									0.423†	0.243
Sequential ambidexterity$_t$ X Age$_t$									0.057*	0.026
Sequential ambidexterity$_t$ X MMC$_t$									-0.157**	0.055
Explore$_t$					0.059***	0.010	0.048***	0.013	0.067***	0.013
Explore$_{t-1}$					0.003	0.007	-0.015†	0.009	-0.013	0.011
Exploit$_t$					0.018	0.021	-0.013	0.022	-0.005	0.022
Dominance$_t$			0.319**	0.092	0.276**	0.089	0.294**	0.093	0.366***	0.103
Age$_t$			-0.048***	0.009	-0.050***	0.009	-0.048***	0.009	-0.055***	0.009
Multi-market competition (MMC)$_t$			0.031	0.030	-0.044	0.033	-0.029	0.033	0.017	0.036
Market exit$_t$	0.012	0.009	0.016†	0.008	0.013	0.008	0.015†	0.008	0.013	0.008
Market diversity$_t$	0.059***	0.012	0.066***	0.017	0.078***	0.020	0.060**	0.019	0.052**	0.019
Market growth$_t$	0.114**	0.034	0.098**	0.034	0.103**	0.034	0.099**	0.034	0.098**	0.034
Market concentration$_t$	0.006	0.030	-0.026	0.031	-0.022	0.031	-0.023	0.031	-0.024	0.031
Firm size$_t$	-0.046***	0.005	-0.042***	0.005	-0.044***	0.005	-0.046***	0.005	-0.045***	0.005
Firm growth$_t$	0.179***	0.019	0.165***	0.019	0.157***	0.019	0.159***	0.019	0.163***	0.019
Year dummies: 1991-2000										
Constant	0.084***	0.019	0.122***	0.033	0.192***	0.041	0.203***	0.041	0.157***	0.043
df	16		19		22		24		30	
Wald χ^2	775.69		813.69***		872.26***		917.83***		963.21***	
Models			(2)-(1)		(3)-(2)		(4)-(3)		(5)-(4)	
$\Delta\chi^2$			38.00***		58.57***		45.57***		45.38***	

N=4513 with 1005 firms; Subscripts *i* omitted; Year dummies omitted and available upon request; Semi-robust standard errors; †<.10,*<.05,**<.01,***<.001

TABLE 4: GEE regression results

	Model 6		Model 7		Model 8		Model 9		Model 10		Model 11	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Simultaneous ambidexterity$_t$			0.053*	0.025	0.113*	0.055						
Simultaneous ambidexterity$_t$ X Dominance$_t$					-0.653***	0.170						
Simultaneous ambidexterity$_t$ X Age$_t$					0.002	0.023						
Simultaneous ambidexterity$_t$ X MMC$_t$					-0.052	0.037						
Sequential ambidexterity$_t$									0.075**	0.029	0.150*	0.074
Sequential ambidexterity$_t$ X Dominance$_t$											0.027	0.232
Sequential ambidexterity$_t$ X Age$_t$											0.064*	0.026
Sequential ambidexterity$_t$ X MMC$_t$											-0.141*	0.048
Explore$_t$	0.059***	0.010	0.042***	0.012	0.061***	0.012						
Explore$_{t-1}$							0.016*	0.007	-0.001	0.008	0.003	0.010
Exploit$_t$	0.019	0.021	0.011	0.022	0.019	0.021	0.025	0.021	0.002	0.021	0.004	0.021
Dominance$_t$	0.279**	0.089	0.295**	0.092	0.405***	0.094	0.311**	0.091	0.319**	0.093	0.321**	0.104
Age$_t$	-0.050***	0.009	-0.049***	0.009	-0.050***	0.009	-0.048***	0.009	-0.046***	0.009	-0.055***	0.010
Multi-market competition (MMC)$_t$	-0.041	0.032	-0.030	0.032	-0.015	0.033	0.013	0.032	0.022	0.032	0.056	0.035
Market exit$_t$	0.014†	0.008	0.014†	0.008	0.014†	0.008	0.013	0.008	0.015†	0.008	0.013	0.008
Market diversity$_t$	0.079***	0.020	0.077***	0.020	0.076***	0.020	0.074***	0.019	0.059**	0.019	0.053**	0.019
Market growth$_t$	0.103**	0.034	0.102**	0.034	0.102**	0.034	0.099**	0.033	0.096**	0.033	0.096**	0.033
Market conccentration $_t$	-0.023	0.031	-0.023	0.031	-0.024	0.031	-0.024	0.031	-0.025	0.031	-0.024	0.031
Firm size$_t$	-0.044***	0.005	-0.045***	0.005	-0.045***	0.005	-0.041***	0.005	-0.042***	0.005	-0.042***	0.005
Firm growth$_t$	0.159***	0.019	0.161***	0.019	0.165***	0.019	0.164***	0.019	0.166***	0.020	0.167***	0.020
Year dummies: 1991-2000												
Constant	0.188***	0.039	0.183***	0.039	0.159***	0.041	0.117**	0.040	0.128**	0.041	0.102*	0.043
df	21		22		25		21		22		25	
Wald χ^2	870.15***		916.07***		943.22***		820.64***		833.05***		852.74***	
Models	(6)-(2)		(7)-(6)		(8)-(7)		(9)-(2)		(10)-(9)		(11)-(10)	
$\Delta\chi^2$	56.46***		45.92***		27.15***		6.95*		12.41**		19.69***	

N=4513 with 1005 firms; Subscripts *i* omitted; Year dummies omitted and available upon request; Semi-robust standard errors; †<.10,*<.05,**<.01,***<.001

Appendix A: Definition and Specification of Contingency and Control variables

Market exit$_{i,t}$. We measure the number of discontinued markets for firm *i* in year *t* as a count of the product markets that exist in year *t-1* but not in year *t*. We include this measure because the number of a firm's product markets and changes to it may impact firm performance (Cottrell and Nault, 2004).

Market diversity$_{i,t}$. We measure market diversity by adopting the entropy logic that has been used in prior literature on corporate diversification (Palepu, 1985). There is a growing body of within industry diversification studies that suggest that diversification may have a significant impact on firm performance (e.g., Cottrell and Nault, 2004; Li and Greenwood, 2004; Stern and Henderson, 2004). Let $p_{ij,t}$ in year *t* denote the proportion of firm *i*'s sales in product market *j*. We define market diversity$_{i,t}$ = $\sum_j p_{ij,t} \ln(1/p_{ij,t})$ where the number of products (i.e., *j*) in which a firm generates sales is time varying.

Market growth$_{i,t}$. A firm's position across growing markets can influence the sales growth (Robins and Wiersema, 1995). Thus, we control for sales growth in the product markets supported by the firm. *Market growth$_{i,t}$* for firm *i* in year *t* is the sum, over all product markets, of the growth of product market *j* multiplied by the firm's proportion of sales in that product market (i.e., $\sum_j P_{ij,t}$ $Growth_{j,t}$). $Growth_{j,t}$ is computed as the log of the size of market *j* in year *t* divided by the size of the same market in year *t-1* or $\ln(\Sigma_{ij} x_{ij,t} / \Sigma_{ij} x_{ij,t-1})$.

Market concentration$_{i,t}$. We measure the firm's market concentration$_{i,t}$ as the weighted sum of the proportion the firm's sales in that product market *j* multiplied by the share of the four largest firms in the market (i.e., $\sum_j P_{ij,t}$ $Top4_{j,t}$). Market concentration is a descriptor of industry structure that can impact firm performance.

ln(Firm size$_{i,t}$). We measure firm *i*'s size in year *t* as the natural logarithm of the firm's total sales, in millions of dollars, across all the platforms, products, and regions. Firm size may impact firm growth (Sorenson and Stuart, 2000).

Firm growth$_{i,t}$. We measure Firm growth$_{i,t}$, as the log of the total revenues in year *t* divided by total revenues in year *t-1* (Carroll and Hannan, 2000) or $\ln(\Sigma_j x_{ij,t} / \Sigma_j x_{ij,t-1})$. Although it is customary to include in a panel design the contemporaneous value of the dependent variable, we include this control to also address its potential impact on exploration (Katila and Ahuja, 2002).

Year$_t$. Finally, we include a set of indictor variables that are contemporaneous with the independent variables to capture industry effects such as the total size of the software sector and the numbers of firms, platforms, and product markets in that year. They are omitted in the results tables but are available upon request.

Appendix B: Our Approach to Ambidexterity Measurement based on Product Similarities in the Software Markets

FIGURE B1: Graphical representation of product similarity and exploitation

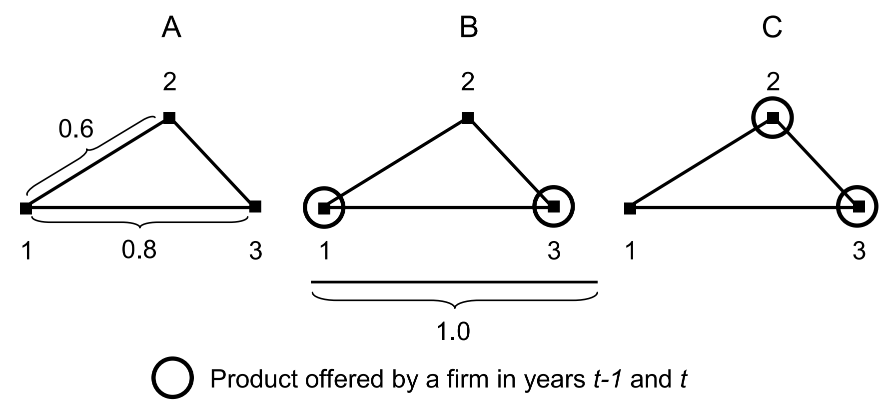


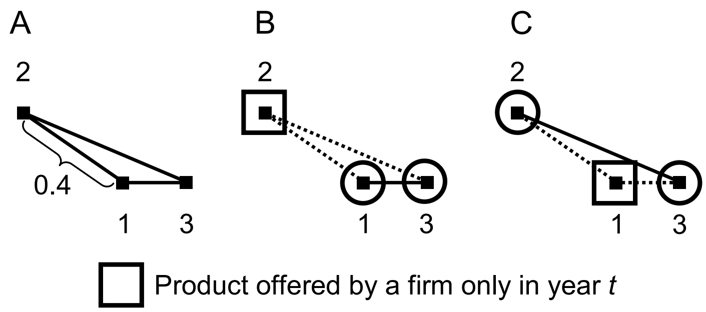
Figure B1 graphically represents to scale product similarity and firm exploitation. Without lose of generality, Figure B1A represents the overlap or similarity between three products, 1 through 3, in year *t*. The length of the line segment between any product pair denotes the degree of similarity with a score of 1.0 denotes complete similarity. If we also assume that overlaps are symmetric, the similarity between products 1 and 3 (i.e., 0.8) is greater than the similarity between products 1 and 2 (i.e., 0.6) or $\overline{13} > \overline{12}$.

Now consider a firm α, whose product offerings are denoted as circles in B1B. Firm α offers products 1 and 3 in years *t-1* and *t*. In contrast, consider another firm β, denoted in Figure B1C, that offers products 2 and 3 in the years *t-1* and *t*. A comparison of Figures B1B and B1C suggests that firm α is exploiting more than firm β because the former firm's products are more similar than the latter's products.

Figure B2 represents to scale product dissimilarity and firm exploration. Figure B2A represents the dissimilarity between the same three products in Figure B1A. Note that the sum of the lengths of segment $\overline{12}$ in Figure B2A (i.e., 0.4) and segment $\overline{12}$ in Figure B1A (0.6) equals 1.0 or dissimilarity = 1 – similarity between any product pair.

Now consider the two Firms α and β defined previously. Firm α offers new product 2 in year *t* or explores in year *t-1* (i.e., Figure B2A). The dotted line segments represent the new product's dissimilarity to Firm α's existing products 1 and 3. In contrast, firm β in year *t* offers product 1, by also exploring in year *t-1* (i.e., Figure B2C). Firm α is exploring more than Firm β because the dissimilarities between Firm α's existing and new products (i.e., $\overline{12}$ and $\overline{32}$) is greater than the dissimilarity between Firms β's existing and new products ($\overline{21}$ and $\overline{31}$).

FIGURE B2: Graphical Representation of Product Dissimilarity and Exploration



Appendix C. Robustness Tests

The integrity of our findings rests on the quality of data underlying our analysis. We compared the number of firms in the IDC data with the number of firms tracked and represented in other industry surveys (such as Compustat or ValueLine) and found that IDC always has the most extensive coverage; and IDC is the most often quoted data source in the software (and the IT) sector. We assessed the coverage of IDC data (in terms of total sales of IDC -covered firms) with data on the software industry reported in Campbell-Kelly (2003) for the post-1995 period and we found that the IDC data covers over 80% of the total industry sales.

Another source of problem with the data quality is how the company dealt with mergers and acquisitions. When a merger or acquisition occurs between two software firms, IDC assigns the product sales of the acquired company to the acquiring company ex-post for specific time period based on their judgment. The acquired company is still in the database for the period before this adjustment period. For example, suppose a company (X) that existed separately from 1990 till 1999 was acquired by company (Y) in 1999, X still is in the database for some period from 1990 till 1999. We still retain X as a separate entity till the merger. During the period we studied till 2001, there have been less than 50 acquisitions.

We test the robustness of our results in multiple sub-sample analyses. First, we test the model by comparing the results to another model that considers only the recent three years (cross-sectional data involving 1868 observations—see model A in Table C1). The model used to test the hypotheses is replicated as Model C. The coefficient for sequential ambidexterity is 0.463 ($p<.05$), providing support for the hypothesis. Finally, we used data from 1995 to 2002 (when the IDC database covers 80% of the total industry sales – see model B in Table C1) and found the results to be similar to our full sample. These additional set of analysis shows that the results are robust and demonstrates the veracity of our findings. The second robustness test focused on the possible impact of including firms involved in mergers and acquisitions. Models A′, B′, and C′ in Table C2 show the results from this analysis after excluding firms involved in mergers. Models A′ and B′ are the same time frames as Models A and B in Table C1. Model C’ is the full sample, like Model C, but incorporating mergers. We find that our pattern of the hypotheses supported by the full sample is qualitatively similar albeit at a lower levels of fit. These sub-sample robustness tests strengthen the results of the study.

TABLE C1: Robustness Tests with Subsamples

	Model A		Model B		Model C	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Simultaneous ambidexterity$_t$	0.351	0.254	0.147*	0.067	0.085	0.057
Simultaneous ambidexterity$_t$ X Dominance$_t$	-1.042	0.886	-0.614*	0.254	-0.859***	0.199
Simultaneous ambidexterity$_t$ X Age$_t$	-0.097	0.091	-0.058*	0.024	-0.008	0.023
Simultaneous ambidexterity$_t$ X MMC$_t$	-0.171	0.221	-0.030	0.047	-0.022	0.041
Sequential ambidexterity$_t$	0.463*	0.200	0.187*	0.093	0.183*	0.080
Sequential ambidexterity$_t$ X Dominance$_t$	0.504	0.674	0.333	0.308	0.423†	0.243
Sequential ambidexterity$_t$ X Age$_t$	0.008	0.039	0.043†	0.025	0.057*	0.026
Sequential ambidexterity$_t$ X MMC$_t$	-0.310*	0.142	-0.157*	0.063	-0.157**	0.055
Explore$_t$	0.100**	0.032	0.059***	0.015	0.067***	0.013
Explore$_{t-1}$	0.010	0.018	-0.003	0.012	-0.013	0.011
Exploit$_t$	0.055†	0.032	0.013	0.023	-0.005	0.022
Dominance$_t$	0.261	0.214	0.365**	0.109	0.366***	0.103
Age$_t$	-0.059***	0.017	-0.052***	0.010	-0.055***	0.009
Multi-market competition (MMC)$_t$	0.063	0.089	0.021	0.042	0.017	0.036
Market exit$_t$	0.018	0.016	0.010	0.009	0.013	0.008
Market diversity$_t$	0.087*	0.036	0.062**	0.022	0.052**	0.019
Market growth$_t$	0.005	0.049	0.133**	0.041	0.098**	0.034
Market concentration$_t$	0.027	0.049	-0.040	0.033	-0.024	0.031
Firm size$_t$	-0.049***	0.010	-0.043***	0.006	-0.045***	0.005
Firm growth$_t$	0.088***	0.025	0.152***	0.021	0.163***	0.019
Year dummies: 1991-2000						
Constant	0.059	0.095	0.134**	0.049	0.157***	0.043
Sample years	2000-2001		1995-2001		1991-2001	
Observations / panel	1.9		4.0		4.5	
N	1868		4053		4513	
df	21		26		30	
Wald χ^2	176.77***		731.49***		963.21***	

Subscripts *i* omitted; Year dummies omitted and available upon request; Semi-robust standard errors; †<.10,*<.05,**<.01,***<.001

TABLE C2: Robustness Tests with Mergers

	Model A′		Model B′		Model C′		Model C	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Simultaneous ambidexterity$_t$	0.509	0.315	0.166	0.122	0.030	0.099	0.085	0.057
Simultaneous ambidexterity$_t$ X Dominance$_t$	-1.274	2.643	-0.328	1.130	-1.368†	0.815	-0.859***	0.199
Simultaneous ambidexterity$_t$ X Age$_t$	-0.135	0.114	-0.070†	0.038	0.007	0.036	-0.008	0.023
Simultaneous ambidexterity$_t$ X MMC$_t$	-0.244	0.259	0.002	0.117	0.034	0.091	-0.022	0.041
Sequential ambidexterity$_t$	0.646†	0.335	0.237†	0.144	0.280*	0.143	0.183*	0.080
Sequential ambidexterity$_t$ X Dominance$_t$	-3.878†	2.031	-1.442	1.706	-1.476	1.369	0.423†	0.243
Sequential ambidexterity$_t$ X Age$_t$	0.044	0.053	0.057*	0.027	0.069*	0.034	0.057*	0.026
Sequential ambidexterity$_t$ X MMC$_t$	-0.503†	0.261	-0.247*	0.116	-0.275**	0.105	-0.157**	0.055
Explore$_t$	0.098†	0.051	0.033	0.023	0.056*	0.024	0.067***	0.013
Explore$_{t-1}$	0.036	0.036	0.020	0.020	0.003	0.018	-0.013	0.011
Exploit$_t$	0.034	0.036	-0.001	0.027	-0.017	0.025	-0.005	0.022
Dominance$_t$	0.520†	0.309	0.513*	0.209	0.574**	0.205	0.366***	0.103
Age$_t$	-0.090***	0.021	-0.050***	0.013	-0.049***	0.012	-0.055***	0.009
Multi-market competition (MMC)$_t$	0.041	0.116	0.057	0.065	0.073	0.051	0.017	0.036
Market exit$_t$	0.019	0.031	0.015	0.015	0.023†	0.014	0.013	0.008
Market diversity$_t$	0.093*	0.044	0.046	0.031	0.031	0.027	0.052**	0.019
Market growth$_t$	0.015	0.056	0.154**	0.054	0.123**	0.044	0.098**	0.034
Market concentration$_t$	0.030	0.053	-0.058	0.037	-0.048	0.035	-0.024	0.031
Firm size$_t$	-0.046***	0.011	-0.045***	0.007	-0.049***	0.006	-0.045***	0.005
Firm growth$_t$	0.077*	0.030	0.156***	0.022	0.178***	0.021	0.163***	0.019
Year dummies: 1990-2000								
Constant	0.130	0.120	0.115	0.070	0.112†	0.057	0.157***	0.043
Sample years	2000-2001		1995-2001		1991-2001		1991-2001	
Observations / panel	1.8		3.7		4.0		4.5	
N	1420		2879		3123		4513	
df	21		26		30		30	
Wald χ^2	132.16***		436.45***		544.69***		963.21***	

Subscripts *i* omitted; Year dummies omitted and available upon request; Semi-robust standard errors; †<.10,*<.05,**<.01,***<.001

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