NAVIGATING AN ERA OF CONVERGENCE: COMPETITIVE CONSEQUENCES OF ALLIANCE EXPERIENCE AND ATTENTION FOCUS

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ABSTRACT

Industry Convergence is impacting multi-billion dollar markets including at least 50% of top 500 firms' industries in the U.S. Yet, this phenomenon is underdeveloped in both theorizing and operationalization. A limited research on convergence almost exclusively focuses on macro-level structure changes, while we know little about strategic implications of firm-level entrepreneurial actions in this context. Until two or more industries converge, they can be easily differentiated; where they converge, there is neither one nor another but only a new industry. This presents a unique context for advancing the understanding of our theories as well as managerial practices. I structure my dissertation into two essays to explore two sets of firm-level actions. My first essay examines the sequential relationship between alliance experience and interindustry initial acquisitions. Building on organizational learning and resource dependence theory, this study reveals the condition that firms do not rely on alliance to make subsequent acquisition. In my second essay, I propose that firms need to develop a deep depth of field (i.e. competing with a great number of heterogeneous competitors) in order to sustain performance during an era of convergence. A deep depth of field is analogous to a picture in which the foreground and background are both in focus. Using product market competition among firms in the telecommunications equipment and computer networking industries during the 1991-2003 period, I validate this argument. With the depth of field construct, this study bridges the attention-based view and industry evolution research. I also create two empirical indicators for measuring the extent and the locus of industry convergence.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

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Much more grows in the garden than that which is planted there. Through this dissertation journey, I learned that whom you grow up with is much more important than what topics you selected and where you stay. Choosing a mentor that is right for you can carry you a long way. Fortunately, I've gotten a couple of excellent mentors during the dissertation process.

I have had a passion about industry convergence since I finished my first-year doctoral program. Using criteria that I picked up in the seminar of research foundation seminar, I found this context promising and unique. On the other hand, return on investment for studying convergence was fraught with uncertainty and ambiguity since the topic was still in its infancy stage of theoretical development. Thus, in my second year there had been several times that I stared out our Mervis Hall's window and pondered questions regarding the direction of this topic - just like the way that most Harvard business cases begin. It would be a lie if I tell you I had no scruples about this market entry decision. I was privileged to have John Prescott as the chairman of my committee. John's guidance helped me to drive through fog of this dissertation subject and his insight raised my thinking up to a higher level. He encouraged me to get up with a smile whenever I was knocked down by journal rejection. As a professionalist in the area of competitive intelligence, he taught me how to judge myself by filtering critical signals from irrelevant noises as well as not to be bothered by outside pressures and adversities. He has a considerable influence on how I want to live my scholar life.

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1.0 INTRODUCTION

Industry convergence (IC) is the blurring of industry boundaries between previously separate industries where their respective firms did not compete with one another. A conservative estimate of the breadth and financial impact of IC suggests that 50% of the industries in which the Standard and Poor's 500 firms compete have either undergone or are undergoing IC. The wide range of industries undergoing IC include photo-equipment and consumer electronics (Srinivasan, Haunschild, & Grewal, 2007), computer and music distribution (Burgelman & Grove, 2007), film and video game (Brookey, 2010), and semiconductor and biotech (Avenel et al., 2007). While IC is impacting multi-billion dollar markets, theorizing about the co-evolution of industries during IC and the empirical operationalization of IC is underdeveloped in the field of management.

Research has recognized the relevance of industry convergence since it creates opportunities for new strategies to emerge, destroys competitive advantages while solidifying others, and establishes new institutional arrangements (Bettis, 1998; Hamel & Prahalad, 1996). Despite recent interest in IC, the literature has been limited for several critical reasons. First, industry evolution studies (e.g. industry life cycle and dominant design) have traditionally focused on firm behavior and performance consequences within the relatively well-defined boundaries of a given industry (Greenstein & Khanna, 1997). However, as Burgelman & Grove (2007) posit, today's globalizing world is increasingly characterized as converging, such that intra-industry research would no longer be sufficient for understanding converging competitive landscapes created by technology substitution/integration, deregulation and changing consumer preferences. Second, while a few studies have begun to investigate the phenomenon of IC, they have almost exclusively focused on market-level structural dynamics (Katz, 1996; Wirtz, 2001), the strategic implications of firm-level entrepreneurial action and how the actions impact their competitive advantages have been largely downplayed. Third, valid and reliable empirical indicators of IC have not emerged. Most of IC studies are either conceptual papers or anecdotal stories with two exceptional papers that focus on empirics in the aspects of new product introduction (Srinivasan et al., 2007) and diversification (Burgelman & Grove, 2007). Nevertheless, both of them did not develop operationalization for IC. The paucity of such studies severely limits our understanding of the process through which convergence unfolds.

1.1 POSITIONING INDUSTRY CONVERGENCE WITHIN THE CONVERGENCE LITERATURE

In the modern era of business, one of the more recent conceptualization of convergence originated in the late 1970s. In 1977, Nippon Electric Company (NEC) articulated a vision of convergence between communication networks and computers (cf. Yoffie, 1997). In 1978, Nicholas Negroponte, founder and chairman of MIT Media Lab, used an illustration of three overlapping sectors (computing, publishing/printing, and broadcasting) moving together and suggested that the phenomenon is an important research agenda. Rosenberg (1976), analyzing the evolution of machine tool, sewing machine and automobile sectors, indicated that increased manufacturing productivity was accompanied by the technological convergence in each of the industries. The term ‘convergence’ has taken on a variety of meanings primarily representing some combination of technology, product/services and industry convergence. In other words, while we are in an era of convergence there are a variety of perspectives as to “what it is”

It is important to place IC within the context of the broader convergence literature. In addition to IC, two forms of convergence have been documented in the literature: technology and product/service convergence. Technology convergence is defined as the process by which different industries come to share similar technology bases (Gambardella & Torri, 1998)—e.g. the television and computer industries share the TFT-LCD display technology. Product/service convergence is defined as the process by which products are formed by integrating multiple functionalities that previously belonged to different products (Gill, 2008; Han, Chung, & Sohn, 2009)—e.g. the electronic book with a TV-watching/gaming function or the integration of internet/cable/phone services.

Since convergence is a multifaceted and co-evolving phenomenon, it is not surprising that our knowledge regarding convergence has accumulated in a fragmented fashion across a variety of disciplines including technology, strategy, economics, entrepreneurship and marketing. My rationale for focusing on IC is grounded on the competition-based mechanism (Hedstrom & Swendberg, 1998). In essence, the competition mechanism explains why and how firms compete within and across industries in their attempt to gain a competitive advantage. Thus, the concept of competition or rivalry encompasses both structural (position) and process dimensions (Chen, 1996; Scherer & Ross, 1990). “The essence of rivalry is a striving for potentially incompatible positions combined with a clear awareness of the parties involved that the positions they seek to attain may be incompatible (Scherer & Ross, 1990, 16). Chen (1996) in an influential paper further clarified the competition mechanism by developing a framework linking market commonality and resource similarity which predicts the likelihood of interfirm rivalry. While firms compete on the basis of technologies and products, they do so within the context of industries. Therefore, the selection of IC is appropriate for my purposes.

1.2 EMPIRICAL CONTEXT

My empirical setting is the voice-data convergence of the telecommunications equipment and computer networking industries between the years 1989-2003. During the 1990s', the traditional technological base (circuit-switching technology) in the telecom equipment industry was challenged and subsumed by Internet-protocol-based technology (packet-switching technology). Packet-switching technology enabled competition between the two industry's firms beginning in 1989. In response to threats and opportunities in the new markets, telecom equipment firms initiated alliances, acquisitions, and product market expansion to reduce uncertainty related to the unfamiliar computer network context. At the same time, while computer networking firms own core technologies required for competing in the era of convergence, they lacked of valuable relationships and channels to major customers in need of new voice-data products. This situation induced computer networking firms to take similar actions as telecom equipment firms did.

From a retrospective view, we have already known that the Internet is the ultimate trend and demand for multimedia had an exponential growth in the late 1990s. However, this picture for most of telecom and computer firms was not unclear and ambiguous when convergence begun. For managers facing those infrastructure changes "within" that period, they have limited knowledge of how the new industry worked, how it was changing, and what would happen to key parameters in each of segments and the extent of new entry. Therefore, this context is appropriate for examining my research questions and testing my hypotheses.

1.3 DISSERTATION STRUCTURE: TWO ESSAYS

My dissertation begins to fill the void mentioned earlier with two empirical studies. I employ learning theory as well as cognitive/sociological perspectives to identify strategies for competing and navigating the IC world in two topics: alliance/acquisition and managerial attention.

Essay one focuses on alliance experience effects on initial acquisitions. Entry into a converging industry via acquisition (as opposed to internal development) helps capture opportunities since it addresses bounded rationality and time compression diseconomies. Intriguingly, why do firms make an initial acquisition when the ultimate outcome of convergence is still unclear? I argue that when a firm emphasizes inter over intra-industry alliance experience it is more likely to initiate an initial acquisition in a converging industry. However, as the extent of IC increases, firms become less dependent on leveraging alliance experience in making initial acquisitions. In this essay, I create a continuous measure of IC based on product market integration of the two converging industries.

Essay two views strategic decision making through the lens of managerial attention. I ask: how do high-performance firms develop an understanding of this ambiguous industry convergence context. I argue that firms, which attend to their changing competitive environment with a deep focus, perform better than others. A deep focus is analogous to a picture in which the foreground and background are both in focus. Using product market competition among firms in the telecommunications equipment and computer networking industries during the 1991-2003 period, I show that a deep focus is positively related to performance and two additional interesting findings: (1) the performance benefit of a deep focus weakens when the firm operates in product markets where convergence is occurring and (2) a firm‘s deep focus is not associated with performance if most of its competitors have a shallow focus.

2.0 ESSAY ONE: HOW INTER-INDUSTRY ALLIANCE EXPERIENCE LEADS TO INTER-INDUSTRY ACQUISITIONS

When the boundaries of industries overlap, collide and converge, creating opportunities and threats among firms which previously had not been in competition, resource dependence theory (RDT) predicts that firms will engage in strategic action to manage emerging uncertainty and resource dependences (Pfeffer & Salancik, 1978). Alliances and acquisitions are two of the most employed strategic actions firms use to manage uncertainties since to some degree they absorb interdependencies in the external environment. Yet little is known regarding the roles and interrelationships between alliances and acquisitions in an industry converging (IC) context (Burgelman & Grove, 2007; Stiegliz, 2003). We are motivated to address this gap in the inter-temporal alliances and acquisitions research stream for two reasons (Porrini, 2004; Zaheer, Hernadez & Banerjee, 2010; Lin, Peng, Yang, & Sun, 2009; Shi, Sun, & Prescott, 2012; Zollo & Reuer, 2010). First, as an increasing number of firms encounter IC, we examine whether and how the predictions of RDT extend to include IC as part of its boundary conditions. Second, our understanding of how firms employ multiple dependence-reducing strategies is underdeveloped since studies that include both alliances and acquisitions in their theory and research design is relatively new (Yang, Lin & Lin, 2010). Both of our motivations speak to two research directions identified by Hillman, Withers and Collins (2009) as promising approaches to enhance the resource dependence stream of research.

Drawing on RDT and the learning perspective, we examine (1) the inter-temporal relationship between alliance experience and initial inter-industry acquisitions in an IC context and (2) the direct and moderating effect of extent of industry convergence. According to RDT linkages with external others constitutes a form of interdependence and as a result organizational survival becomes uncertain (Pfeffer & Salancik, 1978). IC brings novel forms of interdependence by disrupting firms' industry boundaries and exposing them to new competitors, suppliers, customers and stakeholders in the converging industry.

When considering whether to initiate alliances and acquisitions under conditions of uncertainty such as those presented by IC, firms adopt courses of action that promote flexibility and minimize risk (Hambrick, Finkelstein, Cho, & Jackson, 2005). While alliances and acquisitions share many commonalities, acquisitions require significantly higher levels of financial and managerial commitment (Yin & Shanley, 2008). Thus, firms are initially more likely to form alliances and as uncertainties are resolved acquisitions become an equally or more attractive option (Porrini, 2004).

An important contribution of the learning perspective (March, 1991) is the recognition that as a consequence of bounded rationality, firm action is typically based on prior experience. Intra-industry alliance experience originating from partners within a firm's core industry results in exploitation learning whereas inter-industry alliance experience gained through forming alliances with partners from a converging industry involves exploration learning (Lavie & Rosenkopf, 2006).[2] According to the learning perspective, the degree to which a firm's alliance experience is focused in its core industry versus the converging industry influences subsequent acquisition activity.

We conceptualize the two types of alliance experience as a relative construct: inter/intra-industry alliance experience to reflect the fact that due to resource and attention constraints firms make explicit trade-offs involving the type of experience to emphasize (Gupta, Smith, & Shanley, 2006). During IC, inter/intra-industry alliance experience exerts two learning-related mechanisms; uncertainty reduction and attention diverting; influencing a firm's likelihood of undertaking an initial acquisition in an adjacent converging industry. A firm's initial inter-industry acquisition is the first acquisition a firm makes in an adjacent converging industry (Song & Walkling, 2000).

Alliance experience constitutes a form of uncertainty reduction that provides learning about a firm's external context. A firm's exploratory learning in the form of inter-industry alliance experience provides valuable declarative (know-what) and procedural (know-how) knowledge (Bresman, 2010; Garud, 1997) that sufficiently reduces uncertainties related to the initiation of an acquisition. As a result, learning benefits arise from knowledge gained from partner-specific interactions and from other forms of external learning that allow an organization to learn about key aspects of its environment (Wong, 2004). The reduction of key external uncertainties, explains why a firm's inter-industry alliance experience exerts a positive influence on the likelihood of an initial inter-industry acquisition in the context of IC.

In contrast a firm's intra-industry alliance experience decreases the likelihood of an initial acquisition in the converging industry due to an attention diverting mechanism (Cyert & March, 1963; Hedstrom, 1998; Ocasio, 1997). When a firm focuses attention on its core industry, it diverts attention from external learning in the adjacent converging industry and thus lowers the likelihood of resolving uncertainties regarding the cost/benefits of initiating an initial acquisition.

We find strong evidence that a firm's inter/intra-industry alliance experience positively influences the likelihood of making an initial acquisition in the converging industry.

Inter-temporal alliance-acquisition relationship research has focused on the role of contingencies including the nature of acquisition tasks (Zollo and Reuer, 2010), the resolution of partner-specific uncertainties (Porrini, 2004; Zaheer *et al*., 2010), and institutional differences (Lin *et al.,* 2009). The extent of IC as a moderator of the relationship has not been examined. In this light, our second objective is to understand the direct and moderating impact of the extent of IC on the alliance experience–acquisition relationship. IC creates opportunities for new strategies to emerge, destroys competitive advantages while solidifying others and establishes new institutional arrangements. However, theorizing and empirical analysis in an IC context is underdeveloped (Burgelman & Grove, 2007). We offer a novel perspective for conceptualizing and opertationalizing the extent of IC defined as the degree of cross-industry product-market diversification by the collective set of firms in the converging industries. As the extent of IC increases the boundaries between the two or more industries increasingly overlap as well as the degree of product coherence among the firms (Li and Greenwood, 2004; Teece, Rumelt, Dosi, and Winter, 1994). As the extent of IC increases, and uncertainties are reduced through competitive interaction, IC has a direct effect on the likelihood of initiating an initial acquisition in the adjacent industry while at the same time the effect of inter/intra industry alliance experience remains significant albeit at a lower level. As the extent of IC increases, the positive influence of a firm's inter/intra-industry alliance experience on the likelihood of initiating an initial acquisition in the adjacent industry decreases.

There is substantial evidence that firms undertake a variety of action to manage environmental interdependence including acquisitions (Lin *et al.,* 2009), alliances (Park &

Mezia, 2005), restructuring the board of directors (Kor & Misangyi, 2008), political action (Hillman, Zardkoohi, & Bierman, 1999), and executive succession (Daily, Certo, & Dalton, 2000). However, RDT research has rarely considered how firms employ multiple interdependence-reducing strategies (Hillman *et al.,* 2009). The paucity of such studies severely limits our understanding of how different resource dependence strategies influence one another. We contribute to the body of resource dependence research by focusing on the inter-temporal relationship between inter/intra-industry alliance experience and inter-industry acquisitions. The positive inter-temporal relationship between inter/intra-industry alliance experience and the likelihood of an initial inter-industry acquisition decreases as the extent of IC increases.

Many firms are confronted with an era of convergence (Burgelman & Grove, 2007; Lee & Olson, 2010). Management research on convergence has focused on either stage-based conceptual frameworks or case studies. Complementary research that conceptualizes and measures the extent of IC and its impact on strategic relationships is almost nonexistent. We begin to fill this void by offering a quantitative indicator of the extent of IC and employ it as an independent and moderator of the alliance experience-acquisition relationship.

2.1 THEORY DEVELOPMENT AND HYPOTHESES

Building on RDT and the organizational learning perspective, we develop hypotheses explaining why a firm's inter to intra-industry alliance experience precedes its initial inter-industry acquisition in an industry convergence (IC) context as well as how the extent of IC has a direct and moderating effect on the use of the two uncertainty-reducing strategies.

2.1.1 Inter/Intra-Industry Alliance Experience and Initial Acquisition in an IC Context

From the resource dependence perspective, firms need to interact with their environment to secure necessary external resources (Pfeffer & Salancik, 1978; Ulrich and Barney, 1984; Hillman *et al.,* 2009). When the environment changes such as during IC it provides opportunities for interconnections between previously unconnected firms. The resulting interdependence creates uncertainties that are problematic since a firm's existing routines for anticipating the future may not be as relevant in the new context. As Pfeffer and Salancik" (1978: 69) observed, "changes can come from anywhere without notice and produce consequences unanticipated by those initiating the changes and those experiencing change". As a result, firms take actions to minimize uncertainty and the constraints of interdependence. We focus on alliances and acquisitions, two important forms of strategic action firms use to reduce uncertainty (Hitt & Tyler, 1991; Harrigan & Newman, 1990; Park & Mezias, 2005).

Our position is based on three research-grounded premises: (1) when the extent of IC is low, alliances in the adjacent converging industry are preferred to acquisitions to manage emerging interdependence since they provide access to resources at a lower risk (Yin & Shanley, 2008), (2) due to bounded rationality and managerial attention constraints a de-emphasis on intra-industry alliance experience relative to inter-industry experience facilitates uncertainty-reducing learning in the converging industry (Ocasio, 1997), (3) uncertainty-reducing inter-industry alliance experience affects future acquisition activity (Zollo & Reuer, 2010) by significantly increasing the likelihood of initiating an acquisition in the converging industry.

Both acquisitions and alliances help absorb interdependencies although in differing degrees. Acquisitions reduce competitive uncertainties by absorbing current or potential competitors. Since firms are not always in a position to reduce interdependence through acquisitions, social coordination with interdependent others via alliances is an alternative for managing mutual dependence (Pfeffer & Salancik, 1978: 145). Similar to acquisitions, alliances provide access to resources but at a lower risk (Yin & Shanley, 2008). Unlike acquisitions, however, alliances provide a lower degree of absorption. As a result, alliances provide less control over interdependent others than acquisitions.

When the extent of IC is low, as firms are exposed to new forms of interdependence they take action to restore certainty and stability to their environment. In this context, alliances with partners in the adjacent industry provide access to a variety of resources and experience that reduces uncertainty while providing the additional benefit of investment flexibility. In contrast, acquisitions in the converging industry provide more external control by absorbing interdependence with potential competitors but at the cost of reduced flexibility. At a time when the extent of IC is low, acquisitions are risky because the competitive landscape is in a state of flux (Burgelman & Grove, 2007; Lee & Olson, 2010). Firms are thus more likely to initiate inter-industry alliances before inter-industry acquisitions.

Alliance experience builds firm-specific inter-organizational routines that (Zollo, Reurer, & Singh, 2002) channels managerial attention (Ocasio, 1997). During IC, emphasizing intra-industry exploitative alliance experience leads to the refinement of existing capabilities some of which are becoming obsolete due to IC, hinders external learning about the adjacent industry due to the diversion of attention away from the converging industry, and thus lowers the likelihood of initiating an initial acquisition in the adjacent industry (Cohen & Bacdayan, 1994). In contrast, emphasizing inter-industry exploratory alliances exposes firms to new learning opportunities which require the modification of existing capabilities or the development of new ones that focuses attention on external learning in the converging industry and increases the likelihood of an initial acquisition.

Intra-industry and inter-industry alliance experience are forms of exploitation and exploration external learning that influences a firm's attention and priority structure (Lavie & Rosenkopf, 2006). We conceptualize the two types of alliance experience as a continuum where there is an explicit attention and resource trade-off between the two activities. Gupta *et al.* (2006) assert that exploration and exploitation should be conceptualized as an integrated (single) construct when the following criteria are central to a research question. First, when the resources or attention needed to simultaneously pursue exploration and exploitation are scarce, firms must decide how to trade-off one activity relative to the other. In the allocation of resources and attention to alliance activity, managers are confronted with constraints given the variety of other organizational activities that seek attention and resources. Second, when an activity is located within a single domain (e.g. corporate development), exploration and exploitation activities are generally mutually exclusive. In other words, the demands of the two activities are often inconsistent, cannot be satisfied simultaneously and pursuing conflicting goals results in managers attending to their demands sequentially (Cyert & March, 1963).

When the extent of IC is low, a firm's alliance portfolio is comprised of relatively more intra as compared to inter-industry alliances, since firms tend to form local relationship (repeated ties with current partners or a partner's partners) (Gulati, 1995). When a firm emphasizes intra-industry alliances, it is more likely to confront issues, generate solutions and structure procedural and communication channels that make salient and give priority to the objectives of intra-industry exploitative learning (Ocasio, 1997). The focus of managerial attention centers on intra-industry external learning activities in which the firm has more experience. Thus, the likelihood of an initial acquisition in the converging industry decreases because managerial attention is focused on intra-industry exploitative learning creating a perceptual blindspot that it is too early or not necessary to initiate an acquisition.

A shift in managerial attention to inter-industry alliance-based external learning occurs when there is a shift in experience. While a shift in attention can be the result of adverse experience, the reduction of competing demands or a change in goal preferences (Cyert & March, 1963; Ocasio, 1997), our focus centers on a shift in experience related to initiating inter-industry alliances. When a firm increases its relative focus on external learning in the inter-industry environment, external learning in the intra-industry environment receives less attention.

When a firm's environment shifts in a novel and unfamiliar way that challenges bounded rationality, the most appropriate type of interdependence-reducing strategy is not obvious. In this case, firms tend to rely on prior experience (Pfeffer & Salancik, 1978). While a firm's acquisition experience helps in next acquisition (Haleblian & Finkelstein, 1999), its prior alliance experience also provides valuable information for future acquisitions (Lin *et al.,* 2009; Wang & Zajac, 2007). Given the risks of a full absorption acquisition strategy, in a changing context such as IC, a plausible approach is for firms to first initiate alliances as an uncertainty-reducing strategy before initiating an acquisition.

From an ex-ante perspective, firms do not know whether they will eventually convert alliance experience into an initial acquisition or whether there are substitutes such as competitive intelligence. However, alliance experience enhances a firm's likelihood of an acquisition when they have access to or an understanding of strategic resources crucial to competing in the converging industry. When firms develop sufficient external learning that provides plausible evidence for the need and appropriateness of an acquisition, they will act (Lin *et al.,* 2009; Zollo

& Reuer, 2010). As Weick, Sutcliffe and Obsfeld (2005) conclude in their review of the sensemaking perspective, managers do not need an accurate picture of an "interruption" (i.e., IC) but rather one that is sufficiently plausible to make them comfortable with acting. While it is possible that a firm will make an initial acquisition without inter-industry alliance experience, the likelihood is significantly reduced when it has not invested in external learning to access essential and timely information for plausible decision-making under high levels of uncertainty.

Hypothesis 1: A firm's inter/intra-industry alliance experience increases the likelihood of an initial acquisition in an adjacent converging industry.

2.1.2 The Extent of IC

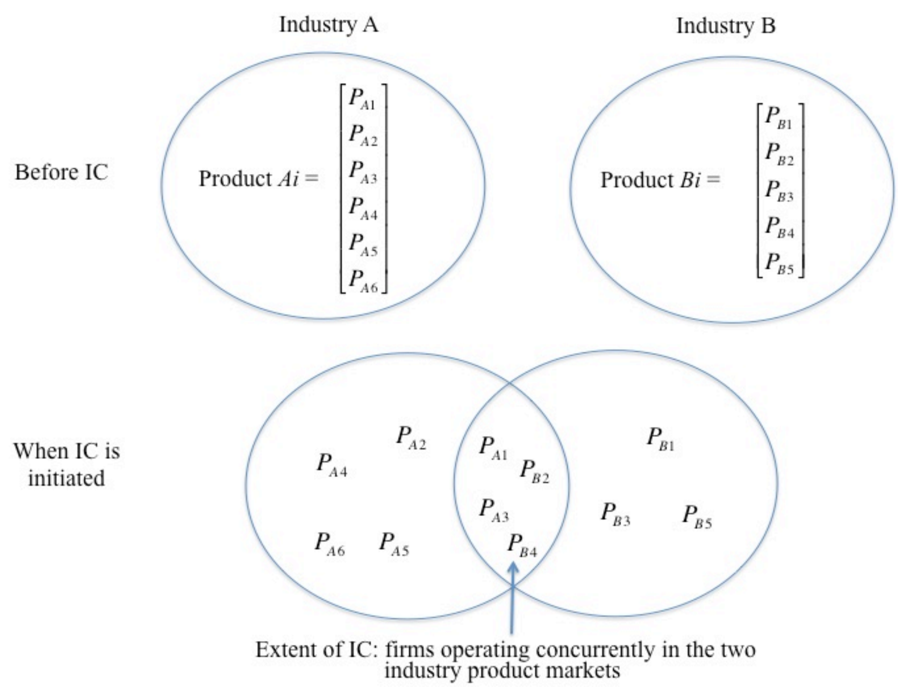
How does the extent of IC affect the use of the alliance and acquisition resource dependence strategies? We first offer our approach for conceptualizing IC and then examine the direct and moderating effects of extent of IC on the inter/intra-industry alliance experience-acquisition relationship. We adopt a cross-industry product-market diversification approach for theorizing the extent of IC. The extent of IC is an outcome of cross-industry product-market diversification undertaken by the *collective set of firms* striving to manage IC interdependences.

Traditionally, IC has been conceptualized as a dynamic process consisting of three stages: separate, converging and converged (Stiegliz, 2003). In the separate stage, macro and micro drivers of IC are emerging and the industries operate relatively independently. In the converging stage, the boundaries of the industries begin to overlap. At some point, the converging industry's boundaries become sufficiently blurred where the industries become de facto converged. Research indicates that the journey from the beginning of convergence (separate stage) to the point where convergence takes off (converging stage) typically requires decades due to the complex interplay among multiple IC triggers (Schnaars, Thomas, and Irmak, 2008) many of which are latent until circumstances are suitable for their manifestation. The converged stage is a period where industry change has settled down.

While an ordinal conceptualization of IC is intuitively appealing, provides an organizing framework for the stages of IC and represents alternative system states (Dubin, 1978), its primary limitation is the absence of meaningful quantitative spacing between the values for the stages making comparisons of the relative extent of IC or the degree of difference within and across stages problematic.[3] An alternative that we adopt is an industry-level, ratio-based conceptualization "*extent of IC*" defined as the degree of cross-industry product-market diversification for the set of competitors in two or more converging industries. A distinguishing characteristic of a ratio-based conceptualization is a non-arbitrary zero point. If the collective set of firms' cross-industry product-market diversification is zero, conceptually the two industries are independent. When the ratio is one, it conceptually represents complete integration of the industries. In most cases the ratio would be expected to be significantly less than one because firms typically do not compete in all product-markets as a result of their strategies, resources, managerial preferences, institutional constraints or other micro-foundations of strategy.

Theoretical justification for product-market diversification is also based in the resource dependence perspective. As Pffefer and Salancik (1978:109) note, in addition to alliances and acquisitions, diversification is an effective strategy to lessen dependence on present product-markets. Diversifying into the converging industry product-markets reduces an organization's vulnerability from relying on product-markets within their core industry. The collective action of firms' cross-industry product-market diversification makes their respective industries more inter-related. Our framing is consistent with Teece *et al.*'s (1994) product coherence concept. They suggest that when firms display remarkable similarities in the product-markets in which they diversify, coherence occurs among these product-markets. Consequently, firms are coherent to the extent their products are related. The product coherence concept has been used in within-industry contexts but not in a cross-industry converging context (Li & Greenwood, 2004). When there are a sufficient number of firms operating in a given pair of product-markets, inter-firm learning between the converging industries occurs. To put it differently, the density of firms concurrently operating across the two industries' set of product-markets reflects the extent of IC.

Figure 1 illustrates the extent of IC based on a cross-industry product market approach.



Note: Assume that a given set (P_{A1}, P_{A3}, P_{b2} *and* P_{b4}) of product-market pairs across two industries has been impacted by supply substitution. The greater the number of firms competing simultaneously in the two industry product-market pairs, the more related the two industry products-markets become. Firms' cross-industry product-market diversification is an indication of the extent of IC as it reduces the distance between converging industries.

2.1.3 Direct Impact of Extent of IC

Firms' resource dependence strategies for managing interdependence collectively alter eco-system interconnectedness. In our case, firms are engaging in alliances, acquisitions and product-market diversification. According to Pffefer and Salancik (1978: 71), actions taken to manage interdependence (such as product-market diversification) may, in the long run, increase interdependence among environmental elements, requiring further action (such as acquisitions) to manage the new uncertainties. When the extent of IC is low, our position is that firms are more likely to initiate inter-industry alliances to reduce uncertainty since they provide more flexibility at a lower risk than acquisitions especially when the competitive landscape is in a state of flux. However, as the extent of IC increases learning from collective product-market diversification may sufficiently reduce uncertainty such that firms undertake acquisitions irrespective of their alliance experience.

We hypothesize that inter-firm learning resulting from collective cross-industry product-market diversification has a direct impact on firms' acquisition activity in the converging industry. Collective cross-industry product-market diversification provides inter-firm learning and reduces uncertainties about IC as a result of competition between the two converging industries' firms. As the two industries' firms undertake product-market diversification they become competitors in terms of product-market commonality. Firms competing in the same product-markets are more likely to view each other as competitors (Chen, 1996). Prior IC research has demonstrated that convergence is likely to lead to increased competition (Greenstein & Khanna, 1997; Katz, 1996).

When IC gives rise to competition among firms that were previously not competitors, competitive interdependence, a form of uncertainty becomes salient. In order to reduce competitive interdependence – interdependence derived from the outcomes of competitive interrelationships among multiple organizations, firms initiate acquisitions to stabilize their environment (Mizruchi & Yoo, 2003; Hitt & Tyler, 1991). Initial acquisitions in a converging industry not only reduces competitive interdependence but also increases the power of the resulting larger organizations. Therefore, we expect that as the extent of IC increases the result is a higher likelihood of firms initiating their initial acquisition.

Hypothesis 2: The likelihood of an initial acquisition in an adjacent converging industry will increase as the extent of industry convergence increases.

2.1.4 Moderating Impact of Extent of IC

When collective product-market diversification between converging industries increases inter-firm learning it reduces IC uncertainties in several forms. First, the resulting increase in cross-industry product-market density expands the set of referent others from which a firm can learn about the converging market (Srinivasan, Haunschild, & Grewal, 2007). Interaction experience with similar others is one of the best sources of learning, since it eases the difficulty of understanding and digesting new information (Ingram & Yue, 2011). For example, Srinivasan *et al.* (2007) found that in the converging digital camera market, the greater number of firms involved in the introduction of new digital camera products, the more others firms learned from firms' new product decisions through mimetic and non-mimetic learning. Prior studies on benefits of competitive experience have confirmed this form of interfirm learning (Baum & Ingram, 1998).

Second, the increasing density of cross-industry firms attracts investment from complementors and suppliers, leading to enhanced learning through multiple and divergent sources. For example, the recent convergence between the personal computer and cell phone industry took off once the supporting infrastructure (e.g. various kinds of application software supporting Apple's and Google's Android systems) became well-developed. Incentives for application software developers to make investments in the Smartphone platform were enhanced when they observed more and more computer and information technology firms engaging in product-market diversification in the cell phone industry. Lastly, an increasing number of firms operating concurrently in the converging industries enhance the opportunity for exchange of personnel between firms (Li & Greenwood, 2004). This form of interfirm learning reduces uncertainties since employees carry knowledge across firms.

The inter-firm learning mechanism triggered by firms' cross-industry product-market diversification can substitute for uncertainty reduction provided by inter-industry alliance experience. When firms in a given industry learn about an adjacent converging industry through several sources (e.g., competitive experience in product markets, their suppliers, and employee mobility), the need for inter-industry alliance experience becomes less important. As we suggested above, the higher the extent of IC, the more integrated the converging industries become. Therefore, as these industries gradually blend into each other, intra- and inter-industry alliances are less distinguishable. Consequently, interfirm learning derived from the collective behavior of firms' cross-industry product-market diversification serves as a substitution for individual firm learning from inter/intra industry alliance experience. Hence, firms rely less on alliance experience for uncertainty reduction for making an initial acquisition.

Hypothesis 3: The positive effect of a firm's inter/intra industry alliance experience on the likelihood of an initial acquisition in an adjacent converging industry decreases as the extent of industry convergence increases.

2.2 RESEARCH METHO

We selected the telecommunications equipment industry (the focal industry: SIC 3661, 3663, and 3669) that has undergone convergence with the computer networking industry (the adjacent converging industry: SIC 3576) as our empirical context. Their blurred industry boundaries have been recognized as a salient case of convergence (Lee, 2007). In the 1980s, these industries belonged to the telecommunications and the computer sectors respectively. Firms in the telecom equipment industry (e.g. Nortel) relied on circuit switching technology as a core asset, while the core asset of firms (e.g. Cisco) in the computing networking industry was packet switching technology. Although circuit switching has the advantage of quality for voice calls, it is inefficient for data transmission. Thus, the new technology (packet switching) originating in computer networking was subsuming the old technology (circuit switching). In addition, core activities (the recurring actions that firms perform to attract/retain suppliers and buyers) in the telecom equipment were threatened. As the usage of the Internet grew in the 1990s, telecom service firms (buyers) found that traditional circuit switching technology made network capacity insufficient and couldn't fulfill the demand for data traffic, which forced telecom equipment firms to change their marketing and production activities. These firms also searched for new suppliers as the old product architecture became obsolete. This situation can be viewed as one form of IC that is triggered by supply side substitution forces. Many telecom equipment makers whose expertise was in circuit switching technology begun to beef up their packet switching capability by way of acquisitions in the computing networking industry. These deals provide an ideal context to examine a firm's initial acquisition.

COMPUSTAT was used to identify the two industry's set of firms. The earliest packet-switching communication equipment product was introduced in 1989, so our data collection started from 1989. The year 2003 was selected as the end time point of our observation period because convergence slowed down in anticipation of deregulation and new technology – the industry started to migrate toward a new generation network structure (OECD, 2008).

The number of telecom equipment firms during the study period was 147. The data source used to compile strategic alliances is Thompson Financial SDC. We identified alliances formed (1) between telecom equipment and computer networking industry (inter-industry alliances, n=52) and (2) within the telecom equipment industry (intra-industry alliances, n=166). The number of telecom equipment firms that had at least one alliance during the period 1989-2003 is 63. In order to confirm the representativeness of these 63 equipment firms, we calculated their total sales revenue in 1999 as a percentage of the total sales revenues of the overall telecom equipment market estimated from Standard and Poor's Industry Survey. Our sample contributes 76% of the sales. Recognizing that SIC categories 3661/3663/3669 contain firms which do not have any alliances, we reviewed the remaining 82 firms that had no alliance activity (24% of sales). None of them are powerful firms (global top 10 players). The telecom equipment industry was historically dominated by a few giant firms significantly influenced industry evolution. The inclusion of these firms in our analysis allows us to test whether and when firms with (or without) alliances are likely to acquire in the converging industry. We trace SDC's alliances back to 1987 to ensure there is no left-censoring issue. The SDC database was used to retrieve acquisition deals that telecom equipment firms completed with computer networking firms. The total number of initial acquisition deals initiated during the 1989-2003 period is 25. These deals were verified using Lexis-Nexis. The total number of initial acquisitions initiated by firms in the computer networking industry was 4. The relatively small number of acquisitions by computer networking firms is consistent with our conceptualization that the telecom equipment industry was being subsumed by the PC network technology.

Consistent with our conceptualization of extent of IC based on product-market diversification, we compiled firm product-market portfolios using the CorpTech Directory database for our measures of the extent of IC (see below). The section "Who Makes What" identifies the profiles of all public firms operating in the telecom equipment and computer networking industries by product types. The Directory lists 65 product lines for the two industries and further categorizes these product lines into 17 product classes. In 1989, CorpTech assigned each product class based on whether it was a data-based or voice-based communication product. In the early years of IC (i.e. 1989), it is reasonable to assume that data-based communication products (37 product lines) belong to the computer networking industry and voice-based communication products (28 product lines) fit into the telecom equipment industry

2.2.1 Dependent variable

The dependent variable, *initial acquisition likelihood*, is a dummy variable indicating whether a firm had an initial acquisition in the computer networking industry. For example, if a telecom equipment firm made an initial acquisition in the computer networking industry in 1996, the variable is coded as 0 from 1989 to 1995 and 1 in 1996. We only count initial acquisitions in which telecom equipment firms are acquirers and computer networking firms are targets. We include their acquisition activities that target both prior alliance partners and non-alliance partners. We made sure that equity-based alliances were not counted as initial acquisitions to avoid causality issues related including alliances as both an independent and dependent variable.

All of the independent and control variables are lagged one year, since we assume that alliance effects on the occurrence of an acquisition event are not immediate.

2.2.2 Independent variable

For the variable *inter/intra-industry alliance experience*, we measure the ratio of inter-industry alliance experience to the sum of inter-and intra-industry alliance experience. Following previous work, we measure alliance experience by using the cumulative number of prior alliances (Anand & Khanna, 2000). Inter-industry alliance experience denotes the cumulative number of prior alliances that a telecom equipment firm had in the computer networking industry by counting all alliances formed from 1989 up to, but not including, the year when the focal firm made an initial acquisition. Intra-industry alliance experience is measured by the cumulative number of prior alliances that a telecom equipment firm had in its industry up to the initial acquisition year. Consistent with prior alliance experience literature (Lin *et al.,* 2009; Rothaermel, 2001), our measure is a continuous proxy of external learning based on the emphasis a firm places on inter relative to intra-industry alliances. The measure is also consistent with our attention-diverting mechanism since the tendency to emphasize one type of alliance over the other influences managerial attention and resources directed towards the focal or converging industry.

CorpTech was used to develop our measure *extent of IC*. The data for firms' product-market portfolios was assembled in a longitudinal firm-product matrix format by including firms (telecom equipment and computer networking) and their products (voice and data-based communication). We use the 15 yearly firm-product matrices from 1989 to 2003 to create our measure - extent of IC; the number of firms operating simultaneously in any pair of products across the two industries (i.e. one voice product and one data communication product). We used a three-step process. First, using firms' product portfolio information in the firm-product matrices, we create product-product matrices indicating the number of firms concurrently engaged in any pair of products. This dyadic approach is consistent with Li and Greenwood's (2004) method. That is, the relatedness between a pair of markets can be measured via calculating the density of firms operating concurrently in the two markets. Second, in line with our conceptualization, to operationalize product coherence between the two industries, we retrieve information only from the cells in which there are firms competing simultaneously in pairs of voice- and data- products. For example, "network component" is one product line in the data category, and "telephone switching equipment" is a product line in the voice category. The number of firms simultaneously operating in the two product lines is an indicator of the degree to which the two products were becoming coherent. The greater number of firms operating in a pair of products is an indication of increasing coherence. For example, a value of 20 indicates that there are 20 firms operating in a given pair. If the number is zero, this means a given pair of products is incoherent (unrelated), since no firms from the two industries concurrently operate in the two products. CorpTech provides 37 data-based and 28 voice-based product lines. Thus, we generate 1036 (37 x 28) voice-and-data pairs. Third, we sum the cells for the set of voice and data-based products and then derive the final value of product coherence at year t by dividing the sum by the total number of all possible pairs (1036).

To create the interaction variable the extent of IC measure is multiplied by the independent variable inter/intra-industry alliance experience. To avoid problems of multicollinearity, the interaction variables were centered by subtracting the sample mean from the individual values.

2.2.3 Control variable

We control for several variables found to influence acquisition activity. Prior studies suggest that financial capability facilitates firm acquisitions and cash is the medium mostly used (Hitt, Ireland and Harrison 2001). A lack of free cash flow may limit a firm's capability to acquire a converging industry firm. Therefore, we included the variable *cash flow*. The variable *slack resource* is controlled by measuring the ratio of total assets to debts (Lin *et al.,* 2009). Organizational slack allows firms to have more discretion in response to environmental shifts and lower debt financing costs.

Firms learn to make acquisitions from prior acquisition experience (Haleblian and Finkelstein,1999). Following Beckman and Haunschild's (2002), we use a firm's cumulative number of acquisition deals to measure *prior acquisition experience*. Since an initial inter-industry acquisition is a risky action firms who had low prior performance may undertake risky strategic actions (Haunschild, 1993). We control for firm performance by measuring one-year-lagged *return on asset (ROA)* a performance measure relevant to our industry (Dowling and McGee, 1994). Based on previous research, *firm size* (the natural logarithm of net sales), *firm age*, and *firms' number of alliances* are controls (Lin *et al.,* 2009). Firm size is expected to have a positive effect on acquisition likelihood, while firm age is expected to negatively affect acquisition likelihood. The variable firm's numbers of alliances is measured by the number of alliances that a firm had in a given year and is expected to have a positive impact on acquisition likelihood, since this variable helps capture firms' annual alliance formation tendency that is unrelated to the uncertainty reduction impact of alliance experience on acquisition likelihood.

To reduce the concern of alternative explanations, we controlled for three additional variables specific to our context. The variable *wireless focus* is controlled by measuring whether the firm's business focus was in the wireless equipment segment. The segment underwent growing market demand during the 1900s, which might reduce a firm's incentive to make an initial acquisition. The variable is coded 1, if the firm's SIC code is 3663 (radio- related equipment), otherwise 0. We control for an internal development effect using a Herfindahl concentration ratio for *product scope*; the breadth of 17 product classes in the voice- and data-based product-markets in which a firm has diversified. As part of their corporate strategy thrust, a firm may acquire a converging industry firm. The greater the product scope the more likely a firm will make an initial acquisition. Finally, we control for the variable *R&D intensity* (R&D expense/ net sales). Research has shown that R&D intensity is one factor influencing acquisition likelihood in the context of high-tech industries (Heeley, King, & Covin, 2006). We expect that high levels of R&D expense decrease the likelihood that a firm will make an acquisition in the converging industry.

2.2.4 Analysis Model

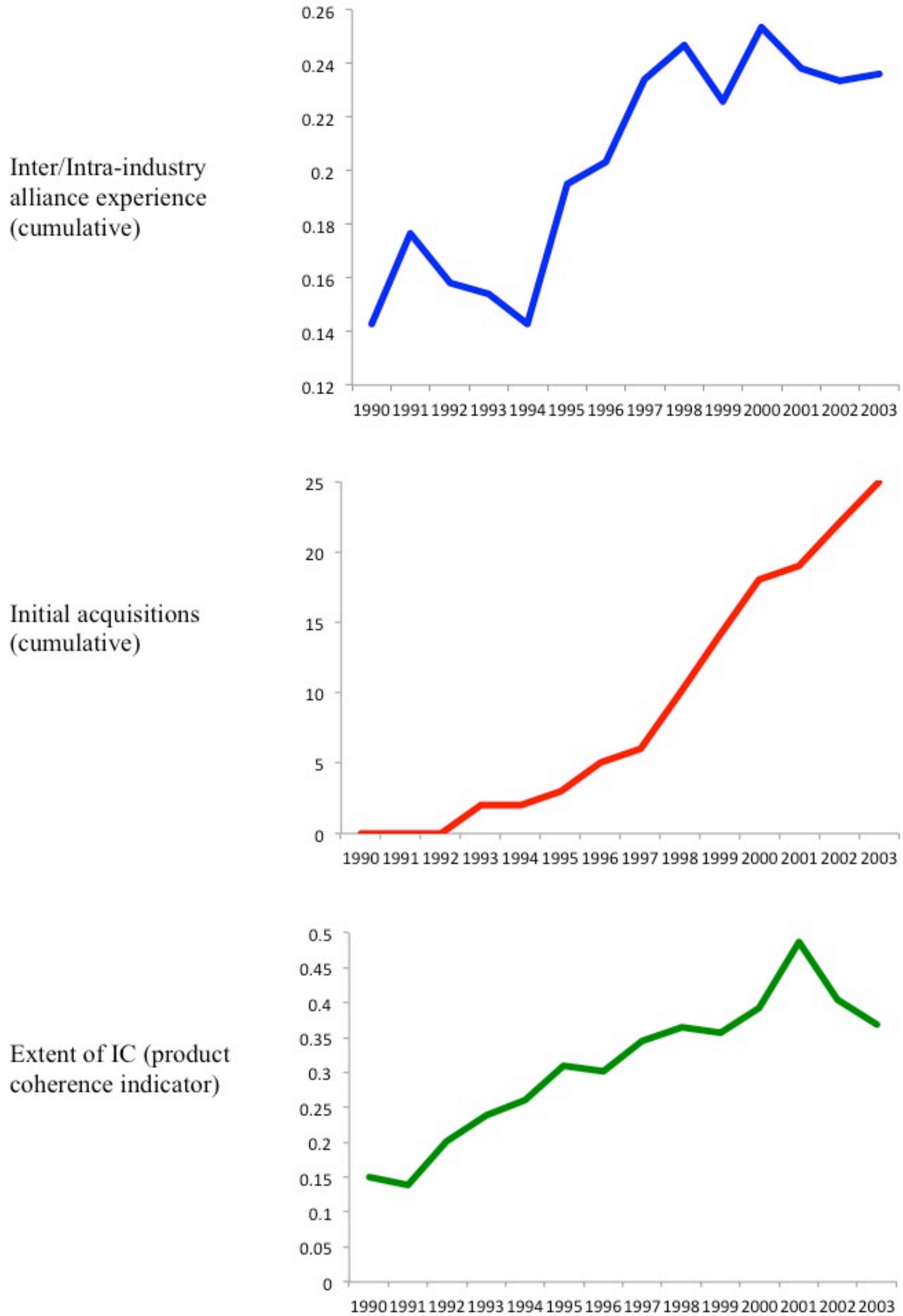
We estimate the likelihood of telecom equipment firms' initial acquisition in the computer networking industry using event history analysis (i.e. hazard rate model). The likelihood of an initial acquisition is the probability that an acquisition will be observed at time t, given that no acquisition occurred prior to time t. This approach accommodates time-varying components and allows right-censored data. We employ a piecewise exponential model, a semi-parametric models in which the baseline hazard rate is allowed to vary in each predefined time period. Other kinds of parametric models have more restrictive time dependence assumptions (Blossfeld & Rohwer, 1995). To estimate the hazard rates, we divided the data into yearly spells that are controls for year effects. Since we have firm-year observations, we use the "cluster" option in Stata, to calculate robust standard errors allowing for intra-firm correlation, relaxing the usual requirement that the observations be independent.

2.3 RESULTS

2.3.1 Descriptive Analysis

Figure 2 presents the telecom equipment firms' inter/intra-industry alliance experience, cumulative initial acquisitions for the computer networking companies and the pattern for extent of IC between 1990 and 2003. The data shows a steady increase in initial acquisitions and extent of IC and a slowing-down trend of extent of IC after 2000, which corresponds to the historical pattern of convergence noted earlier. On analyzing the temporal changes of firms' inter/intra-industry alliance experience, three interesting patterns emerge. First, we found an initial inter/intra-industry alliance spike and then decline in the 1990–1994 period. It is likely that firms were experimenting with inter-industry alliances during this period. Second, the figure shows a sharp rise during the 1994 to 1998 period. A time-lag correlation comparing alliance experience (1994-1998) with initial acquisition (1995-2000) was 0.9. The correlation is descriptive evidence that firms converted inter/intra-industry alliance experience into subsequent initial acquisitions. The third interesting finding is that while the industry alliance experience trend slowed after 1998, the initial acquisition trend continued. This is consistent with our hypothesis that firms relied less on inter-industry alliance experience for making initial acquisitions as the extent of IC increased.

Figure 2. Telecommunication Equipment Firms' Inter/Intra-Industry Alliance Experience, Initial Acquisition and Extent of IC



Note: The values in the inter/intra-industry alliance experience chart are derived at the industry level via the equation: (telecom firms' inter-industry alliance experience) / (telecom firms' inter-industry alliance experience + intra-industry alliance experience)

2.3.2 Regression Analysis

Table 1 reports the descriptive statistics and correlations. All correlation coefficients are less than 0.5 except for the one between firms' alliance number and prior acquisition experience. The mean variance inflation factor (VIF) is 1.65 (min: 1; max: 3.68), which is well below the recommended criteria of 10. Table 2 presents the firms' initial acquisition likelihood from the piece-wise exponential model.

Model 1 is the baseline model including only control variables. The firm variables size, age, cash flows, acquisition experience, wireless focus, and alliance number are consistently significant across the models indicating that controlling for these variables provides a conservative test. Hypothesis 1 receives support in Model 2, 3, and 4 (β = 4.673, 3.678, and 6.1, p < 0.01, 0.05 and 0.001respectively). Thus, inter/intra-industry alliance experience is positively associative with initial inter-industry acquisition. The coefficients in Table 2 are not hazard rates. To derive hazard rates, one needs to calculate the exponential values of the coefficients. As an example, we use the coefficient of inter/intra-industry alliance experience (6.1) in Model 4. The inter/intra experience variable ranges from 0 to 1. Therefore a 0.1 unit increase results in an increase in the hazard rate (i.e. initial acquisition likelihood) by 182 % ($e^{0.61}$ = 1.82).

Hypothesis 2 states that the extent of IC has a positive impact on the likelihood of firms' initial inter-industry acquisition. The coefficient for the extent of IC is positive and significant in both Models 3 and 4 (Model 3: β = 11.673, p<0.001; Model 4: β = 11.421, p<0.001) supporting Hypothesis 2. The coefficient (11.421) in Model 4 means that a 0.1 unit increase in the extent of IC results in an increase in the likelihood of an initial acquisition by 313% ($e^{1.1421}$ = 3.13),

The interaction effect of inter/intra-industry alliance experience and extent of IC is negative and significant in Model 4 (β = -43.303, p<0.05) supporting hypothesis 3. When there is a 0.1 unit increase in the extent of IC, a 0.1 unit increase of a firm's emphasis on inter- over intra-industry alliance experience results in a decrease in the likelihood of an initial acquisition by 35% (0.1*0.1*-43.303 = -0.043 → $e^{-0.043}$ = 0.65). This suggests a substitution effect where as the extent of IC increases the positive effect of inter/intra-industry alliance experience on the likelihood of an initial acquisition weakens. We plotted the interaction in Figure 3 using one standard deviation above and below the mean to capture high and low extent of IC. Consistent with Figure 2, the low and high extent of IC occurred respectively in the two periods: 1989-1991 (the average extent of IC = 0.2) and 2001-2003 (the average extent of IC = 0.4). This suggests that when the extent of IC is low, firm inter/intra-industry alliance experience increases the likelihood of a firm making its initial acquisition. However, as the extent of IC increases from 0.2 to 0.4, the slope of the positive impact of a firm's relative inter/intra-industry alliance experience on an initial acquisition decreases. The figure demonstrates that the extent of IC and relative inter/intra-industry alliance experience are substitutes for initiating an initial acquisition. The threshold point is where the two IC-extent lines cross (inter/intra-alliance experience = 0.27). For low extent of IC, when a firm's emphasis on inter- relative to intra-industry alliance experience is less than 0.27, it is less likely to make an initial acquisition than under a high extent of IC. The opposite occurs when inter-/intra-industry alliance experience is larger than 0.27. This implies that when the environment is characterized by high uncertainty (where the extent of IC is low) firms that exceed the threshold level (0.27 in our context) are more likely to initiate their initial acquisition.

We assessed the robustness of our results. We considered the effect of the bursting dot-com bubble in 2000. The formation of alliances dropped after the dot-com bubble which could inflate our results. We removed data after the year 2000 and reran our piecewise exponential hazard models. The results were qualitatively the same as those in Table 2 in terms of sign and significance. We also reviewed the distribution of initial acquisitions during the period between 1989 and 2003 and found no skewing of the data around the year 2000. Then, we tested if different types of alliances changed the results. Following Zollo and Reuer (2010) we decomposed our alliance data into joint ventures and non-equity alliances. Individually, neither joint venture nor non-equity alliance experience has a significant effect on initial acquisition, which is similar to Zollo and Reuer's (2010) results. For a third robustness check we removed firms that did not have any alliances during our study period and found consistent results. Finally, we assessed the rival hypothesis that learning about partner-specific uncertainties is a primary driver of initial acquisitions. We reviewed whether our sample firms acquired any of their previous alliance partners (see Table 3). Of the 25 initial acquisitions, the number of acquisitions made by firms with at least one inter- or intra-industry alliance was 17. For the 17 acquisitions, there was only one firm whose initial acquisition was with a partner in the computer networking industry. Thus, the rival hypothesis was not supported. We offer explanations for this intriguing finding in the discussion section.

Table 1. Descriptive Statistics and Correlation (Essay One)

		Mean	S.D.	1	2	3	4	5	6	7	8	9	10	11	12
1	Initial acquisition	0.021	0.143	1.000											
2	Firm size	4.097	1.922	0.173	1.000										
3	Firm age	18.751	19.963	0.061	0.379	1.000									
4	Cash Flow	97.045	615.987	0.237	0.402	0.309	1.000								
5	Slack resource	0.110	0.216	0.005	-0.001	0.232	-0.007	1.000							
6	Prior acquisition experience	0.478	1.252	0.209	0.465	0.321	0.341	-0.073	1.000						
7	ROA	-0.117	0.733	0.019	0.239	0.111	0.027	-0.036	0.028	1.000					
8	Wireless focus	0.444	0.497	-0.063	-0.125	0.089	-0.054	-0.035	-0.050	-0.058	1.000				
9	Product scope	0.381	0.318	0.085	0.255	0.078	0.143	-0.039	0.203	0.000	0.162	1.000			
10	R&D intensity	0.159	0.310	0.002	-0.232	-0.186	-0.019	-0.084	-0.002	-0.335	-0.006	0.013	1.000		
11	Firm alliance number	0.247	1.041	0.127	0.417	0.283	0.257	-0.019	0.538	0.031	0.030	0.166	-0.027	1.000	
12	Inter/intra-industry alliance experience	0.013	0.072	0.196	0.330	0.218	0.285	-0.049	0.406	0.056	-0.118	0.178	-0.010	0.315	1.000
13	Extent of IC	0.296	0.096	0.091	0.054	-0.161	0.010	-0.080	0.019	-0.197	0.029	0.110	0.225	-0.072	0.031

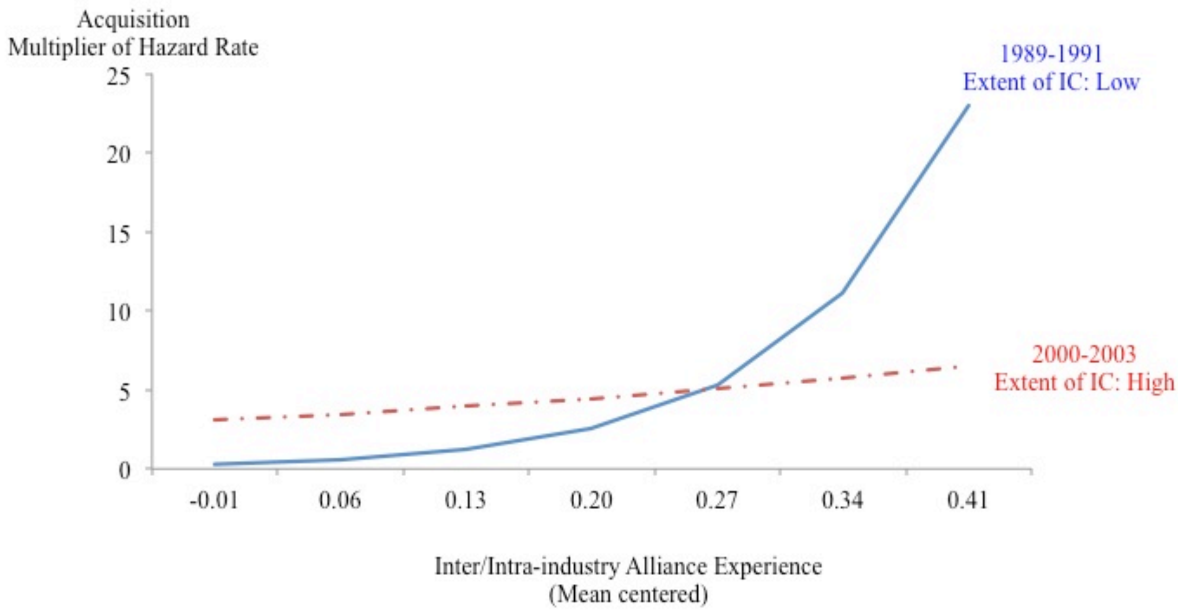
N = 1231. Correlations above 0.06 are significant at p <0.05

Table 2. Alliance Experience and Initial Acquisition Likelihood in an Adjacent Converging Industry

	Model 1	**Model 2**	**Model 3**	**Model 4**
Control variables				
Yearly effect	Included	Included	Included	Included
Firm size	-0.507***	-0.492***	-0.431***	-0.430***
	(0.091)	(0.087)	(0.095)	(0.094)
Firm age	-0.058*	-0.058**	-0.044*	-0.046*
	(0.029)	(0.022)	(0.021)	(0.020)
Cash Flow	0.001***	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Slack Resource	-0.473	-0.284	0.205	0.189
	(0.821)	(0.641)	(0.614)	(0.618)
Prior acquisition experience	0.476**	0.439***	0.415***	0.419***
	(0.145)	(0.108)	(0.091)	(0.087)
ROA	0.574+	0.386	0.808*	0.835*
	(0.310)	(0.304)	(0.353)	(0.342)
Wireless focus	-1.512**	-1.224**	-1.341**	-1.323**
	(0.483)	(0.451)	(0.456)	(0.449)
Product scope	0.008	-0.283	-0.254	-0.171
	(0.489)	(0.506)	(0.557)	(0.560)
R&D intensity	-4.424*	-4.719+	-4.122+	-3.897+
	(2.205)	(2.468)	(2.168)	(2.003)
Firm alliance number	0.349*	0.337**	0.296*	0.291*
	(0.162)	(0.130)	(0.118)	(0.114)
H1:Inter/intra-industry alliance experience		4.673**	3.678*	6.100***
		(1.527)	(1.502)	(1.725)
H2: Extent of IC			11.673***	11.421***
			(1.798	(1.853)
H3: Interactions				
Inter/Intra-industry alliance experience × Firm diversification balance				-43.303*
				(21.003)
Log-likelihood	-68.626	-63.228	-53.160	-52.208
Wald chi-square	15590.5	7834.37	10177.76	2554.09

The analysis is based on 1231 firm-year observations covering 147 firms and 25 initial acquisition events.
Estimated standard errors adjusted for clustering on subjects appear in parentheses.
+p<0.10; *p<0.05; **p<0.01; ***p<0.001

Figure 3. The Moderating Impact of Extent of IC on the Inter/Intra Alliance Experience - Acquisition Relationship



Note: The graphic is based on the parameters estimated from Model 4 in Table 2

2.4 DISCUSSION

In eras of high uncertainty, such as during IC, RDT predicts that undertaking strategic initiatives is problematic. Within this general problem domain, we examined one class of important yet underexplored decisions involving inter and intra-industry alliance experience and initial acquisitions during an era of IC characterized by increasing levels of collective cross-industry product-market diversification. As a result of these strategic initiatives, we found that firms engage in multiple types of uncertainty-reducing strategies where their *emphasis* changed over time from intra-industry alliances to inter–industry alliances and then to acquisitions.[5] Using a RDT and learning perspective lens, our discussion focuses on three areas: extending the boundary conditions of the alliance experience-acquisition relationship to a cross-industry context, the conceptual development and measurement of extent of IC and the managerial implications of early warning indicators in an era of IC.

We extend resource dependence research by examining whether and how firms adapt to an era of IC through the inter-temporal use of alliances and acquisitions. First, research focusing on the alliance-acquisition relationship has not employed a RDT lens, except for Yin and Shanley's (2008) conceptual work. Equally importantly, prior research using RDT has examined alliance and acquisition dependence-reducing strategies separately. As a result, each research stream seldom talks to one another. We begin to bridge this gap by focusing on the combinational use of these two important resource dependency actions. Accordingly, our study responds to the call by Hillman *et al.* (2009) for developing more studies exploring how firms use multiple uncertainty-reducing strategies.

Second the alliance experience–acquisition relationship has important theoretical and practical implications because it sheds light on how the reduction of uncertainty impacts strategic decisions. We responded to calls by Lin *et al.* (2009) and Zollo and Reuer (2010) for developing a more complete understanding of when we should expect that alliance experience is linked to acquisition activity. Our premise is that research examining the role of alliance-related experience and its impact of subsequent acquisitions has focused on intra-industry contexts or on partner-specific learning irrespective of context (Porrini, 2004; Zaheer *et al.,* 2010). Since IC is an increasingly common phenomenon, our finding of a significant inter-temporal alliance experience–acquisition relationship in a cross-industry context is a logical extension and introduces an important contingency. It is worthwhile to explore the degree to which our findings generalize to other IC contexts.

An intriguing finding from our post-hoc analysis was that only one firm acquired an alliance partner. We conjecture that while partner-specific uncertainty reduction (e.g. information asymmetry) is important and the focus of extant research (Reuer & Ragozzino, 2008; Zaheer *et al.*, 2010), uncertainty reduction about the competitive landscape and assessing competitor competency-building and action-response profiles is important in eras of IC. We offer three plausible explanations for this conjecture. First, evolving competitive dynamics renders partner-specific competencies less relevant. As a result, current partners may be less appropriate targets for an initial acquisition. Understanding the strategic significance of evolving competitive dynamics is one of the core activities of external learning. Second, developing knowledge of the acquisition-opportunity set is an important type of external learning. It is often assumed that valuable targets are scarce and thus competitors may initiate preemptive acquisitions. However, in our context, the market for acquisition targets did not dry up as the extent of IC increased. Instead, evidence suggests that it increased. Third, given the dynamic landscape, as targets assess their strategic position and undertake strategic initiatives they change the character of partner-specific uncertainties.

The conceptualization and operationalization of IC via the assessment of collective firms' cross-industry product-market diversification contributes to IC literature in several ways. The IC literature has primarily focused on the antecedents of convergence, while devoting less attention to the process through which convergence unfolds (Burgelman & Grove, 2007). This is partly because valid and reliable empirical indicators of IC have not emerged. We began to address this limitation by developing an "extent" indicator which complements the stage view of IC. While not necessitating objective data, our quantitative approach produces a reliable, well-defined indicator that can be tracked over time. Although objective definitions of product-markets are never perfect, when developed by knowledgeable stakeholders such as trade associations with input from managers they should be valid. Our extent of IC measure is both theoretically-based and managerially relevant. Future research can employ the measure to explore a variety of IC-related questions such as IC velocity, pace, sequence, and their relationship to strategic action and firm outcomes. We also encourage the development of other IC indicators.

Prior research has mostly assumed that there is only one product-market for each industry undergoing convergence (Greenstein & Khanna, 1997). Our conceptualization and operationalization relaxes the single product-market assumption. Through assessing the density of firms operating in "multiple" product-markets across industries, managers can better assess the degree to which industries overlap as well as the implications. In most cases industries converge asymmetrically across the two industry's set of product-markets and the identification of the product markets most affected by IC provides value information for the design and implementation of strategic initiatives. Our measure of extent of IC is at the industry level. Examining inter-temporal relationships between firm-level product-market diversification, alliance and acquisition interrelationships is unexplored. Yet these three uncertainty reducing actions represent the primary sources of firm growth. Including all three simultaneously while challenging would likely provide nuanced explanations of their interrelationships, mechanisms and outcomes.

An additional managerial implication relates to early warning systems (Grabo, 2004). Developing early warning indicators during IC provides managers with intelligence that minimizes surprise while providing sufficient time to initiate pre-emptive moves or fast responding countermoves. We identified three early warning indicators: inter/intra-industry alliance experience, initial acquisitions in the converging industry and the extent cross-industry product-market convergence. If a competitor emphasizes inter over intra-industry alliance experience, one may anticipate that it has a high likelihood of an initial acquisition in the adjacent industry. If the competitor is a market leader, its initial acquisition will significantly impact the competitive landscape by legitimizing cross-industry acquisitions, leading to imitation and other forms of legitimizing behavior thus accelerating IC. When the extent of cross-industry product-market diversification reaches a threshold, IC is a foregone conclusion.

Our results should be viewed in light of several limitations. We recognize that our uncertainty reduction and attention-based mechanisms provide explanations of the alliance experience - initial inter-industry acquisitions relationship in one type of IC context where one industry capability was being substituted by another capability. There are other types of IC such as when two industry capabilities complement each other. Thus, the generalizability to other IC contexts needs to be established. We think, however, that our logic is generalizable to other types of IC contexts and cross-industry strategic relationships, although the form and magnitude of relationships may change. Hence, we call for more studies on different types of IC. Studies that explore how other boundary conditions affect the cross-industry alliance experience – acquisitions relationship will provide valuable insights. For example, how do boundary conditions, such as firm size, emerging industry structures, globalization and evolving institutional norms impact the cross-industry alliance–acquisition relationship? Similarly, studies that explore external learning for other cross-industry topics, such as executive relocation, knowledge transfer, and multi-market competition would improve our understanding of the generalizability and boundary conditions for the uncertainty reducing and attention mechanisms. Research that explores the alliance - acquisition relationship in other types of IC would allow comparative assessments across contexts.

While 25 cross-industry acquisitions representing a small number on which to base our conclusions, there are at least three reasons why this number is to be expected and meaningful in an IC context. First, intra-industry acquisitions were also initiated during our study period. Second, from a managerial perspective, one would not expect a significantly higher number of cross-industry acquisitions for a variety of plausible reasons including the desire of potential acquiring firms to remain independent and "go on their own", a perception that there are a limited number of "attractive" targets in the adjacent industry, targets that prefer to remain independent, antitrust considerations and available targets that are perceived not to "fit" with a potential acquirer. Finally, our uncertainty reducing and attention-diverting mechanisms can operate in opposing directions: simultaneously increasing and decreasing the likelihood of an initial acquisition. Thus, their overall effect will vary across firms. Given that the number of acquisitions is likely to be small in IC contexts, detailed qualitative research could explore the processes of external learning and other strategic topics for a subset or the population of acquisitions.

We did not measure external learning, uncertainty reduction or attention directly (Ancona & Caldwell, 1992; Bresman, 2010). Empirical indicators for these mechanisms would permit the development of mediated models and the opportunity to develop multilevel models examining how forms and attributes of external learning are structured by micro-level actions. In addition to interviewing and survey-based methods, one approach for operationalizing external learning is the content analysis of firm and industry documents identifying evidence that firms are engaging in uncertainty reduction or directing attention to issues in the adjacent industry, potential targets and industry convergence.

3.0 ESSAY TWO: DEPTH OF FIELD AND FIRM PERFORMANCE

When the boundaries between industries become blurred, ambiguity arises in the sense that identifying, distinguishing and assessing competitors actions and intentions problematic. This unique nature of IC leads me to ask: where and how should firms direct their attention toward a fuzzy competitive environment. Drawing on the attention-based view (Ocasio, 1997), this paper attempts to examine the performance effect of firm attention on multiple competitors during industry convergence. Specifically, I adopt Ocasio's (1997:190) "situated attention" perspective and view firms' competition with multiple competitors as a situation that shapes their attention on the changing landscape.

This inquiry is theoretically important for two key reasons. First, despite recent interest in IC (Greenstein & Khanna, 1997; Burgelman & Grove, 2007), the literature has been limited in one important aspect. Researchers investigating this phenomenon have almost exclusively focused on market-level structural dynamics (Katz, 1996; Wirtz, 2001), ignoring how firms achieve competitive advantage during IC. Although a few studies have begun to explore the strategic implications of firm-level actions, including new product introduction (Srinivasan et al., 2007) and diversification (Burgelman & Grove, 2007), this set of research did not examine performance linkages. The paucity of such studies severely limits our understanding of the strategies needed for success in an era of IC.

Second, IC provides a good setting to revisit the attention-based view theory. The central tenet of this theory is that firms cannot attend to all issues due to limited capacity and thus sequential attention on a specific issue prevents distraction by irrelevant ones (Cyert & March, 1963; Greve, 2008). This important assumption directs literature to focus on firm attention toward *specific* issues (e.g. Durand, 2003; Eggers & Kaplan, 2009; Vissa, Greve, & Chen, 2008). However, less effort has been made to examine what if and when firms need to simultaneously attend to *multiple* issues. Sullivan's (2009) and Rerup's (2008) work are exceptional examples that shed insights on the intraorganizational arena. My study focuses on the interorganizational competition area. Arguably, attending to a single competitor can be viewed as a specific issue to firms, while attending to a large set of competitors would be seen as involving with multiple and complicated issues (Chen, 1996; Miller, 1993). Attending to multiple competitors is crucial during IC, firms need to identify a new set of competitors from the adjacent converging industry as well as recognize which intra-industry competitors are taking action to seize market opportunities in the adjacent industry. This paper intends not only to tackle this inattention problem but also to examine conditions under which firms need to balance their attention toward a few vs. multiple competitors.

Where should firm direct its attention during IC? This paper developed a construct – Depth of Field (DOF). In photography, DOF is the range from the near to the far objects that appears to be in focus in an image. When the objects in the foreground are emphasized but those in the background are deemphasized, the DOF is in a shallow focus. If one prefers a clear landscape picture, she needs to adjust focus by letting objects in both the foreground and background appear sharply clear, which is known as deep focus (Sanchez-Burks & Huy, 2009). Ocasio (1997) suggests that decision-makers' attention focus depends on "the particular context or situation they find themselves in". Adopting this situated attention perspective, this study defines DOF as *the number and variety of competitors with which a firm competes.* Situated attention is based on an objective consideration suggesting that firms attend to one another through interacting and engaging in market competition (Baum & Korn, 1996; Jayachandran, Gimeno, & Varadarajan, 1999; Tsai, Su, & Chen, 2011). Market competition serves as a competitive situation which stimulates and shapes a firm's attention to its landscape change. The greater number and variety of a firm's competitors, the deeper a firm's DOF. The core argument of this paper is that a deep DOF stimulates a broad attention to what is going on in a changing landscape and thus assists the firm in reducing competitive ambiguity.

I further propose that several challenges will occur when a firm deepens DOF. Specifically, I investigate three conditions (i.e. locus of convergence, competitors' DOF, and firm age) that impede or promote the extent to which firms derive benefits from a deep DOF. These conditions represent challenges from different levels respectively (the environment, competitor, and organizational level). To test these hypotheses, I use the context of voice-data convergence between the telecom equipment and PC networking industries from 1991-2003. I found that the positive performance effect of a deep DOF weakens when (1) IC occurs in most of a firm's product markets, (2) a firm's competitors' DOFs are shallow and (3) the firm is relatively old.

The study contributes to the literature in two ways. First, by introducing the DOF construct, this paper enriches the connection between the attention-based view and industry evolution literature. A deep focus is particularly important in a blurring environment change context where industry and firm boundaries are in a state of flux, because it helps firms to overcome inattention through engaging competition with multiple/different competitors. Second, this research extends firm attention theory through the development of a contingency model showing how a firm can optimize its attention across multiple issues (i.e. deep focus) as opposed to focusing on specific ones (i.e. shallow focus). My empirical analysis demonstrates the relative impact of contingencies on the DOF-performance relationship. First paragraph. The figure below is inserted so that there is an item in the sample List of Figures.

3.1 THEORETICAL BACKGROUND

I ground the DOF construct in organizational attention literature. The attention of a firm can be understood as the noticing, encoding, interpreting, and focusing of time and effort by the firm on both issues and answers (Ocasio, 1997: 189). A wide range of disciplinary studies has centered on organizational attention (Hansen & Hass, 2001; Pollock, Rindova, & Maggitti, 2008; Tuggle et al., 2010). Researchers have used two approaches including (1) situated attention: contexts where firms are situated and exposed (e.g. Durand, 2003; Sullivan, 2010; Vissa et al., 2010) and (2) cognitive attention: managers' mental template (e.g. Reger & Huff, 1993; Cho & Hambrick, 2006; Nadkarni & Barr, 2008). Controlling the second approach, this paper focuses on the former. As for the context, given that IC is a complex phenomenon and the literature is still emerging I focus on a supply substitution type of IC (see Appendix A for the details of IC taxonomy).

3.1.1 How Contexts Shape Awareness - Situated Attention

In the attention-based view literature, the characteristics of situation determine how organization takes time and effort to scan, notice, encode and interpret issues (Ocassio, 1997; Cyert & March, 1963). This view is rooted in social psychology. A succinct description about this view can be found in Cialdini, Reno and Kallgreen's (1990) work: whether individuals litter or not in public parks depends on the intensity of their exposure to different written signs, other individuals' littering, and how frequent parks constantly clean littering.

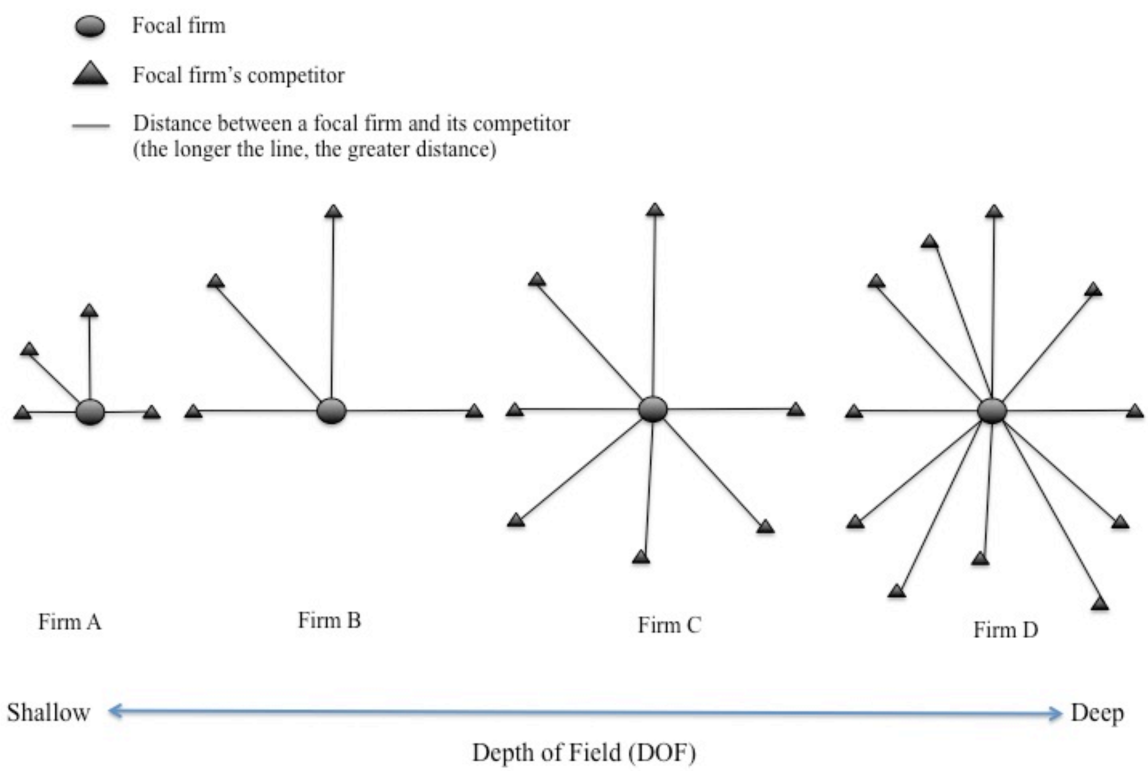
The situated attention perspective has been applied in several areas of the management field. In the behavioral theory of firm, situation refers to reference points that an organization uses to determine its aspiration level. Reference points may come from its own historical performance or other organizations' performance. When organizations found actual performance below (above) their aspiration level, they will shift attention toward risky (risk-averse) actions (Iyer & Miller, 2008; Greve, 2008; Vissa et al., 2010). In social network theory, situation can be viewed as the structural elements of contexts that an organization interacts with. For example, a good network position (e.g. centrality or structural hole) helps a firm be aware of events in many markets and alert to the problems competitors are focused on (Freeman, 1979; Burt, 1992: 116). In competitive dynamics research, resource similarity and market commonality between a focal firm and a given rival will draw the focal firm's attention and thus enhance its competitive awareness on that rival (Chen, 1996). This research focuses on attention toward a set of competitors, instead of only one. During IC, situated attention is similar to a discovery-driven view of knowledge acquisition, such as 'knowing as doing' (Spender, 1996) and 'seeing as the consequence of experience' (McGrath & MacMillan, 1995; Rentsch, Heffner, & Duffy, 1994), which serves as an effective way of drawing managerial attention and thereby enhances their understanding of the competitive environment.

3.1.2 Depth of Field

The DOF concept is still in the infant stage in industry evolution studies, but has gained attention in the areas of organizational and consumer behavior. In organizational behavior, DOF is used in leadership research and described as the ability to recognize the composition of diverse emotions within an organization (Sanchez-Burks & Huy, 2009). Although fear is prevalent among a majority of employees during strategic change, a minority of them may have “hope” for change. So, change leaders’ success is contingence on their ability to adjust their DOF from a setting that brings into a single group’s emotion to a setting in which one can capture diverse patterns of shared emotions in a collective. In marketing, researchers apply DOF to help marketing managers design visual presentation tools that provide more context than detail or present various alternatives within a given visual field to consumers (Lurie & Mason, 2007). Lurie and Mason (2007) claim that visual presentation that provide greater details (a shallow focus) may lead to overconfidence since users make assessment based on fewer observations, whereas visualizations that provide greater context (a deep focus) lower decision makers’ costs of adding alternatives to a consideration set for users. Therefore, DOF affects how decision makers access, evaluate and ultimately use information. A shallow focus leads to a better understanding of the details of a particular object (e.g. product). A deep focus is good for faster navigation around the whole picture as well as avoiding the problem of overconfidence where decision makers tend to eliminate alternatives from consideration.

This suggest that the conceptual use of DOF is intuitively compelling and promising for industry evolution research (including IC) because it addresses how firms confronted with a changing environment can develop the understanding of other organizations competing in the environment. This study intends to contribute the use of DOF in the competition arena and define it as the number and variety of competitors with which a firm competes. Firms pay attention to competitors through interacting and engaging in market competition with them (Tsai et al., 2011; Jayachandran et al., 1999). When industry boundaries blurred, the competitive environment that firms construct is an incomplete reality (White, 1981). The number of competitors assists in enriching a firm's competitive knowledge structure (McNamara, Luce, & Tompson, 2002). The more competitors with which a firm engages market competition, the more broadly the firm attends to its competitive environment. By the notion of the "variety" of competitors, I refer to the degree to which a firm has competitors that are different from it in terms of product market commonality. I concentrate firms' situation on product market competition which directs and shapes their attention, since product market is the fundamental unit of analysis of industry change (Klepper & Thompson, 2006). Competition is the function of market commonality: the greater the market commonality between two firms, the more similar they are, the more they view each other as close competitors (Chen, 1996; McPherson, 1983; Peteraf & Bergen, 2003). Competing with rivals that have different market profiles than the firm widens its competitive knowledge (Miller & Chen, 1996). Consequently, the variety of competitors expands the area of a firm's attention on its competitive landscape. Figure 4 illustrates how a deep vs. shallow DOF creates a different understanding of a landscape. Assume that there are four firms which have different DOF respectively. Firm A has the shallowest DOF, since it derives the landscape picture mainly from a few close competitors. On the other hand, firm D owns the deepest DOF in that it is exposed to many distant competitors thus expanding the area of its DOF. Note that firm D has a deeper DOF than firm C because of the number of competitors. Taken together, a focal firm's DOF is comprised of the number of its competitors as well as the dissimilarity between itself and its competitors.

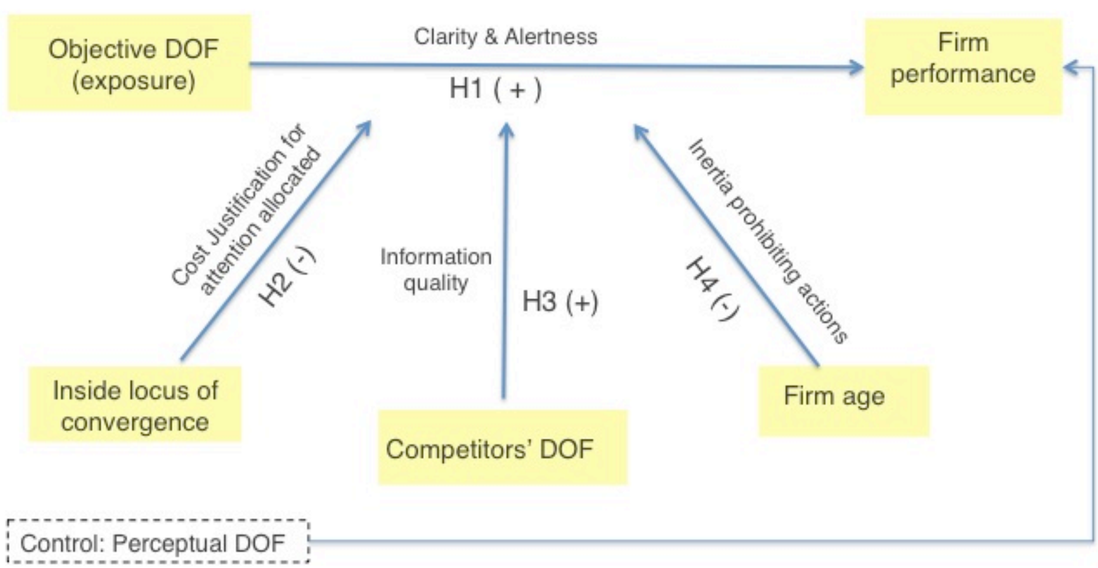
Figure 4. A Conceptual Map of Firm's DOF



3.2 HYPOTHESES

How does a deep DOF influence firm performance during IC? As noted earlier, the goal of this paper is to develop a DOF-performance contingency framework. Figure 5 summarizes the direct effect of DOF as well as three contingencies. While a deep DOF has a positive impact on performance, the contingencies at the industry, competitor and firm levels arise from the result of extending a firm's DOF from a shallow to deep focus. At the industry level creating a deep focus is costly in that it requires firms to broaden their product markets and may result in attention overcapacities (Rerup, 2009). The justification of attention allocated to a deep DOF needs to be based on whether firms' product markets are inside a locus of convergence (i.e. the product markets where IC occurs across industry boundaries). Thus, the locus of convergence (see concept explanation below) is used as the first contingency. Second, at the competitor level firms have to overcome attention overload problems based on the extent to which they can filter important signals from irrelevant noise through analyzing their competitors. Thus I examine how one's competitors' DOF moderates the DOF-performance relationship. Third, at the firm level, transforming the understanding of the diverse competitive landscape into strategic actions requires internal changes which conflict with organization inertia (e.g. Hannan & Freeman, 1984). Since the rigidity occurs with senescence, this paper examines firm age as a moderator.

Figure 5. A Contingency Model of DOF and Firm Performance during IC



3.2.1 Baseline

I claim that two mechanisms operate the relationship between a deep DOF and performance. The first mechanism is clarity. A deep focus is developed through competing with multiple different competitors. Having many or different competitors alone would not create a clear landscape picture. Although there is a benefit of diversity, firms may still find confusing and difficult to interpret the information they gain. For example, the fact that one firm competes with a few of different competitors is very likely to create a perplexing, rather than clear, picture due to insufficient numbers. A statistical analogy would be useful for better understanding why this is the case. In statistics, to have a wider range of confidence level, ones need to have both of large sample size and standard deviation. The number of competitors is the sample size, while the heterogeneity of competitors is standard deviation (Fiegenbaum & Thomas, 1995; Rhee, Kim, & Han, 2006).

In addition to the clarity argument, a deep focus through competing with multiple different competitors creates another mechanism for firm: alertness. Alertness is a process in which a firm maintains a constant state of cautiousness with respect to its competitors. In the literature, alertness has been described as not only vigilance for potential threats (Janis, 1972) but also the ability to discover entrepreneurial opportunities (Kirzner, 1973, 1992). Alertness is manifested in a situation where individuals position themselves in the flow of information such that the probability of encountering opportunities without a deliberate search is maximized (Kaish & Gilad, 1991). A deep DOF escalates a firm's state of vigilance by putting firms in this position of competitive information flow.

After IC is initiated, firms are confronted with difficulties in identifying potential competitors when protecting their core markets or recognizing opportunities in entering new markets. Avoiding competitive blindspots therefore is the key performance driver during IC (Khanna & Greenstein, 1997). The problem of competitive blindspots has been linked to overconfidence problems stemming from the biases due to unclear understanding and carelessness (Ng *et al.,* 2009; Russo & Schoemaker, 1992; Zahra & Chaples, 1993; Zajac & Bazerman, 1991). Therefore, a deep focus creates the mechanisms of clarity and alertness which reduce the problems of competitive blindspots, thereby enhancing firm performance during IC.

H1: During industry convergence, a high level of DOF is positively related to firm performance.

3.2.2 DOF Challenge: Cost Justification for Attention Allocated

Creating a deep DOF is costly. Although competing with many and distant competitor provides opportunities allowing firms to be aware of the variability and commonality of competitors during IC, firms will have to devote enormous attentions as well as to carry excess capacity, if they aim to derive a comprehensive clear picture of the landscape. The context of IC makes deepening DOF more difficultly since the landscape is changing. Day and Schoemaker (2004) liken the attempt to fully scan one's competitive landscape to military reconnaissance missions. If the war situation is constantly changing, one will need to fly reconnaissance missions over and over, which is very costly. Costs of developing a deep DOF include product market entries, coordination across business units, defending against competitors' attacks, and overhead for constantly scanning the environment. Consequently, cost justification is a challenge for firms when develop a deep DOF during IC.

To investigate how IC impacts the performance effect of a deep focus, I use the degree of firms' cross-industry product market diversification as a base for capturing the extent to which industries converge in Figure 1. Specifically, through assessing the density of firms operating in "multiple" product markets across industries, one can create a map indicating what I terms *locus of convergence* (i.e. the product markets where IC is occurring across industry boundaries). In other words, the product market is an appropriate unit of analysis for studying IC and locus of convergence identifies the product markets most affected by IC. The strategic implications of firm cross-industry product market diversification is that it blurs industry boundaries via reducing the distance of cross industry product markets, reduces entry barriers for neighboring industry firms and thus makes competitor identification and assessment more difficultly.

I contend that if locus of convergence is in the product markets where firms are operating, firms should shrink their area of DOF into a shallow focus. This argument corresponds to the predictions of state uncertainty (i.e. an inability to assign probability as to the likelihood of future events) and effect uncertainty (i.e. an inability to predict the effect of any given environmental stage on one's organization) in the environment literature (Milliken, 1987; Miller & Shamsie, 1999).[1] Milliken (1987: 137) notes that "knowing, for example, that a hurricane is headed in the general direction of your house does not mean you know how it will affect your particular house (e.g. will your house be left standing?)". Arguably, firms that operate in product markets impacted by IC, to a more or less extent, are aware that they are under the era

[1] Milliken's third type of uncertainty (response uncertainty) may also be a mechanism explaining how convergence affects firm performance. Future research could focus on this interest area – for example, firms' decision speed of responses as analogous to shut speed of taking a picture.

of convergence. What managers cannot predict is that how convergence will impact their own organizations. In this case, it is safer to stick with a narrower scope of product markets where managers have better controls (Miller & Shamsie, 1999). When a hurricane is entering the zone where you are living, you should focus on finding a safe location to ride out the storm. Similarly, when IC impacts a given product market, it creates hefty entry threats to firms operating there. Firms should focus on competitors that are similar to them. Therefore, it is better to narrow one's DOF. In contrast, if a firm is operating in product markets outside locus of convergence, it should develop a deep DOF. If you, for example, live in a zone nearby a hurricane, you will desire to know the future trajectory of the hurricane by collecting as much information as you can. The uncertainty for firms operating outside locus of convergence is whether and when IC will impact their product markets. Managers in this kind of firms are confronted with state uncertainty. Accordingly, they should deepen DOF.

> *H2: During industry convergence, a firm's product market emphasis within the locus of convergence (product markets where the convergence is occurring) will negatively moderate the DOF - performance relationship.*

3.2.3 DOF Challenge: Attention Overload

In addition to attention allocated in various competitors, another challenge is attention overload. This challenge is subtly different than the one in the previous section because the attention overload issue is the challenge for what you actually derive from a deep DOF, whereas the cost justification issue is the challenge for what you need to pay to gain a deep DOF. As a firm deepens its DOF, information received by managers disproportionally increases. To a large extent, a deep DOF requires attention that may approach or exceed the firm's information processing capabilities. Day and Schoemaker (2004: 132) note that attention overload increases the likelihood of confusion to managers; thus “to see everything is seeing nothing”. Supporting this view, research recognizes that managers tend to simplify their knowledge structure by focusing on relevant information while ignore irrelevant issues (Daft & Weick, 1984; Porac & Thomas, 1994; Reger & Huff, 1993). The advantage is that the filter assists managers in attending to a small set of information. Nevertheless, it does not guarantee the quality of the filtered information.

This suggests that the resolution of attention overload challenge of a deep DOF rests on to what extent firms can filter important signals from irrelevant noises when deriving a picture of the changing landscape. One of fundamental task in competitive intelligence is to reduce the noise-to-signal ratio: targeting the signals that are critical to organizations and decreasing the volume of noise (Prescott & Miller, 2003). Imagine that a deep DOF may create dozens of or nearly one hundred dots in a firm’s radar screen. When most of competitors a firm engages with have a shallow focus, their competitive moves filtered into this firm’s radar will turn out to be useless or obsolete information. On the contrary, when a firm is situated with a large set of competitors who have a deep focus, it can take advantage by leveraging competitors’ information-processing capability through exposure to meaningful signals (Homburg, Grozdanovic, & Klarmann, 2007; Ingram & Baum, 1997). Combining a firm own DOF and its competitors’ DOF leads to a better judgment in reducing the noise-to-signal ratio, thus reducing the attention overload challenge.

H3: During industry convergence, competitors' DOF will positively moderate the DOF - performance relationship.

3.2.4 DOF Challenge: Inertia Prohibiting Actions

To convert the benefit of a deep DOF into performance, firms need to take actions based on inputs from a variety of competitors. IC is fraught with disruptive opportunities and threats, such actions typically require strategic initiatives deviating from what firms are currently doing, which very likely conflicts with firms' reliability and accountability: the source of structural inertia (Hanna & Freeman, 1984). One key factor compounding inertia is firm age. While older organizations would have developed mature infrastructures for processing external information than younger ones, they may not fit an IC context where formerly separate industries are brought together, which changes the basis of competition (Greenstein & Khanna, 1997). Older firms establish bureaucratic routines that create inertia (Hannan & Freeman, 1984). They are subject to the liability of obsolescence because they become unresponsive to changes in the external environment (Barron, West, & Hannan, 1994; Ranger-Moor, 1997). The aging process increases a firm's tendency to build on and refine its previous technological activities (Sorensen & Stuart, 2000: 88). As a firm ages, its internal clockspeed will become a burden if external clockspeed is accelerating. The inertia prevents firms from taking action even when they become aware that some competitors are experimenting in new products or services. I predict that when developing a deep DOF, older firms will encounter more inertia challenges than younger firms. Research has shown that it is because mature firms could not make connections between organizational resources/systems and sustainable product success (Dougherty & Hardy, 1996). This makes difficult or slow down strategic initiative even when old firms have a deep focus. Young firms who have a deep focus, by contrast, suffer less from the problems of inertia and therefore have more advantages of leveraging benefits from a deep focus. They have more incentives to take actions, since managers in young firms recognize that they have fewer burdens regarding bureaucracy and am willing to modify their competitive positions.

H4: During industry convergence, age of the firm will negatively moderate the DOF - performance relationship.

3.3 RESEARCH METHOD

3.3.1 Empirical Context

The convergence between the telecommunications equipment (SIC: 3661, 3663, and 3669) and computer networking (SIC: 3576) industries serves as my empirical context for several reasons. First, convergent technology and the growth of the Internet eroded boundaries between the two industries enabling competition between the two industry's firms beginning in the 1990s which trigged IC. In the 1980s, these industries belonged to the telecommunications and the computer sectors respectively. Firms in the telecommunications equipment industry (e.g. Nortel and Alcatel) relied on circuit switching technology as a core asset, while the core of firms (e.g. Cisco and 3Com) in the computing networking industry is packet switching technology. Circuit switching was designed for voice traffic of telecommunications network service. When someone dials a voice call, the network saves a network path for the entire duration of the call but cannot share it with others. In contrast, the packet switching is designed for data traffic of Internet Protocol (IP) in which data are broken into small segments called packets. IP does not need to save a path for the entire duration of the call. Because of supply-side and demand-side drivers, the industries of voice communication and data communication began to converge in the 1990s. Services that were traditionally provided by circuit switching technology then were subsumed by networks that used packet switching technology. Packet switching technology foster the development of new services/products, such as the integration of voice mail and email, teleconferencing, white boarding, and networking switches (Lee, 2007). Second, as the usage of the Internet grew in the 1990s, telecommunications service firms (buyers) found that traditional circuit switching technology made network capacity insufficient and couldn't fulfill the demand for data traffic, which forced telecom equipment firms to change their marketing and production activities. Moreover, these firms had to search for new suppliers because the old product architecture becomes obsolete. These force together speed up the integration of voice and data communication (e.g. ADSL and Internet telephony equipment). The above two reasons indicated that convergence between the two industries had been initiated in the early 1990s (See Appendix B for details of industry context). Finally, during the convergence, some firms were disrupted (underperformed and failed), while others performed well. The heterogeneity of firm performance provides variation in dependent variable.

3.3.2 Data

COMPUSTAT was used to identify firms in the telecommunications equipment industry (SIC: 3661, 3663, and 3669) and the computer networking industry (SIC: 3576). Using CorpTech Directory, I compiled firm product portfolio for these two industries. In the directory, the section "Who Makes What" describes the profiles of all firms involved in technology-intensive industries by product types. This study selected public firms. The reliability of the database has been confirmed in prior literature (Lee, 2007). The packet-switching equipment product was commercialized in the early 1990s, so the data collection started in 1991. I then trace these firms' product portfolios for 13 years until the end of 2003. In 2003, the convergence slowed down in anticipation of deregulation and new technology—the industry started to migrate toward a new generation network structure (OECD, 2008: 15).

The CorpTech Directory provides 65 product lines for the above two industries. I use these product lines as the bases of firms' DOF. CorpTech further classifies these product lines into 17 product classes (see Table 3). They also categorize each product class by whether its fundamental technology is a data-based or voice-based communications product. Although distinction of data- or voice-based products becomes difficult as IC progressed, in the early converging stage (i.e. year 1989) it is safe to argue that data-based communications products (37 product lines) belong to the computer networking industry and voice-based communications products (28 product lines) fit into the telecom equipment industry. To ensure that all of firms from COMPUSTAT actually belong to the two industries, I screen out those firms that do not have product lines in either the telecommunications equipment or computer network industries. This procedure reduced the total sample size to 1436 firm-year observation covering 225 firms (telecom equipment: 143; computer networking: 82). The data is assembled in a longitudinal firm-product matrix format including firms (telecom equipment vs. computer networking) and their products (voice- vs. data-based). The number of firms in the data panel is unbalanced across years, because some firms discontinued operations, whereas others entered into the panel.

Table 3. Product Classes of the Telecommunications Equipment and Computer Networking Industry

CORPTECH'S CODE	VOICE- OR DATA-BASED	PRODUCT CLASS	EXAMPLE
TEL-BR	VOICE	Broadcasting/Receiving Equipment	Mobile radio system
TEL-CI	DATA	Communication Interfaces	RS-232 interface
TEL-CS	DATA	Communication Security Devices	Encryption devices
TEL-DC	DATA	Data Concentration Equipment	Data terminal
TEL-EM	DATA	Electronic Mail Equipment	Facsimile equipment
TEL-MX	DATA	Multiplexers/Modems	Modem
TEL-NW	DATA	Communication Networks Equipment	LAN (Local Area Networks) equipment
TEL-SI	DATA	Signal-Related Equipment	Signal propagation device
TEL-SM	VOICE	Satellite/Microwave Communication Equipment	Satellite reception/transmission equipment
TEL-TD	DATA	Telecom Distribution Equipment	T-1 equipment
TEL-TE	VOICE	Telephone/Voice Equipment	PBX (Private Branch Exchange) equipment
TEL-TR	VOICE	Transmission Systems Equipment	Transmission antenna
TEL-ZD	DATA	Other Data Communication Equipment	Teleconferencing systems
TMA-SS	VOICE	Security/Safety Equipment	Alarms/Intrusion detection
PHO-FO	DATA	Fiber Optic Equipment	Fiber-optic receivers/demutiplexer
SOF-CS	DATA	Communication Software	LAN software
SUB-ES	VOICE	Electronic Subsystem	Amplifiers

3.3.3 Dependent variable

The dependent variable, *firm performance*, is firm one-year-lagged sales divided by one-year-lagged total employees (sales productivity). I chose this operationalization for several reasons. First, my theory is conceptualized within the competition research domain. Competitive strategy studies have used sales-related variables as their performance measurement (e.g. Ferrier, 2001). The denominator of this variable captures the extent to which a firm gains or loses market sales from their rivals. Second, since my context involves two industries, using traditional performance metrics, such as ROS or ROA, is not appropriate. The profit margin structure differs across the telecommunications equipment and computer network industries. Third, I did not select Tobin's Q, because in the later 1990s, the stock price of many firms in these industries were overvalued and exaggerated (Sterling, Bernt, & Weiss, 2006).

3.3.4 Explanatory variable – DOF and moderators

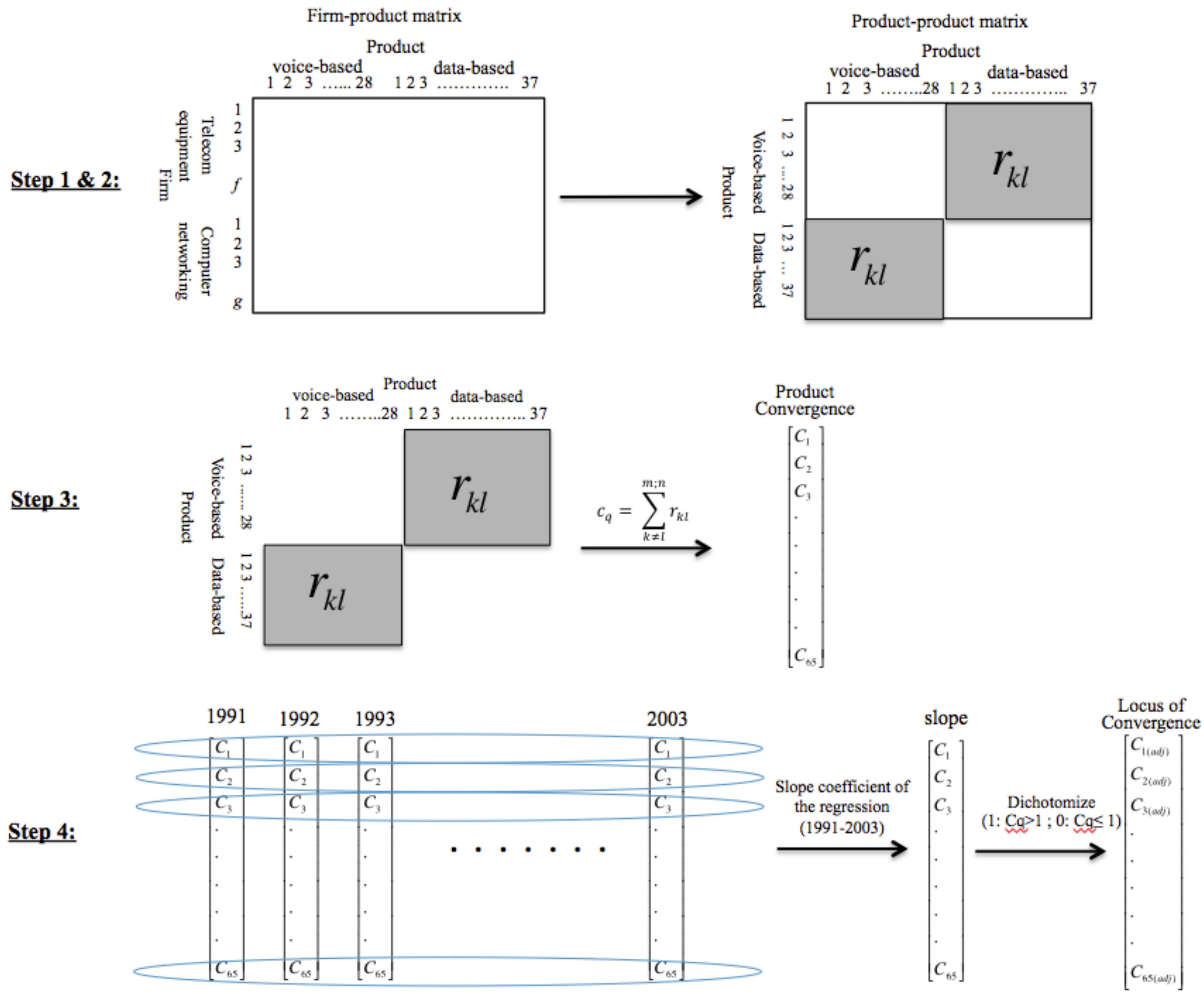
DOF is based the situation attention perspective which suggest competition contexts that firms are exposed to stimulate and shape their attention. However, cognitive research suggests managerial cognition is inter-related with situated attention (Ocasio, 1997). Therefore, it is important to empirically understand whether cognitive attention (perception-based: the intensity and breadth of firm perception about the competitive environment) affects the situated attention predictions (exposure-based) or vice versa. I control for the perceptual DOF in my model (see below).

For *Objective DOF,* I follow Boyd, Gove, & Hitt's (2005: 245) approach of construct measurement by incorporating measures of two dimensions (i.e. number and variety of competitors) of the construct into a single item through using a summative approach. Based on Figure 1, the two measures should not be tested separately. The integrative measure is generated via three steps. First, I identify the number of a focal firm's competitors via the firm-product matrix data. I create a dummy matrix I_{ij} where 1 indicates that firm i and j are competitors; 0 indicates that they are not competitors. I categorize that two firms are competitors when one firm has more than one product market overlap with the other firm. The use of more than one overlap is a conservative measure as well as coherent with the attention-based consideration. The fact that firms have more than one market overlap forces them to pay more attention to a subset of their competitors and become familiar with their strategy, capabilities, and actions (Jayachandran et al., 1999). Second, the variety of competitors is measured as the average distance between a focal firm and its competitors. I construct the distance among all firms at the dyadic level by examining the extent to which firms compete in the same product classes. Specifically, for any pair of firms, I measure the extent to which the distributions of the two firms are dissimilar from each other across 17 product classes (see Table 1), year by year. I ran the regression analysis and found the results based on 17 product classes and 68 product lines are the same. The distribution is captured by a multidimensional vector, $P_i = (P_i^1 \dots P_i^s)$, where P_i^s represents the number of product lines that firm *i* competing in product class *s*. Distance between any pair of firms is then: $d_{ij} = 1 - \frac{P_i P_j'}{\sqrt{(P_i P_i')(P_j P_j')}}$, where $i \neq j$. The distance measure varies from 0 to 1, with a value of 1 indicating firm *i* and *j* do not have any product market overlap. Finally, I obtain each firm's DOF measure via an equation: $DOF_i = \sum_{j=1}^{N} I_{ij} \times d_{ij}$, where I_{ij} is a dummy competitor matrix derived in step 1; d_{ij} is a given competitor *j*'s distance from the focal firm *i*; and N is the number of firms.

The model is based on three contingency variables: inside locus of convergence, competitors' DOF, and firm age. For each firm, a variable denoted by *inside locus of convergence* is used as a proxy for capturing the extent to which a firm's product markets are where IC is occurring. I took five steps to derive this proxy. Figure 4 demonstrates step 1-4. One, I transform firm-product matrices into product-product matrices year by year. Using firms' product portfolio information in firm-product matrices, I create product-product matrices indicating the number of firms operate concurrently in any pair of products. This approach is consistent with Li and Greenwood's (2004) method. That is, the relatedness between a pair of markets can be measured via calculating the density of firms operating concurrently in the two markets. Two, in line with the statement that cross-diversification serves as a base for measuring the degree of IC in Figure 6, I retrieve information only from the cells in any pairs between voice- and data- products (r_{kl}) for operationalizing the relatedness between two industry respective products. Three, I generate the indicator of product convergence for each product lines via the equation: $c_q = \sum_{k \neq l}^{m;n} r_{kl}$. Product convergence is a vector, $c_q = (c_1, c_2, c_3, \ldots \ldots c_{65})$. In the dataset, there are 65 product lines provided by the CorpTech Directory. Four, applying Dess and Beard's (1984) method, I obtain locus of convergence by using the slope coefficient of the regression line of time regressed against the value of product convergence (c_q) for the thirteen years between 1991 and 2003 inclusive. This treatment considers the growth coefficient of product convergence in each product line. To mitigate the concern about the market size of individual product line, I use value 1 as a cutoff value (slope 1 means that the growth rate of product convergence for a given product is 100% over 13 years). The final indicator of locus of convergence is a dummy vector (1 represents that a given product is under IC; 0 indicates that it is not). I label this vector as $c_{q(adj)}$. Finally, I produce the variable of *inside locus of convergence* via an equation: $\sum_{q=1}^{65}(p_{iq} \times c_{q(adj)})$, where p_{iq} is an indicator of firm i's portfolio diversification on 65 product lines. p_{iq} serves as a weight for incorporating convergence influence on firms. The more products a firm allocates in the product markets where IC is occurring, the higher the value of inside locus of convergence.

For the variable *competitors' DOF*, is measured by the average of a focal firm's competitors' DOF. *Firm age* is measured as the difference between the firm's founding year and the year in which it first entered the observation period. I then create three interaction variables by multiplying the three moderators with the main independent variable DOF.

Figure 6. Measure for Locus of Convergence



3.3.5 Control variables

Perceptual DOF. Measuring managerial attention has been a challenge for researchers. Given the rapidly changing nature of IC and the fact that cognitive attention can shift over time, survey based retrospective questions is not appropriate for my context. An increasingly used source for measuring attention is company annual reports. The method of content analysis is used to calculate word counts. It is typical for companies' executives to be involved in developing annual reports (Cho & Hambrick, 2006). Prior studies have shown empirical linkages between managerial attention captured by keywords in letters to shareholders and 10-k reports (Eggers & Kaplan, 2009; Nadkarni & Barr, 2008; Cho & Hambrick, 2006). Thus, for the variable *perception-based DOF,* I construct a list of keywords by looking into Telecom industry trade magazines and history-related materials (see Appendix C). The total number of words in company annual reports is counted to capture the degree to which each firm's attention to its competitive landscape shift. I then normalize each firm perceptual attention by dividing the total number of words in each shareholder letter. Following Eggers & Kaplan's (2009) approach, I calculate this perception variable as three-year decaying stock variable to capture attention during a window of time. I multiply the ratio by 1000 for the purpose of interpretation. The letters are retrieved from Mergent Online and Thompson One database. 746 letters (149 firms) are located. Compared to exposure-based DOF samples, this is because there are 693 reports that could not be obtained from libraries or the SEC database.

Firm size is controlled by using the natural logarithm of total sales. *Firm slack* may also affect firm performance, especially when the rapid changing environment requires firm to do exploratory activities. I use firm cash divided by its long-term debt for this measure. A firm's *industry origin* is used as a proxy for its internal resources and capabilities, which are key factors influencing performance. Because of the heterogeneity of consumer needs and technologies, firms originate from one industry may carry different resources and capabilities from firms coming from the other industry (Lee, 2007). As noted earlier, two industry firms are different in the sense that one comes from a voice-origin market while the other is from a data-origin market. Telecommunications equipment firms (SIC: 3661, 3663 and 3669) are coded 1, while computer networking firms (SIC: 3576) are code 0.

I control for the variable of *product breadth*, since firms tend to diversify their products in a highly uncertain environment. It is calculated by the Herfindahl concentration ratio across the 17 categories of product markets provided by CorpTech databse: $W_i = 1 - \sum_{s=1}^{17} P_{is}^2$,where P_{is} denotes the proportion of firm *i*'s total product lines categorized in class *s* (see Table1). The measure ranges from 0 to 1, with 1 indicating the highest level of product breadth. In addition, since the attractiveness of product markets (e.g. market growth) in which firm compete may affect its performance (Podolny et al., 1996), I control for this effect. Given that the data source is unavailable for market sales for each product line, I use the variable *product market attractiveness* operationalized as the number of competitors that a firm has divided by the number of products where the firm competes. The more competitors in a firm's product lines, the greater the firm benefits from legitimacy effects. For example, if a firm has four products and a total of four competitors, the aggregated density degree would be 1.

Since the ability to absorb learning from competitors is critical for the relationship between DOF and performance, this study employs two variables to control for this effect. Following prior research (Cohen & Levinthal, 1990; Phelps, 2011), I use R&D intensity (R&D expense divided by total sale) and patent stock (the number of telecommunication-related patents granted during the past four year) as proxies. Finally, I control for negative competition effects by using a variable *competitors' strength* measured as the average of a focal firm's competitors' sales. Consistent with prior research (Barnett, 1997), this variable control for the negative effect of strong competitors with abundant resources imposing on firm performance.

3.3.6 Analysis Model

I use cross-sectional time-series regressions with random-effect and generalized least square estimators (GLE). Fixed-effect models reduce degrees of freedom and potentially generate unstable results for a panel that has short time period (the time period per firm in my data ranges from 2 to 13 years). In addition, there are different assumptions between random- and fixed-effect models (Hsiao, 2003). Results generated from fixed-effect models cannot be extrapolated to a time period outside of the sample period, while random-effect model can be generalized to a longer time span. Thus, fixed-effect model may constrain the generalization of this study's prediction. Finally, fixed-effect models would delete time variables, which prevent us from identifying certain years in which IC had a particular influence on my model. Including year effect is also advantageous, since there may be a punctuated impact on performance (e.g. the year when Internet bubble broke). In addition, the result of Hausman specification test confirms that random-effect model is more appropriate than fixed-effect model. Finally, to handle potential autocorrelation problems (i.e. the correlation of errors across adjacent years), I incorporate first-order autoregressive errors in the models. The inclusion of AR(1) autoregressive coefficient in the model serves as a conservative test and thus increasing confidence in the causal interpretation of findings.

3.4 RESULTS

Table 4 reports the descriptive statistics and correlations. Since this study's model is built on interaction effects and the correlations between some variables are over 0.5, I carefully check for multicollinearity. Variables were centered by subtracting the sample mean from the individual values before the interaction variables were created. The values of variance inflation factors (VIF) are all under the critical value (i.e. 10) and the average VIF is 2.4, thus ruling out multicollinearity. Figure 7 illustrates the comparison of performance trends (1991-2003) between firms that a deep vs. shallow focus with arbitrary values. This chart demonstrates that firms who consistently maintain a deep focus perform better than firms with a shallow focus.

Figure 7. DOF and Firm Performance (1991-2003)

Performance:
$1000 US per Employee

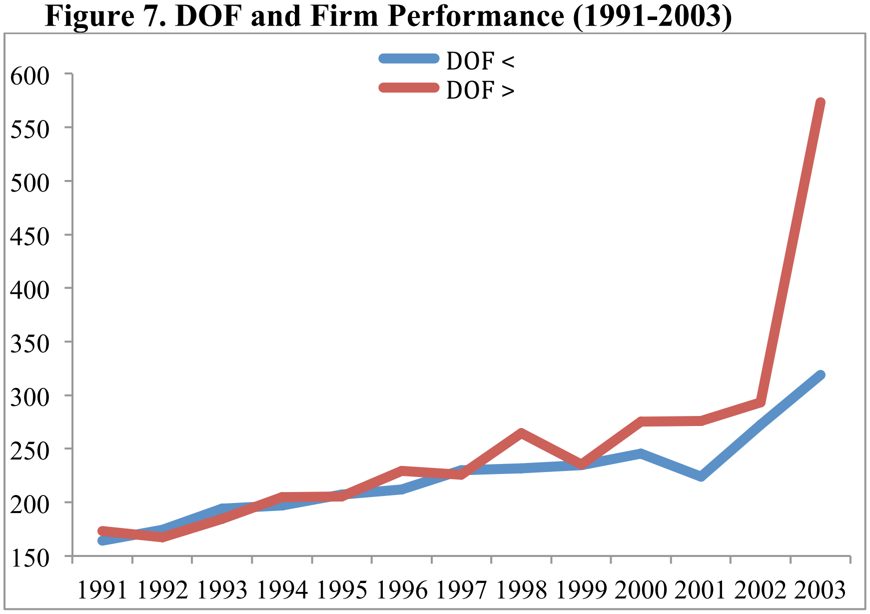


Table 4. Descriptive Statistics and Correlation (Essay Two)

		1	2	3	4	5	6	7	8	9	10	11	12	13
1	Firm performance	1.000												
2	Firm size	0.104	1.000											
3	Firm slack	-0.012	-0.139	1.000										
4	Industry origin	-0.097	0.130	-0.112	1.000									
5	Product breadth	0.034	0.260	0.015	0.009	1.000								
6	Product market attractiveness	0.085	-0.006	0.042	-0.213	-0.025	1.000							
7	R&D intensity	-0.024	-0.177	0.075	-0.060	0.016	0.045	1.000						
8	Patent stock	0.019	0.411	-0.026	0.090	0.181	-0.014	-0.008	1.000					
9	Competitors' strength	-0.010	0.013	0.029	0.126	0.268	0.069	0.026	-0.008	1.000				
10	Inside locus of convergence	0.014	0.009	0.031	-0.057	-0.032	0.489	0.031	0.017	0.161	1.000			
11	Competitors' DOF	0.072	0.117	0.058	-0.006	0.568	0.228	0.032	0.054	0.573	0.138	1.000		
12	Firm age	-0.058	0.333	-0.107	0.280	0.158	-0.100	-0.033	0.412	0.007	-0.068	0.005	1.000	
13	DOF (objective)	0.098	0.410	-0.015	-0.035	0.611	0.204	0.023	0.406	0.061	0.086	0.406	0.268	1.000
	Mean	238.73	4.27	1.12	0.67	0.42	16.83	0.33	34.43	2468.93	0.74	0.07	21.83	4.26
	Standard deviation	357.54	1.99	3.38	0.47	0.31	9.29	3.34	204.69	3574.75	0.31	6.32	17.03	5.82
	Min	0	-5.12	0	0	0	1	0	0	0	0	-7.6	1	0
	Max	1272	10.53	119.12	1	0.9	51	105.5	2672	37580	1	19.79	133	34.72

N = 1436. Correlations above 0.05 are significant at $p < 0.05$.

		1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	Firm performance	1.000													
2	Firm size	0.050	1.000												
3	Firm slack	-0.008	-0.153	1.000											
4	Industry origin	-0.105	0.111	-0.240	1.000										
5	Product breadth	0.048	0.325	-0.044	-0.001	1.000									
6	Product market attractiveness	0.072	-0.080	0.093	-0.250	-0.049	1.000								
7	R&D intensity	-0.010	-0.205	0.374	-0.216	-0.004	0.193	1.000							
8	Patent stock	0.004	0.052	0.003	0.083	0.280	0.095	0.036	1.000						
9	Competitors' strength	0.001	0.475	-0.065	0.100	0.223	-0.037	-0.027	-0.013	1.000					
10	Inside locus of convergence	0.016	-0.030	0.070	-0.039	-0.095	0.475	0.059	0.177	0.005	1.000				
11	Competitors' DOF	0.077	0.108	0.039	-0.105	0.580	0.196	0.093	0.550	0.037	0.092	1.000			
12	Firm age	-0.057	0.391	-0.210	0.289	0.233	-0.106	-0.159	0.007	0.493	-0.025	0.022	1.000		
13	DOF (objective)	0.102	0.472	-0.038	-0.051	0.624	0.144	0.030	0.058	0.448	0.046	0.371	0.367	1.000	
14	DOF (perceptual)	0.069	0.149	0.099	-0.151	0.023	0.063	0.012	-0.037	-0.046	0.076	-0.006	-0.104	0.034	1.000
	Mean	261.64	4.73	1.05	0.69	0.43	17.18	0.18	49.48	2484.79	0.76	0.28	22.93	4.56	2.14
	Standard deviation	476.47	1.89	1.57	0.46	0.31	8.88	0.33	252.38	3486.38	0.30	6.13	15.83	6.18	2.82
	Min	5.36	-2.72	0	0	0	1	0.01	0	0	0	-7.60	2	0	0
	Max	12724	10.53	19.75	1	0.90	51.00	5.89	2672	32751	1.00	18.07	89	34.72	26.80

N = 746. Correlations above 0.07 are significant at $p < 0.05$.

Table 5 presents the result of random-effect regression for the effect of exposure-based DOF on firm performance. Model 1 includes only the control and moderating variables and then I test the hypotheses by entering the main independent variable and each set of interaction effect Model 2 - 5. Model 6 reports the full model. The outcome of control variables shows that industry origin has significant effects on firm performance (Model 1-4: $p < 0.1$). Telecom equipment firms exhibit lower performance than computer networking firms during IC. This corresponds to the fact that the circuit-switching network was converged into the packet-switching network. Telephony firms tended to protect their previous technology core and were likely to be blindsided and disrupted.

Table 5. GLE Random-Effect Panel AR (1) Models for Performance (with objective DOF variable)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Control variables						
Year effect	Included	Included	Included	Included	Included	Included
Firm size	22.919**	19.825*	18.348*	19.949*	20.008*	18.226*
Firm slack	-0.224	-0.129	-0.325	-0.319	0.016	-0.464
Industry origin	-64.323*	-61.401+	-64.515*	-61.299+	-58.969+	-63.264*
Product breadth	-4.051	-61.517	-71.407	-12.887	-70.400	-28.045
Product market attractiveness	3.187+	2.365	2.638	2.121	1.976	2.127
R&D intensity	0.022	-0.194	-0.215	-0.011	-0.196	-0.019
Competitors' strength	-0.005	-0.004	-0.004	-0.002	-0.003	-0.002
Firm age	-1.663+	-1.844+	-1.799+	-1.675+	-1.952+	-1.690+
Inside locus of convergence	-42.468	-43.523	-118.356*	-41.076	-38.186	-131.910*
Competitors' DOF	4.989+	4.455	5.093+	7.817*	3.994	8.574**
Patent stock	0.015	-0.024	-0.007	-0.006	0.090	0.113
H1: DOF (objective)		6.555*	7.192*	-0.307	8.187*	1.194
H2: DOF (objective) x Inside locus of convergence			-26.346*			-33.607**
H3: DOF (objective) x Competitors' DOF				1.709**		1.876**
H4: DOF (objective) x Age					-0.224+	-0.184
Number of firm-year	1436	1436	1436	1436	1436	1436
Number of firm	225	225	225	225	225	225
Observation/firm	6.4	6.4	6.4	6.4	6.4	6.4
Wald X^2	37.32	37.32	42.56	44.45	37.43	54.6
Autocorrelation coefficient AR (1)	0.42	0.42	0.41	0.42	0.42	0.41

+p<0.10; *p<0.05; **p<0.01; ***p<0.001

Hypothesis 1 receives support. The independent variable, DOF, has significant positive effects in Model 2, 3, and 5 ($p < 0.01$), although it is not significant in the full Model. This is consistent with the position regarding the necessity of understanding DOF benefits and challenges through a contingency model.

In strong support of Hypothesis 2, Model 3 and 6 reveal that the positive impacts of DOF on firm performance is significantly reduced when the firm is inside locus of convergence (Model 3: $\beta = -26.346$, $p < 0.05$; Model 6: $\beta = -32.98$, $p < 0.01$), which suggests that when convergence hits product markets where a focal firm currently competes, the firm who has a shallow DOF enjoys better performance. A shallow focus allows the firm to pay more attention to how convergence will impact its own product markets.

Model 4 and 6 respectively show that competitors' DOF significantly enhances the positive effect of DOF on firm performance (Model 4: $\beta = 1.709$, $p < 0.01$; Model 6: $\beta = 2.027$, $p < 0.01$). Thus, Hypothesis 3 is supported. Competitors' DOF assists the focal firm in enriching its information processing capability in exploiting DOF benefits.

Confirming Hypothesis 4, model 5 indicates that younger firms benefit more from DOF than older firms ($\beta = -0.224$, $p < 0.1$). Established routines and inertia in older firms reduces their ability to resolve inertia, which inhibits initiative actions after deriving valuable information from a deep DOF.

Two additional interesting results are found after I analyze the patterns across all models. One, examining Model 4 and Model 6, I found that when entering competitors' DOF as a moderator, what is relevant for performance is the interaction effect of firm's DOF and competitors' DOF, not the main effect of firm's DOF (see the DOF coefficients in Model 4 and 6). This reinforces my argument with respect to the challenge of attention overload. Developing a deep DOF during IC is not enough, unless a firm can enhance its ability to separate critical signals from the volume of noise generated via DOF. Attending to competitors which have a deep DOF is one solution confirmed empirically. Two, I discovered that the relative impact of each contingency on the relationship between DOF and firm performance is different. Comparing Model 3 and 6, I found that the interaction effect of age and DOF becomes weaker when adding other interaction effect (inside locus of convergence or competitors' DOF). On the basis of the significance of the three contingencies in Model 6, the results show that the moderators of inside locus of convergence and competitors' DOF have stronger impacts on DOF performance than the age moderator. To illustrate the two aforementioned findings, I depict the three interaction results using one standard deviation above and below the mean to capture high and low value of each moderator. Figure 8 reveals that a deep DOF does not create firm performance when its competitors' DOF is shallow. This is consistent with the finding that overcoming attention overload is really the key in developing a deep DOF. This figure also exhibits that locus of convergence and competitors' DOF have more slope difference between high and low level than firm age, suggesting that external moderators have more impacts on the DOF-performance relationship than internal factors in the context of IC.

Figure 8. Contingencies of the DOF-Performance Relationship

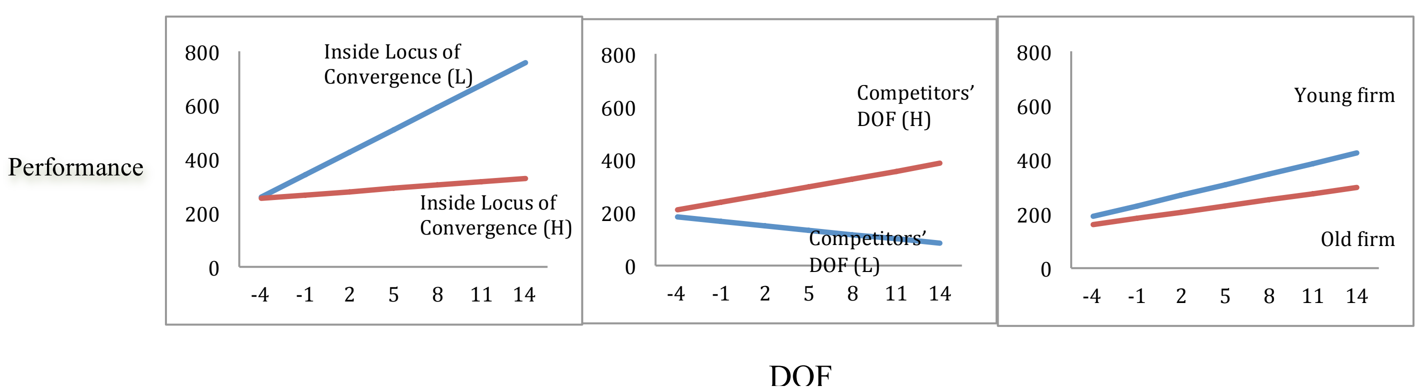


Table 6 presents the result of random-effect regression for the effect of both exposure-based and perception-based DOF on firm performance. The results in Model 1-5 show that the statistical significance pattern on H1, H2, H3, and H4 is similar to those of Table 3. This suggests that exposure-based DOF impacts are not influence by the introduction of perception-based DOF and that the two DOF variables are two different constructs. The low correlation between perception-based and exposure-based DOF ($r = 0.1$) reinforces the fact that the two variables are in orthogonal domains. Interestingly, Model 6 reveals that the interaction of perception-based and exposure-based DOF has a strongly significant effect on performance ($\beta = 7.753$, $p < 0.001$). Taken together, the two variables should not be integrated into one construct. To examine whether there is inter-temporal relationship between perception-based and exposure-based DOF, I lagged exposure-based DOF and regress it on perception-based DOF to see if exposure attention serves as a filter to frame a firm's perceptional attention on the environment. However, the result shows no significance.

I performed several analyses to assess the sensitivity and robustness of the results. I test if different industry origin changes the results. DOF benefits for firms in the industry where their fundamental technology were being substituted (telecom equipment firms) may be different from for firms in the industry where their fundamental technology were substituting another (computer networking firms). I decomposed data into two sets by industry origin: telecom equipment and computer networking firms. I found no significantly different patterns between telecom equipment and computer networking firms. A reasonable speculation is that during IC the two industry firms gradually become indistinguishable since these firms' cross-industry diversification blurs their previous industry identity. Therefore, it is appropriate to pool the two types of firms in the dataset. In addition, the empirical results include firms that operate in only one product line. This case may raise a concern that the reason why firms could not benefit from DOF is simply that they do not have resources to deepen DOF. I therefore excluded this kind of firm from the sample set and reran the analysis, but find no qualitatively different results. Finally, since the mechanism of the DOF model is based on benefit/challenge arguments, one alternative model specification on the relationship between DOF and performance would be curvilinear. I made an effort by checking the square term effect of DOF on performance. I did not find significant results. This suggests that during IC a firm's performance neither increasingly drops nor enhances as it deepens its DOF from a moderate to a high level. Hence, a linear relationship is a better fit for my model. An interesting extension would be to test if the curvilinear impact of DOF on performance is more appropriate in other settings than in the IC context, such as the relatively boundary-stable industries.

Table 6. GLE Random-Effect Panel AR (1) Models for Performance (with objective and perceptual DOF variable)

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Control variables						
Year effect	Included	Included	Included	Included	Included	Included
Firm size	-0.174	-1.754	-0.365	-0.805	-2.725	-2.532
Firm slack	-7.859	-7.164	-8.466	-6.950	-7.074	-3.151
Industry origin	-80.477	-89.293+	-79.766	-74.343	-85.503	-99.506+
Product breadth	-68.251	-68.551	-19.769	-101.737	-35.131	-23.579
Product market attractiveness	1.910	2.401	2.008	1.428	2.249	2.420
R&D intensity	-55.929	-53.727	-54.342	-55.567	-50.964	-56.874
Competitors' strength	0.000	-0.001	0.001	0.000	0.000	0.000
Firm age	-2.584	-2.610	-2.104	-2.210	-1.743	-2.027
Inside locus of convergence	-70.869	-177.183+	-71.810	-68.725	-197.632*	-227.511*
Competitors' DOF	2.577	3.404	6.929	2.190	8.583	10.552*
Patent stock	-0.016	0.011	0.010	0.123	0.154	0.231+
DOF (perceptual)	15.813*	15.669*	16.542*	16.449*	16.990*	16.092*
H1: DOF (objective)	11.992*	12.403*	4.523	15.945**	6.384	3.467
H2: DOF (objective) x Inside locus of convergence		-43.823*			-52.451**	-61.844***
H3: DOF (objective) x Competitors' DOF			2.053*		2.496*	3.198**
H4: DOF (objective) x Age				-0.314+	-0.237	-0.209
DOF (objective) x DOF (perceptual)						7.753***
Number of firm-year	746	746	746	746	746	746
Number of firm	179	179	179	179	179	179
Observation/firm	4.2	4.2	4.2	4.2	4.2	4.2
Wald X^2	32.73	39.56	37.31	36.13	49.3	86.55

+p<0.10; *p<0.05; **p<0.01; ***p<0.001

3.5 DISCUSSION

The purpose of the present work is to examine the performance linkage of firms' depth of field during IC by proposing a contingency framework. Overall, a firm's deep DOF contributes to its performance during IC. Furthermore, I found that the performance benefit of a deep DOF is weakened when convergence occurs in product markets where a firm competes, when most of its competitors have a shallow DOF, and when the firm is relatively old. This study contributes to literature in several unique ways.

First, this paper adds to the intersection of industry evolution and organizational attention literature by advancing the construct of DOF. Explanations of firm performance during industry changes have been developed on the basis of two views that progressed independently: industry structure (Scherer & Ross, 1990) and organizational attention (Daft & Weick, 1984; Bogner & Barr, 2000). Although a few of recent studies begun to connect the two lines of research (Nadkarni & Barr, 2008; Nadkarni & Narayanan, 2007), they mainly focus on cognition-based attention. This paper sheds an insight on the performance predicator of firms under industry changes by bridging the gap between the two research streams from a different angle those pioneering studies. As Ocasio (1997) pointed out, theories of attention have deemphasized the role of structure (how the composition of context affects organizational attention). In Simon's (1947) seminal work, structure plays an equally important role as cognition does. In this paper, the exposure-base DOF construct is ground at the structure view of social psychology. DOF has a dual emphasis on a focal firm's and its competitors' product market configuration. In other words, a deep focus is a joint outcome of the firm and competitors' market entry decisions. DOF, therefore, is particularly important in the dynamic context of IC where industry boundaries coevolve with firm boundaries. A deep focus puts a firm in a position that draws its attention to multiple different competitors simultaneously and helps to appreciate more complex and sometimes contradictory interpretation of what the changing competitive landscape means. Consistent with Tsai et al. (2011), this paper holds a view that firms should carefully and dynamically manage their market configuration and enter product markets that are of strategic significance for exposure to many dissimilar competitors during IC.

In a HBR interview (Fryer & Stewart, 2008), Cisco's CEO (John Chambers) share how he was able to read market trends before anyone else did through his childhood experience and a lesson learnt from battling with IBM. At the time Cisco became the dominant player in computer network, equipment makers only competed with other equipment makers, while software firms competed with other software firms. Competing in both of these markets allowed Cisco to move more quickly with cutting-edge developments than its rivals that compete only in the equipment business. While this purpose of this paper is not to examine where a firm's deep focus comes from (i.e. how a firm knows which of product markets can deepen its DOF), studying the antecedents of firms' DOF is a fruitful area of future research.

It is useful to use DOF data to take a closer look at the Cisco's case. Table 7 illustrates the changes of Cisco's DOF across time. In 1991, Cisco only had one major multimarket competitor, MICROCOM. In 1995, because of product market expansion, it encountered 14 competitors. At this point, Cisco's competitor variety was 0.393 and DOF was 5.502 (14 x 0.393). In 2002, Cisco had established a deep DOF (20.628) through exposing to 54 competitors (see Table 7: the competitor variety score ranges from 0.86 to 0.15). The data implies that

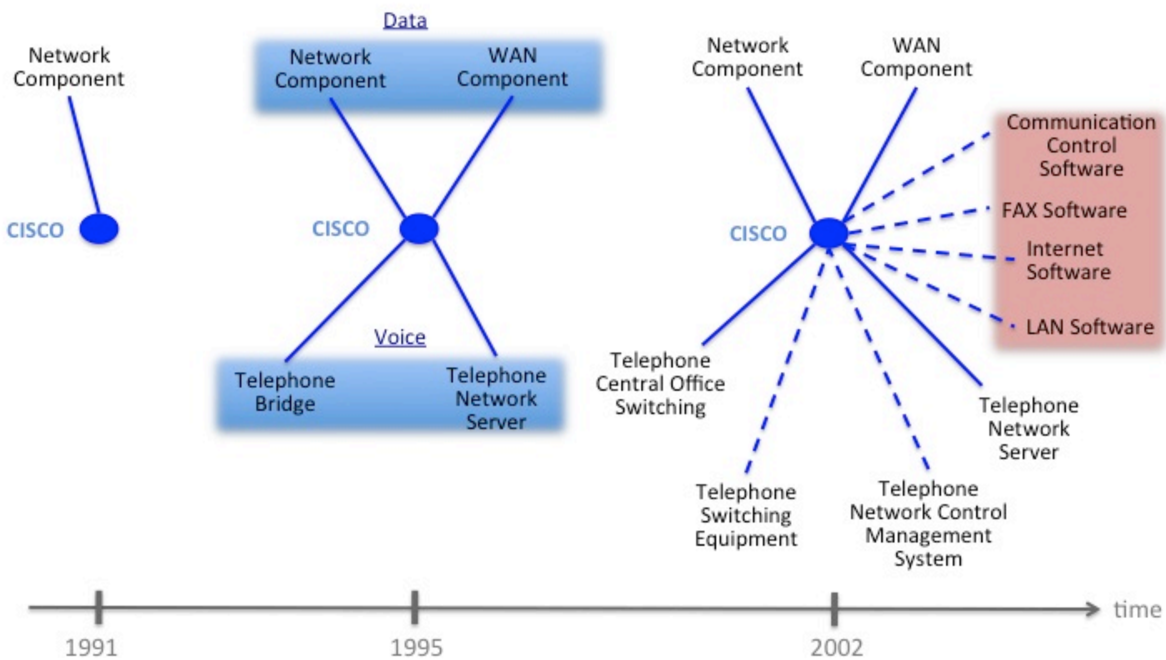
Cisco's top management team had a vision as to where to meet diverse competitors. According to Figure 9, Cisco had established market presence in voice-related segments in 1995 and software-related products in 2002. The two strategic moves enabled the company to expose numerous different competitors, thus deepening DOF. Here is another interesting finding. In Figure 9, 3COM' distance to Cisco in 1995 was 0.454, while the distance in 2002 decreased to 0.178. This is consistent with my earlier argument that DOF is the joint outcome of a focal firm's and its competitors product configuration. The value of 0.178 suggests that Cisco and 3COM had become similar to each other in 2002. Cisco would not have been able to sustain a deep DOF if it diversified into the same product markets as competitors did.

The contingency model also makes a contribution to organizational attention theory by resolving the tension between the limitation of organizational attention scarcity and the requisite for attention breadth. Because of limited capacity, managers attend to a few specific issues that they consider crucial, and then allocate attention to other issues subsequently (Cyert & March, 1963). Recent behavioral theory of the firm's studies kept sharpening our knowledge of sequential attention (Greve, 2008; Iyer & Miller, 2008; Vissa et al., 2010). Indeed, sequential attention has the values of attention stability and quality for firms (Rerup, 2011) and prevents firms from recognizing emerging and/or peripheral issues that may change its environment. IC is an appropriate context for investigating how firms can reconcile this tension. Evidences of this paper provide a managerial implication that firms need to *optimize* their DOF according to the locus of IC as well as competitors' focus depth. In fact, attending toward specific issue (a shallow focus) still has its own value especially when firm is within the locus of convergence. On the other hand, a deep focus may backfire firm performance when it attends to a lot of shallow-focus competitors. As far as firm age is concerned, the results reveal that performance effect of a firm's attention toward multiple different competitors would vary in different points in the firm's age. Older firms derive less benefit from a deep focus than younger firms. The result should be carefully interpreted within the context of IC. Firm age represents the length of time that the firm has experienced the pre-convergence environment, which becomes a liability when the firm attempts to filter in and assimilate a large amount and wide range of competitors' move information

Figure 7. Cisco's DOF in the 1990s

1991		1995		2002	
Competitor	**Distance to Cisco**	**Competitor**	**Distance to Cisco**	**Competitor**	**Distance to Cisco**
MICROCOM	0.500	SCIENTIFIC-ATLANTA	0.771	SCIENTIFIC-ATLANTA	0.864
		WEGENER	0.564	ZHONE TECHNOLOGIES	0.855
		MICRODYNE	0.484	INTERPHASE	0.832
		ADC TELECOMMUNICATIONS	0.469	TERAYON COMMUN SYSTEMS	0.748
		3COM	0.454	VIASAT	0.738
		INTERPHASE	0.452	COPPER MOUNTAIN NETWORKS	0.686
		CROSSCOM	0.423	ADAPTEC	0.661
		MICROCOM	0.388	CASTELLE	0.657
		FOCUS ENHANCEMENTS	0.293	MOTOROLA	0.648
		GANDALF TECHNOLOGIES	0.293	SORRENTO NETWORKS	0.642
		CASCADE COMMUNICATIONS	0.270	LARSCOM	0.585
		SHIVA	0.270	BROOKTROUT	0.580
		BAY NETWORKS	0.207	COMVERSE TECHNOLOGY	0.550
		TELCO SYSTEMS	0.178	ITRON	0.520
				AVAYA	0.507
				UTSTARCOM	0.475
				COMDIAL	0.441
				C-COR	0.375
				SONICWALL	0.372
				TEKELEC	0.367
				WESTELL TECH	0.360
				LUCENT	0.357
				ECHELON	0.347
				VINA TECHNOLOGIES	0.327
				MRV COMMUNICATIONS	0.327
				NETWORK EQUIPMENT TECH	0.325
				POLYCOM	0.315
				COMPUTER NETWORK TECH	0.315
				MCDATA	0.288
				TUT SYSTEMS	0.288
				AVICI SYSTEMS	0.288
				AVOCENT	0.288
				DIGI INTERNATIONAL	0.288
				ENTERASYS NETWORKS	0.288
				SBE	0.288
				ASANTE TECHNOLOGIES	0.287
				ECI TELECOMMUNICATIONS	0.283
				FIRST VIRTUAL COMMUNICATIONS	0.246
				CYBER DIGITAL	0.238
				ZOOM TECHNOLOGIES	0.210
				ADC TELECOMMUNICATIONS	0.197
				NETOPIA	0.193
				LANTRONIX	0.182
				3COM	0.178
				NORTEL NETWORKS	0.171
				MCK COMMUNICATIONS	0.161
				TELLIUM	0.161
				ERICSSON TEL	0.161
				EMULEX	0.156
				APPLIED INNOVATION	0.151
				EXTREME NETWORKS	0.151
				FOUNDRY NETWORKS	0.151
Number of competitors: 1	Variety of competitors: 0.5	Number of competitors: 14	Variety of competitors: 0.393	Number of competitors: 52	Variety of competitors: 0.382

Figure 9. Cisco's Product Portfolio in the 1990s



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Third, this paper extends IC research by providing a measure for investigating the degree of IC via conceptualizing the notion of locus of convergence. Prior research mostly assumes that there is only one product market for each industry undergoing convergence (Greenstein & Khanna, 1997). My operationalization relaxes the single product market assumption (Klepper & Thompson, 2006) and illustrates a nuanced and novel approach of assessing the extent of IC. Operationalization of IC has been a bottleneck in IC studies and therefore most studies have been qualitative and descriptive in nature. With this empirical indicator, one can explore various kinds of IC dynamics, including rate, turbulence, and asymmetry. Locus of convergence therefore serves as a foundation for future studies on the above three facets of IC. Another value of locus of convergence is that IC becomes testable and can be linked with the antecedents of IC. As noted earlier, the process aspect of IC receives little attention. One promising avenue is to connect industry convergence with technology convergence, which has been viewed as one of IC's triggers. The convergence literature has developed measures indicating the extent to which firms are involved in technology convergence by using the patent co-citation data across industries (Avenel *et al.,* 2007; Gambardella & Torrisi, 1998). Researchers can examine how the extent of IC varies due to different types of technology convergence. Finally, assembling maps of locus of convergence longitudinally allow managers to develop an understanding of a dynamic view of IC.

My results should be viewed in light of several limitations. First, as mentioned in Appendix A, I develop the DOF theory of firm performance by focusing on one type of IC. One future research direction could be to integrate the categorization of IC with this paper by asking a question: do different types of IC affect the utility of DOF. Second, I recognize that the notion of DOF rests on the assumption that the understanding of newly developed patterns in the competitive landscape should be accurate. An emerging line of managerial cognition research shows that the way firms interpret their environment, such as controllability and positive/negative expectation, is more important than how accurately they know their environments (Sutcliffe & Weber, 2003). For instance, future studies can decompose DOF into perceptual accuracy and interpretation (i.e. how they frame new situations) about firm's competitive environment and then test the relative impact on performance. Finally, generalizing this study's framework and the DOF argument to other industries is important. Other kinds of industry evolution, such as industry-level vertical (de)integration, would be ideal for studying the generalizability of my findings.

4.0 EPILOGUE

In conclusion, I developed one framework for the understanding of how firms use alliance experience and initial acquisition to resolve uncertainties brought by IC. I also illustrated a promising construct of DOF for explaining firm performance difference during IC. The two essays made contributions to a growing body of alliance-acquisition relationship research as well as the industry change literature. Further extensions of these ideas will enrich theory about IC and will provide managers with important insight on how to avoid competitive blindspots and discover entrepreneurial opportunities in the world of convergence.

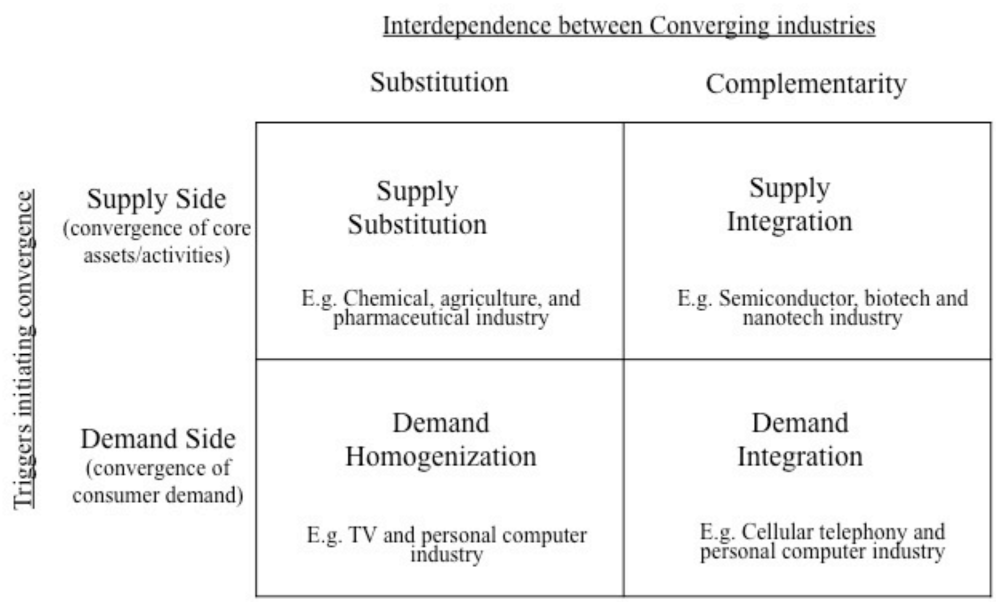
As Hamel and Prahalad (1996: 240) suggest, our industrialized society has shifted toward a new economy in which many industries are in “a state of flux”. Nevertheless, the theorizing regarding IC has been under-developed for over a decade. The moral of my story is that IC is one of important topics for managers in the 21st century. The era of convergence is upon us; it is thus and opportune time to create an impactful research agenda.

APPENDIX A: WHAT INDUSTRY CONVERGENCE MEANS

While this paper is not to resolve the complex set of issues involving the definitions and classifications of IC, it is important to provide a conceptual backdrop that serves as a boundary condition for this study. In doing so, I embrace the conceptualization of multiple types of IC. Building on prior research (Christensen, 2011; McGahan, 2004; Pennings & Puranam, 2000), I provide a synthesis highlighting two dimensions: interdependence and triggers (see Figure 10). Interdependence is defined as the form of mutuality between two industries. There are two forms of interdependence underlying convergence. IC can be substitution-based when consumers consider a product in one industry interchangeable with another industry's product or complementarity-based when users consider that products work better together than separately (Greenstein & Khanna, 1997). Substitution-based IC typically renews existing industry structures. Digital imaging technology has restructured the photo equipment and consumer electronics industry structures by involving devices that take and process pictures using electronics instead of film. Complementarity-based IC creates new market/industries. The combination of drug and device technologies have created several new markets such as drug-coated devices and drug delivery devices where new products deliver drugs directly into human bodies, providing greater efficiency and therapeutic effect than oral forms of drug delivery.

From the triggers or antecedent perspective, IC can be initiated due to supply- or demand-side factors (Pennings & Puranam, 2000). One the supply side, technology convergence has been recognized as a cause of IC. McGahan (2004) suggests the use of core asset (e.g. technology, product or know-how) and core activity (e.g. purchasing, operation or distribution) for analyzing industry evolution. Because her approach considers a wide variety of firm-related IC antecedents, I classify it as a supply-side antecedent. Supply-side antecedents are the convergence of core asset and activity either acting independently or in combination. On the demand side, convergence can be the result of consumers perceiving products from different industries functionally similar or complementary. Adner (2002) posits that while technological disruption can explain the reason why the distinction between the impacted markets becomes blurred, how consumer evaluate the technology plays an equally important role.

Figure 10. Taxonomy of Industry Convergence



Note: Adapted from prior research on IC (Christensen, 2011, McGahan, 2004, Pennings & Puranam, 2000)

Combining the two dimensions generates four types of IC: supply substitution, supply integration, demand homogenization and demand integration (see Figure 7). In *supply substitution*, convergence is initiated when the core asset/activity bases of two or more industries become similar in the sense that they can satisfy the same set of needs. Research on converging technologies (Rosenberg, 1976) and general-purposed technologies (Bresnahan & Trajtenberg, 1995) are illustrations of this type of IC. In the early 2000s, firms' abilities to manipulate the genetic codes of living things led to the convergence of the agriculture, chemical, and pharmaceutical industry (Enriquez and Goldberg, 2000). When a chemical company, such as Monsanto and DuPont invent genetically modified seeds and sell to farmers, they become agricultural companies' competitors. In *supply integration*, convergence occurs when the different industry core asset/activities are brought together to create new kinds of industries, markets or products. Kodama's (1992) technology fusion concept is an example. For instance, the semiconductor, biotech and nanotech IC has recently created one new sector (Hacklin, 2008).

In *demand integration*, convergence is driven by the fact that there is a need from the customer's side for one stop shopping, a concept related to product bundling in the marketing literature (Prasad, Venkatesh, and Mahajan, 2011). A notable example is the convergence of cellular telephony and the computer industry. One of the main reasons that the smart phone market has taken off is that consumers desire devices that can satisfy mobile social networking needs (e.g. Facebook, Twitter). The fourth type, *demand homogenization* is reflected in the growing similarity of needs across groups of consumers that relate one industry to another. For instance, while consumers used to think of PC and TV as serving different purposes, there are more and more people considering them as substitutes for one another, which facilitate the convergence between personal computer and TV industry. Note that demand homogenization may or may not be driven by the advent of supply substitution. For example, the case of genetic modification convergence in supply substitution is currently facing a barrier regarding how to manage the public's opposition and fear to genetic foods.

Given that the literature is still emerging I focus on one type of IC (supply substitution) for the sake of theoretical and empirical clarity but also because it is important and interesting in its own right.

APPENDIX B: TELECOM INDUSTRY CONTEXT

How did voice-data convergence *exactly* influence the Telecom and PC networking industries? To answer this question, one needs to understand how their industry infrastructure (the way communication systems are connected) was fundamentally changed in the 1990s. I leverage Fransman (2002)'s layer model to explain this fundamental transformation (see Figure 8). His model is developed on the basis on OSI (Open Systems Interconnection) concept – a prescription of characterizing and standardizing the functions of a communications system in terms of abstraction layers. Similar communication functions are grouped into the same layers. A layer serves the layer above it and is served by the layer below it.

In 1980s, the Telecom industry infrastructure is based on a simple three-layer model. These layers were vertically integrated within a few telecom operators. Thus, the engine of innovation of telecom equipment was located in these monopolies' R&D laboratories (e.g. AT&T's Bell Laboratories and BT's Martlesham Laboratories) which played the key role of implementing new generations of switches, transmission system equipment. Given high vertical integration, telecom operators were able to create a closed innovation system characterized as high entry barriers. Also, under this system, the innovation process was slow and sequential. This feature fits well with the circuit-switch network which requires a extremely high degree of reliability. Equipment failure could lead to the entire network shut down.

Figure 11. The Telecom Industry Infrastructure Change in the 1990s

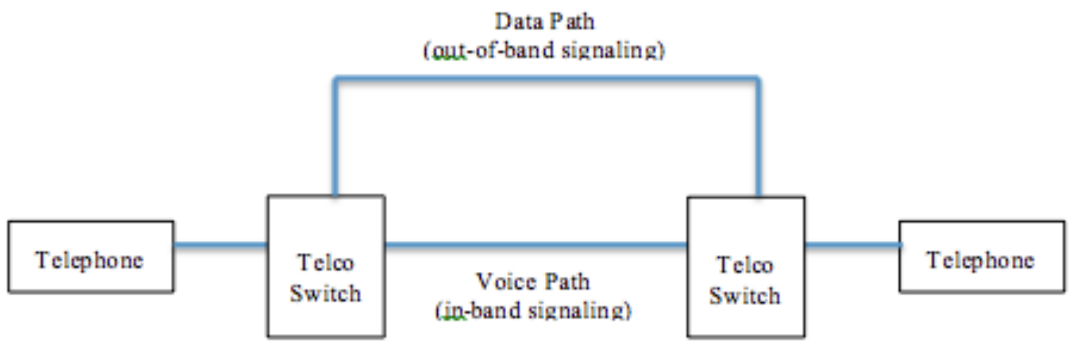
1980s	1990s	
	Layer 5: Application layer (web design, content providers, broadcasting services)	News Corp, Amazon, Reuters
	Layer 4: Navigation Layer (browsers, search engines, portals)	Google, Yahoo
	Layer 3: Connectivity layer (Internet access, Web hosting)	ISPs
	<u>IP interface</u>	
Layer 3: Service layers (voice, fax, 800 services)		
Layer 2: Network layer (circuit-switched network)	Layer 2: Network layer (packet-switch network - DSL, Ethernet, frame relay, ATM network)	AT&T, Qwest
Layer 1: Equipment layer (switches, transmission equipment)	Layer 1: Equipment & Software layer (switches, transmission, routers, servers, billing software)	Nortel, Lucent, Cisco

(Adapted from Fransman, 2002)

In the 1990s, the advent of IP (one generic Internet technology including packet-switching technology and the World Wide Web) transformed the Telecom industry in two ways. It makes communication across a diverse of networks possible. This enlarges the size of each layer. More importantly, IP allows the layers above IP interface to operate separated from the layers below IP interface. Using one example of IP technologies (i.e. digital switch), Figure 11 illustrates how that works. Digital switches are the devices controlling the process and interacting other systems. Out-of-band signaling system is one type of networks under digital switch concept (Sterling et al., 2006). Traditionally, within in-band signaling system, the call and information about the call travelled in the same path. This limited space for information. It was also an inefficient since it occupied the whole call path. In out-of-band signaling, the call and information about the call travel over different paths. As the Figure 9 shows, the call traveled in the regular telephony network, information about the call went through a separate packet-switched data network. With digital switch, Telecom operators could offer more new services in a creative and less costly way.

Just like the example in Figure 11, many new types of communication networks linking people became possible, and yet they could continue to operate in the traditional telephony network. Three new layers emerged (see Layer 3, 4, and 5 in Figure 8) in the 1990s. The change of communication layers has important implications for understanding the evolution of the Telecom industry. IP facilitated the division of labor in knowledge creation, thus reducing the incentives for telecom operators to include equipment (Layer 1 in the 1980s) within their organizations. Therefore, Layer 1 (in the 1990s) was outsourced to specialized equipment makers (e.g. Lucent, Nortel). IP also lowered entry barriers of telecom equipment by bring firms from computer industries previously considered to be separate from the Telecom industry. Finally, newly emerged layers (Layer 3-5) in the 1990s further nurtured the demand for Layer 1 and 2. While the empirical setting of this paper focuses on firms in Layer 1, Figure 12 suggests that the viability of Layer 1 is highly dependent on the other four layers. From a retrospective view, we have already known that the Telecom industry underwent boom and bust during the 1991-2003 period. However, for managers facing those infrastructure changes “within” that period, they have limited knowledge of how the new industry worked, how it was changing, and what would happen to key parameters in each of layers and the extent of new entry. Managers’ knowledge is embodied in their understanding of the business landscape. The DOF construct introduced in this paper helps to explain how firms cope with this industry change.

Figure 12. Digital Switch

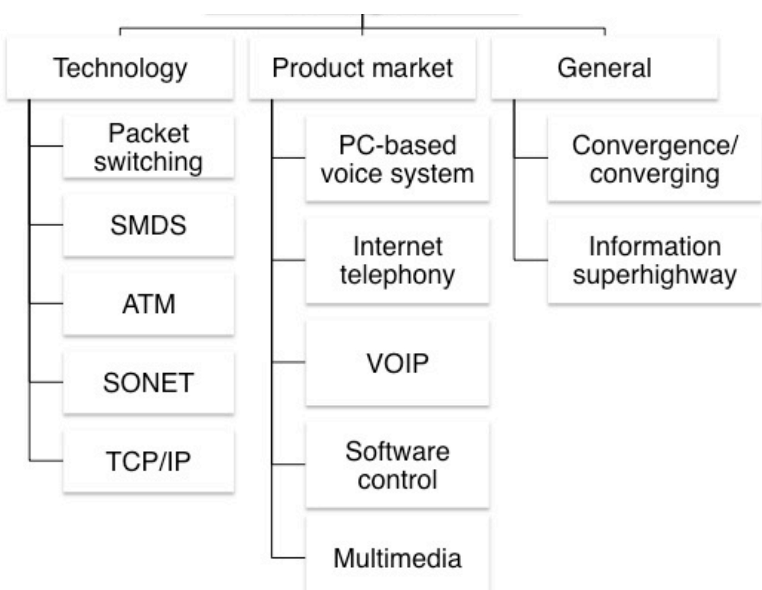


(Adapted from Sterling et al., 2006)

APPENDIX C: MEASURING ATTENTION TOWARD LANDSCAPE SHIFT

I establish a list of words to measure firm attention by using CEO letters to shareholders. One may concern that those letters may not communicate firms' actual views to shareholders, either because it is the public relation department (not CEO) who addresses something that financial institutions prefer to know. The first case is unlikely because all letters were sent out under CEO signature and closely edited by them (Cho & Hambrick, 2006). Figure 13 shows the words associated with CEOs' perception on their landscape. These words are categorized into three groups: technology-related, product-market-related, and convergence in general.

Figure 13. List of Words Measuring Attention to Landscape Shift



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