Organizing to learn, learning to organize: Path dependent and path independent learning in the formation processes of R&D consortia

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Abstract

This study examines path dependence and path independence in organizational learning processes with respect to the formation of interorganizational relationships. We focus on whether companies engage in more than one mode of learning as they form new consortium relationships. This study builds on prior work, which identifies two different consortium formation processes. We analyze the patterns of R&D consortia formation processes, in the United States, over a 22-year period. The data include 3767 independent consortium joining events for 1063 companies entering into alliances with 737 consortia in the period 1984-2005. From this analysis we are able to identify patterns of path dependence and path independence with respect to the formation processes that companies choose. Drawing parallels with the learning processes of learning-by-doing, adaptive learning and improvisation, we argue that while history is a strong force for inertia, external environmental conditions, and individual firm characteristics are a significant force for path-independence. These results not only suggest that path dependence and independence are present in the process of organizational structuring, but also provide evidence for the sources of path independence. These results provide support for the emerging perspective of organizational ambidexterity, where companies engage in multiple types of learning.

Key words: Path dependence; organizational innovation; R&D consortia; organizational learning; ambidexterity

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The ability to identify partners for collaboration, form productive cooperative relationships and assimilate new knowledge and capabilities from these arrangements is significant for firm effectiveness in dynamic environments (Hamel, 1991; Lorenzoni & Lipparini, 1999). This research focuses on how firms acquire the ability to identify partners and build research and development (R&D) consortia. In examining this important phenomenon, we highlight the influence of path dependence in consortium formation behavior and seek to identify firm and environmental factors that lead to path breaking and path independent behavior by firms.

R&D consortia may be defined as contractual alliances between two or more partners, formed to share the costs and benefits of research and development activities (Hagedoorn, 2002). These consortia offer a lower-cost and flexible approach to the acquisition of technological capabilities when compared with the firm's internal development of such capabilities. R&D consortia facilitate the sharing of risk, encouraging collaboration and the development of new knowledge that fosters the creation of new capabilities (Gomes-Casseres, et al., 2006). As part of a wide range of possible interorganizational ties and external sources of knowledge, we focus on these consortia because they are a known source of new capabilities that have been found to improve firm financial and stock market performance (e.g., Hagedoorn & Schakenraad, 1994; Kale, Dyer & Singh, 2002; Sarkar, Echambi & Harrison, 2001).

Firms differ markedly in their ability to identify and exploit opportunities for external knowledge acquisition (Gulati, 1999; McEvily & Zaheer, 1999). The challenges associated with the formation and maintenance of close ties between otherwise independent firms are formidable. These challenges include identifying partners with compatible goals, building a stable relationship, managing conflicts, avoiding or controlling partner opportunism, and ensuring effective knowledge transfer (Das, 2006; Inkpen & Tsang, 2005). It is clear that new knowledge obtained from inter-firm cooperation can lead to technological advantages. However, because such advantages can be short-lived, firms must also become adept at continuously identifying, developing and capitalizing on interorganizational relationships (Doz, 1996; Teece, Pisano & Shuen, 1997; Zollo & Winter, 2002).

Heterogeneity in firms' abilities to identify and exploit opportunities for the formation of interorganizational relationships can itself be a source of competitive advantage (Gulati, 1999; McEvily & Zaheer, 1999). Therefore, it is important to understand the extent to which such capabilities are subject to inertial forces in the form of path dependence, and the factors that may be associated with, or facilitate path breaking, and path independence for individual firms.

The sources of firm heterogeneity with respect to the formation of alliances are not completely understood. However, most research interest has focused on firms' internal resources and their embeddedness in networks of relationships as a key influence on the partner identification and alliance formation process (Gulati, 1999; Inkpen & Tsang, 2005; McEvily & Marcus, 2005). We build on this embeddedness perspective by introducing important organizational, relational and environmental contingencies into the explanation of how firms become adept at finding partners and building new relationships. We examine the impact that these factors have, jointly and independently, on path dependencies in the choice of consortium formation process. Thus, the research question we ask is: How do firm characteristics, firm prior experience, industry and inter-organizational environments influence path dependence in the R&D consortia formation processes?

This paper makes a number of contributions to the literature on path dependence, organizational learning and R&D consortia. This research provides an empirical test of path-dependence in the context of consortium formation. We also examine factors that support path breaking and path independence in this context. The present study provides evidence of these three distinct processes for firms learning to form R&D consortium relationships. Furthermore, we identify antecedents for each learning process, and the relative marginal contribution of each of these diverse forces for this organizational capability.

Our second contribution is to connect path independence with the phenomenon of ambidexterity. Ambidexterity requires both being good at aligning existing capabilities to exploit them to the fullest and being good at adapting to new opportunities (Birkinshaw & Gibson, 2004; Tushman & O'Reilly, 1996). Recent examinations of ambidexterity have focused on product and process innovation (Birkinshaw & Gibson, 2004; He & Wong, 2004; Lavie & Rosenkopf, 2006). It is important to recognize that innovation takes place outside of the realms of product and process. Organizational innovation provides an alternative context in which innovation can be a source of competitive advantage. This study provides evidence for ambidexterity in an organizational innovation, as well as the antecedents of this phenomenon. Specifically, we look for evidence of exploitation, exploration and ambidexterity *in the processes through which R&D consortia are formed*.

A third contribution of our research is in the integration of longitudinal data at both the consortium and firm levels in our analysis of organizational learning. Thus, we examine the interplay among established interorganizational networks, individual firm histories and the formation of R&D consortia formed in the U.S. over a 22 year period--from the establishment of the National Cooperative Research Act (NCRA) in 1984 through to 2005. Our study offers a unique empirical examination of the development of a significant form of organizational learning over time and across industries.

Theory and Hypotheses

Though increasing attention has been given to the development of collaborative capabilities by firms (Ahuja, 2000; Ireland, Hitt & Vaidyanath, 2002), this literature has largely focused upon the motives for forming alliances and the structures of these alliances and factors leading to knowledge acquisition, integration and exploitation. Less attention has been paid to the dynamic formation processes underlying alliances (Doz, 1996; Ring & Van de Ven, 1994). The success of an alliance is ultimately dependent upon the effective cooperation and coordination of partners (Doz, 1996), coupled with the ability to absorb new knowledge (Zahra & George, 2002). To successfully exploit external knowledge sources, firms must first identify suitable partners, form alliances, develop trusting, cooperative associations, transfer and assimilate knowledge (Das & Teng, 1998; Zahra & George, 2002).

Doz et al. (2000) identify two distinct formation processes for R&D consortia (see Table 1 for details). Consortia formed spontaneously by firms that are already aware of one another may be referred to as 'emergent consortia.' Those consortia are formed among firms that operate in an emergent network with common suppliers, customers, and alliance partners. Emergent consortia formation processes reflect several interdependent factors. Notably, potential members will often operate in the same or a related industry, be served by the same suppliers, or serve the same group of customers. These conditions increase the likelihood that the future partners already be aware of one another, even though they may not have directly worked together. Further, the presence of common resource needs and strategic goals increases the likelihood that firms will know about their future partners, and share environmental threats and technological opportunities. Moreover, technological relatedness between firms increases their ability to understand a potential partner's knowledge base.

Insert Table 1 About Here

The second consortium formation process that Doz et al. (2000) identified is labeled as 'engineered.' In this formation process, firms are typically unaware of the existence of their potential partners, or at least of the relevant capabilities that may be available through collaborative relationships. Because these organizations operate in different strategic arenas, they are likely to have fewer common threats, shared interests or network ties (Gulati, 1999). Firms that do not face the same environment, do not come from similar industries, and do not have high levels of technological relatedness are expected to have difficulty finding one another (Das & Teng, 1998). These factors reduce the likelihood of emergent alliance formation processes from occurring. This leads to opportunities for individual or organizational ‘champions or even third parties -- such as universities or government agencies, -- to serve to link potential partners (Doz et al., 2000).

These two formation processes involve qualitatively different organizational skills, routines, and capabilities with respect to alliance formation and management. Specifically, partner identification, the initiation of contact, bargaining, developing contracts, and finally the structuring of relationship governance mechanisms are expected to vary systematically across emergent and engineered forms of consortia. In order to better understand the development of these capabilities, and to identify influential factors, we turn to organizational learning theory (Argote, 1999; March, 1991).

Organizational Learning Theory

Organizational learning theory highlights multiple learning processes, including learning-by-doing, adaptive learning, trial and error, experimental learning, and improvisational learning (March, 1991; Miner et al., 2001). We focus on three learning processes that may be applicable to the development of path-related capabilities for forming R&D consortia: learning-by-doing (i.e., history or path dependence), adaptive learning (i.e., path breaking), and improvisational learning. These three processes are indicative of the learning dynamics underlying exploitation, exploration, and ambidexterity in the context of organizational innovation. While exploitation involves the incremental refinement of existing routines (learning by doing), exploration involves an active search for new routines (adaptation), and ambidexterity involves a careful balancing of the two opposing processes in a form of improvisation. We further expand on these ideas in the following paragraphs.

The literature suggests that capability development occurs through learning-by-doing (Levinthal & March, 1993; March, 1991; Nelson & Winter, 1982). Learning-by-doing describes situations in which experience leads to an increasing understanding of a process, which tends to result in increased efficiency (Argote, 1999). Learning-by-doing leads to the development of strategic capabilities through a routine building process. That is, organizational routines are acquired, developed and refined as a consequence of successful responses to operational challenges and opportunities. When successful responses are identified, they are repeated and thus become encoded into an organization's knowledge base in the form of standard operating procedures. This encoding process results from the nature of human agents who are boundedly rational (March & Simon, 1958). In this case, local search for problem solutions and the development of standard operating procedures, or routines are rational outcomes Ultimately, learning-by-doing implies that effective past behavior will be reinforcing, and that established routines become a significant influence on subsequent behaviors (March, 1991; March & Simon, 1958; Nelson & Winter, 1982).

As organizations engage in forming R&D consortia they acquire important tacit information that they can use in selecting partners, sharing proprietary information and structuring appropriate contracts. As a result of learning-by-doing, organizations move along a learning curve, reducing the time and resources spent on subsequent consortia formation processes. However, if firms do learn to organize as a result of experience, then much of their learning about R&D consortia formation will be specific to the type of formation process with which they have previous experience. The two consortia formation processes (emergent vs. engineered) will generate different experiences regarding partner identification, information sharing and structuring contracts.

Emergent consortia require only that a firm be open to partnering with firms that most likely, they already know. The definition and valuation of proprietary knowledge is easiest when partner firms face similar markets and competitive threats, and contracting is relatively straightforward when the purpose of a consortium is narrowly focused. In contrast, engineered R&D consortia bring together organizations that are more likely to face different competitive challenges. These organizations do not operate in the same environment and are expected to be less aware of their shared interests. The value of the knowledge to be exchanged is also more likely to vary across consortium members, depending on the uses to which it may be put. Therefore, the value of this knowledge will be more difficult to define and agree upon, possibly leading to greater complexity in contracting. The open-ended nature and broadly defined purpose of engineered R&D consortia can also create greater challenges regarding the structuring of contracts. In sum, the knowledge necessary to identify, negotiate and manage partner relationships is expected to be quite distinct across the emergent vs. engineered R&D consortia formation processes.

When applied to consortium formation, the learning-by-doing argument suggests that firms become increasingly skilled at forming R&D consortia as they gain experience in the consortium formation process. Learning-by-doing represents exploitative learning (March, 1991) as it involves leveraging existing knowledge and capabilities through the repetition of prior behaviors. Through repetition, prior experience is refined leading to greater efficiency, which may be reflected in reduced cost, greater frequency or speed of formation, or increased effectiveness of new relationships. The behaviors in this case represent the processes of partner identification, relationship structuring, partnership management etc. Experience with these elements of consortium formation help to build organizational routines for handling them, so that subsequent decisions to join a consortium will be likely to leverage and benefit from these routines in terms of reduced costs, errors, and time for each subsequent formation exercise.

Following the logic of the learning-by-doing hypothesis, we expect that because the two consortium formation processes (emergent vs. engineered) involve quite different activities they will lead to different sets of formation routines. According to the learning-by-doing perspective, firms' experience with joining emergent consortia will positively influence the formation process chosen for future consortia. Prior experience will increase the likelihood that the same process is used for forming future consortia. Similarly, experience with engineered consortia will influence the formation process chosen so that new consortia will be more likely to be formed through an engineered process. Furthermore, if the skills and experience involved in formation are different for emergent and engineered R&D consortia, then firm experience with one type of formation process will be of limited applicability to the other type of formation process. This offers the possibility of a strong test of the learning-by-doing hypothesis with respect to the development of a consortium formation routine. That is, we expect that prior experience with one formation type will have limited influence upon the formation of consortia of the other type. This suggests the following pair of hypotheses:

Hypothesis 1a: Accumulated experience with emergent R&D consortium formation processes is positively related to the probability that organizations form future R&D consortia through emergent processes, but not through engineered processes.

Hypothesis 1b: Accumulated experience with engineered R&D consortium formation processes is positively related to the probability that organizations form future R&D consortia through engineered processes, but not through emergent processes.

If learning-by-doing is the only process by which development of capabilities occurs, then once a firm has started to form a given type of R&D consortium it will be bound by its own routines to continue on a path with this process, exploiting prior knowledge and capabilities. However, this ignores the ability that some organizations have for engaging in exploratory learning (Levinthal & March, 1993; March, 1991). Therefore, we must consider sources other than prior experience that may influence the processes used to form new R&D consortia (McEvily & Marcus, 2005). From a theoretical perspective, we need to explain how firms develop new capabilities, despite the myopic effect of prior experience (March, 1991).

Within the lens of organizational learning theory, additional learning mechanisms such as adaptation, experimentation and improvisation can influence capability development in dynamic environments (e.g., Eisenhardt & Tabrizi, 1995; Miner, et al. 2001). Adaptive organizational learning is defined as changes to behavior in response to some stimulus (March, 1983). However, to clearly distinguish between learning based on prior experience and learning as a result of other processes, here we adopt a narrow definition of adaptive organizational learning that restricts it to those behavioral changes that occur in response to external stimuli.

Adaptive organizational learning is stimulated when external circumstances demand a novel response. Examples include radical technological or competitive shifts. Such a situation demands the search for new combinations of assets, processes and capabilities that are at the heart of adaptive learning. A defining feature of adaptive learning is the search for new routines. Therefore, in the context of organizational innovation adaptive learning is inherently exploratory. The implication of adaptive learning is that when external stimuli are sufficiently strong, firms will develop new routines that form the basis of their capabilities. With respect to R&D consortia formation, adaptive learning involves switching from an established consortium formation routine to a new routine. In other words, a firm with an established routine for forming R&D consortia through emergent processes may respond to some external stimulus that causes it to adapt its formation preferences to the alternative, engineered, formation process (and vice versa).

Though many forces encourage companies to adapt, the dynamism of the competitive environment and the actions of other firms in the industry are likely to have a great impact. High technology industries are dynamic settings that offer great opportunities for the acquisition of new technological knowledge from external sources such as universities and government labs. These industries provide multiple external stimuli to which organizations must respond by altering their decision rules and routines (Brown & Eisenhardt, 1995). Firms operating in high technology industries have higher probability of switching their routines than firms in low technology industries.

A second important source of external stimulus for adaptive learning is the behavior of other firms within the same industry. Learning-by-doing can lead to a tendency to preserve existing dominant routines. However, when there are high rates of consortium formation within the industry environment this has the potential to demonstrate the efficacy of alternative routines that should be explored. Bolton (1993) for example found that R&D consortium joining became an institutionalized decision. After early adopters had formed a consortium, the use of a consortium became a commonly accepted practice. Therefore, industry level experience with the formation processes increase the probability that individual organizations are exposed to knowledge of the alternative consortium formation processes and their benefits (and costs). These observations suggest the following hypothesis:

> Hypothesis 2: The probability of path breaking, adaptive learning which results in a change of the dominant routine with respect to consortium formation process will be related to (a) the dynamism of the environment, and (b) to the rate of learning which is occurring in the industry.

A third form of learning occurs in situations in which neither external stimuli, nor prior histories are the most significant cause of behavioral changes. In some organizational contexts, proactive processes of experimentation and improvisation can support capability development (Miner et al., 2001). Rather than being the outcome of prior history, improvisation and experimentation reflect deliberate acts facilitated by past routines (e.g., Brown & Eisenhardt, 1995; Eisenhardt & Tabrizi, 1995; Moorman & Miner, 1998; Weick, 1998). Further, as opposed to reactive responses to some external shocks or opportunity, improvisation and experimentation signal processes of enactment in which new knowledge is actively sought either for its own sake, or resolve a specific organizational problem (Miner et al., 2001). Improvisation suggests that an organization can "work with the unexpected" (Weick, 1998: p.544) therefore both exploring and exploiting opportunities. Learning is more improvisational when the design and execution of a solution occur simultaneously, and more experimental when it involves planned variations in underlying conditions (Miner et al., 2001).

In the context of consortia formation processes, improvisational learning is ambidextrous. Ambidextrous organizations must be simultaneously capable of exploiting existing knowledge and capabilities while exploring new opportunities (Birkinshaw & Gibson, 2004). Therefore, while prior experience must inform subsequent action, it should not constrain it by developing into core rigidities (Leonard-Barton, 1992) or competency traps (Levitt & March, 1988).

The practical significance of this form of learning is that the ability to experiment and improvise is heterogeneous across firms, reflecting firm-specific characteristics. Some firms will be more likely to develop new routines and also be less constrained by past routines than others. Studies of new product development (e.g., Brown & Eisenhardt, 1995; Eisenhardt & Tabrizi, 1995; Miner et al., 2001) that contrast planned and experiential learning identify several differences in the organization of the work, the project team, and the characteristics of project leaders. Recent examinations of organizational ambidexterity also focus on differences in characteristics such as organizational structure (Benner & Tushman, 2003; Tushman & O'Reilly, 1996) top management team composition (Beckman, 2006), organizational context and leadership (Gibson & Birkenshaw, 2004). Therefore, we expect systematic differences between those firms more able to engage in experimentation and improvisation with R&D consortia formation processes.

With respect to R&D consortia formation, we expect that ambidexterity with formation processes will be indicated in an absence of constraint by established routines. Firms that are more flexible and able to improvise will exhibit higher rates of switching between formation process routines. These firms are likely to have cultures, systems and procedures that are conducive to experimentation and encourage change. While a number of organizational and environmental characteristics may influence the propensity to try new things, firm size and slack resources are expected to exert a significant influence.

Smaller firms are expected to be more flexible, innovative and able to take more risks. Smaller firms are less constrained by the demands of customers and expectations of suppliers. Firms with fewer employees are also subject to less organizational inertia because the routines are embedded within fewer individuals, and change processes take less time to impact the entire organization. Therefore, we expect that organizational size in terms of number of employees will be inversely related to improvisation in consortium formation processes.

Change and experimentation imply uncertainty and risk. Firms that have greater slack resources available to them usually have a greater degree of discretion in managerial decision-making (e.g., George, 2005). This discretion facilitates organizational adaptation to environmental turbulence and supports the development of new capabilities (Nohria & Gulati, 1996). Since it is easier for managers to take risks when resources are plentiful, we can expect that firms with more financial freedom in the form of slack resources will be more likely to experiment with alternative consortium formation processes.

The literature suggests that although improvisational learning allows firms to break away from established routines, paradoxically experience is an important resource upon which individuals, groups, and entire organizations can draw when improvising new solutions (Miner et al., 2001; Weick, 1998). Prior practices serve as referents by providing both inspiration and constraint for subsequent actions (Miner et al., 2001). Therefore, while experimentation and improvisation may be characterized as exploratory 'probes into the future' (Brown & Eisenhardt, 1995), we can expect that these efforts are influenced by prior experience. However, the influence of the past differs from the path dependency of learning-by-doing. In improvising, prior experiences provide only a jumping off point for further exploration and innovation through reinterpretation, embellishment or variation (Weick, 1998).

Theory and research on improvisation therefore suggest that, in combination with organizational flexibility, prior experiences provide a basis for the development of new responses or routines (Brown & Esienhardt, 1995; Miner et al., 1998; Weick, 1998). In the context of R&D consortium formation this implies that improvisational learning will be a joint function of organizational properties that support flexibility and firms' prior experience with R&D consortium formation processes. We can expect that smaller firms with more experience will be more improvisational than larger firms. Furthermore, experienced firms with more slack resources will be more improvisational than those with fewer slack resources. This suggests the following pair of hypotheses:

Hypothesis 3a: There will be a negative interaction between prior experience with prior R&D consortia formation and organizational size that will decrease the probability of path independence.

Hypothesis 3b: There will be a positive interaction between prior experience with prior R&D consortia formation and slack resources that will increase the path independence.

Data and Methods

In order to test the study's hypotheses, we use a three-stage research design that includes data collection from multiple primary and secondary sources. Preliminary analysis involved identification of the formation processes of a sample of 53 R&D consortia from primary data used in Doz et al. (2000). This was followed by the identification of a set of proxy variables to indicate the formation process for 737 R&D consortia formed between 1984 and 2005. In the final stage we test this study's hypotheses using the sample of 737 R&D consortia and 1063 firms.

The preliminary analysis used data reported in Doz et al. (2000). That dataset consisted of detailed information on the formation process of 53 R&D consortia. Doz et al. (2000) used partial least squares (PLS) analysis to identify the key characteristics of the consortium formation process. Through PLS, five stages were identified: (1) the presence of a triggering entity; (2) seeking domain consensus; (3) the open solicitation of members; (4) member expectations for continuity; and (5) formal alliance structure. As is reported in Doz et al. (2000) each stage consisted of several different constructs which were in turn each derived from a number of different variables. Although the authors used these data to identify the two paths of emergent and engineered formation processes, they did not evaluate whether a particular formation process was emergent or engineered. For our study, we first wanted to know if a particular consortium formation was emergent or engineered. To develop a single score reflecting the formation process, we used the Doz et al (2000) data. For each of the five formation stages we calculated each consortium's weighted value and then rescaled all the consortia scores from 1=emergent and 2=engineered. After doing this for each stage, we then averaged each consortium's scores for the five stages to derive a single score, which was between 1 and 2. In order to conduct the next stage of our analysis, we then rounded the single score to either a 1 or a 2, Thus, each of the 53 consortia was categorized as either emergent (scored as 1) or engineered (scored as 2), according to the average of its factor scores. Of the 53 consortia, 32 were classified as "engineered" and 21 as "emergent."

Next, we used discriminant analysis to identify proxy variables for consortium formation process. We examined a wide range of potential discriminating variables from the industry, consortium and firm level of analysis. All of these variables were tested in a discriminant model with the consortium formation process as dependent variable. The analysis correctly classified 79 percent of the consortia, an improvement of almost 30 percent over chance. Press's Q statistic, an indicator of classification accuracy, is also significant (χ^2 = 12.736, 1 d.f., p<.01).

This discriminant function was then used to infer the formation processes for our sample of 946 R&D consortia formed between 1984 and 2005. In order to reduce the likelihood of misclassification we eliminated the 22 percent of consortia for which the joining process was most ambiguous, reducing the number of consortia in the sample from 946 to 737. Thus, 295 emergent and 442 engineered consortia were identified, representing a total of 1775 (47.1%) individual joining events for emergent consortia and 1992 (52.9%) individual joining events for engineered consortia. We used these data to analyze the study's hypotheses. The sample for this stage of our analysis was the 3767 individual joining decisions of 1063 companies that joined one or more of the 737 R&D consortia.

Dependent variables

For hypotheses 1a and 1b, which assess the effect of learning-by-doing, the joining of each type of consortium is the dependent variable of interest. Here the joining event is coded 1 for a consortium whose formation process has been identified as emergent and 2 for joining a consortium whose formation process has been identified as engineered. The data for this variable are obtained from the preliminary stages of the analysis.

Hypothesis 2a and 2b are concerned with adaptive learning, where decisions to join reflect a change in an existing dominant routine. The question arises, what is the number of episodes of a particular activity that must occur before a routine can be said to be established? Clearly, one event is not a routine. Two occurrences of the same event must be an absolute minimum requirement to be called a routine. However, to be consistent with the theory that consortium formation capabilities are heterogeneous in a population of firms, we would expect that only a minority of firms in the sample could have built such a capability. As the average number of joining events in this sample was 2.8, three events represent an above average number of consortium joining decisions by a firm. Therefore, we operationalize a dominant consortium formation routine as occurring when a firm has history of at least three consortium joining episodes involving a single process *and* no experience with the alternative process. Switching can occur from emergent to engineered, or from engineered to emergent. In both cases, the switching variable is coded as 1 for switch, or 0 for no switch. Data limitations, resulting partly from our conservative definition of a routine, mean empirically separating the direction of routine switching results in a sample that is too small. However, as we have no specific hypotheses regarding the direction of the routine switch, the more conservative definition of routine is desirable.

Hypotheses 3a and 3b concerned with the antecedents of ambidextrous firm capability development through improvisation. We operationalize improvisational learning as frequent switching of consortium joining process. Firms that improvise are not constrained by existing routines and can make frequent switches between formation types. Improvisational learning is measured by the cumulative number of switches between routines made by each firm in the period.

<u>Independent variables</u>

Prior formation experience. This variable measures an organization's accumulated past experience with the formation processes. For every firm, this involved a frequency count of joining experiences in emergent and engineered consortia for each year in the study. These frequencies were summed in a cumulative total for each year from 1984 to 2005 so that for each year, a running total of the frequency of experiences with each formation process was created. For hypotheses 3a and 3b the firm cumulative experience with both formation processes was combined into a single measure of firm joining experience.

Industry cumulative experience. This variable indicates the extent to which other firms in the industry are also joining R&D consortia through either emergent or engineered processes. Because the *U.S. Federal Register* provides a comprehensive source for records of legitimate R&D consortia in the U.S., our sample from 1984 to 2005 also should be comprehensive regarding the number of firms from each industry that join these consortia. Therefore, our measure involves a frequency count of the consortium joining activities of all firms from each industry. We measured industry using the four digit SIC. As a result, 212 industries were represented in this study. A separate measure was created for each type of experience (i.e., industry experience with emergent consortia and with engineered consortia).

Environmental Dynamism. We operationalize the dynamism of the industry using a classification of high technology versus non high technology. High technology is defined in terms of whether an industry on average makes R&D investments that exceed five percent of sales. We also cross-checked this definition with lists published by the American Electronics Association, Bureau of the Census, Bureau of Labor Statistics, and the Organization for Economic Cooperation and Development. We coded an industry as high technology when it was identified as such by at least four out of these five sources.

In recognition that high technology firms are considerably heterogeneous in their technology, knowledge base, time frames for innovation and product development, and regimes for knowledge appropriation and spillover (e.g., Kodama, 1992; Kotabe & Swan, 1995), we further divided the high technology classification into three groups: high technology services including software manufacturers, technology consultants, and contract research organizations (technology service firms); high technology manufacturers of products assembled primarily from electronic and mechanical components (mechanical technology firms), and high technology manufacturers of products created at a molecular level, including biotechnology, pharmaceutical and chemical products (biochemical technology firms). While mechanical technology firms exhibit shorter product development cycles, they also suffer from weaker patent protection and have to deal with higher risks and opportunities from knowledge spillovers. In contrast biochemical technology firms tend to have longer development cycles, with far stronger patent protections and consequently more limited risks of knowledge spillover. By distinguishing among these various forms of high technology firms we are explicitly acknowledging that there are qualitatively different competitive dynamics and technological trajectories which may influence the learning processes that we examine in this study. A dummy variable coded 1 for mechanical technology firms, 2 for biochemical technology firms, and 3 for technology service firms. The comparison variable for all three groups is non-high technology firms.

Company Size. For hypotheses 1a, 1b, 2a and 2b, company size is a control variable, and is operationalized as the number of employees for each year of the study. We obtained our data from Standard & Poor's *Research Insight* database. For hypotheses 3a and 3b we use hierarchical regression analysis. Therefore, for this last analysis we take an average of the log of the number of employees across the period 1984 to 2005.

Slack Resources. This variable is measured as the current ratio, for each year of the study. We obtained data on each firm's current assets and current liabilities from the Standard & Poor's *Research Insight* database. For hypotheses 1a, 1b, 2a and 2b, slack resources are treated as a control variable. For hypotheses 3a and 3b, in which we use hierarchical regression, slack resources are a variable of interest and we create an average value for the period under study.

Interaction term: cumulative experience by organizational size; cumulative experience by slack resources. For the hypothesized interaction terms we multiply each firm's cumulative experience with all forms of consortia by its size, and its average slack resources. These variables therefore combine data from the Standard & Poors *Research Insight* database with that obtained from the *U.S. Federal Register.*

Control variables. In order to examine each learning process, we include the other independent variables in each model. Therefore, in hypothesis 1a, and 1b where we examine the effects of company prior experience, we also include controls for company size, slack resources, industry type and industry cumulative experience with the two formation processes. In hypothesis 2a and 2b, we focus on the effect of industry and environment on adaptive learning. We therefore control for company size, slack resources, and the cumulative experience of the firm with each formation process. Finally, in hypotheses 3a and 3b we focus on how firm characteristics individually and combined with prior experience influence improvisational learning. We therefore control for the effect of cumulative industry experience on learning behaviors. In addition, for hypotheses 3a and 3b we control for total assets. This was measured as the log of total assets as reported by the firm, averaged for the period of the study. These data were obtained from Standard & Poor's *Research Insight* database.

Analysis

We evaluated the hypotheses using event history analysis and hierarchical regression analysis. The event history model used is a Cox proportional hazards regression model with time dependent covariates (Allison, 1984). In this model, the dependent variable is each firm's decision to join a consortium. This event can be described in one of three alternative states: an emergent vs. engineered vs. no consortium formation process. Each decision to join is treated as an independent observation in this analysis, allowing a firm to be observed more than once if it joins multiple consortia during the period of the study. As we have hypothesized that prior experience has an important influence on subsequent decisions, the assumption of independence of dependent variables is violated. However, by directly including prior experiences as an independent variable in the model, this problem is mitigated (Allison, 1984).

The Cox model with time dependent covariates allows the inclusion of independent variables that change in value in each time period. However, an important issue associated with the use of event history analysis is that of left and right censoring, in which one or more occurrence of the event of interest is not included within the sample either because they occurred before data gathering began, or after it was concluded. In this study, our sample includes the first joiners for every consortium, thereby eliminating the problem of left censoring. Furthermore, there is no firm in the sample that does not join either an emergent or an engineered consortium at some point during the study period, thus eliminating the problem of right censoring. For hypotheses 1a and 1b, two separate Cox regression models are examined, one assessing the proportional hazard rate for the decision to join an emergent consortium, and the second to assess the proportional hazard rate for the decision to join an engineered consortium. For hypotheses 2a and 2b, a single model is constructed examining the decision to switch from a dominant routine for consortium formation.

A limitation of the Cox model is its inability to accept missing data. This can become problematic when dealing with a dataset including so many firms over a 22-year period with variables drawn from multiple secondary sources. In particular, limitations arise because firms were either not in existence at the beginning of the period, or no longer in existence at the end of this period. To mitigate this problem, we have split the dataset into two equal time periods, 1986-1995 and 1996-2005. This approach has the added benefit of ascertaining the stability of results across the two periods. To ensure that dividing the dataset did not substantively change the results, we have also analyzed the complete dataset. Because of space constraints we report the results for the divided dataset here. The unreported results are available from the authors upon request.

Results

Our first pair of hypotheses (1a and 1b) suggest that firms' accumulated prior experiences with a particular consortium formation process are associated with an increased probability of subsequent consortium formation though the same process. The results of the analyses are presented in Tables 2a to 2b.

Insert Table 2a & 2b About Here

Table 2a presents the results for the Cox regression of joining an emergent consortium in the period 1986 to 1995. In model 1, we enter the control variables for firm size, slack resources, and industry type. The model overall is significant ($\chi^2 = 24.218$, p<.001). The coefficient for slack resources is statistically significant (Expβ = 1.000, p<.001) although this variable has no practical influence on the decision to join an emergent consortium. The coefficient for industry accumulated experience with engineered consortia formation processes is also significant (Expβ = 0.969, p<.001). This coefficient indicates that this variable reduces the probability of joining an emergent consortium by 3.1 percent for every additional unit of industry experience (i.e., every accumulated joining event in that industry). In model 2 we introduce the individual firms' accumulated experience with joining engineered consortia. The overall model is significant ($\chi^2 = 29.158$, p<.001) and improves the model significantly over the first set of controls ($\Delta\ \chi^2 = 4.581$, p<.05). The effect of prior experience, at the firm level, with engineered consortium formation reduces the probability of forming a consortium through emergent processes by close to 10 percent for every additional unit of firm experience (one unit for each joining event). In model 3 we introduce firm accumulated experience with forming emergent consortia. In this case, the model is again significant ($\chi^2 = 50.639$, p<.001), and the inclusion of this variable adds to the power of the model, with a positive change in the χ^2 ($\Delta\ \chi^2 = 23.818$, p<001). The coefficient for prior experience with emergent consortia (Expβ = 1.080, p<.001) indicates that for every additional prior experience with formation of this type of consortium increases the probability that a firm will form a new consortium through this process by 8 percent.

Table 2b repeats the analysis for the period 1996-2005. In model 1, we include the main group of control variables: size, slack, industry type, and industry accumulated experience. We find the overall model to be significant (χ^2 = 50.158, p<.001), and the coefficients for slack (Expβ = 1.000, p<.001) and high technology service industries (Expβ = 2.034, p<.001) are both significant. Of interest is the fact that in this sample, firms in high technology services are more than twice as likely to join an emergent consortium as firms in low technology industries, reflecting a significant increase in the presence of software consortia during this time. In model 2, we include the additional variable of firm accumulated experience with engineered consortia (Expβ = 1.030, n.s.) and find no significant improvement relative to model 1 ($\Delta\chi^2$ = 3.042, n.s.). In model 3, we include the measure of accumulated experience with joining emergent consortia and observe a significant overall model (χ^2 = 67.846, p<.001) with a significant increase in the chi-square ($\Delta\chi^2$ = 14.9000, p<.001). The coefficient indicates that for each prior experience with emergent consortia increases the probability of joining another consortium using this method by nearly 5 percent (Expβ = 1.048, p<.001).

Insert Table 3a & 3b About Here

Table 3a summarizes the results for our analysis of emergent consortium formation activities during the period 1986 to 1995. In model 1, we introduce the main control variables and the model overall is significant (χ^2 = 65.777, p<.001). Here, we can see that prior industry level experience with both engineered (Expβ = 1.058, p<.001) and with emergent consortia (Expβ = 0.942, p<.001) are in the expected direction, increasing (by 5.8 percent) and reducing (by 5.6 percent) respectively, the probability that a firm will itself join a consortium formed through an engineered process. In model 2, we introduce firm level experience with engineered consortia and note that a unit increase in this variable reduces the probability of joining consortia through engineered processes by 8.5 percent. This model is significant overall (χ^2 = 76.589, p<.001) and increases the χ^2 value significantly ($\Delta\chi^2$ = 12.435, p<.001). In model 3, we include the firm history of joining engineered consortia and find that this also improves the χ^2 value ($\Delta\chi^2$ = 22.875, p<.001) and that a unit increase in this variable accounts for a significant 27 percent increase in the probability that a firm will join another consortium through an engineered process (Expβ = 1.271, p<.001).

We repeat the analysis for engineered consortia formed in the period 1996-2005. This analysis is summarized in table 3b. The results are consistent with the previous period. In model 1 (χ^2 = 20.335, p<.001), we note that industry level accumulated experience with engineered consortia increases the probability of formation through this process by 2.4 percent per unit of experience (Expβ = 1.024, p<.001), and industry experience with emergent consortia reduces this probability by 2.7 percent (Expβ = 0.973, p<.001). When we include firm level accumulated experience with joining emergent consortia we find that each additional unit of experience reduces the probability of forming an engineered consortium by 3 percent (overall model χ^2 = 27.755, p<.001). Finally, when we introduce the influence of firm accumulated experience with engineered consortia, we find the model to be significant overall (χ^2 = 46.578, p<.001) and the additional variable accounts for a significant $\Delta\chi^2$ ($\Delta\chi^2$ = 20.291, p<.001). The effect of each unit of prior joining experience for engineered consortia is to increase the probability of forming future consortia through this process by close to 20 percent.

Taken together, these results strongly support hypotheses 1a and 1b that prior experience is a significant predictor of the development of capabilities for forming new R&D consortia. Furthermore, the evidence is quite clear that experience with each formation type does not generalize to the alternative formation type. Thus, it appears that these two formation processes are distinct in terms of the formation knowledge and capabilities that are developed.

Hypotheses 2a and 2b suggests that adaptive learning will be observed when external stimuli cause firms to override existing dominant routines. We operationalize adaptive learning as a change in an established routine for the formation of new R&D consortia. The development of these routines is illustrated by the prior analysis with relevant accumulated experience increasing the probability of formation through the same process. Therefore, a strong test of adaptive learning would be evidenced in the interruption of the accumulation of experience when a firm attempts to join an R&D consortium through a process with which it has no experience.

Insert Table 4 About Here

Table 4 summarizes the results of the Cox regression analysis of the effect of external stimuli on the decision to switch from one dominant formation process to another. The first two columns present the results for the period 1986-1995 and the second pair of columns presents the results for 1996-2005. In model 1a, we introduce the control variables of firm characteristics and firm level accumulated experience. This model is significant overall (χ^2 = 139.209, $p<.001$) and several of the individual coefficients are also significant. Size is statistically significant (Expβ = 1.000, $p<.001$), but practically not significant since it does not alter the probability of switching joining routine. Firm accumulated history in both engineered (Expβ = 1.879, $p<.001$) and emergent (Expβ = 1.128, $p<.001$) are both significant and both substantially increase the probability of switching. It is likely that this result is caused by our definition of the dependent variable - switching formation process – as occurring after more than three prior joining events in either of the processes. Thus only firms with an above average number of joining experiences in a single formation process will be able to switch routine by definition. However, the inclusion of firm history also allows us to more clearly isolate the influence of the external factors on the switching of a dominant routine.

In model 1b, we add the influence of industry type, and industry level accumulated experience with emergent and engineered consortium formation process. This model is significant overall (χ^2 = 162.014, p<.001) and the inclusion of the external stimulus variables add significantly to the power of the model ($\Delta\chi^2$ = 41.364, p<.001). In comparison to the low-technology firms, firms in a high technology manufacturing environment are not significantly more likely to switch consortia joining routines. However, bio-chemical technology firms were significantly more likely to switch routines than low technology firms (Expβ = 1.909, p<.001). The coefficient indicates that firms in bio-chemical industries are 90 percent more likely adaptively switch routines than firms in low-technology industry environments. For firms in high technology service industries we find that it is 80 percent less likely that these firms will switch routines in comparison to low technology firms (Expβ = 0.199, p<.001).

Models 2a and 2b repeat this analysis for the period 1996-2005. Model 2a, which includes only the controls for firm size (Expβ =1.000, p<.001), slack resources (Expβ=1.172, n.s.), and accumulated experience with engineered consortia (Expβ =1.172, p<.001), is significant overall (χ^2 = 263.315, p<.001). These results are consistent with the previous period. In model 2b we include the variables for the external stimuli. The model overall is again significant (χ^2 = 294.759, p<.001) and the addition of the environmental stimulus variables together contribute significantly to the explanation of routine switching even after controlling for firm experience and other characteristics ($\Delta\chi^2$ = 61.901, p<.001). In this second period, we find that firms in high technology manufacturing industries are 167 percent more likely to switch their dominant routines than are low technology firms (Expβ=2.674, p<.001). Although only marginally statistically significant (Expβ=1.579, p<.10), it is 58 percent more likely that firms in biochemical technology industries will switch than will low technology firms. With respect to the extent to which other firms in the industry are joining each type of consortium, we observe that each time a firm in the same industry joins an engineered consortium, it reduces the chance of switching by five percent (Expβ=0.95, p<.001). Each time a firm in the same industry joins an emergent consortium, it increases the probability of switching routines by five percent (Expβ=1.049, $p<.001$).

To summarize, results support hypothesis 2a and 2b that external environmental stimuli are a significant cause of adaptive learning with respect to consortium formation. Interestingly, the extent to which other firms in the same industry are joining engineered versus emergent consortia appears to have opposite effects. Industry rates of engineered consortium formation appear to reduce the likelihood of switching, while industry rates for emergent consortium formation increase switching activities.

Hypotheses 3a and 3b suggest that firm size and slack resources interact with accumulated experience to increase the probability of improvisational learning, defined as frequent switching of formation processes. Table 5 presents the results of the hierarchical regression analysis.

Insert Table 5 About Here

Model 1, which includes the control variables only, is significant (*Adj.* R^2 =0.046, F =4.943, $p<.001$) although only the control for assets is significantly (β=0.158, $p<.001$) related to routine switching. In model 2, the main effect variables are added to model 1. Model 2 is significant overall (*Adj.* R^2 =0.199, F =14.533, $p<.001$) and the main effects explain a significant amount of additional variance in routine switching (ΔR^2=0.156, ΔF = 31.821, $p<.001$). There are non-significant main effects for company size (β=-0.029, n.s.) and slack resources (β=0.008, n.s.) and a significant main effect for slack resources (β=0.415, $p<.001$).

In model 3, we assess the effect of an interaction between company size and total company experience with consortium formation processes on routine switching. Model 3 is significant overall (*Adj.* R^2 =0.308, F =22.777, $p<.001$) and the inclusion of the interaction term explains a significant amount of additional variance in routine switching (ΔR^2=0.108, ΔF = 76.418, p<.001). The interaction between organizational size and company experience of consortium formation is negative and significantly related to routine switching (β=-1.115, p<.001) which is consistent with hypothesis 3a.

Finally, in model 4, we assess the effect of an interaction between slack resources and total company experience with consortium formation processes on routine switching. Model 4 is significant overall (*Adj.* R^2 =0.245, F =16.902, p<.001) and the inclusion of the interaction term explains a significant amount of additional variance in routine switching (ΔR^2=0.47, ΔF = 30.254, p<.001). There is a positive and significant interaction effect between organizational slack resources and company experience of consortium formation (β=0.679, p<.001) on routine switching, consistent with hypothesis 3b.

These results together provide good support for hypotheses 3a and 3b concerning the influence of organizational characteristics on improvisational learning, even after controlling for the influence of contextual factors. Furthermore, the hypothesized interaction between experience and organizational factors that support (or inhibit) flexibility are both present in the expected directions. In the next section, we will discuss the implications of our results.

Discussion

In this study, we have sought to explore how organizations develop or switch from a path for building inter-firm relationships in the form of cooperative R&D consortia. The focus has been on the two different formation processes which have previously been identified in the literature (Doz et al., 2000). These relationships are significant because they provide access to new knowledge and capabilities. It is this knowledge acquisition aspect of R&D consortia that has previously been a principal focus in research. Scholars have asked why and under what conditions do firms partner in R&D consortia and have examined the characteristics of these alliances that lead to success or failure (Anand & Khanna, 2000; Gulati, 1999; McEvily &

Zaheer, 1999). The present study examines the less commonly studied question of what factors influence organizational learning with respect to formation processes of R&D consortia. Our results suggest that there are at least three organizational path processes at work, and that these are the result of diverse dynamic factors at the firm, industry and environmental level. This study therefore builds on the notion that inter-organizational relationships reflect multiple levels of embeddedness (Hagedoorn, 2006).

The objective of the study was to understand three path processes on the formation of R&D consortia: path dependence, path breaking and path independence. It has been widely argued that with experience over time, organizations tend to develop and refine their standard operating procedures and routines, align their strategies and capabilities, and that this is a central and perhaps inevitable feature of organizational life that results from the natural characteristics of bounded human rationality and the resulting local search for satisfactory solutions. Some have even argued that learning-by-doing and continuing with an existing path should be considered a null hypothesis (Grandoori & Kogut, 2002). The empirical evidence developed in this study confirms the significance of learning-by-doing for the development of routines for R&D consortium formation. The results unambiguously demonstrate that for every additional year of experience with membership in each consortium, there is a significant increase (between 5 and 27 percent) in the probability of joining another consortium formed through the same process. This effect is achieved after controlling for the other firm, industry and environmental factors hypothesized to impact the development of consortia ties.

Further strong evidence in support of this hypothesis is the fact that the effect of prior experience is specific to the type of formation process being used. Not only is experience with the alternative formation process not related, but also it is significantly negatively related to subsequent formation processes. That is, there is a significant 1 and 6 percent *decrease* in the probability of formation of a consortium through a given process, for every additional year of experience with membership in a consortium formed through the alternative process. These results provide unique and powerful evidence for the importance of prior experience on subsequent organizational innovation.

If learning-by-doing represents the case of exploitation in organizational innovation, the case of exploration must be represented by the existence of a routine breaking innovation. Therefore, while there is not a consensus as to whether exploration and exploitation are orthogonal constructs or in fact represent opposite ends of a continuum (Gupta et al., 2006), we suggest that in cases of organizational innovation, exploration and exploitation should be considered as mutually exclusive phenomena at two ends of a continuum. Adaptive learning, defined as a change in behavior occurring in response to some external stimulus, represents one important aspect of exploration in organizational innovation. As firms are exposed to increasing levels of external stimuli that suggest (or necessitate) new organizational responses, the probability of a routine breaking organizational innovation will increase.

This reflects the notion of embeddedness with respect to an industry (Hagedoorn, 2006). In particular, where other firms in the industry are building experience with R&D consortium formation, this increases the exposure of the focal firm to these organizational innovations and increases the probability that adaptive processes will occur. In addition, firms that are operating in more dynamic environments, such as high technology industries, are also likely to be exposed to more frequent stimuli for adaptation. Our results are generally supportive of the presence of this path breaking process. We find evidence that for firms in each of the high technology sectors relative to low-technology industries there is typically an increase in the probability of routine breaking organizational innovations. Our study also provides evidence of a significant increase in routine breaking organizational innovation in response to the industry level of experience with R&D consortia formed through emergent processes. It appears that path breaking processes, which lead to the development of new organizational capabilities, find significant stimuli in industry and environmental conditions.

Finally, we have suggested that in the context of organizational innovation, path independence will be indicated by a pattern of consortium formation that does not reflect the presence of a single dominant routine. Some firms can engage in forms of experimental or improvisational learning that take advantage of prior experience, without being bound by it. These firms are able to develop new routines as well as continuing to refine existing capabilities, and thus avoid the problem of the competency trap. To do so, these organizations leverage those characteristics that support flexibility. We have argued that organizations that are smaller in terms of the number of employees, and those which have greater slack resources are among those more likely to not be constrained by routine and to switch frequently between formation types. However, consistent with the view that even improvisation is enhanced by experience (Weick, 1998), we find that prior history of consortium formation is necessary to limit the negative influence of organizational size and enhance the positive influence of slack resources on improvisational learning. A necessary condition for such improvisational or ambidextrous behaviors is organizational flexibility, granted by small size and available slack resources. However, this must be complemented by the other necessary condition of prior experience. We observe that higher levels of organizational ambidexterity are associated with the combination of experience and these other characteristics.

This research is not without limitations. Our reliance on secondary sources for firm level data has required that we focus only on publicly traded firms. Therefore, our results should be generalized to other organizations only with caution. Second, we have focused only on the paths of those firms that joined these consortia in the first year of operation. This deliberate choice enabled us to exclude organizations that may have joined for reasons other than those that we have explored here. It is possible, in fact likely, that there are other processes such as imitation, which would be strongly indicated by an examination of the patterns of consortium joining behavior over time. This will make an interesting topic for future research. Limitations of the Cox regression model with respect to missing data also led us to exclude a large number of observations. Missing data is an inevitable problem in a study conducted over a 20-year period and involving multiple secondary data sources. The large remaining sample size, and the positive support from conducting two separate analyses lead us to believe that this problem should not be overstated however.

A number of future research directions are worth examining. Not least of these is the issue of how patterns of organizational innovations may unfold over time. Further research, and conceptualization, is required on the issue of whether in fact path independence is something that involves simultaneous exploration and exploitation, or a process of punctuated equilibrium in which long periods of exploitation are followed by brief periods of exploration (Gupta et al., 2006). Perhaps path independence can take either form, and the type depends on contingencies such as the type of organizational change that is being considered. A further avenue for research is the question, unanswered in the present study, of whether path independence as important from the perspective of organizational innovation as it is held to be in the context of product innovation. Exploration of such phenomena could consider the impact of path independence upon relevant performance outcomes. For example, ambidexterity in the context of inter-organizational relationships might examine alliance effectiveness or organizational learning.

This study seeks to examine the development of capabilities for the formation of inter-organizational relationships through a lens that links this phenomenon to path-related processes. Our empirical study has provided initial support for these ideas. We hope that this also provides insights into the multiple levels of factors influencing path dependence. When it comes to path-related activities, organizations are embedded not only in their environments, but also in their own past. Firms that are able to exploit their experience, their industry knowledge and their environment are rare, but these organizations may have a distinct advantage for developing important capabilities for finding and building cooperative relationships.

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Table 1. R&D Consortia Formation Process Activities

Formation Stage	Description of Factors	Emergent	Engineered
Triggering Entity	The existence of a triggering entity is likely to be critical to the emergence of some R&D networks. In cases in which technologies are not as well specified, or where tacit know-how is to be employed triggering entities may be required. A triggering entity may be required to lesson the concerns of participants that the costs and benefits of collaboration will be shared "fairly". Triggering entities may be individuals, firms, agencies of governments, or environmental events.	No direct effect May not be required	Necessary for formation
Seeking Domain Consensus	Efforts to produce consensus by sense making and understanding processes undertaken during negotiation processes. As these processes develop they will reflect agreement regarding expectations about performance, who is in and out, the scope of the alliance, definitions of equity and efficiency. Intellectual, strategic, cultural and ethical issues are included. When there have been prior relationships between participants, some shared expectations are likely to be present from the onset of the collaboration.	Open to interested parties, likely to be similar organization – snowball effect	Triggering entity targets diverse members – hub and spoke effect
Open Solicitation	Additional partners may be sought for strategic reasons. The more closely allied those reasons are to the firm's existing product/market objectives, the more likely it seems that the search for partners will focus on firms which will be reasonably familiar to the managers of the focal firm. Most areas of science or technology, whether in a country or a region of a country, involve a few firms and public research institutes and/or universities who between them carry out the bulk of the research in that area	Defining boundaries	Aligning interests
Continuity of Expectation	Participants who have had no experience with each other can only construct a shadow of the future as they gain experience. Many R&D networks are of limited duration, linked with specific projects with given time horizons. Networks embedded in larger social structures, however, may cause their members to have greater expectations of continuity.	Strong, until opportunity or threat is dealt with	Very low at onset
Formal Structure	The participants in an R&D network must be able to deliver expectations over a sustained period of time. The way in which they design the structure of the collaboration will be helpful. External events will affect relationships over time. Given a changing external environment, success is likely to be a function of a number of other design factors. For example, the ways in which the different firms communicate with each other, and build common understandings of the task at hand, is likely to be affected by the network's structure.	Tight coupling to constrain opportunism	Filling structural holes, loose coupling

Table 2a: Results for 1986-1995 (for joining an emergent consortium)

Determinants	Model 1 Exp(B)	Model 2 Exp(B)	Model 3 Exp(B)
Size	1.000	1.000	1.000
Slack	1.000***	1.000***	1.000***
Industry			
Type m	0.946	0.934	0.756
Type b	0.998	0.986	0.853
Type s	1.177	1.141	1.231
Industry experience engineered	0.969***	0.980	1.001
Industry experience emergent	1.008	1.004	0.982
History of Joining Engineered Consortia		0.909*	0.828***
History of Joining Emergent Consortia			1.080***
Chi-square	24.218***	29.158***	50.639***
Change in Chi-Square		4.581*	23.818***

Note: *** p<.001; ** p<.01; *p<.05

Table 2b: Results for 1996-2005 (for joining an emergent consortium)

Determinants	Model 1 Exp(B)	Model 2 Exp(B)	Model 3 Exp(B)
Size	1.000	1.000	1.000
Slack	1.000***	1.000***	1.000***
Industry			
Type m	1.232	1.233	1.159
Type b	1.068	1.070	1.018
Type s	2.034***	2.132***	2.307***
Industry experience engineered	0.992	0.989*	1.000
Industry experience emergent	1.005	1.006	0.992
History of Joining Engineered Consortia		1.030	0.954
History of Joining Emergent Consortia			1.048***
Chi-square	50.158***	51.562***	67.846***
Change in Chi-Square		3.042	14.900***

Note: *** p<.001; ** p<.01; *p<.05

Table 3a: Results for 1986-1995 (for joining an engineered consortium)

Determinants	Model 1 Exp(B)	Model 2 Exp(B)	Model 3 Exp(B)
Size	1.000	1.000	1.000
Slack	1.000	1.000	1.000
Industry			
Type m	1.054	1.092	1.142
Type b	0.747	0.750	0.756
Type s	0.000	0.000	0.000
Industry experience engineered	1.058***	1.046***	1.021
Industry experience emergent	0.942***	0.962***	0.985
History of Joining Emergent Consortia		0.915***	0.872***
History of Joining Engineered Consortia			1.271***
Chi-square	65.777***	76.589***	96.287***
Change in Chi-Square		12.435***	22.875***

Note: *** p<.001; ** p<.01; *p<.05

Table 3b: Results for 1996-2005 (for joining an engineered consortium)

Determinants	Model 1 Exp(B)	Model 2 Exp(B)	Model 3 Exp(B)
Size	1.000	1.000	1.000
Slack	1.000	1.000	1.000
Industry			
Type m	1.045	1.043	1.065
Type b	1.018	1.009	1.005
Type s	0.000	0.000	0.000
Industry experience engineered	1.024***	1.019***	1.004
Industry experience emergent	0.973***	0.981*	0.996
History of Joining Emergent Consortia		0.970**	0.903***
History of Joining Engineered Consortia			1.199***
Chi-square	20.335***	27.755***	46.578***
Change in Chi-Square		6.368**	20.291***

Note: *** p<.001; ** p<.01; *p<.05

Table 4: The effect of environmental stimuli on the development of capabilities

	1986-1995		1996-2005	
Determinants	**Model 1a Exp(B)**	**Model 1b Exp(B)**	**Model 2a Exp(B)**	**Model 2b Exp(B)**
Size	1.000***	1.000***	1.000***	1.000***
Slack	1.000	1.000	1.000	1.000
History of Joining Engineered Consortia	1.879***	2.122***	1.172***	1.431***
History of Joining Emergent Consortia	1.128***	1.126***	1.017*	0.957***
Industry				
Type m		0.888		2.674***
Type b		1.909***		1.579@
Type s		0.199***		
Industry experience engineered		0.969***		0.950***
Industry experience emergent		1.031***		1.049***
Chi-square	139.209***	162.014***	263.315***	294.759***
Change in Chi-Square		41.364***		61.901***

Note: *** p<.001; ** p<.01; *p<.05; @ p<.10

Table 5: Regression analysis of firm characteristics on improvisational routine switching

Variables	Model 1	Model 2	Model 3	Model 4
Log Assets	0.158***	0.094	0.063	0.063
Industry cumulative experience with emergent consortia	0.16	-0.33	-.080	-.055
Industry cumulative experience with engineered consortia	0.228	0.167	0.205	0.191
Industry type – mechanical	-0.066	-0.056	-0.051	-0.063
Industry type – biological	-0.015	-0.011	0.005	-0.015
Industry type - service	-0.095	-0.046	-0.038	-0.047
Company size – log employees		-0.029	0.369***	0.027
Slack resources - Current Ratio		0.008	-0.008	-0.424***
Company cumulative experience with all forms of consortia		0.415***	1.324***	-0.081
Company size x total company experience			-1.115***	
Slack resources x total company experience				0.679***
Adjusted R^2	.046	.199	.308	.245
F-value	4.943***	14.533***	22.777***	16.902***
ΔR^2		0.156	0.108	0.047
F-Value for ΔR^2		31.821***	76.418***	30.254***

Note: *** p<.001; ** p<.01; *p<.05