UC Berkeley
UC Berkeley Electronic Theses and Dissertations

Title
Organizational Identity and Interorganizational Alliances

Permalink
https://escholarship.org/uc/item/2v52k1zc

Author
Choi, Emily Wu

Publication Date
2012

Peer reviewed|Thesis/dissertation

Organizational Identity and Interorganizational Alliances

by

Emily Wu Choi

A dissertation submitted in partial satisfaction of the

requirements for the degree of

Doctor of Philosophy

in

Business Administration

in the

Graduate Division

of the

University of California, Berkeley

Committee in charge:

Professor Waverly W. Ding, Co-Chair
Professor James R. Lincoln, Co-Chair
Professor Jo-Ellen Pozner
Professor Neil D. Fligstein

Fall 2012

Organizational Identity and Interorganizational Alliances

Abstract

Organizational Identity and Interorganizational Alliances

by

Emily Wu Choi

Doctor of Philosophy in Business Administration

University of California, Berkeley

Professors Waverly W. Ding and James R. Lincoln, Co-Chairs

This dissertation examines the relationship between organizational identity and the formation and performance implications of interorganizational alliances. The first study investigates the effect of an organization's identity on its initial alliance portfolio formation, addressing how becoming comprehensible through organizational identity is a fundamental step in order for a new organization to be accepted by the market. Through different categorizations, some new organizations will be more comprehensible and possess clearer identities in the market than others. I develop a theory of how this variation affects the search for alliance partners in terms of the speed of alliance formation and the diversity between the new organization and its partners. The second study investigates how organizational identity affects the impact of alliances on performance outcomes. Alliances that explore and experiment tend to affect organizational outcomes negatively, at least in the short term. Although exploration strategies facilitate learning and adaptation in the long run, they incur costs due to the nature of experimentation. I advance an alternative perspective that organizational identity plays a role in this alliance-performance link. Depending on the strength of an organization's identity in terms of how coherent and taken-for-granted its categorization or social grouping is, the effect on performance may be more or less negative. Overall, this research indicates that organizational identity matters both to an organization's initial alliance portfolio formation and to the impact of this alliance portfolio on performance outcomes. This work contributes to the literature streams of both organizational identity and alliances, and presents the first systematic investigation of the link between them.

Dedicated to

Özalp Özer

I could not imagine this journey without you. I am blessed to have you in my life.
Now, on to the next journey together!

Table of Contents

List of Tables

List of Figures

iii

Acknowledgments

1.　　Introduction

This dissertation examines links between organizational identity and the formation and performance implications of interorganizational alliances. Organizational identity is defined by attributes of an organization that are central, enduring, and distinctive (Albert and Whetten, 1985). Such attributes belong to both the micro and macro levels of an organization. At the micro level identity is influenced by an organization's unique traits, practices, and competencies, and at the macro level by social forms, categories, and group affiliations (Whetten, 2006). This dissertation concerns organizational identity at the macro level—where identity typifies an organization by its category or group affiliation, and compels the organization to remain consistent with the social codes related to its claimed identity (Hsu and Hannan, 2005; Pólos, Hannan, and Carroll, 2002).

Organizational identity at the macro level is an important feature of industry dynamics: it explains why industries are distinguished from one another, why new markets can be founded in mature industries, and why some market segments do not grow (Carroll and Swaminathan, 2001; Hannan and Freeman, 1977; McKendrick and Carroll, 2001). At the same time, industry dynamics create complementarities and competition among firms, which affects the formation of strategic alliance portfolios (Eisenhardt and Schoonhoven, 1996; Gulati, 1995; Stuart, 1998). Strategic alliances are typically bilateral relationships between organizations designed to accomplish a long-term project or goal in order to improve aspects of the organizations' respective value chains such as research and development, or marketing and distribution. A strategic alliance portfolio is the concurrent set of alliances in which an organization engages; it is also defined as an egocentric network that encompasses a focal organization and its direct relationships with partnering organizations (Wasserman and Faust, 1994). Alliances are particularly widespread in technology-intensive industries where fast-paced changes necessitate organizations to combine strengths to compete and to speed up innovation activities (Powell, 1990).

A connection between organizational identity and alliances undoubtedly exists, but little prior research has systematically investigated this connection. Some exceptions can be found in sociology and management research. They have provided us with the insight that when selecting alliance partners, organizations consider their identities. For example, Lincoln and McBride (1985) demonstrated that grounded on the principle of homophily, organizations tend to form relationships based on similar identity attributes such as internally held social values. Also, Stuart (1998) showed that firms tend to select partners that are classified in technology segments that are similar to those firms. Finally, related to social-psychological literature and theories of sense-making, Ring and Van de Ven (1994) proposed that when two organizations have a congruent understanding of each other's identity in relation to other organizations, formalizing an alliance between them becomes likely. Because little research has explicitly investigated the connection between organizational identity and alliances, we lack full knowledge about the conditions under which identity matters to such important strategic actions as alliance formation. We also lack understanding of whether alliances that deviate from an organization's identity would substantively impact its performance outcomes.

Nevertheless, both organizational identity and alliances have important implications on organizational survival and merits closer examination together. In rapidly changing technology industries, an organization must acquire legitimacy by offering a clear identity—in the sense that the organization can be understood and is considered a member of a legitimate market category (Kennedy, 2008; Zuckerman, 1999). An organization must also access important resources and knowledge; it is likely to do so by establishing partnerships with other organizations in its environment. Yet, applying the adage "you are known by the company you keep" suggests that an organization's choice of partners should matter in forming or maintaining a clear identity. For example, alliances with partners that on balance are congruent with the organization's classification are likely to confirm its identity and present the organization coherently; conversely, partners that on balance are incongruent with the organization are likely to portray it incoherently.

The focus of this dissertation is therefore to more closely examine the connection between organizational identity and interorganizational alliances. Chapter Two investigates the effect of an organization's identity on its initial alliance portfolio formation. It asks the question, how does the comprehensibility of an identity—a fundamental issue a new firm faces—affect how it forms alliances? Chapter Three investigates how organizational identity affects the influence of alliances on organizational performance. It asks the question, how does the strength of an organization's identity affect the impact that its exploration alliances have on its performance? Chapter Four concludes with a summary of this dissertation's theory and findings as well as discusses some important next steps for future research.

2. How the Comprehensibility of Identities Affects Early Alliance Formation

2.1 Introduction

Forming strategic alliances help new firms address their liabilities of newness, such as the lack of both resources and efficient operational processes. Such liabilities cause new firms to have a higher risk of failure than older and more established firms (Stinchcombe, 1965). By forming alliances, firms can obtain resources and know-how more reliably and efficiently than they could on their own (Aldrich, 1979; Powell, 1990). In addition, by forming a large and diverse set of alliances, new firms will have better access to resources and a better chance of survival (Baum, Calabrese, and Silverman, 2000). However, not all new firms require a large and diverse alliance portfolio. Liabilities of newness also contribute to the stratification of firms within an industry (Stinchcombe, 1965). As new firms are founded at different times and in different places, they are naturally endowed with different levels of resources. Among other things, these differences cause new firms to vary in size, location, and technology use (Baum and Haveman, 1997; Sine, Haveman, and Tolbert, 2005). Furthermore, depending on the resources available to a new firm, forming alliances may be more or less imperative (Eisenhardt and Schoonhoven, 1996).

New firms also start with different levels of cognitive legitimacy, which may also impact their alliance formation. Cognitive legitimacy is the degree to which an audience, defined in this chapter as a set of potential customers, recognizes the new firm. It is further helpful to relate cognitive legitimacy to how well or how effortlessly an audience comprehends the firm based on the firm's fit with the audience's conception of social reality and an established way of life (Meyer and Rowan, 1977; Suchman, 1995). By fitting in, a firm is predictable, meaningful, inviting to the audience, and in short, comprehensible (Suchman, 1995). Arguably, a new firm's primary concern should be attaining comprehensibility from potential customers. Because a new firm with no history will most likely be identified with the product it introduces, potential customers must first recognize and understand the firm's product before they can comprehend the firm. Accordingly, the more novel a new firm's product, the less comprehensible the new firm will be (Aldrich and Fiol, 1994).

By forming alliances to signal information about its product, a pioneering firm may help potential customers understand the firm. By choosing partners whose products have overlapping characteristics and then announcing these partnerships, a new firm can convey information about its own product. This proposal is founded on the principles of homophily (Lazarsfeld and Merton, 1954) and the argument that a firm's set of alliance partners acts as signals from which an audience can make inferences about the firm (Podolny, 1993). Varying levels of comprehension about new firms should affect how they form alliances to convey information to potential customers, yet we lack perspective on this issue. Would an extremely low comprehensible new firm be more likely to form more partnerships to help potential customers understand it than a familiar new firm would? Or, would the firm's extremely low comprehensibility prevent the new firm from forming more partnerships than a familiar new firm would? This chapter addresses the question of how the most fundamental hurdle a new firm faces—becoming comprehensible—affects how it forms alliances.

In this chapter, I propose a theory about the influence of a new firm's comprehensibility on its early alliance formation. To do so, I highlight a perspective that a new firm's comprehensibility depends on getting categorized within an existing taxonomy and is further affected by the degree of focus producers preceding the firm have established in the category. This perspective is informed by both principles of categorization in cognitive science (Rosch, 1978) and insights in organizational ecology (Hannan and Freeman, 1977, 1989; Hannan, Pólos, and Carroll, 2007). The degree of focus producers place on a category affects how clearly the category is defined and how likely an audience would be able to recognize the category and comprehend the producers belonging to it. At best, a pioneering firm will be categorized and comprehensible to potential customers, thus allowing them to evaluate and possibly purchase products from the firm. At worst, a pioneering firm will be deprived of a category label by which to be identified. The degree to which potential customers are able to recognize the new firm's product category will likely affect how the firm will form alliances to become comprehensible.

I will focus on two characteristics of alliance formation: the rate at which a new firm forms partnerships and the degree of dissimilarity between the firm and its set of partners (henceforth called, partner set diversity). These characteristics have been important foci of research. Studies have indicated that they improve the firm's performance (Baum et al., 2000), learning opportunities (Powell, Koput, and Smith-Doerr, 1996) and decision-making (Beckman and Haunschild, 2002).

An investigation of the effect of a new firm's comprehensibility on the rate of formation and diversity of its early partnerships is important for two reasons. First, management research has focused on the struggle of pioneering firms to overcome their low comprehensibility, identifying many strategies that help in this struggle. For instance, entrepreneurs may use strategies such as influencing convergence around a standard technology to create and sustain new markets (Aldrich and Fiol, 1994) or claiming a new market actively so that they become the cognitive referent for it (Santos and Eisenhardt, 2009). Entrepreneurs may also pursue a strategy of configuring an efficient network of partners in order to improve their early performance (Baum, Calabrese, and Silverman, 2000). Yet, little research has investigated how such strategies might be affected by the very fact that the firm is new and must be labeled by categories that vary in the degree to which an audience can clearly define them. If every new firm must be associated with a category, then firms start out positioned in a cognitive social structure where some new firms will be more comprehensible to audiences than others. Moreover, the efficacy of strategic behavior a new firm engages in to become established may be affected by its starting position within this structure.

Second, investigating the effect of a new firm's comprehensibility on the rate and diversity of its early alliances is relevant to interfirm network studies. Ample evidence suggests that interfirm networks have a substantial impact on new firm outcomes; hence, it is important to consider how networks form in the first place. Several researchers have focused on untangling the endogenous processes of alliance formation by investigating the conditions in which firms without prior ties form alliances (e.g., Beckman, Haunschild, and Phillips, 2004; Rosenkopf, Metiu, and George, 2001; Sorenson and Stuart, 2008). However, few papers have sought causal explanations for the structure of alliance networks in an entrepreneurial setting, which is a pertinent situation to

4

investigate initial alliance formation. Among those studies that have considered the matter, Hallen (2008) investigated the influence of founder ties and the firm's early accomplishments on its initial venture capital relationships. Additionally, Özcan and Eisenhardt (2009) uncovered how leaders of new technology firms visualize their firms in the technology architecture of their industry while developing their alliance portfolios. I hope to contribute to the literature by examining the role a new firm's comprehensibility plays in forming its initial set of alliances.

The empirical setting that this chapter investigates is the U.S. software industry. I examine a sample of 499 software firms founded between 1992 and 1997 and the alliances they formed during their first seven years of existence. During the period the firms were founded, the Internet was first commercially available and the software industry began to experience significant changes. The Internet attracted many entrepreneurs who introduced new software products or experimented with new business models related to the new technology. During this period, I observed a variation in how new software firms fit into a prevailing product category system. A new firm may either have made a better version of a current product and fit into a previously and clearly defined category or introduced a pioneering product with the new technology and fit into a new and less clearly defined category. In addition, the software industry is a suitable setting for studying alliances because the competitiveness of the industry and the nature of software itself necessitate cooperation among many different software firms. The firms in the sample were all founded in California, where, at the time of this study, there was the greatest concentration of software startups in the U.S.

I will begin by discussing how the comprehensibility of a new firm depends on its categorization, and then suggest how alliances are signals of organizational identity. Next, I will propose my hypotheses about the rate of alliance formation and the degree of dissimilarity between the firm and its set of partners (partner set diversity). Then, I will describe in more detail the empirical setting and methodology for analysis. Finally, I will discuss the results of my analysis and suggest future studies.

2.2   Theory Development

2.2.1   Categorization and Comprehensibility of a New Firm

Categories and the process of categorization are fundamental to the way we understand the world around us. Cognitive scientists define a category as a concept for a set of things (e.g., entities, natural objects, or events) that are considered equivalent (Rosch, 1978). The process of categorization is "the mental operation by which the brain classifies objects and events. This operation is the basis for the construction of our knowledge of the world. It is the most basic phenomenon of cognition…" (Cohen and Lefebvre, 2005: 2). Rosch (1978) identified two fundamental principles of categorization. The first principle maintains that the function of categories is providing cognitive economy. Categories allow maximum information about objects or events to be processed with the least amount of cognitive effort. The second principle suggests that a system of related categories, or taxonomy, creates the impression that the world exists in a cognitively structured order, rather than in an arbitrary or unpredictable condition.

Naturally, categories figure in the study of organizations. For example, researchers have considered what causes organizational leaders to categorize strategic issues as threats or opportunities, and how such labels subsequently affect their interpretation of and response to the issue (Jackson and Dutton, 1988). Others have discussed how organizational leaders create cognitive taxonomies of the organizations in their environments in order to make sense of the variety of these organizations and, in particular, to define the set of their competitors (Porac and Thomas, 1990). For instance, Scottish knitwear producers define a cognitive taxonomy of their industry based on a few salient organizational attributes such as size and location; this taxonomy also maps closely onto the structure of rivalry relationships between those producers (Porac, Thomas, Wilson, Paton, and Kanfer, 1995). Finally, organizational scholars use industry categories such as the United States Standardized Industry Classification (SIC) codes to delineate a set of organizations for research purposes. SIC codes correspond to classes of organizations based on similarities in their products or services. In particular, they may be used in research to empirically define a population of organizations that share a common form and fate in life (Hannan and Freeman, 1977).

Category systems may be structured along vertical and horizontal dimensions that enable cognitive economy and a structured perception of the world (Rosch, 1978). The vertical dimension of taxonomy distinguishes categories from one another in terms of their level of abstraction, which concerns their level of inclusiveness. The level of inclusiveness refers to a hierarchical structure in which each category is fully included within a vertically higher-level category. Categories that are more inclusive are more abstract. For instance, the category labels; *MacBook*, *computer*, and *technology product*, increase in the level of inclusiveness and in the level of abstraction. Importantly, the most useful level of abstraction for cognitive economy and the most representative of the perceived world is what Rosch (1978) calls the basic level.

The basic level is where categories are most differentiated; members of a category at the basic level share the most number of common attributes within the category and have the least number of distinct attributes shared with other categories. The basic level can be formalized as a probabilistic concept of cue validity (see Rosch, Mervis, Gray, Johnson, and Boyes-Braem, 1976) or by a set-theoretical approach to similarity (see Tversky, 1977). The key point is that when identified with a basic level category, an object provokes a "click of comprehension" (Rosch, 1978: 255). Rosch suggests that basic level categories are somewhere at the midpoint of the vertical dimension—that is, neither at the most nor the least level of abstraction. Categories that are one level of abstraction above a basic level become less differentiated than basic level categories because they share fewer common attributes. For instance, in the category hierarchy— *MacBook, computer,* and *technology product*—the basic level is *computer*. The superordinate category, *technology product*, is less differentiated than *computer* because members of *technology product* could also be software, a mobile phone, or a semiconductor product and therefore not share many common attributes. Categories that are one level of abstraction below a basic level become less differentiated than basic level categories because they share many common attributes with members of other subordinate categories. For instance, the subordinate category, *MacBook*, is less differentiated than *computer*. Members of *MacBook* will share many attributes such as size and function with members of other subordinate categories, such as *IBM Thinkpad, HP ProBook*, and *Acer Aspire*.

The horizontal dimension of taxonomy distinguishes categories from one another in terms of prototypical members. Prototypical members have attributes that are most representative of all entities in a category and least representative of entities outside the category (Rosch, 1978). Consider the following are basic level categories in the taxonomy for high technology products: *computer*, *mobile phone*, and *semiconductor*. They share common attributes such as their reliance on electricity, made on a manufacturing line, and made of plastic and metal materials. Despite their common attributes, these horizontal categories are differentiated in terms of their prototypical members. For instance, *computer* suggests a prototypical member for the category; the prototypical computer has attributes, such as design and functional use that are more representative of items categorized as *computer* than those that are not, such as a mobile phone and a semiconductor. We tend to distinguish categories from one another in terms of prototypical members because often the attributes of categories at the same vertical level of abstraction are not entirely clear-cut (Rosch, 1978). The horizontal dimension further enables cognitive economy and a structured perception of the world.

In so far as a new firm fits in a category system, can be labeled by a differentiated category, and resembles the prototypical member of the category, the firm will be comprehensible to potential customers. Furthermore, by associating with a differentiated category, the firm will attain an identity and enable a specific subpopulation of potential customers to recognize the firm (Hsu and Hannan, 2005). To note, the concept of identity in this context is different from the traditional concept of organizational identity, which focuses on the distinctive qualities about an organization (Albert and Whetton, 1985). After all, categories, each of which is used to label many similar organizations, cannot identify what makes each organization distinctive (Gioia, Price, Hamilton, and Thomas, 2010). In the context of this research, a firm's identity is defined in terms of how the category by which it is labeled is differentiated from other categories.

Underlying the association of a differentiated category with identity is the premise that each category has a corresponding audience who views members of the category with expectations and meaning. In the beer industry, for example, microbrewers and their customers created a sharp social identity of beer consumers that drew a distinction between micro-brewed and mass-produced beer categories (Carroll and Swaminathan, 2000). When an audience, a set of customer in this case, has a strong social identity, it tends to reach a high level of agreement concerning the attributes of the category and possesses strong expectations about what constitutes membership in that category (Hsu and Hannan, 2005). The definition of a category will correspond to the distinct social identity of its audience, such as the category of micro-brewed beer corresponding to the social identity of the producers and consumers of such beer. In that categories reflect social identities, when an individual organization joins, or identifies itself with a category, it will, by default, have assumed the qualities and rules associated with that identity. In this sense a differentiated category is linked with a distinct identity. With identity attained through membership in a differentiated category, a new firm will make clear to which specific set of potential customers it intends to be meaningful. In other words, when a new brewery is categorized as a microbrewer, it makes its identity clear to not just any beer consumer, but to a specific set of beer consumers who will view the new brewery with more meaning than other consumers will.

Once the firm has made its identity clear through membership in a differentiated category, the firm can then be evaluated by a specific set of customers. While being evaluated by customers is critical, it remains impossible until the firm has first made its identity clear. Phillips and Zuckerman (2001) called attention to such two-step process, and termed it a two-stage candidate-audience interface, where firms (candidates) are a set of actors competing with one another to form a relationship with another set of actors, the audience. To choose the best candidate, an audience needs to make comparisons, and so it "limits its attention to a discrete consideration set of like alternatives" (p. 383). A candidate that demonstrates itself to be a member of the audience's comparison set has a chance of being selected as the best candidate to form a relationship in the second stage. In other words, having an identity derived from a differentiated category qualifies a firm to be a candidate among others with the same identity; otherwise it is not eligible for further evaluation and loses an opportunity to sell its product. In the stock market, for example, firms whose categorization does not entirely correspond to a specific set of analysts, will be overlooked and discounted by those analysts (Zuckerman, 1999).

Due to the inherent dynamics of different industries, however, some basic level categories to which a new firm could belong will not be equally differentiated from other categories and hence they will not be able to impart a clear identity on the firm. Three reasons may explain such categories. First, in industries where technologies evolve quickly, firms may form new categories by blending existing ones. A new category formed by blending many categories, by definition, is not differentiated; multiple categories will correspond to multiple sets of customers. A firm that joins a blended category is likely to have an unclear identity; the firm would be unclear to which set of consumers it intends to be comprehensible and meaningful. For example, Internet technology enabled the introduction of products combining PBX (Private Branch Exchange) telephone systems and LAN (Local Area Networks) computer network systems into a new category called, Multimedia Telecommunications. Before the 1990s, the two categories—PBX telephone systems and LAN computer systems—were differentiated from each other. As the products blended into Multimedia Telecommunication products, it became difficult for customers to ascribe features such as switching controls and unified messaging, that had previously been associated with PBX and LAN product categories, respectively, to one category and not to the other. Furthermore, since typically two different departments within a firm had previously supported PBX and LAN systems, the loss of each category's differentiation affected managers who were unable to decide which department should support the combined products (Investext Group, 1997).

Second, in quickly evolving industries, entrepreneurs may create new category names. New category names would have low differentiation at the beginning because few members are able to clearly define the category. Additionally, a new category would tend to lose its differentiation as *de alio* firms, new entrants from other industries will seek to take advantage of the new technology. In doing so, *de alio* firms will blend the old category to which their products belong with the new, diluting the definition of the new category (Khessina and Carroll, 2008). Third, due to dynamics in an industry, basic level categories may become more or less differentiated over time. For instance, as producers in the disk drive industry placed more manufacturing focus on the disk array product segment, the disk array category became more differentiated, or perceptually focused, resulting in customers increasingly regarding the disk array population as a

potential new organizational form (McKendrick and Carroll, 2001; McKendrick, Jaffee, Carroll, and Khessina, 2003).

As a result of these dynamics in industry category systems, categories at the basic level will vary by their degree of differentiation. Hannan et al. (2007) formalized this variation as an average grade of membership as well as conceptualized a category with lower differentiation as having a fuzzier (low contrast), as opposed to a crisper (high contrast), boundary. This variation among categories in their degree of differentiation makes some categories more identifiable to a specific audience than others. To the extent that categories impart identities to new firms, according to the category with which they are labeled, some new firms will be more comprehensible to an audience set than other new firms. In this sense, firms exist in different positions in a cognitive social structure from their beginning. New firms in less differentiated categories will be less comprehensible and less identifiable to a specific audience than those firms in highly differentiated categories.

It is likely that the founders of new firms recognize their firms' position in a cognitive social structure. When entrepreneurs begin a new venture, they have a sense of whether their product is new and less comprehensible or simply a better version of an existing product and more comprehensible. In other words, entrepreneurs should be aware that their new firm's position in the market is either innovative or imitative. Often, they have experience in other organizations in the same industry as the new firm they are starting (Audia and Rider, 2005) and so should have some sense of how differentiated the categories used to label their firms are. It is likely that entrepreneurs respond to this knowledge when they form alliances and announce those alliances to the general market.

2.2.2   Alliances as Signals of Identity

Alliances enable firms to exchange resources and information. At the same time, an audience is able to infer information about the firms by observing their alliance partners. This point can be explained with signaling theory, a concept introduced in Spence (1973) (Podolny, 1993, 2001). According to this theory, signals are, in general, observable and capable of communicating information from agents with more information to agents with less information (Spence, 2002). For example, within a market, a seller will know more than a buyer about his product's quality; the greater this information asymmetry, the more the seller will focus on providing signals to communicate information about product quality and the more the buyer will rely on these signals to infer that quality. Podolny (1993) argued that one type of signal that indicates the quality of the seller's product is his status, as ranked according to his network relationships. A seller's network relationships will affect how a buyer perceives him. In particular, if a seller has prestigious customers, distributors, or other partners, their prestige will be transferred to him. As a result, the buyer will rank him of higher status than other sellers, as well as of higher quality than other sellers. Consistent with this argument, Stuart, Hoang, and Hybels (1999) showed that an entrepreneurial firm's relationships with prestigious investment partners increase the market's perception of the firm, as evidenced by the higher initial public offering prices of firms with such relationships.

Based on the relationships a focal firm forms, an audience could also infer the firm's categorization, or identity. This argument is supported by the principle of homophily (Lazarsfeld and Merton, 1954); similar firms tend to form ties with each other more than dissimilar firms do (Lincoln and McBride, 1985; McPherson, Smith-Lovin, and Cook, 2001). Empirical evidence has shown that firms with many similar attributes such as values, sentiments, and status, tend to form interorganizational ties (e.g. Lincoln and McBride, 1985; Podolny, 1993). Technology firms, in particular, will form ties with other technologically similar firms to collaborate on innovations, as they are better able to exchange knowledge with each other than technologically dissimilar firms (Mowery, Oxley, and Silverman, 1996; Stuart, 1998).

A potential customer who possesses little information about a new firm and what it produces, is nevertheless able to infer this information from the identity of the firm's partners. In markets, firms tend to announce their new partnerships by issuing news releases. From such an announcement, a potential customer can learn more about the firm that issued it. As an analogy, consider in a social situation, an individual (a firm) introducing her friend (a partner) to a third party (a potential customer); even as the individual introduces her friend, the third party will be able to infer some characteristics about the individual herself. For instance, if the friend is training for a marathon; the third party may infer that the individual also likes to run or is athletic in some way. Parallel to the idea that alliances communicate status cues that suggest quality (Podolny, 1993), this argument suggests that alliances communicate identity cues that are meaningful to a specific audience, such as a specific set of potential customers. Where status acts as a signal to audiences, communicating information about a firm's quality, identity acts as a signal to potential customers, indicating a firm's categorization so that a specific set of potential customers will identify it, and then will further evaluate it.

As with information concerning status, information concerning identity that is communicated through an alliance meets the two criteria of a signal (Spence, 1973; Podolny, 1993). First, new firms are able to partially manipulate identity signals: an entrepreneur has some choice over the category labels she uses to identify her firm. For instance, in the software industry, new firms have the option of either using an existing category label or introducing a new label to the industry. Pontikes (2008) found that this choice is affected by how well existing labels are defined; specifically, new firms tend to introduce new labels when existing ones related to their technologies are not clearly defined. Moreover, the founder of the firm, given some energy and time, may be capable of selecting partners that belong to categories more or less similar to that of her own firm. Furthermore, once an alliance is formed, the founder may choose to announce her partnerships in a press release and indicate information about her firm.

Second, the difficulty of obtaining the signal is negatively correlated with the degree to which the firm possesses the unobserved quality. In other words, the signal that comes from forming an alliance should be relatively easy, or less costly, to obtain when the firm actually possesses the underlying identity. This correlation makes the signal credible. It can be costly for an entrepreneur to identify her firm with an unfitting category or form an alliance with a potential partner in a category unrelated to her firm. It is likely that a firm categorized with a label incongruent with its product will be misidentified and evaluated negatively. Additionally, it is likely to take more effort to work with a partner in a category unrelated to the firm than with a partner in a category related to the firm.

10

2.2.3 The Effects of Comprehensibility on the Search for Alliance Partners

Up to this point I have discussed the affiliation between a new firm's identity and a differentiated category to which it belongs. As the category becomes less differentiated, the firm's identity becomes less clear and thus the firm becomes less comprehensible to any one specific set of customers. This poses a problem for the new firm as being less comprehensible increases the risk that no customer group will include the firm in its comparison set for further evaluation. The firm is likely to address this problem by forming alliances. Alliances have the potential to indicate information about the firm and clarify its identity, which will decrease the firm's risk of being overlooked.

A new firm whose identity is not clear due to belonging to a less differentiated category is likely to quickly form alliances as a strategy to address its unclear identity. For these new firms with low comprehensibility, signaling the specific nature of their identity becomes essential. Kennedy (2008) has researched how the media will notice a new type of firm so that it can be counted as an emerging population; he focused on how new firms move from not being noticed and not counted, to being fully counted. Here, the concern is how new firms become noticed and more clearly identified; that is, how they move from being partially counted to being fully counted. Partially counted new firms, in a sense, face an anxiety similar to the one faced by middle-status candidates in Philips and Zuckerman's candidate-audience interface model (2001). They are likewise on the threshold of either belonging to a specific audience's comparison set or being overlooked and out of consideration.

In that new firms in less differentiated categories are less comprehensible, they face a high risk of not being identified by a specific set of customers, it is likely that they will exert more effort to signal relevant information through alliances than will new firms in more differentiated categories. As a result of this effort, less comprehensible new firms will form alliances faster than more comprehensible new firms will. This proposal will be empirically tested as the first hypothesis:

> *H1: Less comprehensible new firms form alliances at a faster rate than more comprehensible new firms do.*

2.2.4 The Effects of Comprehensibility on the Search for Partners Different from the Firm

The degree of a new firm's comprehensibility may also affect the firm's choice of alliance partner in terms of product profile. If a general audience can infer the identity of a firm by understanding the identity of its partners, it is likely that a less comprehensible new firm will focus its efforts on forming partnerships with firms who have product profiles similar to its own. Doing so will strengthen the salience of the features the firm and its partners share. By highlighting shared features, a new firm can make clear by which set of customers it intends to be identified. At the least, such a partnership will improve the visibility of a new firm's product or its business and attract some customers. Moreover, it is likely that for a less comprehensible

new firm, associations with partners whose product profiles are dissimilar from its own may only confuse potential customers about a new firm's business, and be at risk that no customers will take notice. Potential partners will likewise be motivated to form an alliance with a less comprehensible new firm. Their identities may also be unclear and increasing the salience of its product category would also help them. In addition, because these potential partners may be also low in comprehensibility, they may not have other alliance offers to consider.

I propose that the more comprehensible a new firm becomes (i.e., the more differentiated its category becomes), the less it would be concerned with highlighting its similarities with other firms; rather, it would be more willing to seek partners in categories different from its own. The firm will be less concerned to highlight similarities with other firms because a set of customers can identify the new firm and begin evaluating it already. By seeking partners in different categories, a new firm demonstrates to its set of potential customers that its product has a wide market appeal, as it is complementary with many other products in its field. In addition, the new firm could indicate that, through its partners, it has access to a broad range of ideas, information, and technologies that increases its ability to operate and make decisions effectively (Baum et al., 2000, Beckman and Haunschild, 2002). If the firm demonstrates that it has such access, its set of potential customers will perceive the firm as attractive. In this way, the firm gains legitimacy in the pragmatic sense. Pragmatic legitimacy of a firm relates to whether the firm has met the interests of an audience, a set of customers (Suchman, 1995). Hence, the more comprehensible a new firm is, the more it will engage with partners that belong to categories other than its own, and therefore the more diverse set of partners it will form. From the other side of the relationship, potential partners with product profiles different from the new firm will likewise be motivated to demonstrate their firm is complementary with other products.

However, the positive effect that a new firm's comprehensibility has on the diversity of its partner set reaches a limit. At a certain point, a new firm's willingness to engage with partners in other categories becomes constrained by the greater comprehensibility the new firm already possesses from belonging to a differentiated category. When a new firm is associated with a highly differentiated category, it is likely that a specific set of customers has clearly identified the firm. Also, the firm has likely conformed to the characteristics of the customers' comparison set, which are defined by the category's prototypical member. Because the audience will clearly understand the firm's purpose and function, it will have strong expectations about how the new firm should continue to look and behave (Hsu and Hannan, 2005; Hannan et al., 2007). Such strong expectations are likely to keep the firm from engaging with too many partners with different product lines. For instance, firms are more likely to divest from businesses in categories unrelated to theirs, as associations in too many other markets will confuse analysts about the core purpose of a firm (Zuckerman, 2000). Likewise, a new firm positioned in a highly differentiated category will be less willing to engage with too many businesses associated with different product categories. Rather, the new firm will prefer to engage with partners that help maintain its coherence and identity—those with product profiles that resemble its own. Otherwise, by engaging with partners with different product profiles, the firm risks losing its perceived coherence and its customers' interest. Such loss of customer interest has been found in other settings. For instance, in the movie industry, films that belong to multiple genres often receive poor responses because moviegoers cannot make sense of them (Hsu, 2006). Additionally, in the

market for temporary jobs, freelancers who had a history of jobs in notably different categories are likely to be perceived as erratic and less likely to be hired for a job (Leung, 2010).

Constraints due to competition represent another reason why highly comprehensible new firms will prefer partnerships with firms that have similar product profiles. Highly comprehensible new firms are likely joining a competitive environment. They belong to highly differentiated categories and are easy for resource providers to comprehend. The conditions of such categories are welcoming for new firms. Investors can estimate predictable financial returns, suitable suppliers already exist, and employees can anticipate stable employment. Because these categories are welcoming, they are also likely, at equilibrium, to be competitive (Freeman and Hannan, 1977, 1989). The benefits of a highly differentiated category are likely to attract many firms and increase competition within it.

When faced with competition, highly comprehensible new firms are likely to engage with partners in categories similar to, rather than different from their own. This may be due to two reasons. First, in order to survive in a competitive environment, new firms must increase their efficiency by lowering production costs and introducing new products quickly. The strategy to compete on cost and time lead firms to favor alliance partners with whom they share similar knowledge and technology backgrounds, as they can communicate and exchange information with these partners efficiently (Cohen and Levinthal, 1990; Mowery et al., 1996; Stuart, 1998). Rather than be distracted by partners that focus in different product categories, new firms faced with competition are likely to select partners who belong to categories similar to their own. Second, competitive environments tend to be characterized by uncertainty due to the volatility of the market. New firms are likely to cope with this uncertainty by forming alliances and cooperating with similar or familiar partners (Beckman et al., 2004; Gulati, 1995). Accordingly, the potential partners of a highly comprehensible new firm will tend to belong to the same category as the firm, and thus will likely be similarly motivated to form an alliance because these potential partners face the same uncertainty from competition and should benefit from the partnership as well. Moreover, firms that belong to a highly differentiated category will view a new firm that joins the category as a rival and may feel threatened. Faced with a competitive threat, these firms may initiate a cooperative relationship with the new firm to preempt direct competition (Pfeffer and Salancik, 1978; Thompson, 1967).

To summarize this section, the more comprehensible a new firm is, the clearer its identity and a specific set of customers will take notice of it. Recognition from a specific set of customers will relieve the firm of clarifying its identity through alliances with firms in product categories similar to its own. The recognition will give the firm the opportunity to engage with partners in product categories different from its own, and thus demonstrate pragmatic legitimacy. At a certain point, however, a new firm's comprehensibility can be so high that it becomes constrained by identity expectations and the competition within its highly differentiated category; once a firm has passed this point, it will tend to engage with partners whose product categories overlap with its own in order to maintain its coherence. Hence, due to constraints on their identities, new firms at both the high and the low end of comprehensibility will tend to select partners who belong to categories similar to their own, while firms in the middle, due to the desire to gain pragmatic legitimacy, will tend to select partners who belong to categories

different from their own. This curvilinear relationship between a new firm's degree of comprehensibility and the diversity of its partner set will be tested with the second hypothesis:

> *H2: A curvilinear (inverted U-shape) relationship exists between the comprehensibility of new firms and the degree of dissimilarity (diversity) of their partner sets.*

The first two hypotheses consider the effect of a new firm's comprehensibility on alliance formation, but they do not specify the type of alliance to which they refer. Firms tend to engage in several types of alliances; for instance, Barley, Freeman, and Hybels (1992) identified 10 types of alliances within the biotechnology field. Each type of relationship achieves a different purpose. For the most part, collaborative, or horizontal alliances can be distinguished into two types: technology-related and marketing-related. In technology-related alliances, firms research and develop new products together. They may also technically integrate their products so they function together. In marketing-related alliances, firms co-brand, distribute or resell each other's products.

Technology-related alliances are more difficult to create and maintain than marketing-related alliances. Technology alliances are not trivial undertakings for the firms involved; to accomplish their goals, both sides must contribute important resources, including the time of valuable employees assigned to work with the partnering firm. In contrast, partners in marketing alliances generally intend to help each other inform the market about their respective products. Doing so may require only that each firm have its sales departments learn about and be prepared to sell its partner's products.

The difference in the difficulty to form technology and marketing alliances may influence the type of alliance a new firm will favor. As less comprehensible new firms may focus on quickly forming many alliances, they may prefer ties that are easier to establish and thus form marketing-related alliances faster than technology-related alliances. In addition, the difference in the difficulty to form the two types of alliances may relate to the difference in the strength of ties between partners. To develop a technology alliance, partnering firms will need to put forth more effort in the relationship than in a marketing alliance. To co-develop and integrate products in a technology alliance, the partnering firms would need to exchange substantial information, and communicate regularly over a long period. In contrast, to co-brand or jointly sell products in a marketing alliance, the partnering firms will likely share less information and communicate over a shorter period of time. As partnering firms will put more effort to work together in a technology alliance, the alliance would tend to produce a stronger tie between the firms than a marketing alliance would.

The stronger ties produced by technology alliances may relate to stronger and more convincing signals of information than from marketing alliances. Potential customers are likely to assume that partners in a strong relationship are more sincere about their affiliation than in a weak relationship. As such, a new firm may favor technology alliances to signal information about its identity or demonstrate complementarities with other products in its field. To indicate its identity, a less comprehensible new firm will favor technology partners that have similar product profiles to its own. In addition, as its comprehensibility increases, to gain pragmatic legitimacy,

the new firm will favor technology partners that have product profiles different from its own to emphasize product complementarities and wide market appeal. Lastly, to conform to both the identity and competitive constraints of a highly differentiated category, a highly comprehensible new firm will favor technology partners that have similar product profiles to its own. Hence, the inverse-U relationship that exists between the comprehensibility of new firms and the diversity of their partner sets would likely be more pronounced for technology alliances than for marketing alliances. Based on these proposals, I will test the following hypotheses:

> H3a: Less comprehensible new firms will form marketing alliances faster than technology alliances.

> H3b: The inverse-U relationship between the comprehensibility of new firms and the degree of dissimilarity (diversity) of their partner sets will be more pronounced for technology alliances than for marketing alliances.

2.3   Empirical Setting: The Software Industry

The software industry only started forming in the 1950s. Despite the relative shortness of its existence, the software industry has grown steadily into a major contributor to the United States economy and is quickly expanding in other parts of the world, especially in India and China. In 2008, the U.S. spending on software products was $136.6 billion, which represents 46 percent of the world software market (Business Software Alliance, 2008). When the professional services that typically accompany software products are counted towards this total, this value is estimated to be much higher, $450 billion (Desmond, 2008). Moreover, in 2007, the software industry employed 1.7 million people in the U.S. and had a real annual growth rate of 14 percent, outpacing all other economic sectors in the U.S. (Business Software Alliance, 2008). Although software seems ubiquitous in the consumer market and one might think that the industry derives most of its revenue from consumers, in fact, the majority of software revenues (83 percent) come from businesses (Thormahlen, 2011). Business managers view software as an investment to improve both their internal productivity and their interactions with suppliers and customers.

The software industry is a suitable empirical setting for studying alliances. Firms in high technology industries typically tend to form alliances to share complementary skills and know-how (Mowery et al., 1996), increasing their performance and innovation (Shan, Walker, and Kogut, 1994; Stuart, 2000). Alliances in the software industry are also important for these reasons and well researched in the strategy literature (e.g., Lavie, 2007; Singh, 1997). Moreover, software experts view alliances as a way to create a sustainable market for a firm. A software product is essentially a set of instructions (a program), written by programmers using a computer language protocol, that tells computers how to operate or to perform some business functions through the computer interface. The intangible nature of software requires that a firm develops an ecosystem of partners (Messerschmitt and Szyperski, 2003), in which co-development and strategic distribution partnerships can help a firm innovate and inform customers about the use and quality of its products. Additionally, a software application must typically integrate with other applications or systems, such as databases; however, a producer that specializes in developing an application may not have the skills to also integrate with other systems efficiently.

Thus, it is common for firms to seek partners that will make systems integration easier. Finally, because writers create software, little capital investment is necessary to develop it and the barriers to enter a software market are low. As a result, customers can choose from many products and firms must compete for their business. By forming alliances to co-develop ways of making software products easier to install and use, a firm can gain access to and increase its appeal among a greater number of users.

The software industry also provides a suitable empirical setting for studying the categorization of new firms. A historical account of the industry highlights the significance of software taxonomy (Campbell-Kelly, 2003). The classification was driven by the industry's fast growth. Two important advancements in microprocessor technology, which allowed smaller, faster and less expensive computers to be produced, caused major transition and growth in the software industry. The first advancement, from mainframes to minicomputers in the 1960s, reduced the costs and increased the capabilities of computers. At the same time, software and hardware development became decoupled, which led to a wave of new companies that focused solely on developing software for business use. Two of the companies founded during this early period that still survive are SAP and Computer Associates. The next advancement, from minicomputers to personal computers in the 1970s, allowed another wave of software companies to emerge. Further increasing the popularity of computers, this generation of software firms introduced "shrink-wrapped" software for the mass market. For instance, Software Arts, which produced VisiCalc, a personal financial planning application, was one of the most successful software firms founded during this second wave. Microsoft and Lotus are also among the early companies of this wave that were successful.

By the early 1970s, the explosive growth of the software industry and the expansion in the variety of ways that software could be used necessitated that intermediaries begin to classify software products so that their substantial impact on the economy could be understood (Campbell-Kelly, 2003). Intermediaries divided software products into two major categories. The first major category is the systems software, which is software that provides or supports a computer's basic functions; software in this category includes operating systems and utilities that optimize or maintain a computer system. The second major category is applications software, which consists of end-user programs such as those used for financial planning. It is rare that one firm produces software in both categories. Typically, programmers of application software will assume the presence of systems software working in the background. Because software is intangible and written with a specific computer-system- or end-user- purpose in mind, market analysts categorized software products, and the firms who produced them, according to their applications, or business function uses. For instance, Vantive Corporation, founded in 1993, makes software that helps businesses integrate the phases of a sales cycle. Rather than categorizing the firm by the language protocol the programmers used to write the software, or by the software's underlying database or technical architecture, industry analysts labeled it, according to the software's application: a sales force automation software firm (Frye, 1993).

By the end of the 1970s, industry analysts and journalists reached a consensus on a classification system for the industry (Campbell-Kelly, 2003). In 1984, this system was used by the U.S. Department of Commerce in its first study of the industry. In 1987, the U.S. Census Bureau subdivided the Standard Industrial Classification (SIC) categories for computer services and

software into nine subclasses, three of which; 7372, 7371, and 7379 comprised the core of the software industry. In 1990, statistics concerning members of these three subclasses began being published in the *Statistical Abstract of the United States*. Because the U.S. constituted at least 95% of the world's software products market at the time, this system became the most widely accepted way of classifying the market (Campbell-Kelly, 2003). This classification can be described briefly. Systems software is divided into five major subcategories: operating systems, database management systems, programming aids, transaction processing controls, and utilities. Application software is categorized as either industry-specific or cross-industry. Generally, software products that are only useable within a single industry are classified as industry-specific, whereas software products that relate to business processes common among different industries (such as payroll and project management) are classified as cross-industry. One cross-industry software application is, Enterprise Resource Planning (ERP); in 1993, SAP, Oracle, J.D. Edwards, and PeopleSoft were among the top producers of ERP software (Hodges and Melewski, 1993). Beneath these main subdivisions of systems and applications software, there are secondary and tertiary layers of classifications.

In 1992, the software industry was again affected by a major technological advancement—the commercialization of the Internet and, one year later, the introduction of the first World Wide Web (Web) browser, Mosaic. I selected the early Internet years as this study's empirical time frame for three reasons. First, by 1992, there was an established taxonomy for software firms that had matured since the last period of technological change in the 1970s. After a few decades of settling, the software classification system is likely to reflect the cognitive structure shared in the industry. Second, Internet technology led to the creation of many new firms developing various software applications. Based on an independent data-collection firm, Corporate Technology Information Services, Inc. (CorpTech), a count of all business software firms in the U.S. between 1992 and 2003 indicates that from 1993 to 1994, the number of U.S. software firms increased most dramatically—by 160 percent (see Figure 1 below). Such a surge in new firms, as well as their foment around the new technology, is a characteristic response to significant technological change in many industries (Anderson and Tushman, 1990).

Figure 1: Number of Firms in the U.S. software industry by year (1992-2000)
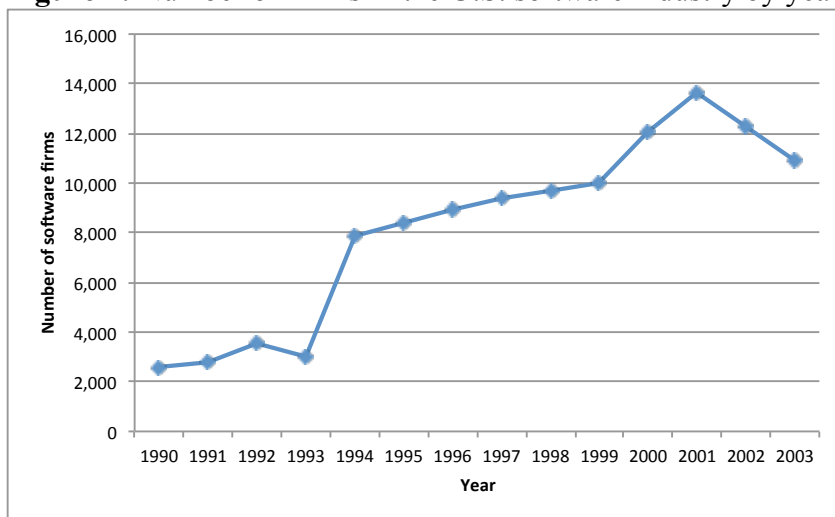
(Source: CorpTech)

Third, related to the second point, we can assume that the categorizations of the many new firms during this period varied widely. Although the Internet became generally available in 1992, it did not catch on immediately and many firms were slow to adopt and to innovate using the new technology. Even by 1997, the impact of Internet technology had not yet fully impacted the industry: among the top 500 software companies in the U.S., 41 percent were selling products related to the Internet, yet these products accounted for only 2 percent of their sales revenue (Frye, 1997). Moreover, because entrepreneurs used the technology in various ways, there should be a wide variation in the degree of comprehensibility of new firms at the time of their launch. For instance, some new firms may have introduced Internet-related products that were novel (at the time), yet not well understood. Meanwhile, other new firms may have introduced products that used Internet technology to improve existing applications, and so could be understood easily.

2.4   Methodology

For my analysis I gathered data from four sources: Corporate Technology Information Services, Inc. (CorpTech), Lexis-Nexis Academic, Thomson Reuters VentureXpert database, and the National Bureau of Economic Research (NBER) U.S. Patent database (Hall, Jaffe, and Trajtenberg, 2001). CorpTech maintains a comprehensive taxonomy of technology products and a directory of public and private high technology firms based in the United States. It annually updates the information about each firm, such as the kinds of products the firm makes, its location, and ownership status. Moreover, it identifies new firms in the industry by searching phone books, press releases and industry trade magazines. CorpTech was founded in 1985 and sells its data to research organizations and firms that do business-to-business market research. Based on its longevity, I assumed that the data is sufficiently reliable and unbiased for research purposes; several researchers who study high technology firms (e.g., Baron, Hannan, and Burton, 1999; Sine, Mitsuhashi, and Kirsch, 2006; Stuart et al., 1999) have used the CorpTech directories as a source of data. Indeed, some researchers have used CorpTech's directory to study, in particular, the software industry (e.g., Cockburn and MacGarvie, 2009).

Lexis-Nexis Academic maintains a comprehensive online collection of news articles including company-issued press releases. To obtain alliance information, I searched the archive of press releases for each firm's name. Obtaining alliance information from archived sources was appropriate for two reasons. First, currently available alliance databases, such as the Thomas Reuter's financial transactions database, SDC Platinum, do not track all alliance types, nor do they track all alliances involving young or privately owned firms. Moreover, unlike at least one other industry, the software industry does not have a secondary data source of alliance activities: the biopharmaceutical industry has *www.recap.com* (previously, Recombinant Capital, Inc.), an online database of firms and their alliances. Researchers (e.g., Eisenhardt and Schoonhoven, 1996; Stuart 1998) studying the semiconductor industry have used the strategy of collecting alliance data from press releases and trade magazines.

Second, press releases are formal communications that firms issue to direct information to the media, which directs the information to the market. By issuing newsworthy events through press

releases, firms can manage the market's perceptions of the firm by giving reporters something to say about it. As new alliance partners are newsworthy, it is likely that new firms will issue press releases about the alliance and provide insight into how they seek to identify themselves with the alliances. The publications I included in my search were press release outlets such as *PR Newswire* and *BusinessWire,* and local and regional newspapers, such as the *San Jose Mercury News* and the *Orange County Register*. I sought to limit the search to alliances that were related to horizontal technology and marketing alliances, that is, those in which both firms mutually contributed to developing a product or implementing a marketing strategy; therefore, I performed searches with keywords such as "technology partnership or alliance," "co-development," "co-brand," and "joint implementation," as well as any applicable verb forms. I omitted press releases that concerned vertical alliances such as buyer and seller relationships, one-way licensing agreements, and equity partnerships. To confirm that I had not overlooked major alliances, I also cross-referenced alliance announcements with the Thompson Reuters SDC Platinum alliance database. I used the last two databases, VentureXpert and the NBER U.S. Patent database to track information concerning venture capital firms' investment activities and information on utility patents, respectively.

2.4.1   Sample Construction

The firms from which I constructed my sample were founded between the year that the Internet became available for commercial use, 1992 and 1997, the year before the Internet bubble started to grow. I stopped the research timeline in 1997 to avoid noise from the bubble, during which any firm with an "e-" at the beginning or a ".com" at end of its name seemed to have instant legitimacy as indicated by their quick access to venture capital funding (Masnick, 2003). In addition, I limited geographic variability during this time frame, focusing on firms founded in California. Many of the software firms established during this period were founded in California due to its regional advantages (Saxenian, 1990). In the 1980s, leading database companies, headquartered in Northern California, had attracted abundant programming talent. By the 1990s, programming skills were more concentrated in California than anywhere else in the United States (Campbell-Kelly, 2003). A survey of CorpTech data indicates that in 1992, 17.9 percent of business software firms (627 firms) were based in California; the state with the next highest population of firms was Pennsylvania, with 7.9 percent. Massachusetts came in a close second with 7.3 percent of the population. California continued to be the state to have the largest population of software firm during the study time period, with at least 10 percentage points more than the state with the next highest population of firms. Additionally, at the time of this study, a significant amount (40 percent) of the U.S. Internet traffic either originated or terminated in California (Gromov, n.d.).

To construct the sample of new firms established in California, I obtained archived CorpTech directories from 1992 to 1998. Because there is often a delay between the establishment of a new firm and the registration of its details in the directory, I collected information concerning firms founded during a given year by examining the directory from the following year. Next, I searched the Internet and Lexis-Nexis to verify that the firms in this sample indeed matched my time period and geographic criteria. After this verification was complete and duplicate records removed, a final total of 499 firms were in the sample. Finally, for each firm, I collected seven

years of annual data concerning its alliance activities, venture capital funding, and patenting. I had identified seven years as the threshold when a firm transitions from being new to being established. The median age at which a firm in the software industry fails is seven years (Li, Shang, and Slaughter, 2010); moreover, from the point of view of investors, if a firm has received two major rounds of external funding, which is assumed to take about seven years and continues to show the potential for a significant return, investors will tend to regard the firm is no longer in a startup stage, but rather in a growth stage (Hall, 2011). Of the 499 firms analyzed, 290 (58 percent) announced one alliance or more during the time of study. Those firms, on average, formed alliances with 1.6 partners per year.

2.4.2 Rate of Alliance Formation and Partner Set Diversity

Two outcome variables will be analyzed to test the hypotheses: a firm's rate of alliance formation and the degree of dissimilarity (diversity) in its partner set (partner set diversity). Partner set diversity will be measured by an index that indicates the degree of dissimilarity between a focal firm and its partners. The degree of dissimilarity corresponds to a measure of its diversity as it indicates the extent to which the focal firm is affiliated with or has access to new technologies and knowledge through its partners. Although there are many qualities by which a focal firm and its set of partners may be judged dissimilar, in this study, I define dissimilarity in terms of the specific product or service lines in which the firms are engaged. Products represent the most subordinate level of categories in CorpTech's taxonomy; examples of products include: route scheduling software, freight dispatch software, and order entry/processing software, each of which is a member of the category, warehousing/distribution software.

The partner set diversity index is calculated as a ratio of the number of distinct products represented in the partnership (y) in which the focal firm is not involved (x-y), y being the number of products represented by the focal firm, to the number of distinct products represented in the partnership (x); (x-y)/(x), then averaged if more than one partner constitute the focal firm's partner set. For example, focal Firm A and its partner together engage in a total of five products. If Firm A is engaged in four of the products, then the index of dissimilarity is 0.2 [=(5-4)/5]. However, if Firm A is engaged in only one of the products, then this index is 0.8 [=(5-1)/5]. In the latter case, there is less overlap between Firm A and its partner's product line. In other words, in the latter case, the diversity of products that Firm A becomes affiliated with through its partnership is greater than the former case. Additionally, the partner set diversity index indirectly indicates the extent to which Firm A gains access to additional product technologies and markets through its partners; the closer the firm's partner set diversity index is to one, the more it will become affiliated with different products and technologies through its partnerships. This index is essentially the inverse of the measures of overlap that are used to determine the degree of similarity between firms' technologies (Mowery et al., 1996) and the degree to which other firms encroach on a focal firm's technology space (Podolny, Stuart, and Hannan, 1996). Other researchers use a similar partner set diversity measurement identifying the degree to which the technologies of a firm's partners both differ from the firm's and from each other's (Phelps, 2010; Sampson, 2007).

20

2.4.3 Degree of Comprehensibility

To measure a firm's degree of comprehensibility, I first measured the degree of differentiation of the category in which it belongs. To do so, I employed the formulation that defines a category's average grade of membership—that is, the average degree to which members of a category focus their efforts within it (Hannan et al., 2007). When many firms associated with a category develop most, if not all, of their products within it, it is a highly differentiated category. This classification identifies the category as clearly defined and distinctive from other categories. Conversely, when many firms associated with a category develop products in other categories, they dilute the category's distinctiveness, making it a low differentiated category. A low differentiated classification identifies the category as ambiguously defined and not distinct from other categories. This measure of category differentiation has been used to compare legitimacy among subpopulations of foreign banks established in Shanghai (Kuilman and Li, 2009) as well as to indicate the degree of leniency of meanings among category labels within the software industry (Pontikes, 2009).

Comprehensibility, or more generally, cognitive legitimacy, has been measured in several other ways, including how quickly new practices spread among organizations in a field (e.g., Tolbert and Zucker, 1983) or by how frequently the media reports on a new product (e.g., Kennedy, 2008; Sine, Haveman, and Tolbert, 2005). For the present study, a category's average grade of membership is an appropriate measure to use, as this study seeks to examine comprehensibility among numerous subpopulations of firms within one industry, rather than determine whether or not one subpopulation is comprehensible or not. On the whole, a subpopulation may be comprehensible; however, as changes within the industry engender new or blended market categories, other subpopulations may emerge within it that are more or less comprehensible compared to one another. This study requires a measure that is relative; the average grade of membership in the software taxonomy will indicate the relative comprehensibility of firms within an industry.

I took two steps to measure a firm's degree of comprehensibility. First, for every year analyzed, following Hannan et al. (2007), I computed the average grade of membership for each software-related category. To do so, I determined each firm's grade of membership in each category. Suppose Firm B sells a total of four products in Categories X and Z; three of those products are in Category X and one of those products is in Category Z. Firm B's grade of membership in Category X is 0.75 (=3/4) and is 0.25 (=1/4) in Category Z. Categories X and Z are then each assigned an average grade of membership that is determined by averaging the grades of memberships from every firm that belongs to it. An average grade of membership measure close to one indicates that a category is highly differentiated and its segmentation from other categories is crisp and a measure close to zero indicates a category is not differentiated and its segmentation from other categories is fuzzy.

I calculated the average grade of membership measure for the categories in the middle tier of CorpTech's taxonomy, as mid-level categories tend to have the highest levels of abstraction according to the principles of categorization (Rosch, 1978). CorpTech's taxonomy of high technology products and services is organized into three hierarchical levels. Categories at the top level correspond to entire industries, such as software, telecommunications, and computers. The

middle level identifies sub-industry categories that are used to classify software according to its use or business application. Within the software industry, there are 31 sub-industry categories, such as accounting software, artificial intelligent software, and warehouse/distribution software; these 31 categories correspond to those classified under the software-related (SIC) codes (i.e., 7371, 7372 and 7379). Subordinate to these 31 sub-industry categories, CorpTech specifies 298 product lines. To calculate the average degree of membership in each of the 31 sub-industry categories, I determined the amount of focus the firm has in each of those 31 categories, by using as a proxy the number of product lines a firm produces within each category.

Once I had calculated each category's averaged grade of membership, I performed the second step, calculating the firm's degree of comprehensibility. I assigned to each firm in my sample the averaged grade of membership of the category to which it belonged from the year before. In situations where a new firm belonged to more than one category, I assigned a weighted average based on the number of products the firm had in each category. Suppose in year 1, Category X has an averaged grade of membership score of 0.75 and Category Z has an averaged grade of membership score of 0.25. In year 2, new Firm C is founded producing two products in Category X and one product in Category Z. Therefore, in the year of its founding, Firm C is assigned a degree of comprehensibility of 0.58 (=[0.75*2+0.25*1)]/3). The closer this number is to one, the more differentiated the firm's categorization and the more comprehensible it is.

2.4.4   Control Measures

Past studies have suggested other factors that may account for the characteristics of a firm's alliance portfolio. To determine the marginal effect of a firm's degree of comprehensibility on its rate of alliance formation and partner set diversity, I controlled for specific measures regarding firm-related, alliance portfolio and environmental characteristics. To account for firm-related characteristics, for each firm I determined the amount of *venture capital (VC) funding* it received, its number of issued patents, and whether it was founded as a subsidiary, as opposed to *de novo*. As the amount of VC funding a new firm receives will indicate the degree of endorsement it is given by investors, larger amounts may be more likely to attract potential partners to the firm. To perform this analysis, I calculated the total amount of venture capital given to each firm each year and took the natural log of these amounts. I searched the Thomas Reuter VentureXpert database to acquire this data.

Potential partners may also be attracted to the new firm according to how many patents it is granted, as they indicate the firm's innovativeness, which may compensate for a firm's low degree of comprehensibility. I assigned a dummy variable to each firm for each year I studied indicating whether it had one or more patents in that year (*patent dummy*). My analysis was insensitive to the firm's actual count of patents. I collected the patent information from the NBER U.S. Patent Citations Database (Hall, Jaffe, and Trajtenberg, 2001). For lack of complete information on the founding teams for each firm, the VC funding and patent dummy variables also served as proxies for the skills and social capital of the firm's founding team. Studies have shown a relationship between a firm's founding team and the firm's acquisition of resources (Baron, Hannan, and Burton, 2001; Beckman and Burton, 2008; Eisenhardt and Schoonhoven, 1996). Finally, while most of the firms were founded as independent and privately held, some

firms were founded as a subsidiary of an established firm. A firm's alliance formation may be affected by whether it was founded as a subsidiary. In general, new firms that have a parent company in another market (*de alio*) will have access to more resources at their inception than independent *de novo* firms (Khessina and Carroll, 2008). In particular, due to the connection with their parent firms, potential customers may already have an understanding of *de alio* firms' products. Hence, I assigned an indicator variable, *founded as a subsidiary,* to those firms.

In addition to the firm-related characteristics discussed above, I also accounted for certain events that occurred during the first seven years of each firm's existence. First, I determined whether each firm had an initial public offering (IPO). As an IPO is a signal of legitimacy, it can be safely assumed that when a firm has an IPO, it is clearly comprehensible by an audience; moreover, public firms are endorsed and considered low risk, making them attractive partners. I assigned a dummy variable to each firm that had an IPO in the year of its IPO and each subsequent year it remained public (*IPO status*). Second, I determined whether each firm had been acquired but retained its identity, becoming a subsidiary of another firm (*acquired – subsidiary status*). An acquisition, much like an IPO, may also be a signal of legitimacy: when a firm is acquired an external audience has comprehended the firm enough for another firm to manage its assets. I likewise assigned a dummy variable to each firm that was acquired in the year of its acquisition and in each subsequent year it was a subsidiary.

The next two factors I controlled for, intends to account for the firm's tendency to grow and diversify its alliance portfolio. First, a firm's *number of category memberships* suggests the number of directions in which it may intend to diversify. With the possible intention to diversify, the more likely its number of dependencies on other firms will increase; and the more likely it will form alliances with them (Pfeffer and Salancik, 1978; Thompson, 1976). Hence, a firm's high number of category affiliations could account for its motivation to quickly seek many partners. Additionally, I determined the *average age* of the firm's partner set, as the age of its partners may also influence its subsequent alliance formation. More legitimate organizations will tend to transfer legitimacy to less legitimate ones (Baum and Oliver, 1991). Generally, older firms tend to be more legitimate than younger firms. Hence, by forming partnership with older firms, new firms may acquire legitimacy, which may subsequently attract more partners. However, because an older partner is more likely to have abundant resources, the new firm may be less likely to form more alliances. Either the firm's partners may provide it with sufficient resources and it does not seek more partners, or the firm may exhaust its own resources (e.g. time and energy) to take advantage of its partners', reducing its capacity to form additional relationships.

Finally, I controlled for different environmental conditions in which each firm operated by introducing a set of dummy variables that would account for unobserved heterogeneity in conditions that may have affected a firm, such as the intensity of competition that it faced. Competitive conditions tend to increase a firm's likelihood of forming alliances (Eisenhardt and Schoonhoven, 1996; Stuart, 1998) and influence with which firms will enter partnerships (Gulati, 1995; Beckman et al., 2004). Many firms belonged to more than one category and even devoted a portion of their focus to another industry, such as computer hardware or telecommunications. Firms that focus only in categories related to software face a different set of environmental conditions (e.g., more or less competition) than firms that focus in both software- and

telecommunication-related categories. Therefore, I created a set of dummy variables that corresponds to the firms' *industry focus*. I observed 16 combinations of industry focus and created a dummy variable for each combination. Table 1a provides a summary of the variables described above and the bivariate correlations. Table 1b provides a correlation matrix of the variables.

Table 1a

Descriptive Statistics (N = 2971)

Variable	Mean	s.d.	Min	Max
1. Number of alliances (all)	1.11	3.00	0	34
2. Number of alliances (technology)	0.33	1.10	0	18
3. Number of alliances (marketing)	0.78	2.26	0	29
4. Degree of partner set diversity (all)	0.44	0.25	0	0.98
5. Degree of partner set diversity (technology)	0.40	0.27	0	0.96
6. Degree of partner set diversity (marketing)	0.41	0.26	0	0.98
7. Firm's degree of comprehensibility	0.44	0.07	0.18	0.85
8. VC funding (logged)	1.83	3.59	0	11.66
9. Patent (0/1)	0.02	0.15	0	1
10. Founded as subsidiary (0/1)	0.08	0.28	0	1
11. IPO status (0/1)	0.08	0.27	0	1
12. Acquired - subsidiary status (0/1)	0.04	0.19	0	1
13. Number of category memberships	2.33	1.39	1	9
14. Average age of partner set	0.55	1.11	0	5.99
15. Industry focus	7.83	3.68	1	16
16. Age of the firm	3.67	1.92	1	7
17. Year	1998	2.35	1992	2003
18. Year Founded	1995	1.43	1992	1997

Table 1b

Correlation Matrix (N = 2971)

Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1 Number of alliances (all)																	
2 Number of alliances (technology)	0.77																
3 Number of alliances (marketing)	0.95	0.54															
4 Degree of partner set diversity (all)	0.08	0.08	0.06														
5 Degree of partner set diversity (technology)	0.10	0.08	0.09	0.76													
6 Degree of partner set diversity (marketing)	0.08	0.08	0.07	0.89	0.59												
7 Firm's degree of comprehensibility	-0.08	-0.04	-0.09	-0.02	-0.02	-0.02											
8 VC funding (logged)	0.31	0.24	0.29	0.07	0.09	0.05	-0.08										
9 Patent (0/1)	0.14	0.15	0.11	0.01	0.02	0.01	-0.01	0.02									
10 Founded as subsidiary (0/1)	-0.05	-0.02	-0.06	-0.04	-0.04	-0.05	0.04	-0.10	-0.01								
11 IPO status (0/1)	0.24	0.19	0.23	0.01	0.01	0.03	-0.09	-0.03	0.06	-0.07							
12 Acquired - subsidiary status (0/1)	-0.03	-0.01	-0.03	0.01	0.01	0.01	-0.03	-0.05	0.07	-0.05	-0.03						
13 Number of category memberships	-0.02	-0.03	-0.01	-0.20	-0.12	-0.16	-0.13	-0.04	0.03	0.05	0.11	0.00					
14 Average age of partner set	0.43	0.34	0.40	0.07	0.07	0.08	-0.10	0.28	0.07	-0.04	0.24	0.00	0.00				
15 Industry focus	0.00	0.00	0.01	-0.06	-0.03	-0.05	-0.16	0.01	-0.01	-0.02	0.06	0.00	0.25	0.00			
16 Age of the firm	0.02	0.02	0.02	-0.05	-0.05	-0.01	-0.16	-0.07	0.05	-0.01	0.28	0.19	0.09	0.15	0.06		
17 Year	0.06	0.05	0.06	0.02	0.02	0.07	-0.24	0.02	0.00	-0.05	0.24	0.15	0.13	0.18	0.17	0.79	
18 Year Founded	0.07	0.05	0.07	0.09	0.09	0.13	-0.19	0.13	-0.07	-0.06	0.02	-0.01	0.10	0.10	0.20	-0.04	0.58

2.4.5   Models and Analyses

The data constitute an unbalanced panel of 499 software firms. The number of years for which annual data about a firm exists varies due to different kinds of firm termination, including going out of business or becoming absorbed by another firm through an acquisition. To verify the

reasons a firm dropped out of the CorpTech directory, I either cross-referenced the VentureXpert database or conducted an Internet search of the firm. Table 2 depicts the number of firms founded in each year that continued to operate in each of the seven subsequent years. The numbers include firms that went public or became a subsidiary of another firm while keeping its identity. More than half survived through seven years. The average number of firm-year observations is six.

Table 2

Number of firms founded each year and continued to exist over seven years

Founding Year	Number of new firms (Age 1)	Number of firms still in existence by age					
		Age 2	Age 3	Age 4	Age 5	Age 6	Age 7
1992	25	25	25	25	21	20	17
1993	30	30	29	29	28	25	20
1994	57	57	57	57	51	45	42
1995	112	112	111	98	90	80	69
1996	133	132	124	117	113	92	71
1997	142	140	134	131	109	83	69
Total Number	499	496	480	457	412	345	288

The first analysis I performed considers a firm's rate of alliance formation as a time varying function of firm-related, alliance portfolio and environmental characteristics. To estimate the time-specific event of forming an alliance, the analysis method was an event-history. I used a Cox proportional hazard model (Cox 1972), which estimated the relative risk of forming an alliance among more or less comprehensible firms. Each firm was considered at risk of an event at the start of the year. I used the stcox procedure in Stata 11, which handles right censoring in the data. While 290 firms formed at least one alliance across the study time period, each year, on average, 120 firms formed at least one alliance. Table 3 presents the number of firms that entered an alliance each year. The percentage of firms entering an alliance increased each year, peaked in the fourth year, and then slightly decreased. Past research (e.g., Eisenhardt and Schoonhoven, 1996; Stuart, 1998) as well the numbers in Table 3 shows the number of firms that entered an alliance by year. It indicates that alliance formation tends to increase as firms age. Hence, I included in this analysis a measure of firm age, which is the number of years that lapsed since the time of a firm's founding. I also included the number of alliances in the year before to account for endogenous occurrences of alliance formation.

Table 3

Number of firms that entered an alliance by year (age)

Year (age)	Number of firms	Total at risk firms	Percent
1	25	499	5%
2	88	496	18%
3	175	480	36%
4	185	457	40%
5	155	412	38%
6	126	345	37%
7	86	288	30%
Average	120	425	29%

The second analysis I performed considers the partner set diversity—the degree of dissimilarity between each firm and its partners, again as a function of firm-related, alliance portfolio and environmental factors. An index close to one indicates that a firm's partner set diversity is high. An index of zero indicates a firm has not formed an alliance or that the firm's and its partners' product lines completely overlap. One other interpretation for an index of zero is the firm formed an alliance but did not announce it in a press release. I verified this third possibility by searching company websites in the Internet archive database (archive.org) for 15 randomly selected firms. For each firm, I had found at least in one year, one new partner logo on a firm's website but did not have a corresponding alliance announcement in a press release in the same year. Hence, it is likely that firms tend to intentionally avoid announcing a partnership. This inaction may indicate the firm's choice to maintain focus on its identity, rather than introduce an outside affiliation. Hence, a firm's index of zero for partner set diversity due to not announcing alliances can be considered measures that fall below the observable zero index that is due to partners with completely overlapping product lines. With this perspective, I regarded the degree of diversity at zero to be truncated. I therefore used a Tobit regression model to ensure that estimates of the truncated dependent variable were unbiased.

In addition, for the analysis of partner set diversity, I included a set of dummy variables to represent each of the years between 1992 and 2003, inclusively, in order to account for annual trends in alliance formation. For all models, I obtained clustered robust standard errors to account for heteroskedasticity and within firm correlation. Finally, all independent variables lag by one year in the analysis.

2.5   Results

In Table 1, the correlations among variables included in each model are relatively low and did not raise concerns of multicollinearity. In addition, I calculated the variance inflation factors of all variables by ordinary least squares regression and post-estimation. All variation inflation factors were at an acceptable level of 2.98 or less. The average measure of the degree of firm comprehensibility was 0.44; the standard deviation was 0.07, the minimum measure was 0.18 and the maximum measure was 0.85.

Table 4a reports the hazard ratios of the Cox proportional hazard model, which tests the hypothesis that less comprehensible new firms form alliances at a faster rate than more comprehensible firms do. Models 1 and 2 report the hazard ratios when industry focus dummies are not considered. The negative ratio of a firm's degree of comprehensibility on the rate of alliance formation in model 2 lends support for the first hypothesis. Moreover, this ratio reduces more when controlling for multiple industry focus in model 4. Model 4 indicates that holding all variables constant, the most comprehensible firm will form alliances at a rate that is 1.25 percent less than the least comprehensible firm (p < 0.05, one-tailed test). Other effects on the hazard rate are worth discussing. Firms that have many partners in its portfolio tend to be at higher risk of alliance formation than those firms with fewer partners. This finding resonates with prior research that indicate the more a firm associates with partners the more involved it will be in a network and form more partnerships (Powell et al., 1996). Also, as predicted, firms that attract

more venture capital funding tend to form alliances faster than those that have less funding. Interestingly, when controlling for all other variables, as firms increase in age, the rate of forming an alliance lowers, rather than increases. This decrease may be due to the tendency that as firms age they have better chances of survival. With better chances of survival, they become less concerned about forming alliances and focus on other strategic actions.

Table 4a

Event-History analysis of alliance formation - Effect of a firm's comprehensibility on the rate of alliance formation (All alliances)

Variable	Model 1	Model 2	Model 3	Model 4
Lagged alliance count	0.189***	0.200***	0.158***	0.168***
	(0.059)	(0.062)	(0.056)	(0.057)
VC funding (logged)	0.121***	0.119***	0.120***	0.118***
	(0.013)	(0.013)	(0.014)	(0.014)
Patent (0/1)	0.163	0.182	0.400	0.408
	(0.407)	(0.406)	(0.378)	(0.377)
Founded as subsidiary (0/1)	-0.180	-0.175	-0.165	-0.157
	(0.242)	(0.239)	(0.242)	(0.238)
IPO status (0/1)	0.113	0.100	0.055	0.040
	(0.428)	(0.436)	(0.426)	(0.438)
Acquired - subsidiary status (0/1)	-0.476	-0.477	-0.954	-0.967
	(0.599)	(0.592)	(1.003)	(0.962)
Number of category memberships	-0.039	-0.045	-0.001	-0.008
	(0.038)	(0.039)	(0.039)	(0.039)
Average age of partner set	0.035	-0.007	0.112	0.075
	(0.164)	(0.179)	(0.142)	(0.153)
Age of firm	-0.101*	-0.097*	-0.102*	-0.097*
	(0.058)	(0.058)	(0.059)	(0.059)
Firm's degree of comprehensibility		-0.956*		-1.245**
		(0.655)		(0.718)
Industry focus (dummies)	N	N	Y	Y
Number of events	289	289	289	289
Observations	1,839	1,839	1,839	1,839
Degrees of freedom	9	10	24	25
Log-Likelihood	-1645	-1644	-1633	-1632

*** $p<0.01$, ** $p<0.05$, * $p<0.1$;
two-tailed test for control variables and one-tailed test for hypothesized effects
Robust standard errors are in parentheses.

To check the robustness of the hazard model results, I also addressed the dependent variable as a non-negative count variable. Doing so led me to employ a zero-inflated negative binomial regression; the variance of the variable exceeded its mean and the number of zeros in this set was excessive. A Voung test confirmed the choice ($z = 6.81$, $p > z < 0.000$) to employ a zero-inflated negative binomial regression rather than a standard negative binomial model. The average number of alliances per firm, per year was 1.11, with a maximum number of 34 alliances. Table 4b reports the estimates from this regression, which demonstrates the likelihood that a firm will have many partners in its portfolio.

Table 4b

Analysis of alliance formation as a non-negative count variable - Effect of a firm's comprehensibility on number of alliances (All alliances)

Variable	Zero-inflated negative binomial models			
	Model 1	Model 2	Model 3	Model 4
Lagged alliance count	0.097***	0.099***	0.097***	0.099***
	(0.013)	(0.013)	(0.013)	(0.013)
VC funding (logged)	0.062***	0.062***	0.063***	0.062***
	(0.010)	(0.010)	(0.010)	(0.010)
Patent (0/1)	0.180	0.191	0.146	0.149
	(0.198)	(0.195)	(0.204)	(0.200)
Founded as subsidiary (0/1)	-0.292	-0.258	-0.340	-0.324
	(0.195)	(0.202)	(0.201)	(0.206)
IPO status (0/1)	0.544***	0.508***	0.518***	0.483***
	(0.153)	(0.152)	(0.154)	(0.151)
Acquired - subsidiary status (0/1)	-0.101	-0.103	-0.133	-0.149
	(0.328)	(0.314)	(0.326)	(0.311)
Number of category memberships	-0.011	-0.019	-0.019	-0.029
	(0.042)	(0.042)	(0.043)	(0.044)
Average age of partner set	0.162***	0.168***	0.153***	0.157***
	(0.037)	(0.037)	(0.037)	(0.037)
Firm's degree of comprehensibility		-1.266**		-1.463***
		(0.565)		(0.592)
Constant	-0.511**	0.040	-0.590**	-0.018
	(0.236)	(0.333)	(0.256)	(0.352)
Year dummies	Y	Y	Y	Y
Industry focus (dummies)	N	N	Y	Y
Observations	2,339	2,339	2,339	2,339
Degrees of freedom	17	18	32	33
Log-Likelihood	-2488	-2485	-2476	-2473
R-squared	-	-	-	-

*** $p<0.01$, ** $p<0.05$, * $p<0.1$;
two-tailed test for control variables and one-tailed test for hypothesized effects
Robust clustered standard errors are in parentheses.

Model 1 in table 4b, indicates the effect of the control variables on a firm's number of alliances. Several variables seem to have a significant effect. First, receiving more VC funding and having an IPO both significantly increase the number of alliances a firm forms. These two attributes increase a firm's ability to attract partners and its involvement within its field. Additionally, the average age of a firm's current partners also influences the number of partnerships a firm enters. Having older partners tends to increase a firm's alliance activities rather than decreasing its activities due to older partners expending the capacity of the firm. Even after adding industry focus dummies in models 3 and 4, these control variables continue to have a significant effect. Model 4 includes the measure of firm comprehensibility. The estimates obtained with model 4 suggest that the influence of this variable is negative and significant ($p < .01$, one-tailed test), offering additional support for Hypothesis 1—firms will tend to form fewer partnerships due to lower hazard rates of alliance formation as they become more comprehensible. Specifically, a unit increase in a firm's comprehensibility decreases the number of alliances by an expected log

count of 0.93, which signifies that for every one standard deviation increase in firm comprehensibility, a firm reduces the number of alliances by 9.7 percent (=1-exp(-1.463*0.07)).

Below, table 5 presents estimates from the Tobit regression model, which tests the relationship between the comprehensibility of a firm and the degree of partner set diversity is an inverted-U. The average degree of partner set diversity, was 0.44, and the standard deviation was 0.25. In model 1, a few control variables have significant effects on partner set diversity. When a new firm becomes a public company and when it is affiliated with older partners, its partner set diversity tends to increase. This makes sense: while attaining public status and associating with more established firms, a new firm would focus on maintaining pragmatic legitimacy by further expanding its access to other domains through partnerships. In contrast, the more software categories in which a firm focuses—an indicator of its degree of diversification—the less different its partners will be from itself. This effect may be due to the fact that a firm with many product lines is already affiliated with many market niches; therefore, there would be fewer uncovered niches for it to be affiliated with through partnerships. Model 2 includes the measure of firm comprehensibility. This variable can be observed to have a marginally significant negative effect on a firm's degree of partner set diversity ($p < .09$, one-tailed test), suggesting that a more comprehensible firm is more likely to maintain a set of partners similar to itself. These results seem to support the idea that the more clearly a firm can be identified by a set of potential customers, the more the firm will value consistency and a focused identity. Model 3, additionally includes the squared term of firm comprehensibility and provides a better model fit than model 2 according to a better log likelihood. The squared term produces results that are negative ($p < .05$, one-tailed test) and indicates that an inverse-U relationship exists between a new firm's comprehensibility and its partner set diversity. This relationship supports the proposal that due to constraints on their identities, new firms at the highest or lowest level of comprehensibility will tend to maintain a set of partners with products lines overlapping its own. Less comprehensible new firms are motivated by a desire to make their identities more salient, whereas highly comprehensible new firms desire to appear consistent and focused. Firms in the middle, due to the desire to gain pragmatic legitimacy, will tend to select partners who belong to categories different from their own.

Overall, the results obtained in model 3 support Hypothesis 2. The inflection point, at which firms demonstrate the greatest partner set diversity, is at 0.39 degrees of comprehensibility where the degree of partner set diversity is 0.21 (see Figure 2). The non-linear relationship between a firm's comprehensibility and its degree of partner set diversity demonstrates the following characteristics: a new firm that is two standard deviations (0.14) more or less comprehensible than a new firm at the inflection point will form an alliance portfolio three percent less diverse than that firm's.

To ensure the robustness of my results, I additionally employed a fractional logit specification in models 4 to 6. This model, proposed by Papke and Wooldridge (1996), is a quasi-maximum likelihood estimation method that specifically addresses outcome variables that are ratios and can have a value of exactly zero or one. This model provides results consistent with those obtained in the Tobit regression model.

Table 5

Tobit Regression and Fractional Logit Models - Relationship between a firm's comprehensibility and its partner set diversity (All partners)

Variable	Tobit Regression Model			Fractional Logit Model		
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
VC funding (logged)	0.001	0.001	0.001	0.004	0.003	0.003
	(0.002)	(0.002)	(0.002)	(0.005)	(0.005)	(0.005)
Patent (0/1)	-0.045	-0.046	-0.047	-0.158	-0.161	-0.166
	(0.031)	(0.031)	(0.031)	(0.109)	(0.108)	(0.108)
Founded as subsidiary (0/1)	-0.037	-0.036	-0.036	-0.108	-0.104	-0.105
	(0.029)	(0.029)	(0.028)	(0.104)	(0.103)	(0.102)
IPO status (0/1)	0.043*	0.042*	0.042*	0.144	0.138	0.141
	(0.025)	(0.025)	(0.025)	(0.091)	(0.090)	(0.089)
Acquired - subsidiary status (0/1)	0.034	0.034	0.035	0.110	0.108	0.111
	(0.034)	(0.034)	(0.034)	(0.119)	(0.119)	(0.120)
Number of category memberships	-0.033***	-0.034***	-0.035***	-0.159***	-0.164***	-0.167***
	(0.005)	(0.005)	(0.005)	(0.018)	(0.018)	(0.018)
Average age of partner set	0.010*	0.010*	0.010*	0.032*	0.030	0.030
	(0.005)	(0.005)	(0.005)	(0.019)	(0.019)	(0.018)
Firm's degree of comprehensibility		-0.187**	1.069**		-0.765**	3.819*
		(0.113)	(0.647)		(0.400)	(2.565)
Firm's degree of comprehensibility ^ 2			-1.384**			-5.085**
			(0.706)			(2.843)
Constant	-0.050	0.021	-0.248		-1.494***	-2.470***
	(0.074)	(0.084)	(0.167)		(0.360)	(0.673)
Year dummies	Y	Y	Y	Y	Y	Y
Industry focus (dummies)	Y	Y	Y	Y	Y	Y
Observations	2,971	2,971	2,971	2,971	2,971	2,971
Degrees of freedom	31	32	33	32	33	34
Log-likelihood	-932.3	-929.3	-926.7	-1444	-1444	-1444

*** $p<0.01$, ** $p<0.05$, * $p<0.1$; two-tailed test for control variables and one-tailed test for hypothesized effects
Robust clustered standard errors are in parentheses.

Figure 2: The relationship between a new firm's comprehensibility and its partner set diversity
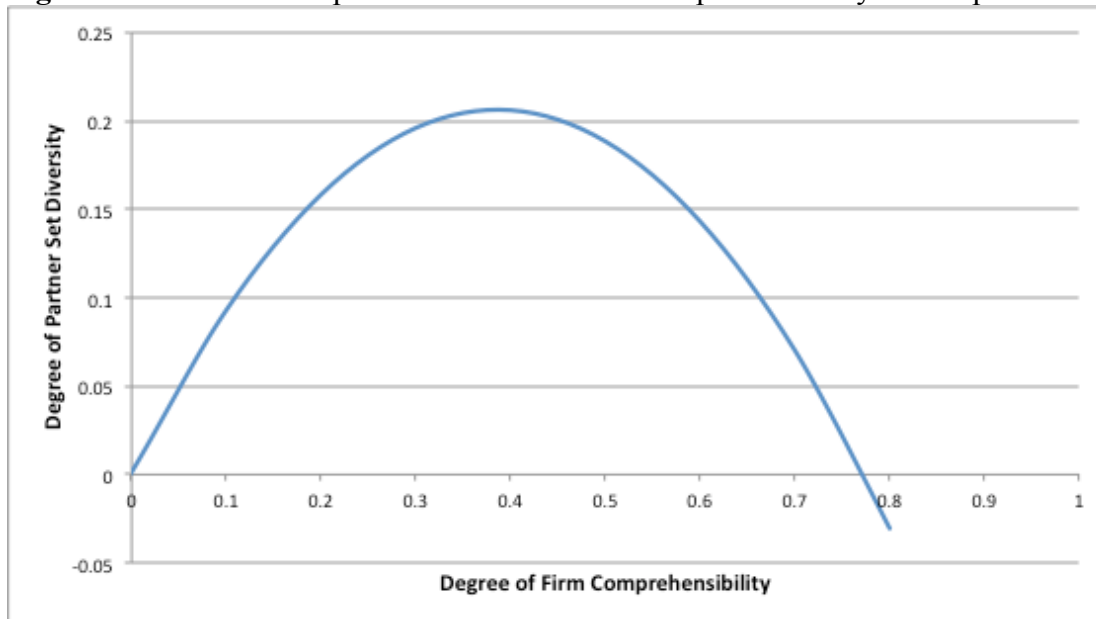
Figure 2: Model 3 in Table 5 produced this figure, which depicts the inverse-U relationship that exists between a new firm's comprehensibility and its partner set diversity. This relationship supports the proposal that due to constraints on their identities, new firms at the highest or lowest level of comprehensibility will tend to maintain a set of partners with products lines overlapping its own. Less comprehensible firms are motivated by a desire to make their identities more salient, whereas highly comprehensible firms desire to appear consistent and focused. Firms in the middle, due to having less pressure to either make their identities salient or to appear consistent, will tend to concentrate on gaining pragmatic legitimacy, and hence, will tend to select partners who belong to categories different from their own to indicate wide market appeal. Overall, the results obtained in model 3 support Hypothesis 2. The inflection point, at which firms demonstrate the greatest partner set diversity, is at 0.39 degrees of comprehensibility where the degree of partner set diversity is 0.21

To test Hypotheses 3a I employed two sets of event history models to analyze the two alliance types separately. These estimates indicate whether a firm is more likely to have a greater risk of forming partners that are marketing-related or technology-related. In table 6a, models 1 and 2 provide hazard ratios concerning technology alliances and models 3 and 4 provide hazard ratios concerning marketing alliances. In both sets of models, each of the control variables, the lagged alliance count, VC funding, and the average partner age can be observed to have a significant risk of forming alliances of both types. While firms that became public significantly increase the risk of forming technology alliances, becoming public does not affect the risk of forming marketing alliances.

In models 2 and 4, the measure of firm comprehensibility is added. The results obtained in both models indicate a significant risk of forming both types of alliances; however, the risk is higher by 10 percent in forming marketing related alliances ($p < .05$, one-tailed test) compared to forming technology alliances ($p < .07$, one-tailed test). These results offer some support for Hypothesis 3a as they suggest that less comprehensible new firms are more at risk to form marketing alliances than technology alliances.

Table 6a

Event-History Analysis - Comparing the rate of technology and marketing alliance formation

	Technology Alliance		Marketing Alliance	
Variable	Model 1	Model 2	Model 3	Model 4
Lagged alliance count	0.356*	0.356*	0.152***	0.140***
	(0.183)	(0.183)	(0.050)	(0.054)
VC funding (logged)	0.138***	0.136***	0.116***	0.113***
	(0.017)	(0.017)	(0.014)	(0.014)
Patent (0/1)	0.213	0.208	0.268	0.268
	(0.472)	(0.474)	(0.401)	(0.401)
Founded as subsidiary (0/1)	0.267	0.269	-0.448	-0.432
	(0.239)	(0.238)	(0.298)	(0.296)
IPO status (0/1)	0.763***	0.750***	0.220	0.189
	(0.279)	(0.278)	(0.425)	(0.427)
Acquired - subsidiary status (0/1)	0.401	0.393	-0.903	-0.870
	(0.483)	(0.480)	(0.715)	(0.691)
Number of category memberships	0.047	0.040	-0.014	-0.019
	(0.045)	(0.045)	(0.043)	(0.043)
Average age of partner set	0.269***	0.265***	0.332***	0.331***
	(0.048)	(0.049)	(0.051)	(0.052)
Age of firm	-0.030	-0.028	-0.068	-0.063
	(0.070)	(0.069)	(0.055)	(0.055)
Firm's degree of comprehensibility		-1.138*		-1.239*
		-0.795		(0.762)
Industry focus (dummies)	Y	Y	Y	Y
Number of events	212	212	262	262
Observations	2,223	2,223	1,998	1,998
Degrees of freedom	18	19	18	19
Log-Likelihood	-1179	-1178	-1474	-1473

*** p<0.01, ** p<0.05, * p<0.1;
two-tailed test for control variables and one-tailed test for hypothesized effects
Robust standard errors are in parentheses.

Table 6b presents estimates from the zero-inflated negative binomial regression. In model 2, the effect of a firm's comprehensibility on technology alliances is not significant, whereas in model 4, the effect of a firm's comprehensibility on marketing alliances is negative ($p < .07$, one-tailed test). These results, though marginally significant, together with results from the hazard ratios support the claim that less comprehensible new firms are more likely to form marketing alliances than technology alliances.

Table 6b

Comparing the effect of a firm's comprehensibility on the number of technology and marketing alliances

Variable	Technology Alliance		Marketing Alliance	
	Model 1	Model 2	Model 3	Model 4
Lagged alliance count	0.180***	0.182***	0.125***	0.126***
	(0.058)	(0.058)	(0.016)	(0.016)
VC funding (logged)	0.047***	0.046***	0.057***	0.057***
	(0.015)	(0.016)	(0.012)	(0.012)
Patent (0/1)	0.538*	0.532*	0.226	0.234
	(0.312)	(0.307)	(0.180)	(0.179)
Founded as subsidiary (0/1)	-0.154	-0.145	-0.384	-0.377
	(0.368)	(0.370)	(0.240)	(0.243)
IPO status (0/1)	0.557**	0.538**	0.480***	0.465***
	(0.216)	(0.218)	(0.149)	(0.150)
Acquired - subsidiary status (0/1)	-0.446	-0.457	-0.300	-0.297
	(0.398)	(0.393)	(0.209)	(0.208)
Number of category memberships	-0.101	-0.104	-0.034	-0.042
	(0.083)	(0.083)	(0.042)	(0.043)
Average age of partner set	0.162**	0.165**	0.140***	0.143***
	(0.072)	(0.073)	(0.038)	(0.039)
Firm's degree of comprehensibility		-0.573		-0.972*
		(0.695)		(0.647)
Constant	-0.827*	-0.601	-0.854**	-0.483
	(0.435)	(0.531)	(0.337)	(0.420)
Year dummies	Y	Y	Y	Y
Industry focus (dummies)	Y	Y	Y	Y
Observations	2,339	2,339	2,971	2,971
Degrees of freedom	32	33	34	35
Log-Likelihood	-1341	-1341	-2462	-2461
R-squared	-	-	-	-

*** p<0.01, ** p<0.05, * p<0.1; two-tailed test for control variables and one-tailed test for hypothesized effects
Robust clustered standard errors are in parentheses.

Table 7a compares estimates obtained with Tobit regression models, demonstrating that the inverse-U relationship that exists between a firm's comprehensibility and the degree of partner set diversity is more pronounced with technology alliances than with marketing alliances. Models 1 to 3 estimate the partner set diversity of technology alliance portfolios and models 4 to 6 estimate the partner set diversity of marketing alliance portfolios. In both sets of models, each of the control variables; IPO status, the number of category memberships, and the average age of partners can be observed to have a significant effect on a firm's partner set diversity in both types of alliances. These effects are consistent with those models in Table 5 where alliances were analyzed together. Analyzed separately, technology and marketing alliances are affected differently by other control variables. Venture capital funding and patenting increases a firm's partner set diversity among technology alliances and not among marketing alliances. Also, when firms are founded as a subsidiary, they tend to have low partner set diversity when pursuing marketing related alliances.

In models 3 and 6, the measure of firm comprehensibility and its squared term are added. In both models, the inverse-U relationship is significant; the log likelihoods indicate that these models fit better than the ones that include only the main effect of firm comprehensibility. However, the coefficients in models 3 and 6 differ: firm comprehensibility has a steeper impact on the partner set diversity of firms in technology alliances than those in marketing alliances. A test of equivalence indicates a significant difference between the main term and squared terms. For firms in technology alliances, the inflection point is at 0.42 degrees of comprehensibility at which the degree of partner set diversity is 0.45. For firms in marketing alliances, the inflection point is at 0.43 degrees of comprehensibility at which the degree of partner set diversity is 0.30. Figure 3 compares the effects of firm comprehensibility on partner set diversity demonstrated in these two models, showing that the inverse-U relationship is more pronounced among firms forming technology alliances than those forming marketing alliances. Table 7b shows similar results when employing a fractional logit specification. These results indicate support for Hypothesis 3b.

Table 7a

Tobit Regression Model - Comparing the relationship between a firm's comprehensibility and its partner set diversity in technology and marketing alliances

| | Tobit Regression Model | | | | | |
| | Technology Alliance | | | Marketing Alliance | | |
Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
VC funding (logged)	0.003*	0.003*	0.003*	0.000	-0.000	0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Patent (0/1)	-0.056*	-0.056*	-0.059*	-0.029	-0.029	-0.031
	(0.033)	(0.033)	(0.033)	(0.034)	(0.034)	(0.034)
Founded as subsidiary (0/1)	-0.038	-0.037	-0.037	-0.053*	-0.053*	-0.053*
	(0.029)	(0.029)	(0.029)	(0.032)	(0.032)	(0.032)
IPO status (0/1)	0.061**	0.060**	0.061**	0.052**	0.052**	0.052**
	(0.027)	(0.027)	(0.026)	(0.025)	(0.025)	(0.025)
Acquired - subsidiary status (0/1)	0.047	0.047	0.049	0.022	0.021	0.023
	(0.035)	(0.035)	(0.035)	(0.036)	(0.036)	(0.036)
Number of category memberships	-0.017***	-0.018***	-0.019***	-0.026***	-0.027***	-0.028***
	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Average age of partner set	0.010*	0.010*	0.010*	0.013**	0.013**	0.013**
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Firm's degree of comprehensibility		-0.153	2.134***		-0.080	1.400**
		(0.137)	(0.726)		(0.114)	(0.600)
Firm's degree of comprehensibility ^ 2			-2.517***			-1.631***
			(0.808)			(0.659)
Constant	-0.674***	-0.617***	-1.109***	-0.078	-0.047	-0.364**
	(0.124)	(0.129)	(0.200)	(0.076)	(0.087)	(0.157)
Year dummies	Y	Y	Y	Y	Y	Y
Industry focus (dummies)	Y	Y	Y	Y	Y	Y
Observations	2,971	2,971	2,971	2,971	2,971	2,971
Degrees of freedom	31	32	33	31	32	33
Log-likelihood	-1274	-1273	-1266	-1126	-1126	-1123
Psuedo R^2	0.212	0.213	0.217	0.184	0.184	0.186

*** $p<0.01$, ** $p<0.05$, * $p<0.1$; two-tailed test for control variables and one-tailed test for hypothesized effects
Robust clustered standard errors are in parentheses.

Table 7b

**Fractional Logit Models - Comparing the relationship between a firm's comprehensibility and
its partner set diversity in technology and marketing alliances**

| | Fractional Logit Model | | | | | |
| | Technology Alliance | | | Marketing Alliance | | |
Variable	Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
VC funding (logged)	0.009	0.008	0.009	-0.001	-0.001	-0.001
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Patent (0/1)	-0.203*	-0.205*	-0.212*	-0.099	-0.101	-0.107
	(0.110)	(0.109)	(0.110)	(0.117)	(0.117)	(0.117)
Founded as subsidiary (0/1)	-0.115	-0.112	-0.114	-0.158	-0.156	-0.157
	(0.099)	(0.098)	(0.098)	(0.114)	(0.113)	(0.112)
IPO status (0/1)	0.181*	0.175*	0.181**	0.173*	0.170*	0.174*
	(0.094)	(0.093)	(0.092)	(0.091)	(0.091)	(0.091)
Acquired - subsidiary status (0/1)	0.156	0.154	0.157	0.061	0.060	0.063
	(0.115)	(0.116)	(0.116)	(0.122)	(0.122)	(0.122)
Number of category memberships	-0.111***	-0.115***	-0.121***	-0.141***	-0.144***	-0.148***
	(0.019)	(0.019)	(0.018)	(0.018)	(0.018)	(0.018)
Average age of partner set	0.026	0.025	0.025	0.041**	0.040**	0.040**
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
Firm's degree of comprehensibility		-0.606*	7.121***		-0.402	5.144**
		(0.457)	(2.800)		(0.393)	(2.367)
Firm's degree of comprehensibility ^ 2			-8.559***			-6.159**
			(3.159)			(2.659)
Constant	-5.994***	-5.766***	-7.414***	-1.782***	-1.630***	-2.810***
	(0.998)	(1.008)	(1.158)	(0.322)	(0.355)	(0.622)
Year dummies	Y	Y	Y	Y	Y	Y
Industry focus (dummies)	Y	Y	Y	Y	Y	Y
Observations	2,971	2,971	2,971	2,971	2,971	2,971
Degrees of freedom	33	34	35	32	33	34
Log-likelihood	-1420	-1419	-1417	-1440	-1440	-1439
bic	-22504	-22498	-22493	-22560	-22553	-22547
aic	0.979	0.979	0.978	0.992	0.992	0.992

*** p<0.01, ** p<0.05, * p<0.1; two-tailed test for control variables and one-tailed test for hypothesized effects
Robust clustered standard errors are in parentheses.

Figure 3: Comparing the relationship between a new firm's comprehensibility and its technology partner set diversity to the relationship between a new firm's comprehensibility and marketing partner set diversity
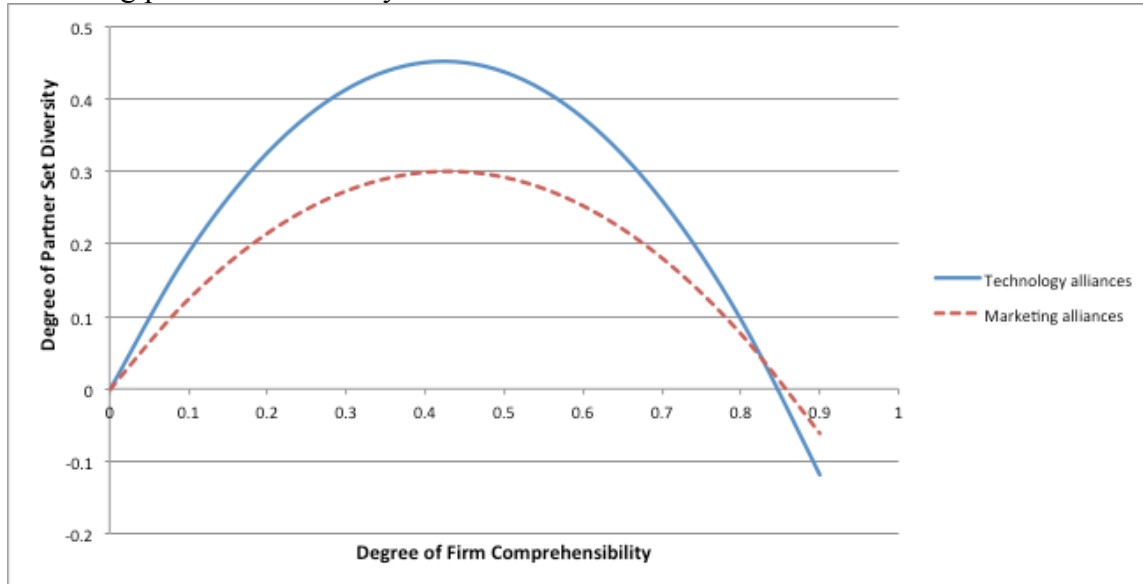
Figure 3: Models 3 and 6 in Table 7a produced this figure, which separates the inverse-U relationship that exists between a new firm's comprehensibility and its partner set diversity by technology and marketing alliances. As partnering firms will put more effort to work together in a technology alliance, the alliance would tend to produce a stronger tie between the firms than a marketing alliance would. Furthermore, as technology alliances are stronger ties, they will be more convincing signals of information. As such, a new firm may favor technology alliances to signal information about its identity or demonstrate wide market application. As proposed, the inverse-U relationship is more pronounced among firms forming technology alliances than those forming marketing alliances. A test of equivalence indicates a significant difference between the main term and squared terms. For firms in technology alliances, the inflection point is at 0.42 degrees of comprehensibility at which the degree of partner set diversity is 0.45. For firms in marketing alliances, the inflection point is at 0.43 degrees of comprehensibility at which the degree of partner set diversity is 0.30. These results indicate support for Hypothesis 3b.

2.6   Chapter Conclusion

While researchers have investigated strategies with which new firms are able to overcome their liabilities of newness, the question of how the very issue of being new, in that it entails being relatively more or less comprehensible, might shape those strategies, deserves to be considered in its own right. This chapter has investigated how a new firm's relative level of comprehensibility affects its strategic actions— alliance formation, in particular. I drew upon the theory that new firms are more or less comprehensible as a function of how well they resemble a set of preceding firms that constitute a category and the degree to which that category has been clearly differentiated by those preceding firms (Aldrich and Fiol, 1994; Hannan and Freeman, 1977; Hannan et al., 2007). New firms that resemble existing firms that constitute a differentiated category will be more comprehensible than those that resemble ambiguous firms that constitute a less differentiated category. For a new firm, being comprehensible matters because it determines whether an audience will be able to identify the appropriate comparison set for the firm and thus be able to evaluate it further (Philips and Zuckerman, 2001). Moreover, a firm's comprehensibility influences the alliance partnerships that it will form, due to the tendency of alliances to act as signals (Podolny, 1993), including, as proposed in this chapter, cues of identity. I determined the effect of comprehensibility on a firm's alliance engagement by observing the firm's rate of alliance formation and the degree of diversity in its partner set.

My analysis found support for the claim that the more comprehensible a new firm is, the less pressure the firm will face to signal its identity and therefore the slower will be the firm's rate of alliance formation. Additionally, my investigation indicated that due to constraints on new firms' identities, a curvilinear (inverse-U) relationship exists between a new firm's degree of comprehensibility and its degree of partner set diversity. Less comprehensible new firms, such as those that pioneer new products, face pressure to signal their identities more clearly and thus tend to associate with partners similar to themselves; therefore, these firms tend to have a low degree of partner set diversity. However, with greater comprehensibility, firms face competing pressures: on the one hand, a firm's imperative to signal a clear identity lessens, engendering a greater degree of partner set diversity that demonstrates pragmatic legitimacy; on the other hand, a firm's need to maintain a coherent identity increases, a situation that favors consistent identity, engendering a lower degree of partner set diversity. While a pioneering new firm (a firm with low comprehensibility) will tend to have many partners, its partners will tend to be firms of its own type. In comparison, while a traditional new firm (a firm with high comprehensibility) will also tend to have partners of its own type, it will tend to have few partners. Finally, I demonstrated that as technology alliances are more difficult to obtain and are stronger signals of identity than marketing alliances, less comprehensible new firms will tend to form more marketing alliances than technology alliances; moreover, the inverse-U relationship between firm comprehensibility and partner set diversity is more pronounced among firms in technology alliances than those in marketing alliances due to stronger identity signaling from technology alliances.

An alternative explanation for this non-linear relationship between a new firm's comprehensibility and partner set diversity may be that firms at the low and high ends of comprehensibility have no other choice but to form partnerships with firms similar to themselves. It may be that potential partners perceive both firms with low comprehensibility and

those with high comprehensibility as too innovative and too common, respectively. Potential partners may be skeptical about the viability of a new firm with low comprehensibility and likely to turn down cooperative opportunities with the firm; the only partners willing to invest time in a relationship with the new firm may be those that are similar to it and facing similar struggles. Likewise, potential partners may be likely to turn down cooperative opportunities with a highly comprehensible new firm, skeptical not about its viability, but that is not innovative enough to successfully compete; in this case, the only partners willing to invest in a relationship with the new firm may be similar firms looking to pool resources or preempt competition. However, this alternative explanation unrealistically assumes that alliances form solely because potential partners choose to do so. By definition of a partnership, both sides of the alliance must choose to enter it. Admittedly, the focus of my own analysis of alliance formation was one-sided—taken from the perspective of new firms. Nonetheless, explaining why new firms engage in different sets of partners from the perspective of the new firm is more realistic than from the perspective of potential partners.

It is likely that partnerships form because new firms pursue potential partners intentionally and actively, rather than potential partners pursue new firms. As new firms are not established and less visible to other firms than incumbent or more established firms, it seems unlikely that, without their own initiation and persuasion, new firms would receive partnership proposals. Also, evidence from several inductive studies concerning alliances formed by new firms (e.g., Larson, 1991; Özcan and Eisenhardt, 2008), as well as my own personal conversations with entrepreneurs[1]; indicate that entrepreneurs must do the convincing toward firms with whom they seek partnerships to form them. Still, the notion that potential partners may or may not be willing to form an alliance with a new firm suggests an opportunity to investigate how the willingness of potential partners and the intentions of new firms match. One could study the intentions of both members of a potential partnership to determine the locus of effort in partner selection. It may be worthwhile to identify the set of partners that a new firm targets and compare it to its actual sets of partners; this comparison may reveal conditions under which intentions of both firms will match, or otherwise may suggest that it is often one side, presumably, the new firm's side, that convinces the other firm to enter a partnership.

More attention should be paid to how a firm's degree of comprehensibility can be measured. According to arguments in the literature, audiences comprehend new firms through their categorizations; hence, in this study, by measuring the degree to which categories are well defined and distinctive, I was able to determine the relative degree to which new firms are comprehensible and identifiable to a specific potential set of customers. Following the formalization by Hannan et al. (2007), I measured the average degree of membership for each category within CorpTech's taxonomy of software firms and attributed the corresponding measure to each firm in my sample.

Another valid measure of firm comprehensibility may be based on how categories are defined by the media and the amount of attention the media gives to each category. However, as the media

---

[1] Personal communications with Lorenzo Martinelli, Senior Vice President of Corporate Strategy at E2open, May 2009; and Dr. Robert Phillips, Founder and Chief Science Officer of Nomis Solutions, June 2009.

tends only to track new or current information, a set of firm categories constructed using media reports is likely to be incomplete. Moreover, it may be difficult to determine whether a high number of media reports about a firm category indicates that a type of firm is clearly defined, or only that it is associated with an intriguing but passing fad that has attracted media attention. Trade journals may be better for determining the degree to which a firm is comprehensible. *Software Magazine*, an independent trade magazine since 1998, may serve this purpose, as it discusses software firms and categories both new and old. However, the discussion of new and old categories in its pages is primarily driven by its rankings of the top 500 revenue-generating firms, which are self-nominated to the list. A set of firm categories that includes only the highest revenue firms is also likely to suffer from selection bias. After evaluating the empirical alternatives, using CorpTech's taxonomy and determining the average grade of membership measure of each category within the taxonomy seemed to be the most justifiable approach for determining a firm's degree of comprehensibility in this study.

Understanding how the measures of a firm's category average grade of membership and its span of categories interact with one another is another opportunity for further research. Both measures indicate some degree of legitimacy from an audience, but how should we understand these two measures when used together? In this chapter, a firm's differentiated category, measured by its average grade of membership, indicates a degree of cognitive legitimacy related to comprehension from an audience. In other research, while the category's average grade of membership is not investigated, entities that span multiple categories indicate a degree of legitimacy in terms of their appeal to an audience (e.g., Hsu, 2006; Leung, 2010; Zuckerman, 1999).

We might understand the interaction of comprehensibility and appeal engendered by these two measures in the following way. A firm's level of appeal determined by it spanning categories is conditioned on the contrast of those categories. For instance, in the case of a firm spanning two low differentiated (ambiguous) categories, audiences may not comprehend the firm and it would be meaningless to judge its appeal. However, in the case of a firm spanning two highly differentiated categories that each strictly corresponds to two sets of audiences, those audiences may comprehend the firm but not find it appealing. A firm's age could additionally influence this interaction. It may be that spanning ambiguous categories is riskier for younger firms than it is for older firms. While a young firm will need to attract the attention of an audience by establishing a clear identity, as argued in this chapter; in contrast, an older firm does not because its established reputation and status will compensate for a lack of clear identity. However, without status, the risk for these older firms of not being appealing to audiences might be greater than the risk for younger firms of not being comprehensible to audiences. As firms age, pressure to stay inert becomes greater as audiences expect it to remain reliable and stable (Hannan and Freeman, 1977, 1984); expanding into a different category may challenge the expectations of their audience and risk losing their support. Future research on the interaction between comprehensibility, appeal and age might be worthwhile.

3. An Organizational Identity Perspective on the Effects of Exploration Alliances on Firm Performance

3.1 Introduction

The notion that alliances are mechanisms by which to gain access to new knowledge and technology is a prominent perspective in the literature of organizational learning. This perspective, which broadly dominates the alliance literature, understands a focal organization's alliances as conduits that facilitate the flow of resources and information between the organization and its partners. By entering alliances, an organization is able to gain access to new knowledge and technology (Powell, Koput, and Smith-Doerr, 1996; Mowery, Oxley, and Silverman, 1996) and acquire or further secure the critical skills and material resources on which it is dependent (Pfeffer and Salancik, 1976).

Another perspective that also broadly dominates the alliance literature identifies an organization's alliances as cues from which relevant audiences can infer qualitative information about the organization when little is known about it (Podolny, 1993; 2001). Alliances are able to serve as such cues because they are typically made visible, in press releases and annual reports, to relevant audiences, including both direct resource providers such as customers, suppliers and employees, as well as intermediating resource providers such as firm analysts and product reviewers (Hsu, 2006; Zuckerman, 1999). Relevant audiences can make a number of assumptions about a focal organization merely by its associations with other organizations. For instance, they can infer whether an organization is in possession of external legitimacy (Baum and Oliver, 1991), where it ranks in a status hierarchy (Podolny, 1993), and how superior its product quality is (Stuart, Hoang, and Hybels, 1999). By considering the ways that alliances serve as conduits of knowledge and resources together with how they act as signals of information, researchers can more comprehensively assess the implications that alliances have for organizational outcomes.

The question of whether alliances benefit organizations has generated an important stream of empirical inquiries. To this stream, the organizational learning literature has made significant contributions, maintaining that alliances fall into two categories, exploration alliances and exploitation alliances, according to their mode of organizational adaptation (Koza and Lewin, 1998). While organizations in exploitation alliances use their partnerships to improve upon and implement their current capabilities, in exploration alliances the focus is on experimentation and discovering new knowledge. In the long term, exploration facilitates learning and adaptation, but, due to the costs of experimenting beyond the organization's current capabilities, it comes at the expense of poor performance in the short term (Levinthal and March, 1993; March, 1991). The negative effects of exploration alliances on organizational level outcomes have been investigated in numerous research papers, yet little work has thus far been done to consider how these alliances signal information about the organizations that pursue them and subsequently affect the performance outcomes of those organizations. Accordingly, a more comprehensive analysis of the effect of exploration alliances on organizational outcomes should also include a discussion of the function of such alliances to signal an organization's pursuit of new knowledge beyond its current capabilities.

This chapter attempts to provide an additional perspective on how exploration alliances affect organizational performance outcomes. Drawing on the perspective that alliances communicate information about organizations, I posit that a focal organization's exploration alliances will serve as signals of potential organizational change: the more extensive an exploration alliance is (in terms of how far-reaching it is or how different a focal organization and its partners are), the more significant a potential change it will represent. According to structural inertia theory and an identity-based understanding of an organization's core feature, a high degree of organizational change is destabilizing (Hannan, Baron, Hsu, Koçak, 2006; Hannan and Freeman, 1984). Change will disrupt an organization's routines and prior investments, impairing its ability to function efficiently. In addition, organizational change will call into question the automatic, taken-for-granted identity expectations upon which members inside and relevant observers outside the organization have come to rely (Albert and Whetten, 1985; Hannan and Freeman, 1984; Hannan et al., 2006; Hsu and Hannan, 2005; Pólos, Hannan, and Carroll, 2002; Whetten, 2006). If an organization's set of exploration alliances is extensive and indicates too great a deviation from its established identity, relevant audiences will likely have doubts about the organization. Should this occur, the organization's ability to garner support, and hence its valuation and performance, will be negatively affected.

Essentially, however, the degree to which relevant audiences will respond negatively to an organization's extensive exploration alliances should depend on the degree to which the organization's identity is taken for granted—that is, the degree to which audiences understand the organization and expect it to exhibit appropriate features and behaviors. Henceforth, I will refer to the taken-for-grantedness of an organization's identity as identity strength. An organization to which a strong identity has been attributed, and which is therefore burdened with expectations of congruence with that identity, should engender much greater concern by forming exploration alliances than an organization with a weaker identity. Accordingly, the research question this chapter considers is: how does the strength of an organization's identity affect the impact that its exploration alliances have on its performance?

The general proposal of this chapter is that an organization's exploration alliances are likely to be associated with negative performance and that its identity strength will influence the extent of this negative effect. In particular, I argue that, due to the inherent tendency of exploration strategies to change an organization's core routines and violate the expectations that relevant audiences hold of it, exploration alliances will tend to be associated with negative performance, at least in the short term, among organizations with taken for granted, or strong, identities. Conversely, when an organization's identity is weak, because it is either incoherent or contested, this negative association between exploration alliances and performance will be reduced. In other words, the negative effects of an exploration orientation on the organization's performance will be milder when the organization lacks a strong identity.

To test my proposals, I examine two empirical settings: entrepreneurial firms in the U.S. business software industry and keiretsu member firms in the Japanese electronics industry. Two settings are considered to improve this study's generalizability; moreover, these settings offer unique contexts in which to investigate two distinct operationalizations of alliance exploration orientations, as well as of the identity strength of firms. Following established research methods,

I use the function and structure of an alliance to identify it as an exploration or exploitation alliance (Lavie, Kang, and Rosenkopf, 2011; Lavie and Rosenkopf, 2006). Additionally, I determine an exploration alliance's extensiveness using a measurement of the "distance" between the focal organization and its alliance partner appropriate for each context. Finally, in the context of new software firms I measure identity strength in terms of a firm's category coherence; in the context of keiretsu firms, in terms of the keiretsu's institutional legitimacy.

This research offers three contributions to the literature. First, it contributes to our general understanding of the link between alliance formation and organizational level performance. The practice of alliance formation has become ubiquitous, particularly in high technology industries where partners are necessary to cope with frequent innovation and recurring cycles of new market creation and old market obsolescence (Anderson and Tushman, 1990; Powell, 1990). The study of alliances as a type of interorganizational relationship has been an active area of research since early organizational theory proposed that a typical organization will be dependent upon the environment of other organizations in which it operates (Nohria and Eccles, 1992). Reviews to date suggest that organizations benefit from alliances under various conditions (e.g., Gulati, 1998, Wassmer, 2010). Within the field of organizational learning, alliance scholarship has advanced our understanding of these conditions significantly, yet researchers have thus far overlooked organizational identity as a possible contingency in the alliance-performance link. This is surprising as research indicates that in rapidly changing technology industries, each organization must acquire external legitimacy by having a clear identity, in the sense that it can be understood and considered as a member of a legitimate category (Aldrich and Fiol, 1994; Kennedy, 2008; Zuckerman, 1999). Furthermore, when applied to organizations, the axiom, "You are known by the company you keep" would seem to suggest that an organization's choice of partners should influence the formation and maintenance of its identity. For instance, alliances with partners that, on balance, are congruent with the organization's classification should confirm its identity and make the organization coherent, whereas alliances with partners that primarily belong to other classifications may dilute or change the identity of the organization, making it less coherent and legitimate. Combining organizational learning perspectives on alliances with a focus on identity (which to my knowledge has not been undertaken), may provide additional insight into the alliance-performance link.

Second, this study intends to contribute to the discussion, in the literature of organizational learning, concerning the degree of balance that organizations should seek between exploration and exploitation orientations. Gupta, Smith, and Shalley (2006) challenged the assumption of March (1991) that an organization must balance these two orientations to succeed, contending that, depending on its type, an organization is better off focusing on either exploration or exploitation. They proposed, for instance, that dedicated research and development organizations benefit more from a high degree of exploration than from a balanced orientation, while dedicated manufacturing organizations benefit more from a high degree of exploitation. From an organizational sociology perspective, research and development firms and manufacturing firms may be viewed as instances of organizational identities; that is, they are organizational types from which meaning can be inferred and which engender expectations of how an organization of each type should look and feel (Hsu and Hannan, 2005). One difficulty in talking about identity is that, in practice, identity definitions may be disputed or become less observable and useful over time; accordingly, Brubaker and Cooper (2000: 14) argued, we should instead view identity

as a social process in which how one identifies oneself, as well as how one is identified by others, are implicated. In line with this argument, this chapter contributes to the literature the suggestion that the strength of organizational identity, rather than the identity itself, should be considered when investigating the extent to which an organization should seek a balance between exploration and exploitation.

Finally, this chapter adds to the ongoing discussion of organizational adaptation and selection. Structural inertia theory posits that while organizations try to change and adapt to their environments, they no longer demonstrate the same reliability and accountability, both of which are favorable for selection, when they adopt those changes (Hannan and Freeman, 1984). This proposal has led past researchers to investigate conditions in which the benefits of change will outweigh its destabilizing effects. For instance, Haveman (1992) determined that when sharp environmental shifts threaten the existence of an organizational form, change will improve an organization's chances of survival, although only as long as the change maintains its existing competencies. Another important contingency is an organization's age: while organizations become increasingly inert over time, they tend to accrue more resources with which to reduce the deleterious effects of change when it does occur (Delacriox and Swaminathan, 1991; Hannan and Freeman, 1984). In this chapter, identity strength is considered as another important contingency in an organization's ability to overcome the deleterious effects of organizational change.

The chapter proceeds as follows. The next section explicates why expansive exploration alliances should act as indicators of significant organizational change and thus affect an organization's performance negatively. The following section argues that these negative outcomes should be contingent on the strength of an organization's identity. Following this, the methods section will introduce the two empirical settings, present context-specific hypotheses, discuss the empirical results and conclude with a brief discussion on their implications.

3.2   Theory Development

3.2.1   Exploration alliances as an indicator of organization identity change

The ability to survive as a business is related to how well an organization can adapt to its general and competitive environment. Thus, an organization must both exploit its current capabilities and explore ways to innovate new ones (March, 1991). The need to pursue both exploration and exploitation activities corresponds to the contingency perspective that organizations must adopt organic structures so they can be flexible when environmental conditions change, as well as mechanistic structures so they can be efficient when environmental conditions are stable (Burns and Stalker, 1961). Exploration involves activities related to experimentation, innovation, and the discovery of new knowledge, while exploitation involves activities focused on improving efficiency and refining existing capabilities and methods of execution (Levinthal and March, 1993; March, 1991). The immediate returns from exploration will tend to be negative because an organization must expend present resources pursing a new discovery in hopes of some future benefit, whereas the immediate returns from exploitation will tend to be positive because an organization will accrue present benefits from the utilization of its current capabilities (Levinthal and March, 1993; March, 1991). Recent studies have investigated the ways that organizations

balance exploration and exploitation (Beckman, 2006; Fang, Lee, and Schilling, 2010; Lavie and Rosenkopf, 2006). They may do so by exploring in one alliance mode and exploiting in another alliance mode (Lavie et al., 2011), or by pursuing the two orientations sequentially, either during different phases of a project (Rothaermel and Deeds, 2004) or according to changing aspiration levels (Greve, 2007). Balance in this context is also represented as ambidexterity, the ability of organizations to explore and exploit simultaneously (Tushman and O'Reilly, 1996); several empirical studies have investigated the ambidexterity construct (e.g., Cao, Gedajlovic, and Zhang, 2009; He and Wong, 2004; Lin, Yang, and Demirkan, 2007).

Studies concerning balance consistently demonstrate that exploration has negative (or low) implications for organizational performance. Experimentation comes with significant costs, in that an organization must expend both personnel and financial resources on the acquisition of new knowledge and capabilities outside of its current scope (March, 1991). Furthermore, while such efforts are costly in terms of the lost opportunity to use the same resources on exploitation (i.e., on improving current capabilities), the potential returns on these efforts are difficult to predict. The negative effects of exploration alliances on organizational performance have been demonstrated empirically in several contexts. For instance, in the context of new product development, Hoang and Rothaermel (2010) have investigated the performance of biotechnology research and development projects, finding that external, alliance-based exploration experience increases time to drug approval. Additionally, Yamakawa, Yang, and Lin (2011) have found that, within various industries, a high ratio of exploration alliances tends to have a negative effect on firm performance. Moreover, by reviewing the content of firms' press releases, which are likely to include announcements of exploration alliances, Uotila, Maula, Keil, and Zahra (2009) have discovered that, among manufacturing firms, too heavy of an exploration focus is associated with diminishing firm market value. Finally, Rothaermel (2001) has indicated that although in some contexts, such as in the biotechnology industry, exploration alliances may positively affect new entrant performance, these alliances nevertheless remain less beneficial than exploitation alliances.

While past scholarship has primarily attributed the short-term negative effects of exploration alliances on performance to the costs of experimentation, researchers have overlooked another likely explanation: that exploration alliances signal organizational change, and if this change is too extensive relevant audiences are likely to react against the organization, causing poorer organizational performance. It is evident that exploration alliances may be employed as indicators of change, as they meet the two criteria of a signal (Spence, 1973). First, an organization has some degree of influence over the type of partner and the type of alliance it pursues; it can even choose whether to announce an exploration alliance as newsworthy information by issuing a press release. Second, because the signal that forming an exploration alliance sends is relatively easy to give, the signal is credible. Exploration alliances require organizations to expend time and effort learning from partners and experimenting in new areas; accordingly, they clearly act as signals of potential organizational change related to those areas. In addition, alliances generally reflect the strategic intentions of the organization (Koza and Lewin, 1998), and it has been empirically shown that alliances do indeed help change organizations. Take, for instance, the case of International Business Machines (IBM) Corporation: known as a computer-manufacturing firm, it was able to reposition itself as a

technology services firm in the 1990s by forming exploration alliances (Dittrich, Cuysters, and DeMan, 2007).

From alliance announcements, relevant audiences can infer that some organizational change is impending. Alliances, as well as other forms of interorganizational relationships, such as interlocking directorates, entail at least a minimal degree of change, such as the adoption of incremental innovations or business practices (Davis, 1991; Westphal, Gulati, and Shortell, 1997) or of a new market and distribution channel. As these kinds of minor changes simply improve upon an organization's current capabilities, they are associated with exploitation strategies; such changes are not likely to incite negative reactions since they are consistent with the organization's core capabilities. Exploration alliances, however, indicate a more significant degree of change, as they relate to new technology development and are primarily motivated by an organization's desire to discover new opportunities (Koza and Lewin, 1998). Implicit in these goals is the organization's intention to incorporate new knowledge and routines, which differ from those it already possesses, from external sources (Cohen and Levinthal, 1990; Levitt and March, 1988); routines are the organizational properties, such as forms, strategies and technologies, "around which organizations are constructed and through which they operate" (Levitt and March, 1988: 320). As exploration alliances are about discovering and incorporating new routines and capabilities, they are likely to signal more significant organizational change than exploitation alliances do. Furthermore, the more extensive an exploration alliance is, the more likely it is to signal an impending change that will affect the organization's core, entailing a potential change in its identity (Hannan et al., 2006; Hannan and Freeman, 1984).

A well-established definition characterizes organizational identity as the attributes of an organization that are central, enduring, and distinctive (Albert and Whetten, 1985). Whetten (2006) has suggested that these attributes belong to several levels; at the lowest level, identity is influenced by an organization's unique traits, practices and competencies, while at the highest level, established social forms, categories, and group affiliations contribute to identity. Studies of attributes at the lowest level investigate how internal members of an organization share beliefs about who they are as a collective actor (Albert and Whetten, 1985); studies of attributes at the highest level consider how actors, both internal and external, compel the organization to remain consistent with the social codes related to its claimed identity (Hsu and Hannan, 2005; Pólos et al., 2002). In this chapter, I focus on organizational identity in terms of attributes of the highest level, at which an organization derives its identity from social categories and group affiliations. Social categories and group affiliations have several implications for a focal organization's identity strength (Hannan, Pólos, and Carroll, 2007). When the definition of a social category or group is widely shared, holds meaning and is taken for granted, its individual members (organizations) will inherit a strong identity: relevant audiences will hold strong expectations about its members, and its members will incur devaluation for violating those expectations. In contrast, when the definition of a social category or group is ambiguous, not widely shared, or contested, associated organizations will inherit a weak identity, relevant audiences will hold weak expectations about them, and they will be less likely to incur devaluation for violating those expectations.

To this point, I have been suggesting a connection between alliances and organizational identity. This is not a new idea; this connection has been previously recognized in work by sociologists.

According to the principle of homophily, organizations tend to form relationships based on shared attributes that may reinforce their organizational identities. For instance, social values may be an important part of an organization's identity; such organizations will tend to seek partners that hold the same values (Lincoln and McBride, 1985). The connection between alliances and organizational identity has also been alluded to in the management literature. For instance, Schermerhorn (1975), in discussing the costs associated with interorganizational cooperation, notes that one such cost may be an unfavorable impact on an organization's identity. Though Schermerhorn doesn't elaborate on his definition of identity, he may be referring to organizational image, as he also suggests that an organization may avoid interorganizational cooperation in order to prevent damaging its desired image. Nooteboom (1992) further observes that organizations face additional costs in forming alliances; this observation challenges the prediction of transaction cost economics, which Nooteboom answers by arguing for a long-term view of transaction relationships, and recognizing that through alliance interactions, identity can be developed or changed. He maintains that to develop new technologies, organizations must remain open to outside ideas by continuing to pursue alliance relationships, even if the corresponding transaction costs increase. Additionally, Ring and Van de Ven (1994) contemplate the nature of identity in their discussion of how interorganizational relationships develop. Drawing on social-psychological literature and theories of sense-making, they propose that organizations understand each other's identity in relation to other organizations; when two organizations have a congruent understanding, formalizing an alliance becomes likely. Though the definition of identity is not elaborated on in the previous two papers, when these studies are taken together, they nonetheless suggest that each organization has a sense of its own identity, will consider its identity (constraints) when selecting a cooperative partner, and will expect that, due to close interactions with a partner, its identity may change.

3.2.2   The Downside

Why, from an identity perspective, should exploration alliances affect organizational performance negatively? It can reasonably be assumed that, for its exploration alliance to yield new, (commercially) successful outcomes, an organization will most likely reconfigure its internal structures and modify its prior commitments so that it can assimilate new knowledge, new skills, and new operations; according to structural inertia theory, such significant changes are likely to cause poor performance and organizational failure (Hannan and Freeman, 1977, 1984). Structural inertia theory posits that in order to mobilize resources from external and internal constituents, organizations must demonstrate reliability and accountability; to meet these requirements, organizations tend to become stable, or structurally inert. Inertia also tends to be fostered by members of an organization developing moral values concerning organizational structures (Selznik, 1949), or by the leadership of an organization holding a commitment to the status quo (Hambrick, Geletkanycz and Fredrickson, 1993). Additional concepts related to structural inertia discussed in the literature include historical imprinting, path dependencies, routines, and competency traps (Stinchcombe, 1965; Nelson and Winter, 1982; Levinthal and March, 1993).

Regardless of their actual content, attempts to change or diversify into unrelated businesses will affect organizational structures and prior commitments and thus will disrupt stability (Barnett

and Carroll, 1995; Barnett and Freeman, 2001; Haveman, 1992). Instability causes organizations to become less reliable and less accountable; in this situation, internal and external constituents will begin to doubt or react against the organization and become less willing to remain committed to it and provide it with resources (Hannan and Freeman, 1984). Considered from another perspective, change resets an organization to a like-new state and subjects it to liabilities of newness, as it introduces many new elements to the organization (Amburgey, Kelly, and Barnett, 1993). The claims of structural inertia theory have been supported in several empirical studies (see Barnett and Carroll, 1995 and Carroll and Hannan, 2000, chapter 16 for reviews).

The force of inertia is strongest on core organizational attributes—organizational identity, in particular. Hannan and Freeman (1984) have defined 'core' in terms of the structural and strategic features of an organization that form the foundation upon which it obtains legitimacy and mobilizes resources. They list the following as an organization's core attributes: its stated goals; its core technology, such as capital investments or employee skills; the customer orientation expressed in its marketing strategy; and the form of authority that defines exchanges between it and its members. The authors identify organizational identity as an organization's core because it carries the most legitimacy with which to garner and allocate resources. For instance, in their discussion of universities, Hannan and Freeman propose that it would not be an issue if a university changed the textbooks used for instruction, as textbooks are peripheral attributes of the organization and merely reinforce the university's curriculum, but that it would be a serious issue if a university changed its curriculum, such as from arts and humanities to vocational education; such a change would incite strong resistance from faculty and students as the curriculum "represents the core of the university's organizational identity and underlies the distribution of resources across the organization" (Hannan and Freeman, 1984: 156).

An identity-based perspective suggests that the disruption of an organization's identity will violate the default expectations that relevant audiences hold of it (Hsu and Hannan, 2005; Pólos et al., 2002) without support from relevant audiences, the organization will struggle to survive. Baron, Hannan and Burton (2001) suggest that an organization's employment model is a key aspect of its core identity as it is central to building a reliable and accountable organization: potential employees want some assurance that the organization has a suitable culture and a reasonable human resource system. The authors found that changing the employment model that had initially been established in a new firm tended to be disruptive, increasing employee turnover and subsequently decreasing organizational performance. Moreover, Baron (2004) and Hannan et al. (2006) establish more conclusively that an organization's employment model is a key attribute of its identity and hence is under the utmost pressure to remain stable. They demonstrate that changes to established employment models violate organizational identity expectations, disrupt the employee-organization relationship, and result in negative performance outcomes such as slower growth and an increased likelihood of failure.

It should be noted that an identity change does not even have to occur to violate identity codes. In forming an extensive exploration alliance, not only will an organization pursue a direction glaringly incongruent with its established identity, but it will also signal its intention to modify that identity. This signal alone is enough to decrease relevant audiences' commitment to the

organization, at least in the short term.[2] Take, for instance, the field of open-source development, which is characterized by a particular commitment towards a distinct identity within the software industry. Open-source firms embrace the development philosophy that by freely distributing their products and widely collaborating across firm boundaries, they will improve the quality and lower the cost of software for the common good (opensource.org). This identity contrasts with that of the more common type of firms, those that produces proprietary software, and members of the open-source community who believe strongly in its ethos to maintain this contrast. Hence, when, Novell, an open-source firm, announced a patent agreement with Microsoft, a proprietary firm, in 2006, the open-source community was up in arms. Novell was accused of making "a deal with the devil" and many of Novell's key employees resigned (Emigh, 2007). One of Novell's top developers who left publically went so far as to announce that until Novell revoked its patent agreement with Microsoft, its employees would be "pariahs" in the open-source community (Gonsalves, 2006).

My first proposal (P1) summarizes the arguments made above. Potential identity change, as indicated by the formation of extensive exploration alliances, is likely to violate identity expectations held by relevant audiences. Initially, these audiences will doubt and become less committed to the organization, a reaction that will negatively impact the organization's performance. Hence,

> P1: Extensive exploration alliances are associated with decreased organizational performance because such alliances represent a failure to meet identity expectations.

3.2.3 A Caveat

The above proposal is especially applicable when an organization has an identity derived from a social category or group that is strong. I use "strength" to refer to the degree to which an organization is taken for granted by relevant audiences; that is, how exclusively relevant audiences understand the organization according to its categorization and automatically assume that it possesses the appropriate features and behaviors. When taken for granted, an organization's identity is understood to constrain the organization with socially enforced features and behaviors, or codes; a violation of these codes will reduce its valuation (Hsu and Hannan, 2005; Pólos et al., 2002;). However, not all classifications for organizations will reach a taken-for-granted state. Over time some may become obsolete due to external shifts in technology or the deinstitutionalization of groups that had defined the category. When a category is not taken for granted, organizations associated with it will inherit a weak identity or, in the case of

---

[2] Of course, innovation (i.e. exploration) may be central to the identity of many high technology firms; innovation is necessary for firms to compete and frequently simply to maintain their competitive position within their existing market category. My argument primarily relates to the short-term main effects of an exploration orientation on performance outcomes. The anticipated negative effects may be buffered by a firm's age and past experiences, so that relevant audiences of firms such as Hewlett-Packard or Sony, which are known for their innovativeness, are able to overcome the initial doubts that new exploration strategies typically engender. Nevertheless, if we also consider exploration in terms of diversification into areas that are distant from a focal firm's competencies, we can expect that too much exploration (diversification) will cause firm analysts to discount the firm (Zuckerman, 2000).

obsolescence, lose their identity entirely. Tripsas (2009) discusses an instance in which an organization lost its identity when a shift in technology made its core technology obsolete. Such environmental shifts present challenges to an organization because both internal and external audiences will be unclear about its new identity for some time, during which audiences will become increasingly concerned with defining the organization's new identity and less concerned with enforcing prior identity codes (Tripsas, 2009).

When an organization's identity is weak or obsolescent, audiences become less concerned with enforcing identity codes simply because those codes are not present. Although a strong identity clearly defines the actors associated with it, it also introduces commitments that those actors must meet, limiting their freedom to change. In contrast, a weak identity, though it does not provide a clear definition, begets freedom and flexibility. Relevant to this discussion is the concept of maintaining a 'robust identity' through ambiguous action (Padgett and Ansell, 1993). Exemplified by Cosimo de'Medici and his rise to political power in the 15th century, the strategy of taking an ambiguous position and leaning toward multiple interests places an actor in a situation where he can avoid direct attacks from opponents because they are unable to pin his interests down (Padgett and Ansell, 1993). Similarly, a weak identity places an organization in a position where it cannot be pinned down or constrained by identity codes; thus, any action the organization takes cannot be directly confronted as a violation. Indeed, when organizations are associated with a weak or obsolete identity, not only are they less affected by identity violations, but core organizational changes may not even be considered actual violations of identity codes and cause the devaluation of the organization. Accordingly, in this situation, extensive exploration alliances may have a less detrimental impact on performance than predicted.

This phenomenon may be anecdotally observed in the situation of Yahoo during the early years of the company. Founded in 1994, Yahoo quickly became successful and expanded into many areas of business by creating a large and diverse alliance portfolio of technology partners (Rindova, Yeow, Martins, and Faraj, 2012). In the early days of the Internet, this was acceptable to consumers, as they used Yahoo as a portal to access a number of activities, including reading email and the news and performing searches. As consumers became more sophisticated, however, they did not want to access everything through a single portal, but rather desired to cherry-pick the best web site for each activity (Hill, 2012). While competing Internet firms increasingly focused in single technology fields, Yahoo continued to explore different areas. By 2002, the media noted that Yahoo was having an "identity crisis"; it had branched out in too many directions and was trying to become everything to everyone (Walker, 2002). Yet even as analysts pushed Yahoo to become more focused and clearly identify itself—as a media company or a technology company, for instance—they seemed unconcerned that its ongoing pursuit of technology (exploration) alliances could potentially dilute Yahoo's identity further (Barlas, 2010). I contend that the analysts did not consider Yahoo's exploration alliances to be potential disruptions to a stable identity because Yahoo did not have a stable identity to begin with. From the perspective of relevant audiences, Yahoo's lack of identity meant that there was no identity 'rule' or 'code' to constrain their expectations, so the signals of change that could be inferred from its exploration alliances were irrelevant.

If extensive exploration alliances have a negative impact on an organization's performance because they signal organizational identity change, then organizations with a weak (i.e. less

taken-for-granted) identity should experience a less negative impact on performance. In other words, when an organization's identity is weak, the negative impact that extensive exploration alliances have on performance will be mitigated. The second proposal (P2) summarizes this statement.

P2: Weak organizational identity will reduce the negative effect of exploration alliances on performance.

3.3   Methodology

I will test the above proposals in two empirical settings: among new firms in the software industry and keiretsu firms in the Japanese electronics industry. By studying two distinct settings, I am able to improve the generalizability of my proposals. Before describing the empirical settings, starting with the software industry, I will clarify my approach to measuring the key explanatory variables—exploration alliance extensiveness and identity strength.

Exploration alliance extensiveness. Previous research has defined exploration and exploitation alliances in terms of their function and structure (Beckman, Haunschild, and Phillips, 2004; Lavie et al., 2011; Lavie and Rosenkopf, 2006; Rothaermel, 2001). When considered in terms of function, exploration-oriented alliances are those involving the discovery of new knowledge, such as through technology development, while exploitation-oriented alliances are those like marketing and distribution that leverage current knowledge. When understood in terms of structure, however, exploration-oriented alliances are those involving new partners, while exploitation-oriented alliances involve prior partners. In discussing entrepreneurial firms in the software industry, I identify alliances according to their function; additionally, to indicate the extensiveness of exploration alliances, I calculate the distance between the product market space of the focal firm and that of its partners. However, in considering keiretsu member firms in Japan, I define exploitation and exploration alliances according to their structure—whether an organization's alliance partners are prior partners or new. In this context, I additionally determine the extensiveness of a new (exploration) partner by using a partners' keiretsu affiliation, identifying a new partner that is independent of a keiretsu as more "distant" and extensive in exploration than a new partner in the same keiretsu as the focal firm—this partner would be considered a "closer" partner and less extensive in exploration.

Identity strength. For entrepreneurial software firms, establishing a clear identity is crucial. New firms are more prone to failure than established firms because they lack legitimacy and need to establish new working relationships (Stinchcombe, 1965); to survive, a new firm must quickly gain legitimacy and justify its existence (Aldrich and Fiol, 1997; Suchman, 1995). An organization must have a clear identity, such as one derived from market categories, to accomplish this. Market categories help analysts and consumers recognize organizations as members of a comparison group so they can be evaluated (Phillips and Zuckerman, 2001; Zuckerman, 1999). This same principle applies to film actors, in that an actor who is typecast in an acting category earlier in his career will facilitate evaluation of his performance and tend to have a more successful career as time passes (Zuckerman et al., 2003). Not only will members of an organization lacking a clear identity fail to pursue a common goal, but external audiences will

be unable to recognize and evaluate the organization as well. This is particularly true of new high-technology firms, which the media identifies as having "skeptical business customers who would prefer to deal with a more stable company" (Potts, 1992). Hence, I measure the degree to which a software firm's identity, as derived from its product categorization, is perceptually clear. I do this in two ways: by determining the number of distinct categories of which a firm claims to be a member, and by identifying the distinctiveness of those categories. Both approaches indicate a degree of identity strength as they relate to how clear an organization identifies itself.

In considering keiretsu member firms, I take advantage of historical events in the Japanese economy and treat this study as a natural experiment. In 1991, Japan entered a sharp economic recession, which the news media attributed to the keiretsu system. As a result, beginning in 1991, the keiretsu groups seemed to lose legitimacy and unravel (Auerback, 1991). I construct my sample around this event, treating the years before 1991 as a period in which keiretsu identity was strong and the years beginning in 1991 as a time when it was weak. The following table summarizes my approach to operationalizing exploration alliance extensiveness and identity strength in the two empirical contexts.

Table 8: Summary of approach to operationalize exploration alliances and weak and strong identity

Empirical setting	Extensive exploration alliances	Weak identity	Strong identity
Entrepreneurial Software Firms	Technology alliance partners that are most distant from the focal firm's product domain	Identity derived from a product category that is less clearly defined Spanning many product categories	Identity derived from a product category that is more clearly defined Spanning fewer product categories
Keiretsu Member Firms	New alliance partners that are non-keiretsu member firms (independent firms)	Keiretsu firm identity beginning in 1991, when the keiretsu became contested and deinstitutionalized	Keiretsu firm identity prior to 1991, when the keiretsu was a strong institution

3.4   Empirical Setting 1: Entrepreneurial Software Firms

Start-up firms in the business software industry represent a suitable setting for testing my proposals for two reasons. First, alliances—both exploration- and exploitation-oriented—are ubiquitous in the industry, as industry competition and the intangible nature of business software requires that firms develop a functionally diverse portfolio of partners (Messerschmitt and Szyperski, 2003); the software industry has been the focus of many alliance studies (e.g., Lavie, 2007; Lavie and Rosenkopf, 2006) for this very reason. Second, the business software industry is a good setting in which to observe variation in the strength of organizational identities derived

from categories established by market participants: in the software industry, category taxonomy is particularly significant due to the proliferation and diversity of the industry's products and applications (Campbell-Kelly, 2003). The software industry is characterized by fast-paced changes resulting from new technology and new firm entrants. Because of these dynamics, industry participants tend to expand the taxonomy frequently by introducing new applications (i.e. products and services). A detailed investigation of category labels in the software industry demonstrates that software firms are able to create new category labels for new innovations with relative flexibility and lack of restriction (Pontikes, 2010).

The categorization dynamics within the software industry may influence how strong a firm's categorization-derived identity is, the weakest firms being those that are vaguely categorized because they are so new and do not fit exactly into an established product category, the strongest being those that are clearly categorized because they fit into a well-established and well-defined category. Categorization is an important aspect of identity. We tend to associate objects with category labels, which give us some comprehension about the objects (Rosch, 1978). Just as systems of category labels are fundamental to our understanding of the world, the label(s) with which we associate a new firm or its new application will be fundamental to our recognition and comprehension of the firm. Because a firm's category is so essential for understanding what it does, categories imbue firms with identity and meaning (Hsu and Hannan, 2005). Categorization is also important when we seek to evaluate a firm by comparing it to similar firms. Hence, for entrepreneurs, categorizing their firms within existing categorization systems within their industries is a fundamental task, as doing so establishes their firms' identities. Otherwise, a firm will fail to be noticed and suffer from poor evaluations if it is not clearly categorized (Zuckerman, 1999). My sample includes both vaguely and clearly categorized start-up firms, which correspond to firms with weak and strong identities, respectively.

3.4.1   Time to Initial Public Offering

One indicator of a start-up software firm's early success is its ability to transition from private ownership to public ownership through an initial public offering (IPO) event. A start-up firm that reaches this milestone indicates that it has 'made it,' establishing itself as a viable business that will continue to grow. Although not all start-up firms choose to go public, the benefits of doing so motivate many firms to choose that path. The finance literature identifies four reasons that firms are motivated to go public: raising a large amount of capital with minimal costs in order to grow or to acquire other businesses; converting the investments of the founders and early investors into wealth; positioning themselves as easier targets for acquisition; and achieving strategic goals such as increasing the legitimacy and reputation of the firm (Brau and Fawcett, 2006; Lerner, 1994; Pagano, Panetta, and Zingales, 1998; Ritter and Welch, 2002). Moreover, timing is an important factor in the decision to go public. Start-up entrepreneurs tend to take a company public when market and industry conditions are favorable and the market is receptive to other IPOs in the firm's industry sector (Pagano, Panetta, and Zingales, 1998; Lowry and Schwert, 2002). During the time period in which I analyze software firms, 1993-2003, the IPO market was very attractive, especially during the late 1990s; the successful IPOs of America Online in 1992 and Netscape in 1995 were credited with starting a strong IPO market in the e-commerce and software industries that lasted until the end of 2000. In the media, this attractive

IPO market has also been attributed to the economy and the investment infrastructure of the 1990s, which made the IPO event a common performance milestone for start-up technology firms (Abate, 2010). Indeed, it is likely that, during this time, many software start-ups planned to go public from their inception.

Hence, during the time period and among the sample of start-up firms I consider in this study, accomplishing an IPO was generally not a matter of if, but when. In the context of this study, therefore, time to IPO is an important indicator of performance success. Although some have seen this period as characterized by irrational investors who would invest in any firm merely because it had a ".com" name, Lee (2001) has established that investors were in fact not easily fooled by such name changes. Only when a ".com" name change was accompanied by actual structural changes, such as acquiring or forming an alliance with an internet firm or closing a retail store, was more value added (in terms of the trading volume and price of the firm's stock) to an established firm.

In this chapter, I argue that firms with extensive exploration alliances will take longer to reach an IPO. Potential investors may interpret such alliances as evidence that a new firm is not stable and will make more changes before becoming stable; accordingly, the start-up firm would benefit from delaying its IPO. However, this assumes that the start-up has a strong identity. A strong identity provides investors with clear criteria for evaluating a firm when it is ready to go public; investors across the board would be disappointed if such a firm failed to meet expectations. When a start-up firm's identity is weak, however, the criteria with which to evaluate it are less clear. A weak identity may invite evaluations based on varying criteria; as expectations would be diverse, only some segments of a firm's investor audience would be disappointed by any particular outcome. A firm may even choose to pursue this sort of robust identity so that it will have greater flexibility to pursue different markets (Padgett and Ansell, 1993). Hence, a start-up with extensive exploration alliances may delay its IPO less if it has a weaker identity than it would if its identity were strong. The following hypotheses will test the above arguments.

> *H1: Extensive exploration alliances will have a negative effect on (will lengthen) a start-up's time to IPO.*

> *H2: Depending on the start-up's identity strength, the negative effect of extensive exploration alliances on time to IPO will be moderated, such that for a start-up with a weaker identity, the negative effect on the time to IPO will be reduced (time to IPO will be less lengthened).*

3.4.2 Data

I analyzed a sample of business software firms drawn from the Corporate Technology Information Services (CorpTech) database of high technology firms. I selected firms founded between 1992 and 1997, inclusive of those years. In 1992, the Internet became commercially available, shifting the technological environment; new firms entering the market after 1992 most likely introduced new products that took advantage of the new technology. New entrants can introduce products in one of two ways: either by launching a novel product in an undefined

market or by finding a novel way to improve upon an existing product in a defined market. Firms in the former category will have weaker identities than those in the latter. To limit geographic variability, I also restricted my sample to firms founded in California, where during the period of my study, it had the highest concentration of software firms in the world (Campbell-Kelly, 2003). The total sample consists of 361 new software firms.

I collected longitudinal data for each firm over seven years, starting with the year it was founded. For instance, I tracked alliance activity among the youngest cohort of firms (those founded in 1997) from 1997 to 2003. I collected alliance data using the press release announcements issued by each firm, and researched each firm's IPO event, product categories, sales revenues, venture capital (VC) funding, and patent information as well. My primary sources of data were the CorpTech directory, which I used to obtain data about firm categorization, IPO events, and sales revenue, and Lexis-Nexis Academic, which I used to obtain alliance data and to confirm IPO event information. Additionally, I obtained VC funding information from the Thomas Reuters VentureXpert database and patent information from the National Bureau of Economic Research U.S. Patent database.

3.4.3   Variables

The dependent variable, *time to IPO*, is a non-repeating event for each firm. The process of an IPO may take up to a year, as it involves preparing the organization for the event and drafting disclosure documents for the U.S. Securities Exchange Committee (SEC). Because of this delay, I lagged the independent variables by one year.

To measure the independent variable, *exploration alliance extensiveness*, I first divided a firm's alliances into those with an exploration orientation and those with an exploitation orientation. Following established research practices, I categorized technology, research and development, and new product development alliances as exploration alliances and marketing and distribution alliances as exploitation alliances (Lavie and Rosenkopf, 2006; Rothaermel, 2001). Rather than simply tabulating the number of exploration and exploitation alliances each firm had, I went a step further and determined product market distance—that is, the degree to which a focal firm's product market focus is distant from its partner's—for each of the firm's alliances; this calculation provides a sense of the extensiveness of a firm's exploration alliances and the reach of its exploitation alliances. Operationally, I determined the structural equivalence of two firms using a similarity (difference) measure based on the Euclidean distance between them (Burt, 1976). Two firms are considered structurally equivalent if they share the same pattern of ties to other actors; in this case, if they share the same pattern of product category memberships. Thus, I constructed a category-by-category matrix of all product categories with which all software firm listed in the CorpTech directory was associated; using the matrix, I determined the number of firms that belonged to each pair of intersecting product categories. This approach resembles the method Stuart (1998) used to measure technology similarity (dissimilarity) between two firms, except that where he employs patent citation patterns, I use category membership patterns. Two categories are structurally equivalent (similar) if they share the same vector of firm counts; using UCINET 6, I determined the structural equivalence for each category-by-category pair. Next, I applied the Euclidean distance measures to each category pair associated with a focal firm and its

partner. I then averaged all distance measures for each focal firm and its set of exploration and exploitation alliance partners. To address nonlinearities, I standardized the measure around a value of 1. I produced one measure expressing the extensiveness of a focal firm's set of exploration alliance partners and one measure expressing the breadth of a focal firm's set of exploitation alliance partners. The latter measure is utilized as a control variable.

I measured the strength of each new firm's identity in two ways; both approaches rely on the CorpTech categories under which the firm is classified. The first measure is the number of distinct product categories (*Num of Product Categories*) with which each firm is affiliated; to address the right skew, I took the natural log of this variable. This measure can be used to indicate a firm's identity strength due to the nature of categories. Categories, such as those found in directories like CorpTech, emerge when a group of objects, entities, or events acquires some shared distinction that is externally perceived and recognized (McKendrick et al., 2003). A distinct category has external meaning, which increases its legitimacy and distinguishes how the grouping of organizations associated with it is the same as or different from other groupings of organizations. When an individual organization belongs to a distinct category, it will be associated with a single external meaning, presumably making the organization's identity clear. However, when an individual organization is classified under multiple distinct categories, it will be associated with multiple and potentially conflicting meanings, making the organization's identity vague. In other words, the greater the number of distinct product categories a firm is affiliated with is, the less coherent the firm's identity is likely to be. Counting the number of categories that an organization is affiliated with corresponds with measuring the niche width of generalist and specialist entities (Baum and Singh, 1994; Freeman and Hannan, 1983; Hsu, 2006); generalists allocate resources to cover a broad market area but are likely to become a "master of none", whereas specialists focus resources in a single area and are likely to be recognized for a particular competency (Hsu, 2006; Freeman and Hannan, 1983).

The second measure of identity strength indicates the distinctiveness of the category (*Category Distinctiveness*) to which a firm belongs. In so far as an organization derives its identity from the category under which it is classified, then the degree to which the category itself is distinctive should affect the strength of the organization's identity (Hannan et al., 2007). A distinct category will be delineated from others by a so-called crisp boundary; an organization affiliated with such a category will have a strong identity, in that it will be easy to compare and contrast the organization with others. Conversely, an indistinct category will have a fuzzy boundary, providing less of a clear delineation between it and other categories; an organization affiliated with such an ambiguous category will have a weak identity, in that comparing and contrasting the organization with others will be difficult. Following Hannan et al. (2007), I determine a category's distinctiveness, and hence a firm's identity strength, by calculating each category's average grade of membership.

I took two steps to determine category distinctiveness at the firm level. These steps are also described in the previous chapter. First, for every year analyzed I computed the average grade of membership for each software-related category employed in CorpTech. To do so, I first had to determine the grade of membership for each firm affiliated with each category. Suppose Firm B sells a total of four products in Categories X and Z; three of those products are in Category X and one of those products is in Category Z; accordingly, Firm B's grade of membership in

Category X is 0.75 (=3/4) and is 0.25 (=1/4) in Category Z. Each of these categories is then each assigned an average grade of membership that is determined by averaging the grades of memberships of every firm that belongs to it; an average grade of membership measure close to one indicates that a category is highly distinctive, while a measure closer to zero indicates that a category is less distinctive than others. Once I had done this, I was able to calculate the identity strength of each firm in my sample by assigning to it the average grade of membership associated with the category it belonged to during the previous year. When a new firm belonged to more than one category, I assigned it a weighted average based on the number of products the firm had in each category. Suppose in year 1, Category X has an average grade of membership measure of 0.75 and Category Z has an average measure of 0.25. In year 2, new Firm C is founded, producing two products in Category X and one product in Category Z. Therefore, in the year of its founding, Firm C is assigned a degree of distinctiveness of 0.58 (=[0.75*2+0.25*1)]/3). The closer this number is to one, the more distinct the firm's categorization is, and hence the stronger its identity is. Finally, I reverse coded this measure to facilitate interpretation when I analyzed the results.

In my model, I also accounted for additional firm level characteristics found to affect a firm's time to go public in order to control for other factors that may impact a firm's time to IPO. As earlier research has shown that as firms grow larger, they tend to go public (Pagano et al., 1998), for each firm I included a measure of firm size based on its annual *sales growth* figures in CorpTech; the larger a firm's sales growth, the more likely it would be to go public. To handle nonlinearities, I transformed this measure by taking its exponential value. In addition, I also employed each firm's *total number of alliances* as an indicator of firm size, as past research has observed a correlation between time to IPO and the size of a firm's alliance portfolio (Gulati, 1998). Moreover, as the prestige of a firm's alliance partners may draw positive attention, which may also motivate the firm to go public, I determined the percentage of each firm's alliance partners that were ranked in the Software 500 list (*percent of partners ranked*) as well.

Heavy investment in a firm also tends to prompt an IPO (Pagano et al., 1998); accordingly, I determined the amount of annual investment each firm received from venture capital (VC) investors (*amount of VC funding*) and took the natural log of this value. In addition, I determined the *cumulative amount of VC funding* a firm received through the year two years prior to a potential IPO year, and took the natural log of this value as well. Investors generally want to see a return on their investments within three to seven years; potentially, as the cumulative amount of VC funding a firm has received increases, the more pressure from VC investors the firm will face to liquidate its investments through an IPO. Since holding patents has also been shown to affect the timing of IPOs (Cockburn and MacGarview, 2009; Shane and Stuart, 2002), I also included measures for the *number of patents* filed by a firm each year, as well as for the stock of patents *(Cumulative patents)* the firm had accumulated through the years up to two years before a potential IPO; to address right skew, I took the natural log of cumulative patents. Finally, I included a dummy variable to represent the period from 2001, when the Internet bubble burst, to 2003, when the time frame of my study ends, during which the rate of IPOs slowed down (*2001 to 2003*).

3.4.4　Model and Analysis

Modeling the effect of exploration alliance extensiveness on the time to IPO. To examine a firm's IPO event as a single, non-repeated event, I employ an event history model; specifically, I use a Cox proportional hazard model (Cox, 1972). This specification models the likelihood that an IPO event will occur at time (year) t given that an IPO did not occur in the time before t. The following is the model used for the analysis: $h_i(t) = h_o(t)*\exp[\beta X(t - 1)]$, where $h_o(t)$ is the baseline hazard function, and $X(t - 1)$ is the vector of covariates for firm i at time $t - 1$. It is possible that as time passes, the effect of the predictors will not remain the same in all years, therefore violating the proportional hazards assumption. Hence, I compared models with and without time-varying covariates added and conducted a likelihood-ratio test; I determined that the proportional hazard assumption holds.

An increase in the hazard function can be interpreted as a decrease in time to IPO. If Hypothesis 1 is supported, the hazard function for the variable *exploration alliance extensiveness* should be negative. Additionally, if Hypothesis 2 is supported, the interaction between exploration alliance extensiveness and identity strength should be positive. Right censoring occurs as I follow new firms for seven years beginning with the year of their inception. The number of IPO events to occur within the time period of this study is 70. The numbers of firms in my sample to go public each year are shown in the table below; on average, it took these firms 4.5 years to reach an IPO event.

Table 9: Number of IPO events in sample

Year of IPO	Total
1995	3
1996	4
1997	5
1998	8
1999	27
2000	19
2001	3
2002	1
Total	70

3.4.5　Results

Tables 10a and 10b show the summary statistics and correlations of the variables. I further calculated the variance inflation factors of all variables using ordinary least squares regression and post-estimation. Multicollinearity was not a concern as all variance inflation factors were at an acceptable level of 2.59 or less. Due to random missing data, the total number of firm-year observations was 1,031.

Table 10a

Descriptive Statistics (N = 1031)

Variable	Mean	s.d.	Min	Max
1 IPO (dummy)	0.02	0.13	0	1
2 Exploration alliances (y-1)	1.39	1	1	9.47
3 Exploitation alliances (y-1)	1.47	1	1	9.44
4 Identity strength (y-1)	0.56	0.07	0.32	0.82
5 Num product categories (y-1) (ln)	0.89	0.66	0	2.83
6 Sales growth (y-1)	1.18	0.51	0	2.72
7 Total alliances (y-1)	0.39	0.74	0	3.50
8 Percent partners listed in SW500 (y-1)	0.05	0.18	0	1
9 Annual VC Funding (y-1) (ln)	2.14	3.90	0	11.66
10 Cummulative VC Funding (y-2) (ln)	3.86	4.96	0	12.04
11 Total patents (y-1)	0.08	0.49	0	8
12 Cummulative patents (y-2) (ln)	0.16	0.48	0	3.74
13 Year 2001-3 (dummy)	0.16	0.36	0	1

Table 10b

Correlation Matrix (N = 1031)

Variable	1	2	3	4	5	6	7	8	9	10	11	12
1 IPO (dummy)												
2 Exploration alliances (y-1)	0.02											
3 Exploitation alliances (y-1)	0.02	0.34										
4 Identity strength (y-1)	-0.06	0.10	0.09									
5 Num product categories (y-1) (ln)	-0.02	-0.02	0.01	0.09								
6 Sales growth (y-1)	0.05	0.03	0.08	0.01	-0.03							
7 Total alliances (y-1)	0.05	0.56	0.57	0.13	-0.01	0.13						
8 Percent partners listed in SW500 (y-1)	0.07	0.24	0.18	-0.01	-0.03	0.04	0.23					
9 Annual VC Funding (y-1) (ln)	0.15	0.20	0.24	0.12	-0.03	0.06	0.27	0.08				
10 Cummulative VC Funding (y-2) (ln)	0.11	0.31	0.34	0.16	0.00	0.11	0.45	0.14	0.72			
11 Total patents (y-1)	-0.01	0.01	-0.02	0.00	0.08	0.01	0.00	-0.03	-0.03	0.06		
12 Cummulative patents (y-2) (ln)	0.05	0.03	0.00	-0.06	0.04	0.05	0.07	-0.04	0.01	0.12	0.65	
13 Year 2001-3 (dummy)	-0.06	0.08	0.06	0.14	0.13	-0.07	0.08	0.06	-0.03	0.13	-0.07	-0.05

Table 11 shows the results of the Cox regression when identity strength is measured according to the number of product categories (*Num of Product Categories*) under which a firm is classified. Model 1 includes the maximum likelihood estimations of the control variables that could influence the likelihood that a firm will go public. As expected, increased *sales growth* significantly increases the likelihood a firm will go public, as do a large *amount of VC funding* and a high *number of patents*. Consistent with the overall trend in the industry at the time, the years *2001 to 2003* are associated with a decreased rate of IPOs. Model 3 adds the measure of exploration alliance extensiveness. Hypothesis 1 proposed that extensive exploration alliances will have a negative effect on a start-up's time to IPO. Yet while the results do indicate that these alliances do have a negative effect on time to IPO, this effect lacks significance; thus, these results do not lend support to H1. In Hypothesis 2, I proposed that this anticipated negative effect would be lower among start-ups with weaker identities, reducing the delay in time to IPO. Hence, in model 5, I added the interaction between exploration alliance extensiveness and identity strength. These results show a negative and significant main effect (p < .05); moreover, the interaction term is positive and also significant (p < .05), lending support to both H1 and H2. As the focus of this chapter is organizational change as signaled by exploration alliances, I offered no prediction concerning how exploitation alliances would affect time to IPO; nevertheless, model 6 seems to suggest that the pattern for exploitation alliances is similar to the pattern for exploration alliances: more extensive exploitation alliances result in an increased time

to IPO, but when interacted with weak identity, this time increase is reduced. All variables are shown in model 7.

Table 11
Event-History analysis of exploration alliances on time to IPO;
Identity strength measured as a firm's number of category memberships (361 firms)

Variable		Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Sales growth (y-1)		0.617**	0.607**	0.639**	0.709**	0.570**	0.766**	0.778***
		(0.286)	(0.292)	(0.292)	(0.317)	(0.284)	(0.309)	(0.295)
Total alliances (y-1)		0.344	0.356	0.480	0.520	0.585*	0.597*	0.882***
		(0.308)	(0.317)	(0.322)	(0.319)	(0.317)	(0.307)	(0.290)
Percent partners listed in SW500 (y-1)		0.876	0.862	0.940*	0.933*	0.925*	1.051*	1.117**
		(0.538)	(0.543)	(0.544)	(0.529)	(0.541)	(0.547)	(0.549)
Annual VC Funding (y-1) (ln)		0.202*	0.200*	0.208*	0.207*	0.218	0.210*	0.235*
		(0.121)	(0.121)	(0.124)	(0.118)	(0.135)	(0.115)	(0.128)
Cummulative VC Funding (y-2) (ln)		0.015	0.017	0.014	0.013	0.003	0.007	-0.006
		(0.127)	(0.126)	(0.128)	(0.124)	(0.138)	(0.122)	(0.132)
Total patents (y-1)		-0.867	-0.919	-0.933	-0.887	-0.834	-1.033	-0.903
		(0.698)	(0.727)	(0.741)	(0.711)	(0.734)	(0.795)	(0.760)
Cummulative patents (y-2) (ln)		0.729*	0.737*	0.770*	0.734*	0.671	0.759*	0.709
		(0.419)	(0.428)	(0.423)	(0.428)	(0.463)	(0.428)	(0.450)
Year 2001-3 (dummy)		-38.551***	-29.708***	-29.661***	-32.044***	-40.469	-31.660***	-38.940***
		(1.943)	(1.932)	(1.937)	(1.906)	(0.000)	(1.853)	(1.777)
Num Product Categories (Identity strength) (y-1)			0.139	0.127	0.135	-0.792	-0.720	-1.565**
			(0.341)	(0.341)	(0.336)	(0.578)	(0.577)	(0.788)
Exploitation alliances (y-1)					-0.238		-0.809***	-0.778**
					(0.158)		(0.301)	(0.305)
Exploitation alliances (y-1) * Identity strength (y-1)							0.577**	0.500**
							(0.251)	(0.250)
Exploration alliances (y-1)	H1			-0.193		-0.761**		-0.796**
				(0.173)		(0.311)		(0.328)
Exploration alliances (y-1) * Identity strength (y-1)	H2					0.623**		0.612**
						(0.278)		(0.264)
Observations		1,031	1,031	1,031	1,031	1,031	1,031	1,031
Degrees of freedom		8	9	10	10	10	11	13
Log likelihood		-89.36	-89.29	-88.99	-88.91	-87.96	-88.09	-86.69

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1, two-tailed tests

Table 12 also shows the effects of exploration alliances and identity strength on time to IPO, although in this case, a firm's *category distinctiveness* is used as the measure of identity strength. The results seem to be consistent with the results in table 11, in which a firm's number of product categories is used as the measure of identity strength. Again in model 12, the main effect of exploration alliances on time to IPO is negative, but lacks significance. However, model 5 once more yields results indicating a negative and significant main effect ($p < .05$) and an interaction term that is positive and also significant ($p < .05$). These results differ from those in table 11 primarily in that model 6 of table 12 indicates no significant effect on time to IPO resulting from the interaction between exploitation alliances and category distinctiveness.

Table 12

Event-History analysis of exploration alliances on time to IPO;
Identity strength measured as a firm's category distinctiveness (361 firms)

Variable		Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7
Sales growth (y-1)		0.617**	0.593**	0.624**	0.658**	0.642**	0.663**	0.721**
		(0.286)	(0.283)	(0.282)	(0.305)	(0.293)	(0.303)	(0.315)
Total alliances (y-1)		0.344	0.405	0.541*	0.525*	0.528	0.514	0.690**
		(0.308)	(0.308)	(0.314)	(0.314)	(0.334)	(0.315)	(0.344)
Percent partners listed in SW500 (y-1)		0.876	0.730	0.811	0.806	0.907*	0.783	0.968*
		(0.538)	(0.595)	(0.589)	(0.583)	(0.547)	(0.576)	(0.517)
Annual VC Funding (y-1) (ln)		0.202*	0.195	0.201	0.199*	0.196	0.199*	0.202*
		(0.121)	(0.120)	(0.123)	(0.118)	(0.121)	(0.118)	(0.120)
Cummulative VC Funding (y-2) (ln)		0.015	0.027	0.026	0.025	0.034	0.025	0.030
		(0.127)	(0.128)	(0.130)	(0.127)	(0.129)	(0.126)	(0.128)
Total patents (y-1)		-0.867	-0.630	-0.634	-0.625	-0.554	-0.654	-0.586
		(0.698)	(0.685)	(0.694)	(0.688)	(0.700)	(0.687)	(0.701)
Cummulative patents (y-2) (ln)		0.729*	0.537	0.571	0.547	0.571	0.568	0.617
		(0.419)	(0.452)	(0.441)	(0.458)	(0.425)	(0.465)	(0.444)
Year 2001-3 (dummy)		-38.551***	-37.827***	-35.814***	-40.098	-29.570***	-30.114***	-29.862***
		(1.943)	(1.993)	(1.994)	(0.000)	(1.885)	(1.997)	(1.851)
Category distinctiveness (Identity strength) (y-1)			-4.504	-4.496	-4.156	-11.310**	-2.719	-9.272
			(3.549)	(3.448)	(3.662)	(5.052)	(5.744)	(7.104)
Exploitation alliances (y-1)					-0.191		0.359	0.575
					(0.167)		(1.324)	(1.239)
Exploitation alliances (y-1) * Identity strength (y-1)							-0.961	-1.438
							(2.384)	(2.283)
Exploration alliances (y-1)	H1			-0.205		-3.095**		-3.322**
				(0.174)		(1.518)		(1.588)
Exploration alliances (y-1) * Identity strength (y-1)	H2					5.171**		5.530**
						(2.632)		(2.702)
Observations		1,031	1,031	1,031	1,031	1,031	1,031	1,031
Degrees of freedom		8	9	10	9	11	11	13
Log likelihood		-89.36	-88.41	-88.08	-88.19	-87.18	-88.15	-86.79

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1, two-tailed tests

Overall, the analysis lends support for Hypotheses 1 and 2. The results from table 11, model 7, seem to suggest that engaging in extensive exploration alliances will increase a start-up's time to IPO by 6.02% [=exp(-.796)]. However when the identity of the start-up is relatively weak, as determined by the number of categories with which it's affiliated, the increased time to IPO will be reduced by 6.14% [=exp(.612)]. These results support this chapter's general proposal. The results suggest that, in the case of start-up software firms in the late 1990s to early 2000s, exploration alliances do tend to increase a firm's time to an IPO; due to the nature of exploration, a start-up firm with a clear identity that pursues exploration alliances will be perceived as unsettled or unreliable by investors who understand that clear identity, leading the firm to delay its IPO. However, if the start-up firm has an unclear identity due to its categorization to begin with, not all investors may perceive the start-up as unsettled or unreliable. This freedom from an unconstraining identity allows a firm to pursue exploration alliances without reducing its chance at a successful IPO; the results suggest that such firms are indeed less likely to delay an IPO.

3.5   Empirical Setting 2: Keiretsu-member Firms

In the mid to late 20th century, two types of business groups dominated the Japanese economy, horizontal keiretsu and vertical keiretsu. The keiretsu are generally described as "clusters of independently managed firms maintaining close and stable business ties, cemented by governance mechanisms such as presidents' councils, partial cross-ownership, and interlocking directorates." (Lincoln and Gerlach, 2004: 15). Horizontal keiretsu are sets of firms connected by systems of cross-shareholding relationships; they are considered 'horizontal' in that they are centered around a central bank and include firms operating in various industries. Vertical keiretsu are groups of firms connected within multiple tiers of suppliers and distributors; they are considered 'vertical' as they are centered around a single manufacturer and concentrate in one industry. Both forms of keiretsu emerged after World War II, mostly out of the structures of family-owned conglomerates, *zaibatsu,* that had existed since Japan's feudal period but which were dismantled under the U.S. Occupation at the end of WWII. Following the emergence of the keiretsu, Japan's economy rose steadily; by the 1980s, its growth began to surpass that of the U.S. Many scholars attributed Japan's economic success to the keiretsu system in general and to the management of operations within the vertical keiretsu in particular (e.g., Dore, 1983; Dyer, 1996). Indeed, many U.S. firms attempted to implement some operational strategies employed by the vertical keiretsu (Womack, Jones, and Roos, 1990).

Although today the keiretsu system has nearly vanished, in the 1980s, it was highly institutionalized and created strong strategic group identities. A strategic group identity is defined in the literature, as "a set of mutual understandings, among members of a cognitive intraindustry group, regarding the central, enduring, and distinctive characteristics of the group" (Peteraf and Shanley, 1997: 166). This definition emphasizes the principles of cognitive categorization as discussed in Rosch (1978)—that while perceptions of the group's boundaries may be fuzzy, its identity is implied through history, discourse, and interactions (Peteraf and Shanley, 1997: 167). Even when a keiretsu operated in multiple industries, members of the keiretsu were able to recognize the group's boundaries through its network of historically structured and enduring relationships (Lincoln and Gerlach, 2004).

Other factors contributed to the strength of the keiretsu. First, the keiretsu had a high status in Japan, as those that emerged out of the powerful pre-war zaibatsu clans consisted of the country's largest and longest established firms (Lincoln and Gerlach, 2004). Even keiretsu that did not originate in the zaibatsu were prestigious due to their large size and ability to compete successfully overseas (Lincoln and Gerlach, 2004). Significantly, prestige tends to reinforce a group's identity (Peteraf and Shanley, 1997). Second, the keiretsu had the backing of the Japanese government. The government encouraged close cooperation among business group members by instituting policies that fostered collaboration. Moreover, government officials would frequently look the other way when keiretsu competed using unfair practices, such as using unrecorded transfers of funds from a stronger firm to a weaker firm within the same keiretsu to balance assets and keep the group as a whole financially stable (Lincoln and Gerlach, 2004). One explanation for the government's leniency may be that officials were hoping the keiretsu system would help Japan recover from the losses of WWII (Lincoln and Gerlach, 2004).

Belonging to a keiretsu meant several things for a firm. First, the firm would receive strong economic and social support that independent firms lacked. As a keiretsu member, a firm belonged to a network of enduring relationships associated with significant resources, such as a major bank, a dedicated supply chain, or both (Gerlach, 1992). Within each keiretsu, firm presidents would meet regularly to share strategies and offer each other support (Lincoln and Gerlach, 2004). If any firm in the group demonstrated poor performance, a fellow member would come to its rescue (Lincoln, Gerlach, and Ahmadjian, 1996). Second, as a member of a keiretsu, a firm derived its identity largely from its keiretsu, suggesting that it was under strong expectations to conform to its group's identity and to help maintain its group's boundaries by upholding the system of working relationships. Indeed, using block-modeling techniques, Lincoln and Gerlach (2004) show that the network of interfirm relationships that characterized the keiretsu kept the boundaries of each group relatively cohesive during the economically stable years of the 1980s. The obligation to maintain a group's boundaries was so strong that even in the late 1990s, after the keiretsu had somewhat lost legitimacy, remnants of this behavior could still be found among employees of keiretsu firms who remained careful to select partners from within their own keiretsu group rather than from outside the group (Lincoln and Guillot, 2007).

The keiretsu system represents a unique instance of a strong identity eventually weakening due to drastic shifts in the business environment. Starting in 1990, the Nikkei, Japan's stock market index, began a steep and prolonged decline. In a span of nine months alone, the index fell 48% from its peak of 38915.87 on December 29, 1989 (Auerback, 1991). This steep decline followed a five-year bull market during which the economy became overinflated by risky loans at cheap rates, a situation that was blamed on the keiretsu system (Auerback, 1991). Analysts believed that keiretsu firms had become inefficient and uncompetitive; some identified the very practices that gave the keiretsu an advantage, such as shifting resources from stronger firms to weaker firms within a group, as the source of the problems (Lincoln and Gerlach, 2004). Before long, the Japanese government responded by changing financial reporting requirements in such a way that resource transfers between firms within a keiretsu could no longer be concealed (Lincoln and Gerlach, 2004). In addition, the government strengthened anti-trust laws, an action that was seen to "attack a cornerstone of the 'keiretsu' system" (Sanger, 1991). Although researchers using block-modeling techniques were unable to detect a noticeable deterioration in keiretsu network structures, the business press nevertheless maintained that the relationships that constituted the keiretsu system were breaking down (Lincoln, Gerlach, and Ahmadjian, 1998). According to media reports, after the Japanese economy began to crash, the keiretsu identity lost much of the legitimacy and strength that it had formerly possessed. The economic crisis was so severe that, in the few decades since, Japan has still not fully recovered. Japan refers to these decades its "lost decade" and its "second lost decade" (Bevacqua, 1999; Tabuchi, 2009).

The occurrence of the economic crash provides a unique opportunity to perform a natural experiment in which the beginning of 1991 is demarcated as the treatment effect *deinstitutionalization*, or weakening of the keiretsu identity, in the study design. I take advantage of this period of drastic change in Japan to test the proposals under consideration in this paper. I propose that before 1991, when the keiretsu identity is strong, exploration alliances will tend to affect a keiretsu member firm's performance negatively, and that in the period beginning in 1991, when the keiretsu identity becomes weak, this negative effect will be smaller.

3.5.1 Operationalizing Exploration Alliances in the Keiretsu Context

Past research has understood exploration alliances in terms of network structure; as an alliance involving a new partner introduces new working relationships and content to a focal firm's existing portfolio of partners, such partnerships can be considered exploration alliances (Beckman et al., 2004; Lavie and Rosenkopf, 2006; Lin et al., 2007). Accordingly, I consider alliances with new partners in my analysis. In addition, I also distinguish between partners chosen from within a firm's keiretsu and those from outside it. In the context of the keiretsu system, a keiretsu member firm forming a new partnership outside the boundary of its group would constitute further extending its exploration alliance; a new partner from outside of a firm's keiretsu group will be unfamiliar to it and may hold different assumptions about appropriate interactions than one from within its own keiretsu group. The perspective that firms pursuing exploration alliances may be understood as extending beyond their group identity boundaries parallels the idea that such firms may be viewed as extending beyond their technological and organizational boundaries (Rosenkopf and Nerkar, 2001). Hence, in the context of this study, a focal keiretsu firm's selection of a partner from within its own group constitutes an exploitation alliance, while its selection of a partner from outside of its group constitutes an exploration alliance. Moreover, the focal firm's selection of a new, unfamiliar partner from outside of its group constitutes further extending an exploration alliance.

Accordingly, we should expect to find evidence that a keiretsu member firm's performance will be adversely affected when it forms partnerships with firms outside of its keiretsu group, especially when those partners are new to it. A keiretsu firm can form two types of exploration alliances: those in which it selects a partner from a different keiretsu, and those in which it selects a partner that is not affiliated with any keiretsu (i.e., an independent firm). In the context of the Japanese keiretsu system, a focal keiretsu firm's collaboration with a firm from another keiretsu may be perceived differently from its collaboration with an independent firm; for instance, it is possible that partnerships with independent firms may be more exploratory than partnerships with firms of another keiretsu, as it could be more inconsistent for keiretsu firms to work with independent firms that are not affiliated or familiar with the keiretsu system. In addition, forming networks outside the keiretsu system rather than simply outside of a focal firm's keiretsu group may be perceived as a step towards weakening the keiretsu system as a whole; in theory, this could ultimately delegitimize the keiretsu groups themselves. Hence, I consider a keiretsu firm's extensive exploration alliances in terms of those alliances formed with new, independent firms.

Below, I restate the chapters's first proposal into testable hypotheses that reflect the empirical data concerning the keiretsu:

> *H3a: A keiretsu firm that selects a higher proportion of partners from different keiretsu will exhibit poorer financial performance than a keiretsu firm that selects a higher proportion of partners from within its own group.*

H3b: A keiretsu firm that selects a higher proportion of partners that are independent firms will exhibit poorer financial performance than a keiretsu firm that selects a higher proportion of partners from a different keiretsu.

H3c: The negative effects on performance from different keiretsu and independent partners will be greater when the partners that the keiretsu firm selects are also new to it.

Identifying 1991 as the point when the keiretsu identity began to deinstitutionalize and weaken, I further consider how the effects of exploration alliances on firm performance changed beginning in 1991; when the keiretsu identity is weaker, it is likely that the relative negative effects postulated in the set of H3 will be reduced, as relevant audiences may react less negatively to a keiretsu member firm expanding beyond the boundaries of its keiretsu identity in this situation. Hence, the second proposal is considered in the keiretsu context with the following set of hypotheses:

H4a: Beginning in 1991, the selection of partners from different keiretsu will have a smaller negative effect on a keiretsu firm's performance than it will prior to 1991, when the keiretsu category is presumed stronger.

H4b: Beginning in 1991, the selection of independent firms as partners will have a smaller negative effect on a keiretsu firm's performance than it will prior to 1991, when the keiretsu category is presumed stronger.

H4c: The reductions in negative effects on performance from different keiretsu and independent partners will be greater when the partners that the keiretsu firm selects are also new to it.

3.5.2   Data

I tested the hypotheses on a sample of 82 keiretsu member firms in the Japanese electronics industry during a 11-year period from 1986 to 1996; this sample was formed using secondary data initially gathered by Lincoln and Guillot (2007)[3]. As firms in the electronics industry form and announce strategic alliances often, the data was collected by reviewing strategic alliance announcements that appeared in Japan's top five economic and industrial newspapers during the 11-year period. After sorting through the firms referenced in the strategic alliance announcements and identifying those whose business was primarily in the electronics industry, 82 keiretsu member firms remained in the sample. Each firm in the sample is referenced in at least one partnership announcement during the time period. The five years prior to 1991 constitute the period when the keiretsu identity was strong. The six years following the stock market crash, including the year 1991, constitute the period when the keiretsu identity became weak.

---

[3] I thank James R. Lincoln and Didier Guillot for the use of their data to test this chapter's proposals. The authors collected the data to study changes in institutional policy and the effects of these changes on alliance formation (Lincoln and Guillot, 2007).

3.5.3 Variables

The dependent variable, performance, is measured in terms of a firm's return on assets (ROA), which is defined as the ratio of net earnings before taxes over total assets. This ratio corresponds with how well a firm is able to generate income with its assets; a high ratio indicates that a firm is efficient in its use of assets to earn income. This ratio is widely used in organizational and strategic management studies to measure firm performance. It has also been used in previous studies to measure keiretsu firm performance in particular (Lincoln et al., 1996).

To measure the degree to which a firm favored exploration alliances, I analyzed alliances formed with new partners separately; in this study, I considered a partner to be new if it had no prior relationships with the focal firm in the previous five years. In addition, I determined the keiretsu affiliation of each of a focal firm's alliance partners to further indicate the firm's exploration orientation, identifying three proportions for each firm for each of the years being analyzed. The first is the proportion of a firm's partners in each year that are from the same keiretsu; as these partners are "close" to the focal firm in the sense that they share a strategic group identity and are familiar with each other, such partnerships may be classified as *exploitation alliances*. The second is the proportion of a firm's partners in each year that are from a different keiretsu; as such partners are "distant" from the focal firm, in that they do not share the same keiretsu identity and may be less familiar with each other, these partnerships may be classified as *exploration alliances*. The third is the proportion of a firm's partners in each year that are independent of a keiretsu; these partnerships, which may be considered even more distant than different keiretsu partnerships as they involve partners that lack a keiretsu identity entirely and may be even less familiar to the focal firm, may be classified as *extensive exploration alliances*.

Together, these three proportions add up to one each year for each firm. I chose one year as the time frame in which to determine these proportions because public firms typically summarize or report their activities by year; relevant audiences, such as analysts, evaluate firm activities based on annual reports. To indicate the effect of the period when the keiretsu identity is weak, I include a dummy variable for the six years from 1991 to 1996.

To control for several variables that could affect ROA, I account for the firm's ROA, as well as other indicators of the firm's financial health, in the previous year. In particular, I take *solvency* and *liquidity* into account; solvency, which is long-term debt divided by current assets, indicates how efficiently a firm manages debt, while liquidity, which is current assets minus inventory divided by current liabilities, indicates a firm's ability to repay debt. As the number of relationships a keiretsu firm forms may affect its ability to obtain resources, I also accounted for the *total number of alliances* (both inside and outside the keiretsu) each firm entered in the previous year. Finally, I included year dummies to control for annual trends.

3.5.4 Models and Analyses

Modeling the effect of selecting partners from the same keiretsu vs. from outside the keiretsu on performance. The key consideration in analyzing the effect of a firm's choice of alliance partners on its performance is that the choice is not random. Due to unobserved heterogeneity among

keiretsu firms, some firms chose partners only outside their own keiretsu. These firms may have been "inferior" to other member firms in their keiretsu in some way, forcing them to choose outside firms as partners; conversely these firms may have been "superior" to other firms in their keiretsu making it suitable for them to partner with outside firms. The analysis is potentially complicated by the fact that partner selection is endogenous to firm characteristics, as these characteristics are correlated with firm performance. This causes biased estimates of firm performance. Such selection bias can be to some extent removed with the inverse probability of treatment (IPTW) regression technique (Hirano, Imbens, and Ridder, 2003; Nichols, 2008). In essence, this approach attempts to create a pseudo population for the final stage of estimate of partner choice effect, in which the probability of selection into certain partner choice regime is estimated and used as the basis for weighing the second stage regression and adjusting for selection biases in that regression.

First, using logit regression, I determined the probability, conditional on the observable characteristics, that a firm would select a same keiretsu partner. The covariates in this model include indicators of a firm's financial health lagged one year: its return on assets (t-1), its sales growth (t-1), its solvency (t-1), and its liquidity (t-1), as well as its total number of alliances (t-1) and calendar year fixed effects. Using this method, I was able to determine the probability that a keiretsu-member firm would choose only the same keiretsu partners conditional on its pre-performance measure. Next, I computed weights based on the predicted probability of treatment (i.e., choosing only same-keiretsu partner) such that each firm-year observation with more serious confounding problems is associated with a lower weight and each firm-year observation with less serious confounding problems is associated with a higher weight. The magnitude of the weights determines the contribution of each firm-year observation to the score function in the likelihood estimation of the effect of same-keiretsu partner on a firm's performance such that those observations with less of the selection-bias contribute most to the score function. In essence, with the weights incorporated, I am rebalancing the sample of firms such that it bears more resemblance to a population in which assignment to treatment (partnering with same-keiretsu firms) is random. Hirano et al. (2003) suggest that this inverse probability of treatment weight (IPTW) approach provides an efficient estimate of the average treatment effect. The choice to use propensity scores in a weighing approach is further discussed by Azoulay, Ding, and Stuart (2009).

I tested the hypotheses using a pooled OLS regression model with the IPTW scheme and cluster-robust standard errors. The following is the general regression model I used to analyze the data: $Y_t = B0 + B1*X_{t-1} + B2*Post\text{-}1991 + B3*Same\text{-}K_{t-1} + B4*Diff\text{-}K_{t-1} + B5*Indep_{t-1} + e_{t-1}$, where Y_t is the performance outcome, ROA. The coefficient, B0, is the intercept by firm; B1 is the coefficient to indicate the average main effects of X_{t-1}, the control variables lagged by 1 year; B2 is the coefficient for the years assigned a dummy variable to indicate the period the keiretsu category was weakened; B3 is the coefficient for the proportion of *exploitation alliances* during the previous year; B4 is the coefficient for the proportion of *exploration alliances* (with different keiretsu) during the previous year; and B5 is the coefficient for the proportion of *extensive exploration alliances* (with independent firms) during the previous year. Finally, e_{t-1} accounts for random error.

If the first set of hypotheses is supported, the coefficient for exploration alliances with different keiretsu partners should be less than the coefficient for exploitation alliances (H3a: B4 < B3), and the coefficient for extensive exploration alliances with independent firms should be less than the coefficient for exploration alliances with different keiretsu partners (H3b: B5 < B4). That is, as indicated by negative ROA measures, a higher proportion of different keiretsu partners should be more associated with lower performance than a higher proportion of same keiretsu partners, and a higher proportion of independent partners should be associated with lower performance than both of these. In addition, when analyzing the effect of only new partners, these negative associations will be even greater (H3c).

To find support for the second set of hypotheses, I interacted the six years of weak keiretsu category (1991 to 1996) with the three proportions in the model:

$Y_t = B0 + B1*X_{t-1} + B2*Post-1991 + B3*Same-K_{t-1} + B4*Diff-K_{t-1} + B5*Indep_{t-1} + B6(Same-K_{t-1}*Post-1991) + B7(Diff-K_{t-1}*Post-1991) + B8(Indep_{t-1}*Post-1991) + e_{t-1}$,

where the coefficient B6 represents the effects of the *exploitation alliance* proportion on performance during the years when the keiretsu identity is weak; the coefficient B7 represents the effects of the *exploration alliance* proportion on performance and the coefficient B8 represents the effects of the *extensive exploration alliance* proportion on performance during the same years. If the second set of hypotheses is supported, the interaction between the weak identity years, as indicated by a dummy variable, and the proportion of different keiretsu alliances should be positive (H4a: B7 > 0), as should the interaction between the weak identity years and the proportion of independent firm alliances (H4b: B8 > 0). Positive interactions would indicate that the negative main effects on performance are lower during the time period beginning in 1991, when I presume the keiretsu identity to be weak. Additionally, these positive interaction effects should be greater when analyzing only new alliance partners (H4c).

3.5.5   Results

I report the mean, standard deviation, and correlations of the variables in the model in table 13, below. I calculated the variance inflation factors of all variables by ordinary least squares regression and post-estimation. All variation inflation factors were at an acceptable level of 3.85 or less.

Table 13

Descriptive Statistics (N = 752)

Variable	Mean	s.d.	Min	Max	1	2	3	4	5	6	7	8	9	10
1 ROA	0.03	0.05	-0.37	0.18										
2 ROA (t-1)	0.03	0.05	-0.37	0.26	0.79									
3 Sales growth (t-1)	0.37	0.79	0.00	4.99	0.04	0.03								
4 Sovency (t-1)	0.05	0.09	0.00	0.84	-0.19	-0.28	-0.11							
5 Liquidity (t-1)	1.71	1.41	0.24	16.54	0.20	0.22	-0.11	-0.28						
6 Total Alliances (t-1)	0.70	1.79	0.00	10.00	-0.05	-0.04	0.70	-0.08	-0.09					
7 >1991	0.55	0.50	0.00	1.00	-0.17	-0.19	0.06	0.11	0.06	0.02				
8 Years	91.11	3.39	86.00	96.00	-0.09	-0.19	0.05	0.12	0.05	-0.03	0.91			
9 Same keiretsu partners (t-1)	0.09	0.26	0.00	1.00	0.03	-0.03	0.10	-0.04	0.07	0.13	-0.07	-0.03		
10 Different keiretsu partners (t-1)	0.10	0.26	0.00	1.00	-0.02	-0.04	0.56	-0.03	-0.06	0.51	0.01	0.00	-0.02	
11 Independent partners (t-1)	0.05	0.16	0.00	1.00	-0.10	-0.06	0.40	-0.08	-0.08	0.37	0.00	-0.01	0.01	0.24

Table 14a and 14b presents both weighted and unweighted regression results. Table 14a shows results for alliances with both prior and new partners, whereas the table 14b shows results for alliances with only new partners. As selection bias has already been addressed, I will discuss only the weighted results. Model 1 in table 14a shows only the coefficients of the control variables. Model 2 adds the proportions of alliance partners that are in the same keiretsu, in different keiretsu, and independent firms, which corresponds with exploitation, exploration, and extensive exploration alliances, respectively. When the coefficients obtained with the model are compared, there appears to be no difference between having a high proportion of different keiretsu partners and having a high proportion of same keiretsu partners. Although the fact that one of these coefficients is positive and the other negative suggests a different, this difference lacks significance; hence, H3a is not supported. However, when the coefficients representing proportion of independent partners and proportion of different keiretsu partners are compared, the coefficient for the former is significantly more negative ($p < .05$) than the coefficient for the latter; thus, H3b is supported.

Table 14a

OLS regresssion analysis of the proportions of same/different/independent keiretsu partners on ROA (82 firms)
 Analysis of both new and prior partners

		Panel 1: All Partners (New and Prior)					
		IPTW			Unweighted		
		Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
ROA (t-1)		0.864***	0.856***	0.853***	0.771***	0.767***	0.765***
		(0.046)	(0.041)	(0.036)	(0.062)	(0.062)	(0.061)
Sales growth (t-1)		0.001	0.007*	0.005*	0.001	0.003*	0.003*
		(0.002)	(0.004)	(0.003)	(0.001)	(0.001)	(0.002)
Sovency (t-1)		0.020	0.010	-0.005	0.020	0.017	0.017
		(0.021)	(0.019)	(0.019)	(0.013)	(0.012)	(0.012)
Liquidity (t-1)		0.001	0.001	0.001	0.001	0.000	0.000
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Total Alliances (t-1)		0.001	0.001	0.002*	0.000	0.000	0.000
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
After 1991		0.004	0.010	0.016	-0.014	-0.013	-0.012
		(0.008)	(0.009)	(0.011)	(0.011)	(0.011)	(0.011)
Same keiretsu partners (t-1)			0.007	0.015**		0.005	0.008
			(0.005)	(0.006)		(0.003)	(0.005)
Different keiretsu partners (t-1)	H3a		-0.016	-0.015		-0.001	-0.003
			(0.012)	(0.013)		(0.004)	(0.006)
Independent partners (t-1)	H3b		-0.035**	-0.097**		-0.021	-0.033
			(0.018)	(0.038)		(0.014)	(0.029)
Same keiretsu partners (t-1)*After 1991				-0.020***			-0.007
				(0.007)			(0.006)
Different keiretsu partners (t-1)*After 1991	H4a			0.002			0.002
				(0.015)			(0.008)
Independent partners (t-1)*After 1991	H4b			0.086**			0.020
				(0.037)			(0.028)
Constant		0.004	-0.001	-0.005	0.022**	0.021*	0.021*
		(0.008)	(0.009)	(0.010)	(0.011)	(0.011)	(0.012)
Observations		752	752	752	752	752	752
R-squared		0.819	0.835	0.851	0.689	0.694	0.696
df_m		14	17	20	14	17	20

*** $p<0.01$, ** $p<0.05$, * $p<0.1$; two-tailed test
Robust clustered standard errors are in parentheses.
All models include year dummies

68

Table 14b presents only the effects of alliances involving new partners with whom a firm had no prior relationship, at least during the past five years; the results in this table can be compared with those in table 14a. As table 14b represents only alliances with new partners and thus different keiretsu alliances and independent firm alliances that are even more explorative, we should expect the results to indicate poorer performance; indeed, model 8 in table 14b does indicate that performance, as measured by ROA, is decreased. When it involves a new partner, the effect of a different keiretsu alliance is a 3.2% decrease in ROA. Although this decrease is only marginally significant ($p < .10$), the results indicate that new partners of different keiretsu affect performance more negatively than both new and prior partners of the same keiretsu. Additionally, the effect of an independent firm alliance involving a new partner is a 3.9% decrease in ROA ($p < .05$), a decrease 0.4% greater than the corresponding figure in table 14a. These results indicate support for H3c; partners outside the firm's keiretsu incur greater negative effect on performance when those partners are new.

Table 14b

OLS regresssion analysis of the proportions of same/different/independent keiretsu partners on ROA (82 firms)
 Analysis of only new partners

		Panel 2: New Partners					
		IPTW			Unweigted		
		Model 7	Model 8	Model 9	Model 10	Model 11	Model 12
ROA (t-1)		0.864***	0.851***	0.848***	0.771***	0.764***	0.760***
		(0.046)	(0.044)	(0.042)	(0.062)	(0.061)	(0.061)
Sales growth (t-1)		0.001	0.001	0.001	0.001	0.002	0.002
		(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
Sovency (t-1)		0.020	0.010	0.004	0.020	0.017	0.016
		(0.021)	(0.018)	(0.017)	(0.013)	(0.012)	(0.012)
Liquidity (t-1)		0.001	0.001*	0.001	0.001	0.001	0.000
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Total Alliances (t-1)		0.001	0.001	0.001	0.000	0.000	0.000
		(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
After 1991		0.004	0.007	0.005	-0.014	-0.013	-0.013
		(0.008)	(0.008)	(0.008)	(0.011)	(0.011)	(0.011)
Same keiretsu partners (t-1)			0.002	0.005		0.010**	0.018***
			(0.005)	(0.005)		(0.005)	(0.007)
Different keiretsu partners (t-1)	H3c		-0.032*	-0.045*		-0.008	-0.013
			(0.017)	(0.024)		(0.007)	(0.012)
Independent partners (t-1)	H3c		-0.039**	-0.107**		-0.027	-0.055
			(0.019)	(0.044)		(0.021)	(0.046)
Same keiretsu partners (t-1)*After 1991				-0.011			-0.016
				(0.007)			(0.010)
Different keiretsu partners (t-1)*After 1991	H4c			0.024			0.011
				(0.031)			(0.014)
Independent partners (t-1)*After 1991	H4c			0.096**			0.049
				(0.044)			(0.046)
Constant		0.004	0.003	0.006	0.022**	0.022*	0.022**
		(0.008)	(0.008)	(0.007)	(0.011)	(0.011)	(0.011)
Observations		752	752	752	752	752	752
R-squared		0.819	0.839	0.855	0.689	0.696	0.701
df_m		14	17	20	14	17	20

*** p<0.01, ** p<0.05, * p<0.1; two-tailed test
Robust clustered standard errors are in parentheses.
All models include year dummies

Returning to table 14a, model 3 includes the interaction terms between the three proportions of alliance partners and the dummy variable indicating weakened keiretsu identity starting in 1991. The results indicate that post-1991, the negative effect associated with having different keiretsu partners and independent partners demonstrated in the years prior to 1991 is reduced, although only in the case of alliances with independent partners is this effect significant ($p < .05$). Hence, while H4a is not supported, H4b is. Nevertheless the results overall support the proposal (P2), which maintains that the negative effect that exploration alliances have on performance will be diminished during times when organizational identity (in this case, keiretsu identity) is weak. Interestingly, model 3 also reveals that the interaction between weak identity and proportion of exploitation alliances (same keiretsu partners) is significantly negative ($p < .01$). I had not expected performance to be moderated negatively by exploitation alliances when firms have weak identities. In the keiretsu context, however, this makes sense: because the economy had declined so steeply and the keiretsu system was being dismantled, the selection of same keiretsu partners would not garner the same level of support it had before. Not only was Japan trying to do away with the keiretsu system altogether, but keiretsu member firms were also financially depleted already.

By comparing the results of model 3 in table 14a with those of model 9 in table 14b, I am able to determine whether, when identity is weak, the negative effect of extensive exploration alliances on performance is reduced more among alliances involving new partners (H4c). The results indicate no interaction effect on performance when the post-1991 dummy and different keiretsu alliances with new partners are analyzed, but when independent firm alliances with new partners are analyzed the interaction effect is positive ($p < .05$); this implies that the negative effect associated with selecting a new partner from an independent firm (extensive exploration alliance) is lower when keiretsu identity is weakened. Hence, H4c is partially supported. Nevertheless, the results do indicate that when organizational identity is weak, the negative effect of extensive exploration alliances (those with only new partners) on performance outcomes will be reduced.

Overall, the results from the analysis of keiretsu member firm alliances indicate support for the general proposals that extensive exploration alliances are associated with a decrease in organizational performance and that this decrease will be reduced when organizational identity is weak. In other words, exploration alliances seem to be detrimental to a firm's performance, contingent on the firm having a strong identity.

3.6   Chapter Conclusion

Alliance research has explored numerous reasons that organizations are motivated to form alliances. These reasons are rooted in various theoretical perspectives, including resource dependency (Pfeffer and Salancik, 1976), strategic needs and social imperatives (Eisenhardt and Schoonhoven, 1996), organizational learning (Powell et al., 1996) and legitimacy (Dacin, Oliver, and Roy, 1997). Nevertheless, the questions of whether, and more importantly, under which conditions, alliances improve a firm's performance have yet to be thoroughly answered. Many factors, such as the type of alliance, the conditions under which the alliance is formed, and asymmetries between alliance partners, contribute to the impact of an alliance on a focal firm's performance. As such, the causal mechanism between alliances and firm performance cannot be

understood simply in terms of a firm's motivation to improve its performance (Stuart, 2000). The present research has closely considered organizational identity as one mechanism that plays a contingent role in the relationship between alliances and firm performance.

The tendency of exploration alliances to have a negative effect on organizational outcomes due to the costs they incur has generally been discussed in the context of the view that alliances function as conduits of knowledge and resources between partners. In this chapter, I have sought to apply another perspective that has yet to be explored as deeply, namely that alliances signal information about a focal firm. I have proposed that exploration alliances indicate change, and that the more extensive an exploration alliance is, the more significant a change it signifies. This explanation attributes the negative effect associated with exploration alliances to the fact that relevant audiences react negatively to indications of change. However, because these audiences have weaker expectations about firms that lack a clear, taken-for-granted identity, I suggest that this negative effect should be contingent on the strength of the firm's identity.

I investigated these proposals in two empirical settings and tested context-specific hypotheses, finding general support for the proposals. In the context of start-up software firms, I found that new firms that engaged in extensive exploration alliances (indicated as partners in product categories that are far-reaching) went public at a relatively low rate, but that this low rate was reduced when a start-up firm had a less clear identity, as indicated by its lack of clear categorization. Similarly, in the context of keiretsu firms, I found that the return on assets performance ratio was lower among firms in extensive exploration alliances (indicated as alliances with new independent partners), but that this negative effect on return on assets was reduced during a period when the keiretsu identity was contested and weakened.

The implication of these findings is that under conditions of weak organizational identity (be it from an organization's ambiguous categorization or from the delegitimization of the category group in which it belongs), organizations may somewhat avoid the short-term deleterious effects of exploration strategies, thus giving a boost to its strategic positioning in the meantime. However, given the imperative for firms to establish a clear and strong identity in order to be evaluated, the question for future research is, how long will the disadvantages of having a weak identity catch up and render the positive boost in strategy no longer useful? In general, in order to coherently pursue goals and be evaluated an organization needs to stake a claim on an identity, or reestablish their next identity if environmental conditions change. Though in the meantime, internal and external organizational constituents might be frustrated and confused about the organization (Tripsas, 2009), at least the exploration strategies they will pursue to help establish their new identity claim will be regarded with less criticism than normal.

A general conclusion of this study is that organizational identity does influence the outcome of strategic actions. The research indicates that the implications a firm's strategic actions have for organizational outcomes depend on the strength of the firm's identity. Although strategic alliances themselves have been heavily researched, few studies have specifically addressed the relationship between alliances and identity or investigated the effect of their interaction on organizational outcomes. Though some studies have examined how identity affects other organizational actions, such as pricing and conformity (Benjamin and Podolny, 1999; Phillips and Zuckerman, 2001), these studies define identity in terms of an organization's status position

rather than in terms of its ability to confirm expectations of what it is (or does). More researchers should consider organizational identity strength when seeking to understand why some strategic actions have varying impact on outcomes, or even why some strategic actions are not taken at all.

However, the pursuit of such research presents the initial challenge of measuring identity strength, as attributes of identity exist at several levels and in various context-specific formats. While I examined identity attributes at the highest level, at which firm identity strength is derived from social categories (found in the software industry) and group affiliations (such as the keiretsu), there are several other ways in which identity strength could have been obtained. For instance, researchers who sought to confirm that an idea or belief was widely accepted and taken-for-granted could measure its rate of adoption (e.g. Tolbert and Zucker, 1983) or identify an intensification of rhetoric (e.g. Abrahamson and Fairchild, 1999). Moreover, researchers could survey both the internal and external constituents of an organization to determine the strength of their feelings about an organization's identity (e.g., Tripsas, 2009). Nevertheless, it would seem that an essential factor in any measure of identity strength is the degree to which a given identity attribute has become institutionalized and taken-for-granted enough to be something real and constraining on an organization. Further discussion about different ways that this construct might be approached could ease the challenge of conducting future empirical work and thus advance theory building.

4.   Conclusion

While prior research offers insights into the link between organizational identity and alliances, this work presents the first systematic investigation of this connection. In doing so, this project contributes important insights to organizational theory, and in particular to our understanding of the important implications of coherence and strength of organizational identity on interorganizational alliances.

Chapter Two analyzes the effect of an organization's identity on its initial alliance portfolio formation. While prior studies have investigated how new firms use alliance strategies to overcome their liabilities of newness, the focus of this chapter is how the very issue of being new shapes these strategies. I theorize that the more comprehensible a new organization becomes, the less pressure it faces to provide signals that clarify its identity to demonstrate cognitive legitimacy, and so the lower the rate of forming alliances. Additionally, due to the pressure on less comprehensible new organizations to be clearly identifiable, as well as the constraint on highly comprehensible new organizations to maintain a coherent identity, a curvilinear (inverse-U) relationship exists between an organization's comprehensibility and the degree to which the organization's partners have product profiles different from its own, and thus having a set of diverse alliances. Hence, while a pioneering new firm (a firm with low comprehensibility) tends to have many partners, those partners tend to be firms of the same type (yielding a less diverse alliance portfolio). In comparison, while a more traditional new firm (with high comprehensibility) also tends to have partners of the same type, it tends to have fewer partners to begin with. Finally, a firm in the middle tends to have partners that are most different from its own type (yielding a more diverse alliance portfolio)—the imperative to signal a clear identity is low, engendering a greater degree of freedom to choose diverse partner types that demonstrate pragmatic legitimacy.

Chapter Three investigates how organizational identity affects the impact of alliance portfolios on organizational performance. More specifically, this chapter focuses on exploration alliances, which tend to negatively impact performance, at least in the short term. I theorize that this negative impact depends on the strength of the organization's identity in terms of how coherent and taken-for-granted its categorization or social grouping is. The view that exploration alliances are indications of an organization's intention to change its core identity leads to the presumption that when the organization's identity is strong, expectations on the firm to maintain its identity are also strong; thus, the change indicated by exploration alliances would lead to negative reactions towards the organization, which would hamper the organization's performance outcomes. However, when the organization's identity is vague or weak, expectations on the firm to maintain its identity are weak as well. Thus, the change indicated by exploration alliances would be less of an issue, and the negative effect of such alliances on performance outcomes would be lower. Empirical analyses of U.S. software and Japanese keiretsu firms support identity strength as a contingency between exploration alliances and their negative effect on performance. An implication of this finding is that firms with vague identities that engage in exploration alliances have an advantage, at least in the short term, compared to firms with strong identities engaging in similar alliances.

A broad conclusion of this dissertation is that organizational identity—the position of organizations in cognitive social structures—has significant implications on strategic actions. Such a link between structure and action is related to the broader sociological insight that social structures constrain organizational behavior and shape economic opportunities (Burt, 1992; Granovetter, 1985; Podolny, 1993; White, 1981). I took a particular interest in entrepreneurial firms, as legitimacy through identity is important to their survival. Other studies have also examined links between structure and action in an entrepreneurial setting in the context of other social structures. For example, academic scientists holding prestigious positions are more likely to create a biotech firm or join the advisory board of a new start-up than scientists in less-prestigious positions (Stuart and Ding, 2006; Ding and Choi, 2011). Positions of social status also influence with whom a placement agent will broker venture capital funds (Rider, 2009), and with whom a new firm is likely to form investment ties (Hallen, 2008). Moreover, geographic positions have been shown to affect the likelihood of a certain type of firm being founded (Audia, Freeman, and Reynolds, 2006). Finally, the position of a venture capital firm within a social network determines the geographic dispersion of its funds (Sorenson and Stuart, 2001). I hope the research outlined in my dissertation will contribute to and also inform this stream of literature.

Future research could investigate co-evolutionary links between organizational identity and alliances. For the most part, this dissertation focuses on how identity influences alliances; nevertheless, how alliances influence identity may be equally important. Research indicates that partnering firms tend to converge on technologies or product markets. For instance, Mowery et al. (1996) showed how organizations transfer knowledge and subsequently create closely related inventions. In addition, Dittrich et al. (2007) traced the evolution of IBM's change from one market category to another through partnerships. Taking a broader view, alliances are means to move organizations to different social positions. A diverse set of partners can increase an organization's stock of knowledge and move it closer to the center of research activities (Powell et al., 1996), or a prestigious partner can influence perceptions about the organization's level of quality and where it may stand in the status hierarchy (Podolny, 1993; Stuart et al., 1999). It is evident that through alliances, organizations can change their position in market structures, identify with different market categories, and in turn potentially influence the structures in which other organizations obtain their identities. Such influence on identity may be systematic; hence, more research on this co-evolutionary link would increase our understanding of the influential role that alliances play in organizational identity change.

Another path for future research is related to the process of new firm survival. Previous research has suggested that firms with many partners and access to diverse resources through these partners have a high chance of survival (Baum et al., 2000). Combining this insight with the results in Chapter Two leads to the implication that alliances represent an indirect link between a firm's position in a cognitive structure and its economic outcomes. New firms with low or high comprehensibility are less likely to survive than those with average comprehensibility, because such firms have less diverse partner sets. Additionally, because these firms tend to have the fewest partners, highly comprehensible new firms would have particularly poor chances of survival. Investigating these implications on a new firm's survival represents an opportunity for research. One could consider factors that might intervene over time to improve a firm's economic outcomes. Chapter Three considered, for example, that vague or weak identities might

at least lower the negative effects that exploration alliances incur on short-term performance. Another direction is to investigate how the market might shift to favor less or more comprehensible new firms, or how a firm may successfully attract a prestigious partner to endorse it—potentially prolonging its existence (Stuart et al., 1999) despite a vague or weak identity. Finally, one might consider how a less comprehensible new firm could wait for its identity-signaling alliances to increase its comprehensibility to the point that an audience accepts it, and only then focus on forming alliances with a more diverse set of partners to gain pragmatic legitimacy to increase its longevity. In fact, there is support for the idea that changes in a firm's partnerships (and the timing of those changes) might account for the indirect link between a firm's comprehensibility and its chances of survival. For instance, strategy researchers have shown that entrepreneurs change the composition of their firms' alliance portfolios when these firms reach an early growth stage (Hite and Hesterly, 2001). They found that in a firm's emergent stage, a high proportion of its relationships tend to be motivated by personal ties or social identification; however, when the firm ages, its relationships are increasingly motivated by calculations about potential economic benefits.

Nonetheless, if alliances are reinforcing and path dependent as some scholars have shown (e.g., Gulati and Gargiulo, 1999), both less and more comprehensible new firms should have a lower chance of survival than firms with average comprehensibility, due to lower diversity in the partner sets of such firms. Indeed, it is possible that entrepreneurs will intentionally categorize their firms using intermediately comprehensible labels, even if those labels do not entirely represent the attributes of the firm. Such symbolic labeling would be rational (Meyer and Rowen, 1977), and may well be considered a strategy to stay in the balance between being overlooked and directly competing (Deephouse, 1999). Such strategy highlights the ironic situation faced by start-up firms. New ventures prosper because they offer something innovative, but risk being incomprehensible or overlooked if they are too innovative; however, if new ventures identify their offering as something familiar to avoid being overlooked, they fail to meet the expectation that entrepreneurs should innovate. A closer investigation of such labeling strategy among entrepreneurs is another opportunity for organizational research.

In closing, this dissertation contributes to the general study of organizational theory, and in particular to the study of alliance formation and its performance implications. I draw from categorization theory to identify how the groups of which organizations are members will determine their degree of identity coherence and strength, and how this variation affects the formation of alliance portfolios. I also draw from organizational learning perspectives on alliances to understand how organizational identity may play a contingency role on performance outcomes. My hope is that this work will help lay the foundation for more research on the important link between organizational identity and interorganizational alliances.

References

Abate, T. 2010. Instead of IPOs, startups look to be acquired. *San Francisco Chronicle*. September 12, 2010.

Abrahamson, E. and G. Fairchild. 1999. Management fashion: Lifecycles, triggers, and collective learning processes. *Administrative Science Quarterly*. 44(4) 708-740.

Albert, S. and D. Whetton. 1985. Organizational identity. In L. L. Cummings and B. M. Staw, eds. *Research in Organizational Behavior*. Greenwich, Conn: JAI Press, 263-295.

Aldrich, H. E. 1979. *Organizations and Environments*. Englewood Cliffs, NJ: Prentice-Hall.

Aldrich, H. E., and C. M. Fiol. 1994. Fools rush in: The institutional context of industry creation. *Academy of Management Review*. 19(4) 645-670.

Amburgey, T. L., D. Kelly and W. P. Barnett. 1993. Resetting the clock – the dynamics of organizational change and failure. *Administrative Science Quarterly*. 38(1) 51-73.

Anderson, P., and M. L. Tushman. 1990. Technological Discontinuities and Dominant Designs: A Cyclical Model of Technological Change. *Administrative Science Quarterly*. 35(4) 604-633.

Audia, P. G., J. H. Freeman, and P. D. Reynolds. 2006. Organizational foundings in community context: Instruments manufacturers and their interrelationship with other organizations. *Administrative Science Quarterly*. 51(3) 381-419.

Audia, P. G., and C. I. Rider. 2005. A garage and an idea. What more does an entrepreneur need? *California Management Review*. 48(1) 6-28.

Auerback, M. 1991. Japan Inc.'s days are numbered. *The Wall Street Journal*. September 3, 1991.

Azoulay, P., W. Ding and T. Stuart. 2009. The impact of academic patenting on the rate, quality and direction of (public) research output. *Journal of Industrial Economics*. 57(4) 637-676.

Barlas, P. 2010. Yahoo picking up dance partners; Zillow, 4 others just this year; Portal teaming up in such competitive Internet arenas as dating shopping, jobs. *Investor's Business Daily*. August 17, 2010.

Barley, S. R., J. Freeman, and R. C. Hybels. 1992. Strategic alliances in commercial biotechnology. In Nohria, N. and Eccles, R.G., eds. *Networks and Organizations*. Cambridge, MA: Harvard Business School Press, 311–347.

Barnett, W. P. and G. R. Carroll. 1995. Modeling internal organizational change. *Annual Review of Sociology*. 21 217-236.

Barnett, W. P. and J. Freeman. 2001. Too much of a good thing? Product proliferation and organizational failure. *Organization Science.* 12(5) 539-558.

Baron, J. N. 2004. Employing identities in organizational ecology. *Industrial and Corporate Change.* 13(1) 3-32.

Baron, J. N., M. T. Hannan, and M. D. Burton. 1999. Building the iron cage: Determinants of managerial intensity in the early years of organizations. *American Sociological Review*. 64(4) 527-547.

Baron, J. N., M. T. Hannan and M. D. Burton. 2001. Labor pains: Change in organizational models and employee turnover in young, high-tech firms. *American Journal of Sociology*. 106(4) 960-1012.

Baum, J. A. C., T. J. Calabrese, and B. S. Silverman. 2000. Don't go it alone: Alliance network composition and startups' performance in Canadian biotechnology. *Strategic Management Journal*. 21(3) 267-294.

Baum, J. A. C., and H. A. Haveman. 1997. Love thy neighbor? Differentiation and agglomeration in the Manhattan hotel industry, 1898-1990. *Administrative Science Quarterly*. 42(2) 304-338.

Baum, J. A. C., and C. Oliver. 1991. Institutional linkages and organizational mortality. *Administrative Science Quarterly*. 36(2) 187-218.

Baum, J. A. C. and J. V. Singh. 1994. Organizational niches and the dynamics of organizational founding. *Organization Science*. 5(4) 483-501.

Beckman, C. M. 2006. The influence of founding team company affiliations on firm behavior. *Academy of Management Journal*. 49(4) 741-758.

Beckman, C. M., and M. D. Burton. 2008. Founding the future: Path dependence in the evolution of top management teams from founding to IPO. *Organization Science*. 19(1) 3-24.

Beckman, C. M., and P. R. Haunschild. 2002. Network learning: The effects of partners' heterogeneity of experience on corporate acquisitions. *Administrative Science Quarterly*. 47(1) 92-124.

Beckman, C. M., P. R. Haunschild, and D. J. Phillips. 2004. Friends or strangers? Firm-specific uncertainty, market uncertainty, and network partner selection. *Organization Science*. 15(3) 259-275.

Benjamin, B. A. and J. M. Podolny. 1999. Status, quality, and social order in the California wine industry. *Administrative Science Quarterly*. 44(3) 563-589.

Bevacqua, R. 1999. The lingering death of Japan, Inc. *The Wall Street Journal*. October 22, 1999.

Brubaker, R. and F. Cooper. 2000. Beyond "identity". *Theory and Society*. 29(1) 1-47.

Burns, T. and Stalker, G. M. 1961. *The Management of Innovation*. London: Tavistock.

Burt, R. S. 1992. *Structural Holes: The Social Structure of Competition*. Cambridge, MA: Harvard University Press.

Burt, R. S. 1976. Positions in networks. *Social Forces*. 55(1) 93-122.

Business Software Alliance. 2008. Software industry facts and figures. Retrieved from: http://www.bsa.org.

Brau, J.C. and S.E. Fawcett. 2006. Initial public offerings: An analysis of theory and practice. *Journal of Finance*. 61(1) 399-436.

Campbell-Kelly, M. 2003. *From Airline Reservations to Sonic the Hedgehog: A History of the Software Industry.* Boston: MIT Press.

Cao, Q., E. Gedajlovic and H. Zhang. 2009. Unpacking Organizational Ambidexterity: Dimensions, Contingencies, and Synergistic Effects. *Organization Science*. 20(4) 781-796.

Carroll, G. R., and M. T. Hannan. 2000. *The Demography of Corporations and Industries.* Princeton, New Jersey: Princeton University Press.

Carroll, G. R., and A. Swaminathan. 2000. Why the microbrewery movement? Organizational dynamics of resource partitioning in the US brewing industry. *American Journal of Sociology*. 106(3) 715-762.

Cockburn, I. M., and M. J. MacGarvie. 2009. Patents, thickets and the financing of early-stage firms: Evidence from the software industry. *Journal of Economics & Management Strategy*. 18(3) 729-773.

Cohen, H., and C. Lefebvre. 2005. Bridging the Category Divide. In H. Cohen and C. Lefebvre, eds. *Handbook of Categorization in Cognitive Science*. Oxford, UK: Elsevier, Ltd.

Cohen, W. M., and D. A. Levinthal. 1990. Absorptive Capacity: A New Perspective on Learning and Innovation. *Administrative Science Quarterly*. 35(1) 128-152.

Cox, D. R. 1972. Regression models and life-tables (with discussion). *Journal of the Royal Statistical Society Series B*, 34(2) 187-220.

Dacin, M. T., C. Oliver and J. P. Roy. 2007. The legitimacy of strategic alliances: An institutional perspective. *Strategic Management Journal*. 28(2) 169-187.

Davis, G. F. 1991. Agents without principles – the spread of the poison pill through the intercorporate network. *Administrative Science Quarterly*. 36(4) 583-613.

Deephouse, D. L. 1999. To be different, or to be the same? It's a question (and theory) of strategic balance. *Strategic Management Journal*. 20(2) 147-166.

Delacroix, J. and A. Swaminathan. 1991. Cosmetic, speculative, and adaptive organizational change in the wine industry – a longitudinal study. *Administrative Science Quarterly*. 36(4) 631-661.

Desmond, J. P. 2008. Innovation alive and well. Retrieved from: softwaremag.com/content/ContentCT.asp?P=2789

Ding, W. W. and E. Choi. 2011. Divergent paths to commercial science: A comparison of scientists' founding and advising activities. *Research Policy*. 40(1) 69-80.

Dittrich, K., G. Duysters and A. P. de Man. 2007. Strategic repositioning by means of alliance networks: The case of IBM. *Research Policy*. 36(10) 1496-1511.

Dore, R. 1983. Goodwill and the Spirit of Market Capitalism. *British Journal of Sociology*. 34(4) 459-482.

Dyer, J. H. 1996. Does governance matter? Keiretsu alliances and asset specificity as sources of Japanese competitive advantage. *Organization Science*. 7(6) 649-666.

Eisenhardt, K. M., and C. B. Schoonhoven. 1996. Resource-based view of strategic alliance formation: Strategic and social effects in entrepreneurial firms. *Organization Science*. 7(2) 136-150.

Emigh, J. 2007. Microsoft-Novell Deal: Nightmare in Linux land. Information Week. February, 3, 2007. Retrieved from: www.informationweek.com/microsoft-novel-deal-nightmare-in-linux/197002662?pgno=1.

Fang, C., J. Lee and M. A. Schilling. 2010. Balancing Exploration and Exploitation Through Structural Design: The Isolation of Subgroups and Organizational Learning. *Organization Science*. 21(3) 625-642.

Freeman, J. and M. T. Hannan. 1983. Niche width and the dynamics of organizational populations. *American Journal of Sociology*. 88(6) 1116-1145.

------- 1989. Setting the record straight on organizational ecology - Rebuttal to Young. *American Journal of Sociology*. 95(2) 425-439.

Frye, C. 1993. Automation integration phases of sales cycle (sales force automation software). *Software Magazine*. September 15, 1993.

------- 1997. What a web year! *Software Magazine*. July 2, 1997.

Gerlach, M. L. 1992. *Alliance Capitalism: The Social Organization of Japanese Business*. Berkeley: University of California Press.

Gioia D. A., K. N. Price, A. L. Hamilton, and J. B. Thomas. 2010. Forging an Identity: An insider-outsider study of processes involved in the formation of organizational identity. *Administrative Science Quarterly*. 55(1) 1-46.

Gonsalves, A. 2006. Well-known developer leaves Novell over Microsoft deal. Information week. Retrieved from: http://www.informationweek.com/well-known-developer-leaves-novell-over/196701771.

Granovetter, M. 1985. Economic-action and social-structure - the problem of embeddedness. *American Journal of Sociology*. 91(3) 481-510.

Greve, H. R. 2007. Exploration and exploitation in product innovation. *Industrial and Corporate Change*. 16(5) 945-975.

Gromov, G. n.d. Growth of the Internet – Statistics.
Roads and Crossroads of the Internet History. Retrieved from: http://www.netvalley.com/cgi-bin/intval/net_history.pl?chapter=8. Accessed on: August 1, 2011.

Gulati, R. 1995. Social structure and alliance formation patterns: A longitudinal analysis. *Administrative Science Quarterly*. 40(4) 619-652.

------- 1998. Alliances and networks. *Strategic Management Journal*. 19(4) 293-317.

Gupta, A. K., K. G. Smith and C. E. Shalley. 2006. The interplay between exploration and exploitation. *Academy of Management Journal*. 49(4) 693-706.

Gulati, R., and M. Gargiulo. 1999. Where do interorganizational networks come from? *American Journal of Sociology*. 104(5) 1439-1493.

Hall, B. H., A. B. Jaffe, and M. Trajtenberg. 2001. The NBER patent citation data file: Lessons, insights and methodological tools. NBER Working Paper 8498.

Hall, M. 2011. When Is A Startup No Longer A Startup? Retrieved from: http://articles.businessinsider.com/2011-02-08/strategy/29978992_1_scale-companies-jack-dorsey.

Hallen, B. L. 2008. The causes and consequences of the initial network positions of new organizations: From whom do entrepreneurs receive investments? *Administrative Science Quarterly*. 53(4) 685-718.

Hambrick, D. C., M. A. Geletkanycz and J. W. Fredrickson. 1993. Top executive commitment to the status-quo – some tests of its determinants. *Strategic Management Journal*. 14(6) 401-418.

Hannan, M. T., J. N. Baron, G. Hsu and O. Koçak. 2006. Organizational identities and the hazard of change. *Industrial and Corporate Change*. 15(5) 755-784.

Hannan, M. T., and J. Freeman. 1977. Population ecology of organizations. *American Journal of Sociology*. 82(5) 929-964.

------- 1989. *Organizational Ecology*. Cambridge, MA: Harvard University Press.

------- 1984. Structural inertia and organizational-change. *American Sociological Review*. 49(2) 149-164.

Hannan, M. T., L. Pólos, and G. R Carroll. 2007. *Logics of Organization Theory: Audiences, Codes, and Ecologies.* Princeton, NJ: Princeton University Press.

Haveman, H. A. (1992). Between a rock and a hard place- organizational change and performance under conditions of fundamental environmental transformation. *Administrative Science Quarterly*. 37(1) 48-75.

He, Z. L. and P. K. Wong. 2004. Exploration vs. exploitation: An empirical test of the ambidexterity hypothesis. *Organization Science*. 15(4) 481-494.

Hill, A. 2012. Yahoo's got an identity crisis. Retrieved from: http://www.marketplace.org/topics/business/yahoos-got-identity-crisis

Hirano, K., G. W. Imbens and G. Ridder. 2003. Efficient estimation of average treatment effects using the estimated propensity score. *Econometrica*. 71(4) 1161-1189.

Hite, J. M., and W. S. Hesterly. 2001. The evolution of firm networks: From emergence to early growth of the firm. *Strategic Management Journal*. 22(3) 275-286.

Hoang, H. and F. T. Rothaermel. 2010. Leveraging internal and external experience: exploration, exploitation, and R&D project performance. *Strategic Management Journal*. 31(7) 734-758.

Hodges, J., and D. Melewski. 1993. Top 100: market approaches $17B; development shifting to client/server; sales up 23%. *Software Magazine*. July 1, 1993.

Hsu, G. 2006. Jacks of all trades and masters of none: Audiences' reactions to spanning genres in feature film production. *Administrative Science Quarterly*. 51(3) 420-450.

Hsu, G., and M. T. Hannan. 2005. Identities, genres, and organizational forms. *Organization Science*. 16(5) 474-490.

Hsu, G., M. T. Hannan, and Ö. Koçak. 2009. Multiple Category Memberships in Markets: An Integrative Theory and Two Empirical Tests. *American Sociological Review*. 74(1) 150-169.

Investext Group. 1997. Multimedia telecommunications market review and forecast chapter VII: Computer-Telephone integration. *Multimedia Telecommunications Association*. July 8, 1997.

Jackson, S. E., and J. E. Dutton. 1988. Discerning Threats and Opportunities. *Administrative Science Quarterly*. 33(3) 370-387.

Kennedy, M. T. 2008. Getting counted: Markets, media, and reality. *American Sociological Review*. 73(2) 270-295.

Khessina O. M., and G. R. Carroll. 2008. Product demography of de novo and de alio firms in the optical disk drive industry, 1983-1999. *Organization Science*. 19(1) 25-38.

Koza, M. P. and A. Y. Lewin. 1998. The co-evolution of strategic alliances. *Organization Science*. 9(3) 255-264.

Kuilman, J. G., and J. T. Li. 2009. Grades of Membership and Legitimacy Spillovers: Foreign Banks in Shanghai, 1847-1935. *Academy of Management Journal*. 52(2) 229-245.

Larson, A. 1991. Partner networks: Leveraging external ties to improve entrepreneurial performance. *Journal of Business Venturing*. 6(3) 173-188.

Lavie, D. 2007. Alliance portfolios and firm performance: A study of value creation and appropriation in the US software industry. *Strategic Management Journal*. 28(12) 1187-1212.

Lavie, D., J. Kang and L. Rosenkopf. 2011. Balance Within and Across Domains: The Performance Implications of Exploration and Exploitation in Alliances. *Organization Science*. 22(6) 1517-1538.

Lavie, D. and L. Rosenkopf. 2006. Balancing exploration and exploitation in alliance formation. *Academy of Management Journal*. 49(4) 797-818.

Lazarsfeld P. F., and R. K. Merton. 1954. Friendship as a social process: a substantive and methodological analysis." In M Berger, ed. *Freedom and Control in Modern Society*. New York, NY: Van Nostrand, 18–66.

Lee, P. M. 2001. What's in a name.com?: The effects of '.com' name changes on stock prices and trading activity. *Strategic Management Journal*. 22(8).

Lerner, J. 1994. Venture capitalists and the decision to go public. *Journal of Financial Economics*. 35(3) 293-316.

Leung, M. D. 2010. Dilettante or Renaissance Man? How the sequence of category memberships affects credibility in an online market for services. Working Paper.

Levinthal, D. A. and J. G. March. 1993. The myopia of learning. *Strategic Management Journal*. 14(special issue) 95-112.

Levitt, B. and J. G. March. 1988. Organizational learning. *Annual Review of Sociology*. 14 319-338.

Li S., J. Shang, and S. A. Slaughter. 2011. Why Do Software Firms Fail? Capabilities, Competitive Actions, and Firm Survival in the Software Industry from 1995 to 2007. *Information Systems Research*. 21(3) 631-654.

Lin, Z., H. B. Yang and I. Demirkan. 2007. The performance consequences of ambidexterity in strategic alliance formations: Empirical investigation and computational theorizing. *Management Science*. 53(10) 1645-1658.

Lincoln, J. R. and M. L. Gerlach. 2004. *Japan's Network Economy: Structure, Persistence and Change.* New York: Cambridge University Press.

Lincoln, J. R., M. L. Gerlach, and C. L. Ahmadjian. 1996. Keiretsu networks and corporate performance in Japan. *American Sociological Review*. 61(1) 67-88.

Lincoln, J. R., M. L. Gerlach, and C. L. Ahmadjian. 1998. Evolving patterns of keiretsu organization and action in Japan. In L.L. Cummings and B.M. Staw, eds. *Research in Organizational Behavior.* Greenwich, Conn: JAI Press, 20 303-345.

Lincoln, J. R. and D. Guillot. 2007. The permeability of network boundaries: the changing process of strategic alliance formation in the Japanese electronics industry. Working paper.

Lincoln, J. R., and K. McBride. 1985. Resources, homophily, and dependence – organizational attributes and asymmetric ties in human service networks. *Social Science Research*. 14(1) 1-30.

Lowry, M. and G. W. Schwert. 2002. IPO market cycles: Bubbles or sequential learning? *Journal of Finance*. 57(3) 1171-1200.

March, J. G. 1991. Exploration and exploitation in organizational learning. *Organization Science*. 2(1) 71-87.

Masnick, M. 2003. Nanotech Excitement Boosts Wrong Stock. URL: http://www.techdirt.com/articles/20031204/0824235.shtml#comments. December 04, 2003.

McKendrick, D. G., and G. R. Carroll. 2001. On the genesis of organizational forms: Evidence from the market for disk arrays. *Organization Science*. 12(6) 661-682.

McKendrick, D. G., J. Jaffee, G. R. Carroll, and O. M. Khessina. 2003. In the bud? Disk array producers as a (possibly) emergent organizational form. *Administrative Science Quarterly*. 48(1) 60-93.

McPherson, M., L. Smith-Lovin, and J. M. Cook. 2001. Birds of a feather: Homophily in social networks. *Annual Review of Sociology*. 27 415-444.

Messerschmitt, D. G. and C. Szyperski. 2003. *Software Ecosystem: Understanding an Indispensable Technology and Industry.* Cambridge, Massachusetts: MIT Press.

Meyer, J. W., and B. Rowan. 1977. Institutionalized Organizations: Formal Structure as Myth and Ceremony. *American Journal of Sociology*. 83(2) 340-363.

Mowery, D., J. E. Oxley, and B. S. Silverman. 1996. Strategic alliances and interfirm knowledge transfer. *Strategic Management Journal*. 17(Winter special issue) 77-91.

Nelson, R. and Winter, S. 1982. *An Evolutionary Theory of Economic Change*. Harvard University Press, Cambridge, Massachusetts.

Nichols, A. 2008. Erratum and discussion of propensity-score reweighting. *The Stata Journal*. 8(4) 532-539.

Nohria, N. and Eccles, R. G. 1993. Introduction. In *Networks and Organizations: Structure, Form and Action*, edited by Nohria, N. and Eccles, R. G. Boston, Massachusetts: Harvard Business School Press.

Nooteboom, B. 1992. Towards a dynamic theory of transactions. *Journal of Evolutionary Economics*. 2 281-299.

Opensource.org. 2012. Retrieved May 20, 2012. URL: Opensource.org

Özcan, P., and K. M. Eisenhardt. 2009. Origin of alliance portfolios: Entrepreneurs, network strategies, and firm performance. *Academy of Management Journal*. 52(2) 246-279.

Padgett, J. F. and C. K. Ansell. 1993. Robust action and the rise of the Medici, 1400-1434." *American Journal of Sociology*. 98(6) 1259-1319.

Pagano, M., F. Panetta and L. Zingales. 1998. Why do companies go public? An empirical analysis. *Journal of Finance*. 53(1) 27-64.

Papke, L. E., and J. M. Wooldridge. 1996. Econometric methods for fractional responses with an application to 401(k) plan participation rates. *Journal of Applied Econometrics*. 11(6) 619–632.

Peteraf, M. and M. Shanley. 1997. Getting to know you: A theory of strategic group identity. *Strategic Management Journal*. 18(Summer special issue) 165-186.

Pfeffer, J., and G. R. Salancik. 1978. *The External Control of Organizations: A Resource Dependence Perspective.* New York: Harper and Row

Phelps, C. C. 2010. A longitudinal study of the influence of alliance network structure and composition on firm exploratory innovation. *Academy of Management Journal*. 53(4) 890-913.

Phillips D. J., and E. W. Zuckerman. 2001. Middle-status conformity: Theoretical restatement and empirical demonstration in two markets. *American Journal of Sociology*. 107(2) 379-429.

Podolny, J. M. 1993. A status-based model of market competition. *American Journal of Sociology*. 98(4) 829-872.

------- 2001. Networks as the pipes and prisms of the market. *American Journal of Sociology*. 107(1) 33-60.

Podolny, J. M., T. E. Stuart, and M. T. Hannan. 1996. Networks, knowledge, and niches: Competition in the worldwide semiconductor industry, 1984-1991. *American Journal of Sociology*. 102(3) 659-689.

Pólos, L., M. T. Hannan and G. R. Carroll. 2002. Foundations of a theory of social forms. *Industrial and Corporate Change*. 11(1) 85-115.

Pontikes, E. G. 2008. Fitting in or starting new? An analysis of invention, constraint, and the emergence of new categories in the software industry. Paper presented at the Academy of Management Annual Conference, Anaheim, California.

Porac, J. F., and H. Thomas. 1990. Taxonomic Mental Models in Competitor Definition. *Academy of Management Review*. 15(2) 224-240.

Porac, J. F., H. Thomas, F. Wilson, D. Paton and A. Kanfer. 1995. Rivalry and the Industry Model of Scottish Knitwear Producers. *Administrative Science Quarterly*. 40(2) 203-227.

Potts, M. 1992. Leaning hard on software: A mellower but still driven Steve Jobs plots Next's strategic shift. *The National Post*. November 22, 1992.

Powell, W. W. 1990. Neither market nor hierarchy: Network forms of organization. In L.L. Cummings and B.M. Staw, eds. *Research in Organizational Behavior*. 12 295-336. Greenwich, Connecticut: JAI Press.

Powell, W. W., K. W. Koput, and L. Smith-Doerr. 1996. Interorganizational collaboration and the locus of innovation: Networks of learning in biotechnology. *Administrative Science Quarterly*. 41(1) 116-145.

Rider, C. I. 2009. Constraints on the Control Benefits of Brokerage: A Study of Placement Agents in US Venture Capital Fundraising. *Administrative Science Quarterly*. 54(4) 575-601.

Rindova, V. P., A. Yeow, L. L. Martins and S. Faraj. 2012. Partnering portfolios, value-creation logics, and growth trajectories: A comparison of Yahoo and Google (1995 to 2007). *Strategic Entrepreneurship Journal*. 6(2) 133-151.

Ring, P. S. and A. H. Vandeven.1994. Developmental processes of cooperative interorganizational relationships. *Academy of Management Review*. 19(1) 90-118.

Ritter, J.R. and I. Welch. 2002. A review of IPO activity, pricing, and allocations. *Journal of Finance*. 57(4) 1795-1828.

Rosch, E. 1978. Principles of Categorization. In E. Rosch and B.B. Lloyd, eds. *Cognition and Categorization*. Hillsdale, NJ: Erlbaum.

Rosch, E., C. B. Mervis, W. D. Gray, D. M. Johnson, and P. Boyes-Braem. 1976. Basic objects in natural categories. *Cognitive Psychology*. 8(3) 382-439.

Rosenkopf, L., A. Metiu, and V. P. George. 2001. From the bottom up? Technical committee activity and alliance formation. *Administrative Science Quarterly*. 46(4) 748-772.

Rosenkopf, L. and A. Nerkar. 2001. Beyond local search: Boundary-spanning, exploration, and impact in the optical disk industry. *Strategic Management Journal*. 22(4) 287-306.

Rothaermel, F. T. 2001. Incumbent's advantage through exploiting complementary assets via interfirm cooperation. *Strategic Management Journal*. 22(6-7) 687-699.

Rothaermel, F. T. and D. L. Deeds. 2004. Exploration and exploitation alliances in biotechnology: A system of new product development. *Strategic Management Journal*. 25(3) 201-221.

Sanger, D. E. 1991. Japan sets tough rules on business. *The New York Times*. July 15, 1991.

Santos, F. M., and K. M. Eisenhardt. 2009. Constructing markets and shaping boundaries: Entrepreneurial power in nascent fields. *Academy of Management Journal*. 52(4) 643-671.

Sampson, R. C. 2007. R&D alliances and firm performance: The impact of technological diversity and alliance organization on innovation. *Academy of Management Journal*. 50(2) 364-386.

Saxenian, A. L. 1990. Regional networks and the resurgence of Silicon Valley. *California Management Review*. 33(1) 89-112.

Schermerhorn, J. R. 1975. Determinants of interorganizational cooperation. *Academy of Management Journal*. 18(4) 846-856.

Selznick, P. 1949. TVA and the Grass Roots. Berkeley, CA: University of California Press.

Shan, W., G. Walker, and B. Kogut. 1994. Interfirm cooperation and startup innovation in the biotechnology industry. *Strategic Management Journal*. 15(5) 387-394.

Shane, S. and T. Stuart. 2002. Organizational endowments and the performance of university start-ups. *Management Science*. 48(1) 154-170.

Sine, W. D., H. A. Haveman, and P. S. Tolbert. 2005. Risky Business? Entrepreneurship in the New Independent-Power Sector. *Administrative Science Quarterly*. 50(2) 200-232.

Sine, W. D., H. Mitsuhashi and D. A. Kirsch. 2006. Revisiting Burns and Stalker: Formal structure and new venture performance in emerging economic sectors. *Academy of Management Journal*. 49(1) 121-132.

Singh, K. 1997. The impact of technological complexity and interfirm cooperation on business survival. *Academy of Management Journal*. 40(2) 339-367.

Sorenson, O., and T. E., Stuart. 2001. Syndication networks and the spatial distribution of venture capital investments. *American Journal of Sociology*. 106(6) 1546-1588.

------- 2008. Bringing the context back in: Settings and the search for syndicate partners in venture capital investment networks. *Administrative Science Quarterly*. 53(2) 266-294.

Spence, M. 1973. Job Market Signaling. *Quarterly Journal of Economics*. 87 355-374.

------- 2002. Signaling in retrospect and the informational structure of markets. *American Economic Review*. 92 434-459.

Stinchcombe, A. L. 1965. Social Structure and Organizations. In J.G. March, ed. *Handbook of Organizations*. Chicago, IL: Rand McNally, 142-193.

Stuart, T. E. 1998. Network positions and propensities to collaborate: An investigation of strategic alliance formation in a high-technology industry. *Administrative Science Quarterly*. 43(3) 668-698.

------- 2000. Interorganizational alliances and the performance of firms: A study of growth and innovation rates in a high-technology industry. *Strategic Management Journal*. 21(8) 791-811.

Stuart, T. E., and W. W. Ding. 2006. When do scientists become entrepreneurs? The social structural antecedents of commercial activity in the academic life sciences. *American Journal of Sociology*. 112(1) 97-144.

Stuart, T. E., H. Hoang, and R. C. Hybels. 1999. Interorganizational endorsements and the performance of entrepreneurial ventures. *Administrative Science Quarterly*. 44(2) 315-349.

Suchman, M. C. 1995. Managing Legitimacy - Strategic and Institutional Approaches. *Academy of Management Review*. 20(3) 571-610.

Tabuchi, H. 2009. When consumers cut back: An object lesson from Japan. *The New York Times*. February 22, 2009.

Thompson, J. D. 1967. *Organizations in Action*. New York, NY: McGraw-Hill.

Thormahlen, C. 2011. Staying strong: Publishers explore new business models as demand rises. *IBISworld Industry Report 51121 Software Publishing in the U.S.* February 2011.

Tolbert, P. S., and L. G. Zucker. 1983. The institutional sources of change in the formal-structure of organizations – the diffusion of civil-service reform, 1880-1935. *Administrative Science Quarterly*. 28(1) 22-39.

Tripsas, M. 2009. Technology, Identity, and Inertia Through the Lens of "The Digital Photography Company". *Organization Science*. 20(2) 441-460.

Tushman, M. L. and C. A. O'Reilly. 1996. Ambidextrous organizations: Managing evolutionary and revolutionary change. *California Management Review*. 38(4) 8-30.

Tversky, A. 1977. Features of similarity. *Psychological Review*. 84(4) 327-352.

Uotila, J., M. Maula, T. Keil and S. A. Zahra. 2009. Exploration, exploitation, and financial performance: Analysis of S&P 500 corporations. *Strategic Management Journal*. 30(2) 221-231.

Walker, L. 2002. Profitable Yahoo keeps looking for its identity. *The Washington Post*. July 18, 2002.

Wassmer, U. 2010. Alliance Portfolios: A Review and Research Agenda. *Journal of Management.* 36(1) 141-171.

Westphal, J. D., R. Gulati and S. M. Shortell. 1997. Customization or conformity? An institutional and network perspective on the content and consequences of TQM adoption. *Administrative Science Quarterly*. 42(2) 366-394.

Whetten, D. A. 2006. Albert and Whetten revisited - Strengthening the concept of organizational identity. *Journal of Management Inquiry*. 15(3) 219-234.

White, H. C. 1981. Where do markets come from? *American Journal of Sociology*. 87(3) 517-547.

Womack J.P., D. Roos, D. Jones. 1990. T*he Machine That Changed the World: the Story of Lean Production*. New York: Rawson Associates.

Yamakawa, Y., H. Yang and Z. Lin. 2011. Exploration versus exploitation in alliance portfolio: Performance implications of organizational, strategic, and environmental fit. *Research Policy*. 40(2) 287-296.

Zuckerman, E. W. 1999. The categorical imperative: Securities analysts and the illegitimacy discount. *American Journal of Sociology*. 104(5) 1398-1438.

------- 2000. Focusing the corporate product: Securities analysts and de-diversification. *Administrative Science Quarterly*. 45(3) 591-619.

Zuckerman, E. W., T. Y. Kim, K. Ukanwa and J. von Rittmann. 2003. Robust identities or nonentities? Typecasting in the feature-film labor market. *American Journal of Sociology*. 108(5) 1018-1074.