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Technological Characteristics and R&D Alliance Form: Evidence from the U.S. Biotechnology Industry

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Abstract

This study seeks to advance and test the knowledge-based theory of the firm as it applies to explaining the governance structure of R&D alliances. Unlike transaction-cost economics, the knowledge-based theory attempts to explain organizational form not primarily in terms of incentive misalignment but in terms of the creation, acquisition, and coordination of productive capabilities. To study the role played by firm-specific technological competencies, I consider three technological characteristics of an alliance technological similarity, technological relatedness, and technological diversity. With a sample of 111 biotech-biotech R&D alliances, I find that technological relatedness and diversity increase the probability that allying firms would select the higher integration mode. Technological similarity, though, bears a non-monotonic relationship with organizational choice. Overall, the results support the knowledge-based argument that the idiosyncrasy in technological traits influences which type of alliance forms would be selected by allying firms.

Journal of Economic Literature Classification: L22, O32, L65

Keywords: technology, governance, alliance, R&D

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1. Introduction

Since the 1970s, R&D alliances have become an important way through which firms acquire, develop and create new technologies. Many literatures discuss why alliances appear so frequently and what their effects are (Shan et al. 1994; Chan et al. 1997; Powell et al. 1996; Zucker et al. 1998; Niosi 2003). Less has been asked about what influences the firm's choice of alliance forms. Alliances take on numerous forms, ranging from licensing contracts to collaborations to joint ventures to mergers and acquisitions. A discussion on the determinants of the choice among alliances forms would deepen the understanding of the boundary of the firm. Specifically, the proliferation of lateral relationship in high-technology industries, such as pharmaceuticals, biotechnology, and semiconductors, provides a unique opportunity to examine the arguments in the knowledge-based theory of the firm.

This study seeks to advance and test the knowledge-based theory of the firm as it applies to explaining the governance structure of R&D alliances. In particular, it investigates organizational choices by US public biotechnology firms among three types of alliances: R&D agreements, R&D collaborations and minority equity R&D alliances[1]. It employs three measures to describe the technological characteristics of an alliance: technological similarity, technological relatedness, and technological diversity. The results suggest that the idiosyncrasy in technological traits influence what type of alliance forms would be selected by allying firms.

[1] As defined by ReCap: in a research agreement, a sponsoring party engages another party to perform R&D services in the discovery and/or lead stages of an R&D project; in a development agreement a sponsoring party engages another party to perform R&D services beyond the stage of lead generation; in a collaboration agreement, two or more parties perform research and/or development activities in a single R&D program.; an equity agreement describes the issuance of a minority share (<50%) of legal ownership interest in an entity. I define minority equity R&D alliance as research agreements, development agreements or collaborations that involve an equity agreement.

On the question of how technological similarity affects the firm's ability to integrate knowledge, two lines of thought in the knowledge-based perspective predict two distinct relations. The study argues that the difference arises only because researchers analyze two different aspects of the firm's knowledge-related activities: managing and learning. The results provide supportive evidences for both streams of thought. Allying firms with more divergent technologies are more likely to select a more highly integrated alliance form. At higher levels of technological similarity, however, the relationship between technological similarity and organizational choice reverse the direction: a higher degree of technological similarity leads to a higher integration mode in alliances. It suggests dynamic changes in the gains and costs in learning and managing. The gains for learning within the boundary of the firm exceed the managing costs when technologies are highly dissimilar, suggesting the firm would integrate divergent technologies. The gains diminish as similarity in technologies increase. When technologies are highly similar, managing costs, which are lower for more homogenous technological portfolio, became a greater influence on the firm's decision on the organizational choice.

In measuring technological relatedness, it adopts the survivor measure originally designed by Teece et al. (1994). The results show that closely complementary technological capabilities increase the probability that allying firms would select the higher integration mode, that is, minority equity R&D alliances over R&D collaborations, or R&D collaborations over R&D agreements, although the length of establishment may reduce this influence.

Firms also differ with respects to technological diversity. Diversity of current technological stock influences firms' future technology-related decisions. For a given level of technological similarity, a technological generalist may be more willing and able to bring technologies in-house than a technological specialist. The empirical test shows that the technological diversity of the client firm[2] is positively related to the probability of selecting a high integration mode, with technological similarity controlled.

In the paragraphs follow, I first review the literature on the knowledge-based theory of the firm and its application to the organizational choice of R&D alliances. Then I develop the theory on the basis of the knowledge-based theory and present the hypotheses to be tested on how technological characteristics influence organizational choices. Description of the U.S. biotechnology industry, the sample used, measures and statistical models follows. I present the empirical results by comparing three models: "transaction costs perspective", "traditional knowledge-based approach", and "complete knowledge-based approach", respectively. A discussion on the findings concludes.

2. The knowledge-based theory of the firm, technological capabilities and R&D alliances

The idea of looking at firms in terms of their resource endowments goes back to the seminal work of Penrose (1959), who defines a firm as "a pool of resources the utilization of which is organized in an administrative framework." Wernerfelt (1984) includes machine capacity, customer loyalty, production experience, and technological leads as examples for attractive resources of firms. Many researches following Penrose's definition focus on technological knowledge endowed in the firm. The endowment of knowledge, also called capabilities or competence by various writers, is different among

[2] As defined in ReCap: an R&D firm is "the party in the alliance associated with the technology's research and development." An client firm is "the party in the alliance that is gaining access to a technology developed by the R&D partner."

firms and consequently influences the firm's behavior and performance. Part of this resource is "knowing that", but much of it is "knowing how", which is not reducible to mere information to be passed on but consists also of experience and skills. A resource-based perspective of the firm thus entails a knowledge-based theory of the firm.

In the knowledge-based theory, firms are viewed as bundles of technological capabilities. This theory brings a new perspective in answering "why does the firm exist?" Since Coase (1937), researchers have believed that a firm exists as an "incentive coordination" mechanism solving the problem of how the members of a firm can be rewarded and induced to work efficiently (Alchian and Demsetz 1972). Unlike previous theories of the firm, the knowledge-based theory always looks to "qualitative coordination"[3] as the mechanism that aligns the creation, acquisition, and coordination of technological knowledge of the various players (Langlois 1997).

From inter-firm R&D alliances, firms can get access to new technologies, realize economies of scale and scope in their R&D activities, and shorten development time. These benefits may spread out beyond the life of the alliance, as firms learn skills and gain competencies form their partners. Yet, to benefit from R&D alliances, firms must create an organizational structure that supports the efficient recognition, assimilation, and application of knowledge-based assets.

Coase's 1937 paper on "The Nature of the Firm" suggests that organizational choice is decided by a cost comparison between the market and the firm. In the ensuing

[3] "The firm is an institution that lowers the costs of qualitative coordination in a world of uncertainty, where by *coordination* I mean the process of aligning the knowledge and expectations of the parties who need to cooperate in production, and by *qualitative* coordination I mean coordination involving the transmission of information beyond price and quantity." (Langlois 1997, p. 6)

literatures, different understandings of the sources of costs led to different explanations of why firms exist.

In transaction-cost economics, opportunism has long been in the main concern. And hierarchy is the weapon of choice against transaction costs brought on by opportunistic behavior. Pisano (1990, 1991) studies the make-or-buy decision of R&D alliances in biotechnology industry using this approach. I argue that transaction costs economics' emphasis on incentive alignment and its unwillingness to analyze knowledge coordination makes it inappropriate for the question of R&D alliances, whose main objective is to acquire and create new technologies. Moreover, it is hard to relate the characteristics of knowledge assets with the probability of opportunistic behavior. Some argue that the probability of opportunistic behavior is low when knowledge is highly similar because there is no new knowledge for leakage (Sampson 2004). This is not necessarily true.

Unlike transaction costs economics, the knowledge-based theory of the firm attempts to explain organizational form not primarily in terms of opportunism or incentive misalignment but in terms of the creation, acquisition, and coordination of productive knowledge or capabilities. It assumes that opportunism is unrelated to the characteristics of the technological assets.

Two papers in the current literature apply the knowledge-based theory to explaining the organization form of alliances. Sampson (2004) uses a sample of 237 alliances during 1991-1993 in the telecommunication equipment industry to test hypotheses derived from transaction-cost economics and knowledge-based theory. Her result is in favor of transaction-cost economics. Colombo (2003) studies alliances among the world largest IT companies. His results show that both theories can explain part of the organizational arrangement. When discussing the knowledge-based theory, these two studies restrict their attention in investigating only how learning influences organizational choice and similarity is the only technological characteristic included in their model.

In the model, I suggest that technological similarity has different effects in the two technology-related activities within an alliance: managing and learning (Penrose 1959; Richardson 1972; Loasby 1998; Conner and Phrahalad 1996). The previous literature suggests that other technological characteristics apart from similarity also influence the firm's behavior. I consider technological relatedness (Hagedoorn and Duysters 2002) and technological diversity (Stuart 1995) in the model.

3. Technological characteristics and organizational choice: theory and hypotheses

Unanimously, the knowledge-based theory views the firm as a bundle of technological capabilities and sees the firm as qualitative coordination mechanism that aligns the creation, acquisition, and coordination of knowledge of the partners. On the question of firms' ability to integrate knowledge, however, this theory would seem to be of two minds. One strand of thought holds that firms are limited in integrating and using knowledge very different from what they already possess; the other strand suggests that firms have advantages over markets precisely when knowledge is most different from the existing base.

The first line of thought, arguing that the firm is better at integrating similar knowledge than dissimilar knowledge, goes back to Penrose (1959)'s *The Theory of the Growth of the Firm,* where she provided us with excellent accounts of how firms grow in directions set by their capabilities and how these capabilities themselves slowly expand and alter. Richardson, in his 1972 paper "The Organization of Industry", expands this idea and points out that the firm would find it expedient to concentrate on activities requiring similar capabilities. Coordination of dissimilar knowledge has to be brought about either through inter-firm *ex ante* cooperation, or through the process of adjustment by the market mechanism. Loasby (1998)'s "The Organization of Capabilities" is of special importance as it explicitly distinguishes indirect capabilities from direct capabilities. Direct capabilities involve knowing how to do certain things by the firm itself, whereas indirect capabilities involve knowing how to get things done for the firm by others. Penrose, Richardson, and Loasby's discussion focuses on indirect capabilities. Indirect capabilities are of two kinds: the firm may be able to get things done for itself either by gaining controls of others' capabilities through hierarchies or by obtaining access to them across markets. A cost comparison between control and access decides the choice between firms and markets. Loasby (1998, p. 152) believes that "it is not even sensible to extend a firm into areas of activity that require capabilities which are significantly different from those already developed."

Conner and Prahalad develop the other view in their 1996 paper, "A Resource-based Theory of the Firm: Knowledge Versus Opportunism." Its theme is that the organizational mode through which individual firms cooperate affects the knowledge they apply to business activities. They argue that a firm is superior to a market in learning dissimilar knowledge. Thus, when the firm needs to learn dissimilar knowledge, it should do so through integration.

Both lines of thought view the firm as a bundle of capabilities or technological knowledge. Also, both aim at developing an empirically relevant and complementary theory based on irreducible knowledge differences between individual firms rather than on the threat of purposeful cheating or withholding of information. It is the great similarity between them that makes their contradictory conclusions even more interesting.

The difference arises only because these writers analyze two different aspects of the firm's knowledge related activities: managing and learning. Penrose, Richardson and Loasby elucidate how the firm gets things done for itself by either gaining control of or obtaining access to other's knowledge. They believe that firms have a higher managerial cost when technologies are dissimilar. Conner and Prahalad, however, emphasize that the firm passes its capabilities onto others by either directing others within the boundary of the firm or having its own capabilities internalized by others in the market. They believe that firms are more efficient in learning dissimilar knowledge than markets. The former group of researchers compares those two kinds of indirect capabilities to choose between control and access, while the latter studies whether gains in direct capabilities, that is, do-it-by-yourself abilities, can better be obtained within an organization like the firm or through the market.

Inter-firm cooperation is concerned very often with the transfer, exchange and pooling of knowledge between cooperating firms. Thus, managing the other's knowledge and passing on one's own knowledge (or learning the other's knowledge) are two different activities dwelling in the same process. In order to see the whole picture, a valid conceptual framework needs to consider them simultaneously.

3.1. Managing technology

Penrose (1959) points out that hierarchical administration is itself a capability with limits, which implies that including too diversified knowledge within the boundary of the firm would result in diseconomies of scale in the management resources of the firm, something originally alluded to by Coase (1937, p. 394) under "decreasing returns to the entrepreneur function." In Richardson's (1972) opinion, organizations would tend to specialize in activities where their capabilities offer some comparative advantage. He believes that these activities will generally be similar in the sense of requiring similar knowledge. Thus, managing technology suggests:

Hypothesis 1a: With all else equal, in technological alliances greater similarity in allying firms' technological portfolios will result in a higher propensity for high integration modes.

This line of thought also suggests that technological relatedness influences the decision on the choice between firms and markets. Loasby (1998) believes that control has substantial advantages but it is likely to be more costly than access. Firms can access more than they can control. Therefore, they should limit their attempts at control to those capabilities which are both "crucial and manageable" Loasby (1998, p. 149). By "crucial and manageable" capabilities, he means a range of related skills. He believes knowledge development must be guided in a compatible direction and in appropriate ways.

> It is therefore clearly not sensible to attempt to manage an economy as one enormous firm; it is not even sensible to extend a firm into areas of activity that require capabilities which are significantly different from those already developed, and so it is not surprising that firms so often develop a product portfolio which depends on a range of related skills. (Loasby 1998, p. 152)

Another reason that firms would retain closely related technologies within its boundary is related to the dynamic transaction costs in the market. Langlois (1992, p. 99) defines dynamic transaction costs as “the costs of persuading, negotiating, coordinating, and teaching outside suppliers” or as “the costs of not having the capabilities you need when you need them.” Such costs increase with technological relatedness between firms, because closely related or closely complementary technologies are usually necessary for firms’ production and development. The more related the technologies are, the higher the probability that the firm will need it frequently; thus it would be more costly to leave the access to the technologies in the market.

In a word, the firm should retain within its boundary only a set of “related” technologies requiring more or less the same kind of knowledge in order to minimize managerial costs and dynamic transaction costs.

Hypothesis 2: With all else equal, in technological alliances the greater relatedness in allying firms’ technological specialization will result in a higher propensity for high integration modes.

3.2. Learning technology

Learning technology suggests a different relationship between technological similarity and organizational choice from that suggested by the analysis of managing costs. On the one hand, since the firm is familiar with the knowledge that is similar to its own base, if it wants to acquire more knowledge in this line, market contracting is relatively cheaper, because there is less asymmetric information about knowledge compared with the situation in which the firm has to learn highly different knowledge. Meanwhile, it is usually costly to compromise between two firms’ managerial styles even when they manage identical knowledge bases. On the other hand, as Conner and Phrahalad (1996) assert, the firm is relatively more efficient than the market in learning highly different knowledge, even after considering management frictions.

Conner and Prahalad (1996) argue that the organizational mode through which individuals cooperate affects the knowledge they apply to business activity. The difference in the knowledge that is brought to bear under the two organizational modes would impact the choice of mode itself. They mainly consider two effects that organizational modes have on knowledge transfer: “knowledge substitution effect” and “flexibility effect.”

The knowledge substitution effect is about how the parties’ starting knowledge endowments are blended and used. The ability of a firm to learn the partner firm’s knowledge in the market varies with the degree of difference in their knowledge bases. The more similar the target knowledge is to the firm’s own knowledge base, the easier it is to acquire the partner’s knowledge. Alternatively, the more dissimilar the target knowledge is, the more difficult (i.e. the higher the cost) for the firm to master it through the market.

Conner and Phrahalad (1996) emphasize that different economic organizations facilitate knowledge transfer differently because of different ways in economizing on bounded rationality. Market contracts solve bounded rationality by specialization only, while firms economize on cognitive limitations through both specialization and knowledge-substitution or what Langlois (1997, p. 6) calls “qualitative coordination.” In their argument, a firm has to understand and accept the other firm’s knowledge before it takes any action in accordance with the other’s knowledge in the market. However, within the boundary of a firm, employees can be directed on the basis of the employer's knowledge without internalizing it first.

The initial knowledge status of cooperating parties affects the benefits brought by knowledge substitution in different organization modes. Conner and Prahalad (1996) suggest that expected difficulties in knowledge absorption cause cooperating parties to favor a firm, because the organizational integration would allow one firm's knowledge dominate the other's. It implies that the greater is the initial difference in the knowledge between two organizations, the more likely is a firm to be used in the cooperation.

Conner and Prahalad (1996) define flexibility as the ability of the organization to apply and develop knowledge. I agree with them that different economic organizations have different flexibility. However, I give different explanations for the difference. In Conner and Prahalad's view, flexibility is mainly a problem of market uncertainty. If market conditions are expected to be highly uncertain, they conclude, a market contract has higher costs in flexibility since many follow-up renegotiations will be necessary because of changes in the future. The costs are low within the firm because it is easier to change directions in the firm in response to both internal and external changes.

Their conclusion depends on the assumption that it is desirable for cooperation between the two firms to continue. However, this may not be true all the time. In fact, as market conditions changes, cooperation between the two firms may turn out to be infeasible, and it becomes better for both parties to terminate the cooperation or to change partners. In this case, a market contract is more flexible because its cost to change the cooperative relationship is low. The firm, in contrast, has higher costs to terminate cooperation. I consider it inappropriate to assert that the firm is more flexible in an uncertain world based only on considering the problem of renegotiation.

Loasby (Foss 1997, p. 12) draws the analogy of an economic organization as a reservoir, that is, a pool of resources (capabilities). Different capabilities have different present and future values to the organization: some are currently useful while some are idle but may be useful in the future. Firms require both because nobody can predict exactly what is going to happen in the future. The analogy tells us that the firm can store knowledge whose potential uses they do not immediately know. It is common to obtain and reserve some idle technologies in the evolutionary process of the firm (such as side products from research and development activities) which are of "no use" at present. If the same research and development is carried out in the market, those technologies may be ignored and lost because there are immediate costs to incorporate or store the knowledge but no immediate benefits in sight. Basically, it is a "no rider" problem. However, the "idle" knowledge may be important for future development and competition. The costs are much lower for the firm to reserve "idle" technologies after they have already come in existence. In this sense, the firm is more flexible than the market in incorporating the unexpected technology output from R&D activities. Also, the firm as a reservoir is better at maintaining continuity in knowledge application and development.

Uncertainty is an inherent characteristic of R&D activities. The similarity between the knowledge bases of two cooperating R&D partners is an important factor that affects the degree of uncertainty. The less similarity between the two partners there is at the beginning, the more difficult it is for them to predict the process of cooperating in R&D, and the higher will be the uncertainty in R&D results.

Therefore, a firm is superior to a market in learning dissimilar knowledge because of substitution and flexibility effects. The market organization is better for learning when the partners have similar knowledge, since the costs for writing and carrying out the contract are relatively low. In this case, integration generates little knowledge gain, while incurring significant set-up cost. By contrast, when the target knowledge is quite different, it is difficult to learn through contracting because of both unfamiliarity and uncertainty. Thus, it is better to integrate with the organization owning that knowledge when the firm learns some knowledge quite dissimilar to what it already knows. Considering knowledge substitution and flexibility, learning technology suggests:

Hypothesis 1b: With all else equal, in technological alliances greater divergence in allying firms' technological specialization will result in a higher propensity for high integration modes.

This argument is consistent with Cohen and Levinthal (1990)'s discussion of "absorptive capacity." They suggest that the ability to evaluate and utilize outside knowledge is largely a function of the richness of the preexisting knowledge structure of the firm. They point out that "learning is cumulative, and learning performance is greatest when the object of learning is related to what is already known." (Cohen and Levinthal 1990, p. 131) It also implies, when knowledge is dissimilar, integration is preferred in order to compensate for the lack of absorptive capacity in the market.

3.3. Technological diversity

Technological diversity has an effect on both learning and managing technology. In terms of learning, technology diversity influences gains through knowledge substitution and flexibility. Research in the area of cognitive and behavioral sciences suggests that diversity enhances a firm' learning and innovation abilities in two ways: experiences in learning dissimilar knowledge and novel associations with and linkage to existing knowledge (Cohen and Levinthal 1990). Thus, a more diversified firm accumulates more experiences in learning. In terms of managing technology, managing costs are different for a technological generalist and a technological specialist in integrating same knowledge. I argue that generalists have lower costs in learning and managing dissimilar technologies because of accumulated experiences.

Hypothesis 3: With all else equal, in technological alliances the greater diversity in allying firms' technological portfolios will result in a higher propensity for high integration modes, technological similarity constant.

4. The U.S. biotechnology industry

According to the Department of Commerce (DOC) 2003 survey, biotechnology is defined as the application of molecular and cellular processes to solve problems, conduct research, and create goods and services. Biotechnology emerged as an industry in the late 1970s and it has been in rapid development since then, especially from the mid-1980s. R&D activities are the most prominent driver of the growth. The R&D intensity of biotech business lines was 33.4% in 2001, compared with 9.5% for the firms' entire businesses and 4.3% for total U.S. corporate R&D spending. Furthermore, the firms' near-term business strategies are still focused primarily on R&D activities. In the 2003 survey, 53% of the respondents say their business strategy is to develop technologies that can be licensed to others and 47% are seeking opportunity to acquire technologies from other companies through licensing arrangements. Active research and development makes biotechnology a good candidate to study and test the knowledge-based theory of the firm.

There are seven areas for biotechnology application according to the Department of Commerce[4] . Some researchers (e.g. Powell et al. 1996) concentrate on human health service because of different incentives and regulations between human health activities and agriculture or environmental remediation. Many researchers (e.g. Barley et al. 1992) treat the wide array of biotechnology companies as comparable. I follow this approach and include R&D alliances between all for-profit public biotechnology firms established after 1976 in the sample.

In the current U.S. statistical system, biotechnology is not an independent industry. It is not feasible to choose firms according to SIC or NAICS categories. For the alliance data, I simply rely on ReCap data's categorization of firms (See below). For the biotechnology industry sample in calculating technological relatedness matrix, I rely on the collection of public companies listed on NYSE and NASDAQ (See below).

5. Data and method

To study the relationship between technological characteristics and organizational choice, I use alliance and firm data in the biotechnology industry and U.S. patent data for

[4] The seven areas include (DOC 2003, p. 10) human health, animal health, agriculture and aquacultural / marine, marine & terrestrial microbial, industrial & agricultural-derived processing, environmental remediation & natural resource recovery and others.

the knowledge base of the firms. The main source of alliance data is from ReCap, which contains high-level summaries of more than 13,500 alliances in the life sciences which have been formed since 1973. I employ publicly listed NYSE and NASDAQ biotechnology and pharmaceutical firms in the calculation of the survivor measure of technological relatedness.

5.1. Alliances data

I study biotech-biotech alliances during 1998-2000 in the U.S. There are three restrictions on biotech firms in the sample: (1) Only U.S. firms are included. This is because I use U.S. patents to build the firm's knowledge base. Including only U.S. firms avoids the bias brought by the patent application intention. Also, R&D alliances involving foreign companies may have different incentives from those domestic alliances (Sampson 2004). (2) Only firms incorporated after 1976 are included. By this time constraint, I concentrate on newly established biotechnology firms. America's first firm to exploit rDNA, Genentech, was established in 1976. Old firms, such as big pharmaceutical firms, are also doing research and development in biotechnology. However, both their knowledge bases and their characteristics are quite different from those of new biotechnology firms. (3) Only public firms are included. This constraint arises from data availability. I need to build a profile for each firm in the sample, such as incorporation year, the number of employees, the family tree, and R&D expenses. Such information is difficult to obtain for private firms.

I collect a sample of 111 alliances during 1998-2000 between U.S. public biotech firms established in or after 1976. Among various alliances forms, I study the following three types: R&D agreements, R&D collaborations and minority equity R&D alliances. Table 1 shows a summary of the sample.

[Table 1 here]

I create profiles for each firm and identify their family trees by the following sources: (1) Mergent Industrial Manual, Mergent OTC Industrial Manual and Mergent OTC Unlisted Manual (2001-1999); (2) LexisNexis/company profile and SEC filing (online database at University of Connecticut Libraries); (3) ReCap data base (June 2004-June 2005).

5.**2. Patents as an indicator for technological capabilities**

Different indicators have been applied in studying technological activities of firms. The ideal way would be to obtain the firm’s R&D expenditure and split it into different technological sectors. However, R&D information is rarely available at the firm level, not to mention at the activity level. Some researchers use survey data, which is hard to generalize. These weaknesses of R&D and survey data explain the relative success of patents as an indicator of firms’ innovation activities. The United States Patent and Trademark Office (USPTO) keeps records of patents it assigned since 1790. More important, USPTO provides consistent technology classification for each patent it assigned. The completeness, continuousness, and consistency of the patent data provide us a good indicator for the firm’s technology capabilities.

I use *Delphion* to collect patent data, including the patent number, the granted date, the filed date and the current U.S. classification for each patent. There are two classifications for US patents: US classification and International Patent Classification. I use US classification in the study because it emphasizes the technological aspect of patents. The patent portfolio of a firm includes all patents assigned to itself and to all its subsidiaries in a sample year.

There are some potential problems in using patents, though. Technologies from different disciplines may be closely integrated. And arbitrariness cannot be avoided in the division between certain patent classes (Cantwell 2004). Even without the problems with patents classifications, it is necessary to recognize that patents have limited use outside high-tech industries. Moreover, the codified knowledge embodies in patents usually cannot be readily translated into production and commercialization.

Cantwell (2004) have tried to alleviate the difficulties in directly using the patent classification system by devising a classification scheme that groups together patent classes that are the most technological related. Each patent in the data has been classified according to this scheme. Some technology sectors do not appear. Also, because I study only the biotechnology industry, I further divide Sector 12 (Pharmaceutical and Biotechnology) into four subclasses[5]. After these adjustments, patents are classified into 16 technological sectors.

5.3. A survivor measure for technology relatedness in the biotechnology industry: sample and methodology

To collect a sample for the biotechnology industry, I have checked carefully several databases for biotech companies, including *BioScan*, *ReCap*, *Bio* member directory, and *Mergent* (*Mergent* Industry Review and *Mergent* Industry Code). The collections of biotech firms are quite different in each database. The main reason for inconsistency is that there has not yet been a unified definition of "biotechnology

[5] Class 12 Biotechnology is divided into 4 subclasses: 424 and 514: Class 121; 435: Class 122; 436: Class 123; 800: Class 124.

industry" and also because of the close relationship between the new biotechnology and the old pharmaceutical companies. In the current U.S. statistical system, biotechnology is not an independent industry. Since I lack the expertise and detailed information that are needed to decide if a company majors in biotech or not, I depend on a database that has put serious efforts in clearly and consistently defining the biotechnology industry, namely the data from NASDAQ and NYSE listed company profiles.

The NASDAQ Biotechnology Index contains companies that are classified according to the FTSE™ Global Classification System as either biotechnology or pharmaceutical. These companies must also meet other eligibility criteria.[6] NYSE applies the Dow Jones Industry Classification System to identifying biotechnology companies. I combine the listed firms in these two stock markets to construct the sample for the biotech industry. Considering the close relationship between biotech and pharmaceutical companies, I also include pharmaceutical companies listed in NYSE.

The sample includes all the companies that appeared in NASDAQ Biotechnology 100 Index during 2000-2004 (which is available) and companies listed in the NYSE in 2004. The initial sample includes 230 public biotechnology and pharmaceutical companies (including foreign companies). I exclude companies that have none patent and companies that only have patents in a single technology sector. The sample used for relatedness matrix includes 186 companies. According to Ernst & Young's 2004 biotechnology industry report, there are 1,473 biotechnology companies in the United States, of which 314 are publicly held. It is reasonable to believe that the sample is well defined and representative for the U.S. biotech industry.

[6] For details, see NASDAQ website: <http://dynamic.nasdaq.com/dynamic/nasdaqbiotech_activity.stm>

I collect patents for all the 186 companies during 1985-2004. The patent portfolio of a firm includes all patents assigned to itself and to all its subsidiaries. I use *Mergent* and *SEC* filings to identify companies' subsidiary structure. All patents have also been classified according to Cantwell's scheme. Some technology sectors do not appear. Also, we further divide Sector 12 into four subclasses. After these adjustments, patents are classified into 56 technological sectors[7].

There are essentially two fundamental approaches to measure technological relatedness (Cantwell and Noonan 2004). The first considers relatedness to be an *ex ante* phenomenon and points to the underlying scientific or engineering principles as indicating the degree of relatedness between technologies (Breschi et al. 2004). The alternative approach is to view relatedness as an *ex post* phenomenon. I adopt the second approach and the survivor principle in measuring the relatedness between technologies (Teece et al. 1994; Cantwell and Noonan 2004). The relatedness between any two technology sectors i and j (R_{ij}) is :

$$R_{ij} = \frac{n_{ij} - \mu_{ij}}{\sigma_{ij}}$$

Where: n_{ij} = actual number of linkages between technologies i and j;

μ_{ij} = the expected number of linkages between technologies i and j under the hypergeometric distribution; and

σ_{ij} = standard deviation of the number of linkages under the hypergeometric distribution.

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[7] Class 12 Biotechnology is divided into 4 subclasses: 424 and 514: Class 121; 435: Class 122; 436: Class 123; 800 Class 124. Among Cantwell's 56 technology sectors, Class 24, 27, and 55 do not appear.

As suggested by Teece et al. (1994), if firms are assigned technologies randomly, R_{ij} should be insignificantly different from 0. Of the 3,136 possible linkages between pairs of technology sectors, 2740 were observed. An R_{ij} measure of relatedness was calculated for each of such pair. R_{ij} is ranged from 13.6015 to -1.6212. The average relatedness is 3.64 and the standard deviation is 2.62. Thus, the randomness assumption is rejected, which has already been shown by Teece et al. (1994) and Breschi et al. (2004). I further employ the relatedness matrix obtained here to measure technological relatedness between allying firms in the following discussion[8].

6. Model

All hypotheses concern factors that play a role in influecing the likelihood of a particular alliance form chosen between two allying firms. Therefore, I model the probability of an alliance form between two allying firms using a cumulative logit multinomial model. I use a categorical variable (ORG) to indicate the organizational form of alliances. ORG equals 0 when the alliance is R&D agreement, 1 when it is R&D collaboration, and 2 if organized as minority equity R&D alliance. Thus, a higher value of ORG indicates a higher integration mode.

6.1. Model specification: unobserved heterogeneity and network autocorrelation

Before discussing the measurement of the variables included in the models, I note the inclusion of a number of control variables designed to account for unobserved heterogeneity. Heckman and Borjas (1980) have demonstrated that unobserved heterogeneity across observations is likely to result in “occurrence” dependence. In other

[8] The relatedness matrix obtained here includes 56 technological sectors. I use only those 16 technological sectors that appear in allying firms’ patent portfolios.

words, past realizations of a dependent variable are likely to be positively associated with the likelihood that a similar event will occur in the future. To account for unobserved heterogeneity in the data, I following Stuart (1995)'s approach. I include a variable (PALLI) that represents the total number of times that two allying firms have allied before. The reason for including this variable is to try to build into the model the unobserved tendency for two firms to collaborate. A number of factors – such as the presence of a high degree of trust among the two firms because of prior, successful collaboration—could affect the further organizational choice of alliances. This proclivity is likely to be captured by the history of realized partnerships among the two firms in an alliance.

Another type of statistical issue is the network autocorrelation. As noted by Lincoln (1984), the problem with dyadic data is that observations are non-independent: within a time period, the same firm may be involved in multiple dyads, perhaps leading to a "common" actor effect. Although there seems to be no widespread agreement on a computationally inexpensive method to handle network agreement, Lincoln (1984) suggests the inclusion of an additional variable as a "quick and dirty" means to treat autocorrelation in the data. For each alliance, I construct the mean of the dependent variable computed across all other alliances in a year that involve either of the current two allying firms and normalized by the number of firms in the sample of that year.

6.2. Independent variables

(1) Knowledge similarity between allying firms (SIM)

Revealed technological advantage (RTA) (Cantwell and Piscitello 2000) measures the concentration of the firm's technological specialization in favored sectors. The RTA for each particular sector of technological activity is defined by the firm's share in that sector of US patents applied[9] by firms in the same industry, relative to the firm's overall share of all US patents assigned to firms in the industry in question. Specifically, denoting as P_{ij} the number of US patents applied in sector j by firm i in a particular industry, the RTA index is defined as follows:

$$RTA_{ij} = \frac{P_{ij} / \sum_i P_{ij}}{\sum_j P_{ij} / \sum_i \sum_j P_{ij}}$$

Cantwell and Colombo (2000) point out that the reliability of RTA index may be harmed by "small numbers" in patents. Some firms in my sample have a total of only a few patents or a few patents in some classes. Regrouping patents by Cantwell's classification scheme is one of the ways to solve this problem. Only 16 sectors out of the 56 are involved in this study of the biotechnology industry[10]. Also, I use the adjusted RTA suggested by Cantwell and Vertova (2004) to avoid certain computation problem:

$$Adj(RTA_{ij}) + 1 = \frac{RTA_{ij} - 1}{RTA_{ij} + 1} + 1$$

I calculate Pearson's correlation coefficient r_{ik} between RTA distributions of Firm i and Firm k across all the technological sectors. Colombo (2003) suggests that the index r_{ik} measures the technological overlapping between the two firms. Thus, for an alliance between Firm i and Firm k, technological similarity between them equals

$$SIM_{ik} = r_{ik}$$

[9] Different form Cantwell and Piscitello (2000), I establish the firm's patent portfolio according to the patent's application date, instead of grant date. For example, for a firm's patent portfolio in year 2000, I include all granted patents that were applied before January 1, 2001.
[10] I include the technological sectors with more than 10 patents in any of three sample years.

(2) Interaction between technological diversity and technological similarity (SIMDIVC and SIMDIVD):

I have argued that diversity of initial technologies influences a firm's learning ability and managerial costs. For a given level of technological similarity, a diversified firm may be more capable of learning dissimilar knowledge and at the same time may incur lower managerial costs. To test its effect, I include an interaction term between technological diversity and technological similarity.

I use the inverse of the coefficient of variation of the RTA index, CV_i, across all the relevant sectors for the firm, to measure the firm's technological diversity. For Firm i in each period considered, the proxy DIV_i for technological diversity will be the reciprocal of CV_i, that is:

$$DIV_i = \frac{1}{CV_i} = \frac{\mu_{RTA_i}}{\sigma_{RTA_i}},$$

where σ_{RTA_i} is the standard deviation and μ_{RTA_i} is the mean value of the RTA distribution for Firm i (Cantwell and Piscitello 2000).

As the motivation for the client firm and the R&D firm in an alliance may differ, I establish separate interaction terms for them: SIMDIVC is the interaction term for the client firm and SIMDIVD is the interaction term for the R&D firm.

(3) Technological relatedness

The allying firms are aiming at learning from partners. Thus, the technological forte of the partner is what matters the most. RTA index measures the relative technological strength of a firm in a particular technological sector. A firm with a higher RTA in a sector is technologically superior in that sector. Assume two allying firms, i

and j, are active in a total of n technological sectors[11]. Technological relatedness is then calculated as

$$REL_{ij} = \left(\sum_{b=1}^{n} \frac{\sum_{a=1}^{16} \left[Patent_{m,a} \times relatedness(a,b) \right]}{\sum_{a=1}^{16} Patent_{m,a}} \right) \Big/ n \ ,$$

where Firm m is the firm (either Firm i or Firm j) with a higher RTA in the technology sector b. $Patent_{m,a}$ represents the number of patents applied by Firm m in technology sector a. $relatedness(a,b)$ is the relatedness between technology sector a and b obtained from the related matrix calculated by the 2004 biotechnology sample.

6.3. Control variables

To compare with Sampson (2004) and Colombo (2003)'s discussions on the knowledge-based and transaction-cost perspectives, I also include the following control variables:

Breadth of Alliance Activities (BREADTH): "Breadth of Alliance Activities" is set to one when an alliance includes activities beyond just collaborative research and development. Sampson (2004) shows that wider alliance activities lead to a higher level of integration in the alliance form.

Prior and Concurrent Alliances (PALLI): This measure is calculated by the number of prior and concurrent ties between allying firms in the focal alliance (Sampson 2004). She suggests that the more prior and concurrent alliances there are between the allying firms, the less is the probability of opportunistic behavior; thus, the less

[11] To be considered as being active in a technological sector, the firm needs to have at least 6 patents in that sector.

integration is needed. The variable is also included as a control for occurrence dependence problem.

General Firm Reputation (REPU): A firm's reputation effect is the lowest number of prior alliances for all allying firms in the focal alliance. As in the case of the PALLI variable, transaction-cost economics predicts that with a higher reputation, less integration is needed.

I include the following control variables in the model, which are suggested by previous literatures.

The **AGE** is the years of establishment of the younger firm in the focal alliance. **R&D Intensity of the alliance (SIZE)** is the R&D expenditures to employee ratio. I use this index to measure the relative size of alliances. **Difference in R&D intensity (RD_GAP) and difference in technological diversity (DIV_GAP)** between allying firms have sometimes been used as proxies for the extent of divergence of firms' capabilities. I include these two variables to control for any difference in capabilities that has not been captured by technological similarity (SIM), technological relatedness (REL), and technological diversity. To control for time-specific patterns, I have dummies for years 1999 and 2000 (**Y99 and Y00**) in the model.

I also include an interaction term between age and technological relatedness (**RELAGE**). Teece et al. (1994) and Breschi et al. (2004) both suggest that firms develop in a coherent way. Firms are constrained in the directions of their technological search, which is strongly influenced by firms' core technologies and products. I suggest that the firm gives critically related technologies a priority in the process of knowledge acquisition. After years of establishment, the firm would have already obtained the most closely related technologies and formed a relatively stable path of technological expansion. Therefore, technological relatedness may have different influences on younger firms and older firms.

7. Results: comparison among three models

Table 2 and Table 3 show the descriptive statistics and the Pearson correlation matrix of independent and control variables. Results of the econometric estimates of the multinomial logit models are illustrated in Table 4. The table shows the estimates of the coefficients of the independents variables, their standard errors, and the individual and joint significant levels.

[Table 2 here]

[Table 3 here]

[Table 4 here]

The main objective of this study is to highlight the role played by the firm-specific technological characteristics in the choice of R&D alliance forms. I run three models to compare the transaction-cost perspective, the "traditional" knowledge-based theory, and the "complete" knowledge-based theory. The findings of the regressions clearly support the arguments inspired by the knowledge-based theory of the firm.

Model 1 is the model tested by Sampson (2004). I do not include *Narrow or Broad Alliance Activity* because of information availability. Also, I omit the *Multilateral Alliance* because all the alliances are bilateral. In Sampson's model, which is in favor of transaction costs economics, both SIM and the squared term of SIM were significant, which implies a quadratic relationship between organizational choice and knowledge similarity (technological diversity in her model). However, in Model 1 here both terms are insignificant. Also, BREADTH is significant and negative, which means the more different types of activities the alliances involves, the more likely the allying firms choose less integrated organizational mode, which is opposite to the positive and significant estimate from Sampson's model.

The difference between Model 2 and Model 3 is that Model 2 only considers technological similarity, as most studies on the organizational form in the knowledge-based theory did. In Model 2, the coefficient of technological similarity (SIM) is negative and significant, implying a less integrated mode is preferred for alliances between firms with highly similar technologies. The result is consistent with Hypothesis 1b about learning technology. BREADTH is still negative and significant. SIZE is positive and significant. Recall that SIZE is calculated as R&D intensity of the alliance. Thus the higher the intensity of the R&D activity, the more likely the allying firms choose the higher integrated organizational mode. An intensive R&D investment shows the critical importance learning and innovation. With this key business strategy, a firm values gaining knowledge and is willing to bear higher costs in managing dissimilar knowledge.

In Model 3, I include technological similarity, relatedness, and diversity measures and the interactions terms. All technology-related variables are significant, except the interaction between similarity and R&D firms' diversity.

An initial inspection of the results in Table 4 shows general support for the hypothesis about technology similarity derived from the learning-knowledge line of thought – increasing technological dissimilarity between allying firms increases the probability that allying firms choose a more integrated mode. As firms become less overlapped in their technological expertise with their partners, they are more likely to choose a more integrated mode, such as a minority equity R&D alliance instead of a simple R&D agreement. The more dissimilar a firm is from its partner in terms of technological specialization, the greater the need and the gains from enhanced knowledge substitution and flexibility over the course of the alliance. In this sense, firms appear to choose alliance form mainly in response to considerations over learning technology.

At a higher level of technological similarity, however, the results suggest a slightly different story – the relationship between technological similarity and organizational choice reverse in sign. The coefficient on squared technological similarity is positive and significant. Initially, rising similarity decreases the probability of choosing a higher integration mode. However, beyond a certain level of technological similarity, this relationship turns positive. Technological similarity beyond this minimum point actually increases the probability that a more integrated mode is chosen.

To better illustrate the relationship between technological similarity and organization choice, I calculated the expected probability that partners select a minority equity R&D alliance and the expected probability that partners select a collaborative R&D agreement at all levels of technological similarity. Follow Sampson (2004)'s method, I take the estimates form Table 4 and evaluate these estimates at the median values of the independent and the control variables. I then calculate the expected probability over all values of technological similarity in the sample, ranging from -0.50657 to 0.73335. These calculations are graphed in Figure 1 and Figure 2.

[Figure 1 here]

[Figure 2 here]

The figures show that technological similarity definitively bears a non-monotonic relationship with alliances' organizational choice. Allying firms more likely select a more integrated mode as their technological specialization diverges. Beyond a relatively high level of similarity, though, firms are more likely to choose a high integration mode as technological similarity increases. The fact that this effect inverses as partners' technologies become more overlapped lends empirical support to the line of thought emphasizing managerial costs as two firms with similar technologies cooperate (Hypothesis 1a). Firms tend to bring in-house similar technologies which incur lower managerial costs to realize economies of scale in managerial ability. It follows that taking advantage of economies of scale and lower managerial costs is the main concern in R&D alliances between firms with a certain high level of technological similarity.

The coefficient of technology relatedness is positive and significant, which supports Hypothesis 2. Superior in closely related technologies leads to a more integrated mode in R&D alliances. Keeping closely complementary technologies within a closer access realizes the economies of scope of the fixed level of managerial resources and avoids the high dynamic transaction costs caused by leaving complementary technology assets in the market. The interaction term between the years of establishment of younger firms and technological relatedness is negative and significant, though. This shows that firms' technological capabilities grow in a dynamic and path-dependent way. Newly established firm needs to acquire and assimilate closely related technologies. They are more likely to acquire related technologies by integration in R&D alliances. However, the firm's core competence, which decides both its technology profile and growth direction, would become stable after years of development. Thus, older and more established firms would have already established its unique technological portfolio, which contains complementary technologies critical to its survival and growth. Thus, technological relatedness has a weaker influence on organizational choice in the alliances between older firms.

Technological diversity of client firms has a positive and significant interaction with similarity. For a given level of similarity, a technologically diversified client firm increases the probability that an alliance is formed as a highly integrated mode. The finding supports that the firm is stable in its technological strategies – a technological generalist tends to go on as a generalist. The effect of R&D firms' technological diversity is not significant. It may be because that client firms take a more active role in learning and managing new technologies in R&D alliances than R&D firms.

In Model 3, BREATH is still negative and significant. The positive and significant effects of AGE and SIZE suggest that older and R&D intensive firms tend to employ more integrated modes in R&D alliances.

8. Discussion and conclusions

Previous studies have already provided evidence related to the relation between firm's technological capabilities and alliance form. Relying mainly on arguments in transaction-cost approach, Nakamura et al. (1996) contend that joint ventures are generally aimed at combining dissimilar yet complementary specialized intangible assets possessed by different firms. Colombo (2003)'s study supports the knowledge-based theory that in technological alliances divergence in partners' technological specialization results in a higher propensity to use equity form. Stuart (1995) highlights that the firm' technological characteristics, including overlapping technological niches and technological diversity, affect the likelihood of two firms to form an alliance.

The main objective of this paper is to provide a thorough analysis and empirical test of arguments suggested by the knowledge-based theory of the firm as regards the organizational choice of R&D alliances. The findings in the study are consistent with previous researches. And it supports the knowledge-based theory in a more direct way by a thorough analysis of how firms' tacit and idiosyncratic technological capabilities influence the choice of alliance form.

Previous studies believed that it is difficult to test whether an independent knowledge-based theory of the firm is needed besides transaction costs economics in explaining the organizational choice problem since the predictions of such theories often coincide (Sampson 2004; Conner and Phrahalad 1996). However, two problems in current studies may mistakenly lead to the coincidence.

First, to discuss the influence of knowledge similarity on the organizational choice, transaction costs economics assumes a specific relationship between knowledge similarity and the probability of opportunistic behaviors. Transaction cost economics has been highlighting the need to cope with opportunistic behavior and emphasizing using the highly integrated organizational mode to control opportunistic behaviors and reduce opportunism-related transaction costs. As suggested by Colombo (2003), transaction cost economics has no clear predictions as to the influence exerted by knowledge similarity on the choice of the governance mode of alliances. The divergence of partners' technological capabilities may lead to either a decrease or an increase in transaction costs, depending on whether appropriability hazards caused by unintended knowledge spillovers to partners or contractual hazards associated with the "hold-up" problem prevail. It is hard to draw a conclusion generally. The knowledge-based theory, incorporating both learning and managing technology, suggests that if allying firms have dissimilar technology capabilities, they tend to choose a higher integration mode to facilitate knowledge flow. When two allying firms have highly similar technologies capabilities, the main concern of the alliances would be to take advantage of the economies of scale in managing technology, and thus the higher integration mode would be chosen within an alliance between two firms with highly similar technological portfolios. This result is consistent with Sampson (2004) result in the study of telecommunication industry, although she explained the trend through transaction costs perspective. Generally, learning technology is the dominating process in R&D alliances. The negative and significant effects of knowledge similarity is observed in both Colombo (2003) and the study here (Model 2).

The other problem is the lack of differentiation between technological similarity and technological relatedness. There is a tendency to mean "related technology" by saying "similar technology." However, "similar" technologies are not necessarily "related." Richardson (1972, pp. 888-890) defines "similar activities" as "activities which require the same capability for their undertaking," while he explains complementary activities or related activities as " activities … present different phases of a process of production and require in some way or another to be coordinated" and he points out complementary activities need not to be similar. The tire industry is closely complementary (related) to the car industry. However, technologies in these two industries are not necessary similar to each other[12]. Previous researches have been studying the relationship between technology capabilities and organizational choice without unambiguously distinguishing between similar capabilities and related capabilities. The findings show that these two technological characteristics have distinct contributions to explaining the organizational choice. Technological relatedness significantly increases the possibility of allying firms to use a higher integration mode in R&D activities.

Besides technological similarity and relatedness, technology diversity also has a significant impact on the choice of the governance form. The findings show that the firm is consistent in its technological development strategy. At the same level of technological similarity, a technology generalist tends to integrate more technologies within its boundary.

[12] Thanks for Richard N. Langlois for clarifying these two concepts.

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Table 1

R&D Alliances in the U.S. Biotechnology Industry during 1998-2000

Year	R&D Alliances				Firms	Patents
	R&D Agreements	R&D Collaborations	Minority Equity R&D Alliances	Total		
1998	7	16	1	24	34	3506
1999	14	20	3	37	46	4537
2000	21	23	6	50	72	5483
Total	40	59	10	111	115	

Table 2

Descriptive Statistics

Variable	N	Mean	Std Dev	Sum	Minimum	Maximum
Alliance Form **(ORG)**	111	0.71171	0.62359	79	0	2
Technological Similarity **(SIM)**	111	0.27043	0.27699	30.01787	-0.50657	0.73335
Square of Technological Similarity **(SIM * SIM)**	111	0.14916	0.15317	16.55713	0.0000276	0.5378
Technological Relatedness **(REL)**	111	2.07157	0.75692	229.94433	-0.16714	4.29575
Interaction: REL*AGE **(RELAGE)**	111	14.76916	10.12672	1639	-1.83853	50.64456
Interaction: SIM*DIVC[a] **(SIMDIVC)**	111	0.15071	0.20706	16.72923	-0.83341	0.66756
Interaction: SIM*DIVD[b] **(SIMDIVD)**	111	0.14294	0.15613	15.86678	-0.33586	0.5636
Breadth of Alliance Activities **(BREADTH)**	111	0.09009	0.28761	10	0	1
Prior and Concurrent Alliances **(PALLI)**	111	0.16216	0.41649	18	0	2
General Firm Reputation **(REPU)**	111	16.34234	12.42541	1814	0	66
The Age of the allying firm **(AGE)**	111	7.22523	3.96045	802	0	21
R&D Intensity of alliance **(SIZE)**	111	0.13351	0.08393	14.81991	0.00255	0.62573
difference in R&D intensity **(RD_GAP)**	111	0.10976	0.09534	12.18351	0.0007359	0.56975
difference in knowledge diversification **(DIV_GAP)**	111	0.25282	0.24074	28.0625	0.0003812	1.20061
network autocorrelation adjustment **(CORRECT)**	111	0.02673	0.0301	2.96743	0	0.13043

[a] DIVC is technological diversity of the client firm.
[b] DIVD is technological diversity of the R&D firm.

Table 3
Pearson Correlation Matrix

	ORG	SIM	SIM*SIM	REL	RELAGE	SIMDIVC	SIMDIVD	BREADTH
ORG	1							
Alliance Form								
SIM	-0.02299	1						
Technological Similarity	(0.8107)							
SIM*SIM	0.05446	0.77071	1					
Square of Technological Similarity	(0.5702)	(<.0001)						
REL	-0.03395	-0.01208	-0.06224	1				
Technological Relatedness	(0.7235)	(0.8998)	(0.5164)					
RELAGE	-0.10401	0.00032	-0.00748	0.47907	1			
Interaction: REL*AGE	(0.2773)	(0.9973)	(0.9379)	(<.0001)				
SIMDIVC	0.01902	0.885	0.57081	0.00997	0.02631	1		
Interaction: SIM*DIVC	(0.8429)	(<.0001)	(<.0001)	(0.9173)	(0.784)			
SIMDIVD	-0.01421	0.89232	0.63552	0.10708	0.09619	0.79947	1	
Interaction: SIM*DIVD	(0.8824)	(<.0001)	(<.0001)	(0.2633)	(0.3153)	(<.0001)		
BREADTH	-0.20869	-0.04313	-0.02503	0.12148	0.10951	-0.04312	-0.0668	1
Breadth of Alliance Activities	(0.0279)	(0.6531)	(0.7943)	(0.204)	(0.2526)	(0.6532)	(0.4861)	
PALLI	-0.06338	0.17781	0.1787	-0.03475	-0.1454	0.21007	0.20135	0.02872
Prior and Concurrent Alliances	(0.5087)	(0.0619)	(0.0606)	(0.7173)	(0.1278)	(0.0269)	(0.0341)	(0.7648)
REPU	-0.1033	-0.04238	-0.072	0.07766	0.21529	-0.02081	0.06104	-0.11046
General Firm Reputation	(0.2806)	(0.6588)	(0.4527)	(0.4179)	(0.0233)	(0.8283)	(0.5245)	(0.2484)
AGE	-0.04709	0.02795	0.04301	-0.06678	0.80118	0.03574	0.06746	0.06184
The Age of the Allying Firm	(0.6236)	(0.7709)	(0.654)	(0.4862)	(<.0001)	(0.7096)	(0.4818)	(0.5191)
SIZE	0.27292	0.17137	0.05481	-0.08314	-0.09405	0.12473	0.14409	-0.20297
R&D Intensity of the Alliance	(0.0038)	(0.0721)	(0.5678)	(0.3856)	(0.3262)	(0.1921)	(0.1314)	(0.0326)
RD_GAP	0.03069	0.02934	-0.06597	0.20042	-0.00983	-0.01161	0.01317	0.25065
Difference in R&D Intensity	(0.7491)	(0.7599)	(0.4915)	(0.0349)	(0.9184)	(0.9037)	(0.8909)	(0.008)
DIV_GAP	-0.01634	-0.2504	-0.05949	0.14652	0.06374	-0.17889	-0.20027	-0.02188
Difference in Technological Diversity	(0.8648)	(0.008)	(0.5351)	(0.1249)	(0.5063)	(0.0603)	(0.0351)	(0.8197)
CORRECT	-0.07215	-0.01364	-0.07644	0.12102	-0.23289	0.0792	0.02018	-0.02708
Network Autocorrelation Adjustment	(0.4518)	(0.887)	(0.4252)	(0.2058)	(0.0139)	(0.4086)	(0.8335)	(0.7778)

Table 3 (Continued)
Pearson Correlation Matrix

	PALLI	REPU	AGE	SIZE	RD_GAP	DIV_GAP	CORRECT
ORG							
Alliance Form							
SIM							
Technological Similarity							
SIM*SIM							
Square of Technological Similarity							
REL							
Technological Relatedness							
RELAGE							
Interaction: REL*AGE							
SIMDIVC							
Interaction: SIM*DIVC							
SIMDIVD							
Interaction: SIM*DIVD							
BREADTH							
Breadth of Alliance Activities							
PALLI	1						
Prior and Concurrent Alliances							
REPU	0.09809	1					
General Firm Reputation	(0.3057)						
AGE	-0.13257	0.17928	1				
The Age of the Allying Firm	(0.1654)	(0.0597)					
SIZE	-0.02029	0.04999	-0.08861	1			
R&D Intensity of the Alliance	(0.8326)	(0.6023)	(0.355)				
RD_GAP	0.06008	-0.00688	-0.11889	0.35014	1		
Difference in R&D Intensity	(0.5311)	(0.9428)	(0.2139)	(0.0002)			
DIV_GAP	0.16114	0.0234	-0.01215	-0.20719	-0.0516	1	
Difference in Technological Diversity	(0.0911)	(0.8074)	(0.8993)	(0.0291)	(0.5907)		
CORRECT	0.21134	0.16902	-0.37582	0.04941	0.24767	0.12278	1
Network Autocorrelation Adjustment	(0.026)	(0.0762)	(<.0001)	(0.6066)	(0.0088)	(0.1992)	

Table 4

Determinants of Organizational Choice: Estimation of Cumulative Logit Multinomial Model

Parameter	Model 1	Model 2	Model 3
Intercept1 (ORG=2)	-1.7567***	-2.5895***	-5.7139***
	(0.5888)	(0.7292)	(1.6936)
Intercept2 (ORG=1)	1.1872**	0.5627	-2.2760
	(0.5507)	(0.6521)	(1.5975)
SIM	-1.2727	--2.1246*	-8.8635***
	(1.1078)	(1.2330)	(3.3317)
SIM*SIM	2.3426	3.5354	6.9359***
	(2.0513)	(2.1953)	(2.5801)
REL			1.4842**
			(0.6491)
RELAGE			-0.1881**
			(0.0797)
SIMDIVC			5.6977**
			(2.5391)
SIMDIVD			2.3713
			(3.1623)
BREADTH	-1.7040**	-1.4298*	-1.6210**
	(0.7501)	(0.8296)	(0.9308)
PALLI	-0.1424	-0.0646	-0.2736
	(0.4748)	(0.4874)	(0.5191)
REPU	-0.0196	-0.0213	-0.0189
	(0.0158)	(0.0163)	(0.2886)
AGE			0.3703**
			(0.1815)
SIZE		7.0431**	8.7791***
		(2.8745)	(3.1367)
RD_GAP		0.6574	0.7682
		(2.5385)	(2.7216)
DIV_GAP		-0.1922	-0.7108
		(0.8990)	(0.9562)
CORRECT	-3.5646	-6.1385	-10.3184
	(6.8087)	(7.3867)	(8.1665)
Y99	0.0154	-0.0212	0.0539
	(0.5188)	(0.5508)	(0.5743)
Y00	-0.1748	-0.5350	-0.4649
	(0.7362)	(0.5504)	(0.6045)
N	111	111	111
LOG(L)	-97.6257	-93.1116	-87.0614
LR test	9.099	18.1272*	30.2276**
D.O.F.	8	11	16

*** chisq < 0.01
** chisq < 0.05
* chisq < 0.1

Figure 1

The Effect of Technological Similarity on Organizational Choice

(Between ORG=2 and ORG=0)

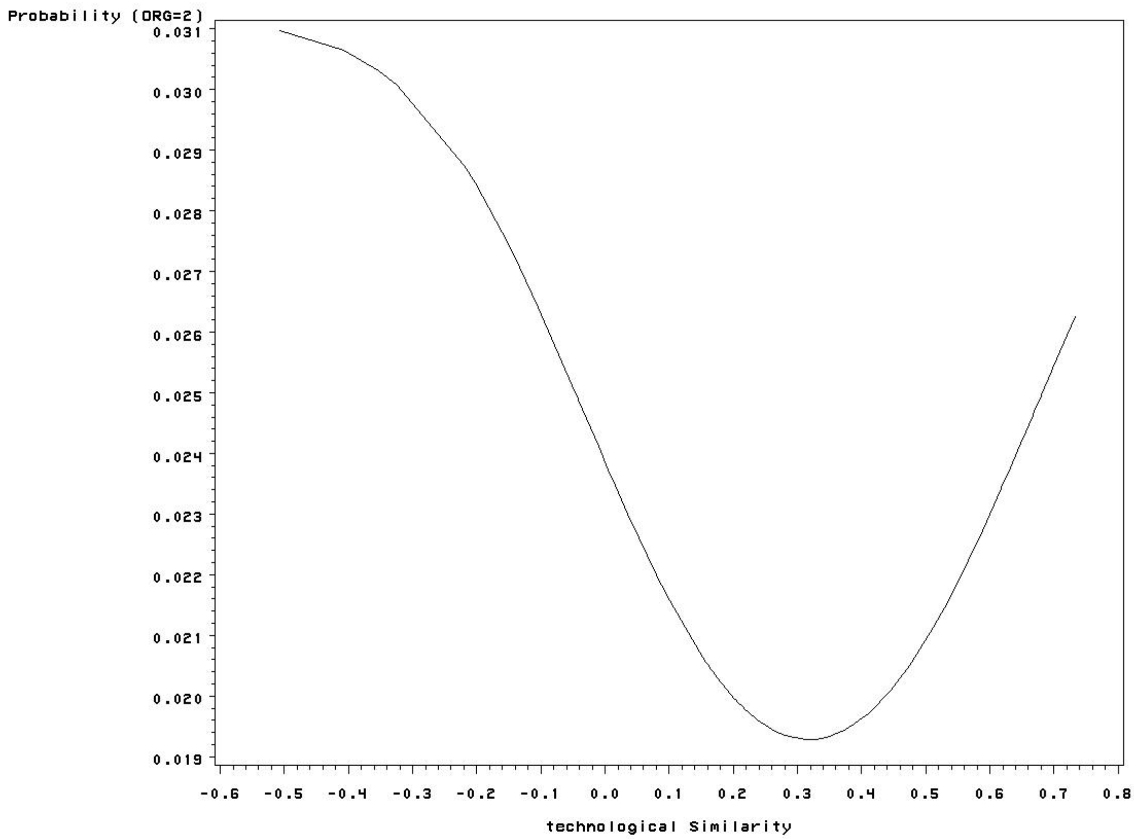

Figure 2

The Effect of Technological Similarity on Organizational Choice

(Between ORG=1 and ORG=0)