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COMPLEMENTARY TECHNOLOGIES, KNOWLEDGE RELATEDNESS, AND INVENTION OUTCOMES IN HIGH TECHNOLOGY MERGERS AND ACQUISITIONS

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Prior research on M&As and invention outcomes has not systematically examined the influence of two types of knowledge differences. Knowledge relatedness has typically been equated with knowledge similarity and the separate influence of knowledge complementarity has been overlooked. Similarly, studies examining innovation outcomes of M&As have typically focused on the role of technological knowledge and overlooked the influence of scientific knowledge. We develop a model of relatedness and invention performance of high-technology M&As that considers science and technology similarity and complementarity as important drivers of invention. We test the model using a sample of M&As from the drug, chemical, and electronics industries and a fine-grained measure of knowledge relatedness that distinguishes between science and technology relatedness. We find that complementary scientific knowledge and complementary technological knowledge both contribute to post-merger invention performance by stimulating higher quality and more novel inventions. This suggests that high-technology firms seeking acquisitions should search for, identify, and acquire businesses that have scientific and technological knowledge that is complementary to their own. Our results also suggest that similarities in knowledge facilitate incremental renewal, while complementarities would make discontinuous strategic transformations more likely, and that absorptive capacity research should be expanded to consider complementarities as well as similarities. Copyright © 2010 John Wiley & Sons, Ltd.

INTRODUCTION

The speed of innovation and need for novel solutions in high-technology industries often motivates firms to extend their resources and capabilities through mergers and acquisitions (M&As) (Hagedoorn, 2002; King, Slotegraaf, and Kesner, 2008). In the latter half of the twentieth century, M&As became a prominent strategy for many companies, large and small. This is exemplified by the fact that global mergers and acquisitions were valued at $3.6 trillion in 2006 (Cimilluca, 2007). Furthermore, the strategic use of acquisitions to acquire new knowledge and capabilities has become a well institutionalized corporate phenomenon (Uhlenbruck, Hitt, and Semadeni, 2007).
2006; Vermeulen and Barkema, 2001). In a study of over 9,000 transactions between 1990 and 2000, Villalonga and Mcgahan (2005) found that the likelihood a firm would choose acquisition over other forms of collaboration increased when the technological resources of the potential target/partner were higher. Technologically rich acquisition targets provide opportunities for organizational learning by exposing the acquirer to new and diverse knowledge (Ghoshal, 1987; Hitt et al., 1996).

Research on high-technology M&As has identified the relatedness of the buyer’s and the target’s technological knowledge as an important predictor of post-merger innovation performance (Cloodt, Hagedoorn, and Van Kranenburg, 2006; Cassiman et al., 2005; Hagedoorn and Duysters, 2002). The positive effect on innovation is, in part, based on absorptive capacity; the more similar the two firms’ technological knowledge, the more quickly the acquired firm’s knowledge can be assimilated and commercially exploited (Cohen and Levinthal, 1990; Lane and Lubatkin, 1998). However, too much similarity reduces the acquirer’s opportunities for learning (Ghoshal, 1987; Hitt et al., 1996). Cloodt et al. (2006), for example, found an inverted U-shaped relationship between technological relatedness and post-merger innovation performance in high-technology industries. Innovation performance (invention quantity) was lowest for M&As in which the firms operated in highly similar or largely unrelated technology areas and highest when there was a moderate degree of overlap. M&As that integrate highly similar technologies narrow the range of potential learning and also reduce the incentives to explore divergent research opportunities available from M&As. Cassiman et al. (2005) found that firms are more likely to reduce research and development (R&D) effort, shorten the time horizon of projects, and emphasize development over research when they acquire targets with similar technologies than when they acquire targets that have complementary technologies. In short, M&As most improve innovation performance when the technological knowledge is similar enough to facilitate learning, but different enough to provide both new opportunities and the incentives to explore them.

Prior research suggests that the independent effects of similarity and complementarity of the acquirer’s and the target’s technological knowledge are important predictors of post-merger innovation performance (Ahuja and Katila, 2001; Cloodt et al., 2006; Cassiman et al., 2005; Hagedoorn and Duysters, 2002). Further, research suggests that science and technology have independent as well as interactive effects on firm innovation performance (Henard and McFadyen, 2005). Science influences not only technology development, but also the techniques available for that exploration (Nightingale, 1998). Therefore, to fully understand the outcomes of M&As between high-technology firms, we need to examine the distinct effects of science and technology similarities and complementarities between the two firms on the innovation outcomes for the merged firm; in this research we focus on inventions.

Using recent research on science, technology, and invention (Makri, Lane, and Gomez-Mejia, 2006; Henard and McFaddyen, 2005), we develop and test a more robust model of relatedness and invention performance of high-technology M&As that considers science similarity and complementarities as important drivers of invention. We propose that the addition of complementary science from an acquisition influences post-merger invention performance directly and indirectly through its interaction with technology. More specifically, complementary scientific knowledge and complementary technological knowledge both contribute to post-merger invention performance.

Our study makes several contributions to our knowledge of M&As. First, the study shows that acquisitions can contribute to higher quality inventions if the appropriate knowledge is acquired. Second, the research emphasizes the importance of knowledge complementarity to the success of high-technology acquisitions. Third, it introduces an objective measure of knowledge relatedness that distinguishes between science and technology relatedness. This measure makes possible a fine-grained assessment of firms’ knowledge relatedness and enables a more comprehensive assessment of the value creation potential between two merging firms. In particular, this research shows

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1 Invention refers to the development of a new idea and the establishment of property rights on that idea. Innovation, on the other hand, refers to the commercialization of the invention. In this study, we restrict our attention to the creation of the actual inventions (patents) rather than their subsequent commercialization, and thus use the term invention to present a wholly accurate view of the invention and innovation process/outcomes.
the importance of science knowledge as a base and the contribution of science knowledge complementarity in M&As to post-acquisition invention performance. Fourth, this research emphasizes the value of the target selection phase of acquisitions because the type and degree of knowledge relatedness are significant determinants of post-M&A success. We first address the two types of knowledge considered, science and technology, and discuss their role in invention to provide the foundation for the definition of knowledge relatedness.

SIMILARITY, COMPLEMENTARITY, AND THE ROLE OF SCIENCE AND TECHNOLOGY IN INVENTION

There has been little consistency in the conceptualization and operationalization of innovation and innovativeness because of the diverse scholastic communities that study this topic (Garcia and Calantone, 2002). Garcia and Calantone suggest that ‘an invention does not become an innovation until it has processed through production and marketing tasks and is diffused into the marketplace’ (Garcia and Calantone, 2002: 112). The solution of a scientific puzzle or the invention of a new technology in the laboratory still remains an invention. Thus, invention includes the basic and applied research that is yet unexploited in the marketplace. Alternatively, innovation involves the exploitation of an invention through product development, manufacturing, marketing, distribution, and after-sales service. As a result, an innovation differs from an invention in that it provides direct economic value to the firm and is diffused to other parties beyond the discovering firm (Garcia and Calantone, 2002; Ahuja and Lampert, 2001).

A popular view in traditional technology management considers invention as a process of recombination (Fleming and Sorenson, 2004). Research in this tradition holds that invention is derived from combining technological components in a novel manner (e.g., Nelson and Winter, 1982, Weitzman, 1996), or from reconfiguring existing combinations (Henderson and Clark, 1990). The recombination process is facilitated by two types of knowledge. The first is knowledge about the core design concepts and the way in which they are implemented in a particular component (scientific knowledge). The second is knowledge about the ways in which the components are integrated and linked together into a coherent whole (technological knowledge). Understanding and differentiating scientific knowledge and technological knowledge are important because science and technology are unique and affect the process of discovery in different ways. The differences between science and technology are discussed next.

The role of science and technology in invention

According to the National Science Foundation, applied research (technology2) involves research projects with specific commercial objectives regarding either products or processes. Alternatively, basic research (science) is the set of ‘research projects which represent original investigation for the advancement of scientific knowledge and do not have specific commercial objectives, although they may be in fields of present or potential interest to the company’ (NSF, 1961: 53). Patents are considered a representation of applied research outcomes, while papers and citations to them are viewed as representations of science (Meyer, 2000).

Technology is driven by pressures from markets for products and services (Clark, 1987; Balmer and Sharp, 1993). Often a firm response to perceived customer needs or competitive moves by rivals begins with an idea of what it needs to develop (i.e., new features to add, performance characteristics to improve, costs to reduce). In contrast, science is driven by the interests and goals of the researchers (Balmer and Sharp, 1993; Clark, 1987). It has a known starting point, but the search moves toward an unknown end (Nightingale, 1998). In short, science cannot be used as a simple direct input into technology development because it is not focused on specific questions (Nightingale, 1998). Rather, scientific findings provide important base knowledge for additional but more directed research. Thus, it plays an important but indirect role.

In recent years, economists and bibliometricians have concluded that the flow between scientific and technological knowledge is neither linear nor one-way (Meyer-Krahmer and Schmoch, 1998; Narin, Hamilton, and Olivastro, 1997). Basic research still plays an important role (Turney, 2

2 Empirical studies have considered patents as a representation of technology, while papers and citations to them are viewed as representations of science (Meyer, 2000; Gittleman and Kogut, 2003).
Complementary Technologies, Knowledge Relatedness

1991), but technology is now acknowledged to assist and inform that research. The interrelatedness is reflected by Rip’s two-branched model of innovation with its emphasis on interconnected processes of exploitation and exploration (Rip, 1992). Science and technology are now seen as ‘dancing partners’ that evolve around each other yet follow different steps in their development (Rip, 1992). While both create new knowledge, science and technology are driven by different motivations and thus seek to do it in different ways (Murray, 2002). Technology similarities within a firm’s knowledge domain lead to local searches and exploitation of what is already known (e.g., Martin and Mitchell, 1998; Stuart and Podolny, 1996). Alternatively, science complementarities lead to distant search behaviors and exploratory processes (Miner, Bassoff, and Moorman, 2001). But, it is important to note that recombinations of technological knowledge can lead to radical advances (Fleming, 2001).

There are important reasons why high-technology firms to invest in science. Firms engage in basic research because of a concern that the fundamental knowledge they need to advance is lacking and unlikely to come from the academic sector (Stephan, 1996). In addition, having a reputation for performing ‘good’ science may be necessary to attract the type of human capital the firm needs to develop inventions and ultimately innovation (Stern, 2004). Further, practicing science internally helps firms to maintain the absorptive capacity necessary to acquire external knowledge (Cockburn and Henderson, 1998; Markiewicz, 2006; Gambardella, 1992). Also, firms may engage in science-based research because it enhances the process of investigation: ‘[it] may transform invention from a relatively haphazard search process to a more directed identification of useful new combinations’ (Fleming and Sorenson, 2004: 910). Additionally, firms engage in science research because it suggests new areas for major technological advances (Dosi, 1982). Finally, evidence suggests that high-technology firms adopting a scientific research orientation outperform those that do not (Henderson and Cockburn, 1994; Gambardella, 1992).

In short, prior work concludes that high-technology firms engage in science-based research because they believe it is valuable as a competitive tool. Numerous studies in pharmaceuticals and biotechnology show that an internal science orientation leads to higher research productivity (Cockburn and Henderson 1998; Cockburn, Henderson, and Stern, 2000; Gambardella, 1992; Powell, Koput, and Smith-Doerr, 1996; Zucker, Darby, and Armstrong, 2002). Patents that build on science are more likely to be cited, hence, more likely to generate additional inventions and value. Therefore, integrating scientific research with technology has a positive impact on a firm’s invention.

### Knowledge relatedness redefined

Defining and measuring relatedness are central issues in strategic management research, but prior research has shown an equivocal effect of relatedness on firm performance (e.g., Mahajan and Wind, 1988; Hill and Hoskisson, 1987; Singh and Montgomery, 1987; Elgers and Clark, 1980). The conflicting results regarding the outcomes of relatedness arise from two interconnected problems. First, relatedness across product and market domains does not necessarily imply relatedness in knowledge domains and vice versa. Because knowledge is the primary resource on which competitive advantage is created, especially for high-technology firms, it is important to examine relatedness in terms of firms’ knowledge domains. Second, relatedness has commonly been defined in broad terms, often using similarity and complementarity interchangeably (i.e., Davis et al., 1992; Farjoun, 1998); others have provided incomplete or tautological definitions of complementarity (Mowery, Oxley, and Silverman, 1998), and a few have ignored it (Lane and Lubatkin, 1998; Ahuja and Katila, 2001).

Larsson and Finkelstein’s (1999) work provides the basis for a more complete definition of knowledge relatedness. Integrating their concepts of ‘economies of sameness’ and ‘combination potential’ (Larsson and Finkelstein, 1999: 6, respectively) with the definitions of science and technology domains presented earlier suggests the following:

- **Science similarity** between firms is the degree to which their scientific research focuses on the same narrowly defined areas of knowledge.

- **Science complementarity** between firms is the degree to which their scientific research...
focuses on different narrowly defined areas of knowledge within a broadly defined area of knowledge that they share.

Technology similarity between firms is the degree to which their technological problem solving focuses on the same narrowly defined areas of knowledge.

Technology complementarity between firms is the degree to which their technological problem solving focuses on different narrowly defined areas of knowledge within a broadly defined area of knowledge that they share.

The definitions of science and technology complementarity refer to knowledge complementarities within a value chain activity (R&D) as opposed to asset complementarities across different value chain activities. While synergies can arise from knowledge relatedness at multiple points of the value chain (Tanriverdi and Venkatraman, 2005), because invention is critical for the success of high-technology firms, it is important to assess knowledge relatedness within R&D. Therefore, focusing on knowledge relatedness in one dimension of the value chain (R&D) provides for a richer and more complete specification of this construct and permits us to directly measure knowledge relatedness at the firm level. Further, limiting the definition of complementarity in this domain facilitates the empirical analysis. Yet, it also supports the broader definition of complementarity in economics in which combining one input with another increases the marginal returns from that input (Milgrom and Roberts, 1990, 1995). Additionally, because science and technology are ‘dancing partners’ (Rip, 1992), enriching a firm’s science knowledge domain can enhance its technology domain. As such, complementarity used herein implies integration potential.

KNOWLEDGE RELATEDNESS AND INVENTION IN HIGH-TECHNOLOGY M&AS

For firms that rely on continuous innovations as a source of competitive advantage, knowledge synergies have become increasingly critical. Ahuja and Katila (2001) and Cloodt et al. (2006) found that relatedness of the acquiring and target firms’ knowledge bases has a curvilinear effect on invention output. Additionally, Cassiman et al. (2005) found that when the merged entities are technologically complementary, their R&D productivity increases. Yet, more research is needed to address the differential effects of science and technology and the effects of knowledge complementarities on invention outcomes.

When two firms similar in both science and technology domains merge and combine their knowledge bases, they are commonly ‘dancing to the same music, using similar steps’ because they are familiar with the types of technological problems likely to surface and rely on similar sets of scientific theories to understand and resolve them. They experience similar ‘know-whats’ (the semantics and challenges of a particular information domain) and similar ‘know-hows’ (an understanding of how semantics and challenges are causally linked) (Lubatkin, Florin, and Lane, 2001). Further, the more similar the new knowledge is to the firm’s existing knowledge, the more easily the new knowledge can be understood, assimilated and applied operationally because of the acquiring firm’s absorptive capacity (Cohen and Levinthal, 1990; Lane and Lubatkin, 1998). Also, experience with similar knowledge domains is likely to make the search process more predictable and more efficient.

These arguments suggest that knowledge similarities (technology similarity in particular) facilitate the exchange and combination of existing knowledge (Nonaka, Takeuchi, and Umemoto, 1996) and encourage exploitation of what is already known. As such, an increase in invention productivity through patents in new technology areas is unlikely to result from combining two scientific and technologically similar firms. Conversely, integrating firms with similar technology and science domains likely enhances invention quantity in the same technology areas on which the acquirer focused before the merger. Formally stating this relationship:

Hypothesis 1a: Similarities in the acquiring and acquired firms’ science and technology domains are positively related to invention quantity in similar technology domains post M&A.

4 We would like to thank Connie Helfat for identifying this issue.
Science similarity suggests that the two firms’ scientists have similar understandings of how technologies work and thereby search for new solutions in the ‘neighborhood’ of older or existing solutions. Such knowledge redundancy diminishes the opportunities for creating radically new knowledge and is unlikely to produce exploratory learning. With similarities, exploitative search is emphasized to the exclusion of exploratory learning. These arguments suggest that knowledge similarities are less likely to contribute to a radically different invention (Fleming, 2001). In fact, the interaction of both types of similarity, technology and science, entails little if any exploratory learning and thus has a negative effect on invention novelty (the degree to which a firm takes inventive risk in new technology areas). The negative relationship is largely the outcome of similarity in science because science is a primary driver of exploration.

On the other hand, the high absorptive capacity produced by the similarity in both knowledge domains provides a significant knowledge base in these domains. The combined knowledge held by the merged firm, therefore, allows it to produce useful, high-quality inventions in the ‘similar’ technology areas occupied by the firms (Fleming, 2001). In addition, DeCarolis and Deeds (1999) and Ahuja and Lampert (2001) suggest that invention quality can be reflected in the citation intensity of a firm’s patents because highly cited patents are considered more useful, of higher quality, and more likely to produce economic value for the inventing firm (Trajtenberg, 1990; Rosenkopf and Nerkar, 2001). These arguments lead to the following hypotheses:

**Hypothesis 1b:** Similarities in the acquiring and acquired firms’ science and technology domains are positively related to invention quality in similar technology domains post M&A.

**Hypothesis 1c:** Similarities in the acquiring and acquired firms’ science and technology domains are negatively related to the novelty of inventions developed post M&A.

While knowledge similarity between the acquiring and acquired firm enhances exploitation and thereby invention productivity, knowledge complementarities (science complementarities in particular), facilitate a process of exploration through experimentation with new competencies and technologies (March, 1991). Thus, acquiring complementary knowledge helps extend the scope of invention search, which in turn contributes to richer inventions; however, it may also increase knowledge integration costs (Katila and Ahuja, 2002). Integrating complementary technology or complementary science can require significant effort because it is more complex and challenging than integrating similar knowledge domains (Grant, 1996). Yet, when the acquiring and acquired firms have knowledge complementarities, they have common knowledge stocks (in broadly defined areas) that facilitate communication and coordination between the units from the two firms after the merger. Also, the common knowledge in broad areas helps each party understand the value of the unique but complementary sets of knowledge. These conditions facilitate the integration of their two complementary knowledge stocks in the merged firm, thereby contributing to increased invention productivity.

Rothaermel, Hitt, and Jobe (2006) found that firms able to integrate complementary knowledge from internal and external sources (through strategic alliances) increased the number of related new products introduced to the market. High knowledge complementarities between the acquiring and acquired firms enhance the merged firm’s ability to use new information in effective ways. In this way, the common general knowledge stocks increase the probability of success in invention search processes (Cyert and March, 1963). Thus, knowledge complementarities contribute positively to more and richer inventions. Stated differently, simultaneous integration of knowledge complementarities in both technology and science post acquisition enhances invention productivity. These arguments lead to the following hypothesis:

**Hypothesis 2a:** Complementarities in the acquiring and acquired firms’ science and technology domains are positively related to invention quantity post M&A.

In addition to their effect on invention productivity, knowledge complementarities affect the novelty and quality of a firm’s inventions (Hall, Jaffe, and Trajtenberg, 2001, DeCarolis and Deeds, 1999; Rosenkopf and Nerkar, 2001). The theory of recombinant invention (Fleming, 2001) suggests that the merger of two firms can potentially lead to
the creation of high-quality inventions when they have similarities in their knowledge bases but also when some fraction of their knowledge is ‘...fairly diverse...to permit effective, creative utilization of the new knowledge’ (Cohen and Levinthal, 1990: 136).

Similar activities in scientific research conducted by the acquiring and acquired firms and their work on technologies that share broadly defined areas of knowledge allow them to communicate, coordinate, and cooperate in effective ways. Yet, their foci of research in different specific knowledge areas of science and technology allow the merged firm to use the complementary knowledge and research from the two previously independent firms in ways that increase the merged firm’s exploration search processes. Exposure to new sets of routines, new modes of reasoning, and challenges to existing understandings of cause-effect relationships helps a firm discover novel solutions to problems it has identified. In Ahuja and Lampert’s words ‘...the irritant of new, imperfectly understood streams of knowledge can foster the pearls of insight’ (2001: 527).

The integration of these complementary knowledge stocks can produce unique combinations and, thus, novel inventions. Moreover, integrating both complementary technologies and complementary science provides the potential for a much greater portfolio of new and unique knowledge combinations. Science knowledge provides the base for advances in technological knowledge; in turn, technological knowledge advances also facilitate the further development and application of science knowledge. The great strides in mapping the human genome, for example, have been made possible by advances in instrumentation and computerized analytical tools—technological knowledge embodied in products and processes. The result is an ongoing series of interactions in which science and technology are ‘dancing partners’ that evolve around each other, yet each follows different steps to do so (Rip, 1992). As such, the interaction between technological and science complementarities of acquiring and acquired firms has a positive effect on the quality of inventions produced by the merged firm. These arguments lead to the following hypotheses:

Hypothesis 2b: Complementarities in the acquiring and acquired firms’ science and technology domains are positively related to invention quality post M&A.

Hypothesis 2c: Complementarities in the acquiring and acquired firms’ science and technology domains are positively related to invention novelty post M&A.

Earlier it was suggested that the merged firm is not likely to develop novel inventions (all else being equal) when the acquiring and acquired firms have high similarity in their knowledge domains. While similarity in technology and science provides substantial absorptive capacity for the acquiring firm to learn from an acquired firm, it also creates significant path dependency. As such, there is a limit to the number of new recombinations that can be created using the same set of knowledge elements. On the other hand, firms with similar knowledge bases need less time and effort to integrate their R&D activities, thereby facilitating invention productivity. Science similarity suggests that the two firms’ scientists have similar understandings of how technologies work and thereby search for new solutions in the ‘neighborhood’ of old or existing solutions. Such knowledge redundancy diminishes the opportunities for creating radically new knowledge; but, when integrated with complementary technology, it can increase potential recombinations, leading to a greater number of inventions. Further, the interaction of technology complementarities with science similarities facilitates the development of influential, high-quality inventions because technology complementarities increase the scope of invention search, thereby contributing to richer and frequently more unique inventions. Formally stated:

Hypothesis 3a: Technology complementarities combined with science similarities in the acquiring and acquired firms’ knowledge domains
are positively related to invention quantity post M&A.

Hypothesis 3b: Technology complementarities combined with science similarities in the acquiring and acquired firms’ knowledge domains are positively related to invention quality post M&A.

Hypothesis 3c: Technology complementarities combined with science similarities in the acquiring and acquired firms’ knowledge domains are positively related to invention novelty post M&A.

Science provides the basis for technological advances and contributes to exploration in the extension of existing technologies and in the development of new technologies. Science complementarities in particular facilitate the process of exploration through experimentation with new competencies and technologies (March, 1991). New competencies promote new and/or improved technology applications, and when combined with similarities in technological knowledge, they enhance invention efficiency and productivity (quantity). Alternatively, experimentation based on science complementarities enhances exploratory learning, which in turn contributes to invention quality and novelty. Therefore, complementary science, when combined with similar technology domains, can provide the base for advances in quantity, quality, and novelty of the technological knowledge. These arguments suggest the following hypotheses:

Hypothesis 4a: Technology similarities combined with science complementarities in the acquiring and acquired firms’ knowledge domains are positively related to invention quantity post M&A.

Hypothesis 4b: Technology similarities combined with science complementarities in the acquiring and acquired firms’ knowledge domains are positively related to invention quality post M&A.

Hypothesis 4c: Technology similarities combined with science complementarities in the acquiring and acquired firms’ knowledge domains are positively related to invention novelty post M&A.

Importantly, the combination of unrelated technology and science could result in the most novel discoveries. For example, the field of computational biology (computer science and biology) resulted from the combination of two very distant knowledge platforms.6 However, while the combination of unrelated technology and unrelated science can potentially produce radical inventions, the speed and ease with which such inventions can be created are likely much lower than with the combination of complementary knowledge platforms due to the lack of necessary absorptive capacity.

METHODS

We tested the hypotheses using a 1996 sample of 95 high-technology M&As (the science domain data were only available for 1996). Our sample was constructed in five steps. First, we used the Securities Data Corporation database (SDC) to select all M&As completed in 1996 in the drugs, chemical, and electronics industries because they are knowledge-intensive industries that use science in the development of inventions (Deng, Lev, and Narin, 2001; von Hippel, 1986). We excluded M&As motivated to obtain access to distribution, gain entry into new markets, obtain financial synergies, or increase market power because such acquisitions do not generate science and technology inputs, and thus are unlikely to affect innovative output. In Ahuja and Katila’s words, ‘nontechnological acquisitions add less to the knowledge base of the acquirer [and] they are less likely to lead to such innovation output-enhancing effects [such as inventive recombinations]’ (Ahuja and Katila, 2001: 199).

Second, following Finkelstein and Haleblian (2002), Harrison et al. (1991), and Chatterjee and Lubatkin (1990), we excluded deals smaller than $10 million and greater than $500 million, because firms tend to adopt a hands-off approach with small acquisitions as their effects are likely to be negligible and acquisitions greater than $500 million tend to be driven by motivations other than knowledge exchange (market power, economies of scale, etc...).

Third, data restrictions necessitated excluding all acquirers that were not publicly traded in the United States. Applications of these criteria for

6 We thank an anonymous reviewer for this example.
selecting the sample resulted in 278 deals: 31 in drugs, 37 in chemicals, and 210 in electronics industries. Fourth, we identified all name variants (i.e., names of divisions, subsidiaries, etc.) for acquirers and targets using the National Register’s Directory of Corporate Affiliations, which contains business profiles and corporate linkages for 114,000 companies worldwide. We matched these to names in the Center for Research Planning (CRP) Science Model™ database because it was essential to have data on both acquirers and targets. These requirements necessarily reduced the sample to 100 deals for which complete data for acquirers and targets were available from the CRP database. The acquirer or the target in each of the remaining 178 deals did not patent or did not publish in scientific journals; in a majority of those deals (150 out of 178), either the acquirer or the target did not publish in scientific journals, thus the reduction in size was driven by lack of science domain data. Further, out of those 150 deals, 133 of them were in electronics while the other 17 were in drugs or chemicals. These differences in numbers reflect the common wisdom that drugs and chemicals are traditionally science-based industries, while electronics is an emerging user of science (Makri and Lane, 2007). Comparative t-tests revealed that the 178 deals eliminated from the study in the first four steps were not statistically different on sales, R&D intensity, and return on assets (ROA) from the final sample, suggesting that their deletion did not materially bias the sample.

Lastly, to ensure that the acquired firm could have a potentially significant effect on the acquiring firm, all deals were eliminated from the sample in which the target firm size was less than five percent of the acquiring firm’s total annual sales. The final sample of 95 deals consisted of 24 in drugs, 27 in chemicals, and 44 in electronics. A sample size of 95 allows us to maintain a power level of 0.80 (Cohen, 1977).

**DEPENDENT VARIABLES**

Because invention outcomes are likely to lag M&A activity, we incorporated lagged measures for our 1996 sample firms. The earliest the merged companies could file for patents resulting from joint R&D efforts is 1997, one year after the deal is completed. Because post-M&A performance has been examined three to five years after the deal completion year (Bettis and Mahajan, 1985; Robins and Wiersema, 1995; Harrison et al., 1991), we used a similar convention and obtained data on invention quantity, invention quality, and invention novelty, for three to five years after the completion of the acquisition (1999–2001). To capture the change in invention outcomes as a result of the merger, we also examined the three-year window pre M&A (1994–1996).

*Invention quantity, quality, and novelty.* We use three measures to capture the change in invention activity pre and post M&A. The first, patent counts, is a direct measure of invention quantity (e.g., Griliches, 1990, 1995, 1998) and used extensively as an indicator of invention productivity (Hitt et al., 1991; Mowery et al., 1998; Malerba and Orsenigo, 1999; Sorensen and Stuart, 2000; DeCarolis and Deeds, 1999; Hall et al., 2001). To construct this change measure we obtained annual data from the U.S. Patent and Trademark Office (USPTO) on the number of patents for which the firm applied three years pre (1994–1996) and three years post M&A (1999–2001). Then, we created three change measures (1999, 2000, and 2001) in order to test the effects of knowledge similarities before the M&A on invention quantity three to five years later. More specifically, those measures were calculated by subtracting the 1994–1996 value from the 1999–2001 value and then dividing that difference by the 1999–2001 value (i.e., the 1994 value was subtracted from the 1999 value for the 1999 change measure, etc.).

The second, patent citations, is the extent to which a firm’s patents are cited in subsequent patents. It measures invention quality because it reflects the ability of a set of patents to support future inventions by creating a ‘ripple effect’ to stimulate subsequent patents. To construct this measure, we calculated the number of citations for five years after the grant date on all patents for which a firm applied in our three-year pre-M&A window (1994–1996) and then divided that by the total number of patents during each of those three years (i.e., we created an annual citations-per-patent ratio). We did the same for the 1999–2001 window and, using the procedure described above for the invention quantity change measures, we constructed three change measures for 1999, 2000, and 2001 using the three to five year invention quality values pre and post M&A. To test Hypothesis1b, invention quality is operationalized as the
number of citations to the acquirer’s patents within the same classes pre and post M&A, weighted by the number of patents within each class.

The third, invention novelty reflects the degree to which a firm’s patent portfolio extends to a broad range of technology classes. The expansion of the range of technologies post M&A indicates that the firm has made some new discoveries outside its existing scope of technology and has taken some inventive risk. To construct this measure, we calculated an index of technological diversification similar to a Herfindahl index of concentration (Hall et al., 2001; Garcia-Vega, 2006). Let $S_{ij}$ denote the percentage of patents that the $i$th firm holds in class $j$, such that: 

$$1 - \sum_{j} s_{ij}^2$$

where $n$ is the total number of patent classes the firm is involved in. If a firm is involved in a wide range of technologies, the measure will be high, whereas if most patents are concentrated in a few fields, it will be low (close to zero). An index of technological diversification was calculated for the three-year pre- and three-to-five year post-M&A windows in order to capture the change in technology scope after the merger. The invention novelty change measures for 1999, 2000, and 2001 were created in a manner similar to the invention quantity and quality change measures.

**Independent variables**

Technology similarity and complementarity measures were created using patent data from the USPTO. The USPTO classifies technologies into 417 main (three-digit) patent classes (Hall et al., 2001). Hall et al., (2001) aggregated these 417 classes into 36 two-digit technological subcategories, which in turn are further aggregated into six main categories. Because the USPTO classifies some patents into multiple classes\(^7\) in order to calculate a more precise measure of technology relatedness, we considered all patent classes for a patent and not only the primary one (Benner and Waldofogel, 2007).

We constructed the similarity and complementarity measures for firms’ science domain using data from CRP’s 1996 Science Model\(^*\) database (CRP). Each year CRP uses the raw data from the Institute for Scientific Information’s (ISI) Science and Social Science Citation Indexes (approximately 500,000 papers annually) and analyzes the patterns of co-citations for each of them (approximately 8 million citations annually). Co-citation analysis uses frequently occurring pairs of citations in peer-reviewed articles to identify the social and intellectual structure of science, and provides insights into how this structure changes over time (Garfield, Sher, and Torpie, 1964; Garfield, 1979). This technique is widely used by science historians (for a review see Kuhn, 1970: 174–181), and has recently been applied to analyses of strategic issues (Lane and Lubatkin, 1998; Deeds, 2001).\(^8\)

CRP’s unit of analysis is the research community (RC) which is composed of two sets of papers: current papers (published in the year being examined) and base papers (earlier papers highly co-cited in that year). A firm’s participation in research communities reflects the research streams in which the firm’s researchers are involved. CRP also considers a firm’s participation in science disciplines with disciplines defined as sets of journals that cite a common literature. Research communities and science disciplines represent a classification of firms’ scientific knowledge that is analogous to the classification system for technologies (patent classes and subcategories respectively). By examining the patterns of co-citation, CRP develops an annual model of the social structure of science and can assess the performance and trends of each area of research.

**Technology relatedness**

*Technology similarity.* Technology similarity between two firms was operationalized using the number of patents in the same three-digit patent classes in 1996. This measure captures the extent to which two firms develop technology in the same patent classes, hence using similar technological knowledge. It is calculated as the number of patents applied for by the target and acquirer that are in the same patent classes, multiplied by the total number of patents the acquirer has in all common classes divided by total acquirer patents.

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\(^7\) We thank an anonymous reviewer for bringing this to our attention.

\(^8\) The validity of CRP’s method of modeling the structure of science underwent in-depth testing by the United Kingdom Advisory Board for the Research Councils (ABRC) in 1983 and 1984 (Healy, Rothman, and Hock, 1986), and more recently by Klavans and Boyack (2006).
Technology complementarity. While the measures of technological overlap are effective proxies for the similarity of technological assets, they do not capture possible technological complementarities. Technological complementarity is operationalized here as the number of patents in the same subcategory but in different patent classes in 1996. This measure mirrors the theoretical conceptualization of complementarity because it captures the integrative potential between two firms. For example, if two firms’ patents build on subcategory ‘Biotechnology’ in the category ‘Drugs and Chemical,’ the extent to which they build on different technological classes (e.g., patent class 435 vs. patent class 800) captures their integrative potential.

Science relatedness

Science relatedness was measured using the two types of data from CRP described earlier: a) indicator of a firm’s participation (membership) in research communities, and b) indicator of a firm’s participation in science disciplines. The first CRP measure used indicates a firm’s membership in an RC, a self-organized (emergent) group of current researchers whose current papers address similar research topics and have a common base bibliography (i.e., similar theories and methods). The second measure indicates a firm’s membership in a science discipline (Disc). If two firms’ scientists publish in the same research communities, it suggests that the firms are familiar with the same methods and theories, and are examining similar research questions. If two firms have scientists who publish in the same science disciplines but in different RCs, they will have some shared knowledge from general research questions, theories, and methods, but also have different areas of specialized expertise. These two types of data permit the calculation of a science similarity and a science complementarity measure.

Science similarity. The logic underlying this construct is that the degree of similarity in research publications of two firms’ scientists reflects the degree of similarity in the firms’ scientific knowledge. Thus, the science similarity variable was operationalized as the overlap in the research communities in which the acquirer and target publish.

Science complementarity. Science complementarity is defined as the extent to which the target and acquirer build on the same science disciplines but not on the same RCs. Thus, it captures the extent to which two firms draw from related but different areas of science and it is based on the number of unique (nonoverlapping) RCs in which each firm participates within the science disciplines that they share.

All measures of science and technology similarity and complementarity are described and summarized in Table 1.

To better illustrate our definitions of science and technology relatedness, consider the following hypothetical example of a merger between two firms (A and B) with an equal number of total patents (20) in a small range of patent categories and subcategories. These relationships are illustrated in Figure 3. Firms A and B each have 12 patents in the subcategory ‘Biotechnology,’ which is under the main category ‘Drugs and Medical.’ The 60 percent overlap in this narrowly defined domain (Biotechnology) between these two firms indicates a high degree of technological similarity. Both firms also have two other patents under the same main category, but in different subcategories: ‘Molecular Biology’ (Firm A) and ‘Microbiology’ (Firm B). The 10 percent overlap in areas of knowledge content focused on different narrowly defined topics (Molecular Biology, Microbiology) but similar broad areas of knowledge (Drugs and Medical) reflects a low degree of technological complementarity. The same type of analyses could be done for the science relatedness of firms A and B.

Because the measures of complementarity are new and highly important to the efficacy of this study, and in response to recent calls to demonstrate the construct validity of important measures in strategic management research (Boyd, Gove, and Hitt, 2005), we took further steps to ensure the construct validity of these measures. To do so, we collected data from trade magazines in the industries represented in our sample. The data provided information on the acquiring and acquired firms’ research content and foci for 24 deals in the electronics industry and for 24 deals in the drug industry (n = 48). We asked two highly qualified professionals (unrelated to this study) to carefully read through all of the information provided for each firm and to rate the knowledge complementarity present between the two firms in each deal. One of the raters has a Ph.D. in computer science
Table 1. Science and technology similarity and complementarity measures

<table>
<thead>
<tr>
<th>Measure</th>
<th>Formula</th>
</tr>
</thead>
<tbody>
<tr>
<td>Technology similarity</td>
<td>$\frac{\text{Overlap All Patent Classes}}{\text{Total Patent A } &amp; \text{T}} \times \frac{\text{Total Acquirer Patent In Common Classes}}{\text{Total Acquirer Patents}}$</td>
</tr>
<tr>
<td>Technology complementarity</td>
<td>$\frac{\text{Overlap All Patent Subcategories}}{\text{Total Patents A } &amp; \text{T}} - \frac{\text{Overlap All Patent Classes}}{(\text{Total Patents A } &amp; \text{T}) \times \text{Total Acquirer Patents}}$</td>
</tr>
<tr>
<td>Science similarity</td>
<td>$\frac{\text{(Number of Overlapping RCs)}}{\text{Total RCs A}&amp;\text{T participate in}}$</td>
</tr>
<tr>
<td>Science complementarity</td>
<td>$\frac{[(\text{Number of Nonoverlapping RCs in Overlapping Disc}1)/\text{Total RCs(A}&amp;\text{T) in Disc}1]+\ldots+[(\text{Number of Nonoverlapping RCs in Overlapping Disc n})/\text{Total RCs(A}&amp;\text{T) in Disc n})]}{\text{Total RCs(A}&amp;\text{T) in Disc n})}$</td>
</tr>
</tbody>
</table>

and the other has a Ph.D. in immunology. They rated the knowledge complementarity between the two firms on a five-point Likert-type scale. We then calculated the correlations between their ratings on knowledge complementarity and our objective measures of technology complementarity and science complementarity. There was a positive and statistically significant correlation between our objective measure of technology complementarity and the raters’ evaluation of knowledge complementarity ($r = 0.69, p < 0.01$). There was also a positive and statistically significant correlation between our objective measure of science complementarity and the raters’ evaluation of knowledge complementarity ($r = 0.41, p < 0.01$). These results provide support for the construct validity of our measures of complementarity.

Control variables

Several variables were used to help control for alternative explanations of the findings. Acquirer characteristics used as controls include industry (e.g., Hoskisson and Hitt, 1990), R&D intensity (e.g., Morck, Shleifer, and Vishny, 1988; Morck and Yeung, 1991), industry weighted average pre-

Figure 1. Science/technology relatedness aggregated across areas

merger ROA, and relative size of target/acquirer in terms of assets (e.g., Haleblian and Finkelstein, 1999). All of these variables have been suggested or shown to affect one or more of the outcomes examined in this study. Also, we accounted for cost reductions that might be associated with the acquisition measured as the change in selling, general, and administrative expenses one year after the deal was completed because of the potential effect on the short-term returns (e.g., ROA). Further, we controlled for prior acquisition experience (Simonin, 1997) as well as the number of post-M&A acquisitions each firm completed following 1996 that could affect invention outcomes. Finally, we controlled for acquirer product diversification and the degree of product/market

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Acquirer product diversification. Acquirer product diversification pre M&A was captured using the entropy measure (Hitt, Hoskisson, and Kim, 1997) for 1996. This index considers both the number of segments in which a firm operates and the proportion of total sales each segment represents, capturing diversification across four-digit Standard Industrial Classification (SIC) industries. Following Hitt et al. (1997), that measure is calculated as follows:

$$Entropy = \sum_i \left( P_i \times \ln(1/P_i) \right)$$

where $P_i$ represents the proportion of sales attributed to business segment ‘i.’

Product/market similarity. Based on Morck, Shleifer, and Vishny (1990), we measured relatedness using four-digit SIC codes from the six main lines of business (by sales) in which an acquirer and target operated. If a firm operated in fewer than six four-digit industries, we used all industries. We classified an acquirer and target as ‘similar’ if they had at least one four-digit SIC code in common among the top six in which they operated at the time of the acquisition (dummy variable).

Statistical analysis

Our hypotheses were tested using ordinary least squares (OLS) estimates. Multicolinearity and autocorrelation indexes indicate that estimations are not affected by such problems. As described above, in these analyses we control for a variety of industry- and firm-specific attributes. We also controlled the potential for endogeneity by using a two-stage least squares (2SLS) approach.
as described in Greene (1993).\textsuperscript{10} In stage one we used the knowledge relatedness (science similarity/technology similarity, science complementarity/technology complementarity, etc.) variables as the dependent variables and the pre-M&A patenting activity of the target as the instrumental variable. Stage two is an OLS regression, but using the newly created instrumental variable. The instrumental variable chosen meets the validity\textsuperscript{11} requirements as it has a nonzero correlation with the knowledge relatedness variables, and also it is not correlated with the outcome variables of the second stage (invention quantity, quality, and novelty).

RESULTS

Table 2 presents descriptive statistics for the variables included in the analyses for the years 1994–1996 and 1999–2001. During 1994–1996, acquiring firms spent on average 11 percent of their sales on R&D and applied, on average, for 48 patents. During 1999–2001, these same firms spent 37 percent of their sales on R&D and applied, on average, for 62 patents.

Acquirers’ and targets’ technological knowledge similarity was 21 percent on average, (21\% of the acquirers’ and targets’ patents applied for in 1994–1996 were classified by the USPTO in the same patent classes), indicating that these firms were building on similar applied knowledge. The range of technological similarity was 0–90 percent, which is in line with Mowery et al.’s (1998) research on technological overlap in alliances where technological similarities were 5–50 percent. Acquirers’ and targets’ technological knowledge complementarity was 18 percent suggesting that 18\% of acquirers’ and targets’ patents in 1996 were classified by the USPTO as being in the same subcategory but not in the same class, signifying that these firms were building on related technological knowledge. The range of value in technological complementarity was 0–80 percent.

While there are no prior benchmarks for technological complementarity, these levels appear to be reasonable.

The levels of scientific similarity are lower than those of technological similarity. On average, about one percent of the acquirers’ and targets’ scientific knowledge was similar with the range 0–11 percent. This suggests that before the merger, few target and acquirer firms addressed similar sets of problems using similar theories and methods. Scientific complementarity is also lower than technological complementarity as on average, about nine percent of the acquirers’ and targets’ scientific knowledge was complementary (similar sets of problems but addressed using different theories and methods) with a range of 0–78 percent.

Science and technology relatedness and invention outcomes

The first hypothesis focused on the effects of science and technology similarity on invention quantity and quality in similar technology domains and on invention novelty overall. Table 3 summarizes the analyses used for testing these effects. Model 1 shows the results of the first-stage regression with knowledge similarities as the dependent variable, while Models 3, 5, and 7 show the results of the second-stage regression analysis. Models 2, 4, and 6 are the base models with the control variables as well as main effects. The results depict a negative and statistically significant interaction effect between science and technology similarity on invention novelty (p < 0.05). The interaction effects between science and technology similarity on invention quantity and quality were not statistically significant, thereby providing no support for Hypotheses 1a or 1b. However, the results provide support for Hypothesis 1c suggesting that high levels of both technology and science similarity create path dependency, thereby harming the development of novel inventions. Note that science and technology complementarity both had positive main effects on invention quality in similar domains. Technology complementarities have a negative effect on invention quantity in similar domains, while science complementarities have an overall positive effect on invention novelty.

To examine these significant interaction effects further, we plotted the results using the same method shown in Hitt et al. (2006). In the graph presented in Figure 4, we show the effects of

\textsuperscript{10} 2SLS approach with our data yielded similar results to the OLS approach.

\textsuperscript{11} We also evaluated the strength of our chosen instrumental variables by running the first stage with and without the instrumental variable and then comparing the overall F statistics. Staiger and Stock (1997) suggest that a difference of five or more is sufficient evidence of strength.
Table 2. Descriptive statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>s.d</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
<th>12</th>
<th>13</th>
<th>14</th>
</tr>
</thead>
<tbody>
<tr>
<td>R&amp;D intensity</td>
<td>0.11</td>
<td>0.56</td>
<td></td>
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<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Cost reductions</td>
<td>0.71</td>
<td>0.15</td>
<td>0.10</td>
<td></td>
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<td></td>
</tr>
<tr>
<td>Prior acquisition experience</td>
<td>8.71</td>
<td>9.60</td>
<td>−0.16</td>
<td>−0.13</td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td># of post-M&amp;A acquisitions</td>
<td>9.19</td>
<td>10.47</td>
<td>−0.11</td>
<td>−0.11</td>
<td>0.28</td>
<td></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Acquirer diversification</td>
<td>0.39</td>
<td>0.55</td>
<td>−0.14</td>
<td>−0.10</td>
<td>0.50</td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Relative size</td>
<td>0.77</td>
<td>1.61</td>
<td>0.26</td>
<td>0.07</td>
<td>−0.26</td>
<td>−0.13</td>
<td>−0.15</td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Technology similarity</td>
<td>0.21</td>
<td>0.25</td>
<td>0.08</td>
<td>0.11</td>
<td>0.07</td>
<td>0.02</td>
<td>−0.16</td>
<td>0.34</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Technology complementarity</td>
<td>0.18</td>
<td>0.19</td>
<td>0.31</td>
<td>0.38</td>
<td>0.08</td>
<td>−0.02</td>
<td>−0.15</td>
<td>−0.19</td>
<td>0.24</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Science similarity</td>
<td>0.01</td>
<td>0.02</td>
<td>−0.02</td>
<td>−0.02</td>
<td>−0.06</td>
<td>−0.08</td>
<td>−0.11</td>
<td>−0.06</td>
<td>−0.02</td>
<td>−0.09</td>
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<td></td>
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<td></td>
</tr>
<tr>
<td>Science complementarity</td>
<td>0.09</td>
<td>0.21</td>
<td>−0.07</td>
<td>−0.05</td>
<td>0.21</td>
<td>−0.05</td>
<td>0.12</td>
<td>−0.13</td>
<td>−0.01</td>
<td>0.13</td>
<td>0.38</td>
<td></td>
<td></td>
<td></td>
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<td></td>
</tr>
<tr>
<td>Invention quantity</td>
<td>62.0</td>
<td>120.0</td>
<td>0.31</td>
<td>−0.08</td>
<td>0.50</td>
<td>0.40</td>
<td>0.37</td>
<td>−0.16</td>
<td>0.12</td>
<td>0.20</td>
<td>0.03</td>
<td>0.27</td>
<td></td>
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</tr>
<tr>
<td>Invention novelty</td>
<td>0.44</td>
<td>0.17</td>
<td>0.08</td>
<td>0.06</td>
<td>0.11</td>
<td>0.09</td>
<td>−0.06</td>
<td>−0.10</td>
<td>−0.08</td>
<td>0.09</td>
<td>0.02</td>
<td>0.10</td>
<td>−0.07</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Invention quality</td>
<td>0.52</td>
<td>0.58</td>
<td>0.25</td>
<td>0.14</td>
<td>0.04</td>
<td>0.33</td>
<td>−0.17</td>
<td>−0.03</td>
<td>−0.20</td>
<td>−0.001</td>
<td>0.09</td>
<td>0.12</td>
<td>0.11</td>
<td>0.15</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Acquirer ROA</td>
<td>2.98</td>
<td>5.62</td>
<td>0.35</td>
<td>0.02</td>
<td>−0.21</td>
<td>−0.01</td>
<td>0.01</td>
<td>−0.02</td>
<td>0.09</td>
<td>0.10</td>
<td>−0.03</td>
<td>0.05</td>
<td>0.06</td>
<td>0.11</td>
<td>0.14</td>
<td></td>
</tr>
<tr>
<td>Target invention quantity pre-M&amp;A</td>
<td>42.0</td>
<td>102.2</td>
<td>−0.05</td>
<td>−0.04</td>
<td>−0.08</td>
<td>0.12</td>
<td>−0.05</td>
<td>−0.03</td>
<td>0.13</td>
<td>0.03</td>
<td>0.04</td>
<td>0.07</td>
<td>−0.07</td>
<td>−0.11</td>
<td>−0.09</td>
<td>−0.002</td>
</tr>
</tbody>
</table>

N = 95. The dependent variables are reported for 1999–2001 (average) while the independent variables are reported for 1994–1996 (average). Relative size is reported for 1996. †p < 0.10; *p < 0.05; **p < 0.01; ***p < 0.001.
Table 3. The effect of knowledge similarities on invention quantity, quality, and novelty (Hypotheses 1a, 1b, 1c)

<table>
<thead>
<tr>
<th>Variables</th>
<th>Hypothesis 1a</th>
<th>Hypothesis 1b</th>
<th>Hypothesis 1c</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Model 1: 1st stage estimate of knowledge similarities</td>
<td>Model 2: Base model</td>
<td>Model 3: 2nd stage estimate of invention quantity in similar domains</td>
</tr>
<tr>
<td></td>
<td>Model 4: Base model</td>
<td>Model 5: 2nd stage estimate of invention quality in similar domains</td>
<td>Model 6: Base model</td>
</tr>
<tr>
<td></td>
<td>Model 7: 2nd stage estimate of invention novelty</td>
<td></td>
<td>Model 7: 2nd stage estimate of invention novelty</td>
</tr>
<tr>
<td>Industry</td>
<td>0.945 1.412</td>
<td>1.398</td>
<td>−3.823***</td>
</tr>
<tr>
<td>Product/market similarity</td>
<td>−1.965* 0.011</td>
<td>−0.014</td>
<td>0.868 0.883</td>
</tr>
<tr>
<td>Number of acquisitions post-M&amp;A</td>
<td>0.770 1.793†</td>
<td>1.779†</td>
<td>−5.441***</td>
</tr>
<tr>
<td>Prior acquisition experience</td>
<td>−2.768** 1.035</td>
<td>0.985</td>
<td>−0.566 −0.520</td>
</tr>
<tr>
<td>Acquirer ROA</td>
<td>−0.304 0.108</td>
<td>0.105</td>
<td>−0.379 −0.374</td>
</tr>
<tr>
<td>Relative size (T/A)</td>
<td>−0.982 −2.312*</td>
<td>−2.297*</td>
<td>2.482** 2.468**</td>
</tr>
<tr>
<td>R&amp;D intensity</td>
<td>1.203 3.769***</td>
<td>3.746***</td>
<td>4.769*** 4.739***</td>
</tr>
<tr>
<td>Acquirer diversification</td>
<td>3.144** −2.080*</td>
<td>−1.962*</td>
<td>1.167 1.075</td>
</tr>
<tr>
<td>Cost reductions</td>
<td>0.173 3.920***</td>
<td>3.895***</td>
<td>0.521 0.511</td>
</tr>
<tr>
<td>Target patents pre-M&amp;A</td>
<td>−0.191</td>
<td></td>
<td>−0.107 −0.253</td>
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<tr>
<td>Science similarity</td>
<td>−0.442 −0.423</td>
<td>0.641</td>
<td>0.272 −0.698</td>
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<tr>
<td>Technology similarity</td>
<td>0.033 0.063</td>
<td>0.239</td>
<td>0.130 −0.981</td>
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<tr>
<td>Technology complementarity</td>
<td>−1.295 −2.864**</td>
<td>−2.849**</td>
<td>2.657** 2.646**</td>
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<td>Science complementarity</td>
<td>5.241** −1.188</td>
<td>−1.118</td>
<td>1.881† 1.785†</td>
</tr>
<tr>
<td>Technology similarity X science similarity</td>
<td>−0.182 0.211</td>
<td>0.22 0.24</td>
<td>0.15 0.24</td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.22 6.54***</td>
<td>4.20***</td>
<td>3.98*** 5.90***</td>
</tr>
<tr>
<td>F</td>
<td>0.42 6.34***</td>
<td></td>
<td>4.24*** 6.23***</td>
</tr>
</tbody>
</table>

N = 218. † p < 0.10; * p < 0.05; ** p < 0.01; *** p < 0.001. The beta coefficients have been divided by the standard error.
technology similarity on invention novelty for two levels of science similarity, low and high (minus one standard deviation from the mean and plus one standard deviation from the mean, respectively). We plotted invention novelty regressed on different levels of technology similarity. As can be seen in Figure 4, novelty is highest when both science and technology similarity are low.

The second set of hypotheses focused on the effects of science and technology complementarity on invention quantity, quality, and novelty. Our approach in testing this set of hypotheses was similar to the first set; Model 1 shows the results of the first-stage regression with knowledge complementarities as the dependent variable, while Models 3, 5, and 7 show the results of the second-stage regression analysis. Models 2, 4, and 6 are the base models with the control variables as well as main effects. The results shown in Table 4 depict a positive interaction effect between science and technology complementarity on invention quality \( (p < 0.05) \) (Model 5) and on invention novelty \( (p < 0.05) \) (Model 7). The interaction effect on invention quantity was positive but moderately significant \( (p < 0.10) \) (Model 3). These results provide strong support for Hypotheses 2b and 2c but only marginal support for Hypothesis 2a. To examine these statistically significant interaction effects further, we plotted the results.

In the graphs presented in Figure 5a, we show the effects of technology complementarity on invention quality for two levels of science complementarity, low and high (minus one standard deviation from the mean and plus one standard deviation from the mean, respectively). We plotted invention quality regressed on different levels of technology complementarity. As can be seen in Figure 5a, the highest level of invention quality is achieved when both science and technology complementarity are high. Finally, we plotted invention novelty regressed on different levels of technology complementarity. As can be seen in Figure 5b, the highest level of invention novelty is achieved when both science and technology complementarity are high. We found noteworthy that acquirer diversification was positively associated with invention quantity and novelty. This is in line with prior research suggesting that diversification can have a positive effect on innovation (Miller, Fern, and Cardinal, 2007; Breschi, Lissoni, and Malerba, 2003).

Hypotheses 3a, 3b, and 3c address the effects of science similarity and technology complementarity on invention quantity, quality, and novelty; Table 5 summarizes the results of the analyses. The results show that the interaction of science similarity and technology complementarity has a positive statistically significant effect on invention novelty \( (p < 0.01) \) but no effects were evident on invention quantity or quality. Thus, Hypothesis 3c receives support but there is no support for Hypotheses 3a or 3b.

To examine the statistically significant interaction effect further, we plotted the results. As depicted in Figure 6a, the highest level of invention novelty is achieved when technology complementarity is high and science similarity is low.

Hypotheses 4a, 4b, and 4c address the effects of technology similarity and science complementarity on invention quantity, quality, and novelty; Table 6 summarizes the results of the analyses. The results show that the interaction of technology similarity and science complementarity has a positive and statistically significant effect on invention novelty \( (p < 0.01) \) but none on invention quantity or quality. Thus, Hypothesis 4c receives support but there is no support for Hypotheses 4a or 4b. To examine the statistically significant interaction effect of technology similarity and science complementarity on invention novelty, we plotted the results. As depicted in Figure 6b, the highest level of invention novelty is achieved when science complementarity is high and technology similarity is low.

**DISCUSSION**

While prior research has yielded equivocal results regarding the relationship between relatedness and
Table 4. The effect of knowledge complementarities on invention quantity, quality, and novelty (Hypotheses 2a, 2b, 2c)

<table>
<thead>
<tr>
<th>Variables</th>
<th>Hypothesis 2a</th>
<th>Hypothesis 2b</th>
<th>Hypothesis 2c</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Model 1: 1st stage estimate of knowledge complementarities</td>
<td>Model 2: Base model</td>
<td>Model 3: 2nd stage estimate of invention quantity</td>
</tr>
<tr>
<td>Industry</td>
<td>-4.415**</td>
<td>1.446</td>
<td>1.721†</td>
</tr>
<tr>
<td>Product/market similarity</td>
<td>0.009</td>
<td>-2.535*</td>
<td>-2.519*</td>
</tr>
<tr>
<td>Number of acquisitions</td>
<td>-3.224**</td>
<td>4.322***</td>
<td>4.304***</td>
</tr>
<tr>
<td>Industry−post-M&amp;A</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Prior acquisition experience</td>
<td>4.060***</td>
<td>5.415***</td>
<td>5.347***</td>
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<tr>
<td>Acquirer ROA</td>
<td>0.751</td>
<td>0.324</td>
<td>0.288</td>
</tr>
<tr>
<td>Relative size (T/A)</td>
<td>-8.017***</td>
<td>1.256</td>
<td>1.312</td>
</tr>
<tr>
<td>R&amp;D intensity</td>
<td>0.472</td>
<td>1.931*</td>
<td>2.038*</td>
</tr>
<tr>
<td>Acquirer diversification</td>
<td>1.661†</td>
<td>1.848†</td>
<td>1.736†</td>
</tr>
<tr>
<td>Cost reductions</td>
<td>0.292</td>
<td>0.431</td>
<td>0.561</td>
</tr>
<tr>
<td>Target patents pre-M&amp;A</td>
<td>1.363</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Science similarity</td>
<td>1.418</td>
<td>-1.653†</td>
<td>-0.944†</td>
</tr>
<tr>
<td>Technology similarity</td>
<td>4.361**</td>
<td>-1.606</td>
<td>-1.621</td>
</tr>
<tr>
<td>Technology complementarity</td>
<td>-0.164</td>
<td>-0.515</td>
<td>4.915***</td>
</tr>
<tr>
<td>Science complementarity</td>
<td>3.091**</td>
<td>1.191</td>
<td></td>
</tr>
<tr>
<td>Technology complementarity X</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>science complementarity</td>
<td>1.558†</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.32</td>
<td>0.40</td>
<td>0.42</td>
</tr>
<tr>
<td>F</td>
<td>10.18***</td>
<td>13.24***</td>
<td>12.48***</td>
</tr>
</tbody>
</table>

N = 218. † p < 0.10; * p < 0.05; ** p < 0.01; *** p < 0.001. The beta coefficients have been divided by the standard error.
performance with M&As, the research reported herein extends our understanding of the relationship. We find that knowledge relatedness is complex and that technological complementarity should be integrated with other forms of relatedness to enhance invention. Prior strategic management research suggested that firms engaging in M&As may produce fewer inventions (Hitt et al., 1996). The Hitt et al. (1996) results are likely representative of acquisitions in general, especially for industrial firms operating in medium- and low-technology markets, as well as for firms in high-technology industries where complementarities in science and technology are rare. Our study shows that firms acquiring others with complementary science and technology knowledge can produce higher quality and more novel inventions.

Overall, the results of this study support the important and pervasive influence of knowledge complementarities, and strongly suggest that firms in high-technology industries interested in making acquisitions should search for, identify, and acquire businesses that have scientific and technological knowledge that is complementary to their own. If they do so, they have a higher likelihood of achieving positive outcomes (especially invention productivity in the form of quality and novelty) from the acquisition.

The findings on knowledge similarity are also potentially important; knowledge similarities had no effect on invention quantity or quality, but had a negative effect on invention novelty. The findings are likely because of path dependencies. When a firm acquires a target with similar technologies (and based in similar knowledge areas of science), it has a high relative absorptive capacity that facilitates integration (Lane and Lubatkin, 1998). However, the similarities likely do not provide enough differences to enrich invention capabilities. Additionally, high similarities in both technology and science knowledge produce significant constraints on the search process because of the path dependencies. As Ahuja and Lampert (2001) suggest, path dependency increases the probability that the firm will experience a familiarity trap where it searches for solutions that are near to existing solutions instead of searching for new ones. Therefore, it reinforces the status quo and is unlikely to produce changes in inventive performance.

The results also point to important conclusions regarding knowledge complementarities. We find that the effects of knowledge complementarities are pervasive when both science and technology complementarities are combined; the integration of the two enriches invention quality and novelty and even marginally increase invention quality as well. When technology complementarities are combined with science similarities, only invention novelty is enhanced; there is no effect on invention quality or quantity. Similarly, when science complementarities are combined with technology similarities, only invention novelty is enhanced; there is no effect on invention quantity or quality. The lack of effects on invention quantity is likely because knowledge complementarities require extra effort to integrate after the merger and the focus of such integration is on producing to realize the potential synergy and produce more novel inventions. Such efforts take time thereby delimiting increases in the number of inventions. Overall the results suggest that while both science and technology complementarities have important effects, the invention outcomes are much richer when both are present.
Table 5. The effect of knowledge similarities and complementarities on invention quantity, quality, and novelty (Hypotheses 3a, 3b, 3c)

<table>
<thead>
<tr>
<th>Variables</th>
<th>Hypothesis 3a</th>
<th>Hypothesis 3b</th>
<th>Hypothesis 3c</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Model 1</td>
<td>Model 2</td>
<td>Model 3</td>
</tr>
<tr>
<td>Industry</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Product/market similarity</td>
<td>-2.743**</td>
<td>1.446</td>
<td>1.466</td>
</tr>
<tr>
<td>Number of acquisitions</td>
<td>-0.427</td>
<td>-2.535*</td>
<td>-2.502*</td>
</tr>
<tr>
<td>Prior acquisition experience</td>
<td>-0.340</td>
<td>5.415***</td>
<td>5.384***</td>
</tr>
<tr>
<td>Acquirer ROA</td>
<td>0.195</td>
<td>0.324</td>
<td>0.317</td>
</tr>
<tr>
<td>Relative size (T/A)</td>
<td>0.258</td>
<td>1.256</td>
<td>1.243</td>
</tr>
<tr>
<td>R&amp;D intensity</td>
<td>1.163</td>
<td>1.931*</td>
<td>1.891†</td>
</tr>
<tr>
<td>Acquirer diversification</td>
<td>1.327</td>
<td>1.848†</td>
<td>1.814†</td>
</tr>
<tr>
<td>Cost reductions</td>
<td>-1.753†</td>
<td>0.431</td>
<td>0.449</td>
</tr>
<tr>
<td>Target patents pre-M&amp;A</td>
<td>3.823***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Science similarity</td>
<td>-1.653†</td>
<td>-1.628†</td>
<td>-1.791†</td>
</tr>
<tr>
<td>Technology similarity</td>
<td>-0.373</td>
<td>-1.606</td>
<td>-1.587</td>
</tr>
<tr>
<td>Technology complementarity</td>
<td>-0.164</td>
<td>-0.200</td>
<td>4.915***</td>
</tr>
<tr>
<td>Science complementarity</td>
<td>6.023***</td>
<td>3.091**</td>
<td>2.790**</td>
</tr>
<tr>
<td>Technology complementarity X</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>science similarity</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.25</td>
<td>0.40</td>
<td>0.41</td>
</tr>
<tr>
<td>F</td>
<td>7.36***</td>
<td>13.24***</td>
<td>11.96***</td>
</tr>
</tbody>
</table>

\*p < 0.10; \*\*p < 0.05; \*\*\*p < 0.01; \*\*\*\*p < 0.001.
Implications for theory and research

M&A research. Evaluating the performance of high-technology acquisitions has received only limited attention (Ahuja and Katila, 2001; Grandstrand and Sjolander, 1990; Gerpott, 1995) and the existing research has mainly examined the effect of acquisitions on the size of the acquirer’s knowledge base. The framework introduced herein allows evaluation of the effects of acquisitions on the types and quality of the acquirer’s knowledge base in addition to size, thereby integrating perspectives from the innovation literature, largely focused on invention, and studies in the corporate control tradition. It allows future research to extend and enrich the prior research on the relationship between acquisitions and inventions (Hitt et al., 1991, 1996; Hoskisson, Johnson, and Moesel, 1994). The current research provides an enhanced understanding of the boundary conditions for the relationships, positive and negative, previously posed by others.

Harrison et al., (2001) and Hitt, Harrison, and Ireland (2001) suggest that the two viewpoints are complementary. They indicate that while an active acquisition strategy does not necessarily reduce managerial commitment to innovation, firms should be vigilant when trying to increase innovation by acquiring other companies. They argue that taking great care in selecting a complementary target followed by an emphasis on innovation after the acquisition can produce greater success. Assessments of technology and science knowledge relatedness (especially in the form of complementarities) among high-technology firms can help identify the best targets to acquire for effective integration and enhancements of invention quantity, quality, and novelty. Yet, our research also suggests that to enhance all three dimensions of inventions requires great care in selecting the target to ensure that knowledge complementarities exist in both science and technology.

Puranam, Singh, and Chaudhuri (2009) suggest that if there is substantial similarity in the knowledge bases between the acquiring and target firm, structural integration is less necessary and its disruptive consequences can be avoided. However, integration is often a necessary but insufficient condition to achieve success with M&As. Thus, future research should explore the effects of structural integration in high-technology acquisitions when the knowledge bases are complementary.

Our research also has implications for the dynamic capabilities research and practice (Helfat et al., 2007). As Helfat and Lieberman (2002) note, firms assess the gap between their existing capabilities and the targeted capabilities to decide whether to seek new capabilities from outside the firm or to develop them internally. This selection capability is crucial for long-term performance, and acquisitions provide opportunities for strategic renewal (Agrawal and Helfat, 2009) if acquirers are able to select targets with capabilities that ‘differ markedly from a firm’s existing skills’ (Capron and Mitchell, 2009: 298). After the firm decides that external sourcing is the most appropriate means for capability renewal, its acquisition selection capability (identification of target[s] with the desired capability[ies]) is critical (Helfat et al., 2007; Benson and Ziedonis, 2009). Our results suggest that similarities in knowledge facilitate incremental renewal, while complementarities would make discontinuous strategic transformations more likely (Agrawal and Helfat, 2009). The theory developed herein
Table 6. The effect of knowledge similarities and complementarities on invention quantity, quality, and novelty (Hypotheses 4a, 4b, 4c)

<table>
<thead>
<tr>
<th>Variables</th>
<th>Hypothesis 4a</th>
<th>Hypothesis 4b</th>
<th>Hypothesis 4c</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Model 1: 1&lt;sup&gt;st&lt;/sup&gt; stage Estimates of technology similarities and science complementarities</td>
<td>Model 2: Base model</td>
<td>Model 3: 2&lt;sup&gt;nd&lt;/sup&gt; stage estimate of invention quantity</td>
</tr>
<tr>
<td>Industry</td>
<td>0.911</td>
<td>1.446</td>
<td>1.435</td>
</tr>
<tr>
<td>Product/market similarity</td>
<td>−0.357</td>
<td>−2.535*</td>
<td>−2.551**</td>
</tr>
<tr>
<td>Number of acquisitions</td>
<td>−1.828*</td>
<td>4.322***</td>
<td>4.143***</td>
</tr>
<tr>
<td>post-M&amp;A</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Prior acquisition experience</td>
<td>1.882*</td>
<td>5.415***</td>
<td>5.311***</td>
</tr>
<tr>
<td>Acquirer ROA</td>
<td>0.134</td>
<td>0.324</td>
<td>0.314</td>
</tr>
<tr>
<td>Relative size (T/A)</td>
<td>−4.487***</td>
<td>1.256</td>
<td>1.130</td>
</tr>
<tr>
<td>R&amp;D intensity</td>
<td>2.892**</td>
<td>1.931*</td>
<td>1.890†</td>
</tr>
<tr>
<td>Acquirer diversification</td>
<td>0.362</td>
<td>1.848†</td>
<td>1.915*</td>
</tr>
<tr>
<td>Cost reductions</td>
<td>1.337</td>
<td>0.431</td>
<td>0.514</td>
</tr>
<tr>
<td>Target patents pre-M&amp;A</td>
<td>−1.383</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Science similarity</td>
<td>1.011</td>
<td>−1.653†</td>
<td>−1.979*</td>
</tr>
<tr>
<td>Technology similarity</td>
<td></td>
<td>−1.606</td>
<td>−1.106</td>
</tr>
<tr>
<td>Technology complementarity</td>
<td>2.415*</td>
<td>−0.164</td>
<td>−0.268</td>
</tr>
<tr>
<td>Science complementarity</td>
<td></td>
<td>3.091**</td>
<td>3.486**</td>
</tr>
<tr>
<td>Technology similarity X science complementarity</td>
<td></td>
<td>−1.635</td>
<td></td>
</tr>
<tr>
<td>Adjusted R²</td>
<td>0.11</td>
<td>0.40</td>
<td>0.41</td>
</tr>
<tr>
<td>F</td>
<td>3.59***</td>
<td>13.24***</td>
<td>12.31***</td>
</tr>
</tbody>
</table>

† p < 0.10; * p < 0.05; ** p < 0.01; *** p < 0.001.
sheds light on the concept of acquisition identification, and emphasizes the importance of complementary knowledge for strategic renewal.

Alliance research. Although our study examined M&As, the findings provide implications for understanding high-technology alliances as well. Prior research has suggested that when the anticipated interdependence between alliance partners is high, greater coordination costs are expected. As a result, a more hierarchical governance structure is often used to manage the alliance (Gulati and Singh, 1998). However, the findings of this study suggest that higher coordination costs do not occur in all technology alliances, especially if the firm is careful to select partners with technology and science complementarities. When such care has been taken to select partners with knowledge complementarities, a hierarchical structure is less necessary to protect the firm’s technology assets. Future research should examine the specific effects of complementary knowledge in alliances, due to higher interdependence, and the resulting type of governance structure compared to alliances based on knowledge similarities between partners.

Interorganizational learning. This study extends our understanding of knowledge complementarity and interorganizational learning (knowledge transfer), specifically the notion of relative absorptive capacity. Lane and Lubatkin (1998) suggest that a firm’s ability to learn from its partner in an alliance depends on the similarity of firms’ knowledge bases, organizational structures, compensation policies, and dominant logics. Our research suggests that the relative absorptive capacity construct should be expanded to include complementarity in firms’ knowledge bases. Future research could examine how ‘relative complementarity’ affects knowledge transfer between alliance partners. For instance, the degree of ‘relative complementarity’ can affect the level of private benefits accrued to each partner (Khanna, 1998), and subsequently the alliance partners’ incentives to invest in learning.

Implications for management practice

This study suggests that managers and members of the board of directors can better evaluate potential acquisition targets and alliance partners by focusing on the knowledge similarity and complementarity between the two firms to assess the probability of achieving unique and valuable synergy (e.g., invention outcomes). Further, it suggests that evaluating a target based on technology complementarities alone is inadequate. Careful analysis of targets is necessary to identify both science and technology knowledge complementarities. However, the typical due diligence processes in M&As commonly focus on financial health (Hitt et al., 2001) and rarely try to identify special knowledge stocks held by targets. Therefore, managers must implement analytical processes that identify the knowledge similarities and complementarities with potential targets.

Accordingly, managers should be encouraged via incentive programs to seek targets for acquisition that hold complementary knowledge. As such, using short-term objective financial criteria to reward those managers (i.e., fiscal performance results) may negate the potentially positive effects of acquiring complementary knowledge by encouraging them to stay within familiar areas of knowledge that provide more immediate returns (e.g., gaining economies of scale). On the other hand, using long-term criteria on which to reward executives can provide incentives for them to search for targets with complementary knowledge to explore new realms of knowledge and use it to develop novel products that create superior value for customers (Sirmon, Hitt, and Ireland, 2007). In fact, this process of integrating knowledge complementarities to develop novel inventions that provide such value represents a form of what Helfat et al. (2007: 21) refer to as ‘asset orchestration.’

Study limitations

Several limitations should be noted. First, the relevance of these findings may be limited to industries where patents are meaningful indicators of invention, but the number of such industries has been growing in recent years. In addition to the drug, chemical, and electronics industries, these findings are relevant to other industries where scientific research is becoming more important, such as soaps, plastics, and food (Makri and Lane, 2007). Second, while patent classification schemas provide a clearer picture of a firm’s knowledge domain than SIC codes, similar to SIC codes, they were developed for another purpose. However, coding conventions facilitate the study of invention-related topics using large samples. Third, while patents generally correlate well with new
products (Comanor and Scherer, 1969), not all are commercialized. Thus, patent quality only partially captures the novelty of commercialized inventions. Future research should examine the novelty of the commercialized products to enable a more thorough evaluation of knowledge relatedness effects on invention outcomes and also on those that are eventually commercialized. Finally, broad data on science knowledge relatedness is difficult to obtain. More datasets with this information should be developed on a broader set of industries to allow our research to be replicated and extended to other industries and across a greater number of years.

Concluding remarks

Many of the theories and constructs used in prior research and practice to evaluate the effectiveness of M&As are entrenched in the old, manufacturing-dominated competitive environment. Yet, in high-technology industries and in an increasing number of other industries (e.g., professional services), knowledge is essential for success (Hitt et al., 2006). Thus, new constructs and approaches are needed to understand the requirements for success in the new competitive landscape (Bettis and Hitt, 1995). This study suggests that in high-technology M&As, firms’ integration of science and technology knowledge may serve as a better indicator of private synergy than assessing relatedness in terms of firms’ market and product portfolios. As such, it provides a base for future research and changes in managerial practices regarding the M&A strategy.

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REFERENCES


