Is high-quality knowledge always beneficial? Knowledge overlap and innovation performance in technological mergers and acquisitions

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Abstract

This research analyses the effects of the knowledge overlap between acquirer and target firms on the performance of technological mergers and acquisitions (M&As). Extending previous research that has focused on the quantitative characteristics of knowledge, this research introduces a framework capturing the effects of both the quantity and quality of knowledge in overlapped and nonoverlapped parts of the knowledge base on subsequent innovation performance. Analyzing a data set of 192 technological M&As of 162 high-technology firms from 2001 to 2009, the results show that a high quality of overlapped knowledge has a positive effect on subsequent innovation performance, while the effect is negative for nonoverlapped knowledge quality. In addition, this research investigates the influence of the knowledge quantity on subsequent innovation performance. The implication of this research is that the knowledge overlap in technological M&As is essential for acquiring high-quality knowledge from the target firm and for improving innovation performance.

Keyword: technological M&A, knowledge overlap, knowledge quality, innovation performance, absorptive capacity

INTRODUCTION

Most of the foundational research on technological mergers and acquisitions (M&As) has focused on the relationship between the knowledge characteristics of the acquirer and target firms and post-acquisition performance (Ahuja & Katila, 2001; Hagedoorn & Duysters, 2002; Cloodt, Hagedoorn, & Kranenburg, 2006; Kapoor & Lim, 2007; King, Slotegraaf, & Kesner, 2008; Sears & Hoetker, 2014; Orsi, Ganzaroli, De Noni, & Marelli, 2015). Because technological M&As are characterized by the integration of the knowledge bases of two different firms, the knowledge overlap of the firms is a useful concept in studying post-acquisition knowledge integration (Sears & Hoetker, 2014). Accordingly, previous studies have investigated the effects of knowledge overlap, specifically the effects of overlapped knowledge and nonoverlapped knowledge, on various dimensions of post-M&A performance, such as inventor productivity (Kapoor & Lim, 2007), post-M&A innovation performance (Cloodt, Hagedoorn, & Kranenburg, 2006; Makri, Hitt, & Lane, 2010; Sears & Hoetker, 2014), knowledge utilization of the target firm's knowledge base (Orsi et al., 2015), and investment in

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the target firm's research and development (R&D) assets (Miozzo, Divito, & Desyllas, 2015). To investigate these impacts of knowledge overlap in technological M&As, the theoretical framework has been continuously adapted and refined, for example, dividing the knowledge base of the target firm into knowledge similarities and complementarities (Makri, Hitt, & Lane, 2010). Recent studies have utilized the framework of Makri, Hitt, and Lane (2010) to investigate the impact of the target firm's overlapped and nonoverlapped knowledge on firm performance (Colombo & Rabbiosi, 2014; Miozzo, Divito, & Desyllas, 2015).

However, previous studies on knowledge overlap in technological M&As have merely focused on the quantitative characteristics of the knowledge base. Specifically, Ahuja and Katila (2001) pay attention to the quantity of knowledge when investigating the effects of knowledge base overlap on subsequent innovation performance. In addition, the previous literature has defined knowledge overlap as the amount of overlapped knowledge without considering qualitative characteristics (Kapoor & Lim, 2007; Makri, Hitt, & Lane, 2010). Phene, Tallman, and Almeida (2012) focus on the amount of both common and unique knowledge of the acquirer and target firms. Sears and Hoetker (2014) extend the concept of knowledge overlap into target overlap and acquirer overlap but consider only the qualitative measures of knowledge overlap, that is, the amount of overlapped knowledge between the acquirer firm and the target firm prior to the M&A.

When analyzing the knowledge base of firms participating in technological M&As, it is important also to consider qualitative aspects of the knowledge, as quantity by itself does not accurately reflect innovation capabilities (Chen & Chang, 2010). Yang, Wei, and Chiang (2014) develop qualitative indicators to be used in technological M&As. Furthermore, arguing that identifying the quality of knowledge is an important factor for the successful knowledge transfer of firms, Yoo (2014) redefines the substructures of perceived knowledge quality and their effects on knowledge transfer. While there is an increasing understanding of the need to consider the quality of the knowledge base when using external knowledge-sourcing strategies such as technological M&As, previous research has fallen short of empirically testing the effects of qualitative knowledge characteristics on post-M&A performance.

To address this research gap, this study investigates the effects of the target firm's knowledge-quality characteristics on the subsequent innovation performance of technological M&As. In line with previous research, the study divides the knowledge base of the firm into an overlapped part and a nonoverlapped part. Subsequently, for each part, this paper investigates the influence of the target firm's knowledge quality on post-M&A innovation performance. The analysis reveals that a high quality of overlapped knowledge has a positive effect, while the effect of nonoverlapped knowledge quality is negative. In addition, this research hypothesizes and confirms the effects of knowledge quantity on subsequent innovation performance.

This study makes several contributions to the research on knowledge management and technological M&As: first, by revealing the double-sided characteristics of high-quality knowledge, this research extends the theory of the knowledge-based view in the field of knowledge management. That is, the study highlights that high-quality knowledge is not always beneficial for a firm's subsequent innovation performance. Second, by extending previous studies that have investigated the relationship between quantitative knowledge base characteristics and subsequent innovation performance in technological M&As, this study highlights the effects of knowledge quality on post-M&A innovation performance. Third, while most previous empirical studies have focused on the quantitative characteristics of knowledge when investigating knowledge overlap and innovation performance in technological M&As, this research investigates the relationship between the quality of knowledge and post-M&A innovation performance. Additionally, the research model of this study provides an integrative framework of overlapped/nonoverlapped knowledge and its qualitative and quantitative characteristics. This allows a more detailed analysis of the target firm's knowledge base characteristics that increase the success of technological M&As.

This paper is structured as follows: the first section reviews the relevant literature, linking it to the hypotheses on the effects of knowledge quality and quantity. The next section provides the specifications of the research data and methods used to empirically test the hypotheses. Using a negative binomial regression model, this research tests the hypotheses using data on 192 technological M&A deals conducted by 162 firms in high-technology industries. After presenting the results, the study concludes with a discussion of the findings and an outlook for future studies.

THEORY AND HYPOTHESES

Knowledge overlap in technological M&As

Previous research has identified various effects of knowledge overlap on post-M&A performance (Ahuja & Katila, 2001; Cassiman, Colombo, Garrone, & Veugelers, 2005; Makri, Hitt, & Lane, 2010; Sears & Hoetker, 2014; Orsi et al., 2015). It has assumed that overlapped and nonoverlapped knowledge are two ends of a continuum and has accordingly measured knowledge overlap using a continuous variable. Overlapped knowledge between two firms reduces nonoverlapped knowledge, and vice versa. The basic assumption behind this line of research is that the nonoverlapped knowledge part provides novel knowledge to the acquiring firm, but simultaneously leads to integration problems because of the lack of absorptive capacity in the unknown fields (Cloodt, Hagedoorn, & Kranenburg, 2006). On the other hand, while overlapped knowledge is not accompanied by such integration problems, it does not provide new knowledge that is important for the firm to create novel recombination (Sears & Hoetker, 2014). By analyzing this effect using a single concept, that is, knowledge overlap, previous research has argued that a moderate balance between overlapped and nonoverlapped knowledge is most beneficial for post-M&A innovation performance (Ahuja & Katila, 2001; Cloodt, Hagedoorn, & Kranenburg, 2006). Extending the research on knowledge overlap and post-M&A innovation performance, Kapoor, and Lim (2007) explain that a moderate level of knowledge overlap has a positive effect on post-M&A inventor productivity, due to the novelty of the nonoverlapped knowledge and the ease of communication that stems from organizational routine similarity. One of the latest studies on knowledge overlap in technological M&As divides the concept of knowledge overlap into target and acquirer overlap and analyses the effect of each type of overlap on the subsequent performance of M&As (Sears & Hoetker, 2014). Sears and Hoetker (2014) identify that an increasing knowledge overlap negatively affects post-M&A innovation performance due to firms' inability to benefit from novel ideas and technologies. They also discover that the effect of overlapped knowledge (absorptive capacity) is less significant than the effect of nonoverlapped knowledge (novelty of knowledge).

Another stream of research provides a more refined framework for the concept of knowledge overlap: knowledge similarities and complementarities. Makri, Hitt, and Lane (2010) first adapt this framework to the literature on technological M&As and find that the knowledge similarity of the target firm is negatively related to post-M&A innovation novelty (Makri, Hitt, & Lane, 2010). Colombo and Rabbiosi (2014) also distinguish the knowledge base into similar and complementary knowledge and examine the effect of firms' technological knowledge characteristics on post-acquisition innovation performance. More recent studies have adopted this framework and identified how knowledge base similarities and complementarities affect investments in the R&D assets of the target firm and target firm knowledge utilization in technological M&As (Miozzo, Divito, & Desyllas, 2015; Orsi et al., 2015). Despite several minor differences in the results, previous studies have commonly identified the importance of nonoverlapped knowledge in organizational learning, thus highlighting the importance of novelty for subsequent innovation performance (Makri, Hitt, & Lane, 2010; Colombo & Rabbiosi, 2014; Sears & Hoetker, 2014)
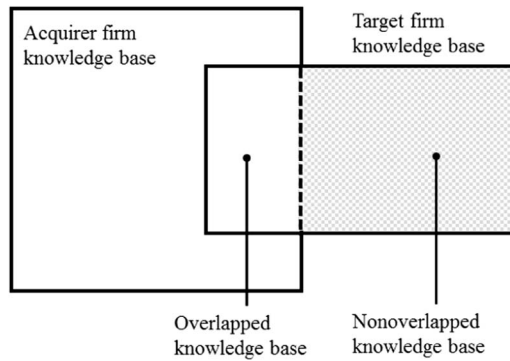
FIGURE 1. KNOWLEDGE OVERLAP IN TECHNOLOGICAL MERGERS AND ACQUISITIONS

However, previous studies have focused on the quantitative degree of knowledge overlap and have overlooked the importance of qualitative aspects in facilitating learning within the overlapped parts of the knowledge base. In this study, we introduce these qualitative aspects of knowledge into the theoretical framework of knowledge overlap and examine how quantitative and qualitative characteristics of overlapped knowledge and nonoverlapped knowledge affect post-M&A innovation performance. Figure 1 depicts the conceptual framework of this study.

The link between knowledge base characteristics and post-M&A innovation performance

According to the theory of organizational learning, knowledge transfer and knowledge creation are the most important processes that allow a firm to turn its acquired external knowledge into a competitive advantage (Argote & Ingram, 2000). Consequently, for technological M&As, whose motivation is to acquire new knowledge and to create new innovation, knowledge transfer and creation represent significant success factors.

Knowledge quality and innovation performance

High-quality knowledge is tacit, complex, and highly asset specific (Kogut & Zander, 1992; Argote & Ingram, 2000). Previous literature on knowledge transfer has argued that the higher the quality of the knowledge, the more complexly it is embedded within a firm's knowledge reservoirs, that is, people, tasks, tools, and their networks (Argote & Ingram, 2000; Argote & Miron-Spektor, 2011). This complexity of high-quality knowledge is the source of its inimitability and asset specificity (Kogut & Zander, 1993; Castro-Casal, Neira-Fontela, & Álvarez-Pérez, 2013). In addition, the ambiguity caused by the tacitness of the knowledge components makes knowledge transfer difficult, especially when there is no overlapped routine compatible with both actors of learning (Uygur, 2013). Furthermore, because high-quality knowledge is formed by the process of 'learning by doing' inside an organization, the key for its creation is the accumulation of experience and knowledge (Nonaka & Takeuchi, 1996). Therefore, it is hard to expect perfect learning of high-quality knowledge merely through the transfer of simple knowledge components (Song, Almeida, & Wu, 2003; Oguz & Sengün, 2011).

However, the existence of overlapped knowledge between the acquirer firm and the target firm can facilitate the transfer of high-quality knowledge. A knowledge overlap indicates common processes and routines shared by the acquirer firm and the target firm (Lane & Lubatkin, 1998). Cohen and Levinthal (1990) suggest that a knowledge overlap between actors provides common technologies, a similar cognitive base, and shared technological languages. The presence of those components results

in a high level of absorptive capacity of the acquirer firm and thus yields a better understanding of the target firm's high-quality knowledge, which improves the knowledge transfer (Phene, Tallman, & Almeida, 2012).

High-quality knowledge, often referred to as cutting-edge or state-of-the-art knowledge in the technological field, is beneficial to the process of knowledge creation. When the acquirer firm already possesses some knowledge in a specific field, advanced knowledge is essential to improve it. Previous literature on technological M&As has highlighted the importance of the nonoverlapped and novel knowledge of the target firm (Cloodt, Hagedoorn, & Kranenburg, 2006; Sears & Hoetker, 2014). However, the contributions of the overlapped knowledge need to be considered as well. Although overlapped knowledge may contain redundant technological solutions, processes and routines might vary due to the different environments in which they were created (Cantwell, 1994). High-quality knowledge is specialized and has a strong originality and impact (Trajtenberg, 1990). It is usually comprised of more efficient routines and allows a wider range of usage than low-quality knowledge (Cho & Pucik, 2005). Therefore, high-quality overlapped knowledge provides the acquirer firm with new technologies, which allow it to further develop and improve the processes, routines, and usage of its existing knowledge. This leads to the following hypothesis:

> Hypothesis 1: In technological M&As, the higher the quality of the overlapped knowledge, the higher the post-M&A innovation performance.

When the high-quality knowledge is nonoverlapped, the acquirer firm will attempt to integrate the knowledge, bearing the inefficiencies resulting from the lack of absorptive capacity. Additionally, the features of high-quality knowledge, such as asset specificity, tacitness, and complexity, make the knowledge transfer more difficult (Spender, 1989; Jasimuddin, Klein, & Connell, 2005; Cloodt, Hagedoorn, & Kranenburg, 2006). Knowledge from nonoverlapping technological fields differs in its processes and routines, which makes it harder for the acquirer firm to transfer and integrate it (Kogut & Zander, 1992). As a result, the target firm's high-quality nonoverlapped knowledge incurs high integration costs due to the inefficiency of the knowledge transfer. This causes the acquirer firm to waste research and development resources, which otherwise would have been used to enhance the core competencies of the firm, thus negatively affecting innovation (Jiang, Tan, & Thursby, 2011). Moreover, the time spent transferring the acquired nonoverlapped high-quality knowledge will prevent the timely creation of new knowledge from the transferred resources (Koput, 1997). That is, high-quality nonoverlapped knowledge has a negative effect by increasing not only the cost but also the time required for the knowledge transfer.

Despite the high costs, nonoverlapped high-quality knowledge that is successfully transferred possesses great combinative potential and will positively influence knowledge creation. The combinative potential and application capabilities of the target firm's high-quality knowledge in fields that are new to the acquirer firm are greater than those of the firm's low-quality knowledge. However, the positive effects of the combinative potential of high-quality knowledge are limited by the lack of the acquirer firm's absorptive capacity. Without any knowledge overlap, the acquirer firm finds it hard to recognize and understand novel recombinations of the high-quality knowledge. This further impedes the creation of new innovation (Lane & Lubatkin, 1998; Phene, Tallman, & Almeida, 2012). Therefore, as the quality of the nonoverlapped knowledge increases, the negative effects from the increasing integration cost prevail over the positive effects from the increasing combinative potential. Moreover, high-quality knowledge from nonoverlapped fields can negatively affect the creation of innovation due to attention allocation problems (Koput, 1997). Jiang, Tan, and Thursby (2011) note that continuous attempts to create innovation in areas without prior background knowledge can negatively affect knowledge creation. This could weaken the firm's core competence through cannibalizing the resources used in current core activities. In other words, high-quality nonoverlapped knowledge leads firms

to wrongly allocate their attention and resources and thus has a negative effect on their core competencies and knowledge creation.

In summary, while high-quality nonoverlapped knowledge possesses great combinative potential, it actually leads to negative effects due to high integration costs and firms' problematic allocation of their limited resources. Therefore, this study hypothesizes that the quality of nonoverlapped knowledge has negative effects on the subsequent innovation performance:

Hypothesis 2: In technological M&As, the higher the quality of the nonoverlapped knowledge, the lower the post-M&A innovation performance.

Knowledge quantity and innovation performance

Transferring overlapped knowledge is much easier because acquirer firms already possess related absorptive capacity (Ahuja & Katila, 2001; Makri, Hitt, & Lane, 2010; Orsi et al., 2015). The knowledge overlap with the target firm facilitates knowledge transfer by allowing the sharing of common technological knowledge and know-how (Kogut & Zander, 1993; Lane & Lubatkin, 1998). According to Phene, Tallman, and Almeida (2012), the knowledge overlap between the acquirer firm and the target firm enables engineers to share a common mindset, to bring about similarity in organizational systems and processes and to facilitate the absorption of knowledge. Consequently, even if the amount of knowledge that the acquirer firm needs to integrate increases, efficient knowledge transfer is possible as long as the acquirer firm possesses sufficient absorptive capacity as a result of overlapping knowledge with the target firm (Kang, Jo, & Kang, 2015).

An increase in overlapped knowledge quantity through technological M&As can also positively influence the process of knowledge creation. As the quantity of overlapped knowledge absorbed by the acquirer firm increases, a recombination of different knowledge and technologies can strengthen the existing core competencies of the firm (Nonaka & Takeuchi, 1996). The increased quantity of overlapped knowledge leads to an active exchange and new combinations with existing knowledge, positively affecting the firm's exploitation of its existent knowledge base (Makri, Hitt, & Lane, 2010).

However, excessive amounts of overlapped knowledge can also negatively affect a firm's knowledge creation. First, a strong increase in the amount of overlapped knowledge raises the probability of knowledge redundancy and reduces the opportunities for learning. High knowledge redundancy decreases the potential for novel recombination, resulting in a negative influence on the creation of new innovations (Ahuja & Katila, 2001; Sears & Hoetker, 2014). Sears and Hoetker (2014) also suggest that a larger amount of overlap between the firms' knowledge bases increases the redundancy of the firms' resources, ultimately fostering the risk of conflict among members and resulting in organizational disruption. In other words, while an increase in the amount of overlapped knowledge helps a firm's exploitation and improves its subsequent innovation performance, an excessive amount of overlap increases redundancy, causes organizational disruption, and ultimately negatively influences subsequent innovation performance. This leads to the following hypothesis:

Hypothesis 3: In technological M&As, an inverted U-shaped relationship exists between the quantity of overlapped knowledge and the post-M&A innovation performance.

In areas where knowledge does not overlap, it requires more time and resources to absorb knowledge due to the acquirer firm's lack of absorptive capacity (Lane & Lubatkin, 1998). When firms with insufficient absorptive capacity face the inflow of an excessive quantity of nonoverlapped knowledge, the resulting information overload impedes the process of learning from knowledge transfer (Ahuja & Lampert, 2001; Phene, Fladmoe-Lindquist, & Marsh, 2006). The acquirer firm's information overload intensifies its confusion regarding which knowledge should be chosen to efficiently create innovation.

The overload also makes it more difficult to timely absorb and integrate the information by delaying the transfer process (Koput, 1997; Hagedoorn & Duysters, 2002). An excessive quantity of non-overlapped knowledge causes high integration costs and inefficiencies in the knowledge transfer through technological M&As (Ahuja & Katila, 2001; Sears & Hoetker, 2014).

On the other hand, an increase in the quantity of nonoverlapped knowledge that is successfully transferred through technological M&As can positively influence the knowledge-creation process. A larger quantity of the absorbed nonoverlapped knowledge results in more recombinations that enable firms to diversify into new technological fields (Larsson & Finkelstein, 1999; Karim & Mitchell, 2000; Graebner, Eisenhardt, & Roundy 2010). The recombination of a firm's nonoverlapped knowledge and knowledge in the existing fields creates more valuable inventions (Yayavaram & Chen, 2015). The nonoverlapped parts of the target firm's knowledge base serve as a toolbox for the acquirer firm to explore new fields. This includes the acquisition, transfer, and use of new knowledge, processes, and routines that were not part of the acquirer firm's pre-M&A knowledge base (Ahuja & Lampert, 2001). In other words, as increasing amounts of nonredundant knowledge are transferred to the acquirer firm, the potential for recombination and the possibility to enter a new technological field increases and improves the firm's innovation output (Phene, Tallman, & Almeida, 2012).

However, the information overload as a result of an excessive amount of nonoverlapped knowledge negatively affects the process of knowledge creation as well as the process of knowledge transfer. First, it disrupts existing innovation activities and complicates the process of knowledge creation by incurring costs and delays, which ultimately negatively influence the acquirer firm's subsequent innovation performance (Chakrabarti, Hauschildt, & Süverkrüp, 1994; Capron & Mitchell, 2004; Cloodt, Hagedoorn, & Kranenburg, 2006). When the acquirer firm absorbs too much nonredundant knowledge, its attention to developing specific technology is distracted, which can inhibit the creation of new innovation (Koput, 1997).

In summary, a large quantity of nonoverlapped knowledge increases the number of possibilities for the novel recombination of knowledge, contributing to the firm's explorative innovation. However, when the quantity exceeds a certain level, the acquirer firm suffers from high integration costs due to an insufficient absorptive capacity and delayed knowledge transfer. Moreover, excessive quantities of nonoverlapped knowledge can disrupt a firm's existing innovative activity. This leads us to the following hypothesis:

Hypothesis 4: In technological M&As, an inverted-U shaped relationship exists between the quantity of nonoverlapped knowledge and the post-M&A innovation performance (Figure 2).

	Overlapped Knowledge	Nonoverlapped Knowledge
Effect of target firm's knowledge base quality	H1 (positive) • High absorptive capacity • Low integration cost • High combinative potential	H2 (negative) • Low absorptive capacity • High integration cost • Resource allocation problem
Effect of target firm's knowledge base quantity	H3 (inverted U) • Strengthen existing core capabilities (↑) • High redundancy (↓)	H4 (inverted U) • High number of recombination (↑) • Low absorptive capacity (↓) • Information overloads (↓)

FIGURE 2. RESEARCH FRAMEWORK SHOWING THE HYPOTHESIZED EFFECTS ON POST-M&A INNOVATION PERFORMANCE

METHOD

Data specification

The hypotheses are tested using a data set of technological M&As conducted in high-tech industries from 2001 to 2009. Technological M&As, that is, M&As with the main motivation of acquiring the target firm's knowledge base, have been a popular strategy for external technology sourcing since the early 2000s (Sleuwaegen & Valentini, 2006; Alexandridis, Mavrovitis, & Travlos, 2012). The upper bound of 2009 provides enough time to observe post-acquisition patenting activity. Information on high-tech industry M&A deals that were conducted in the timeframe of the study was collected from the Thomson Reuters SDC Platinum database. M&A deals that involved firms repurchasing their remaining assets and cases of acquisition of remaining interest were excluded. Additional financial information on the firms was acquired from Datastream. Information regarding the patents granted to the firms was collected through the United States Patent and Trademark Office (USPTO) database. The United States has recorded the highest number of patent litigations in the global technology market. Thus, both US and foreign firms usually apply for US patents to protect their innovation from patent infringement (Albert, Avery, Narin, & McAllister, 1991). In addition, previous research has found that US patents are a good proxy for the study of the innovation of foreign firms (Dosi, Pavitt, & Soete, 1990). Therefore, by using USPTO data, this research does not suffer from differences in the patent application systems in various countries. Following the method of Ahuja, and Katila (2001), only M&A deals in which the target firm had applied for at least one patent in the 5 years prior to the M&A deal are considered technological M&As. The final data set consists of 192 technological M&A deals conducted by 162 acquirer firms. The M&A samples are divided into six subcategories that fall within the information technology and biopharmaceutical industries: communications equipment, computer and office equipment, drugs, electronic and electrical equipment measuring, medical photo equipment, and telecommunications. These six subcategories represent industries that have a strong propensity to conduct technological M&As to acquire new technologies. In the sample, electronic and electrical equipment account for 26% of the M&A deals, followed by drugs with 20%, measuring, medical, and photo equipment with 19%, computer and office equipment with 12%, telecommunications with 11.5%, and communications and equipment with 11%. The 192 M&A cases include deals conducted by major firms such as Johnson & Johnson, GlaxoSmithKline, Oracle, SAP, Acer, and Hewlett Packard (HP). Looking at the national origin of the firms in the sample, the United States has the highest share with 56%, followed by Europe with 21%, and then Asia with 19%. M&A deals of firms from other regions account for only 5% of the total technological M&A deals.

Use of patent data

This research uses patent data to analyze the innovation and knowledge bases of firms involved in technological M&As. Patents are one of the most widely used proxies of innovation in the field of innovation and strategic management (Hall, Jaffe, & Trajtenberg, 2005). Using patent data to analyze innovation is efficient because patent data are systematically compiled, contain detailed information such as patent classes and citations, and can be adopted for multi-industry analysis (Song, Almeida, & Wu, 2003). However, patent data have some limitations with regards to the strength of their linkage with innovation. This research solves the limitations as follows: first, it can be argued that patents are not equal to innovation because not all innovations are patented (Kleinknecht, Van Montfort, & Brouwer, 2002). This research uses data of firms within the biopharmaceutical and information technology industries. Firms in these industries tend to apply for patents for the majority of ideas to secure their profitability and intellectual properties. Both industries are characterized by a high appropriability regime with high incentives for patenting, resulting in a high propensity to patent new

innovations (Puranam & Srikanth, 2007). Previous research also argues that the innovation-to-patent ratio of these industries is above the average of other industries (Arundel & Kabla, 1998). The industry selection of this study relieves the problem of whether innovation can be reflected by the analysis of firms' patents. In addition, to give general implications on technological M&As in high-tech industries, this study conducts a multi-industry analysis. Patents are a commonly used proxy for innovation in high-tech industries as they are heavily used in a broad range of industries.

Second, the patenting activity of a firm may not capture the various aspects of innovation performance, such as organizational learning and improvements to practice. According to previous studies, a patent is a record not merely of the explicit nature of an invented innovation, but also of the knowledge that is embedded in the patented innovation. Thus, it includes the organizational process, practice, and routine built during the process of invention (Almeida & Kogut, 1999; Song, Almeida, & Wu, 2003). Hence, although a patent itself may be considered explicit knowledge, considering the various aspects of knowledge that a patent encompasses, it is reasonable to consider the patent count to be an indicator representing far more than just explicit knowledge creation. Accordingly, previous research on technological M&As and organizational learning have used patent count to measure the subsequent innovation performance of the acquirer firm (Ahuja & Katila, 2001; Hagedoorn & Duysters, 2002; Cloodt, Hagedoorn, & Kranenburg, 2006; Kapoor & Lim, 2007; Puranam & Srikanth, 2007; Rothaermel & Hess, 2007).

Third, it can be argued that the patent itself represents explicit knowledge, not tacit knowledge. However, Mowery, Oxley, and Silverman (1996) state that tacit knowledge is complementary to explicit knowledge, and the two are closely linked with each other. In high-technology industries, both tacit and explicit knowledge are used to create new innovations (Song & Shin, 2008). In other words, the transfer and application of tacit knowledge create innovation, which directly leads to patents (Song, Almeida, & Wu, 2003). Thus, this research also expects that both tacit and explicit knowledge are embedded within a patent and measures the quantity and quality of knowledge using patent data. This method has been widely used not only in the field of technological M&As, but also in a number of studies on knowledge management (Chen & Chang, 2010; Kim, Song, & Nerkar, 2012; Valentini, 2012; Yang, Wei, & Chiang, 2014).

Dependent variable

Subsequent innovation performance

This study utilizes patent data to measure the post-M&A innovation performance of acquirer firms. The patenting activity of a firm can be used to approximate its technological characteristics and innovation performance (Hagedoorn & Schakenraad, 1994; Ahuja, 2000; Rothaermel & Alexandre, 2009; Yoon, Lee, & Song, 2015). Previous research on technological M&As has used patent count to measure the subsequent innovation performance of the acquirer firm (Ahuja & Katila, 2001; Puranam & Srikanth, 2007; Jo, Park, & Kang, 2016). In this research, patent count is employed as a lagged measure for firms' post-M&A innovation performance. This study assumes a lag of 1 year after the M&A deal to account for the time it takes from the transfer of the knowledge to its use in a new patent (Makri, Hitt, & Lane, 2010). Previous studies have shown that the value of technological inventions, especially in high-tech industries, depreciates rapidly (Park, Shin, & Park, 2006; Van de Vrande, Vanhaverbeke, & Duysters, 2009). Thus, it is difficult to assume that patents created more than 5 years after an M&A deal have originated from the knowledge that was transferred as part of the acquisition. Accounting for both the lag in using newly transferred knowledge as well as the depreciation of knowledge, the present research defines *subsequent innovation performance* as the number of granted patents of the acquirer firm that were applied for between 1 and 5 years after

the M&A deal year (Bettis & Mahajan, 1985; Ahuja & Lampert, 2001; Harrison, Hitt, Hoskisson, & Ireland, 2001; Jiang, Tan, & Thursby, 2011).

Independent variables

Overlapped knowledge quality and nonoverlapped knowledge quality

Measuring the quality of overlapped and nonoverlapped knowledge requires two key steps: the first step is to classify the knowledge base as overlapped and nonoverlapped, while the second step is to measure the qualitative characteristics of each part of knowledge.

The classification of a patent according to the United States Patent Classification (USPC) represents the technological characteristics of the patent, and there is a strong possibility that patents with similar technologies are classified within the same class, showing the overlap of the knowledge (Sampson, 2007; Makri, Hitt, & Lane, 2010). The opposite also holds true, that is, when two patents belong to the same patent class, it is implied that they are developed in the same technological field (Sampson, 2007). Therefore, for patents in the same class, the knowledge embedded in the inventions can be considered to be overlapped (Makri, Hitt, & Lane, 2010). More recent research presumes that two different patents in the same patent class are created using common knowledge, representing the overlapped part of knowledge between the knowledge bases of firms. Furthermore, recent research uses patent class data to measure knowledge similarities and overlap (Diestre & Rajagopalan, 2012; Frankort, 2016). Following these studies, we also employ the USPC system to classify the knowledge overlap. Thus, patents of acquirer and target firms within the same class are categorized as overlapped, while the ones in different classes are categorized as nonoverlapped (Carayannopoulos & Auster, 2010; Lin, Wu, Chang, Wang, & Lee, 2012).

The quality of each of the overlapped and nonoverlapped parts is calculated using the impact of the patents. Previous innovation-related research has used the impact of patents to represent knowledge quality (Kim, Song, & Nerkar, 2012; Valentini, 2012). According to Trajtenberg (1990), the impact of a patent refers to the total number of its forward citations. In the present research, *overlapped knowledge quality* and *nonoverlapped knowledge quality* are each calculated as the average impact of all the target firm's patents in the overlapped and nonoverlapped patent classes, respectively.

Overlapped knowledge quantity and nonoverlapped knowledge quantity

The definition of *overlapped knowledge quantity* and *nonoverlapped knowledge quantity* follows the approach described above. The variable *overlapped knowledge quantity* is measured as the number of patents in the overlapped parts of the target firm's knowledge base. Consequently, the variable *nonoverlapped knowledge quantity* is measured as the number of patents in the nonoverlapped parts of the target firm's knowledge base.

Control variables

This research adopts a number of control variables to allow uncovering the effects contributed to the independent variables. Because not all granted patents in the observation period can be directly linked to the performance of technological M&As, following previous research, this study controls for a number of possible additional effects on the post-M&A innovation performance of the acquiring firm (Ahuja & Katila, 2001; Hagedoorn & Duysters, 2002; Chen & Chang, 2010). First, the technical and financial characteristics and capabilities of the acquiring firm that may influence post-M&A innovation performance are controlled using the *acquirer size* and *acquirer R&D capability* variables (Phene & Almeida, 2008). The size of the acquirer firm is calculated as the log value of the average revenue of the 3 years prior to the M&A deal. The R&D capability of the acquirer firm is measured as

the 3-year averaged value of R&D intensity, that is, R&D expenditure divided by total sales of the firm. The R&D intensity of a firm implies the firm's level of effort for innovation and direct input of innovation, thereby affecting post-innovation performance (Hagedoorn & Duysters, 2002). Additionally, the larger the knowledge base of the firm is, the more possibilities of novel recombination exist (Ahuja & Katila, 2001). The influence of the acquirer firm's knowledge base, that is, the patents owned by the acquirer firm, is controlled using the total number of patents granted to the firm prior to the M&A deal. In addition to the quantity of the knowledge stock, the quality of the acquirer firm's knowledge base also affects the firm's innovation performance because possessing high-quality knowledge provides more applicable choices for subsequent recombination (Trajtenberg, 1990). Thus, the study also controls for the quality of the firm's existing knowledge stock by using the average impact of the acquirer firm's knowledge base prior to the M&A deal. A number of dummy variables are introduced to capture cross-border M&As, the deal year and the country of the acquirer firm.

Research model

The dependent variable of this study, *subsequent innovation performance*, is a nonnegative count variable. In such cases, Poisson regression is a common choice of methodology. However, according to the descriptive statistics presented in Table 1, the dependent variable shows overdispersion, which violates the basic assumption of the Poisson regression model. Thus, the present research uses a negative binomial model (Hausman, Hall, & Griliches, 1984).

RESULTS

Descriptive statistics

Table 1 shows the summary statistics and the correlations among the variables used in the research. The correlations among the variables are generally low. In addition, the study carries out a variance inflation factor test to increase the validity of the analysis and rule out a multicollinearity problem caused by the high correlation between variables. All variance inflation factor values are <3, which verifies that there is no multicollinearity problem among the variables (Myers, 1990).

Negative binomial regression results

Table 2 describes the results of the negative binomial regression. Model 1 analyses the influence of the control variables on the dependent variable. Only *acquirer size* is found to have a consistently significant effect. Models 2–4 introduce the independent variables, while Model 5 is the full model that includes all the control and independent variables as well as their square terms.

According to the results of Table 2, *overlapped knowledge quality* shows a positive and significant ($p < .01$) result from Models 2–5. Thus, Hypothesis 1, which states that the target firm's high quality of the overlapped knowledge has a positive influence on post-M&A innovation performance, is confirmed. Hypothesis 2 states that as the quality of the target firm's nonoverlapped knowledge increases, the subsequent innovation performance of the acquirer firm is negatively affected. *Nonoverlapped knowledge quality* shows negative results of $p < .01$ significance in Model 3 and $p < .05$ significance in Models 4 and 5. Thus, Hypothesis 2 is also supported.

To verify the curvilinear relationship stated in Hypothesis 3, both *overlapped knowledge quantity* and its squared term are included in Models 4 and 5. As a result, the first-order *overlapped knowledge quantity* variable shows a positive significance of $p < .01$ in both models. At the same time, the squared term of the *overlapped knowledge quantity* variable (*overlapped knowledge quantity squared*) shows a negative significance

TABLE 1. DESCRIPTIVE STATISTICS AND CORRELATIONS AMONG THE VARIABLES

Variables	1	2	3	4	5	6	7	8	9	Mean	SD
Subsequent innovation performance	1.00									91.35	212.22
Overlapped knowledge quality	0.44	1.00								4.99	5.97
Nonoverlapped knowledge quality	−0.11	−0.09	1.00							6.27	18.29
Overlapped knowledge quantity	0.20	0.19	−0.13	1.00						14.39	20.84
Nonoverlapped knowledge quantity	−0.07	−0.13	−0.02	−0.03	1.00					13.26	62.87
Acquirer size	0.31	0.07	−0.14	0.16	0.19	1.00				5.91	1.13
Acquirer R&D capability	−0.07	−0.09	−0.03	0.07	−0.04	−0.42	1.00			0.27	0.62
Acquirer knowledge base	0.37	0.19	−0.08	0.26	−0.05	0.36	−0.07	1.00		638.40	2437.98
Acquirer technology quality	0.16	0.41	−0.01	0.05	−0.12	−0.02	−0.01	0.14	1.00	12.75	15.88

TABLE 2. NEGATIVE BINOMIAL REGRESSION RESULTS FOR SUBSEQUENT INNOVATION PERFORMANCE

Dependent variable: Subsequent innovation performance	Model 1 (coefficient [SE])	Model 2 (coefficient [SE])	Model 3 (coefficient [SE])	Model 4 (coefficient [SE])	Model 5 (coefficient [SE])
Control variables					
Acquirer size	0.95 (0.17)**	0.89 (0.15)**	0.84 (0.15)**	0.74 (0.14)**	0.78 (0.14)**
Acquirer R&D capability	0.45 (0.32)	0.59 (0.30)†	0.51 (0.29)†	0.14 (0.23)	0.17 (0.23)
Acquirer knowledge base	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
Acquirer technology quality	0.03 (0.01)†	0.02 (0.01)	0.02 (0.01)†	0.03 (0.01)*	0.03 (0.01)*
Independent variables					
Overlapped knowledge quality		0.13 (0.03)**	0.12 (0.03)**	0.10 (0.02)**	0.10 (0.02)**
Nonoverlapped knowledge quality			−0.02 (0.01)**	−0.02 (0.01)*	−0.02 (0.01)*
Overlapped knowledge quantity				0.07 (0.02)**	0.06 (0.02)**
Overlapped knowledge quantity squared				−0.0006 (0.0002)**	−0.0006 (0.0002)*
Nonoverlapped knowledge quantity					0.00 (0.01)
Nonoverlapped knowledge quantity squared					0.00 (0.00)
N	192	192	192	192	192
Control dummy variables	Included	Included	Included	Included	Included
Log likelihood	−878.12	−863.89	−860.48	−849.60	−847.96
Pseudo R^2	0.03	0.05	0.05	0.06	0.07
Likelihood Ratio (LR) χ^2	59.22	87.67	94.48	116.25	119.53
Regression p-value	0.00	0.00	0.00	0.00	0.00

Note. $^\dagger p < .10$; $^* p < .05$; $^{**} p < .01$.

of $p < .01$ in Model 4 and $p < .05$ in Model 5. Thus, the overlapped knowledge quantity between the acquirer and target firms exhibits an inverted-U shaped relationship, verifying Hypothesis 3.

Hypothesis 4 suggests a similar inverted-U shaped relationship also for *nonoverlapped knowledge quantity*. In Model 5, however, both *nonoverlapped knowledge quantity* and its square term

(*Nonoverlapped knowledge quantity squared*) show no significance according to the *p*-value. Thus, Hypothesis 4 is not supported. In summary, Hypotheses 1, 2, and 3 are strongly supported, while Hypothesis 4 is not supported by any statistically significant result and cannot be verified.

As stated in Table 2, some independent variables are highly significant, but the associated coefficients have a seemingly small numeric value. However, one needs to recall that the employed negative binomial regression is a nonlinear regression with the equation of $\ln y = \beta_0 + \beta_2 x_2 + \dots + \beta_p x_p$. Therefore, the actual proportion of variance for each independent variable takes the exponential form of the coefficient. Thus, in this study, the actual proportion of variance for the dependent variable is sufficiently large to show a meaningful impact of the chosen variables on the post-M&A performance of the firms.

Robustness test

In addition to the impact of the patent, prior research has used other methods to measure the quality of a patent. In particular, originality and generality are other exemplary variables representing the quality of patents (Trajtenberg, 1990). To show whether the choice of measurement influences the results, the analysis is repeated using originality and generality as the measures for knowledge quality.

The generality of a patent refers to its use in various fields. According to Trajtenberg (1990), patents with a high generality are actively used not only in the technological field to which they belong but also in wider range of fields. The generality of a patent is calculated as 1 minus the Herfindahl index, measuring the concentration of citations received from patents in different patent classes (Valentini, 2012).

The originality of a patent is an index used to determine how creative a new patent is compared with previous ones. According to the originality index, a patent's quality increases as the underlining patents become more diverse (Rosenkopf & Nerkar, 2001). Because these patents are based on diverse ideas and technologies, they are considered more innovative than other patents that are based on only one field (Trajtenberg, Henderson, & Jaffe, 1997; Valentini, 2012). The originality of a patent is calculated similarly to its generality, using a Herfindahl index-based measure of the backward citations of the patent.

The two indexes are applied to measure the quality of the patents and used to verify Hypotheses 1 and 2 of the present research. The results from this analysis are identical to the results presented in Table 2, which further validates the robustness of this study. The results of the additional tests are displayed in Tables A1 and A2 of the Appendix.

CONCLUSION AND DISCUSSION

This research analyses the effects of knowledge overlap's quantitative and qualitative characteristics on the subsequent innovation performance in technological M&As. Specifically, the study divides the target firm's knowledge base into overlapped and nonoverlapped parts and examines the effects of each part's characteristics on subsequent innovation performance. The results indicate that a higher quality of the overlapped knowledge positively affects post-M&A innovation performance. On the contrary, a higher quality of the nonoverlapped knowledge causes high integration costs due to a lack of absorptive capacity and negatively affects the post-M&A innovation performance. This study verifies these effects by analyzing the post-M&A innovation performance of 162 high-tech firms engaged in 192 technological M&A deals.

By considering the qualitative characteristics of knowledge, this research is able to make a number of contributions to the research on knowledge and technological M&As: first, by uncovering the double-sided characteristics of high-quality knowledge, this research provides a more profound understanding of the knowledge-based view in the field of knowledge management. According to the

knowledge-based view, a firm's competitive advantage arises from the acquisition of difficult-to-imitate and highly asset-specific knowledge (Grant, 1996). Therefore, previous literature on knowledge-based view has extensively stressed the need for firms to transfer or create valuable knowledge (Kogut & Zander, 1992; Tsai, 2001). It also argues that identifying and acquiring high-quality knowledge is important for a firm to sustain a competitive advantage (Nonaka & Toyama, 2002). However, our research explains that while the transferred knowledge can positively impact the mechanism of knowledge creation, the tacit nature of high-quality knowledge makes the transfer of such knowledge costly and inefficient.

Second, this research contributes to the strategic management literature on technological M&As. Extending previous studies that have addressed the knowledge overlap between acquirer and target firms in technological M&As, this research finds a more complex relationship between the knowledge overlap and the subsequent innovation performance in technological M&As. The stream of recent research focusing on knowledge overlap suggests a negative effect of overlapped knowledge on subsequent performance and highlights the importance of acquiring new knowledge with no overlap (Cloodt, Hagedoorn, & Kranenburg, 2006; Colombo & Rabbiosi, 2014; Sears & Hoetker, 2014). However, by extending the point of view and also considering the qualitative characteristics of the knowledge, this research shows a positive impact of knowledge overlap on subsequent innovation performance. Along the same line, by showing that higher quality of knowledge in nonoverlapped fields negatively influences post-M&A performance, this research complements the results of previous studies. We show that in the context of M&A deals that result in the acquisition of high-quality knowledge, the overlapped knowledge plays a more significant role than the nonoverlapped knowledge.

Third, this research provides an empirical study on the effects of qualitative characteristics of knowledge. While the importance of the quality of knowledge has been continuously emphasized in the literature on organizational learning and strategic management, most empirical studies on technological M&As have solely focused on the quantitative characteristics of knowledge when investigating the effect of the knowledge base on post-M&A innovation performance. Until now, researchers have only considered knowledge quality as an output measure of a firm's post-M&A performance and focused on how to measure the quality of a target firm's knowledge (e.g., Valentini, 2012; Yang, Wei, & Chiang, 2014). To our knowledge, this research is the first attempt to fill this research gap and to clarify the effects of the quality of knowledge on the post-acquisition performance of technological M&As.

In addition to the various contributions stemming from the consideration of quality-related characteristics of knowledge, this study provides a comprehensive framework for studying the effects of the knowledge base of acquirer and target firms in technological M&As. This study assumes that the overlapped and nonoverlapped parts of the knowledge base have distinctive characteristics, and it conducts an analysis of the qualitative/quantitative characteristics for each part of the knowledge. This approach allows a more systemic view when analyzing the knowledge base of firms in technological M&As and will contribute to future research in this field.

This research provides several practical implications: first, focusing only on obtaining the high-quality knowledge of the target firm might negatively affect innovation performance. According to this research, integrating knowledge without considering the acquirer firm's knowledge base will incur high managerial costs and integration costs and low marginal returns. Therefore, an acquirer firm should look into the overlap between the target firm's and acquiring firm's knowledge bases to fully utilize the high-quality knowledge of the target firm. There are some M&A cases in which acquiring a target firm with high-quality nonoverlapped knowledge resulted in the failure to obtain synergies through combining the knowledge bases. A good example is the case of HP company's acquisition of Palm, Inc. To cope with rival firms such as Google, Inc. and Microsoft Corporation entering the mobile market, HP acquired Palm, which was the leader of the Personal Digital Assistant industry, with the purpose

of acquiring knowledge in the mobile computing field. Palm was a technology-intensive firm that possessed a large amount of high-quality knowledge in the mobile computing field with accumulated intellectual properties and user experiences. Moreover, Palm was using its own world-class mobile WebOS and platforms at that time. However, HP, which had focused on its existing computer development, could not fully exploit Palm's knowledge due to a lack of overlapped knowledge. HP could not achieve successful learning through the M&A and ultimately failed to enter the mobile market. Another related example is the case of Microsoft Corporation's acquisition of aQuantive, Inc. In response to rival firm Google's acquisition of DoubleClick, Microsoft acquired mobile advertisement company aQuantive. aQuantive was a firm that possessed the high-quality knowledge of an advertisement platform called Atlas, which competed with DoubleClick, a firm acquired by Google, and an advertisement network called DRIVEEpm, which is an advertisement platform for rich media such as online videos. However, the M&As resulted in failure, without pursuing joint projects, owing to the absence of a common knowledge background due to the insufficient knowledge overlap. These cases complement our argument that the lack of overlapped knowledge causes a lack of absorptive capacity, thereby making it more difficult for the acquirer firm to obtain and benefit from the high-quality knowledge of the target firm.

Second, the knowledge overlap helps the acquirer firm to learn and utilize the target firm's high-quality knowledge. The technological M&A cases of Gilead Sciences, Inc. show the positive effect of high-quality knowledge acquisition when considering knowledge overlap. Gilead Sciences is a global biopharmaceutical company specialized in treatments for infectious diseases such as hepatitis and HIV. In 2003, Gilead Sciences acquired Triangle Pharmaceuticals, Inc., which also had strength in infectious diseases, to gain access to the HIV treatment Emtriva, which is situated in the overlapped knowledge area. Gilead Sciences recombined the acquired HIV treatment Emtriva with its existing HIV treatment, Viread, and successfully developed Truvada, which became the standard drug in the HIV treatment market. In 2011, Gilead Sciences acquired Pharmasset, Inc., which also had its strength (high-quality knowledge) in the treatments of infectious diseases. Pharmasset had developed infectious disease treatments such as Sofosbuvir, a treatment drug for hepatitis C. Gilead Sciences, Inc. launched Sovaldi, including Sofosbuvir as its main ingredient. Further, adding the internally developed substance ledipasvir onto Sovaldi allowed Gilead Sciences, Inc. to develop the subsequent drug Harvoni, which proved to be a great success. These cases show that the overlapped knowledge of Gilead Sciences positively affected the creation of novel recombinations when combined with the high-quality knowledge of target firms, such as Triangle and Pharmasset. Likewise, the overlapped knowledge base provides sufficient absorptive capacity for accommodating the complexity of the target firm's high-quality knowledge. Furthermore, to utilize the target firm's high-quality knowledge through technological M&As, paradoxically, the firm should possess overlapped knowledge in advance. As an acquirer firm's diverse knowledge base is more likely to overlap with the target firm's knowledge, acquirer firms need to possess diverse knowledge in order to successfully transfer knowledge and create innovation. As this research has verified, this overlap contributes to transferring the knowledge of the target firm after an M&A and creating new knowledge. Therefore, firms need to foster diversity in their own knowledge portfolio to successfully create innovation through technological M&As.

In summary, the overlap between acquirer and target firms should be wisely exploited in technological M&As. As this research suggests, firms are more likely to appreciate the value of knowledge and utilize it in areas where knowledge overlap exists. Thus, it is necessary to select a target firm with high-quality knowledge in overlapped areas and a sufficient quantity of knowledge in nonoverlapped areas. In other words, the acquisition of high-quality knowledge is needed for innovation where acquirer and target firms share similar knowledge, while acquiring a moderate quantity of knowledge is needed for more innovation in areas unfamiliar to the acquirer firm.

LIMITATIONS AND FURTHER RESEARCH

This research makes several important contributions and introduces a new perspective on the qualitative aspect of knowledge to the research on knowledge overlap in technological M&As. At the same time, there are limitations resulting from the data and definitions employed in the study. This research used patent data in quantitative and qualitative measures of the knowledge bases of both the acquirer and target firms. A firm's patents can serve as an index explicitly showing the firm's knowledge base (Mowery, Oxley, & Silverman, 1998; Ahuja, 2000; Rothaermel & Alexandre, 2009). However, because the likelihood of patenting a new innovation can change over time or across industry sectors, patents might not fully reflect the firm's technological capabilities (Pavitt, 1985). Patent-based indicators also do not capture innovations that are not patented (Kleinknecht, Van Montfort, & Brouwer, 2002). However, this research minimizes the gap using various methods, such as sample selection.

In addition, measuring the knowledge overlap using the USPC system can be incomplete because the USPC system categorizes only the field of the application of the patent and not the nature of the innovation. The research on knowledge overlap has continuously used this measure because common knowledge is embedded in different patents that share the same patent class (Diestre & Rajagopalan, 2012; Frankort, 2016). However, a more practical measure would allow readers to gain more insight on knowledge overlap. Future research could address these shortcomings by using additional data, such as statistics on new product development or surveys. Moreover, considering a larger variety of factors in measuring knowledge quality will result in a more refined framework for researching the effects of qualitative features of knowledge on technological M&As and will thus help managers acquire suitable target firms.

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APPENDIX: ROBUSTNESS TEST RESULT

Tables A1 and A2

TABLE A1. ROBUSTNESS TEST RESULT: KNOWLEDGE GENERALITY

Dependent variable: Subsequent innovation performance	Model 1 (coefficient [SE])	Model 2 (coefficient [SE])	Model 3 (coefficient [SE])	Model 4 (coefficient [SE])	Model 5 (coefficient [SE])
Control variables					
Acquirer size	0.84 (0.16)**	0.91 (0.15)**	0.80 (0.14)**	0.77 (0.14)**	0.77 (0.15)**
Acquirer R&D capability	0.05 (0.26)	0.25 (0.25)	0.13 (0.24)	0.02 (0.22)	0.02 (0.22)
Acquirer knowledge base	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
Acquirer technology quality	3.73 (0.63)**	2.59 (0.61)**	2.34 (0.60)**	1.93 (0.57)**	1.97 (0.58)**
Independent variables					
Overlapped knowledge quality		3.35 (0.76)**	3.25 (0.71)**	2.63 (0.62)**	2.69 (0.62)**
Nonoverlapped knowledge quality			−1.86 (0.55)**	−1.67 (0.53)**	−1.73 (0.54)**
Overlapped knowledge quantity				0.06 (0.02)**	0.06 (0.02)**
Overlapped knowledge quantity squared				−0.0006 (0.0002)**	−0.0007 (0.0002)**
Nonoverlapped knowledge quantity					0.01 (0.01)
Nonoverlapped knowledge quantity squared					0.00 (0.00)
N	192	192	192	192	192
Control dummy variables	Included	Included	Included	Included	Included
Log likelihood	−866.59	−856.80	−851.72	−845.04	−843.35
Pseudo R^2	0.05	0.06	0.06	0.07	0.07
LR χ^2	82.27	101.86	112.01	125.37	128.76
Regression p-value	0.00	0.00	0.00	0.00	0.00

Note. $^\dagger p < .10$; $^* p < .05$; $^{**} p < .01$.

TABLE A2. ROBUSTNESS TEST RESULT: KNOWLEDGE ORIGINALITY

Dependent variable: Subsequent innovation performance	Model 1 (coefficient [SE])	Model 2 (coefficient [SE])	Model 3 (coefficient [SE])	Model 4 (coefficient [SE])	Model 5 (coefficient [SE])
Control variables					
Acquirer size	0.92 (0.15)**	0.98 (0.14)**	0.94 (0.14)**	0.87 (0.14)**	0.87 (0.15)**
Acquirer R&D capability	0.26 (0.29)	0.21 (0.26)	0.14 (0.25)	0.00 (0.24)	0.01 (0.24)
Acquirer knowledge base	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
Acquirer technology quality	3.88 (0.71)**	2.94 (0.70)**	2.78 (0.69)**	2.69 (2.65)**	2.75 (0.66)**
Independent variables					
Overlapped knowledge quality		2.69 (0.57)**	2.55 (0.57)**	1.51 (0.57)**	1.53 (0.56)**
Nonoverlapped knowledge quality			−1.07 (0.45)*	−1.29 (0.43)**	−1.36 (0.44)**
Overlapped knowledge quantity				0.06 (0.02)**	0.06 (0.02)**
Overlapped knowledge quantity squared				−0.0007 (0.0002)**	−0.0007 (0.0002)**
Nonoverlapped knowledge quantity					0.01 (0.01)
Nonoverlapped knowledge quantity squared					0.00 (0.00)
N	192	192	192	192	192
Control dummy variables	Included	Included	Included	Included	Included
Log likelihood	−867.83	−857.72	−855.00	−848.50	−846.98
Pseudo R^2	0.04	0.06	0.06	0.07	0.07
LR χ^2	79.79	100.02	105.46	118.46	121.49
Regression p-value	0.00	0.00	0.00	0.00	0.00

Note. $^{\dagger}p < .10$; $^{*}p < .05$; $^{**}p < .01$.