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Reconfiguring the firm’s core technological portfolio through open innovation: focusing on technological M&A

Seungryul Ryan Shin, John Han, Klaus Marhold and Jina Kang

Abstract
Purpose – The purpose of this study is to investigate the effects of open innovation, especially focusing on technological M&A, on subsequent innovation and changes to the firm’s core technological portfolio.
Design/methodology/approach – The study suggests three types of core technological areas, based on prior focus and experience in technological categories. These are 1) the existing core area, in which the acquirer firm retains its knowledge and expertise, 2) the enhanced core area, where knowledge and expertise in the acquirer firm’s insufficient areas are strengthened, and 3) the new core area, i.e. new knowledge fields in which the acquirer firm ventures into. The study then analyzes the effects of two key knowledge characteristics of the target firm, similarity and complementarity, on post-M&A innovation outcomes in each of the three core technological areas.
Findings – The results confirm that while none of the investigated knowledge characteristics of the target firm is advantageous for post-M&A innovation outcomes in existing core areas, similarity of the target firm does facilitate post-M&A innovation outcomes in enhanced core areas. Moreover, the results confirm that complementarity of the target firm is beneficial for post-M&A innovation outcomes in new core areas.
Originality/value – The study explains the reconfiguration mechanism of a firm’s core technological portfolio. It also suggests an extended framework to analyze innovation outcomes in more detail. Moreover, the study helps to explain why most M&As result in failure.
Keywords Knowledge characteristics, Knowledge management, Open innovation, Core competences, Core technological portfolio, Technological M&A

Paper type Research paper

1. Introduction

A firm’s core technological competence determines its competitiveness in technology-intensive industries (Granstrand et al., 1997; Prahalad and Hamel, 1990; Duysters and Hagedoorn, 2000). Accordingly, firms are required to wisely manage their own core technological portfolio to sustain a competitive advantage. However, firms developing core technological areas solely relying on their own internal development may cause their own “core competencies” to turn into “core rigidities”, which prevent the pursuit of new and promising ideas and technologies (Leonard-Barton, 1992; Kraatz and Zajac, 2001). Thus, firms increasingly utilize open innovation and obtain the knowledge and expertise required to develop and adapt their core technological portfolio from external sources (Chesbrough, 2003, 2006a, 2006b; Vanhaverbeke et al., 2002).

Among the various open innovation modes, this research focuses on technological M&A. As technological M&A allows to absorb not only technological knowledge but also technological expertise and capabilities of the target firm (Ahuja and Katila, 2001; Jo et al., 2016), it has significant impacts on the acquirer firm’s post-M&A internal changes and subsequent innovation activities (Cassiman et al., 2005; Colombo and Rabbiosi, 2014; Kapoor and Lim, 2014).
Therefore, technological M&As provide a suitable setting to examine how utilizing open innovation affects the reconfiguration of the firm’s core technological portfolio.

Much of the existing literature emphasizes that relational knowledge characteristics between the acquirer firm and the target firm’s knowledge bases are an important dyadic factor to be considered in studies of technological M&As (Ahuja and Katila, 2001; Makri et al., 2010; Sears and Hoekter, 2014; Han et al., 2016). Foundational research on technological M&As examined how the similarity of the target firm’s and the acquirer firm’s knowledge affects post-M&A innovation outcomes (Ahuja and Katila, 2001; Cloodt et al., 2006). More recent research classified the relational knowledge characteristics of the target firm into similarity and complementarity, and examined the effect of each target firm knowledge characteristic on post-M&A innovation outcomes (Makri et al., 2010; Ganzaroli et al., 2016). However, the effects of the target firm’s knowledge characteristics on the acquirer firm’s core technological portfolio have not been closely examined. This contrasts with the streams of literature which find that firms’ competitiveness is determined by their core technological areas rather than the overall technology areas of the entire firm (Granstrand et al., 1997; Phene et al., 2012; Chiesa, 2001).

To remedy the shortcomings of prior research, this study examines the effects of technological M&As, especially focusing on knowledge characteristics of the target firm, on the acquirer firm’s core technological portfolio reconfiguration. This research suggests that a firm’s open innovation activities, i.e. external knowledge sourcing, involves the reconfiguration of the firm’s core technological portfolio through three different mechanisms. Accordingly, the study distinguishes the firm’s core technological portfolio into three distinct areas: Existing core area, Enhanced core area and New core area. The study investigates how two key knowledge characteristics of the target firm, i.e. similarity and complementarity, affect post-M&A innovation outcomes in each of the three core technological areas, thereby showing the reconfiguration of the firm’s core technological portfolio.

This study makes several contributions to the research on M&As and technology management. First, it explains how firms reconfigure their core technological portfolio by suggesting three types of core technological area formation mechanisms. Second, it provides a new framework that builds up on the existing dichotomy of innovation, i.e. exploitation versus exploration, and allows to analyze innovation outcomes in detail. Third, the findings of the study might help to explain the high rate of “failed M&A deals” reported in the literature. The study also provides managerial implications by listing guidelines for acquirer firms selecting a proper target firm with matching knowledge characteristics according to the purpose of the technological M&A deal.

The remainder of this paper is structured as follows: Section 2 introduces the concepts of core technological areas and knowledge characteristics of the target firm. Section 3 suggests hypotheses linking the knowledge characteristics and subsequent core technology innovation. Section 4 describes the data sample, variable constructs and statistical methods used to test the hypotheses. Section 5 presents the results of the empirical tests, while Section 6 provides a discussion of the results, as well as the study’s contributions and implications.

2. Theory and concepts

2.1 Core technological areas

Literature suggests that developing core technological areas of competences and expertise is vital for firms to sustain a competitive advantage (Prahalad and Hamel, 1990; Leonard-Barton, 1992; Chiesa, 2001). This is especially important for firms operating in technology-intensive industries (Duysters and Hagedoorn, 2000). According to Granstrand et al. (1997), most firms have distributed core technological areas, rather than
concentrating on a small number of core technological areas, and they create a significant portion of their innovation within these core technological areas. To sustain a competitive advantage, firms are required to keep reconfiguring their core technological portfolio in line with market or technological changes and to furnish expertise in the core technological areas accordingly (Prahalad and Hamel, 1990; Grant, 1996; Chiesa, 2001; Jain, 2015).

When a firm sources knowledge from outside the firm, the reconfiguration of the firm’s core technological portfolio is realized through three distinct change mechanisms. To investigate each change mechanism, this study classifies the core technological areas based on whether the acquirer firm had its strategic focus on the technological area before the external sourcing and on whether the acquirer firm possessed knowledge in the technological area before the external sourcing. First, technological areas, which have been a part of the firm’s core technological portfolio before the external sourcing and still reside within the firm’s core technological portfolio after the external sourcing, are defined as “existing core area”. The firm has retained its strategic focus on the existing core areas. It possessed sufficient technological expertise and capabilities in existing core areas (Granstrand et al., 1997; Prahalad and Hamel, 1990), which allowed it to focus innovation in the technological areas before the external sourcing. Moreover, vigorous innovation activity in the existing core areas established technological trajectories and routines in these technological areas (Dosi, 1982; Nelson and Winter, 1982).

Second, technological areas, which have been a part of the firm’s non-core technological areas before the external sourcing and become a part of the core technological areas of the firm after the external sourcing, are defined as “enhanced core area”. Enhanced core areas have been peripheral to the firm’s strategic focus before the external sourcing. Contrary to the existing core areas, the firm possessed insufficient technological expertise and capabilities in these enhanced core areas (Granstrand et al., 1997). In addition, the technological trajectory and routine are inadequately established in the enhanced core areas due to inactive innovation activities and insufficient experiences (Dosi, 1982; Nelson and Winter, 1982). Changes in the firm’s strategic direction to improve the expertise in the enhanced core areas and to secure competences in these technological areas require technological expertise and capabilities that may complement the acquirer firm’s existing knowledge and expertise to make up for the existing deficiencies (Kraatz and Zajac, 2001; Phene et al., 2012; Makri et al., 2010).

Third, technological areas, which the firm did not possess before the external sourcing but which become a part of the firm’s core technological areas after the external sourcing, are defined as “new core area”. The firm had no technological expertise and capabilities in these new core areas, which implies the absence of technological trajectories and routines (Dosi, 1982; Nelson and Winter, 1982). Changes in the firm’s strategic direction to find a new technological niche require various opportunities for idea cross-fertilization with other existing knowledge or expertise (Björkdahl, 2009; Makri et al., 2010) and technological expertise and capabilities of technological areas with a high degree of novelty from outside the firm (Phene et al., 2012; Kraatz and Zajac, 2001; Kapoor and Lim, 2007).

This study analyzes how technological M&As affect the reconfiguration of the acquirer firm’s core technological portfolio. Consequently, it focuses on the above-mentioned three distinct mechanisms of change, i.e. it investigates the acquirer firm’s post-M&A innovation outcomes in each of the core technological areas suggested: Existing core innovation, Enhanced core innovation and New core innovation. Figure 1 illustrates the reconfiguration of the acquirer firm’s core technological portfolio through an M&A deal and highlights the definitions for each of the core technological areas suggested by this study.
2.2 Knowledge characteristics

This study examines the effects of two distinct knowledge characteristics of the target firm: Similarity and Complementarity. Makri et al. (2010) suggests a framework for knowledge characteristics based on these measures which has found widespread adoption in recent studies (Orsi et al., 2015; Miozzo et al., 2015; Ganzaroli et al., 2016). Extending this framework and definitions provided by Makri et al. (2010), this study defines the similarity and the complementarity of the target firm’s knowledge base. Similarity is the degree to which the target firm has technological knowledge and expertise that are similar to that of the acquirer firm. Higher similarity of the target firm indicates that the target firm has a knowledge base and expertise more similar to the acquirer firm (Makri et al., 2010; Kapoor and Lim, 2007; Larsson and Finkelstein, 1999). This concept also relates to the concept of technological familiarity, i.e. the extent to which the acquirer firm is familiar with and has prior knowledge of the acquiring technological areas (Arts and Veugelers, 2014; Fleming, 2001; Roberts and Berry, 1984). Complementarity of the target firm is the degree to which the target firm possesses technological knowledge and expertise that are new to the acquirer firm but complementary to the acquirer firm’s existing knowledge and expertise. A high complementarity of the target firm implies that the target firm possesses more knowledge that has a high recombinative potential with the acquirer firm’s existing knowledge base (Ahuja and Katila, 2001; Makri et al., 2010) and expertise that complements the acquirer firm’s existing expertise (Kapoor and Lim, 2007; Larsson and Finkelstein, 1999).

3. Hypotheses

In the following section, each of the previously discussed knowledge characteristics of the target firm is linked with the post-M&A innovation outcomes in each type of core technological area. This allows to investigate the reconfiguration of the acquirer firm’s core technological portfolio as a result of the technological M&A.

3.1 Existing core innovation

Existing core areas are where the acquirer firm already possesses technological capabilities and expertise (Granstrand et al., 1997; Prahalad and Hamel, 1990). Moreover, concentrated innovation activities before the M&A allowed the acquirer firm to establish technological trajectories and routines in the existing core areas (Nelson and Winter, 1982; Dosi, 1982). Under these circumstances, similarity of the target firm impedes the innovation in the acquirer firm’s post-M&A existing core areas. The acquirer firm’s knowledge workers in these areas already have sufficient technological expertise and follow established technological trajectories to create innovation in the technological areas on their own.
(Dosi, 1982; Benner and Tushman, 2002, 2003; Burgelman, 2002). Thus, a high level of similarity of the target firm’s knowledge resources results in redundancy of expertise and knowledge in the existing core areas (Ahuja and Katila, 2001; Sears and Hoetker, 2014). Moreover, firms usually eliminate duplicative technological capabilities and expertise after M&As to increase efficiency and maximize the benefits of the M&As (Cassiman et al., 2005). The threat of being eliminated increases the propensity of the acquirer firm’s knowledge workers to refuse accepting the similar expertise of the target firm (Sears and Hoetker, 2014; Larsson and Finkelstein, 1999). Furthermore, integrating two knowledge worker groups with similar expertise but different technological routines (Nelson and Winter, 1982) may cause disruptions in both firms’ technological routines for the technological areas (Ranft and Lord, 2002), thereby reducing innovation productivity in the existing core areas (Kapoor and Lim, 2007; Paruchuri et al., 2006).

Complementarity of the target firm is also detrimental for innovation in the existing core areas. The acquirer firm’s existing core areas are characterized by a strong path dependence in innovation activities as a result of the acquirer firm focusing on innovation in the existing core areas before the M&A (Nelson and Winter, 1982; Dosi, 1982). The acquirer firm’s knowledge workers in the existing core areas tend to follow established technological trajectories (Levinthal and March, 1993; Dosi, 1982). They also tend to resort to local search rather than technological boundary spanning to find new solutions (Rosenkopf and Nerkar, 2001). This has been described as the propinquity trap by Ahuja and Lampert (2001). The propinquity trap leads to the acquirer firm’s knowledge workers in the existing core areas being more likely to find solutions around familiar knowledge areas. It reduces opportunities to have cross-fertilization and recombination with the acquired complementary knowledge and expertise. Moreover, as the acquirer firm has established expertise and competency in the existing core areas, the Not-Invented-Here (NIH) syndrome may come into play (Katz and Allen, 1982). The acquirer firm’s knowledge workers in the existing core areas may degrade and reject externally developed knowledge (Hussinger and Wastyn, 2015). This leads to complementary knowledge and expertise of the target firm not being adopted and utilized. Therefore, despite the complementarity of the target firm having potential to create synergy from cross-fertilization and novel recombination with the existing knowledge base, the acquired complementary knowledge and expertise are less likely to be adopted and utilized during the acquirer firm’s innovation activities in the existing knowledge areas and rather turn into redundancies. Thus, complementarity of the target firm hinders the creation of innovation in these areas.

In summary, the similarity of the target firm gives rise to knowledge workers’ resistance and technological routine disruptions in the existing core areas. Hence, it negatively affects innovation in the existing core areas. Also, the complementarity of the target firm would not be utilized due to the effects of the propinquity trap and NIH syndrome in the existing core areas. Thus, it negatively affects innovation in the existing core areas:

**H1a.** Similarity of the target firm negatively affects post-M&A innovation in existing core areas.

**H1b.** Complementarity of the target firm negatively affects post-M&A innovation in existing core areas.

### 3.2 Enhanced core innovation

Contrary to the existing core areas, enhanced core areas are where the acquirer firm only possessed limited technological expertise and capabilities (Granstrand et al., 1997). Moreover, being peripheral to the acquirer firm’s strategic focus before the M&A implies that technological trajectories or routines in the enhanced core areas are not fully developed (Nelson and Winter, 1982; Dosi, 1982). Under these circumstances, similarity of the target firm facilitates innovation in these areas. Owing to the insufficient expertise and technological routines in the enhanced core areas, the acquirer firm’s knowledge workers
in the technological areas are less likely to resist acquiring the target firm which possesses similar expertise (Larsson and Finkelstein, 1999), and rather welcome and cooperate with the target firm’s knowledge workers (Sears and Hoetker, 2014). Thus, the target firm’s technological routines are less likely to be disrupted (Ranft and Lord, 2002) and the innovation productivity of the target firm’s knowledge workers is more likely to be preserved (Kapoor and Lim, 2007; Paruchuri et al., 2006). Moreover, the combined firm’s knowledge workers can achieve a higher invention productivity and synergies through economies of scale and scope (Makri et al., 2010; Hagedoorn and Duysters, 2002; Larsson and Finkelstein, 1999), which promote innovation outcomes in enhanced core areas.

Complementarity of the target firm is also beneficial for the innovation within the enhanced core areas. As technological trajectories or routines are insufficient in the enhanced core areas, the acquirer firm’s knowledge workers in the technological areas may avoid the “myopia of learning” (Levinthal and March, 1993). Consequently, they are more likely to search for solutions, which may complement the existing knowledge, from outside the acquirer firm’s knowledge base (Rosenkopf and Nerkar, 2001). Complementary knowledge is knowledge with a high potential of combination with the acquirer firm’s existing knowledge (Makri et al., 2010) and is relatively easier for the acquirer firm to learn due to higher absorptive capacity for related technological areas (Cohen and Levinthal, 1990; Ahuja and Katila, 2001). Moreover, as the complementary expertise of the target firm is not duplicated with the expertise of the acquirer firm, the acquirer firm’s knowledge workers in underdeveloped knowledge areas are more likely to cooperate with the target firm’s complementary expertise (Sears and Hoetker, 2014), which provides opportunities for the cross-fertilization of ideas (Greve, 2003; Kang, 2007; Petruzelli and Savino, 2014). This allows the acquirer firm to achieve a higher productivity within the enhanced core areas (Kapoor and Lim, 2007), thereby increasing the enhanced core innovation output.

In summary, the similarity of the target firm supplements the insufficient expertise and innovation productivity in enhanced core areas, thus positively affecting enhanced core innovation. The complementarity of the target firm allows combinations with the existing expertise or knowledge in enhanced core areas, thus positively affecting enhanced core innovation:

- **H2a.** Similarity of the target firm positively affects post-M&A innovation in enhanced core areas.
- **H2b.** Complementarity of the target firm positively affects post-M&A innovation in enhanced core areas.

### 3.3 New core innovation

New core areas are where the acquirer firm had no prior technological expertise and capabilities as well as innovation experiences before the M&A. Under these circumstances, similarity of the target firm deters innovation in new core areas. In order for the acquirer firm to create innovation and secure expertise in new technological areas, acquiring knowledge and expertise that are familiar in new technological areas and learning from the acquired knowledge and expertise are essential (Roberts and Berry, 1984; Ahuja and Lampert, 2001). However, similarity of the target firm is more likely to provide knowledge and expertise in knowledge areas that are already familiar to the acquirer firm rather than knowledge and expertise in new technological areas (Makri et al., 2010). Moreover, prior experience in the familiar knowledge areas forms technological trajectories and routines which allow the firm to obtain immediate returns from the knowledge. This causes the acquirer firm to fall into a familiarity trap (Levinthal and March, 1993; Ahuja and Lampert, 2001). Despite the need for the acquired familiar knowledge to be recombined in unprecedented ways to create novel innovation (Arts and Veugelers, 2014), the familiarity trap increases the likelihood of the acquirer firm to follow existing technological trajectories and routines in utilizing the acquired familiar knowledge (Ahuja and Lampert, 2001). Finally,
as the similar expertise and knowledge of the target firm are more likely to supplement the acquirer firm’s existing technological areas, the acquirer firm is less likely to reallocate its resources and attention to new technological areas (Kraatz and Zajac, 2001; Koput, 1997). Hence, similarity of the target firm hinders new core innovation.

Complementarity of the target firm, on the other hand, facilitates innovation in new core areas. First, complementarity of the target firm broadens the combined firm’s knowledge and areas of expertise, which increases the potential for combinations with the acquirer firm’s existing technological areas (Ahuja and Katila, 2001; Makri et al., 2010; Larsson and Finkelstein, 1999). The broadened knowledge base becomes a source of solutions for the acquirer firm’s search activities (Prabhu et al., 2005). It provides the acquirer firm with various opportunities for idea cross-fertilization (Björkdahl, 2009; Makri et al., 2010; Greve, 2003), which may facilitate novel invention in new technological areas. Second, combining the target firm’s complementary knowledge and expertise with the acquirer firm’s existing expertise may create knowledge and expertise in new technological areas, which the acquirer firm did not have before (Cassiman et al., 2005). Thus, complementarity of the target firm provides opportunities to create novel invention and expertise in new technological areas. In addition, as the acquirer firm did not possess any knowledge or technological routine in the new technological areas, disruption in the target firm’s technological trajectories or routines in the new technological areas may be minimized (Ranft and Lord, 2002). The acquired expertise and in-house development of the target firm can thus maintain its invention productivity in the new core areas (Song et al., 2003; Demsetz, 1988) and facilitate innovation.

In summary, similarity of the target firm, which provides knowledge of low novelty and impedes resource and attention reallocation to new technological areas, negatively affects new core innovation. Complementarity of the target firm, on the other hand, enlarges the combined firm’s search scope to provide various opportunities for idea cross-fertilization and helps in maintaining the target firm’s invention productivity in the new core areas, thus positively affecting new core innovation (Table I):

H3a. Similarity of the target firm negatively affects post-M&A innovation in new core areas.

H3b. Complementarity of the target firm positively affects post-M&A innovation in new core areas.

4. Data and methods

4.1 Data specification

The data sample in this study was collected from the biopharmaceutical industry. The biopharmaceutical industry provides an ideal setting for this research for the following reasons: First, as the biopharmaceutical industry is a technology-intensive industry, each firm’s technological learning, especially innovation in its focus areas, determines the firm’s competitiveness (Bierly and Chakrabarti, 1996). Firms in this industry fiercely develop knowledge and expertise in their own core technological areas to sustain a competitive advantage, thus it allows for an in-depth analysis of the dynamic change and development of a firm’s core technological areas. Second, the industry’s characteristics of a weak appropriability regime and secrecy dearth encourage firms’ patenting activity (De Carolis, 2003; Bierly and Chakrabarti, 1996), allowing to capture a firm’s knowledge base operations through analyzing the firm’s patenting activity. Third, the industry consists of

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several sub-industries spanning diverse knowledge areas, allowing for a multifaceted analysis on the distinct knowledge characteristics within a single industry (Carayannopoulos and Auster, 2010). In addition, firms in this industry actively utilize M&As to keep up with changes in both market and technology (Higgins and Rodriguez, 2006), or to acquire the expertise and knowledge required for research breakthroughs (De Carolis, 2003; Carayannopoulos and Auster, 2010).

The data set was collected based on technological M&A deals made by biopharmaceutical firms from 2001 to 2008. Information on M&A deals conducted between 2001 and 2008 by the firms in the biopharmaceutical industry, which comprises biotech firms, pharmaceutical firms and other chemical and bio-related firms, was drawn from the Thomson Reuters SDC Platinum database. In the next step, self-acquisition M&A deals, which firms usually conduct to acquire remaining assets or interests, were excluded. Patenting information of each firm from 1996 to 2014 was obtained from the US Patent and Trademark Office (USPTO) database. It was ensured that all the considered patents had indeed been granted to the firms. To take only technological M&A deals into consideration, M&A deals involving target firms with no patent granted during the five years prior to the M&A deal were excluded (Ahuja and Katila, 2001; Phene et al., 2012). Each firm’s financial information was obtained from the Datastream database. Removing entries with missing values, the final data set includes 412 technological M&A deals involving 187 acquirer firms.

The final data sample consists of M&A deals conducted by firms from several technological sectors within the biopharmaceutical industry, including major firms such as Boston Scientific Corp, Medtronic Inc, Novartis AG, Du Pont, Abbott Laboratories, Invitrogen Corp and Pfizer Inc. Measuring, medical, photo equipment sector; Drugs sector; and Chemicals and the other bio-related subindustries account for 48.1 per cent, 38.8 per cent, and 13.1 per cent of the M&A deals, respectively. Firms in the data sample have their main base of operation in 20 different countries. Firms based in the USA account for the majority (64.1 per cent) of the M&A deals, followed by firms based in Japan with 14.1 per cent. Firms based in Switzerland, the UK, Denmark and Germany accounted for 6.6 per cent, 3.2 per cent, 2.2 per cent, and 2.2 per cent of the M&A deals, respectively.

4.2 Variables

4.2.1 Dependent variables. The study analyzed firms’ pre- and post-M&A patenting activities, which have been considered as a suitable indicator of a firm’s technological knowledge base operations and innovation output (Patel and Pavitt, 1991; Duysters and Hagedoorn, 2000). The dependent variables were constructed by investigating the acquirer firm’s pre- and post-M&A patenting activities and the change in the acquirer firm’s core technological areas. Following prior research, for pre-M&A activities, the study observed patents granted during the five years prior to M&A deals (Ahuja and Katila, 2001; Cloodt et al., 2006). The study uses a two-year time lag between the M&A deal and the post-M&A acquirer patenting activity observation. A prior research by Popp et al. (2004) examining determinants of the time lag between patent application and patent grant suggests that patent applications require an average of 28 months to be granted. Consequently, much of the prior literature uses a two-year time lag between the M&A deal and the post-M&A acquirer patenting activity observation (Phene et al., 2012; Makri et al., 2010). Subsequently, the acquirer firm’s patents granted within a five-year window after the two-year time lag were included in the observation for the post-M&A period (Phene et al., 2012). This five-year window also allows to capture patents that require more than two years to be granted.

To distinguish the pre- and post-M&A acquirer firm’s core technological areas, the study used a 3 per cent cutoff, as suggested by Granstrand et al. (1997) and used in Phene et al. (2012). For each pre- and post-M&A timeframe, particular technological areas (defined as patent main-classes) whose granted patents make up more than 3 per cent of the total
number of the acquirer firm’s patents granted during each period were considered as the acquirer firm’s core technological areas. Then, the lists of pre- and post-M&A core technological areas were compared to distinguish the three distinctive core technological areas, i.e. existing core areas, enhanced core areas and new core areas:

Existing core technological areas are the technological areas that are found on both the pre- and post-M&A core technological areas lists. Enhanced core technological areas and new core technological areas are the technological areas that are only included in the list of post-M&A core technological areas but not in the list of pre-M&A core technological areas. They are distinguished by prior patenting activities. Enhanced core areas are areas in which the acquirer firm was granted patents during the five years prior to the M&A, while new core areas are the remaining areas in which the acquirer firm had no patent granted during the five-year period prior to the M&A.

Similar to prior research utilizing patent count to measure innovation output (Ahuja and Katila, 2001; Puranam and Srikanth, 2007; Ernst and Vitt, 2000), this study counted the number of the acquirer firm’s patents granted within each of the core technological areas during the above-mentioned post-M&A period to define the dependent variables Existing core innovation, Enhanced core innovation and New core innovation.

4.2.2 Independent variables. Similar to prior research (Ahuja and Katila, 2001; Cloodt et al., 2006; Miozzo et al., 2015), the patents granted to the acquirer firm and the target firm during the five years prior to M&A deals were compared to distinguish the target firm’s knowledge base characteristics. The study constructed variables for each knowledge characteristic of the target firm, Similarity and Complementarity. The study used patent main-class and subcategory classification to distinguish the knowledge characteristics, following the framework suggested by Makri et al. (2010), as many other recent research did (Ganzaroli et al., 2016; Miozzo et al., 2015). The study adopted the US classification system provided by USPTO (2012), which categorizes patent main-classes into 50 relevant subject groups. (Throughout the study, this classification system is referred to as “subcategory” to prevent any confusion with the subclasses defined as subsets of the individual USPTO main-classes.) Utilizing patent main-class and subcategory classification, the study constructed the independent variables through the below-mentioned methods.

Similarity measures the extent to which the pre-M&A target firm’s knowledge base is similar to the pre-M&A acquirer firm’s knowledge base. Following prior research (Ahuja and Katila, 2001; Makri et al., 2010; Petruzelli, 2011), this study considered the overlapped patent main-classes, in which both the acquirer firm and the target firm have patents granted during the five years prior to the M&A, as the target firm’s similar technological areas. The study calculated the independent variable Similarity using the following equation:

\[
\text{Similarity} = \frac{\text{Total target patents in common mainclasses}}{\text{Total granted patents of acquirer and target}}
\]

Complementarity measures the extent to which the pre-M&A target firm’s knowledge base has combinational potential with the pre-M&A acquirer firm’s knowledge base. Following prior studies (Makri et al., 2010; Ganzaroli et al., 2016), the study considered the non-overlapped target firm’s patent main-classes, in which only the target firm has patents granted during the five years prior to the M&A but resides in the subcategories of the pre-M&A acquirer firm’s knowledge base, as the target firm’s complementary technological areas. The study calculated the independent variable Complementarity using the following equation:

\[
\text{Complementarity} = \frac{\text{Total target patents in common subcategories}}{\text{Total target patents in common mainclasses}} - \frac{\text{Total target patents in common mainclasses}}{\text{Total granted patents of acquirer and target}}
\]

4.2.3 Control variables. Several control variables, which may affect the firm’s subsequent innovation activity, were included. First, the acquirer firm’s R&D intensity was included to control the influence stemming from the acquirer firm’s efforts and investments in R&D activities. R&D intensity was computed as the acquirer firm’s R&D expense divided by total
sales measured in the year before the M&A deal (Hall et al., 1986; Phene and Almeida, 2008; Phene et al., 2012). Second, the acquirer firm’s Firm size was included, as prior studies have demonstrated the significant direct effect of firm size on the subsequent innovation performance (Acs and Audretsch, 1988; Cohen and Klepper, 1996). Following prior research (Rosenkopf and Almeida, 2003; Phene and Almeida, 2008; Ahuja and Katila, 2001), the study measured firm size of the acquirer firm by taking the log of the number of employees. Third, to control the influences of the acquirer firm’s innovation ability and knowledge stock accumulated before the M&A (Desyllas and Hughes, 2010; Oettl and Agrawal, 2008; Phene et al., 2012), the study included the absolute size of the acquirer firm’s knowledge base (Acquirer knowledge base). Following Phene et al. (2012), Acquirer knowledge base was measured using the number of the acquirer firm’s patent granted during the five years prior to the M&A. Fourth, the relative size of knowledge base (Relative size knowledge base) was included to control influences that may be caused by the size difference between the knowledge base of the acquirer firm and the target firm (Ahuja and Katila, 2001; Larsson and Finkelstein, 1999). Relative size knowledge base was calculated by dividing the total number of patent granted to the target firm during five years prior to the M&A by Acquirer knowledge base. Fifth, Acquirer diversification was included to control the degree to which the acquirer firm diversified its technological portfolio (Miller, 2004; Garcia-Vega, 2006). The study calculated Acquirer diversification using the formula of the Shannon entropy index: \( \Sigma P_i \times \ln (1/P_i) \), where \( P_i \) is the percentage of the patents granted within the \( i \)th main-class (Ganzaroli et al., 2016). Sixth, Number of M&A deals for the acquirer firm in the same year was included to control the effects of the number of M&A deals the acquirer firm conducted in the same year. Finally, the study introduced four dummy variables, Year dummy, Technological sector dummy, Foreign acquisition dummy and Acquirer firm nationality dummy, which control for the influence from the M&A deal year, the acquirer firm’s specific technological sector, cross-border M&A deal and the acquirer firm’s nationality, respectively.

4.3 Method

As all three of the dependent variables consist of non-negative discrete integer values, Poisson regression or negative binomial regression may be used (Hausman et al., 1984). However, Poisson regression requires that the mean and the variation of the dependent variable should be nearly the same. The dependent variables are over-dispersed, which does not satisfy the requirement to use Poisson regression. Thus, negative binomial regression was used.

5. Results

The descriptive statistics and correlations of the variables used in the analysis are shown in Table II. Most of the correlation values between the variables have acceptable values of discriminant validity, which are lower than the 0.70 threshold (Cohen et al., 2003). Only the correlation between the dependent variable Enhanced core innovation and the control variable Acquirer knowledge base exceeds the 0.70 threshold, which may cause multi-collinearity problems. However, as the control variable Acquirer knowledge base captures the acquirer firm’s knowledge stock (Phene et al., 2012) or invention productivity (Kapoor and Lim, 2007) before the M&A, it should be included to control the influences that could be attributed to the acquirer firm’s existing innovation ability (Oettl and Agrawal, 2008). Thus, the study measured variance inflation factors (VIFs) for each regression model to check whether the multi-collinearity problem exists in each regression model. The mean and the maximum values of VIF for each regression model are indicated in Table III. The mean VIF and maximum VIF values for each regression model fall below 3, which implies that no multi-collinearity problems exist between the variables used in each regression model (Myers, 1990).
<table>
<thead>
<tr>
<th>Variables</th>
<th>Mean</th>
<th>SD</th>
<th>Min</th>
<th>Max</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>
</tr>
</thead>
<tbody>
<tr>
<td>1. Existing core innovation</td>
<td>119.47</td>
<td>234.00</td>
<td>0.00</td>
<td>1,811.00</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2. Enhanced core innovation</td>
<td>13.71</td>
<td>41.42</td>
<td>0.00</td>
<td>529.00</td>
<td>0.33***</td>
<td>1</td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3. New core innovation</td>
<td>6.25</td>
<td>9.35</td>
<td>0.00</td>
<td>64.00</td>
<td>-0.20***</td>
<td>-0.13***</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4. Similarity</td>
<td>0.12</td>
<td>0.17</td>
<td>0.00</td>
<td>0.83</td>
<td>-0.15***</td>
<td>-0.07</td>
<td>0.11***</td>
<td>1</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>5. Complementarity</td>
<td>0.05</td>
<td>0.12</td>
<td>0.00</td>
<td>0.93</td>
<td>-0.18***</td>
<td>-0.12***</td>
<td>0.26***</td>
<td>0.10**</td>
<td>1</td>
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<td></td>
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<td></td>
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<tr>
<td>6. R&amp;D intensity</td>
<td>64.61</td>
<td>1,265.75</td>
<td>0.00</td>
<td>25,684.40</td>
<td>-0.02</td>
<td>-0.02</td>
<td>0.14***</td>
<td>0.03</td>
<td>0.02</td>
<td>1</td>
<td></td>
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<tr>
<td>7. Firm size (Log employee)</td>
<td>3.62</td>
<td>0.90</td>
<td>0.30</td>
<td>5.21</td>
<td>0.41***</td>
<td>0.33***</td>
<td>0.00</td>
<td>-0.19***</td>
<td>-0.30***</td>
<td>-0.05</td>
<td>1</td>
<td></td>
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<td>8. Relative size knowledge base</td>
<td>4.70</td>
<td>45.06</td>
<td>0.00</td>
<td>685.00</td>
<td>-0.05</td>
<td>-0.03</td>
<td>0.12**</td>
<td>0.13***</td>
<td>0.13***</td>
<td>-0.00</td>
<td>0.05</td>
<td>1</td>
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<tr>
<td>9. Acquirer knowledge base</td>
<td>204.00</td>
<td>418.50</td>
<td>1.00</td>
<td>2,617.00</td>
<td>0.59***</td>
<td>0.74***</td>
<td>-0.24***</td>
<td>-0.18***</td>
<td>-0.18***</td>
<td>-0.02</td>
<td>0.45***</td>
<td>-0.05</td>
<td>1</td>
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<tr>
<td>10. Acquirer diversification</td>
<td>2.66</td>
<td>3.63</td>
<td>0.00</td>
<td>27.17</td>
<td>0.30***</td>
<td>0.24***</td>
<td>-0.15***</td>
<td>-0.11**</td>
<td>-0.16***</td>
<td>-0.02</td>
<td>0.38***</td>
<td>-0.07</td>
<td>0.39***</td>
<td>1</td>
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<tr>
<td>11. Number of M&amp;A deals</td>
<td>2.40</td>
<td>1.57</td>
<td>1.00</td>
<td>7.00</td>
<td>0.18***</td>
<td>0.27***</td>
<td>-0.01</td>
<td>-0.23***</td>
<td>-0.15***</td>
<td>-0.04</td>
<td>0.44***</td>
<td>-0.03</td>
<td>0.45***</td>
<td>0.15***</td>
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Notes: ***p < 0.01; **p < 0.05; *p < 0.1
<table>
<thead>
<tr>
<th>Control variables</th>
<th>DV: Existing core innovation</th>
<th>DV: Enhanced core innovation</th>
<th>DV: New core innovation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model 1</td>
<td>Model 2</td>
<td>Model 3</td>
<td>Model 4</td>
</tr>
<tr>
<td>R&amp;D intensity</td>
<td>-0.000 (0.000)</td>
<td>-0.000 (0.000)</td>
<td>-0.002 (0.010)</td>
</tr>
<tr>
<td>Model 5</td>
<td>Model 6</td>
<td>Model 7</td>
<td>Model 8</td>
</tr>
<tr>
<td>Firm size (Logemployee)</td>
<td>0.981*** (0.087)</td>
<td>0.965*** (0.087)</td>
<td>0.881*** (0.087)</td>
</tr>
<tr>
<td>Model 9</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Relative size knowledge base</td>
<td>-0.008*** (0.002)</td>
<td>-0.008*** (0.002)</td>
<td>-0.008*** (0.002)</td>
</tr>
<tr>
<td>Acquirer knowledge base</td>
<td>0.001*** (0.000)</td>
<td>0.001*** (0.000)</td>
<td>0.001*** (0.000)</td>
</tr>
<tr>
<td>Number of M&amp;A deals</td>
<td>-0.147*** (0.043)</td>
<td>-0.148*** (0.043)</td>
<td>-0.140*** (0.042)</td>
</tr>
<tr>
<td>Independent variables</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Complementarity</td>
<td>-0.715** (0.352)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>412</td>
<td>412</td>
<td>412</td>
</tr>
<tr>
<td>Log likelihood</td>
<td>-2.095.00</td>
<td>-2.093.04</td>
<td>-2.082.34</td>
</tr>
<tr>
<td>Prob &gt; χ²</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>LR χ²</td>
<td>361.03</td>
<td>364.95</td>
<td>386.35</td>
</tr>
<tr>
<td>Mean VIF</td>
<td>1.29</td>
<td>1.20</td>
<td>1.29</td>
</tr>
<tr>
<td>Max VIF</td>
<td>1.67</td>
<td>1.67</td>
<td>1.67</td>
</tr>
<tr>
<td>Notes: ***p &lt; 0.01; **p &lt; 0.05; *p &lt; 0.1</td>
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</table>
The results from the negative binomial regression are shown in Table III. Three different dependent variables, *Existing core innovation*, *Enhanced core innovation* and *New core innovation*, were tested. Models 1 to 3 examine the effects of each control variable and the target firm’s knowledge base characteristics on *Existing core innovation*. As Model 1 indicates, the control variables *Firm size*, *Relative size knowledge base*, *Acquirer knowledge base*, *Acquirer diversification* and *Number of M&A deals* have a significant effect on *Existing core innovation*. Especially, the significant negative effect of *Number of M&A deals* on *Existing core innovation* could imply that frequent M&A impedes innovation in the existing core areas. Model 2 confirms that the target firm’s knowledge base *Similarity* has a negative and significant ($p < 0.05$) effect on the post-M&A *Existing core innovation*, which supports H1a. Model 3 examines the effect of the target firm’s knowledge base *Complementarity* on the post-M&A *Existing core innovation*, and confirms its negative and significant ($p < 0.01$) effect. Thus, H1b is also supported.

Models 4 to 6 examine how each control variable and the target firm’s knowledge base characteristics affect *Enhanced core innovation*. Model 4 confirms that the control variables *Firm size*, *Relative size knowledge base*, *Acquirer knowledge base* and *Acquirer diversification* significantly influence *Enhanced core innovation*. Model 5 examines H2a, which suggests a positive relationship between the target firm’s knowledge base *Similarity* and the post-M&A *Enhanced core innovation*, and indicates a positive and significant ($p < 0.05$) relationship between the two variables. Thus, H2a is supported. H2b argues that the target firm’s *Complementarity* positively affects the post-M&A *Enhanced core innovation*. However, Model 6 finds no significant effect of *Complementarity* on the post-M&A *Enhanced core innovation*. Consequently, H2b is not supported.

Models 7 to 9 examine the effects of each control variable and the target firm’s knowledge base characteristics on *New core innovation*. Model 7 demonstrates that the control variables *Firm size*, *Acquirer knowledge base*, and *Acquirer diversification* have a significant impact on *New core innovation*. Model 8 examines H3a, which proposed a negative relationship between the target firm’s knowledge base *Similarity* and the post-M&A *New core innovation*, but shows no significant relationship between the two variables. Thus, H3a is not supported. Model 9 confirms a positive and significant ($p < 0.01$) effect of the target firm’s knowledge base *Complementarity* on the post-M&A *New core innovation*, which supports H3b.

To increase the robustness of the results, an additional robustness test has been performed using dependent variables with a three-year time lag and a four-year window to capture the innovation performance in each of the three distinct core areas. The results of this robustness test, reported in Table AI, validate the robustness of our findings.

6. Discussion and conclusion

This study analyzed a data set of 412 technological M&A deals in the biopharmaceutical industry to examine the impacts of various knowledge characteristics of the target firm on the acquirer firm’s post-M&A innovation outcomes in core technological areas. The empirical results support the main arguments of the study. They confirm that, in technological M&As, 1) none of the investigated knowledge characteristics of the target firm, similarity and complementarity, is advantageous for innovation in the existing core areas where the acquirer firm already has established technological expertise and technological routine before the M&A, 2) similarity of the target firm facilitates innovation in the enhanced core areas where the acquirer firm had only insufficient expertise and inadequate technological routines before the M&A, and 3) complementarity of the target firm is beneficial for innovation in the new core areas where the acquirer firm did not have any expertise or knowledge before the M&A.
This study advances the fields of technology management and M&A research through the following contributions: First, the study explains the reconfiguration processes in the acquirer firm’s core technological portfolio by suggesting three distinct types of core technological areas in the core technological portfolio. Prior research highlights the importance of firms nurturing core competences and expertise because the core competence determines a firm’s competitiveness (Prahalad and Hamel, 1990; Leonard-Barton, 1992). Firms are required to secure core technological components and technological expertise to cope with the rapidly changing market and technology (Chiesa, 2001). Despite the fact that wisely managing core technological portfolio is essential for firms to survive in technology-intensive industries (Prahalad and Hamel, 1990; Duysters and Hagedoorn, 2000), previous literature only discussed why the firm’s core technological portfolio should be wisely managed but did not provide insights into how the reconfiguration of the firm’s core technological portfolio is performed. Extending the literature on the firm’s core technological portfolio, this study empirically analyzes the reconfiguration processes in the firm’s core technological portfolio. The three types of the core technological areas suggested in this research, existing core area, enhanced core area and new core area, allow to explicate the firm’s core technological portfolio reconfiguration occurring through external knowledge sourcing. This research specifically examines the reconfiguration processes of a firm’s core technological portfolio in the context of technological M&As. It enables to observe the reconfiguration processes by analyzing post-M&A innovation outcomes in each of the core technological areas.

Second, the study contributes to the literature on organizational learning by suggesting an extended framework to analyze the firm’s innovation outcomes or learning activities. Since March (1991), the dichotomy of innovation, i.e. exploitation versus exploration, has been extensively adopted in the literature of organizational learning (Levinthal and March, 1993; Tushman and O’Reilly, 1996; He and Wong, 2004; Raisch and Birkinshaw, 2008; Voss et al., 2008). Especially, much of prior research used the concepts of exploitation and exploration in examining how various external sourcing modes affect the firm’s learning and innovation (Stettner and Lavie, 2014; Lavie and Rosenkopf, 2006; Phene et al., 2012; Wagner, 2011; Ganzaroli et al., 2016). However, as not all of the firm’s existing knowledge areas have received an equal amount of prior experience and attention and established the same degree of technological trajectories and expertise, a firm’s exploitation activity should be investigated considering the circumstances and characteristics of each knowledge area. Considering the difference in the extent to which expertise and technological routines have been established in each technological area allows the study to divide exploitative innovation, which builds on existing technological areas (March, 1991; Levinthal and March, 1993), into existing core innovation and enhanced core innovation. This classification is suitable to investigate the firm’s exploitation activities in more detail and to differentiate how acquired knowledge and expertise are applied in each technological area after the M&A. Moreover, advancing prior studies, which merely considered learning or innovation outcomes in new knowledge areas as explorative innovation (March, 1991; Levinthal and March, 1993), this study specifies the explorative innovation that is created in the acquirer firm’s core areas as new core innovation. This allows to examine the firm’s explorative innovation in new knowledge areas that the firm actually focuses on and creates vigorous innovation, which helps improving the firm’s competitiveness.

Third, the findings of the study help to explain the common notion of “most M&As are failing”. Despite firms actively utilizing technological M&As as a means to obtain external knowledge, many reports on M&As reveal a high failure rate of M&As (Deutsch and West, 2010). This study explains this failure of M&As by stressing the importance of a cautious approach in combining the acquirer firm’s and the target firm’s technological expertise and capabilities after the M&A. In the existing core areas, where the acquirer firm’s knowledge workers possess proven strength and ability to create innovation, the knowledge workers are less likely to cooperate with the target firm’s knowledge workers and might even refuse to utilize
the knowledge provided by the acquisition of the target firm. Thus, M&As are more likely to result in failure if a firm utilizes the M&A for the purpose of further strengthening its existing core areas. On the other hand, for the enhanced core areas and the new core areas, where the acquirer firm’s knowledge workers do not possess sufficient technological expertise and capabilities to create innovation, the acquirer firm’s knowledge workers are more likely to embrace target firms with proper knowledge characteristics, thereby creating synergies with the target firm and increasing innovation outcomes. Thus, acquiring a suitable target firm is crucial for M&A success in the enhanced core areas and new core areas.

The findings of this study allow us to provide managerial implications for firms planning to conduct open innovation activities through technological M&A. Firms conduct technological M&A with various objectives of 1) developing existing core technological areas, 2) changing the strategic focus toward their insufficient technological areas and 3) expanding expertise and knowledge into new technological areas. This study provides firms a guideline that allows them to better select a proper target firm with best-suited knowledge characteristic according to their objectives. Specifically, the research suggests firms to look for other knowledge acquisition methods for their existing core technological areas, such as internal development or technological alliances, and to refrain from technological M&As for the purpose of existing core area development. It also suggests firms to select a target firm with similar expertise and knowledge to enhance their insufficient technological areas. Moreover, a target firm with complementarity is suggested as the most promising choice to successfully expand the existing knowledge base into new areas.

Although this study provides a number of important contributions and implications, it has a number of limitations. First, this study focused on technological M&A as a prominent mode of open innovation knowledge sourcing. Open innovation activities are not limited to M&A, however, but can encompass a wide range of modes, which differ, e.g. in scope or the employed mode of governance. Future research should thus try to uncover the effects of other open innovation modes on the firm’s core technological portfolio. Second, the hypotheses of this study were tested on a data set of technological M&As conducted by firms in the biopharmaceutical industry. As industrial effects may differ under other research settings, future studies should test the hypotheses using data from other industries, to generalize the results. Third, the evaluation was based on patent analysis. While this is an accepted and objective approach, patent analysis is known to have limitations, e.g. the inability to capture innovation which is not patented (Kleinknecht et al., 2002; Lane et al., 2006). Thus, future research could address the shortcoming of the patent-based measures and corroborate the findings by using other data sets, such as survey results or new product development statistics.

References


Myers, R.H. (1990), *Classical and Modern Regression with Applications*, Duxbury Press, Boston, MA.


Table AI  Robustness test results

<table>
<thead>
<tr>
<th>DV: Existing core innovation</th>
<th>DV: Enhanced core innovation</th>
<th>DV: New core innovation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model 1</td>
<td>Model 2</td>
<td>Model 3</td>
</tr>
<tr>
<td>R&amp;D intensity</td>
<td>−0.000 (0.000)</td>
<td>−0.000 (0.000)</td>
</tr>
<tr>
<td>Firm size (Logemployee)</td>
<td>1.001*** (0.092)</td>
<td>0.977*** (0.092)</td>
</tr>
<tr>
<td>Relative size knowledge base</td>
<td>−0.009*** (0.002)</td>
<td>−0.008*** (0.002)</td>
</tr>
<tr>
<td>Acquirer knowledge base</td>
<td>0.001*** (0.000)</td>
<td>0.001*** (0.000)</td>
</tr>
<tr>
<td>Acquirer diversification</td>
<td>0.045** (0.022)</td>
<td>0.046** (0.022)</td>
</tr>
<tr>
<td>Number of M&amp;A deals</td>
<td>−0.164*** (0.045)</td>
<td>−0.166*** (0.045)</td>
</tr>
</tbody>
</table>

Independent variables

| Similarity                  | −0.751** (0.372)            | 2.133* (1.172)          | 0.626 (1.937)              | 0.077 (0.455)               | 1.591*** (0.575)            |
| Observations                | 412                         | 412                     | 412                        | 412                         | 412                         |

Control dummy variables

| Included                    | Included                    | Included                  | Included                   | Included                   | Included                   | Included                   | Included                   | Included                   |
| Log likelihood              | −2,003.85                   | −2,001.92                 | −1,992.51                  | −819.97                    | −818.14                    | −819.92                    | −1,010.79                  | −1,010.78                  |
| Prob > χ²                   | 0.00                        | 0.00                     | 0.00                       | 0.00                       | 0.00                       | 0.00                       | 0.00                       | 0.00                       |
| LR χ²                       | 335.37                      | 339.23                    | 358.06                     | 220.96                     | 224.62                     | 221.06                     | 112.83                     | 112.86                     |
| Mean VIF                    | 1.29                        | 1.30                      | 1.29                       | 1.29                       | 1.29                       | 1.29                       | 1.29                       | 1.29                       |
| Max VIF                     | 1.67                        | 1.67                      | 1.67                       | 1.67                       | 1.67                       | 1.67                       | 1.67                       | 1.67                       |

Notes: ***p < 0.01; **p < 0.05; *p < 0.1
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