How Do Mutual Dependence and Power Imbalance Condition the Effects of Technological Similarity on Post-Acquisition Innovation Performance Over Time?

Jie Wu
University of Aberdeen
Business School,
King's College, University of Aberdeen, Aberdeen AB24 5UA
United Kingdom
Email: jie.wu@abdn.ac.uk

Luman Yu
Faculty of Business Administration
University of Macau
Email: mb94604@connect.um.edu.mo
Avenida Padre Tomás Pereira, Taipa
Macau, SAR

Zaheer Khan*
University of Aberdeen
Business School,
King's College, University of Aberdeen, Aberdeen AB24 5UA
United Kingdom
Corresponding author Email: zaheer.khan@abdn.ac.uk

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Abstract

This study investigates how mutual dependence and power imbalance, which have been differentiated by the recent studies adopting the theoretical lens of resource dependence theory (RDT) as two distinct forms of interdependence, change the effect of technological similarity between the acquiring firm and target firm on post-acquisition innovation across times. The analysis of a panel data on merger and acquisitions (M&As) undertaken by the US firms reveals that in the short-run mutual dependence strengthens the effect of technological similarity on post-acquisition innovation, whereas power imbalance weakens it. However, the effect of mutual dependence persists over time, while that of power imbalance declines over time. These findings extend the RDT to the context of technological acquisition and innovation and offer important implications for research and practice.

Keywords: Resource dependence, mutual dependence, power imbalance, acquisitions, technological similarity, innovation performance, M&As

1. Introduction

In an increasingly knowledge-based economy, there has been a significant growth in mergers and acquisitions (M&As), through which new technology and competencies are obtained by firms for developing competitive advantage (Chaudhuri & Tabrizi, 1998; Bower, 2001; Nicholls-Nixon & Woo, 2003; Graebner, 2004; Cloodt, Hagedoorn, & Van Kranenburg, 2006; Colombo & Rabbiosi, 2014; Park & Choi, 2014). A central question of prior M&As literature has been to uncover important mechanisms that enable these acquisitions to improve innovation performance and hence create value for merging entities (Hitt, Harrison, & Ireland, 2001; Grimpe & Hussinger, 2008; King et al., 2020). In a context of technological M&As, obtaining new know-how and developing strong technological competencies through acquisitions have been widely acknowledged as important motives for developing new set of capabilities (Link, 1988; Granstrand et al., 1992; Haapanen et al., 2019). Similarly, scholars have found that if acquired firm knowledge and technology are related or similar to acquiring firm's knowledge base, the subsequent knowledge combination will lead to "surplus" over and above the individuals' resources could create independently (Haspesslagh & Jemison, 1991; Anand & Singh, 1997; Cefis, Marsili, & Rigamonti, 2020). However, inadequate efforts have been devoted to understand whether and how resource dependence of two parties in technological M&As affects the extent to which such knowledge similarity could generate the positive effect for post-acquisition innovation. This question is vital, because so many (technological) M&As fail to achieve their set objectives (e.g., Haleblian et al., 2009; Han, Jo, & Kang, 2018; Renneboog & Vansteenkiste, 2019), and the most important concern which has been widely acknowledged (Steigenberger, 2017) is post-acquisition integration with respect to employee emotional resilience, which can be vital issue at the post-integration stage (cf. Khan et al., 2020). That is, interdependence of two parties in technological M&A determines without a doubt how the positive effect of technological similarity on post-acquisition innovation could be realized, especially as the post-acquisition integration is unfolding over time.

The extant studies have developed two related but distinct dimensions of resource dependence: *mutual dependence and power imbalance*. Mutual dependence captures the overall degree of mutual dependencies of two parties (e.g., i and j) in a relationship. A large sum or the average of actor i's dependence on actor j and actor j's dependence on actor i reflects substantial dependencies between the both parties. However, mutual dependence does not take into account of the dependencies of two parties on each other and how these are balanced or imbalanced. In contrast, power imbalance addresses this concern with regards to the difference between two parties' dependencies on each other. It uses the ratio of the power of the more powerful actors to that of the less powerful actor to capture the difference in the power of each actor over the other (Casciaro & Piskorski, 2005). These two distinct theoretical dimensions of resource dependence certainly have significant implications for the extent to which the "synergy-generating" potential of technological acquisition is fully realized (Casciaro & Piskorski, 2005: 173), which has been totally neglected by prior studies. On the one hand, a high mutual dependence creates substantial incentives for both the parties to consider the use of long-term contracts such as joint ventures (JVs) and strategic alliances or permanent interorganizational arrangements such as M&As as tactics to ensure stable flows of the critical resources which they provide to each other. However, power imbalance could create obstacle for these incentives in the way that the more powerful party is less willing to consider the long-term arrangements (e.g., M&As) to lose its advantageous position, whereas the less powerful party has a constant attempt to pursue a reliable arrangement to mitigate its disadvantageous position. The differences between the two distinct theoretical dimensions should have signfciant implications for technological M&As and its post-acquisition innovation performance, which however, has received little research attention (cf. Hillman, Withers, & Collins, 2009).

This study addresses the above lacunas by investigating how power imbalance and mutual dependence differently affect the effect of technological similarity of two parties in technological acquisition and post-acquisition innovation and how these effects may change over time. We theoretically postulate and empirically find that immediately following a technological acquisition, power imbalance attenuates the effect of technological similarity on post-acquisition innovation, whereas mutual dependence accentuates it. However, as the post-integration proceed, the effect of mutual dependence sustains, but that of power imbalance diminishes over time. The findings of this study in the context of M&A and post-acquisition innovation contributes to the resource dependence theory (RDT) and M&As' literature in two important aspects. First, this study extends two related, but distinct dimensions of resource dependence to the context of technological M&As and innovation performance. Although M&As has been considered as one of the most important strategic actions by the RDT literature to reduce environmental dependence, however, it is surprising that inadequate efforts have been devoted to explore the RDT in the context of technological M&As and innovation performance. Considering that very high odds M&A activities is related to technological M&As, and better post-acquisition innovation occupies a paramount interest in the set objectives of M&As, it is undoubtedly critical to extend the RDT to the context of technological M&As and post-acquisition innovation performance.

Second, this study advances the existing knowledge of power imbalance and mutual dependence as two distinct dimensions of resource dependence. We build on their distinct theoretical logics to develop the arguments with regards to their moderating effects in the relationship between technological similarity and post-acquisition innovation both in the short- and medium-term. We theoretically argue and empirically demonstrate that mutual dependence *strengthens* the effect of technological similarity on post-acquisition innovation, but power imbalance *weakens* it. Moreover, these effects diverge in a longer period. The effect of mutual dependence persists overtime, whereas the effect of power imbalance diminishes. These findings not only offer important insights to the literature on RDT and M&As which has documented the challenges arising from post-integration (cf. Haleblian et al. 2009; Khan et al., 2020), but, more importantly, extend the current RDT perspectives by providing a more fine-grained understanding about the diverging aspects of mutual dependence and power imbalance in technological M&As and post-acquisition innovation, which has hitherto been neglected by the extant studies (cf. Hillman, Withers, & Collins, 2009).

2. Theoretical development

2.1 Technological Similarity and Post-Acquisition Innovation Performance

Technological similarity refers to the degree of knowledge similarity between two parties in a business relationship. High levels of knowledge similarity have a positive effect on acquiring firm's post-acquisitions' innovation performance mainly for three reasons. First, high levels of technological similarity increase the likelihood of the relevance of technology held by the acquired firm to an acquiring firm and thus enhance the latter's combinative capabilities—the ability to integrate the knowledge base from an acquired firm into its technology base rapidly (cf. Ahuja & Katila, 2001; Fleming, 2001; Wu, 2012). Prior studies have supported this argument by showing that high levels of technological similarity facilities learning in alliances (Cloodt, Hagedoorn, & Van Kranenburg, 2006; Schildt, Keil, & Maula, 2012). Such assertions are also supported by the recent scholarship in the context of technological M&As which finds that high level of knowledge overlap between the acquiring and target firm enhances innovation performance (cf. Han, Jo, & Kang, 2018).

Second, given that knowledge acquisition of a firm is characterized by a process of gradual accumulation and path-dependent, knowledge similarity between two parties leads to an acquiring firm's deep understanding of knowledge held by the acquired firm, which is critical for the former to identify, understand, and assimilate a large stock of knowledge possessed by the later and combine with its own knowledge to generate greater value (Lane & Lubatkin, 1998; Sears & Hoetker, 2014). Moreover, similar technological interfaces between acquiring and acquired firms resulted from high levels of technological similarity ease the knowledge flow and improve knowledge sharing between two parties (Mowery, Oxley, & Silverman, 1996; Lew et al., 2016), thereby enriching the acquiring firm's knowledge pool, which is critical for successful innovation. These arguments together suggest that high knowledge similarity contributes to post-mergers' innovation performance. Knowledge similarity can also improve post-mergers' integration due to the less concern of not invented here syndrome (cf. Katz & Allen, 1982; Antons & Piller, 2015), and dissimilar knowledge bases can exacerbate the post-merger integration challenges (e.g., Cloodt, Hagedoorn, & Van Kranenburg, 2006). Firms also need absorptive capacity to integrate the external knowledge for value creating activities and having similar knowledge bases ease the knowledge integration and recombination related challenges which can facilitate innovation in M&As (Zahra & George, 2002). This does not mean that dissimilar knowledge has no value for the acquiring firm as some studies have documented that different knowledge bases are also vital for developing competitive advantage in M&As due to the novelty aspect of dissimilar knowledge (e.g., Kapoor & Lim, 2007; Sears & Hoetker, 2014).

However, the positive effect of technological similarity tends to diminish over time for two reasons. First, given that innovation is essentially a process of combining different knowledge components (Kogut & Zander, 1992; Wu, 2014), an acquiring firm, before formally launching an acquisition, tends to conduct a comprehensive search for valuable knowledge and recognizes which potential target firms possess its needed knowledge. Consequently, immediately following an acquisition, the acquiring firm can easily identify the relevant knowledge possessed by the acquired firm and combine new knowledge with its existing knowledge in order to create more value and pursue growth strategies. However, with the elapse of time, the most relevant combinations have been identified and utilized. The possibility of novel knowledge combinations that would lead to the development of new products and processes will exhaust. Meanwhile, as the acquiring firm has exploited straightforward ways of knowledge combination. The new combinations that include new and old knowledge elements are likely to become more complex (Katila, 2000). This is especially true for an acquiring firm that has developed products that are new to the industry through building on knowledge synergy with target firm. At the early stage following an acquisition, the acquiring firm can easily identify some simple combinations involving low-dimensions (e.g., two-ways) combinations (Fleming, 2001). However, the firm will soon find increasingly difficult and expensive to discover new combinations of knowledge, as easy combinations have been depleted and complex combinations involve high-dimensions (e.g., three-ways or four-ways) combinations. Firms over a period of time as the acquisition progresses may find it difficult to integrate different set of knowledge due to not invented here syndrome (Katz & Allen, 1982; Antons & Piller, 2015). Therefore, the acquiring firm finds it difficult to achieve innovation benefits through technological synergy as time evolves. Scholarship also suggests that in horizontal alliances technological similarity plays a negative role on post-acquisition innovation performance (cf. Colombo & Rabbiosi, 2014). These arguments lead to the following hypothesis:

> Hypothesis 1: There exists a curvilinear relationship between technological similarity and post-acquisition innovation performance.

2.2 Mutual Dependence and Power Imbalance as two distinct types of interdependence

The RDT has become one of the dominant theoretical lens explaining why firms engage in acquisitions (Hillman, Withers, & Collins, 2009). A central tenet which was provided by the RDT is that an organization engages in acquisition to manage its dependence on the external environment for critical resources and to reduce the uncertainty in the flow of needed resources (cf. Pfeffer & Salancik, 1978; Batsakis et al., 2018). Organization depends on other organizations' resources and buyer-supplier networks to achieve their objectives. Among various dependence, a high degree of technological similarity between the two firms raises a deep concern about potential intense competition from a rival, which motivates a focal firm to reduce technological threats of its competitors. Acquisition provides an effective way of absorbing that important competitor's key know-how and technologies (Pfeffer, 1972).

The subsequent RDT studies have developed two distinct dimensions of resource dependence: *mutual dependence* and *power imbalance*. Power imbalance is defined as the difference between two actors' dependencies, and mutual dependence is defined as the sum, or the average of actor i's dependence on actor j and actor j's dependence on actor i (Casciaro & Piskorski, 2005). In other words, power imbalance emphasizes asymmetric dependence between two parties ― that is, the difference in the power of one party over the other, whereas mutual dependence emphasized the sum or average of mutual dependence of two parties in the same relationship (Gulati & Sytch, 2007). That is, the underlying logic of mutual dependence is embeddedness, whereas the underlying logic of power imbalance is power asymmetries (Piskorski & Casciaro, 2006). Embeddedness underlying mutual dependence derives from joint dependence that leads each of two parties to give "heightened attention to the responses and attitude of the other, such that the quality of the relationship becomes one of the main determinants of a satisfactory business tie (Gulati & Sytch, 2007: 37). The concomitant trust, joint action and information sharing increase the levels of joint involvement and coordination, which in turn overcome the problem of moral hazards, thus leading to the partnerships' value-generating potential (cf. Gulati & Sytch, 2007). On the other hand, power asymmetries shape two parties' ability to appropriate value from in an exchange relationship: the party who possesses an advantageous position can use its power to appropriate greater value from the exchanges at the expense of the dependence-disadvantaged party who is motivated to resist such exchanges (Emerson, 1962; Piskorski & Casciaro, 2006).

Despite the insights with respect to mutual dependence and power imbalance having important, but distinct implications promises new exploration of mergers through the lens of RDT (Hillman, Withers, & Collins, 2009), how do these two important, but distinct types of interdependence affect technological similarity and post-mergers' innovation performance, which is at the heart of technological M&As involving knowledge sharing, integration and absorption of two parties' diverse knowledge domains, which in turn, affects the innovation performance (Cloodt, Hagedoorn, & Van Kranenburg, 2006; Kapoor & Lim, 2007; Colombo & Rabbiosi, 2014). To answer this question, it is necessary to understand whether and how mutual dependence and power imbalance may have different implications for the relationship between technological similarity and post-acquisition innovation performance, and how these effects change over time, which unfortunately hitherto has not been systematically investigated and empirically examined.

2.3 The Moderating Role of Power Imbalance on the Effect of Technological Similarity on Post-Acquisition Innovation Performance

Power imbalance results from net-positive dependence of one party over the other: the former is in a power disadvantage while the latter is in a power advantage, which results in a very common situation where less powerful party has to closely monitor its counterpart, that is, dependence-advantage party, who tends to use adversarial tactics to appropriate greater value from the focused exchanges at the expense of the weaker or dependence-disadvantages party (Blau, 1986). Such adversarial relationship constantly motivates power-disadvantaged party to restructure the relationship in order to change its dependence on power-advantage party, but party that is more powerful tends to resist any change in the power structure.

In its extreme imbalance, this power-imbalanced relationship must above all have one consequence for technological similarity of two parties who surrender to the technological acquisition. That is a feeling of unprecedented distrust of each party in the other. This unprecedented trust leads to divergent actions of two parties, which is vividly illustrated by Casciaro and Piskorski (2005: 173) in the scenario where “the pre-merger dominant organization chooses to exchange with the best available partner, thus maintaining its bargaining power. If that best available partner is outside the merged entity, however, the pre-merger dependent organization will not be able to procure critical resources from the pre-merger dominant organization.”

In what is for two parties of a power-imbalanced technological acquisition, post-mergers’ innovation, the most important thing in and after the merger, each party is forced to adopt selfish actions that works for the best of its own benefit at the cost of the other’s. No one has little incentive to take account of the other party’s core interests in such a power-imbalance relationship such as those observed in the acquiring and target firms’ context. Such adversarial relationship not only significantly impairs one party’s ability to identify, transform and absorb similar technologies possessed by the other party, but also results in deceitful and even misleading, purposeful information distortion that weakens the benefit of enhancing knowledge pool conferred by technological similarity.

The power-advantageous party makes whatever possible to prevent any loss of its bargaining power over the power-disadvantageous party, but the power-disadvantageous party is constantly motivated to adopt tactics to change such power imbalance, resulting in divergent actions, along with divergent actions and mistrust, greatly prevent a party from grasping a deep understanding of post-merge knowledge to effectively explore technology-synergy for the innovation-generating activities. Thus, we propose that:

> Hypothesis 2: Power imbalance attenuates the curvilinear relationship between technological similarity and post-acquisition innovation performance.

2.4 The Moderating Role of Mutual Dependence on the Effect of Technological Similarity on Post-Acquisition Innovation

Mutual dependence of two parties increases social solidarity and cooperation in a business relationship (Provan, 1994). Prior studies have suggested that the parties associated with a high level of mutual dependence tend to cultivate a shared understanding concerning interactive behavior and results mutual benefits (e.g., Batsakis et al., 2018). The shared understanding will foster joint action and cultivate mutual trust (Gulati & Sytch, 2007), which is necessary for the transfer of tacit knowledge. It will also enhance the frequency of exchange agreements and increase the quality of interactions between jointly dependent partners, which definitely contributes to inter-organizational exchanges with increased cohesiveness together with fostered affective commitment to the relationship (Lawler & Yoon, 1993, 1996). Joint action facilitates high levels of partners' behavioral flexibility and their ability to resolve operation frictions in business exchanges (Uzzi, 1997). Mutual trust resulting from high levels of joint dependence are also found to increase the quality of information exchange (e.g., accuracy, timeliness and details) as well as the scope of information (e.g., diversity, types) being exchanged (Uzzi, 1996). In addition, a high level of mutual dependence also generates a high level of commitment to the relationship and inhibits self-interest behaviors for immediate benefit at the costs of the long-term relationship (Kelley, 1979; Williamson, 1985; Rusbult et al., 1991).

While shared understanding, mutual trust, joint action and high commitment derived from mutual dependence may not directly create innovation, they contribute to an acquiring firm's combinative capabilities and enable it to quickly identify, transform and absorb new technologies possessed by a potential target firm. Moreover, mutual trust and shared understanding create the conditions necessary for the acquiring firm's deeper understanding of knowledge held by the acquire firm, which, as discussed above, is essential for the generation of technology-synergy for innovation. In addition, high commitment and joint action greatly facilitate knowledge flow and, consequently, enrich the acquiring firm's knowledge pool. Therefore, the benefits resulting from mutual dependence strengthen the mechanisms underlying the positive effect of technological similarity on acquiring firm's post-acquisition innovation performance. Based on this, we suggest that:

> Hypothesis 3: Mutual dependence accentuates the curvilinear relationship between technological similarity and post-acquisition innovation performance.

2.5 The Moderating Role of Power Imbalance vs. Moderating Role of Mutual Dependence

While the degree of power advantage of two parties has a negative moderating role on the positive effect of technological similarity in the short run, this negative moderating effect tends to decline as time evolves. This is because after an acquisition, an acquiring firm is under great pressure to eliminate the differences between two organizations in terms of organizational culture, incentives mechanisms, communication routines, evaluation systems etc. Take, for example, the distress resulted from the incentive imbalance that the executives from either the acquiring or acquired firm feel that will severely affect the whole organization's culture and cohesion. Thus, the acquiring firm needs to lower this stress feeling by re-designing incentive packages to construct a relatively balanced relationship. As Milgrom and Roberts (1992:575) noted, "as long as the central office of the firm maintains some control over its divisions, the political pressures within the organization to equalize pay and opportunities will be large" . Homogenizing forces consistently push two organizations to converge toward each other over the intermediate and the long-term. The enhanced homogenizations greatly neutralize the negative influence of power imbalance in technological acquisition.

On the other hand, the moderating effect of mutual dependence on the positive effect of technological similarity persists over time. As noted above, mutual dependence fosters mutual trust and shared understanding between two parties that perpetuate joint action and high commitment, reduce partners' propensity to adopt opportunistic behaviors and motivate partners to explore new coordination techniques to enhance the transactions (Zaheer, McEvily, & Perrone, 1998; Uzzi, 1996). As the time elapses since acquiring and acquired firms are integrated into a single organization, mutual trust, shared understanding and joint action between two companies are sustained and enhanced over time. Enhanced mutual trust, shared understanding and joint action create a mild environment for mutual understanding and cooperation, which reduces the costs of combining different knowledge bases from two organizations as the time goes. As Haspesslagh and Jemison (1991) noted, knowledge transfer is realized primarily through interactions between the acquired and acquiring units in which both teaching and learning occur on both sides. To take advantage of knowledge combination benefits from technological similarity over time, two parties need to engage in a series of interactions (e.g., intensive team-based meeting, extensive communications within and between R&D units across organizations, and frequent face-to-face interactions) (Gerpott, 1995). Mutual understanding and cooperation enable the acquiring firm to develop a better understanding of the acquired firm's technology and process, which not only increases its combinative capabilities but also alleviates the costs of tackling more complex combinations when all easy combinations have been experimented. This makes the facilitating effect of mutual dependence on the positive effect of technological similarity be held over time. In addition, given that the amount of knowledge being exchanged is determined by the frequency and intensity of communications, however constrained by time and resources, have a bandwidth, the facilitating benefits rendered by mutual dependence on knowledge combination and synthesis associated with technological similarity then turn out to be stable over time. Altogether, we therefore expect that the moderating effect of power imbalance tends to fade over times, whereas that of mutual dependence persist over time, which are formally specified as follows:

> Hypothesis 4: Over time, (a) the moderating effect of power imbalance tends to diminish, whereas (b) that of mutual dependence persists.

3. Data and methods

3.1 Data

We combined the Securities Data Corporation (SDC)'s Mergers & Acquisition (M&A) Database, COMPUSTAT dataset, Bureau of Economic Analysis (BEA)'s annual industry accounts and the national income and product accounts, and WRDS US Patents Database to test our hypotheses. The SDC's M&A Database extracts the information from multiple sources ranging from newspapers to trade journals, to news reports, to business wires, and to Securities and Exchange Commission filings. We applied the following criterions in our search for acquisitions in the database: (a) the acquisitions occurred among all companies in every year during our sample period; (b) the status of acquisitions was completed; (c) both acquiring firms and acquired firms were U.S. firms; (d) acquiring firms were publicly listed in US stock exchange markets to ensure that the complete financial data is available. We then obtained historical data on firm-level financial characteristics from COMPUSTAT's two datasets. The financial information such as employ number, debt structure is available from COMPUSTAT's Fundamental Annual database, and the information about company's sales across different segments is available from COMPUSTAT's Segment database. We linked financial and sale information from COMPUSTAT databases with the acquisition information from SDC's M&A database. Moreover, building on Burt's (1980, 1982) seminal formulation of dependence and constraint, we relied on annual industry accounts and the national income and product accounts (formerly the Benchmark Input-Output (I-O) accounts) for the U.S. economy to develop industrial transactions patterns. We weighted multiplied transaction-based dependence measure by the concentration ratio of the four largest firms in an industry. We then matched transaction-based measure of dependence with the acquisition data according to 6 digits NACIS codes. Finally, we obtained U.S. patent citation data from the WRDS US Patents database. The WRDS US Patents is a widely accepted database that aims to provide easier access to patent data for researchers. We merged patent citation data with the acquisition information obtained from the SDC's M&A database. The final sample contained 1,298 firm-year observations in the period of 2014-2019.

3.2 Dependent variable

To construct our measure of acquiring firm's post-acquisition innovative performance, we observed the number of patents that cited the patents of each acquiring firm following acquisition. Based on the information about the total citations of the cumulative numbers of patents that an acquiring firm was granted, we developed the patent-citation-based measure. Scholars have found that patent citations are a good proxy of the firm-level innovation performance than a simple patent count (Hall, Jaffe, & Trajtenberg, 2000; Piperopoulos, Wu, & Wang, 2018; Wu et al., 2016). We applied a multiplier of a citation truncation weight to the number of citations from US patents through 2019 received by the patent to correct for the truncation of post-2019 cites (see Hall, Jaffe, & Trajtenberg, 2001 for the description of the methodology).

3.3 Independent variables

Following the prior studies (Podolny, Stuart, & Hannan, 1996; Stuart & Podolny, 1996), we measured pairwise *technological similarity* by examining the degree of overlap between a focal firm's patents with those of its counterpart regarding their patent classes. We relied on the information about technological class of patents filed during the years preceding the acquisition. Specifically, we counted the number of citations received by patents of targeting firm in each technological class of International Patent Classification (IPC) as well the number of citations received by patents of acquiring firm. We multiplied these two numbers and then aggregated this pair-wise multiplier across IPC classes. We weighed this summation by the multiplier of the number of patents granted to each of the paired firms. The relative overlap of acquiring and acquired firms' patent portfolios is specified as: Technological similarity = $\frac{\Sigma_k \sqrt{C_{K,A} \times C_{K,B}}}{\sqrt{P_A \times P_B}}$, where P_A represents the number of patents of firm A; P_B represents the number of patents of firm B; $C_{K,A}$ represents the number of citations received by patents of firm A in IPC main 4 character group (K); $C_{K,B}$ represents the number of citations received by patents of firm B in IPC main 4 character group (K); and $\sqrt{P_A \times P_B}$ represents the geometric mean of patent portfolio sizes between firm A and firm B. We calculated this value for each paired firms yearly. To reflect recent technological activities of a firm, we used a moving three-year window to this measure. That is, the averaged values during the preceding three years were used to measure technological similarity for each paired observation.

We measured *power imbalance* by following the approach of Burt (1980, 1982) and Casciaro and Piskorski (2005). Specifically, for a paired relationship between a business unit in industry i and another business unit in industry j, we formally defined the dependence of the business unit in industry i on the other in industry j, as $C_{j \rightarrow i}$ in terms of total purchases, p_{ij}, and total sales, s_{ij}, which were then weighted by four-firm concentration ratios. Specifically, we started from the input-output representation of an economy and computed the total dollars' value of goods sold by industry i to industry j in one year (z_{ij}). This is consistent with Burt's (1982) insight that business units in industry i will be constrained in their exchange with business units in industry j if a large proportion of their sales or purchases need to occur with that industry. We then converted the measure of dependence of industry i on business units in industry j, by multiplying it with the four-firm concentration ratios in industry j, O_j. The measure of dependence is specified as: $C_{j\to i} = (p_{ij} + s_{ij})O_j$, where $p_{ij} = (\frac{z_{ji}}{\sum_q z_{qi}})$ and $s_{ij} = (\frac{z_{ij}}{\sum_q z_{iq}})$.

The above measure is directional. That is, the dependence of a business unit in industry i and a business unit in industry j does not have the same as the dependence of a business unit in industry j and a business unit in industry i. Conversely, we denoted the dependence of business units in industry j on business units in industry i as $C_{i\to j}$ in terms of total purchases, p_{ji}, and total sales, s_{ji}, which were then weighted by four-firm concentration ratios: $C_{i\to j} = (p_{ji} + s_{ji})O_i$, where $p_{ji} = (\frac{z_{ij}}{\sum_q z_{qj}})$ and $s_{ji} = (\frac{z_{ji}}{\sum_q z_{jq}})$.

To obtain the measure of power imbalance between acquiring and acquired firms, we converted the measure of dependence in two steps: firstly we applied the logarithm transformation to the measure of dependence and then took the difference between the dependence of acquired firm in industry i on acquiring firm in industry j and the dependence of acquiring firm in industry j on acquired firm in industry i. The measure of power imbalance was specified as: Power imbalance = $C_{i\to j} - C_{j\to i}$.

Mutual dependence. To construct the measure of mutual dependence between acquiring and acquired firms in industry i and industry j separately, we followed the assumption used by Burt (1982) and summed the measure of the relative power across all the paired exchanges in which acquiring and acquired firms in a particular industry are involved. Mutual dependence = $C_{i\to j} + C_{j\to i}$.

3.4 Control variables

We included various firm and industry-level variables to exclude alternative explanations. Previous studies have shown that the firm size affects the firm performance after acquisition (e.g., Moeller, Schlingemann, & Stulz, 2004). Thus we first controlled for *firm size*, which is measured as the natural logarithm form of acquirer's total assets. Prior studies also suggested that the debt to asset ratio of the firm affects agency costs and thereby influences firm performance (Jensen, 1986; He & Wang, 2009). As such, the *debt to asset ratio* was included in the regression model. Prior studies also suggest that investments in research and development (R&D) by acquiring firms can build strong absorptive capacity, enabling successful utilization and assimilation of external sources of knowledge and leading to better innovation outcomes (Ahjua & Katila, 2001; Puranam, Singh, & Zollo, 2006). To address this concern, we included *R&D intensity* in the analyses, which equals to acquirer's R&D expenses divided by its total assets (Zhao, 2009). Prior studies (e.g., Kapoor & Lim, 2007; Zhao, 2009) have documented that acquiring firm's pre-acquisition innovation performance likely affects its innovation performance after the acquisition. So we controlled the acquiring firm's innovation performance before acquisition. Following Zhao (2009), we measured *pre-acquisition innovation performance* by the number of citations received by patents of a focal firm before acquisition (i.e., time t-3). Besides, considering the impact of the past acquisition experience on the post-acquisition performance (Haleblian & Finkelstein, 1999; Haleblian, Kim, & Rajagoplan, 2006), an acquiring firm's *acquisition experience* was also included as a control variable, which is measured as the number of acquisitions conducted by acquiring firm before acquisition.

Prior studies suggested that the percentage acquired is likely to impact the innovation performance of the acquirer after the acquisition (McCarthy & Aalbers, 2016). Therefore, we included *percentage acquired* in our analyses, which was measured as the Percentage of the target firm's ownership acquired by the acquiring firm. Besides, following McCarthy and Aalbers (2016), we included *target status* as control variables. We identified the status of the acquirer by using a dummy variable. In detail, target status equals to one if the target is listed as public, and zero otherwise.

Prior studies also suggested that firms with high degree of diversification, which may have a negative influence on acquiring firms' post-acquisition performance (Bergh & Lawless, 1998; Decker & Mellewigt, 2007). We measured *corporate diversification* by an entropy measure, which captures the level of diversification of an acquiring firm's production, which was defined as: Corporate diversification = $\sum(P_i \times Ln(1/P_i))$, where P_i refers to the percentage of sales in a particular product segment i; $1/P_i$ refers to the weight assigned to that particular segment. We subtracted the information about P_i from the COMPUSTAT's Segment database. The value of corporate diversification took the values between 0 and 2.865, with higher values meaning greater diversification and, consequently, it has less dependence on a single business for sales.

The degree of technological focus occupies a central position in a firm's technology strategies (Park & Choi, 2014). Prior studies suggested that the degree of technological focus of acquiring firm affects its post-acquisition innovation performance (Granstrand, 1998; Ahuja & Katila, 2001; Suzuki & Kodama, 2004; Colombo & Rabbiosi, 2014). Following previous studies (Schildt, Keil, & Maula, 2012), we measured *technological focus* of acquiring firm's technological activities as a Herfindahl index. We constructed the Herfindahl index based on the patenting in the three years preceding the acquisition using the following formula: $\sum_{i=1}^{k} s_i^2$, where s_i stands for the share of patents in class i during the past three years. The maximum value of 1 represents acquiring firm has all of its patents filed in the same main patent class. Values approaching 0 represents a situation where every patent filed by acquiring firm is in a distinct patent class of its own. Besides, we also controlled for *size asymmetry*, which was measured by the ratio of acquirer's net assets divided by target firm's net assets.

In addition, we included several industry-level factors in our regression models. Prior studies showed that higher levels of industry concentration reduce the probability of acquisition (Gaur, Malhotra, & Zhu, 2013). We thus controlled for the effect of *industry concentration* by creating a Herfindahl concentration ratio based on the sales of all public firms in the same four-digit SIC code as the acquiring firm. The data on the sales of all public firms in the same four-digit SIC code was drawn from the COMPUSTAT. We also controlled industry effect of technology characteristics. Following Hall and Vopel's IND-IDS-SIC Correspondence table, we matched the sampled industries (based on four-digit SIC code) with Chandler's (1994) classifications and created a dummy variable, *high-tech sector*, with non-high-tech sectors being the control group. [1]

3.5 Econometric analysis

Since our dependent variable is innovative performance which is measured by the number of citations received by patents held by a firm, a linear regression model is not appropriate, as it will lead to biased and inconsistent coefficient estimates. It is natural to adopt the categorical data regression model to perform the analysis (Agresti, 2002). One key concern of the count model is that the variance may exceed its mean. Such an instance is reflected in the post innovation performance (see Table 1). We adopted the negative binomial count regression model, which is a conjecture mixture distribution of Poisson for count data. In the negative binomial model, we considered the post innovative performance model at time t where the mean of dependent variable is explained by a set of variables (e.g., technological similarity, mutual dependence, power imbalance etc.). Since we are interested in intermediate and long run effects of post-acquisition innovative performance, we considered five periods after an acquisition, in which t+1 refers to immediately after acquisition, t+3 refers to the intermediate term; t+5 refers to the long term. Henceforth, we estimated five equations with the different

[1] See Appendix 1 for the description of variables.

periods of post-acquisition innovation performance and the same explanatory variables. The negative binomial model is usually derived from Poisson model where the derivation can be found in Cameron and Trivedi (2005). We firstly used the generalized negative binomial regression model to estimate five different dependent variables (i.e., from t+1 post-acquisition performance to t+5 post-acquisition).

4. Results

We reported, in Table 1A and 1B, the descriptive statistics and pairwise correlations of our variables. We investigated potential multicollinearity problems by using variance inflation factors (VIFs). The maximum VIF was 2.32, which is well below the cutoff value 10. This suggests that multicollinearity does not appear to be a problem in the data used in this study. To eliminate potential problem of multicollinearity, the predictor and moderator variables are mean-centered before creating the interaction terms (Aiken & West, 1991). As expected, technological similarity is positively correlated with acquiring firm's post-acquisition innovation performance.

[Insert Table 1A and 1B about here]

We reported, in Table 2, the results of generalized negative binomial (NB) regressions for post-acquisition innovation performance over time. Model 1 reports these results for acquiring firms' innovation performance at the first year after acquisition (t+1); Model 2 reports the results at the second year after acquisition (t+2); Model 3 reports the results at the third year after acquisition (t+3); Model 4 reports the results at the fourth year after acquisition (t+4); and Model 5 reports the results at the fifth year after acquisition (t+5).

[Insert Table 2 about here]

Hypothesis 1 predicts a curvilinear relationship between technological similarity and post-acquisition innovation performance. In Table 2, the coefficient of technological similarity^2

is significantly negative (i.e., β = -0.168, p = 0.010 in Model 1). To illustrate the curve in a more direct way, we plot the inverted U-shaped relationship between technological similarity and post-acquisition innovation performance in Figure 1, which is consistent with Hypothesis 1 prediction.

Although the coefficient of the quadratic term is significant, it is not sufficient to establish an inverted U-shaped relationship. Following previous studies (Lind & Mehlum, 2010; Fernhaber & Patel, 2012; Haans, Pieters, & He, 2016; Dinner, Kushwaha, & Steenkamp, 2019), we conducted a three-step procedure to test the quadratic relationship in a rigorous way. Firstly, the coefficient of the quadratic term needs to be significant and of the expected sign (i.e., negative). As discussed above, the first condition is satisfied. Secondly, the slope of the curve must be sufficiently steep at both ends of the technological similarity range. We found a significant positive slope at the lower bound (i.e., β = 0.038, p = 0.015) and a significant negative slope at the upper bound (i.e., β = -2.107, p = 0.001). Thus, the second condition is also satisfied. Thirdly, the turning point of the curve needs to be located well within the data range. We then estimated the turning point of effect of technological similarity and calculated the confidence intervals based on Fieller method (Fieller, 1954). The value of the turning point is estimated as 0.305 with the 90% Fieller confidence interval [0.059, 0.551]. Since the data range of technological similarity is [0, 6.2], both the minimum and maximum values of technological similarity are outside the confidence interval of the turning point. Therefore, the third condition is satisfied, too. These results together indicate that there exists an inverted U-shaped relationship between technological similarity and post-acquisition innovation performance[2]. Thus, Hypothesis 1 is supported.

[Insert Figure 1 about here]

[2] The results of quadratic relationship tests are reported in Appendix 2.

Hypothesis 2 posits that power imbalance attenuates the curvilinear relationship between technological similarity and post-acquisition innovation performance. In Table 2, the coefficient of the interaction technological similarity × power imbalance is negative and significant (i.e., β = -24.928, p = 0.000 in Model 1) and that of the interaction technological similarity^2 × power imbalance is positive and significant (i.e., β = 11.421, p = 0.001 in Model 1). These results indicate that power imbalance weakens the inverted U-shaped relationship between technological similarity and post-acquisition innovation performance. To illustrate these relationships, we plot them in Figure 2 where the moderating effects of power imbalance at low, medium, and high level on the technological similarity-post acquisition innovation performance relationship are represented by different curves: the curve which represents the medium level of power imbalance is relatively more flattened than the curve which represents low level of power imbalance; the curve which represents the high level of power imbalance is even more flattened than the curve which represents medium level of power imbalance. All these results together therefore support Hypothesis 2.

[Insert Figure 2 about here]

Hypothesis 3 predicts that mutual dependence accentuates the curvilinear relationship between technological similarity and post-acquisition innovation performance. In Table 2, the coefficient of the interaction technological similarity × mutual dependence is positive and significant (i.e., β = 0.338, p = 0.021 in Model 1) and that of the interaction technological similarity^2 × mutual dependence is negative and significant (i.e., β = -0.280, p = 0.014 in Model 1). To visualize these relationships, we plot these relationships in Figure 3 where the moderating effects of mutual dependence at low, medium, and high degrees are represented at different curves: the curve which represents the medium level of power imbalance is much steeper than the curve which represents the low level of power imbalance; and the curve which represents the high level of power imbalance is even steeper that the curve which represents the medium level of power imbalance. These results together support Hypothesis 3.

[Insert Figure 3 about here]

Following Dinner, Kushwaha, & Steenkamp (2019), we further explored the moderation effect by calculating the simple slope (i.e., first-order partial derivative) of technological similarity for firms with different level of power imbalance and mutual dependence. In Table 3, for firms with high power imbalance, technological similarity has a minor and non-significant effect on post-acquisition innovation performance. However, for firms with low power imbalance, technological similarity has a pronounced, curvilinear effect on post-acquisition innovation performance. To illustrate the magnitude of the difference, the effect of technological similarity on post-acquisition innovation performance at low level of technological similarity is 3 times larger for firms with low power imbalance than for firms with high power imbalance. While at high level of technological similarity, the difference in effect is about 5.5:1. Therefore, Hypothesis 2 receives additional support. On the contrary, results in Table 3 also suggest that for firms with low mutual dependence, technological similarity has a minor and non-significant effect on post-acquisition innovation performance. However, for firms with high mutual dependence, technological similarity has a pronounced, curvilinear effect on post-acquisition innovation performance. To illustrate the magnitude of the difference, the effect of technological similarity on post-acquisition innovation performance at low level of technological similarity is 3 times larger for firms with high mutual dependence than for firms with low mutual dependence. While at high level of technological similarity, the difference in effect is about 7:1. Therefore, Hypothesis 3 receives additional support. In conclusion, both Hypothesis 2 and Hypothesis 3 receive additional support from Table 3.

[Insert Table 3 about here]

To test Hypothesis 4a and 4b we undertook two methods as follows. We first referred to Table 2 where the change of the coefficients of the interactions over times (i.e., from time t+1 to t+5) provides certain intuitive way to observe whether and how the moderating effects of power imbalance and mutual dependence vary over time. Hypothesis 4a predicts that the positive moderating effect of power imbalance declines over time. As shown in Table 2, the coefficient of the interaction term, technological similarity × power imbalance, is significant at the first year after the acquisition (i.e., β = -24.928, p = 0.000 in Model 1), and it becomes insignificant at the second, third, fourth and fifth year following the acquisition (e.g., β = -13.409, p = 0.218 in Model 2). Meanwhile, the coefficient of the interaction term, technological similarity^2 × power imbalance, is significant and positive at year t+1 (β = 11.421, p = 0.001 in Model 1) and also significant and positive at year t+2 (β = 10.213, p = 0.059 in Model 2), but becomes insignificant at the third, fourth and fifth year following the acquisition (e.g., β = -72.008, p = 0.997 in Model 3). These results indicate that the moderating effect of power imbalance on the technological similarity-post acquisition innovation performance relationship disappears at the intermediate and long term.

Second, to rigorously test Hypothesis 4a, we combined the data of Model 1, 2, 3, 4, and 5 of Table 2 together to construct a new dataset, where a new variable, *time*, which takes the values from 1 (corresponding to t+1) to 5 (corresponding to t+5) is constructed. We then used this variable to interact with power imbalanced, technological similarity, technological similarity^2 and included them in the analyses. These results which are reported in Table 4 show that the coefficient of the interaction term, technological similarity × power imbalance is significant and negative (i.e., β = -30.885, p = 0.000 in Model 4), but that of the interaction term, technological similarity × power imbalance × time is significant and positive (i.e., β = 9.860, p = 0.000 in Model 4). Meanwhile, the coefficient of the interaction term, technological similarity^2 × power imbalance is significant and positive (i.e., β = 15.767, p =

0.000 in Model 4), whereas that of the interaction term, technological similarity^2 × power imbalance × time, is significant and negative (i.e., β = -3.066, *p* = 0.004 in Model 4). These results suggest that the moderating effect of power imbalance on the effect of technological similarity is weakened by time. The combination of the results of Table 2 and Table 4 provide strong support for Hypothesis 4a.

[Insert Table 4 about here]

We adopted the similar way to test Hypothesis 4b regarding the positive moderating effect of mutual dependence persists over time. As shown in Table 2, the coefficient of the interaction term, technological similarity × mutual dependence, is consistently significant and positive from the first year to the fifth year of post-acquisition (e.g., β = 0.483, *p* = 0.018 in Model 5). Meanwhile, the coefficient of the interaction term, technological similarity^2 × mutual dependence, is consistently significant and negative from the first year to the fifth year of post-acquisition (e.g., β = -0.401, *p* = 0.033 in Model 5). These results indicate that the moderating effect of mutual dependence on the technological similarity-post acquisition innovation performance relationship persists over time.

In Table 4, the coefficient of the interaction term, technological similarity × mutual imbalance is significant and positive (i.e., β = 0.753, *p* = 0.000 in Model 4), but that of the interaction term, technological similarity × mutual imbalance × time is insignificant and negative (i.e., β = -0.007, *p* = 0.850 in Model 4). Meanwhile, the coefficient of the interaction term, technological similarity^2 × mutual imbalance (i.e., β = -0.568, *p* = 0.000 in Model 4) is significantly negative, but that of the interaction term, technological similarity^2 × mutual imbalance × time (i.e., β = -0.022, *p* = 0.156 in Model 4), is insignificant. These results suggest that the moderating effect of mutual imbalance on the effect of technological similarity persists by time. The combination of the results of Table 2 and Table 4 provide strong support for Hypothesis 4b.

For the control variables, the results show the significantly positive effects of pre-acquisition innovation performance and high-tech sector, while the significantly negative effects of debt to asset ratio, R&D intensity, and industry concentration. The negative and significant effect of R&D intensity on post-acquisition could be due to three possible reasons. First, for firms with high levels of R&D intensity, they invest more resources in developing internal R&D capabilities in order to improve their innovation performance. With the increase of its own innovative capabilities, its incentives to acquire other firms to increase its innovative capabilities is in turn reduced. Second, the innovation literature suggests that more internal innovation investments and activities will cause firms and its R&D engineers to be less likely to accept and reject external sources of innovation (Cassiman & Veugelers, 2006). Third, even if these firms acquire other firms, given their strong internal R&D capabilities, they could rely more on their own innovation capabilities, rather than external firms to enhance their innovation performance. In other word, acquiring other firms to increase innovation is less attractive for the firms with high levels of R&D. As such, R&D intensity has a negative effect on post-acquisition innovation.

5. Robustness Tests

To check the robustness of our regression results, we performed additional tests. First of all, because some dummy variables (e.g., high-tech sector) is not time-variant, we adopted firm-year random effect negative binomial regression to rerun the analyses in Table 2. These results[3] are highly consistent with those reported in Table 2. Secondly, it is possible that the counts were generated as a result of Poisson process, but not negative binomial process. We used the Poisson regression model to ensure that the hypotheses hold even if a Poisson

[3] See Appendix 3.

process takes places. These results are also highly consistent with the ones using the generalized negative binomial regression model in Table 2[4].

To further improve the robustness of our model, we took the endogeneity problems into consideration. Firstly, there may exist the reverse causality between technological similarity and dependent variable. In our research design, we employed the different lags in the analyses and the results are robust across years. The introduction of time lag partially alleviates the reverse causality issues. Especially, when the time lag increases (e.g., t+2, t+3, t+4, t+5), the effect of reverse causality diminishes.

Secondly, we adopted a Two-Stage Least Squared (2SLS) model with instrumental variables to address the potential endogeneity problem between technological similarity and post-acquisition innovation performance. Following Lin et al. (2011), we used the mean of technological similarity in an industry, *industry average technological similarity*, and the mean of technological similarity in a location (i.e., state), *location average technological similarity*, as the instrumental variables. Based on previous research (Adams, Chen, & Hong, 2011; Lin et al., 2011), the industry and location average level of technological similarity will be correlated with a firm's technological similarity but are unlikely to directly influence a firm's post-acquisition innovation output. We then conducted several tests to confirm the validity of the instrumental variables. We firstly conducted the Weak Identification test (H_0: The instrumental variables are weak). The Cragg-Donald Wald F statistics is 197.528 with the *p*-value far below 10%, which, compared with the critical value of the Stock-Yogo weak identification test in the 10% maximal IV size being 16.38, is statistically significant. These results thereby reject the null hypothesis, indicating that the instrumental variables are strong instrumental variables. Second, we conducted the Overidentification test (H_0: The instrument variables are exogenous). The Sargan statistics is 1.101 with the *p*-value of 0.294, which is

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[4] See Appendix 4.

statistically insignificant. This result indicates that the instrumental variables are exogenous and uncorrelated with the error terms. Third, we conducted the Under-identification test (H_0: The number of IVs is insufficient). The Anderson canon. corr. LM statistics is 173.293 with the *p*-value of 0.000, which is statistically significant. This result indicates that the number of IVs is sufficient[5]. We further took the logarithm form of the dependent variable and rerun the analyses in Table 2 by using 2SLS method. The results of first-stage analysis indicate a significant relationship between instrumental variables and the independent variable (i.e., technological similarity)[6].

[Insert Table 5 about here]

In Table 5 reporting the results of second stage analysis, the coefficient for technological similarity^2 is negative and significant (i.e., β = -0.039, p = 0.016 in Model 1). Hence, Hypotheses 1 is supported. The coefficient for the interactive term technological similarity $\times$ power imbalance is negative and significant (i.e., β = -1.454, p = 0.099 in Model 1), and the coefficient for the interactive term technological similarity^2 $\times$ power imbalance is positive and significant in Model 1 (i.e., β = 9.733, p = 0.023 in Model 1). Hence, Hypotheses 2 is supported. The coefficient for the interactive term technological similarity $\times$ mutual dependence is positive and significant (e.g., β = 0.083, p = 0.043 in Model 1), and the coefficient for the interactive term technological similarity^2 $\times$ mutual dependence is negative and significant (i.e., β = -0.114, p = 0.009 in Model 1). Hence, Hypotheses 3 is supported. In conclusion, after addressing the potential endogeneity problem, Hypothesis 1, 2 and 3 are all supported. Besides, we re-ran the models in Table 3 by adopting 2SLS method and the results are similar to those in Table 3[7]. Therefore, Hypothesis 4a and 4b receive additional support.

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[5] See Appendix 5 for the results of instrumental variable tests.
[6] The results are reported in Appendix 6.
[7] The results are reported in Appendix 7.

To address a potential concern[8] of power imbalance and mutual dependence as two seemingly contradictory forces may complement or cancel out each other, we conducted additional analyses by generating a triple interaction term and re-running the analyses. As shown in Table 6, the coefficient of the interaction term, technological similarity × power imbalance × mutual dependence, is insignificant and negative (β = -23.313, p = 0.182 in Model 1)[9], indicating there is empirical evidence of neither power imbalance moderates the effect of mutual dependence nor mutual dependence moderates the effect of power imbalance. In other words, the two seemingly contradictory forces (power imbalance and mutual dependence) do not potentially complement or cancel out each other. This could be explained in the following manner. One the one hand, although these types of interdependence are two seemingly contradictory forces, they definitely do not cancel out each other. This is the reason why these two have been conceptually indicated as two distinct types of interdependence and already have been empirically proved to have independent effects. In addition to this, when they serve as two boundary conditions of the relationship between technological similarity and post-acquisition innovation performance, they also work independently. It is this reason why we have developed different hypotheses for these two and did not formulate a hypothesis regarding the triple interaction term.

[Insert Table 6 about here]

6. Discussion and Conclusions

Building on the RDT and M&As' literature, we argue that mutual dependence and power imbalance are two key theoretical constructs that capture two distinct aspects of interdependence, separately serve as two necessary conditions that condition the effect of technological similarity between the acquiring and the target firm on the post-acquisition

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[8] We much appreciate this good comment provided by one reviewer.

[9] The coefficient of the interaction term, technological similarity^2 × power imbalance × mutual dependence is also insignificant (i.e., β = 8.549, p = 0.465 in Model 1).

innovation: mutual dependence strengthens the effect of technological similarity on post-acquisition innovation, whereas power imbalance weakens it. More importantly, these effects diverge over time: the moderating effect of mutual dependence sustains, but that of power imbalance declines. The analysis of a panel data on the technological M&As support the proposed hypotheses. These findings make important contributions to the RDT literature and technological M&A literature in several important aspects.

First, this study extends the RDT literature to a less-examined context of technological M&As and post-acquisition innovation, which is certainly at the center interest of M&As studies (Hillman, Withers, & Collins, 2009). Existing RDT studies have paid inadequate attention to the role of the inter-dependence of the acquire-target relationship in technological M&As and post-acquisition innovation (cf. Batsakis et al., 2018). This study tackles this lacuna by not only asking how technological similarity of the two parties affects acquiring firm's post-acquisition innovation performance, but more importantly separating resource dependence into two distinct dimensions: mutual dependence and power imbalance. We explore how mutual dependence vs. power imbalance could change the effect of technological similarity on post-mergers' innovation in different ways. We empirically found that mutual dependence enhances the positive effect of technological similarity on acquiring firm's post-acquisition innovation performance, but power imbalance weakens that effect. These findings strongly explicate our theoretical standing point that any meaningful studies involving two parties (including technological M&As) should take account of inter-dependence relationships of two parties. More fundamentally, it is critical to separate inter-dependence into two distinct dimensions in terms of power imbalance and mutual dependence, which is essential for the RDT literature to tap the unrealized potential of resource dependency as a powerful explanation of interfirm relationships.

Second, this study contributes to the RDT literature by enriching the implications of two key theoretical constructs of resource dependence. We develop theoretical arguments with respect to how mutual dependence vs power imbalance may affect the relationship between technological similarity and post-mergers' innovation, but in the opposite way. We further develop theoretical arguments delineating how the distinct moderating roles of power imbalance and mutual dependence evolve over time. The empirical results confirm our hypotheses that as time elapses, the moderating effect of mutual dependence persists, but that of power imbalance diminishes. These findings extend the resource dependence theory to the context of technological acquisition and innovation and offer important implications for research and practice. The asymmetric role of power imbalance and mutual dependence in technological M&As and post-acquisition broadens the theoretical implications of two distinct dimensions of resource dependence. Equally importantly, the findings of the different roles of power imbalance vs. mutual dependence in the short- and medium-term obviously go far beyond the existing understanding of power imbalance and mutual dependence and explicitly highlight the importance of incorporating the temporal mode in further developing these two distinct theoretical dimensions of resource dependence.

Third, this study contributes to the technological M&As and post-acquisition innovation literature by departing from prior studies that overwhelmingly focus on the direct relationship between technological similarity and post-mergers' innovation. We propose that any study on technological M&A and post-acquisition should be couched with concrete interdependence of two parties. That is, the role of inter-organizational relationships should be incorporated in a study of technological M&As. This is particularly relevant when there exists a high degree of technological similarity between acquiring and acquired firms coupled with high levels of mutual dependence accompanied by high power imbalance. In such a situation, acquiring firms tend to benefit more from technological acquisition whereas acquiring firms gain less innovation benefit from technological similarity. We suggest that an important calling for research on technological M&As and post-acquisition innovation is to further examine how mutual dependence and power imbalance in the context of M&A influence knowledge transfer, integration and assimilation resulting in distinct post-acquisition innovation performance, and how these effects vary over time.

Managerial Implications

The findings offer important insights to managers. One key implication for managers is to pay attention to the important role of inter-firm relationships especially in terms of power imbalance and mutual dependence for the effect of technological similarity for post-acquisition innovation. It is particularly worthy of noting the opposite effects between these two relationships. On the one hand, mutual dependence is beneficial for mutual trust, joint actions and frequent exchanges of agreements, which thus accentuate the effect of technological similarity on innovation. As such, managers can improve mutual dependence in these aspects to increase the quality of interactions that leads to higher mutual dependence. On the other hand, managers should be cautious about the negative impacts of power imbalance leading to asocial interests and selfish actions, which in turn weakens the effect of technological similarity on post-acquisition innovation. As such, managers should make efforts to help different parties to be aware of their shared interests, goals and norms, through which a friendly and unselfish environment is cultivated, which will attenuate the negative effect of power imbalance.

Limitation and Future Directions

Like other studies, this study has unavoidably limitations that in turn offers important opportunities for future research. First, we develop theoretical arguments with regard to the moderating effects of mutual dependence persists but that of power imbalance declines over time and also provide empirical evidence. Future researchers could explore organizational factors (e.g., mutual trust and joint actions that facilitate knowledge combination and synthesis of firms being involved) may change the effects of mutual dependence and power imbalance. Relatedly, organizational constraints such as the bandwidth of the communications and the nature of knowledge and the intensity of knowledge exchanged may also affect the effects of two distinct dimensions of resource dependence in technological mergers and post-acquisition. Second, there could be significant knowledge overlap between the acquiring and target firms and employees might hide important knowledge, which could further exacerbate the impact of mutual dependence and power imbalance on innovation activities, thus future studies could pay more attention to such issues across other types of alliances as well as such as digital strategic alliances and platform firms and their suppliers. Third, future researchers could explore external environment that could affect the effects of mutual dependence vs. power imbalance. For example, how does environmental dynamism affect the effects of mutual dependence and power imbalance? Will the two dimensions demonstrate the different effects across sectors? Does country or cultural difference play a decisive role? (Shenkar et al., 2020) Lastly, future studies could further extend the temporal dimension of this study (e.g., acquisition timing, pace, and cycles) and reconcile these different temporal elements with the resource dependence in the context of technological M&As and post-acquisition innovation. All these theoretical developments and empirical evidence will certainly enrich the existing understanding about power imbalance and mutual dependence in the context of the technological M&As and post-acquisition innovation with a hope of developing a more comprehensive and consistent framework with a further deepening understanding.

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Figure 1 Direct Effect of Technological Similarity on Post-Acquisition Innovation Performance

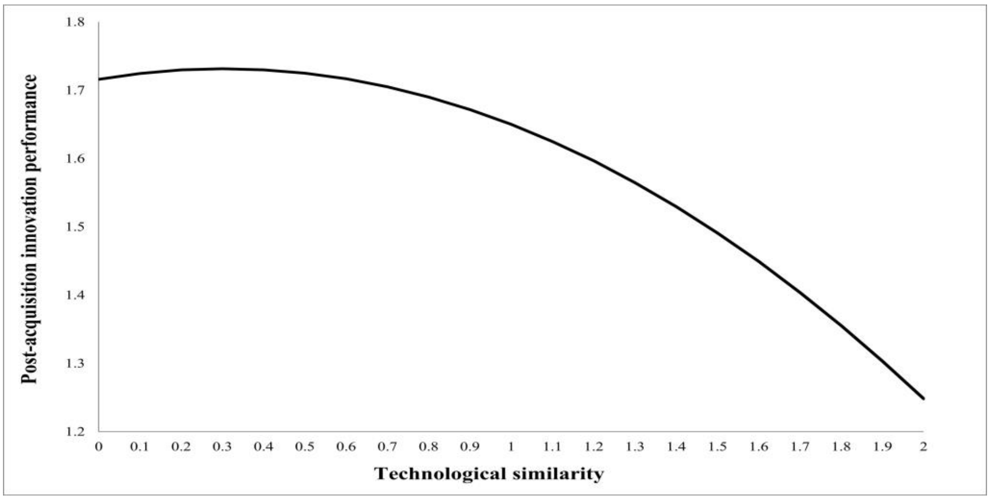

Figure 2 Moderating Effect of Power Imbalance on the Effect of Technological Similarity on Post-Acquisition Innovation Performance

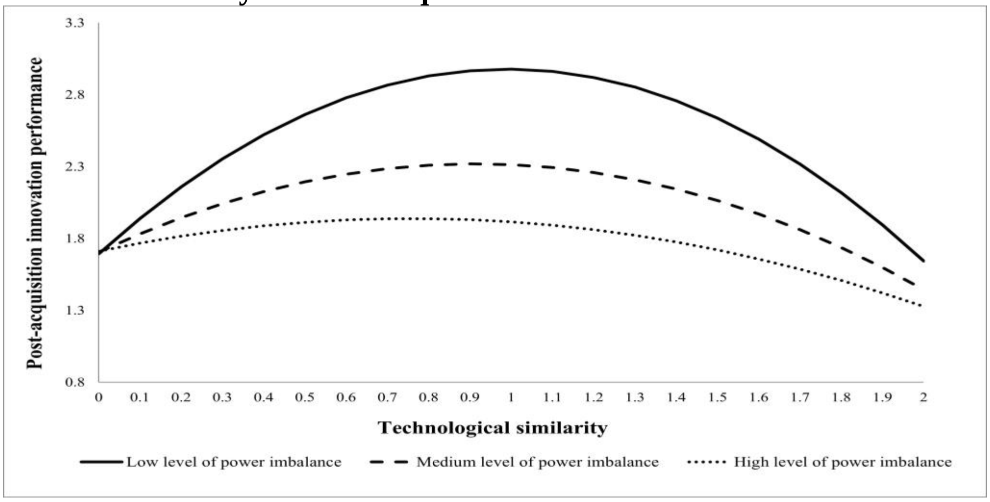

Figure 3 Moderating Effect of Mutual Dependence on the Effect of Technological Similarity on Post-Acquisition Innovation Performance

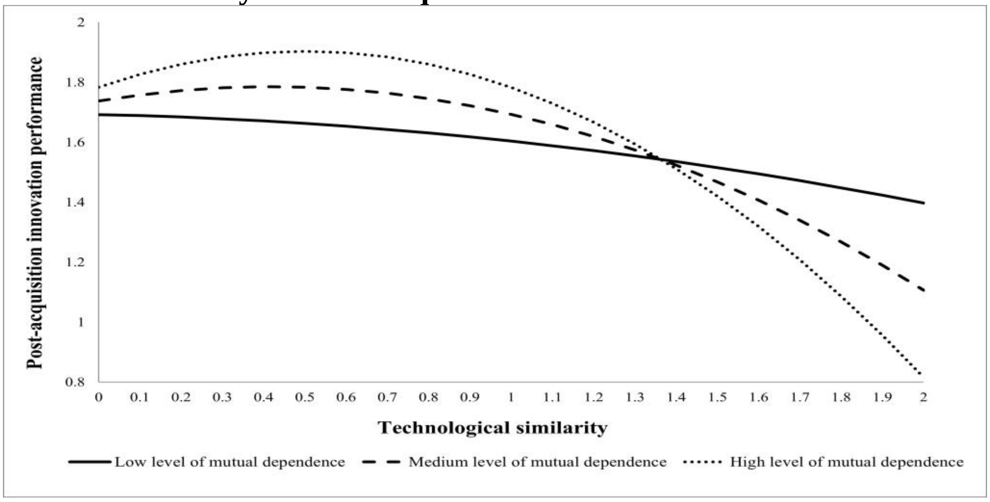

Table 1A Descriptive Statistics

	Variables	VIF	Mean	S.D.	Min.	Max.
1	Post-acquisition innovation performance	-	1.716	2.151	0.000	4.586
2	Technological similarity	1.19	0.249	0.652	0.000	6.200
3	Power imbalance	1.02	0.014	0.133	-0.430	2.279
4	Mutual dependence	1.46	0.368	0.758	0.050	1.000
5	Firm size	2.32	7.264	2.326	0.725	13.520
6	Debt to asset ratio	1.10	0.182	0.155	0.000	1.150
7	R&D intensity [a]	1.35	0.738	2.850	0.000	62.300
8	Pre-acquisition innovation performance	1.73	1.504	1.884	0.000	4.156
9	Acquisition experience	1.27	0.507	0.987	0	7
10	Corporate diversification	1.61	0.195	0.317	0.000	2.865
11	Industry concentration	1.10	0.419	0.240	0.032	1.000
12	High-tech sector	1.27	0.301	0.459	0	1
13	Size asymmetry	1.09	-1.027	0.262	-2.036	9.878
14	Technological focus	1.19	0.001	0.004	0.000	0.168
15	Percent acquired [a]	1.66	42.560	44.250	0	100
16	Target status	1.26	0.617	0.486	0	1
	Interactions		**Mean**	**S.D.**	**Min.**	**Max.**
1	Technological similarity^2		0.598	3.457	0.000	35.028
2	Technological similarity × Power imbalance		-0.001	0.022	-0.253	0.372
3	Technological similarity × Mutual dependence		0.035	0.474	-2.753	2.774
4	Technological similarity^2 × Power imbalance		0.007	0.164	-0.142	0.565
5	Technological similarity^2 × Mutual dependence		-0.142	2.463	-6.938	5.112

Notes: a. In percentage (%); b. N = 1,298 observations.

Table 1B Correlation Matrix

	Variables	1	2	3	4	5	6	7	8	9	10	11	12
1	Post-acquisition innovation performance	1.000											
2	Technological similarity	0.337	1.000										
3	Power imbalance	-0.051	-0.038	1.000									
4	Mutual dependence	-0.068	-0.181	-0.016	1.000								
5	Firm size	0.386	0.143	0.039	-0.288	1.000							
6	Debt to asset ratio	-0.157	-0.042	-0.006	-0.074	0.075	1.000						
7	R&D intensity	-0.141	-0.059	-0.021	0.042	-0.463	-0.147	1.000					
8	Pre-acquisition innovation performance	0.810	0.351	-0.074	-0.077	0.405	-0.156	-0.138	1.000				
9	Acquisition experience	0.046	-0.048	-0.052	0.326	0.034	-0.089	-0.052	0.079	1.000			
10	Corporate diversification	0.160	0.054	0.026	-0.223	0.528	0.057	-0.145	0.160	-0.053	1.000		
11	Industry concentration	-0.111	-0.072	-0.026	-0.019	-0.051	0.070	-0.002	-0.077	-0.096	0.170	1.000	
12	High-tech sector	0.349	0.097	-0.071	-0.030	0.016	-0.169	0.042	0.377	0.000	-0.121	-0.161	1.000
13	Size asymmetry	0.026	-0.008	0.039	-0.110	0.163	-0.023	-0.028	0.015	-0.034	0.144	-0.012	0.048
14	Technological focus	0.248	0.050	-0.021	-0.089	0.261	-0.039	-0.050	0.279	0.061	0.286	-0.036	0.084
15	Percent acquired	0.024	0.096	0.046	-0.444	0.228	0.141	-0.096	0.011	-0.378	0.178	0.042	-0.011
16	Target status	0.018	0.062	-0.007	-0.264	0.098	0.007	-0.054	-0.001	-0.175	0.036	-0.042	0.037

	Variables	13	14	15	16
13	Size asymmetry	1.000			
14	Technological focus	0.116	1.000		
15	Percent acquired [a]	-0.070	-0.033	1.000	
16	Target status	0.015	-0.059	0.429	1.000

Notes: N = 1,298 observations.

Table 2 NB Regression Results on Post-Acquisition Innovation Performance

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
DV: Post-acquisition innovation performance	t+1	t+2	t+3	t+4	t+5
Firm size	0.021	0.040*	0.029	0.014	-0.002
	(0.252)	(0.085)	(0.237)	(0.679)	(0.931)
Debt to asset ratio	-0.458***	-0.391*	-0.892***	-0.891***	-0.532**
	(0.010)	(0.093)	(0.000)	(0.009)	(0.016)
R&D intensity	-8.159**	-6.778**	-9.711**	-14.636***	-13.011***
	(0.012)	(0.041)	(0.022)	(0.009)	(0.002)
Pre-acquisition innovation performance	2.060***	1.776***	1.794***	1.579***	1.498***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Acquisition experience	-0.029	-0.010	0.001	0.011	0.007
	(0.193)	(0.741)	(0.972)	(0.806)	(0.791)
Corporate diversification	0.118	0.164	0.111	0.035	-0.083
	(0.170)	(0.175)	(0.389)	(0.860)	(0.499)
Industry concentration	-0.165*	0.012	0.024	-0.171	-0.287**
	(0.094)	(0.927)	(0.861)	(0.357)	(0.014)
High-tech sector	0.115**	0.308***	0.232***	0.299***	0.176***
	(0.017)	(0.000)	(0.001)	(0.003)	(0.003)
Size asymmetry	0.082	-0.211	0.005	0.066	0.053
	(0.387)	(0.197)	(0.968)	(0.652)	(0.595)
Technological focus	-1.519	0.525	-2.321	2.344	4.345
	(0.671)	(0.919)	(0.660)	(0.768)	(0.241)
Percent acquired	0.000	0.001	0.002**	0.003**	0.001
	(0.572)	(0.260)	(0.044)	(0.020)	(0.172)
Target status	0.009	0.052	-0.035	-0.045	-0.116*
	(0.858)	(0.441)	(0.629)	(0.652)	(0.061)
Power imbalance	0.226	0.219	0.591	0.651	0.569
	(0.343)	(0.374)	(0.994)	(0.995)	(0.959)
Mutual dependence	0.060	0.102*	0.042	0.154**	0.040
	(0.160)	(0.073)	(0.472)	(0.048)	(0.433)
Technological similarity (Tech. similarity)	0.102***	0.330**	2.042	2.337	1.525
	(0.009)	(0.030)	(0.996)	(0.996)	(0.976)
Hypothesis testing					
H1: Technological similarity^2 (Tech. similarity^2)	-0.168***	-0.290***	-0.278***	-0.587***	-0.221**
	(0.010)	(0.001)	(0.008)	(0.001)	(0.037)
H2: Tech. similarity * Power imbalance	-24.928***	-13.409	178.148	187.078	137.042
	(0.000)	(0.218)	(0.997)	(0.997)	(0.980)
H2: Tech. similarity^2 * Power imbalance	11.421***	10.213*	-72.008	-68.444	-54.791
	(0.001)	(0.059)	(0.997)	(0.998)	(0.982)
H3: Tech. similarity * Mutual dependence	0.338**	0.603***	0.502**	0.877***	0.483**
	(0.021)	(0.003)	(0.024)	(0.009)	(0.018)
H3: Tech. similarity^2 * Mutual dependence	-0.280**	-0.477***	-0.443**	-0.962***	-0.401**
	(0.014)	(0.003)	(0.015)	(0.002)	(0.033)
Constant	-0.918***	-1.086***	-0.810	-0.516	-0.113
	(0.000)	(0.000)	(0.108)	(0.445)	(0.566)

Log-Likelihood	-1,782.460	-1,764.490	-1,647.869	-1,468.910	-1,397.672
AIC	3,608.919	3,572.979	3,339.739	2,981.821	2,837.344
Observations	1,298	1,186	1,095	917	825

Notes: Estimated coefficients and associated *p*-values (in parentheses) are reported; Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$ (two-tailed test).

Table 3 Simple Slope Analyses of Moderated Curvilinear Effect

		DV: Post-acquisition innovation performance					
IV: Tech. similarity		Low		Medium		High	
		Marginal effect	*p* value	Marginal effect	*p* value	Marginal effect	*p* value
Direct effect		0.200	0.000	0.173	0.000	-0.186	0.000
Power imbalance	Low	0.290	0.000	0.251	0.000	-0.276	0.000
	Medium	0.200	0.000	0.173	0.000	-0.186	0.000
	High	0.097	0.379	0.039	0.131	-0.051	0.282
Mutual dependence	Low	0.077	0.361	0.034	0.559	-0.045	0.413
	Medium	0.200	0.000	0.173	0.000	-0.186	0.000
	High	0.245	0.000	0.212	0.000	-0.309	0.000

Table 4 NB Regression Results on Post-Acquisition Innovation Performance for Testing Time Effect

DV: Post-acquisition innovation performance	**(1)**	**(2)**	**(3)**	**(4)**
Firm size	0.012	0.010	0.021*	0.021*
	(0.316)	(0.378)	(0.086)	(0.081)
Debt to asset ratio	-0.648***	-0.658***	-0.654***	-0.645***
	(0.000)	(0.000)	(0.000)	(0.000)
R&D intensity	-9.726***	-9.845***	-9.818***	-9.740***
	(0.000)	(0.000)	(0.000)	(0.000)
Pre-acquisition innovation performance	0.426***	0.412***	0.402***	0.403***
	(0.000)	(0.000)	(0.000)	(0.000)
Acquisition experience	0.034**	0.041***	0.019	0.019
	(0.028)	(0.009)	(0.231)	(0.243)
Corporate diversification	-0.037	-0.008	0.025	0.029
	(0.550)	(0.892)	(0.690)	(0.653)
Industry concentration	-0.064	-0.050	-0.066	-0.068
	(0.334)	(0.455)	(0.326)	(0.315)
High-tech sector	0.216***	0.223***	0.246***	0.247***
	(0.000)	(0.000)	(0.000)	(0.000)
Size asymmetry	0.035	0.033	0.057	0.052
	(0.562)	(0.579)	(0.333)	(0.378)
Technological focus	0.212	0.759	1.047	0.966
	(0.935)	(0.772)	(0.692)	(0.716)
Percent acquired	0.001*	0.001	0.001***	0.001***
	(0.064)	(0.170)	(0.003)	(0.002)
Target status	-0.028	-0.026	-0.010	-0.005
	(0.420)	(0.454)	(0.773)	(0.878)
Technological similarity (Tech. similarity)		0.236***	0.418***	0.485***
		(0.000)	(0.000)	(0.000)
Technological similarity^2 (Tech. similarity^2)		-0.046***	-0.363***	-0.384***
		(0.000)	(0.000)	(0.000)
Power imbalance			0.170	0.185
			(0.148)	(0.117)
Mutual dependence			0.042	0.041
			(0.137)	(0.147)
Tech. similarity * Power imbalance			-9.448	-30.885***
			(0.105)	(0.000)
Tech. similarity^2 * Power imbalance			9.297***	15.767***
			(0.001)	(0.000)
Tech. similarity * Mutual dependence			0.699***	0.753***
			(0.000)	(0.000)
Tech. similarity^2 * Mutual dependence			-0.592***	-0.568***
			(0.000)	(0.000)
Time				0.067***
				(0.000)

Hypothesis testing				
H4a: Tech. similarity * Power imbalance * Time				9.860***
				(0.000)
H4a: Tech. similarity^2 * Power imbalance * Time				-3.066***
				(0.004)
H4b: Tech. similarity * Mutual dependence * Time				-0.007
				(0.850)
H4b: Tech. similarity^2 * Mutual dependence * Time				-0.022
				(0.156)
Constant	-0.609***	-0.622***	-0.786***	-0.987***
	(0.000)	(0.000)	(0.000)	(0.000)
Log-Likelihood	-8,060.651	-8,045.611	-8,013.017	-7,996.152
AIC	16,149.300	16,123.220	16,070.03	16,046.300
Observations	5,321	5,321	5,321	5,321

Notes: Estimated coefficients and associated *p*-values (in parentheses) are reported; Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$ (two-tailed test).

Table 5 Robustness Check: 2SLS Regression Results on Post-Acquisition Innovation Performance

	(1)	(2)	(3)	(4)	(5)
DV: Log Post-acquisition innovation performance	t+1	t+2	t+3	t+4	t+5
Firm size	0.050***	0.062***	0.055***	0.052***	0.068***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Debt to asset ratio	-0.255***	-0.190*	-0.355***	-0.277**	-0.241*
	(0.004)	(0.058)	(0.001)	(0.033)	(0.089)
R&D intensity	0.082	0.397	0.185	-0.049	-0.155
	(0.873)	(0.482)	(0.748)	(0.941)	(0.824)
Pre-acquisition innovation performance	1.073***	1.007***	1.085***	1.041***	0.903***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Acquisition experience	-0.020	-0.014	-0.009	-0.003	-0.016
	(0.164)	(0.388)	(0.610)	(0.896)	(0.480)
Corporate diversification	0.086	0.047	-0.016	0.017	-0.101
	(0.114)	(0.448)	(0.809)	(0.841)	(0.300)
Industry concentration	-0.134**	-0.045	0.007	-0.142	-0.212**
	(0.034)	(0.531)	(0.923)	(0.113)	(0.031)
High-tech sector	0.058	0.102**	0.066	0.041	0.051
	(0.102)	(0.011)	(0.110)	(0.411)	(0.353)
Size asymmetry	0.047	-0.072	0.026	0.008	-0.001
	(0.362)	(0.201)	(0.635)	(0.903)	(0.986)
Technological focus	2.141	1.505	-0.175	1.743	0.377
	(0.510)	(0.673)	(0.961)	(0.679)	(0.933)
Percent acquired	0.000	0.000	0.001	0.001	0.001
	(0.412)	(0.791)	(0.133)	(0.142)	(0.348)
Target status	0.009	0.047	-0.002	0.001	-0.036
	(0.757)	(0.150)	(0.952)	(0.976)	(0.427)
Power imbalance	-0.096	-0.170	-0.070	-0.078	-0.184
	(0.403)	(0.183)	(0.583)	(0.648)	(0.331)
Mutual dependence	0.054*	0.082**	0.021	0.007	0.029
	(0.062)	(0.013)	(0.534)	(0.863)	(0.522)
Technological similarity (Tech. similarity)	0.089**	0.153**	0.133*	-0.093	-0.104
	(0.021)	(0.027)	(0.069)	(0.567)	(0.570)
Hypothesis testing					
H1: Technological similarity^2 (Tech. similarity^2)	-0.039**	-0.153***	-0.245***	-0.276***	-0.162**
	(0.016)	(0.001)	(0.008)	(0.003)	(0.033)
H2: Tech. similarity * Power imbalance	-1.454*	-0.168	-0.580	-1.669	-1.385
	(0.099)	(0.867)	(0.561)	(0.196)	(0.340)
H2: Tech. similarity^2 * Power imbalance	9.733**	15.104**	15.944	10.531	15.117
	(0.023)	(0.034)	(0.102)	(0.113)	(0.143)
H3: Tech. similarity * Mutual dependence	0.083**	0.105**	0.208**	0.393***	0.130*
	(0.043)	(0.028)	(0.040)	(0.002)	(0.060)
H3: Tech. similarity^2 * Mutual dependence	-0.114***	-0.236***	-0.425***	-0.585***	-0.357**
	(0.009)	(0.004)	(0.008)	(0.006)	(0.049)

Constant	-0.097	-0.062	0.129	0.210	0.237
	(0.718)	(0.860)	(0.711)	(0.591)	(0.560)
Log-Likelihood	-758.521	-779.654	-702.722	-683.910	-644.088
AIC	1,631.042	1,671.308	1,515.443	1,473.821	1,392.175
Observations	1,298	1,186	1,095	917	825

Notes: Estimated coefficients and associated *p*-values (in parentheses) are reported; Industry and year dummies are included; Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$ (two-tailed test).

Table 6 NB Regression Results on Post-Acquisition Innovation Performance for Testing Triple Interaction Effects

	(1)	(2)	(3)	(4)	(5)
DV: Post-acquisition innovation performance	t+1	t+2	t+3	t+4	t+5
Firm size	0.022	0.039*	0.029	0.015	-0.004
	(0.228)	(0.082)	(0.232)	(0.661)	(0.927)
Debt to asset ratio	-0.449**	-0.396*	-0.903***	-0.896***	-0.489
	(0.012)	(0.085)	(0.000)	(0.007)	(0.180)
R&D intensity	-8.135**	-6.807**	-9.771**	-14.665***	-14.546**
	(0.013)	(0.042)	(0.021)	(0.008)	(0.013)
Pre-acquisition innovation performance	2.054***	1.774***	1.789***	1.576***	1.568***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Acquisition experience	-0.028	-0.010	0.002	0.012	0.013
	(0.204)	(0.750)	(0.952)	(0.798)	(0.810)
Corporate diversification	0.113	0.168	0.116	0.035	-0.042
	(0.188)	(0.156)	(0.359)	(0.851)	(0.848)
Industry concentration	-0.154	0.009	0.018	-0.173	-0.511**
	(0.118)	(0.942)	(0.893)	(0.348)	(0.016)
High-tech sector	0.115**	0.311***	0.240***	0.303***	0.355***
	(0.019)	(0.000)	(0.001)	(0.003)	(0.002)
Size asymmetry	0.078	-0.212	0.003	0.066	0.049
	(0.414)	(0.199)	(0.981)	(0.648)	(0.757)
Technological focus	-1.394	0.573	-2.236	2.453	7.132
	(0.698)	(0.912)	(0.675)	(0.751)	(0.409)
Percent acquired	0.000	0.001	0.002**	0.003**	0.004**
	(0.510)	(0.244)	(0.034)	(0.019)	(0.014)
Target status	0.015	0.049	-0.042	-0.050	-0.180
	(0.775)	(0.477)	(0.565)	(0.621)	(0.114)
Power imbalance	0.690	0.338	0.300	0.524	0.351
	(0.956)	(0.617)	(0.383)	(0.778)	(0.937)
Mutual dependence	0.060	0.103*	0.042	0.154**	0.133
	(0.158)	(0.066)	(0.467)	(0.050)	(0.131)
Technological similarity (Tech. similarity)	0.900	0.943	0.890	1.346	1.575
	(0.956)	(0.617)	(0.383)	(0.778)	(0.937)
Technological similarity^2 (Tech. similarity^2)	-0.181***	-0.291***	-0.289***	-0.594***	-0.499**
	(0.006)	(0.002)	(0.006)	(0.001)	(0.022)
Tech. similarity * Power imbalance	-24.377***	-68.678	-13.437	-68.772	-22.686
	(0.006)	(0.217)	(0.383)	(0.778)	(0.937)
Tech. similarity^2 * Power imbalance	24.751***	13.037*	-132.958	-154.206	-149.231
	(0.005)	(0.098)	(1.000)	(1.000)	(1.000)
Tech. similarity * Mutual dependence	0.369**	0.598***	0.512**	0.883***	0.972**
	(0.013)	(0.003)	(0.020)	(0.007)	(0.012)
Tech. similarity^2 * Mutual dependence	-0.304***	-0.476***	-0.461**	-0.972***	-0.877**
	(0.009)	(0.003)	(0.013)	(0.002)	(0.021)

Hypothesis testing					
Tech. similarity * Power imbalance * Mutual dependence	-23.313	-12.933	392.380	341.766	341.841
	(0.182)	(0.222)	(1.000)	(1.000)	(1.000)
Tech. similarity^2 * Power imbalance * Mutual dependence	8.549	6.064	-168.144	-146.311	-146.181
	(0.465)	(0.214)	(1.000)	(1.000)	(1.000)
Constant	-59.670	-770.388	-1,506.011	-770.877	-254.407
	(0.955)	(0.617)	(0.382)	(0.778)	(0.937)
Log-Likelihood	-1,779.186	-1,765.366	-1,648.492	-1,469.869	-1,315.136
AIC	3,604.372	3,574.733	3,340.984	2,983.738	2,674.273
Observations	1,298	1,186	1,095	917	825

Notes: Estimated coefficients and associated *p*-values (in parentheses) are reported; Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$ (two-tailed test).

Appendix 1 Description of Variables

Variables	Description	Measure
Dependent variable		
Post-acquisition innovation performance	Innovation productivity of acquiring firm after acquisition	Number of citations received by patents of a firm after acquisition
Independent variable		
Technological similarity	Overlap of acquiring and acquired firms in terms of technological domain	Multiplication of the number of citations received by patents in IPC classes for acquiring firm and acquired firms, divided by the geometric mean of patent portfolios sizes
Moderators		
Power imbalance	Power imbalance of acquiring firm over acquired firm	Relative power of acquiring firm over acquired firm minus relative power of acquired firm over acquiring firm
Mutual dependence	Mutual dependence of acquiring firm and acquired firm	Summation of relative power of acquiring firm over acquired firm and relative power of acquired firm over acquiring firm
Time	Time interval between dependent and independent variables	Number of years between the time point of the dependent variable and time point of the independent variable
Control variables		
Firm size	Acquirer's firm size	Natural logarithm form of acquiring firm's total assets
Debt to asset ratio	Acquiring firm's debt to asset ratio	Equals acquiring firm's total debts divided by its total assets
R&D intensity	Acquiring firm's R&D intensity	Equals acquiring firm's R&D expenses divided by its total assets
Pre-acquisition innovation performance	Innovation productivity of acquiring firm before acquisition	Number of citations received by patents of a firm before acquisition
Acquisition experience	Acquisition experience accumulated by acquiring firm	Number of acquisitions conducted by acquiring firm before acquisition
Corporate diversification	Level of dispersions of an acquiring firm	Summation of the proportion of sales in a SIC 4-digit segment over all the segments
Industry concentration	Level of industry competition	The Herfindahl index based on the sales of all public firms in the same SIC 4-digit code as the acquiring firm
High-tech sector	Level of technology characteristics	Following Chandler's (1994) classification
Size asymmetry	Ratio of firm asymmetric	Acquirer's net assets divided by target's net assets
Technological focus	Degree of diversity of a firm's technological activities	The Herfindahl index based a firm's share of patents in IPC classes over the three years preceding the acquisition
Percent acquired	Percentage acquired by the acquirer	Percentage of the target firm's ownership acquired by the acquiring firm
Target status	Public/private status of the target	Equals to one if the target was listed as public, and zero otherwise

Appendix 2 Results of Inverted U-Shaped Relationship Tests

Step 1	
Coefficient of the quadratic term	$\beta = -0.168$, $p = 0.010$
Step 2	
Lower bound	Upper bound
$\beta = 0.038$, $p = 0.015$	$\beta = -2.107$, $p = 0.001$
Step 3	
Turing point	Value = 0.305
	90% Fieller confidence interval for the turning point: [0.059, 0.551]
	Range of independent variable: [0, 6.2]

Appendix 3 Robustness Check: Random Effects NB Regression Results on Post-Acquisition Innovation Performance

	(1)	(2)	(3)	(4)	(5)
DV: Post-acquisition innovation performance	t+1	t+2	t+3	t+4	t+5
Firm size	0.014	0.038	0.021	-0.013	0.004
	(0.574)	(0.142)	(0.453)	(0.707)	(0.905)
Debt to asset ratio	-0.499**	-0.185	-0.611**	-0.558*	-0.709*
	(0.047)	(0.480)	(0.029)	(0.090)	(0.056)
R&D intensity	-9.278*	-4.645	-8.420	-13.750**	-12.907*
	(0.068)	(0.301)	(0.151)	(0.044)	(0.062)
Pre-acquisition innovation performance	2.692***	2.482***	2.521***	2.181***	2.050***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Acquisition experience	-0.030	-0.014	-0.009	0.002	-0.002
	(0.321)	(0.655)	(0.800)	(0.951)	(0.960)
Corporate diversification	0.005	-0.022	-0.048	-0.051	-0.175
	(0.965)	(0.869)	(0.733)	(0.764)	(0.375)
Industry concentration	-0.203	-0.069	-0.005	-0.248	-0.352*
	(0.141)	(0.623)	(0.971)	(0.150)	(0.067)
High-tech sector	0.048	0.123*	0.046	0.129	0.136
	(0.474)	(0.082)	(0.527)	(0.134)	(0.154)
Size asymmetry	0.204*	-0.065	0.154	0.147	0.159
	(0.081)	(0.713)	(0.226)	(0.291)	(0.247)
Technological focus	-0.593	1.610	-1.144	3.901	5.137
	(0.900)	(0.741)	(0.824)	(0.451)	(0.337)
Percent acquired	0.000	-0.000	0.000	0.000	-0.000
	(0.939)	(0.725)	(0.597)	(0.692)	(0.899)
Target status	-0.010	0.093	0.014	-0.039	-0.096
	(0.885)	(0.218)	(0.862)	(0.666)	(0.333)
Power imbalance	0.198	0.209	0.566	0.646	0.552
	(0.675)	(0.654)	(0.996)	(0.996)	(0.958)
Mutual dependence	0.052	0.047	-0.010	0.095	0.019
	(0.388)	(0.462)	(0.877)	(0.220)	(0.824)
Technological similarity (Tech. similarity)	0.122	0.020	1.777	1.957	1.383
	(0.344)	(0.897)	(0.997)	(0.997)	(0.977)
Hypothesis testing					
H1: Technological similarity^2 (Tech. similarity^2)	-0.091***	-0.119***	-0.128***	-0.270**	-0.193*
	(0.001)	(0.006)	(0.003)	(0.044)	(0.053)
H2: Tech. similarity * Power imbalance	-31.364***	-21.940**	174.412	179.083	124.664
	(0.000)	(0.038)	(0.997)	(0.998)	(0.981)
H2: Tech. similarity^2 * Power imbalance	12.434***	10.842**	-73.038	-71.480	-50.242
	(0.005)	(0.037)	(0.997)	(0.998)	(0.982)
H3: Tech. similarity * Mutual dependence	0.205**	0.273***	0.268**	0.289***	0.457*
	(0.014)	(0.007)	(0.027)	(0.008)	(0.064)
H3: Tech. similarity^2 * Mutual dependence	-0.155**	-0.192**	-0.208**	-0.391*	-0.360*
	(0.021)	(0.039)	(0.043)	(0.091)	(0.079)
Constant	-1.291***	-1.460***	-1.471**	-1.152	-0.482

	(0.000)	(0.000)	(0.026)	(0.113)	(0.126)
Log-Likelihood	-1,602.675	-1,563.404	-1,458.365	-1,318.900	-1,188.171
AIC	3249.350	3,170.808	2,960.731	2,683.801	2,420.342
Observations	1,298	1,186	1,095	917	825

Notes: Estimated coefficients and associated *p*-values (in parentheses) are reported; Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$ (two-tailed test).

Appendix 4 Robustness Check: Poisson Regression Results on Post-Acquisition Innovation Performance

	(1)	**(2)**	**(3)**	**(4)**	**(5)**
DV: Post-acquisition innovation performance	t+1	t+2	t+3	t+4	t+5
Firm size	0.023	0.032*	0.022	-0.004	-0.002
	(0.177)	(0.075)	(0.244)	(0.837)	(0.931)
Debt to asset ratio	-0.325**	-0.264	-0.651***	-0.567***	-0.532**
	(0.040)	(0.138)	(0.001)	(0.006)	(0.016)
R&D intensity	-7.468**	-6.313**	-9.392**	-13.866***	-13.011***
	(0.011)	(0.032)	(0.012)	(0.001)	(0.002)
Pre-acquisition innovation performance	2.142***	1.809***	1.826***	1.573***	1.498***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Acquisition experience	-0.033	-0.014	-0.008	0.004	0.007
	(0.124)	(0.552)	(0.746)	(0.873)	(0.791)
Corporate diversification	0.124	0.080	0.034	-0.012	-0.083
	(0.130)	(0.378)	(0.725)	(0.911)	(0.499)
Industry concentration	-0.190**	-0.022	0.016	-0.165	-0.287**
	(0.039)	(0.822)	(0.871)	(0.128)	(0.014)
High-tech sector	0.110**	0.196***	0.127**	0.157***	0.176***
	(0.014)	(0.000)	(0.012)	(0.005)	(0.003)
Size asymmetry	0.028	-0.148	0.020	0.064	0.053
	(0.724)	(0.255)	(0.847)	(0.505)	(0.595)
Technological focus	-0.059	0.872	-1.088	2.941	4.345
	(0.982)	(0.808)	(0.770)	(0.424)	(0.241)
Percent acquired	0.000	0.000	0.001	0.001	0.001
	(0.729)	(0.673)	(0.135)	(0.125)	(0.172)
Target status	0.038	0.054	-0.012	-0.040	-0.116*
	(0.431)	(0.297)	(0.822)	(0.487)	(0.061)
Power imbalance	0.246	0.222	0.502	0.534	0.569
	(0.306)	(0.328)	(0.965)	(0.956)	(0.959)
Mutual dependence	0.086**	0.057	0.014	0.089*	0.040
	(0.032)	(0.188)	(0.756)	(0.061)	(0.433)
Technological similarity (Tech. similarity)	0.149	0.177	1.484	1.562	1.525
	(0.586)	(0.131)	(0.978)	(0.972)	(0.976)
Hypothesis testing					
H1: Technological similarity^2 (Tech. similarity^2)	-0.184***	-0.181***	-0.177**	-0.301***	-0.221**
	(0.002)	(0.005)	(0.019)	(0.001)	(0.037)
H2: Tech. similarity * Power imbalance	-25.552***	-12.840	134.352	133.466	137.042
	(0.000)	(0.163)	(0.982)	(0.978)	(0.980)
H2: Tech. similarity^2 * Power imbalance	12.091***	8.199*	-54.854	-51.291	-54.791
	(0.000)	(0.061)	(0.982)	(0.980)	(0.982)
H3: Tech. similarity * Mutual dependence	0.341**	0.391***	0.338**	0.401**	0.483**
	(0.012)	(0.008)	(0.038)	(0.030)	(0.018)
H3: Tech. similarity^2 * Mutual dependence	-0.303***	-0.298***	-0.286**	-0.467***	-0.401**
	(0.005)	(0.009)	(0.031)	(0.005)	(0.033)

Constant	-1.041***	-0.907***	-0.686***	-0.214	-0.113
	(0.000)	(0.000)	(0.000)	(0.252)	(0.566)
Log-Likelihood	-1,874.665	-1,770.811	-1,655.079	-1,530.376	-1,397.672
AIC	3,691.329	3,583.621	3,352.159	3,102.753	2,837.344
Observations	1,298	1,186	1,095	917	825

Notes: Estimated coefficients and associated p-values (in parentheses) are reported; Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$ (two-tailed test).

Appendix 5 Results of Instrumental Variables Tests

Weak identification test [a]	
H_0: The instrumental variables are weak.	Value = 197.528, p = 0.000
Over-identification test [b]	
H_0: The instruments are exogenous.	Value = 1.101, p = 0.294
Under-identification test [c]	
H_0: The number of instrumental variables is insufficient.	Value = 173.293, p = 0.000

a. The statistics of weak identification test is Cragg-Donald Wald F statistics
b. The statistics of over-identification test is Sargan statistics.
c. The statistics of under-identification is Anderson canon. corr. LM statistics.

Appendix 6 First-Stage Results of 2SLS Regression

	DV: Technological similarity (Tech. similarity)
Firm size	0.001
	(0.931)
Debt to asset ratio	0.047
	(0.672)
R&D intensity	0.036
	(0.959)
Pre-acquisition innovation performance	0.347***
	(0.000)
Acquisition experience	-0.037**
	(0.049)
Corporate diversification	0.009
	(0.892)
Industry concentration	-0.308***
	(0.000)
High-tech sector	-0.127***
	(0.003)
Size asymmetry	-0.029
	(0.680)
Technological focus	-0.502
	(0.458)
Percent acquired	0.000
	(0.761)
Target status	0.024
	(0.517)
Industry average technological similarity	0.949***
	(0.000)
Location average technological similarity	0.107***
	(0.000)
Constant	0.079
	(0.809)
Log-Likelihood	-1,433.710
AIC	2,975.419
Observations	1,298

Notes: Estimated coefficients and associated *p*-values (in parentheses) are reported; Industry and year dummies are included; Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$ (two-tailed test).

Appendix 7 Robustness Check: 2SLS Regression Results on Post-Acquisition Innovation Performance for Testing Time Effect

DV: Log Post-acquisition innovation performance	(1)	(2)	(3)	(4)
Firm size	0.053***	0.052***	0.055***	0.055***
	(0.000)	(0.000)	(0.000)	(0.000)
Debt to asset ratio	-0.277***	-0.279***	-0.266***	-0.268***
	(0.000)	(0.000)	(0.000)	(0.000)
R&D intensity	-0.044	-0.061	0.080	0.081
	(0.872)	(0.824)	(0.769)	(0.766)
Pre-acquisition innovation performance	1.026***	0.990***	0.959***	0.959***
	(0.000)	(0.000)	(0.000)	(0.000)
Acquisition experience	-0.007	-0.002	-0.005	-0.005
	(0.369)	(0.804)	(0.551)	(0.546)
Corporate diversification	0.017	0.013	0.017	0.017
	(0.592)	(0.678)	(0.586)	(0.587)
Industry concentration	-0.116***	-0.099***	-0.073**	-0.073**
	(0.000)	(0.003)	(0.028)	(0.028)
High-tech sector	0.056***	0.063***	0.083***	0.083***
	(0.003)	(0.001)	(0.000)	(0.000)
Size asymmetry	-0.001	-0.000	0.001	0.002
	(0.979)	(0.987)	(0.955)	(0.950)
Technological focus	0.531	0.619	1.477	1.467
	(0.758)	(0.719)	(0.390)	(0.393)
Percent acquired	0.000	0.000	0.000**	0.000**
	(0.372)	(0.526)	(0.028)	(0.028)
Target status	-0.005	-0.009	0.001	0.000
	(0.772)	(0.573)	(0.964)	(0.998)
Technological similarity (Tech. similarity)		0.108**	0.315***	0.313***
		(0.047)	(0.000)	(0.000)
Technological similarity^2 (Tech. similarity^2)		-0.013***	-0.255***	-0.254***
		(0.000)	(0.000)	(0.000)
Power imbalance			0.052	0.047
			(0.354)	(0.405)
Mutual dependence			0.059***	0.058***
			(0.000)	(0.000)
Tech. similarity * Power imbalance			-3.923***	-2.571**
			(0.000)	(0.039)
Tech. similarity^2 * Power imbalance			17.805***	17.814**
			(0.000)	(0.012)
Tech. similarity * Mutual dependence			0.240***	0.274***
			(0.000)	(0.000)
Tech. similarity^2 * Mutual dependence			-0.415***	-0.452***
			(0.000)	(0.000)
Time				0.010*
				(0.059)

Hypothesis testing				
H4a: Tech. similarity * Power imbalance * Time				0.492*
				(0.067)
H4a: Tech. similarity^2 * Power imbalance * Time				-0.091**
				(0.028)
H4b: Tech. similarity * Mutual dependence * Time				-0.012
				(0.550)
H4b: Tech. similarity^2 * Mutual dependence * Time				0.013
				(0.172)
Constant	0.137	0.149	0.056	0.083
	(0.384)	(0.344)	(0.722)	(0.602)
Log-Likelihood	-3,894.984	-3,892.690	-3,849.349	-3,845.896
AIC	7887.967	7,887.379	7,812.698	7,815.792
Observations	5,321	5,321	5,321	5,321

Notes: Estimated coefficients and associated *p*-values (in parentheses) are reported; Industry and year dummies are included; Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$ (two-tailed test).