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Look at U: Technological scope of the acquirer, technological complementarity with the target, and post-acquisition R&D output

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ABSTRACT

Different streams of literature in economics and strategy suggest that several characteristics of a firm's technological base such as diversity, breadth, depth, and R&D portfolio affect its R&D output. Separately, strategy literature on technological mergers and acquisitions (M&As) suggests that the relationship between technological knowledge bases of the acquirer and the target, such as their technological similarities and complementarities, also affects the post-acquisition R&D output. This paper integrates the knowledge from these streams to further our understanding of technological M&As by examining how the pre-acquisition technological scope of an acquirer, encompassing the diversity and breadth of its technological knowledge base, affects its post-acquisition R&D output. Our analysis of a panel of technological acquisitions suggests that the acquirer's technological scope has a U-shaped relationship with post-acquisition R&D output, measured in terms of patent filings. Moreover, technological complementarity between the acquirer's and target's knowledge bases positively moderates this relationship. Results show that acquirers have higher post-acquisition R&D output when their pre-acquisition technological scope is either narrow or broad rather than moderate. Besides, acquirers having a narrow technological scope benefit more from technological complementarities. Our findings have important implications for the effectiveness of corporate R&D strategy and M&A strategy in the hi-tech industries.

1. Introduction

Strategic behavior of R&D-intensive firms has been a popular subject of scientific inquiry because these firms are major contributors to inventions, innovations, and economic growth. The corporate and competitive advantages of these firms significantly depend on dynamic capabilities and innovation which require developing and maintaining a technological base that can help create new technologies and products more frequently than competitors (Teece, 2017; Pisano, 2017). To this end, these firms use several tools of corporate strategy including, among others, mergers and acquisitions (M&As) that allow them to internalize preconfigured bundles of technological resources and capabilities (Ahuja and Katila, 2001; Vanhaverbeke et al., 2002; Hagedoorn and Wang, 2012; Stettner and Lavie, 2014). However, M&As are costly and their success rate is low, hence the need to identify the key determinants of their impact on firm output (King et al., 2008; Graebner et al., *2010*). Accordingly, the role of technological M&As in the R&D output of firms has received significant scholarly attention (Ahuja and Katila, 2001; Cloodt et al., 2006; Zhao, 2009; Makri et al., 2010; Cefis and Marsili, 2015). Research in this tradition has illuminated various aspects of technological M&As, ranging from the selection of acquisition targets to the utilization of acquired knowledge and capabilities (Yu et al., 2016; Rao et al., 2016; Choi and McNamara, 2018). This literature suggests that technological M&As not only affect the acquirer's R&D output but also affect the technological and corporate scope of the firm, which affect its overall performance (e.g., Kaul, 2012; Kaul and Wu, 2016; Valentini, 2012; Valentini and Di Guardo, 2012). However, despite frequent use of the notions of technological scope and technological diversification in the literature on technological M&As, there is a lack of empirical research on how these aspects of firm's technological base may affect its acquisition strategy and post-acquisition R&D performance. The purpose of this paper is to fill this void.

Research on technological M&As has uncovered several attributes of the technological knowledge bases of both acquirers and targets that affect their post-acquisition R&D output. These attributes include the size of their technological knowledge bases (Ahuja and Katila, 2001; Cloodt et al., 2006), technological similarity (Cloodt et al., 2006; Colombo and Rabbiosi, 2014), technological complementarity

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(Cassiman et al., 2005; Makri et al., 2010), and mutual overlap between the technological knowledge bases of acquirers and targets (Sears and Hoetker, 2014). Technological similarity and complementarity are determined by the nature of technology domains comprising their technological bases and interrelatedness among them in terms of technological inputs or outputs. Technological relatedness among domains determines the incentives and costs of transferring and combining knowledge across domains (Breschi et al., 2003; Cassiman et al., 2005) as well as the quantity and quality of the knowledge combinations (Valentini, 2012; Valentini and Di Guardo, 2012; Papazoglou and Spanos, 2018). However, this research has been largely focused on the relationship between the knowledge bases of acquirer and target whereas the composition of knowledge bases in terms of technology domains has been neglected. Composition of acquirer's and target's knowledge bases, such as the variety and interrelatedness of technology domains comprising them, is important because it determines the direction and scope of their technological search and R&D output (Henderson and Cockburn, 1996; Galunic and Rodan, 1998; Macher and Boerner, 2006; Leiponen and Helfat, 2010; Hussinger, 2010). This paper contributes to the literature on technological M&As by explaining how the composition of acquirer's technological knowledge base affects its R&D strategy and output and how this understanding can be useful in M&A strategy.

We argue that the composition of the technological knowledge base of a firm includes not only the variety of technology domains but also their interrelatedness and that variety and interrelatedness jointly determine the scope of a firm's technological knowledge base. We introduce a new patent-based measure to operationalize the construct of technological scope that captures technological relatedness from multiple levels of patent classification hierarchy. We theorize that technological scope of acquirer has a curvilinear (U-shaped) relationship with the post-acquisition R&D output and test our theory using a sample of acquirers selected from the firms having the largest number of patent filings in the US between 1985 and 2005. Results show that the acquirers have higher R&D output when their technological scope is either narrow or broad rather than moderate, suggesting that firms that follow a clear strategy of technological depth or technological breadth perform better than those following a hybrid strategy. One of the key insights from the study is that technological complementarities between the acquirer and target can be horizontal or vertical and acquirers with narrow technological scope benefit from horizontal complementarities. Accordingly, one of the key implications of the study is that before scouting for the acquisition targets to increase R&D output, the acquirer needs to assess the scope of its existing technological base and determine whether it seeks to deepen or broaden it (Pisano, 2017) and whether the strategy requires horizontal or vertical technological complementarities.

The paper contributes to the literatures on R&D strategy and technological M&As in several important ways. First, it operationalizes the concept of technological scope from the perspective of the technological knowledge base of firms and applies it in the context of a cross section of industries. Second, it reconciles the divergence between two streams of literatures, one showing that technological diversification has a curvilinear (inverted-U shaped) relationship with innovation (Leten et al., 2007; Huang and Chen 2010; Kim et al., 2016) while the other suggesting that scope of search positively affects innovation and reinforces itself (Levinthal and March 1993; Rosenkopf and Nerkar, 2001; Leiponen and Helfat, 2010; Kim et al., 2013; Stettner and Lavie, 2014). Third, the findings of this study shed new light on the long-standing debate on whether multi-technology firms need to have distinctive or distributed technological capabilities (Prahalad and Hamel, 1990; Patel and Pavitt, 1997; Granstrand et al., 1997; Pisano, 2017). Fourth, it shows that technological complementarities between the acquirer and target function differently for the acquirers with narrow versus broad technological scope whereby the firms with narrow technological scope benefit more from horizontal technological complementarities. Finally, a better understanding of the relevance of the technological scope of a firm is also useful in practice as it can help determine whether a firm needs to deepen or broaden its technological knowledge base and choose the acquisition targets accordingly (Kaul and Wu, 2016; Yu et al., 2016; Pisano, 2017).

2. Theory and hypotheses

2.1. Theoretical background

The literature on corporate strategy of technology-based firms suggests that the composition of a firm's technological knowledge base significantly affects its technology strategy and R&D output (Macher and Boerner, 2006; Kaul, 2012). Some firms are technologically specialized and operate in closely related technology domains whereas others have diversified technological bases (Granstrand, 1998; Patel and Pavitt, 1997; Granstrand et al., 1997; Breschi et al., *2003*). Firms use their existing technological bases as platforms to diversify into other domains (Kim and Kogut, 1996) and their innovation performance depends on the extent to which their domains of search are technologically related (Cohen and Levinthal, 1990; Stuart and Podolny, 1996; Rosenkopf and Nerkar, 2001; Hussinger, 2010). Further research from the knowledge-based perspective has found that technological diversity of the firm has an inverted-U shaped relationship with R&D output and growth (Leten et al., 2007; Huang and Chen, 2010; Kim et al., 2016) while technological diversity also affects R&D productivity (Choi and Lee, 2021). Technological scope and diversity of a firm's R&D portfolio affect its R&D output due to economies of scale and scope (Henderson and Cockburn, 1996; Macher and Boerner, 2006). A significant portion of these economies emanates from the learning and absorptive capacity acquired through prior R&D (Cohen and Levinthal, 1990).

There are two important aspects of a firm's R&D search, namely focus and scope, that affect the economies of search and invention (Henderson and Cockburn, 1996; Leiponen and Helfat, 2010). From the knowledge-based perspective, focus concerns the degree of concentration of search for inventions within a certain number of domains whereas the scope concerns the breadth and reach of the firm's knowledge base in the technology space. Technological focus has been studied in terms of technological diversification (Leten et al., 2007; Huang and Chen 2010; Kim et al., 2016). This stream of research has concluded that technological diversification has a curvilinear (inverted-U shaped) relationship with innovation and firm performance. Another stream of influential research suggests that the scope of search for invention and innovation positively affects innovation and there are no diminishing returns to search scope (Levinthal and March 1993; Rosenkopf and Nerkar, 2001; Leiponen and Helfat, 2010; Kim et al., 2013; Stettner and Lavie, 2014). The divergence between these two streams suggests that diversity and scope are different facets of a firm's technological base and the understandings of these two streams need to be reconciled because a firm's technological base and innovation play an important role in its technological and corporate diversification as wll as its scope (Breschi et al., 2003; Kaul, 2012; Kim et al., 2013). The reconciliation of this divergence is particularly important because of its relevance to the corporate strategy, R&D strategy, and dynamic capabilities (Teece, 2017; Pisano, 2017). This reconciliation is possible by operationalizing technological scope of the firm and measuring its effect alongside technological diversification. The following sections present the operationalization of technological scope and the examination of its effects in the context of technological M&As.

2.2. Technological scope

R&D is a specialized function of the firm designed to create novel and valuable technological knowledge and artifacts by recombining existing knowledge and artifacts (Fleming, 2001; Arthur, 2007). Firms make significant investments in R&D and there are several factors that affect their R&D output (Teece, 1996; Galunic and Rodan, 1998). Strategy research in the tradition of resource-based and knowledge-based views of the firm suggests that knowledge is the primary input in invention and innovation and hence the technological knowledge base of the firm plays a key role in its R&D output (Kogut and Zander, 1992; Nerkar and Paruchuri, 2005; Yayavaram and Chen, 2015). Accordingly, researchers have sought to identify key attributes of the technological knowledge base that drive R&D strategy and output.

Prior research has identified two important characteristics of a firm's knowledge base: the variety of technology domains comprising it and their interrelatedness (Breschi et al., 2003). The variety among technology domains has been studied from the perspective of technological diversification which has been found to have a curvilinear (inverted-U) relationship with performance (Leten et al., 2007; Kim et al., 2016). Technological interrelatedness between two domains exists when their components can be used substitutively or complementarily (Dibiaggio et al., 2014). Relatedness among domains comprising the technological knowledge base has been studied from the perspective of coherence of knowledge base (Breschi et al., 2003; Nesta and Saviotti, 2005) and similarity or complementarity between two firms (Cassiman et al., 2005; Cloodt et al., 2006; Makri et al., 2010; Colombo and Rabbiosi, 2014). However, technological diversity and interrelatedness among domains have been rarely combined to study their role in a firm's technological performance.

Technology domains are interrelated at varying degrees and hence each pair of domains has a certain degree of proximity or distance between them (Benner and Waldfogel, 2008; Arthur, 2009; McNamee, 2013). The degree of relatedness affects the incentives as well as the costs of transfer and combination of knowledge across different domains (e.g., Stuart and Podolny, 1996; Rosenkopf and Nerkar, 2001). Technological diversity and relatedness determine the composition as well as the breadth of the firm's technological base which determine its ability to create inventions through recombination of knowledge across those domains (Cohen and Levinthal, 1990; Kim and Kogut, 1996; Yayavaram and Chen, 2015). In other words, they jointly determine the technological scope of the firm defined as the span of a firm's technological capabilities over a range of technology domains involving varying degrees of technological interrelatedness.

2.2.1. Narrow versus broad technological scope

Technological scope of a firm is narrow when its technological knowledge base contains a small number of highly interrelated technology domains. On the other hand, technological scope is broad when the firm is operating in a large number of technologically distant domains. Narrow and broad technological scope involve different organizing logics (Argyres and Silverman, 2004; Leiponen and Helfat, 2011; Pontikes and Barnett, 2017) and differ in underlying economics of invention and innovation (Kim et al., 2013; Klingebiel and Rammer, 2014), such as intra- and inter-temporal economies of scale and scope in the utilization of technological resources (Helfat and Eisenhardt, 2004). They also differ in the quantity and quality of technological opportunities afforded by them (Galunic and Rodan, 1998; Katila and Ahuja, 2002; Leiponen and Helfat, 2010; Klingebiel and Rammer, 2014). Narrow technological scope mainly involves economies of scale and broad technological scope largely involves economies of scope in accumulating and deploying technological resources (Henderson and Cockburn, 1996; Macher and Boerner, 2006). Economies of scale emerge from doing more of the same or similar things whereas economies of scope emanate from doing a range of different things that involve resource redeployment or overlap (Stieglitz and Heine, 2007). Therefore, narrow technological scope involves depth and sophistication of expertise whereas broad technological scope involves breadth and diversification of expertise. Accordingly, narrow technological scope involves a specialized pool whereas broad scope involves a diverse pool of technological resources and capabilities.

The dynamics of knowledge combination at the firm level emanate from and are akin to those of individual scientists and teams of scientists working on R&D projects (Kogut and Zander, 1992; Galunic and Rodan, 1998; Dahlander et al., 2016; Caner et al., 2017). Narrow technological scope involves specialization and sustained engagement with a few closely related domains which results in accumulation of expertise and technological assets in those domains (Wang and von Tunzelmann, 2000; Papazoglou and Spanos, 2018). This approach concerns developing and maintaining distinctive technological core capabilities (Prahalad and Hamel, 1990), leveraging and enhancing existing capabilities (Tushman and Anderson, 1986; Stuart and Podolny, 1996), and promoting repeated reuse of knowledge, schemas and routines (Kok, Faems and de Faria, 2019; Mannucci and Yong, 2018). The accumulation of knowledge and capabilities within a few domains allows the creation of novelty through vertical combinations within those domains. That is, new combinations of knowledge are based on the previous combination of ideas and artifacts from the same domains (Zhou and Li, 2012; Teodoridis et al., 2019). New combinations, in turn, create new technological opportunities through new possibilities of combinations with preexisting technologies and artifacts. This suggests that narrow technological scope suits pursuing technological opportunities along existing technological trajectories and increasing the sophistication, variety, and new applications of existing technologies (Caner et al., 2017). It may also allow pursuing emerging technological opportunities along new technological trajectories of existing technologies in other related domains (Kim and Kogut, 1996; Pisano, 2017). Therefore, narrow technological scope allows opportunities for recombinant invention due to the lower dispersion among knowledge elements of the same or proximate domains and similarities among their technological paradigms, regimes and schemas (Galunic and Rodan, 1998; Dosi and Nelson, 2010; Mannucci and Yong, 2018). These capabilities can also be a source of competitive advantage because path dependencies and time compression diseconomies make them difficult and costly to imitate (Barney, 1991; Sydow et al., 2009; Pacheco-de-Almeida and Zemsky, 2007).

On the other hand, broad technological scope involves operating in multiple domains, having distributed capabilities (Granstrand et al., 1997; Patel and Pavitt, 1997; Brusoni et al., 2001) and seeking horizontal combinations of knowledge across domains (Zhou and Li, 2012; Teodoridis et al., 2019). Such a knowledge base has high degree of dispersion of knowledge among individuals (Galunic and Rodan, 1998). Accordingly, these capabilities are suitable for new combinations involving greater variety of knowledge components (Arthur, 2007; Schoenmakers and Duysters, 2010; Caner et al., 2017). These capabilities facilitate broad search strategies and pursuit of a variety of technological opportunities across a large number of domains (Wang and von Tunzelmann, 2000; Leiponen and Helfat, 2010; Kim et al., 2013). The wide range of experimentation accompanying these capabilities also increases the likelihood of the serendipitous discoveries of novel technical effects (Fink et al., 2017). The engagement with a large number of domains also facilitates in identifying new solutions to the problems in existing technologies and finding new applications of existing technological knowledge and artifacts (Kim and Kogut, 1996; Leiponen and Helfat, 2010; Caner et al., 2017). Accordingly, knowledge structures and schemas involved in broad technological scope tend to be highly varied and flexible to pursue technological opportunities in a variety of domains (George et al., 2008; Caner et al., 2017), including imitative innovation (Leiponen and Helfat, 2011). The inventions and innovations emanating from a knowledge base with a broad scope are also likely to be more radical and have wider impact due to the combination of knowledge from multiple domains (Miller et al., 2007; Schoenmakers and Duysters, 2010; Papazoglou and Spanos, 2018; Bekar et al., 2018) and hence create further technological opportunities. Thus, borad scope is valuable because it allows firms to pioneer new technologies and gain first-mover advantages and lead-time benefits (Wang and von Tunzelmann, 2000; Papazoglou and Spanos, 2018). It can also be a source of competitive advantage because combinations spanning diverse technology domains involve high degree of complexity and causal ambiguity, making them hard to imitate (Barney, 1991).

In short, narrow and broad technological scope differ not only in the composition of their technological resource base but also in their organizing logics and the nature of search for inventions and innovations.

2.3. Technological scope and post-acquisition R&D output

Firms can use their existing technological base as a platform to enter related technology domains to exploit their existing technological resources and capabilities and/or explore new technological opportunities (MacDonald, 1985; Kim and Kogut, 1996; Breschi et al., 2003; Rosenkopf and Nerkar, 2001; Levinthal and March 1993; Pisano, 2017). Technological M&As are an important strategic tool to explore and exploit as well as to gain economies of scale and scope in technological resources (Stettner and Lavie, 2014; Cassiman et al., 2005). Acquisition of a technology-based firm can increase technological opportunities for the acquirer in three important ways: deepening the technological base by filling the gaps within and between existing domains of the acquirer, accessing new technological opportunities in the domains of the target, and exploring new opportunities in domains beyond the existing technological scope of the acquirer.

Firms with a narrow technological scope specialize in a small number of interrelated domains. Such firms tend to have distinctive core capabilities, pursue narrow search strategy, and search for technological opportunities in the neighborhood of their existing domains (Stuart and Podolny, 1996; Katila and Ahuja, 2002; Kim et al., 2013; Pisano, 2017). Due to the constraints of absorptive capacity (Cohen and Levinthal, 1990), such firms benefit by acquiring other firms that possess specialized technological knowledge and capabilities closely related to those of the acquirer (Breschi et al., 2003; Kim et al., 2013). Technological relatedness allows both firms to learn from each other quickly, combine the expertise in each other's domains, and find new technological opportunities within, across, and beyond their existing domains (Sears and Hoetker, 2014). It allows the acquirer to use newly acquired knowledge to deepen its expertise and pursue those technological opportunities in its existing domains that were hitherto inaccessible due to the gaps in its knowledge and expertise (Lodh and Battaggion, 2015). Relatedness also enables the acquirer to leverage its existing knowledge and capabilities to pursue technological opportunities in the target's domains of expertise (Kim and Kogut, 1996; Rosenkopf and Nerkar, 2001; Puranam and Srikanth, 2007; Choi and McNamara, 2018). Therefore, narrow technological scope of the acquirer and corresponding depth of expertise have a positive impact on the post-acquisition R&D output of the acquirer.

On the other hand, firms with a broad technological scope are those which operate in multiple and technologically distant domains. Such firms tend to be ambidextrous and have distributed capabilities (Stettner and Lavie, 2014; Patel and Pavitt, 1997; Granstrand et al., 1997), and have greater absorptive and creative capacity to pursue a variety of search objectives (Cohen and Levinthal, 1990; Cohen and Klepper, 1996), including the pursuit of new technological opportunities within existing domains, recombining the knowledge across existing domains, or deploying existing knowledge and capabilities to new domains. However, due to the breadth of their technological base, they tend to use broad search strategies for invention and innovation (Galunic and Rodan, 1998; Leiponen and Helfat, 2010; Kim et al., 2013) and engage in boundary-spanning search that transcends technological and organizational boundaries (Rosenkopf and Nerkar, 2001). Accordingly, such firms can have a variety of motives and uses of technological acquisitions (Graebner et al., 2010). Such acquirers can mobilize their own as well as the acquired firm's knowledge base to search and seize varied technological opportunities within, across and beyond their own and target's domains (Kim and Kogut, 1996; Puranam and Srikanth, 2007; Choi and McNamara, 2018). Such acquirers can also find new technological opportunities in those technology domains which are linked to the domains of the target and also gain access to hitherto distant domains through partnership network of the target (Saboo et al., 2017; Caner et al., 2017; Feldman and Hernandez, 2020). Therefore, due to the large variety of technological capabilities and opportunities for creative recombination, a broad technological scope of the acquirer and the corresponding breadth of expertise have a positive impact on post-acquisition R&D output of the acquirer.

The technological knowledge base of some acquirers may involve multiple but closely interrelated technology domains. Technological proximity of domains limits the scope of search and multiplicity of interrelated domains may lead to unproductive diversity and problems in coordination and collaboration in R&D (Cassiman et al., 2005; Kim et al., 2013). Interdependencies among R&D objectives and overlap in technological expertise may induce conflict and unhealthy internal competition in setting search objectives and allocating resources. Therefore, such firms will find it difficult to pursue focused search comparable to that of firms with a narrow technological scope or conduct a broad search like the firms with a broad technological scope. Accordingly, such firms are likely to be trapped in local and myopic search (Rosenkopf and Nerkar, 2001; Levinthal and March 1993) and have a limited capability to identify or create technological opportunities. Consequently, acquisitions by such firms are likely to aggravate these problems. Therefore, moderate technological scope of the acquirer is likely to have comparatively lower impact on post-acquisition R&D output than can be attained by an acquirer with a narrow or broad technological scope.

In view of this discussion, we hypothesize the following:

H1. Technological scope has a curvilinear (U-shaped) relationship with post-acquisition R&D output, such that the output is high when technological scope is either narrow or broad and low at moderate levels of technological scope.

2.4. Technological complementarity and post-acquisition R&D output

Complementarities and synergies are important determinants of innovation and firm performance (Helfat, 1997; Cassiman and Veugelers, 2006; Stieglitz and Heine, 2007; Teece, 2010; Dibiaggio et al., 2014; Feldman and Hernandez, 2020). Accordingly, researchers have investigated their role in M&As (Cassiman et al., 2005; Makri et al., 2010; Chondrakis, 2016; Yu et al., 2016; Grimpe and Hussinger, 2014). Technological complementarity between acquirer and target exists when each firm possesses such technological resources that are more productive and valuable when they are combined with the technological resources of the other firm. Accordingly, complementarities between the technological knowledge bases of an acquirer and its target exist when their technological capabilities belong to different but related technology domains (Makri et al., 2010). The acquirer can benefit from technological complementarities to create and seize technological opportunities in its existing domains or in the domains of the target by creating new combinations of existing technological knowledge of the two firms (Fleming, 2001; Arthur, 2007). Technological complementarities can also be used to enter other technology domains in which neither the acquirer nor the target have prior expertise but the combination of their technological capabilities can provide a platform to enter those domains (Kim and Kogut, 1996; Saboo et al., 2017). Finally, presence of technological complementarities can also facilitate post-merger integration of the R&D capabilities of the merging firms and increase post-acquisition R&D productivity (Cassiman et al., 2005).

The nature and amount of such technological complementarities are determined by the number of technology domains that each firm is operating in as well as the degree of relatedness between the sets of their respective technology domains. The greater the number of domains of the acquirer that share technological complementarities with its target, the greater the number of technological opportunities available to the acquirer. On the other hand, the degree of relatedness affects the quality of new combinations of technological knowledge in terms of radicalness and complexity of technological opportunities (Valentini, 2012;

Valentini and Di Guardo, 2012; Colombo and Rabbiosi, 2014; Dibiaggio et al., 2014). Radicalness affects the economic and strategic value of an invention because it determines novelty or rarity whereas complexity affects the imitability of an invention. The more distant the domains within and across the portfolios of the acquirer and target, the greater the possibility of radical and complex combinations (Fleming, 2001; Schoenmakers and Duysters, 2010; Papazoglou and Spanos, 2018). Since the number of domains in the technological knowledge base and the degree of their relatedness determine the technological scope of the firm, technological complementarities interplay with the technological scope of the merging firms and moderate its effect on post-acquisition R&D output. Accordingly, the quantity and quality of technological complementarities will also depend on whether the acquirer has a narrow or broad technological scope.

Acquirers with a narrow technological scope operate in a few and technologically proximate domains. They can benefit from technological complementarities with the target in two important ways. First, technological complementarities can allow them to advance and deepen their existing technological capabilities to create and seize technological opportunities in their existing domains by internalizing knowledge and capabilities of the target (Stettner and Lavie, 2014). Second, technological complementarities can help them leverage and extend their existing technological capabilities and allow them to explore new technological opportunities in new domains (Levinthal and March 1993; Kim and Kogut, 1996), thus extending the technological scope of the acquirer. Technological complementarities are even more valuable when target's technology domains are more distant because this situation facilitates extending the reach of the firm in the technology space and affords relatively more radical and novel technological opportunities (Rosenkopf and Nerkar, 2001; Schoenmakers and Duysters, 2010; Papazoglou and Spanos, 2018). Accordingly, the presence of technological complementarities also reduces the costs of technological diversity and allows the acquirers with narrow technological scope to expand their technological scope by crossing the valley of the scope-output curve more effectively and efficiently.

Acquirers with a broad technological scope operate in a large number of technologically distant domains and seek to create varied, broad, radical, and complex combinations for invention and innovation (Cassiman and Veugelers, 2006). They can increase their R&D output by deepening or broadening their technological base through complementary technological knowledge and capabilities of the target in three important ways. First, they can exploit their existing technological capabilities by using complementary knowledge and capabilities of the target to find or create new technological opportunities in their existing domains (March, 1991; Stuart and Podolny, 1996). Second, they can fill the gaps in their technological capabilities to explore technological opportunities in those domains which are new to them but closely related to their existing domains (Rosenkopf and Nerkar, 2001). Finally, they can expand the scope of their technological capabilities to explore technological opportunities in those domains which are technologically distant from their existing domains but related to the target (Levinthal and March 1993; Stettner and Lavie, 2014).

In the light of this discussion, we hypothesize the following:

H2. Technological complementarity between an acquirer and target positively moderates the effect of technological scope on post-acquisition R&D output of the acquirer.

3. Methodology

3.1. Empirical context, data, and sample

In order to test our hypotheses, we adopted a novel and extensive procedure to select a diverse sample of technological acquisitions in which acquiring firms come from several countries, industries, and technology domains. Unlike the conventional method of using industry or patent classes as the basis of sample selection, we started out by identifying 1000 firms that had the highest number of patent applications filed in the US during the period 2005–2009 (both inclusive) as provided in worldwide patent statistical database PATSTAT (Sep-2010 version). We used an extensive procedure to eliminate all textual variations in the names of firms in the database and then computed the total number of patent filings by each distinct firm. Patent applications are frequently used as a valid measure of inventive activity and R&D output (Ahuja and Katila, 2001; Choi and McNamara, 2018). Based on all the patent applications of the 1000 firms, we computed their cosine similarity, which is a measure of technological relatedness of firms (McNamee, 2013). From the cosine similarity matrix of these 1000 firms, we extracted non-overlapping clusters of firms using the spectral clustering method (Newman, 2006; Rubinov and Sporns 2010). This method allows identification of firms which are technologically more similar and hence form a cluster. In order to select a sample of technologically diverse firms, we chose two clusters that were significantly different from each other in terms of the fields of technology they represented. One cluster (154 firms) was related to computing, electronics, and communication technologies whereas the other cluster (81 firms) was related to mechanical, thermal, and aerospace engineering technologies.

Using these two clusters as the base, we searched SDC Platinum to identify M&A transactions by these firms between 1985 and 2005 (both years included). In order to characterize a deal as technological M&A, we identified those deals whereby the M&A target had filed at least one patent application prior to the deal (Choi and McNamara, 2018). Further, we focused the analysis on those firms which had acquired at least 50% of the stake in the target firm (Choi and McNamara, 2018). We used the ownership condition because greater ownership and control is more likely to encourage and facilitate the post-acquisition mobilization and combination of R&D resources between the acquirer and target. However, this condition of ownership coupled with prior patenting inevitably reduces the sample size. We obtained financial data about these firms from Compustat and used OECD exchange rates where financials were not given in US dollars. After excluding the transactions for which data was not available on any of the variables of our interest, the final sample was an unbalanced panel of 176 M&A transactions during 21 years (1985–2005) by technologically diversified firms from 7 countries, nine 2-digit SIC industries and 33 different 4-digit SIC industries. The targets belonged to 16 countries, 12 different 2-digit SIC industries and 64 different 4-digit SIC industries. Therefore, the sample was diverse in terms of technology domains as well as industries and countries and included firms such as Apple and Intel on the one side of the technology spectrum and Boeing and General Motors, on the other.

3.2. Measures

3.2.1. Dependent variables

We used patent applications as a measure of R&D output for several reasons. First, it is a popular tool among firms for protecting their intellectual property and recapture value from their R&D investments. Second, patent application is a reliable indicator of significant inventive activity because of the stringent requirements of the patent law and non-trivial costs involved in submitting and defending the legal claim of invention. Third, patent application allows to discern whether the invention is incremental or new to the firm and its classification is a reliable indicator of the technology field(s) it belongs to. Finally, it is widely accepted and used as a measure of R&D output (OECD, 2015).

We used two variants of post-acquisition R&D output as dependent variables, one for the output of acquirer alone and the other for the combined output of the acquirer and the target. Both are measured as the count of non-incremental and new-to-the-firm patent applications by the acquirer and the target. Accordingly, we counted one DOCDB family as one invention like singletons because a DOCDB family represents a collection of multiple patents which belong to a single invention and all but the parent patent represent incremental inventions. Likewise, all other patent-based measures used in this paper pertain to non-incremental and new-to-the-firm patent applications. Given that prior studies have used post-acquisition output during 3–5 years for measuring R&D output (Ahuja and Katila, 2001; Cloodt et al., 2006; Makri et al., 2010), we left one year period from the date of acquisition deal as a transition period for post-acquisition mobilization and integration of R&D resources and counted the inventive output of the acquirer and the combined firm for t+1+3 and t+1+4 years.

3.2.2. Independent variable: technological scope

Prior research has conceptualized technological scope in terms of the portfolio of R&D projects and operationalized it in terms of research programs or projects (Henderson and Cockburn, 1996; Cockburn and Henderson, 2001). We conceptualize technological scope as the extent of a firm's ability to create new technological knowledge and artifacts in a range of technology domains involving varying degrees of technological interrelatedness. It involves the number of technology domains as well as the relatedness between each pair of technology domains covered by the firm's technological knowledge base. Patents represent codified knowledge and provide a more fine-grained measure of firm's technological knowledge base (Jaffe et al., 1993). Accordingly, we operationalized technological scope in terms of the portfolio of technology domains proxied by patent classes (Leten et al., 2007; Huang and Chen 2010; Kim et al., 2016). Literature on patent-based measures suggests that technological relatedness between fields varies at various levels of classification hierarchy depending on the technological lineage of these fields (McNamee, 2013). For instance, field x1 is more related to another field x2 that descends from the same parent field X than to field y2 which descends from a different parent Y. For instance, International Patent Classification (IPC) subclass G01F (measurement of volume and flow) and G01G (measurement of weight) are more related/proximate to each other than to H01F (magnets and inductors) and H01G (capacitors and switching devices).

We combined this understanding of technological relatedness among domains with the established understanding that technological diversity is greater when technological output of the firm is spread over a greater number of domains. Thus, technological scope can be measured simply by combining technological diversity at various levels of patent classification hierarchy whereby technological diversity weighs more at the higher levels relative to the lower levels. This measure can be represented in a multi-level index of technological scope of a firm *i* as following:

$$\text{Technological Scope index}_i = \sqrt[m]{\text{TD}_k^{\frac{1}{k}}.\text{TD}_{k-1}^{\frac{1}{k-1}}.\text{TD}_{k-2}^{\frac{1}{k-2}}\ldots\ \text{TD}_{k-m}^{\frac{1}{k-m}}} \quad (1)$$

Where TD refers to technological diversity of the firm *i* while *m* is the number of measurement levels chosen in patent classification hierarchy, and k represents the lowest classification level in the analysis.

We used the Herfindahl index of diversification (Quintana-García and Benavides-Velasco, 2008; Kim et al., 2016) to measured technological diversity of the acquirer as the spread of the total number of inventions during three years prior to the date of acquisition over 634 IPC subclasses, 128 classes, and 8 sections. The Herfindahl index was computed as following:

$$\text{TD} = 1 - \text{HHI} = 1 - \sum \text{P}_j^2 \quad (2)$$

Where *P* is the proportion of a firm's inventions in a technology field/domain *j* represented by the IPC subclass.

Accordingly, the technological scope index of a firm *i* is a composite measure of technological diversification at three levels denoted by *m*: IPC section (level 1), classes (level 2), and subclasses (level 3). Like the Herfindahl index, the index ranges between 0 and 1 and measures the spread of firm's patent portfolio over the universal set of subclasses while accounting for their technological relatedness in terms of the IPC classification tree.

3.2.3. Control variables

We used several control variables that can affect the post-acquisition inventive output of the acquirer. Prior research suggests that technological diversity significantly affects R&D output of the firm (Ahuja and Katila, 2001; Leten et al., 2007; Huang and Chen 2010). We controlled for technological diversity of the acquirer measured as the Herfindahl index as noted above (Quintana-García and Benavides-Velasco, 2008). Also included was the control for the absolute size of R&D expenditures because it is endogenously driven by the size of a firm (Knott and Vieregger, 2020). It was measured as the dollar value of R&D expenditures of the acquirer during the year prior to the acquisition transaction. Due to excessive multicollinearity of this variable with conventional financial measures of firm size and unavailability of non-financial data regarding the acquirer at the time of the deal, we did not control for firm size and assume that R&D expenditures sufficiently represent the relative size of the acquirers. For non-US firms, end of period exchange rates of OECD were used for the conversion of financials to US dollars.

We controlled for the relative size of the acquired knowledge base measured as the pre-acquisition R&D output of the target divided by pre-acquisition R&D output of the target during 3 years prior to the deal (Ahuja and Katila, 2001; Cloodt et al., 2006). However, we did not include the control for the absolute size of the acquirer's knowledge base because it pushed multicollinearity beyond acceptable limits. High multicollinearity was expected because pre-acquisition R&D output of the acquirer was highly correlated with the dependent variable and technological diversity and scope were also based on the same output. We also controlled for the effect of dyadic and multi-party R&D alliances of acquirer, measured as the number of R&D alliances during three years prior to the acquisition (DeCarolis and Deeds, 1999). Similarly, the effect of acquisition experience (Puranam and Srikanth, 2007; Laamanen and Keil, 2008) was controlled through a variable measuring the total number of technological and non-technological acquisitions by the firm during three years preceding the deal.

Technological similarity and complementarity between the acquirer and target are also known to affect post-acquisition R&D output (Makri et al., 2010; Colombo and Rabbiosi, 2014). We controlled for these using the established measures as proposed by Makri et al. (2010, p. 613). Technological similarity refers to the degree of overlap between the acquirer and target measured as the number of inventions during three years preceding the acquisition in common IPC classes weighted by relative importance of classes for the acquirer. Technological complementarity measures the number of inventions by the acquirer and target in the same IPC classes but in different subclasses during three years prior to acquisition.

Prior ties between acquirer and target also affect the post-acquisition performance (Vanhaverbeke et al., 2002). We controlled for this effect through a measure involving total number of prior strategic alliances between the acquirer and target during 3-year period prior to the date of acquisition. To control for the effects of geographic distance and localness/foreignness of the target (Chakrabarti and Mitchell, 2013; McCarthy and Aalbers, 2016), we included a binary dummy variable for whether the target belonged to the same country (localness). Similarly, we also controlled for industry relatedness (Lee and Kim, 2016; Cefis et al., 2020) through a binary dummy variable indicating whether they belonged to the same 4-digit SIC industry. Effects of the year of transaction, industry of acquirer and target (2-digit SIC) and country of the acquirer and target were also controlled through respective dummy variables. Summary of key variables is presented in Table 1.

3.3. Model specification

3.3.1. Estimator selection

Since our dependent variables are based on count data, Poisson and Negative Binomial families of models are two options available (Cameron and Trivedi, 2013). Since the data are Poisson-overdispersed (i.e., variance is greater than the mean), we used the Negative Binomial

Table 1
Operational definitions of variables.

Variable	Operational Definition
Post-acquisition R&D output	Count of non-incremental and new-to-the-firm inventions during a specific number of years after the acquisition transaction whereby a DOCDB family of patents is counted as single invention.
Acquirer's Technological Scope	The extent of dispersion of the R&D output of the acquirer over 634 IPC subclasses weighted by their technological relatedness in the IPC classification tree of 8 sections and 128 classes during three years prior to the date of acquisition. $\text{Technological Scope index}_i = \sqrt[m]{TD_k^{\frac{1}{k}}.TD_{k-1}^{\frac{1}{k-1}}.TD_{k-2}^{\frac{1}{k-2}}\ldots TD_{k-m}^{\frac{1}{k-m}}}$
Acquirer's Technological Diversity	The extent of dispersion of the R&D output of the acquirer over 634 IPC subclasses during three years prior to the date of acquisition measured by Herfindahl–Hirschman Index (Quintana-García and Benavides-Velasco, 2008). $TD = 1 - HHI = 1 - \sum P_j^2$
Acquirer's R&D Expenditures	Dollar value ($Million) of R&D expenditures of the acquirer during the year preceding the acquisition transaction.
Relative Size of Knowledge Base	The pre-acquisition R&D output of the target divided by pre-acquisition R&D output of the target during 3 years prior to the deal.
Technological Complementarity	Number of inventions by the acquirer and target in the same IPC classes but in different subclasses during three years prior to acquisition (Makri et al., 2010, pp. 613). = (Overlap All IPC Subclasses/Total Patents A & T) – (Overlap All IPC Classes/Total Patents A & T) × (Total Acquirer Patents in Common IPC Subclasses/Total Acquirer Patents)
Target's Technological Scope	The extent of dispersion of the R&D output of the target over 634 IPC subclasses weighted by their technological relatedness in the IPC classification tree of 128 classes and 8 sections during three years prior to the date of acquisition.
Technological Similarity between A & T	Degree of overlap between the acquirer and target measured as the number of inventions during three years preceding the acquisition in common IPC classes weighted by relative importance of the classes for the acquirer (Makri et al., 2010, pp. 613). = (Overlap All IPC Classes/Total Patents A & T) × (Total Acquirer Patents in Common IPC Classes/Total Acquirer Patents)
Prior Ties Between A & T	Number of prior strategic alliances between the acquirer and target during 3-year period prior to the date of acquisition.
Acquirer's R&D Alliances	Number of R&D alliances by the acquirer during three years prior to the acquisition.
Acquisition Experience	Number of technological and non-technological acquisitions by the acquirer during three years preceding the deal.
Localness of Target	Binary dummy variable indicating whether the acquirer and target belonged to the same country.
Industry Relatedness of A & T	Binary dummy variable indicating whether the acquirer and target belonged to the same 4-digit SIC industry.

model (Hilbe, 2011; Choi and McNamara, 2018). We preferred fixed effects model over random effects model because the former controls for unobserved differences among acquirers in their predisposition to patent (Kumar and Zaheer, 2019). Moreover, there is no substantive reason to assume that the unobserved effects are completely uncorrelated with all the explanatory variables in all periods as it is assumed in the random effects model (Wooldridge, 2020). The fixed effects Poisson with robust standard errors also produced results that were consistent with the fixed effects Negative Binomial model, adding to our confidence in the results presents here.

3.3.2. Multicollinearity and endogeneity

To normalize skewness in frequency distributions and minimize non-essential collinearity among variables, we transformed all variables into natural logarithm and then mean-centered each variable (Cohen et al., 2013). The variance inflation factor (VIF) of all variables was less than 2.45, the mean VIF of every model was less than 1.70 and the condition index of each model was less than 4.60, indicating that multicollinearity was not a significant concern (O'brien, 2007). We also tested for endogeneity of the variables through the Dubin-Wu-Hausman test and found that the residuals of independent variables were not related to our dependent variables, suggesting that endogeneity was not a matter of concern (Antonakis et al., 2010).

3.4. Model execution

We modeled two variants of the dependent variable, post-acquisition R&D output of the acquirer and the combined firm for t+1+3 years and t+1+4 years. The Wald Chi Squared statistic, reported with each model, showed that all models were statistically significant.

4. Analysis

4.1. Model-free information

Descriptive statistics (see Table 2) suggest that the sample is comprised of large and technologically diversified firms that invested substantially in R&D (mean = $ 2710 m). Statistics also suggest that these firms frequently used external sources of technologically knowledge such as R&D alliances and acquisitions.

Since the values of dependent variables were overdispersed and the predictor variables had comparatively small dispersion, bivariate Pearson correlations between them were not significant. However, correlation coefficients provide useful information for other variables. For instance, correlations indicate that inventive output is not only positively related with the size of R&D investment ($r = 0.52$, $p < 0.001$) but also with external sources of knowledge such as R&D alliances ($r = 0.45$, $p < 0.001$) and acquisitions ($r = 0.47$, $p < 0.001$). Moreover, significant positive correlation between R&D alliances and acquisition experience ($r = 0.3$, $p < 0.001$) indicates that firms tend to maintain portfolios of external sources of technologies (Hoang and Rothaermel 2010; Hagedoorn and Wang, 2012; Stettner and Lavie, 2014). Size of R&D investment is also positively correlated with technological scope ($r = 0.31$, $p < 0.001$) and diversity ($r = 0.39$, $p < 0.001$), suggesting that as firms increase R&D, their technological base tends to become broad and more diverse.

The predictor variable, technological scope, is significantly positively correlated with technological diversity ($r = 0.41$, $p < 0.001$) indicating that change in one is accompanied by the change in the other, though the degree of change varies between the two. Technological scope is also positively correlated with external sources of technology such as R&D alliances ($r = 0.17$, $p < 0.05$) and acquisitions ($r = 0.24$, $p < 0.01$) signifying the importance of technological scope in these contexts, hence the need for closer examination.

4.2. Model-specific results

The results of the Negative Binomial regression models showing the effects of technological scope on post-acquisition inventive output of the acquirer and the combined firm are presented in Table 3 and explained in the following.

The Model 0 shows that technological scope significantly affects the post-acquisition output in the absence of any other variable ($B = -10.39$, $p < 0.001$). Similarly, technological scope is significant at $p < 0.001$ in the absence of any other variable for other dependent variables for both periods. We predicted in hypothesis 1 that the relationship between technological scope and post-acquisition output of the acquirer is U-shaped. We modeled this relationship using the t+1+3 years R&D output of acquirer as the dependent variable. The baseline Model 1, that includes the control variables only, is significant as indicated by the

Table 2
Descriptive statistics and correlations.

		Mean	SD	Min.	Max.	1	2	3	4	5	6	7	8	9	10	11	12
1	Acquirer Total Inventions (t+1 + 3)	2866.94	2895.56	70	13398	1											
2	Acquirer Total Inventions (t+1 + 4)	3822.71	3849.24	93	17258	1***	1										
3	Acquirer's Technological Scope	0.956087	0.014924	0.902043	0.988455	0.05	0.05	1									
4	Acquirer's Technological Scope^2	0.914323	0.028340	0.813682	0.977043	−0.12	−0.12	−0.53***	1								
5	Acquirer's Technological Diversity	0.999603	0.000329	0.998441	0.999942	0.03	0.03	0.41***	−0.08	1							
6	Target's Technological Scope	0.805743	0.310311	0	0.999400	0.03	0.02	0.17*	−0.14	0.1	1						
7	Relative Size of Knowledge Base	0.020768	0.076731	0	0.561135	−0.18*	−0.19*	0.07	−0.06	0.01	0.12	1					
8	Acquirer's R&D Expenditures ($Million)	2710.76	2594.27	6	10287	0.52***	0.53***	0.31***	−0.11	0.39***	0.03	−0.1	1				
9	Technological Complementarity	0.058076	0.116109	0	0.630864	0.06	0.06	0.04	−0.11	0.06	−0.03	−0.07	0.13	1			
10	Technological Similarity between A & T	0.251850	0.282003	0	0.984493	−0.07	−0.06	−0.2**	−0.08	−0.42***	0.35***	0.38***	−0.17*	−0.24**	1		
11	Acquirer's R&D Alliances	12.20	26.15	0	272	0.45***	0.44***	0.17*	−0.15	0.23**	0.11	−0.17*	0.48***	−0.02	−0.14	1	
12	Acquisition Experience	10.53	11.48	0	48	0.47***	0.48***	0.24**	−0.14	0.32***	0.06	−0.24**	0.62***	0.07	−0.12	0.3***	1
13	Prior Ties Between A & T	0.18	0.63	0	4	0.13	0.12	−0.03	0	0.05	−0.02	0.18*	0.07	−0.1	0.02	0.24**	0.1

N = 176; A&T (Acquirer and Target).
Independent and control variables are natural log-transformed and mean-centered.
***p < 0.001, **p < 0.01, *p < 0.05; two-tailed.

Wald Chi-Squared statistic. Consistent with prior literature, the model shows that post-acquisition R&D output of the acquirer is negatively affected by technological diversity (B = −1234.62, p < 0.001) and positively affected by the size of R&D expenditures (B = 0.27, p < 0.001), R&D alliances (B = 0.11, p < 0.01), and acquisition experience (B = 0.13, p < 0.01). Localness of target also positively affects R&D output (B = 0.44, p < 0.05). However, target's technological scope, prior ties between acquirer and target, technological complementarity or similarity between acquirer and target, and industry relatedness of the acquirer and target have no significant effect on the inventive output.

We introduced the linear term of technological scope in Model 2. The model fit improves with the linear term which has a significant positive effect of technological scope (B = 6.88, p < 0.01). While the direction and significance of the effects of all variables remain unchanged, the magnitude of most of the variables changes slightly. However, the effect of technological diversity substantially increases with the inclusion of technological scope in Model 2 (B = −1623.16, p < 0.001) because technological scope is inherently connected to technological diversity and hence significantly positively correlated with it as well (see Table 2).

The inclusion of the quadratic term in Model 3 significantly improves the model fit. The quadratic term is significant and positive (B = 275.04, p < 0.01), indicating a U-shaped relationship of technological scope with post-acquisition output, as predicted in hypothesis 1. The coefficient of technological diversity (B = −1258.23, p < 0.001) substantially decreases compared to the previous model, indicating that firms with higher technological scope also have higher technological diversity but the positive effect of the former significantly offsets the negative effect of the latter. Compared to the previous model, in Model 3 the significance of R&D alliances increases slightly (B = 0.13, p < 0.001) and local acquisitions also becomes more significant (B = 0.54, p < 0.01).

We predicted in hypothesis 2 that technological complementarity positively moderates the effect of technological scope on post-acquisition R&D output. To arrive at the full model, we included the interaction term in Model 4. Accordingly, it became the model with the highest fit. The quadratic term of technological scope decreases compared to the previous model but remains significant and positive (B = 294.41, p < 0.01). The interaction term is also significant and positive (B = 61.19, p < 0.01). It is worth noting here that technological complementarity has no significant direct or mediating effect on post-acquisition R&D output. In the presence of quadratic and interaction terms, technological diversity is the lowest (B = −969.16, p < 0.01) among all previous models. Significant positive effects are also found for several other variables, including the size of acquirer's R&D expenditures (B = 0.31, p < 0.001), R&D alliances (B = 0.15, p < 0.001), acquisition experience (B = 0.13, p < 0.05), and local acquisitions (B = 0.43, p < 0.05). On the other hand, we did not find any significant effect of industry relatedness between acquirer and target, prior ties between them or technological scope of target in any of the models.

We replicated all models with the combined R&D output of acquirer and target and with a longer period (t+1+4) and found very similar results. Models 5–7 show the results corresponding to the full model. Models 6 and 7 show that the U-shaped effect of technological scope and the moderating effect of technological complementarity remain significant, but the effect of technological diversity substantially weakens. These results provide further support for the understanding that firms with narrow or broad technological scope have greater post-acquisition R&D output than firms with moderate technological scope.

4.3. *Post hoc analysis*

We conducted several post hoc analyses to ensure that our findings are robust. First, as the focus of our study is the acquirer's inventive output measured for t+1+3 years post acquisition, we also tested our models on the combined firm (acquirer + target) for t+1+3 years (Model 5) as well as t+1+4 years periods (Models 6 and 7). The results of these models are also presented in Table 3 and show similar

Table 3
Negative binomial regression on post-acquisition R&D output.

		Three-Year Post Acquisition Output					Four-Year Post Acquisition Output	
	Model 0	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5 (A&T Combined)**	**Model 6 (Acquirer)**	**Model 7 (A&T Combined)**
Intercept	1.85 (0.11)***	2.53 (0.65)***	2.63 (0.65)***	2.42 (0.64)***	2.8 (0.63)***	2.9 (0.62)***	2.98 (0.55)***	3.08 (0.54)***
Acquirer's Technological Scope	−10.39 (2.56)***		6.88 (2.52)**	10.26 (2.7)***	10.79 (2.58)***	10.77 (2.53)***	9.21 (2.14)***	9.15 (2.1)***
Acquirer's Technological Scope^2				275.04 (87.64)**	262.24 (85.44)**	263.91 (84.41)**	257.67 (73.06)***	259.02 (72.33)***
Acquirer's Technological Diversity		−1234.62 (287.66)***	−1623.16 (314.13)***	−1258.23 (322.43)***	−969.16 (330.17)**	−967.91 (330.22)**	−595.15 (291.23)*	−588.35 (292.8)*
Acquirer's R&D Expenditures ($Million)		0.27 (0.08)***	0.31 (0.08)***	0.34 (0.08)***	0.31 (0.08)***	0.3 (0.08)***	0.33 (0.07)***	0.33 (0.07)***
Relative Size of Knowledge Base		−1.45 (0.86)†	−1.76 (0.83)*	−1.48 (0.84)†	−1.64 (0.84)†	−1.26 (0.78)	−1.24 (0.72)†	−0.82 (0.68)
Technological Complementarity		0 (0.21)	−0.03 (0.2)	−0.01 (0.2)	−0.17 (0.21)	−0.18 (0.21)	−0.21 (0.18)	−0.23 (0.18)
Technological Scope * Complementarity					61.19 (22.67)**	63.83 (22.36)**	57.27 (18.58)**	59.72 (18.35)**
Target's Technological Scope		−0.03 (0.13)	−0.08 (0.12)	−0.12 (0.12)	−0.13 (0.12)	−0.14 (0.12)	−0.09 (0.1)	−0.1 (0.1)
Technological Similarity between A & T		−0.18 (0.16)	−0.18 (0.15)	−0.18 (0.15)	−0.19 (0.15)	−0.18 (0.15)	−0.19 (0.13)	−0.18 (0.13)
Prior Ties Between A & T		0.02 (0.08)	0.06 (0.08)	0.04 (0.08)	0.02 (0.08)	0.02 (0.08)	0.01 (0.07)	0.01 (0.07)
Acquirer's R&D Alliances		0.11 (0.04)**	0.12 (0.04)**	0.13 (0.04)**	0.15 (0.04)***	0.16 (0.04)***	0.14 (0.03)***	0.14 (0.03)***
Acquisition Experience		0.13 (0.05)*	0.1 (0.05)*	0.09 (0.05)†	0.13 (0.05)*	0.14 (0.05)**	0.13 (0.04)**	0.13 (0.04)**
Localness of Target		0.44 (0.21)*	0.49 (0.21)*	0.54 (0.2)**	0.43 (0.19)*	0.41 (0.19)*	0.48 (0.17)**	0.45 (0.17)**
Industry Relatedness of A & T (4 SIC)		0.01 (0.08)	0.03 (0.07)	0.06 (0.07)	0.09 (0.07)	0.08 (0.07)	0.09 (0.06)	0.08 (0.06)
Acquirer's Industry		Yes	Yes	Yes	Yes	Yes	Yes	Yes
Acquirer's Country		Yes	Yes	Yes	Yes	Yes	Yes	Yes
Target's Industry		Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year of Transaction		Yes	Yes	Yes	Yes	Yes	Yes	Yes
Wald Chi-Squared		339.25***	364.01***	394.97***	408.96***	429.3***	487.68***	504.22***
Log likelihood		−1028.097	−1024.4348	−1019.8621	−1016.1599	−1014.6561	−1036.4342	−1035.4131

N = 176; ***$p < 0.001$, **$p < 0.01$, *$p < 0.05$, †$p < 0.10$; Two-tailed. Standard errors are given in parentheses.

relationships, confirming robustness of the main model. Second, we also modeled the data using a Poisson estimator which is a major alternative to the Negative Binomial estimator. Fixed effects Poisson regression with robust standard errors shows similar results as the main model. For t+1+3 years post acquisition output of acquirer, the linear term of technological scope is significant and positive (B = 9.53, p = 0.002) and squared term is also positive and significant (B = 240.52, p = 0.01). The result for the interaction between technological scope and complementarity also resemble the main model (B = 43.95, p = 0.04). For the t+1+4 years post acquisition output of the acquirer, the linear term of technological scope is significant and positive (B = 7.82, p = 0.001) and the squared term is also positive and significant (B = 223.59, p = 0.009). Similarly, the result for the interaction between technological scope and complementarity is also positive and significant (B = 36.05, p = 0.03).

Third, we conducted additional tests for gauging the robustness of the U-shaped relationship (Haans et al., 2016). We located the turning point using the method of Lind and Mehlum (2010). The test showed that slope of the curve was negative and significant at the lower bound (B = −19.66, t = 2.14, p = 0.02) and positive and significant at the upper bound (B = 28.31, t = 3.96, p = 0.00005), thus supporting the presence of U shape of technological scope. The turning point was located at −0.021 with the 95% Fieller interval being −0.050 and −0.011. In terms of observed values presented in Table 2, these results mean that the turning point is 0.937 with a 95% Fieller interval of 0.909–0.945 which is well within the range of data.

Fourth, we also plotted the predicted values of the model using the actual values of technological scope and mean values of other statistically significant variables. The regression curve of predicted values showed the curvilinear relationship consistent with the model (see Fig. 1).

Fifth, we also assessed the robustness of the moderating effect of technological complementarity on the relationship between technological scope and post-acquisition inventive output of acquirer. We used Sobel-Goodman mediation tests and found no mediating effect of technological complementarity or technological scope. We excluded the moderation of the squared term because it induced significant multicollinearity with both linear and squared terms of the predictor variables and its relationship with any of the variants of dependent variables was not statistically significant either. It was also non-essential because technological complementarity is more important to the firms with narrow technological scope to reach the turning point sooner than later. After the turning point, a broad scope of the acquirer's own knowledge base affords ample technological complementarities across its constituent domains such that they encompass the complementarities from the acquisition.

We also examined the significance of the moderating effect on the linear term through simple slope analysis of the regression curve at low and high levels of technological complementarity (Aiken and West, 1991) using the minimum and maximum values of technological complementarity at low and high levels of moderation. Results indicate that the simple slope of the regression curve is positive and significant at low (B = 7.64, p = 0.0064) as well at high levels of technological complementarity (B = 37.59, p = 0.0005). However, as predicted, the slope is much steeper at a high level (see Fig. 2). This suggests that technological complementarity significantly changes the linear function which leads to a shift in the turning point to the left. This is also

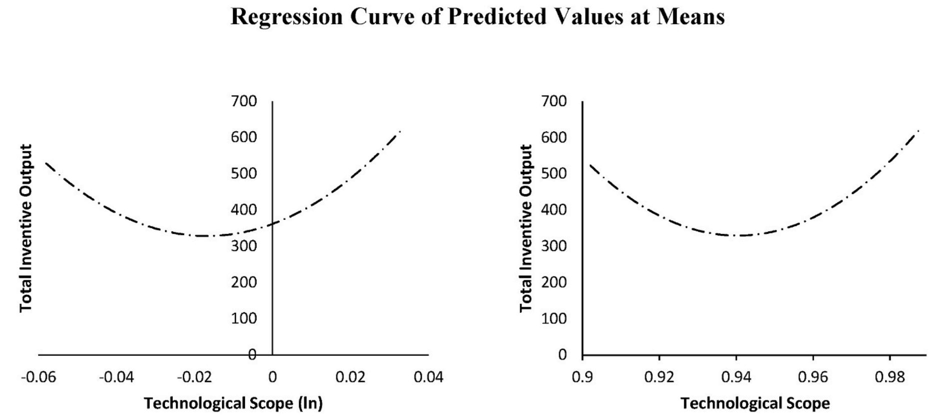

Fig. 1. Regression curve of predicted values at means.

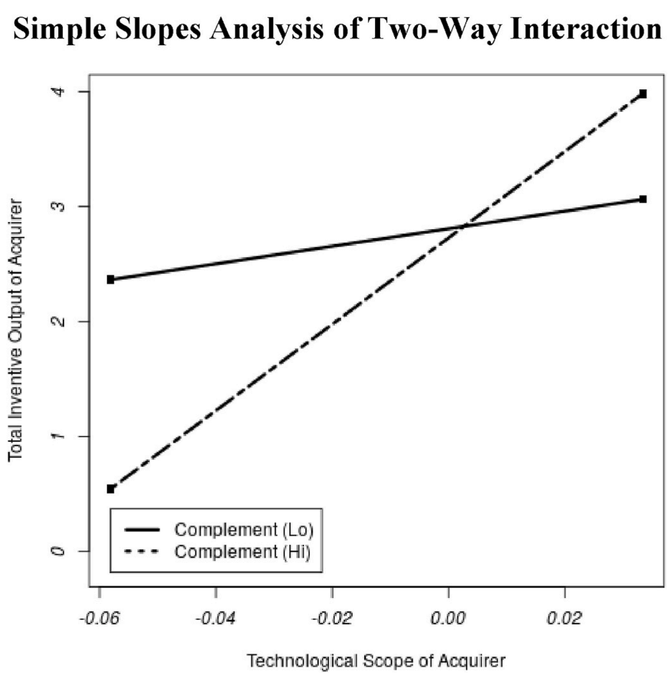

Fig. 2. Simple slopes analysis of two-way interaction.

indicated by the increase in the co-efficient of the linear term and decrease in the co-efficient of squared term of technological scope when we move from Model 3 to 4 by including the interaction term. Further analysis of turning points of other models also confirms this finding.

Finally, following the literature on technological exploitation and exploration and the use of acquisitions in this regard (Quintana-García and Benavides-Velasco 2008; Phene et al., 2012; Choi and McNamara, 2018), we performed additional analysis to examine whether the post-acquisition inventive output belongs to the domains wherein acquirer had prior experience (exploitation) or to the domains new to the acquirer (exploration). We found that 97.83% of acquirers' post-acquisition inventive output during the t+1+3 years belonged to those domains in which it has prior experience of patenting (mean = 2816.10, SD = 2876.61). We computed a dependent variable for the post-acquisition exploitative output, measured as the count of new-to-the-firm patent applications by the acquirer and target in those 4-digit IPC subclasses in which they had at least one patent application before the date of acquisition. Patent application in a subclass is an indicator that the firm had prior experience in the respective technology field. Exploitative output was computed for t+1+3 and t+1+4 years post acquisition. When we applied the main model and post-hoc tests to both variants of the exploitative output, the results were very similar to the main regression model as expected. These results provide further evidence of the robustness of our model and corroborate theories of organizational learning including exploitation versus exploration (March, 1991) and local or problemistic search (Stuart and Podolny, 1996).

5. Discussion

This study advances our understanding of how the composition of a firm's technological knowledge base affects its post-acquisition R&D output. Prior research suggests that firms in R&D-intensive industries need to sense and seize new technological opportunities to stay competitive in the face of rapid technological changes. They need to explore new technological opportunities by exploiting their existing technological resources and capabilities. For instance, they may need new technological knowledge and capabilities to realize technological opportunities in their existing domains and explore new technological opportunities beyond their existing domains (Kim and Kogut, 1996). Consequently, they can use several strategies for accumulation of relevant technological knowledge and capabilities, including internal development and external sourcing through R&D alliances and technological acquisitions (Stettner and Lavie, 2014). Internal development is slow and incremental whereas R&D alliances do not afford full access to valuable knowledge due to several problems such as lack of inter-organizational trust and concerns regarding the appropriation of value. Therefore, firms try to balance exploitation and exploration through different modes of internal development and external sourcing strategies in accordance with the nature and urgency of needs for different types of knowledge and capabilities (Stettner and Lavie, 2014). When firms need to seize new technological opportunities in their existing domains or explore new technological opportunities in new domains, they need a substantial addition of resources and capabilities to their technological base and technological M&As are a popular route despite their high upfront costs and risks of failure in post-acquisition integration (Graebner et al., 2010; Phene et al., 2012; Choi and McNamara, 2018).

The literature shows that technological M&As help improve R&D output and the pre-acquisition technological base and R&D strategies of acquirers play a key role in post-acquisition R&D output (Ahuja and Katila, 2001; Cloodt et al., 2006; Makri et al., 2010; Cefis and Marsili, 2015; Choi and McNamara, 2018). From the perspective of the knowledge-based view of the firm, technological knowledge and R&D capabilities comprise the core of a firm's technological base which determines the R&D output of the firm (Kogut and Zander, 1992; Nerkar and Paruchuri, 2005; Yayavaram and Chen, 2015). However, research on technological M&As has been largely concerned with the relationship between the knowledge bases of the acquirer and target to the neglect of some important internal dynamics within and between the merging firms' knowledge bases. These dynamics stem from the composition of the technological base which involves the variety of technology domains as well as the degree of interrelatedness among those domains. These two aspects have been frequently studied separately in the context of knowledge recombination dynamics and R&D output, but these have been rarely examined jointly. Therefore, there is a need to examine the combined effect of the variety and interrelatedness of domains to enhance our understanding of the role of the technological base of firms in technology acquisition and R&D output.

Research on the composition of a firm's technological base has been limited to the diversity and breadth of the knowledge base. Both these aspects are essentially based on the number of technology domains and do not take into account the relatedness among them. Consequently, empirical findings and theoretical prescriptions have split theory into different research traditions having little communication with each other. The literature on technological diversity has found that there is an inverted-U shaped relationship between technological diversity and R&D output (Leten et al., 2007; Huang and Chen, 2010). This literature suggests that there is an optimal number of technology domains that a firm can productively search and exploit. Therefore, firms operating in a large number of domains suffer from lower R&D productivity and overall performance. On the other hand, the literature on technological breadth suggests that breadth generates greater number of technological opportunities, economies of scope as well as radicalness in R&D output (Leiponen and Helfat, 2010; Schoenmakers and Duysters, 2010).

This divide is further complicated by the literature concerning technological similarity and complementarity between technology domains and firms. This literature suggests that concentration of R&D in closely related domains leads to fewer technological opportunities and generates incremental R&D output (Dibiaggio et al., 2014; Chondrakis, 2016; Caner et al., 2017). The M&A literature in this tradition suggests that target firm's knowledge base should be similar to the acquirer only to the extent that acquirer has the absorptive capacity to integrate the acquired knowledge (Ahuja and Katila, 2001; Cloodt et al., 2006; Chondrakis, 2016). It also suggests that the acquired knowledge needs to be complementary to the acquirer's knowledge to afford new technological opportunities (Makri et al., 2010; Cefis and Marsili, 2015). In light of the theory and evidence presented above, this suggestion is valid if the firm has not yet reached the optimal level of technological diversity and stays focused on core technological capabilities and specialization (Prahalad and Hamel, 1990; Pisano, 2017; Pontikes and Barnett, 2017). However, it is not clear how it works for firms that have a highly diversified technological base or distributed capabilities (Patel and Pavitt, 1997; Granstrand et al., 1997). The latter scenario is important because technological acquisitions are costly and often used by large firms that tend to be technologically diversified. Besides, if acquiring firms avoid technological similarity with their targets and pursue technological complementarities instead, their technological diversity is bound to increase. Unless it is presumed that the benefits of technological complementarities necessarily outweigh the costs of higher technological diversity, it is hard to explain why technologically diversified firms pursue technological acquisitions and how they may find technological complementarities without increasing their technological diversity.

This void in the extant theory exists because of isolated explanations of a firm's technological base either in terms of technological diversity or breadth of the knowledge base. Our study fills this void and bridges the divide by proposing technological scope as a more comprehensive and useful construct to capture the dynamics of firm's technological base. It also provides a more inclusive explanation of firm's R&D strategy and technological acquisitions. It encompasses not only technological diversity and breadth but also incorporates the technological relatedness among the domains comprising the technological base of a firm. Our research shows that technological acquisitions help increase R&D output if firms have either narrow or broad, rather than moderate, technological scope. Firms with a narrow technological scope benefit from technological acquisitions when these facilitate broadening their technological base and increasing technological opportunities through horizontal complementarities for recombination of knowledge across different fields. On the other hand, firms with broad technological scope benefit from technological acquisitions because these help them deepen or broaden their technological base and increase opportunities for recombination of knowledge within and across their existing domains. This study shows that firms with a narrow technological scope benefit from horizontal technological complementarities with the target more than firms with a broad technological scope. Thus, the perspective of technological scope not only bridges the divide between the two research streams concerning diversity and breadth of R&D but also provides deeper insight into the role of technological similarity and complementarity in M&As by providing boundary conditions for technological complementarity.

This research also contributes new insights related to the debate on whether multi-technology corporations have a distinctive core or distributed capabilities (Prahalad and Hamel, 1990; Patel and Pavitt, 1997; Granstrand et al., 1997; Breschi et al., 2003; Pisano, 2017). We find that firms with narrow technological scope tend to have distinctive core capabilities and they use technological acquisitions to leverage these capabilities into other domains which involve complementary knowledge and capabilities (Kim and Kogut, 1996). On the other hand, firms with a broad technological scope tend to have distributed technological capabilities and use technological acquisitions to deepen and broaden their knowledge base.

6. Implications

This research has several implications for future research on the resource-based R&D strategy of firms. First, future research could take a closer look at how firms with a narrow or broad technological scope differ in terms of their organization of R&D (Argyres and Silverman, 2004; Leiponen and Helfat, 2011) or the composition of their R&D personnel and teams in terms of specialists and generalists related to different technology domains (Haas and Ham, 2015; Teodoridis et al., 2019). Second, prior literature as well as our study show that technological complementarities between merging firms play an important role in post-acquisition R&D output. It is clear from our study that firms with a narrow technological scope benefit more from horizontal technological complementarities than firms with a broad technological scope. Further research is needed to ascertain what kind of technological complementarities are more important for firms with a broad technological scope when they engage in technological acquisitions. Operationalizing the notion of vertical complementarities (within domains) and comparing this with existing horizontal complementarities (between domains) appears to be a logical next step to enhance our understanding of technological complementarities within and between domains and firms. Third, the role of technological scope in the context of other modes of accumulating and exploiting R&D resources and capabilities, such as internal development and strategic alliances, can also further our understanding of innovation and corporate growth strategies of R&D-intensive firms.

This study has two important implications for managing technological M&As. First, in order to maximize R&D output through technological acquisitions, a firm needs to choose between strategies related to a narrow or broad technological scope. These strategies involve competing logics and straddling both is likely to be costly and less fruitful. Therefore, the aims of technology acquisition and the choice of the acquisition target need to be aligned with the logic of the R&D strategy of the firm because technological scope affects technological complementarities and acquisitions affect technological as well as corporate scope. This also implies that firms with intermediate levels of technological scope may need to refocus their R&D strategy towards narrow or broad technological scope (Pisano, 2017). Second, firms following a narrow technological scope strategy need to limit their technological base to a few technology domains with a high level of horizontal technological complementarities. Therefore, they can increase their R&D output by acquiring other firms that are specialized in a few domains that are complementary to the acquirer's technological base. On the other hand, firms following a broad technological scope strategy can increase their R&D output by acquiring such firms that offer either vertical or horizontal technological complementarities within the existing domains of the acquirer.

7. Limitations

Our study has a number of limitations. First, since the aim of the study is to examine the role of firms' technological knowledge base in R&D output, the sample is based on prior patenting output. This kind of sampling inherently involves a certain degree of sample selection bias and endogeneity which cannot be fully controlled through statistical techniques. Second, including firms from diverse technology and product domains makes the study more inclusive but also introduces significant heterogeneity in the sample that may not be fully controlled by the econometric models used here. Third, our study concerns a limited part of R&D pertaining to the creation of new technological knowledge, technical effects, and artifacts that are novel and valuable enough to be patented. Due to this focus, our research does not capture other kinds of technological knowledge and artifacts which are not patented. Besides, it is well known that neither all inventive output is patented nor do all patented inventions turn into innovations. Therefore, our findings may not be generalizable to other outputs of R&D and other aspects of firm performance.

8. Concluding remarks

Technological M&As are costly and involve complicated management issues due to the need for integration of complex technological resources and capabilities to produce valuable, rare, and inimitable inventions and technological innovations. These costs and complications can be minimized by selecting the right targets that fit the R&D strategy of the acquirer as reflected in the technological base of the firm. A key characteristic of a firm's technological base is its technological scope which determines the kind of technological opportunities a firm may pursue and the kind of technological resources and capabilities it needs to develop internally or acquired in the market for corporate control. Therefore, managing technological scope is one of the principal tasks in corporate and R&D strategies of the firm. Technological M&As can serve as a useful lever when they afford the right kind of technological opportunities and complementarities to the acquirer. Which kind of technological complementarities and M&A targets can afford the right kind of technological opportunities significantly depends on whether a firm's present technological scope is narrow or broad and whether it wants to reinforce it or swing to the other side without getting trapped in the middle.

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