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Does separation hurt? The impact of premature termination of R&D alliances on knowledge acquisition and innovation

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ABSTRACT

While there is vast research on alliance formation linked to knowledge acquisition and innovation, research is limited on the impact of alliance termination on these same dimensions. Addressing this gap and building on the knowledge-based view of the firm, we analyze the impact of premature alliance termination on knowledge acquisition and innovation outcomes. We apply a difference-in-differences and matching-based estimation to a sample of terminated and non-terminated R&D alliances in the life sciences. Our analysis suggests that alliance termination reduces innovation performance and that innovation output becomes less technologically diverse, while knowledge acquisition becomes less externally oriented. However, we find no relevant drop in acquisition of knowledge from alliance partners post alliance termination. Our exploration of conditional effects shows that firm-level factors, particularly a firm's alliance portfolio, moderate termination effects, while alliance-specific conditions have little impact.

1. Introduction

Research on alliance formation and R&D collaborations in an innovation context has received considerable scholarly attention over recent decades. Studies have examined the overall innovation outcomes of alliances (Baum et al., 2000; Powell et al., 1996; Stuart, 2000) and the underlying mechanisms driving innovation (Jiang and Li, 2009; Lahiri and Narayanan, 2013; Laursen and Salter, 2006). Thereby, studies have not only highlighted the overall benefits of alliances for the acquisition of knowledge in comparison to other organizational forms and markets (Almeida et al., 2002; Gomes-Casseres et al., 2006; Hohberger, 2014), but have also stressed the advantages, particularly in the acquisition of distant or specific knowledge (Rosenkopf and Nerkar, 2001; Subramanian et al., 2018). Much of the existing alliance literature is rooted in knowledge-based perspectives of the firm, which stress (1) that knowledge is a key resource for firm innovation, performance, and survival; and (2) the importance of collaboration for knowledge acquisition and innovation (Almeida et al., 2002; Grant and Baden-Fuller, 2004; Meier, 2011). Consequently, much is known about how alliance formation affects knowledge acquisition as well as the overall impact on innovation outcomes (Meier, 2011).

Despite the fact that all alliances eventually come to an end and the majority do so prematurely (Das and Teng, 2000; Greve et al., 2010), little is known about the implications of alliance termination for firm knowledge acquisition and innovation. This is particularly relevant because alliances are key mechanisms for knowledge acquisition and innovation (Baum et al., 2000; Jiang and Li, 2009; Powell et al., 1996), and these objectives often drive their formation (Hamel, 1991; Kogut, 1988). Understanding termination, and particularly premature termination, is fundamental to build a realistic and complete understanding of alliances and to determine the overall impact of alliances on knowledge acquisition and innovation. Premature termination strips firms of key mechanisms to engage with external partners and their networks, and thus reduces the firm's ability to acquire external knowledge and generate innovation outcomes. It is possible that premature alliance termination has the opposite effect to alliance formation on knowledge acquisition and innovation outcomes. Whereas alliance formation fosters learning and innovation outcomes, alliance termination may reverse the process. However, there also exists initial evidence in related fields showing that knowledge acquisition might continue even when the organizational context is removed (Corredoira and Rosenkopf, 2010; Hoetker and Agarwal, 2007; van Burg et al., 2014). Thus, empirical research on alliance termination is needed to better understand the impact of this common event in the alliance life cycle.

Consequently, to extend research on alliances embedded in the

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knowledge-based view of the firm (KBV), we ask two related research questions: (1) to what extent does premature alliance termination affect external knowledge acquisition, and (2) to what extent does premature alliance termination affect firm innovation outcomes? Knowledge acquisition is associated with the inputs to the innovation process, thus, we measure these indicators via patent references. In particular, we focus on (i) knowledge acquisition from the alliance partner, and (ii) the percentage of external knowledge acquisition in patents. In contrast, the innovation outcome variables are output measures based on the characteristics and success of the focal patents. Specifically, we focus on the performance of the innovation and its technological diversity. The distinction between input and output measures is aligned with the frequently held view in innovation research that innovation is A recombination of prior (knowledge) components and is measured using patents and patent references (Ahuja and Lampert, 2001; Carnabuci and Operati, 2013; Fleming, 2001; Hohberger, 2016). It also aligns with key aspects of the KBV perspective on R&D alliances because it captures the idea that alliances are mechanisms that: (a) facilitate external knowledge acquisition, and (b) can alter a firm's innovation direction and outcomes (Grant and Baden-Fuller, 2004; Meier, 2011; Spender, 1996).

Our analysis is based on a panel of R&D alliances in the life science industry formed from 1990-2003 and compares prematurely terminated R&D alliances (terminated before 2004) and non-terminated R&D alliances with evidence of survival. We employ a difference-in-differences estimation (DID) with firm-alliance specific and year fixed effects and conditional DID estimation. To explore the robustness and heterogeneity of our results, we also examine the impact of frequently discussed firm and alliance conditions on the relationship between alliance termination and knowledge acquisition and innovation. In the case of alliance conditions, we examine joint venture (JV) governance (e.g., Gomes-Casseres, Hagedoorn, and Jaffe, 2006; Mowery et al., 1996; Phene and Tallman, 2012), geographic proximity (e.g., Gomes-Casseres et al., 2006; Hohberger, 2014; Rosenkopf and Almeida, 2003), same-industry alliances (e.g., Hamel, 1991; Mowery et al., 1996), and technological distance between partners (Gilsing et al., 2008; Subramanian et al., 2018). For specific firm conditions, we tested the alliance portfolio size (Frankort et al., 2011; Lahiri and Narayanan, 2013; Wassmer et al., 2017) and level of internal R&D (Cassiman and Veugelers, 2006; Hagedoorn and Wang, 2012).

As one of few empirical investigations into outcomes linked to alliance termination, our study contributes to a better understanding of alliances and research within the KBV. From a phenomenological perspective, we provide relevant insights on a common and impactful issue that has seldom been studied. Alliances are not only ubiquitous across many industries–their focus is often on knowledge acquisition and innovation–particularly in science and technology-driven sectors (e.g., Baum et al., 2000; Stuart, 2000). Premature alliance termination is frequent but still relatively scarcely investigated when compared to the scholarly effort put into alliance formation and management research (Gomes et al., 2016; Zhelyazkov and Gulati, 2016). Empirical evidence on termination is not only needed to gain a better grasp of the impact of termination, but also to improve understanding of the overall value and management of alliances throughout their life spans. This is also important from a managerial perspective, as practitioners can benefit from a detailed understanding of alliance termination and the post-termination phase in order to anticipate actions prior to termination.

From a theoretical perspective, we provide a KBV explanation of the impact of alliance termination on knowledge acquisition and innovation outcomes. We apply established theoretical arguments on the knowledge acquisition and innovation benefits of alliance activity and apply them in the context of alliance termination. Thereby, our results provide a more detailed picture of alliances, where the impact of the termination event is not necessarily symmetrical to the effects of alliance formation. We find a partial reversal of the alliance formation effects proposed by the KBV, particularly in the case of innovation diversity and performance. However, our paper also paints a nuanced picture for the indicators of knowledge acquisition. For example, against our initial expectation, we find that firms rely relatively less on external knowledge acquisition post termination. Similarly, we do not find a decline in knowledge acquisition from the partner firm. We discuss these results in the light of earlier research that examines mechanisms explaining the persistence of knowledge acquisition following the removal of the organizational context (Corredoira and Rosenkopf, 2010; Hoetker and Agarwal, 2007; van Burg et al., 2014).

Furthermore, while not formally hypothesized, our extended analysis provides insight for current debates in alliance research. We find that alliance-specific conditions have little influence on the relationship between premature termination and external knowledge acquisition and innovation outcomes. This again highlights the asymmetry between alliance formation and termination, as alliance conditions have been shown to be relevant in the case of formation (e.g., Almeida et al., 2003; Gomes-Casseres et al., 2006; Mowery et al., 1996; Subramanian et al., 2018) On the other hand, we reveal that the termination effect is conditioned by firm-specific characteristics related to the firm's internal and external knowledge. In particular, we show that a larger alliance portfolio can mitigate the effects of premature termination on knowledge acquisition and innovation. This extends the idea that the alliance portfolio is an important resource for firm knowledge acquisition and innovation outcomes, as access to a larger external knowledge pool seems to help protect against declines in innovation performance, while mitigating the reduced recombination of ex-partner, diverse, and external knowledge.

2. Background research and theory

2.1. Research on alliance termination

Most studies on alliances, whether focused on innovation or other aspects, explore the formation phase (e.g., Colombo et al., 2006; Gomes et al., 2016; Lin et al., 2009; Russo et al., 2019) or alliance evolution and dynamics (e.g., Chung and Beamish, 2010; Hagedoorn and Sadowski, 1999; Reuer et al., 2002). Only limited research explores alliance termination (e.g., Madhok et al., 2015) with a particular focus on the drivers of termination (e.g., Cui et al., 2011; Reuer and Zollo, 2005; Xia, 2011). Very few studies have advanced our understanding of the implications of alliance termination. For example, Zhelyazkov and Gulati (2016) discovered negative relational and reputational consequences of venture capital syndicate withdrawal as the propensity to withdraw from deals reduced new deal formation. Illustrating how alliance termination may be particularly detrimental for start-ups, Singh and Mitchell (1996) found that firm survival is negatively influenced by alliance termination although the effect was attenuated by forming new partnerships. While these studies have broadened our understanding of alliances, they do not specifically examine the impact of termination on the knowledge acquisition and innovation outcomes of firms. This is surprising given that these outcomes are often the raison d'être for forming an alliance (Hamel, 1991; Kogut, 1988) and key mechanisms linked to performance (Baum et al., 2000; Jiang and Li, 2009; Stuart, 2000).

2.2. Knowledge-based view and alliances

The central tenets of the KBV are that knowledge is the firm's most important and primary resource (Grant, 1996) and that the coordination, integration, and management of knowledge is a firm's central activity, if not the main reason for its existence (Kogut and Zander, 1992). A firm's competitive advantage stems from the coordination and combination of different knowledge resources rather than the individual businesses or products (Spender, 1996). The strategic potential of knowledge depends on its complexity, tacitness, and heterogeneity. These characteristics can make knowledge rare and hard to imitate and transfer, and can thus drive sustained competitive advantage of firms (Spender, 1996).

According to knowledge-based theory, strategic alliances are an important tool for the acquisition and transfer of knowledge, especially if the required knowledge resides outside of the firm and cannot be developed through its own ability (Madhok, 1996; Rosenkopf and Almeida, 2003). The relatively interdependent relationship between the partner firms in alliances allows for more face-to-face interaction and closer working relationships than market transactions, and thus enables the effective transfer of tacit knowledge (Mowery et al., 1996; Rosenkopf and Almeida, 2003). Hence, alliance perspectives within the KBV address the issue of the acquisition of knowledge-based resources and capabilities and, simultaneously, the associated transfer and exchange problem (Steensma and Lyles, 2000).

Abundant research on alliance formation and performance has evidenced the positive effect of alliance formation on knowledge acquisition and innovation outcomes (e.g., Jiang and Li, 2009; Stuart, 2000). The KBV has proven to be a useful lens given its focus on internal and external knowledge (Carayannopoulos and Auster, 2010; Grant and Baden-Fuller, 2004). However, the majority of this research measures knowledge and innovation outcomes at a single point in time in relation to the date of alliance formation (e.g., Steensma and Corley, 2000). At the same time, research on alliance dynamics and termination highlights the unstable nature of alliances (e.g., Reuer et al., 2002; Reuer and Zollo, 2005). For example, the acquisition of knowledge has been cited as a driver of both alliance formation and termination in that when the alliance objectives are achieved and a firm has acquired the relevant knowledge from a partner, the alliance is no longer useful (Fang and Zou, 2010; Hamel, 1991). Similarly, there is growing research on the importance of alliance portfolios (Lahiri and Narayanan, 2013; Wassmer, 2008; Wassmer et al., 2017), particularly with regard to firm knowledge acquisition and innovation outcomes (Frankort, 2016; Lavie and Rosenkopf, 2006). Still, research has yet to consider the extent to which termination events impact the gains in knowledge acquisition and innovation outcomes tied to alliance formation.

2.3. External knowledge acquisition

The use of R&D alliances as an organizational mechanism to acquire external knowledge is well established (e.g., Almeida et al., 2003; Gomes-Casseres et al., 2006; Mowery et al., 1996). Alliances are not only an important mechanism for providing access to external knowledge, but they also enable firms to gain a better understanding of the knowledge by observing the application of partner knowledge in joint execution of alliance activities (Inkpen, 1998). The alliance context provides the opportunity for partner firms to develop a shared identity and common language that can help facilitate the transfer of tacit knowledge (Kogut, 1988).

The benefits of acquiring external knowledge from an alliance partner have also been demonstrated in numerous empirical studies (Meier, 2011; Subramanian et al., 2018). In particular, early research on the role of learning in alliances stresses that collaboration enables firms to acquire valuable technological knowledge from partner firms (e.g., Grant, 1996; Hamel, 1991). For example, the classic research from Hamel (1991) showed how firms use alliances to acquire specific knowledge from partners. Gomes-Casseres et al. (2006) and Almeida et al. (2002) argued and demonstrated that alliances are superior to markets for acquiring external knowledge. Mowery et al. (1996) discovered partner-related knowledge acquisition increased when firms formed a JV, regardless of the formation motive, and Oxley and Wada (2009) demonstrated that the transfer of knowledge covered in the scope of a JV agreement is greater than that of knowledge not covered within the agreement.

Terminating an alliance may have an opposite, negative, effect on the ability to acquire knowledge as it removes the mechanisms shown to facilitate external knowledge acquisition. Alliances not only provide the initial access to knowledge, but also the context and interaction needed to exploit partner knowledge (Almeida et al., 2011). An alliance is a setting that helps integrate specialized knowledge through rules and directives, sequencing, routines, and group problem solving (Grant, 1996). Moreover, the alliance context facilitates face-to-face interaction. When an alliance is terminated prematurely, these mechanisms would no longer be available to members post termination, thus hindering knowledge recombination. Furthermore, the social knowledge and shared identity lower coordination costs and influence the direction of search and learning toward partners during the alliance period. When the alliance context is removed by termination, these mechanisms driving knowledge acquisition towards partners are likely constrained.[1] Although the firm might continue to use and develop knowledge from the partner acquired prior to the termination, it may be more difficult to exploit, as the partner interaction is relevant to understand and apply the knowledge in future applications.

Additionally, alliances might not only provide benefits in acquiring external knowledge from the partner, but also from other external sources. Network research frequently states that collaboration creates networks of direct and indirect links with competitors and complementary firms (Ahuja, 2000; Gulati, 1999; Stuart, 1998). Thereby, networks can act as "pipes" for knowledge acquisition and as “prisms" that reflect information about actors and their resources (Podolny, 2001; Soh et al., 2004). The pipes argument in particular has been used to underpin the positive knowledge acquisition effects of collaboration. For example, Owen-Smith and Powell (2004) argue that the spillovers that result from alliances are a function of the practices of network members and the institutional commitments of the dominant firms, such as open regimes of information disclosure. Similarly, Powell et al. (1996) argued that learning, including knowledge acquisition, in the biotechnology sector is located in the network of collaboration between firms. Therefore, alliances not only enable the acquisition of knowledge from the alliance partner, but also from the overall network. Similar to the reduced direct benefits for acquiring external knowledge from the partner, the premature termination of the alliance could also negatively impact a firm's general acquisition of external knowledge. This, in turn, could require the firms to focus on internal knowledge in the innovation process. In network language, a premature termination of an alliance cuts a pipe to the network.[2] Consequently, we argue that a premature termination of an alliance reduces the acquisition of partner-specific knowledge and overall external knowledge, which both shift the balance in use of internal versus external knowledge acquisition further towards internal knowledge.

Hypothesis 1a. The extent to which a firm acquires knowledge directly from an R&D alliance partner will decrease after the premature termination of their alliance.

Hypothesis 1b. The extent to which a firm relies on external knowledge acquisition (relative to total knowledge use) will decrease after premature termination of an R&D alliance.

2.4. Innovation outcomes

Central to the KBV perspective on R&D alliances is the idea that interfirm collaboration is a mechanism for knowledge access and

[1] Nevertheless, arguments for sustained knowledge acquisition post termination can be made–e.g., studies have shown that innovators rely on social relationships to access diverse social communities (e.g., Fleming, 2001; Hargadon and Sutton, 1997; Powell et al., 1996). However, without the specific alliance context, the contact is likely to be less frequent and intense, and thus provides fewer opportunities for knowledge acquisition from the former partner.

[2] It is noteworthy that alliance termination should impact the prisms arguments far less.

exchange, which can alter the firm knowledge base and, consequently, increase the innovation potential of the firm (Grant and Baden-Fuller, 2004; Meier, 2011). Research in this space has uncovered a largely positive relationship between alliance activity and innovation performance. For example, Jiang and Li (2009) found that the interaction of knowledge sharing and creation stemming from alliance activity significantly contributes to partner firms' innovation performance. Almeida et al. (2011) evidenced that R&D alliances increased innovation performance in the biotechnology industry. Similarly, Baum et al. (2000) found that alliances enhanced the innovation performance of biotechnology start-ups. The argument underlying these studies is strongly grounded on greater access to valuable knowledge and improved knowledge exchange within alliances. For example, Baum et al. (2000) propose that the impact on innovation performance is consistent with the common belief that alliance networks form a 'locus of innovation' in high-tech sectors (e.g., Powell et al., 1996) and with the alliance research's focus on alliances as mechanisms to access and transfer technological knowledge. These results are underpinned by research on search and innovation outcomes, which reveals that a more diverse knowledge base in the innovation process is associated with higher innovation performance (Ahuja and Lampert, 2001; Katila, 2002; Phene et al., 2006). Being able to combine distinct perspectives and capabilities, or technologically diverse knowledge, from alliance partners encourages creativity and novel solutions to problems.

This also relates to another important tenet of the KBV perspective on R&D alliances: specifically, the view that alliances enable organizations to leverage underutilized specialist knowledge through integration with diverse external knowledge from partner firms, and thus broaden their scope of innovation outputs (Grant, 1996; Grant and Baden-Fuller, 2004). Building on the idea that R&D alliances are an organizational mode that reconciles knowledge specialization with flexible integration of diverse knowledge, several studies show that R&D alliances can be used to create innovations that incorporate different types of knowledge, and thus, influence the direction of firm innovation (Colombo et al., 2006; Hohberger, 2014; Rosenkopf and Almeida, 2003). Particularly for technology and science intensive industries, innovation takes place along a number of technological and scientific dimensions. In biotechnology, for instance, Powell et al. (1996) suggest that the pace of innovation is rapid and diverse–not only are there a number of research problems that can be solved (or locks that can be opened), but also an increasing number of approaches (or keys) that can be used to solve these problems. Under such conditions, no one firm can possess all of the diverse technological and scientific knowledge needed for successful innovation. Thus, R&D alliances and other knowledge acquisition mechanisms are used to increase the amount and diversity of knowledge for successful innovation (Almeida et al., 2011; Phelps, 2010).

Reversing these arguments for the positive impact of alliances on innovation outcomes, alliance termination may have a negative impact on the diversity and performance of firm innovation. Limiting access to one source of external knowledge, even when related to internal knowledge, may reduce the firm's ability to assimilate new knowledge needed for innovation. Additionally, and similar to the prior arguments, alliances not only provide the initial access to knowledge, but also the context and interaction needed to exploit the partner knowledge (Almeida et al., 2011). Although the firm might continue to use and develop knowledge acquired from the partner prior to the termination, it may be more difficult to exploit it as the partner interaction is important for understanding and applying the knowledge in the future. Furthermore, firms might need new knowledge inputs to leverage their internal knowledge as the potential of prior knowledge is already exhausted. It is frequently argued that innovation is the combination of knowledge components (Fleming, 2001; Weitzman, 1998), and the recombination potential of knowledge inputs is exhaustive (Carnabuci, 2010; Carnabuci and Bruggeman, 2009; Hohberger, 2017; Olsson and Frey, 2002). [3] Consequently, we argue that:

Hypothesis 2a. The premature termination of an R&D alliance reduces firm innovation performance.

Hypothesis 2b. The premature termination of an R&D alliance reduces the technological diversity of firm innovation.

3. Methods

3.1. Research setting and sample

We used panel DID and conditional DID (matching based DID) to explore the impact of termination on external knowledge acquisition and innovation outcomes with a panel analysis of R&D alliances in the life science industry[4] formed from 1990 to 2003. Our treatment group was based on alliances prematurely terminated before 2004 and the counterfactual of non-terminated alliances with evidence of continued survival. To identify premature terminations, we created a vignette of the press releases for each alliance termination. Then, we followed the approach by Gioia et al. (2013) for inductive iterative analysis of qualitative data to code each termination as premature or intended. Similar to earlier termination research (e.g., Pangarkar, 2009; Polidoro et al., 2011), we focused on premature alliance termination, which refers to the ending of formal collaboration agreements that does not coincide with the completion of objectives or contract expiration. Thus, we accounted for whether the alliance was terminated due to "contract expiration" and for the possibility that alliances often terminate early when alliance objectives are met faster. Additionally, alliances that were terminated due to bankruptcy or defunct status of one of the partners were also dropped from the analyses. Finally, we also restricted our investigation to alliances terminated via dissolution (Polidoro et al., 2011), thus excluding alliances that end in internalization or acquisition.

The life science industry is a particularly appropriate context to study alliance termination given the high rates of alliance activity and low rates of success, high uncertainty, long development times, and above average investment and resources needed for the discovery and development of new drugs (Hohberger et al., 2015). The year 1990 was selected as the starting point due to sparse data on alliance formations prior to this date (Schilling, 2009). We selected 2003 as the end date to provide a sufficiently large time window after a potential termination for tracking of patent activity in the National Bureau of Economic Research (NBER) patent file (Hall et al., 2001).

The link to the NBER patent file is important, as the measurement of the innovation and learning-based variables relies largely on patent data. Patent data provides one of the most accepted and reliable sources of knowledge and innovation measures for large-scale archival studies. Due to the relative high reliance on patenting in the life sciences,

[3] In addition to knowledge-based arguments, the disruption caused by premature termination may harm innovation in the short term as attention is redirected to managing the change. Alliance termination can be a time of reorientation and shifting technological focus. The resulting organizational changes can lead to a phase of high levels of anxiety, reorientation, and stressful reactions with a heightened pressure on immediate results and myopic decision making de Rond and Bouchikhi (2004). This is especially likely to be true when the termination is premature, which is the focus of this study.

[4] SIC codes for the life science industry were identified in extant research on the biotech and pharmaceutical industries (e.g., Phene and Tallman, 2012) including: 2833, 2834, 2835, 2836, 3842, 3843, 3844, 3845, 5122, 8071, 8731, 8732, 8733, and 8734. The manual construction of the termination event allowed us to exclude 694 alliances from this sample that did not pertain to the life sciences, defined as all sciences related with organisms and encompasses firms in the fields of biotechnology, pharmaceuticals, biomedical technologies, life systems technologies, nutraceuticals, food processing, environmental science, and biomedical devices.

patent-based measures are seen as a particularly reliable indicator in this sector. Nevertheless, patent-based measures have several inherent limitations that are frequently discussed in the innovation and patent literature, e.g., patent-based measures underestimate the overall innovation activities, and patent officers frequently alter citation information during the patent grant process (Alcácer and Gittelman, 2006; Gittelman, 2008). Given these limitations, it is important to highlight that patent citations can only be seen as indirect measures of knowledge acquisition.

Alliances were identified from the SDC Platinum Database. We included alliances of various governance forms, including purely contractual relationships, alliances with equity stakes, and JVs. To facilitate comparability and increase internal validity by assuring knowledge and innovation related alliance goals, we focused on R&D alliances between for-profit firms. We excluded alliances that were announced but not implemented, multi-partner alliances, and those that upon closer examination were duplicate observations, mere patent acquisitions, bankruptcies, or outside the life science industry. A total of 2,310 R&D alliances met these inclusion criteria. We identified 528 alliances with a termination event and 1,782 alliances with no reported termination through 2015.[5] Before we linked the sample with the NBER patent file to obtain the relevant patent information, we followed Gomes-Casserres et al. (2006) and duplicated the alliance dyads so that each partner appeared as the focal firm. This is appropriate given our study's interest in firm-level implications and the need to control for firm-level heterogeneity in addition to dyadic-level forces. After duplicating the dyads and matching to the NBER patent file, the sample consisted of 645 terminated alliances and 1,162 counterparts (from the individual firm perspective). After excluding non-premature terminations and internalization, the sample consisted of 549 premature R&D alliance terminations (i.e., dissolutions). The final matching with the Compustat databases to obtain firm control variables further reduced the sample to a minimum of 319 premature alliance terminations and 539 counterparts.[6]

3.2. Identification of termination data

The SDC database (similar to most other databases) does not systematically and reliably track and report the termination of alliances (Schilling, 2009). Thus, the alliance termination dates were identified using detailed manual search of company and news-based information (e.g., Factiva) (similar to Lavie, 2007; Park and Ungson, 1997; Xia, 2011). For each alliance dyad, we searched for evidence of alliance termination in press releases using Factiva and Lexis-Nexis, and, if necessary, complemented this with company websites and Google searches. We read the full-text press releases and documents to identify the termination date and outcome (i.e., premature/intended; dissolved/internalized). The termination year was identified through content analysis of the press releases rather than the date of the news itself whenever possible. Then, we created two variables reflecting the termination event (see Table 1). First, *alliance terminated*, was set to 1 for each year the alliance was terminated, including the year of termination, and to 0 for the years the alliance was active. Next, we created the variable *termination year*, which counts the years before and after the alliance termination. Our analysis was based on the 3 years before and 4 years after the termination. This coding allowed us to compare termination events across different points in time.

[5] This corresponds to 22.9%, a rate above the previous study that includes and reports on non-equity alliances (Xia, 2011).

[6] The size of the counterfactual sample was further reduced in the next step by including only non-terminated alliances with evidence of ongoing alliance activity (signs-of-life). See 3.3. Non-terminated alliances and signs-of-life.

3.3. Non-terminated alliances and signs-of-life

To improve the accuracy of our estimations, we accounted for evidence of continued collaboration in order to code for non-terminated alliances. This is important, as we cannot assume that, because there is no reported termination means, the alliance persists. Thus, to ensure that our counterfactual alliances were still in existence, we recorded the persistence of an alliance using press releases similar to the termination identification procedure. Only alliances with evidence of continued activity, signs-of-life (SOL), were considered as counterfactuals and incorporated in our analysis. This reduced the sample of non-terminated alliances from 1,162 to 866 observations. The matching with the Compustat databases further reduced the sample of SOL alliances from 539 to 379 observations.

To conduct our estimations, it was necessary to compare the terminated alliances to non-terminated alliances (counterfactual) at a specific point in time. However, the termination event for the non-terminated alliances does not exist. Thus, we used different procedures to generate a termination event for the counterfactual. For the Panel DID model, we matched the alliances from the terminated sample to the control group of non-terminations based on a randomly-generated termination event during the alliance life of non-terminated alliances. The advantage of this approach is that there are no prior assumptions about the alliance duration or about how alliance knowledge acquisition and innovation outcomes change during the life of the terminated alliance. To test robustness, we also created a sample in which the counterfactual of the non-terminated alliances was based on the average observable alliance duration from the date of formation. The average alliance duration in the sample of terminated alliances is 3.3 years so we estimated our model with an average termination period of three years. This approach accounts for different possible general trends of knowledge acquisition and innovation during an alliance as it leaves the temporal pattern of the alliance intact. However, this approach ignores the different lifespans and potential non-linear trends in alliances.

The conditional DID (matching based DID) allows us to incorporate more specific matching variables. Thus, we first checked the robustness of our previous panel DID by matching on the full set of firm control variables and a random termination date for the counterfactual alliances. Then, we also estimated models based on the best match of the combination of firm-level control variables, alliance duration, and JV governance. The matching for the alliance duration was based on exact matching of the alliance formation year. This ensured a comparison of the same number of years of alliance duration for the terminated alliances and the counterfactual (non-terminated) alliances.

3.4. Dependent variables

We followed earlier studies using patents, patent citations, and IPC patent classes as traceable indicators of firm knowledge and innovation (Gomes-Casseres et al., 2006; Rosenkopf and Almeida, 2003). The patent data was obtained from the NBER patent database, which contains detailed information for USPTO patents applied for from 1975 to 2006.[7]

3.4.1. External knowledge acquisition

We use two indicators to capture the changes in external knowledge acquisition: the knowledge acquisition from the alliance partner and the percentage of external knowledge acquisition (relative to the total knowledge use) in patents. Partner knowledge acquisition is defined as the extent to which a (former) alliance partner acquires knowledge from its alliance partner. It is measured by cross-citations (similar to Mowery et al., 1996; Rothaermel and Boeker, 2008). Cross-citations

[7] Our analysis relies on the patent application date rather than grant date as it is closer to the actual knowledge production since the patent grant process can take multiple years.

Table 1
Standardization of alliance termination years.

Year	1997	1998	1999	2000	2001	2002	2003	2004	2005
Termination	-	-	-	x	-	-	-	-	-
Termination year	−3	−2	−1	0	1	2	3	4	5
Alliance terminated	0	0	0	1	1	1	1	1	1

provide a proxy and indirect indicator of how much of the knowledge a firm acquires originates from the former alliance partner by measuring the extent to which a firm in a given dyad cites the other firm's patents. It is measured as the sum of (backward) citations C to firm j patents in firm i patents in a given year t: $= \frac{C_{i\to j}^{t}}{C_{i}^{t}}$. To control for the overall citation propensity of a firm, we accounted for the total citation C of a firm i in year t.

To capture the relative focus on external knowledge acquisition, we rely on the percentage of external knowledge acquisition via patent references to other firms relative to the total knowledge use. Thereby, the total knowledge use in the innovation process is measured by all patent references, which is comprised of references to patents created by other firms (external citations) and references to patents created by the firm (self-citations). Within patent research, self-citations are often used to approximate cumulative innovation activities and the appropriability of internal knowledge, whereas external citations are used to approximate external knowledge acquisition (Hohberger, 2014; Rosenkopf and Nerkar, 2001; Sorensen and Stuart, 2000). A higher percentage value of our measurement indicates a higher reliance on external knowledge acquisition relative to total knowledge use.

3.4.2. Innovation outcomes

The innovation outcomes are measured based on the characteristics and success of the focal patents. Specifically, we focus on the performance of the innovation and the technological diversity of the innovations of a firm. To measure the diversity of firm innovation outcomes, we use the Blau index of diversity based on patent IPC classes to approximate the technological diversity of firm innovation activities (Lahiri, 2010). The index is calculated with p as the proportion of an IPC class, of a given firm i, and N the number of all IPC classes in year t: $D_I = 1 - \sum_{i=1}^{N} p_{it}^{2}$. To account for any potential downward bias of this diversity measure attributable to fact that the index is calculated including the occurrence of empty patent classes, we followed previous patent research (e.g., Frankort, 2016; Phelps, 2010) and corrected the Blau index by multiplying it with $N_{it}/(N_{it}-1)$, as suggested by Hall et al. (2005). A low value indicates a low level of technological diversity (high technological focus), while a high value suggests a high level of technological diversity.

We used the number of (forward) citations as an innovation performance measure. In patent and technology-based studies, forward citations are a well-established proxy for invention value because they correlate positively with the market value of firms, patent renewals, patent quality, intellectual property values, and technological importance (Hall et al., 2001; Trajtenberg, 1990; Yang et al., 2010). To account for the truncation of the citations measure, we discounted older citation counts with an exponentially decaying component: $e^{-\left(\frac{2006-Y_t}{C}\right)}$, where Y is the patent publication year of patent in t, and C is a constant of knowledge loss, which was set at 5 years (similar to Fleming, 2001).[8]

3.5. Control variables

The question of if and which time variant controls to include in DID design is a nuanced one. Atanasov and Black (2016) argue that the inclusion of covariates, which are unaffected by the treatment, can increase precision and will not introduce bias. For example, time-varying covariates can reduce the importance of non-parallel trends as they account for unobserved heterogeneity potentially causing non-parallel trends. However, the inclusion of controls potentially affected by the treatment can bias the estimated treatment effect (Atanasov and Black, 2016). To avoid misspecification, we ran all models with and without control variables. Stable results across these different specifications should increase confidence in the findings.

We controlled for R&D expenditures, number of employees, sales, advertising expenditures, and cash flow. The number of employees, sales, and cash flow can provide an indication of the firm size, resource availability, and the overall impact of individual alliances. Controlling for R&D expenditures (internal R&D) is particularly important, as it directly relates to the research focus of the firm. Additionally, internal R&D activities might be compliments or substitutes to external R&D activities such as R&D alliances (Hagedoorn and Wang, 2012).

In a similar vein, we also accounted for other external R&D activities, including the formation of R&D alliances, non-R&D alliances, and acquisitions, given that these can affect the resources and attention dedicated to the underlying alliance and create alternative channels for external knowledge. Similarly, we accounted for the size of the R&D alliance portfolio (Lahiri and Narayanan, 2013; Wassmer, 2008), measured as the total number of alliance formations in the past five years, subtracting any premature and intended terminations of those alliances prior to the end of the five-year window. The alliance portfolio is related to the alliance experience of the firm (Wassmer, 2008) and the importance of the individual alliances for a firm. Finally, numerous studies show that technological distance between firms (or proximity) can hamper (or facilitate) knowledge acquisition across alliance partners (Gomes-Casseres et al., 2006; Hohberger, 2014; Rosenkopf and Almeida, 2003). Thus, we accounted for the technological distance of partner firms via the Euclidian distance between the patent portfolios of the partner firms based on IPC classes (Rosenkopf and Almeida, 2003), $\sqrt{\sum (p_{ikt} - p_{jkt})^2}$, where p represents the proportion of patenting activity for a firm i and partner firm j in a given patent subclass k in year t.

3.6. Estimation

Our analyses are based on a generalized DID approach, which accounts for different treatments at different times (Bertrand et al., 2004; Wing et al., 2018). The main assumption of the DID is that confounders varying across the groups are time invariant, and time-varying confounders are group invariant, which is frequently expressed as the "common trend assumption" (Khandker et al., 2009; Roberts and Whited, 2013; Wing et al., 2018). The strategic nature of alliance termination can lead to challenges of this assumption. Thus, we use a combination of three analytical approaches (fixed effect panel DID, lead-and-lag analysis, and conditional DID) to identify and explore these possible biases in our study and increase the confidence in the results.

3.6.1. Panel DID

First, we applied a panel DID with 'alliance-firm' and year fixed effects, where Y_{itj} is one of the dependent variables, for alliance j, of firm i in year t:

[8] We also used raw citation counts for the estimation and found comparable results.

$$E[Y_{ijt}] = \exp(\alpha(Alliance\ terminated_{ijt}) + \beta(Alliance\ terminated_{ijt}{*}\ Treatment_i) + \tau(\mathrm{X})_{it} + \delta_t + \mu_{ij})$$

Thus, *Alliance terminated*$_{ijt}$ is a dummy describing the termination event for an alliance *j*, of firm *i* in year *t*. It is equal to 1 for each year the alliance was terminated, including the year of termination, and 0 for the years the alliance was active. The difference between the treatment and control groups is captured with the dummy *Treatment*$_i$. It is equal to 1 if the alliance was terminated prematurely and equal to 0 for the counterfactual group of non-terminated alliances with continued evidence of survival. To account for time invariant firm (*i*) and time invariant alliance-specific (*j*) effects, we created one firm-alliance specific fixed effects (μij). Year dummies (δt) account for year-specific variance and the different length of the citation windows of the patents. The vector of control variables (X_{it}) includes firm-specific time variant controls for knowledge acquisition and innovation outcomes. The firm-alliance fixed effects (μij) subsume the classical treatment group dummy (*Treatment*$_i$). Unlike classical panel DID estimation, the *Temination*$_{it}$ event is not subsumed in the model due to alliance termination at different points in time. The DID effect is the β of (*Alliance terminated*$_{it}$* *Treatment*$_i$).

We adopted a Poisson quasi maximum-likelihood estimation as it is robust to distributional misspecification and can be applied to count data (e.g., citations) and to continuous non-negative data (e.g., self-citations and Blau index) (Wooldridge, 1997). Following Bertrand et al. (2004), we incorporated robust standard errors clustered at the alliance-firm level to address the potential serial correlations among observations in the DID model.

Despite controlling for general trends (time fixed effects), alliance and firm-specific time invariant attributes, and several time variant firm-specific attributes, concern remains that other time variant effects could lead to misidentification of causal effects. Thus, we extend our analysis to further support a causal interpretation of our findings.

3.6.2. Lead-and-lag analysis

The key assumption for the consistency of the DID estimator is that in the absence of treatment, the average change in the response variable would have been the same for both the treatment and control groups (often referred to as the 'parallel trends' assumption) (Atanasov and Black, 2016; Roberts and Whited, 2013). While this assumption cannot be directly tested, we followed recommendations offered in the literature on DID estimation (Atanasov and Black, 2016; Roberts and Whited, 2013). We used a full set of leading and lagging indicators of the termination variable to estimate the main specification. The model takes the form:

$$E[Y_{ijt}] = \exp(\alpha(Termination_{ijt-3}) + \alpha(Termination_{ijt-2}) + \ldots\ldots\ \alpha(Termination_{ijt+4}) + \beta(Termination_{ijt-3}{*}\ Treatment_i) + \ldots..+\ \beta(Termination_{ijt+4}{*}\ Treatment_i) + \tau(\mathrm{X})_{it} + \delta_t + \mu_{ij}).$$

We used the leading indicators to explore whether knowledge acquisition and innovation outcomes affects the likelihood of termination, in order to determine the extent to which reverse-causality influences the coefficients. This is important because events in the evolutionary path of an alliance can influence its success and final outcomes (Gulati, 1998), and thus premature termination could be related to (poor) alliance performance on objectives such as learning. The leading indicators also serve to identify concerns regarding any omitted changes in the alliance that precede the termination. The lagged indicators help discern the temporal dynamics of termination related to knowledge acquisition and innovation, including the speed of initial impact and rate of continued decay, this being important as the alliance termination might have a delayed impact. Analysis of leads and lags lends itself to graphical interpretation; thus, we plot the lead-and-lag models for each variable. In the case of a 'clean' lead-and-lag graph with no apparent pre-treatment trends, one can assume that any potential shocks had an insignificant impact on the results (Atanasov and Black, 2016).

3.6.3. Conditional DID

Within DID estimation, the treatment and control groups should be relatively similar along observable dimensions relevant for treatment, i.e., balanced (Roberts and Whited, 2013). To reduce potential selection bias, we applied conditional DID (matching based DID) on the pooled pre and post-termination samples. Conditional DID combines the strength of DID and matching approaches, as it extends the conventional DID estimate by reweighing the observations according to the weighting function of a matching estimator (Smith and Todd, 2005). From a matching perspective, the conditional DID estimation relaxes the assumption of conditional unconfoundedness as it allows for unobservable but time invariant differences in outcomes between participants and nonparticipants by comparing the conditional before and after outcomes of the two groups (Heckman et al., 1997).

There are multiple matching estimators with various characteristics and suitability for DID estimation. Thus, it is often recommended to apply multiple estimators to account for the different advantages and limitations of the different matching estimators (Caliendo and Kopeinig, 2008; Heckman et al., 1997).[9] Following the advice from Heckman et al. (1997) and Smith and Todd (2005), we first used kernel matching. Its key advantage is the lower variance that is achieved because more information is used for constructing counterfactual outcomes. This is particularly beneficial for the underlying study due to its relatively small sample size.[10] Next, we applied the bias-corrected nearest neighbor (nn) matching estimation (Abadie and Imbens, 2002).[11] This estimator allows for straightforward integration of exact matching criteria, which enabled us to match on discrete variables, including JV governance and alliance duration. All matching estimations (kernel and nearest neighbor) are estimated on the full set of control variables and only based on SOL counterfactuals.

The combination of fixed effect panel DID, conditional DID and lead-and-lag analysis can reduce key concerns regarding the non-randomness and possible endogeneity of the alliance termination event. First, the panel DID estimation with firm-alliance specific and year fixed effects enabled us to control for unobserved time invariant heterogeneity. Next, using lead-and-lag regressions we were able to assess reverse causality and other unobserved events (Roberts and Whited, 2013). The conditional DID strategies assess possible differences between the treatment and control sample (selection bias). Overall, the combination of these three approaches significantly reduces the risk of misidentification and increases the confidence in a causal interpretation of the results. However, it cannot completely rule out that time-variant alliance-specific effects might influence our results.

[9] For a detailed overview of matching, including the advantages and disadvantages of matching, please see the review by Caliendo and Kopeinig (2008).

[10] We used the Epanechnikov kernel in our estimations, due to its slight superiority in terms of efficiency, and chose a 0.06 bandwidth (similar to Heckman et al., 1997). We also emphasized the common support condition in our analysis to mitigate the risk of bad matches. We show various matching quality indicators in Table A1 before and after the matching (i.e., mean standardized difference, pseudo R2, χ2-test). These indicators suggest that the matching procedure was successful in balancing the covariates.

[11] We allowed for replacement and used robust standard errors from the weighted regressions.

Table 2
Descriptive statistics alliance level.

Variable	Alliances (total)					Alliance (treatment group)					Alliance (control group)				
	n	Mean	S.E.	Min	Max	n	Mean	S.E.	Min	Max	n	Mean	S.E.	Min	Max
Citations	1415	10.70	24.80	0.00	159.06	549	13.58	29.10	0.00	159.06	866	8.88	21.45	0.00	159.06
Techn. diversity	1415	0.40	0.33	0.00	0.97	549	0.46	0.33	0.00	0.95	866	0.36	0.33	0.00	0.97
Ext. knowledge in %	1415	0.913	0.1391	0.19	1.00	549	0.93	0.13	0.19	1.00	866	0.90	0.15	0.19	1.00
Cross citations	1415	0.00	0.00	0.00	0.01	549	0.00	0.00	0.00	0.01	866	0.00	0.00	0.00	0.01
Techn. distance	1415	0.49	0.23	0.00	1.13	549	0.57	0.22	0.00	1.13	866	0.44	0.23	0.00	1.06
R&D expenditures	762	1.39	19.85	0.00	524.00	338	2.67	29.77	0.00	524.00	424	0.36	0.54	0.00	4.05
Employees	739	0.02	0.04	0.00	0.32	330	0.02	0.03	0.00	0.17	409	0.02	0.04	0.00	0.32
Sales	769	31.75	571.79	0.00	15,081.33	339	65.06	860.63	0.00	15,081.33	430	5.49	12.30	0.00	114.66
Advertising	763	0.17	0.48	0.00	4.08	338	0.19	0.54	0.00	2.89	425	0.15	0.42	0.00	4.08
Cash flow	698	0.22	0.81	−7.58	8.01	319	0.32	0.87	−4.29	6.16	379	0.15	0.74	−7.58	8.01
R&D alliances	1415	0.64	1.01	0.00	6.67	549	0.98	1.28	0.00	6.67	866	0.43	0.71	0.00	5.00
Non R&D alliances	1415	0.18	0.40	0.00	3.33	549	0.27	0.51	0.00	3.33	866	0.13	0.30	0.00	2.00
Acquisition	1415	0.43	0.72	0.00	4.33	549	0.61	0.88	0.00	4.33	866	0.32	0.58	0.00	4.00
Alliance portfolio	1409	3.30	4.72	0.00	27.33	549	5.00	5.80	0.00	27.33	860	2.22	3.46	0.00	23.00
Same-industry alliance	1415	0.67	0.47	0.00	1.00	549	0.62	0.48	0.00	1.00	866	0.70	0.46	0.00	1.00
JV governance	1415	0.08	0.27	0.00	1.00	549	0.07	0.25	0.00	1.00	866	0.09	0.29	0.00	1.00
Geographic location	1415	0.13	0.33	0.00	1.00	549	0.15	0.35	0.00	1.00	866	0.11	0.32	0.00	1.00

Table 3
DID main estimation.

Dependent variable	External knowledge acquisition				Innovation outcome			
	Cross citations		Ext. knowledge in %		Citations		Techn. Diversity	
Model	1a	1b	2a	2b	3a	3b	4a	4b
Panel 1: Randomized termination date for countefactual								
Alliance term.	−0.040	−0.107	−0.002	−0.009	−0.059	−0.054*	−0.017	−0.005
	0.123	0.138	−0.003	−0.006	0.038	0.031	0.015	0.018
Alliance term. x treat.	0.618***	0.470*	0.094***	0.105***	−0.264***	−0.310***	−0.179***	−0.237***
	0.204	0.276	−0.007	−0.011	0.078	0.078	0.037	0.041
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Firm-alliance fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Full	Reduced	Full	Reduced	Full	Reduced	Full	Reduced
Panel 2: Averge termination duration for counterfactual								
Alliance term.	0.088	−0.161	0.045***	0.046***	−0.386***	−0.319***	−0.167***	−0.107***
	0.152	0.197	−0.004	−0.007	0.052	0.051	0.020	0.025
Alliance term. x treat.	−0.322	0.351	0.001	0.006	−0.182**	0.136*	−0.171***	−0.131***
	0.237	0.294	−0.006	−0.009	0.086	0.078	0.036	0.043
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Firm-alliance fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Full	Reduced	Full	Reduced	Full	Reduced	Full	Reduced

Note: *** $p<0.01$, ** $p<0.05$, * $p<0.1$; included control variables: Techn. distance, R&D expenditures, employees, sales, advertising, cash flow, R&D alliances, non R&D alliances, acquisition, alliance portfolio; counterfactual based on SOL sample.

4. Findings

4.1. Main analysis

Table 2 shows the descriptive statistics for each alliance observation at the firm level. To make the variables comparable across different alliance termination years and alliance durations, we calculated the descriptive statistics based on the three years before the alliance termination.

Table 3 shows the results for the main DID coefficient[12] for the different outcome variables based on the randomly-generated control group of non-terminated alliances. For each variable, we show the main DID coefficient for the specification with and without control variables, an estimation with the randomized termination date for the counterfactual (Panel 1), and the average alliance duration for the termination date of the counterfactual (Panel 2).

While we found a negative effect for most estimations of external knowledge acquisition from partners (Model 1a and 1b; Panel 1 and 2), only the model with the randomized termination date was significant (Panel 1), providing only limited support for Hypothesis 1a. Regarding Hypothesis 1b, we found a positive and significant effect of termination on the percentage of external knowledge acquisition relative to total knowledge use in Panel 1, but positive and non-significant effects in Panel 2. Thus, the positive and partly significant coefficients suggest that the percentage of external knowledge acquisition is increased by alliance termination, which contradicts Hypothesis 1b. As argued in Hypothesis 2a, we found a significant decline in firm innovation performance (Models 3a and 3b; Panel 1 and 2) following premature

[12] For space considerations, we only show the DID-relevant coefficients, but all models were performed with a full set of control variables and only on SOL counterfactuals.

Table 4
DID lead-and-lag estimations.

Dependent variable	External knowledge acquisition				Innovation outcome			
	Cross citations		Ext. knowledge in %		Citations		Techn. Diversity	
Model	1a	1b	2a	2b	3a	3b	4a	4b
Alliance termination	−0.180	0.113	0.002	0.009	−0.006	0.098	−0.012	0.012
	0.292	0.410	−0.007	−0.017	0.083	0.069	0.032	0.042
Alliance termination	0.080	0.550*	0.006	−0.006	0.026	0.048	−0.007	−0.016
	0.254	0.328	−0.007	−0.017	0.079	0.061	0.034	0.041
Alliance termination	0.016	0.297	0.002	0.004	−0.099	0.016	0.019	0.093**
	0.277	0.394	−0.007	−0.015	0.081	0.066	0.033	0.040
Alliance termination	0.277	0.752**	0.004	−0.008	−0.039	0.001	0.006	−0.021
	0.238	0.351	−0.007	−0.015	0.080	0.060	0.032	0.042
Alliance termination	−0.237	0.278	−0.001	0.001	−0.096	−0.012	−0.028	0.018
	0.283	0.396	−0.007	−0.016	0.075	0.066	0.032	0.042
Alliance terminationAlliance termination	−0.175	0.507	−0.001	−0.003	−0.104	0.086	−0.004	0.058
	0.285	0.438	−0.007	−0.017	0.088	0.073	0.032	0.043
Alliance termination	−0.024	0.323	0.007	0.005	−0.113	−0.002	−0.064*	0.018
	0.274	0.374	−0.007	−0.017	0.078	0.073	0.033	0.042
Termination year (−3) x treat.	0.001	−0.623	−0.028***	−0.035*	0.240**	0.022	0.164***	0.111*
	0.395	0.500	−0.010	−0.019	0.104	0.097	0.048	0.063
Termination year (−2) x treat.	0.041	−0.626	−0.025***	−0.023	0.133	−0.029	0.187***	0.179***
	0.322	0.406	−0.009	−0.019	0.095	0.079	0.049	0.059
Termination year (−1) x treat.	0.159	−0.455	−0.012	−0.021	0.196**	−0.075	0.085*	0.003
	0.364	0.473	−0.008	−0.017	0.090	0.075	0.045	0.054
Termination year (1) x treat.	−0.277	−0.550	0.011	0.025	−0.178*	−0.026	−0.124**	−0.034
	0.345	0.420	−0.008	−0.017	0.094	0.089	0.049	0.062
Tterm. year (2) x treat.	−0.309	−0.582	0.029***	0.029	−0.353***	−0.100	−0.145***	−0.139**
	0.426	0.518	−0.009	−0.018	0.097	0.096	0.049	0.065
Termination year (3) x treat.	0.141	−0.386	0.045***	0.049***	−0.616***	−0.376***	−0.340***	−0.292***
	0.392	0.541	−0.008	−0.019	0.125	0.123	0.055	0.074
Termination year (4) x treat.	−0.566	−0.790	0.046***	0.049**	−0.811***	−0.363**	−0.368***	−0.292***
	0.443	0.545	−0.009	−0.019	0.143	0.151	0.061	0.076
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Firm−alliance fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Full	Reduced	Full	Reduced	Full	Reduced	Full	Reduced

Note: *** p < 0.01, ** p < 0.05, * p < 0.1; included control variables: Techn. distance, R&D expenditures, employees, sales, advertising, cash flow, R&D alliances, non R&D alliances, acquisition, alliance portfolio; counterfactual based on SOL sample.

alliance termination. Finally, we also found a negative and significant effect on the innovation outcome variable of technological diversity across all estimations (Models 4a and 4b; Panel 1 and 2), which supports Hypothesis 2b.

Table 4 shows the results for the lead-and-lag estimation with the random termination year for the non-terminated alliances. The results are very much in line and confirm Table 3, with mixed results for external knowledge acquisition from partners. However, more important than the analysis of individual coefficients is the direction and strength of the coefficients along the time dimension. Negative effects after the alliance termination year ≥0 and small effects before termination (termination years <0) would indicate a clear termination effect with neither anticipatory effects nor indication of reverse causality. The estimation of innovation performance with control variables is a good example of this pattern (Model 3b). Before the termination event, the estimates are only partially significant, and the effects are relatively small. After the termination event, the effects are mostly larger and increasingly significant. By contrast, estimations showing significant positive (or negative) decreasing (or increasing) effects for the pre-termination period indicate violation of the parallel trend assumption and might indicate anticipatory effects or reverse causality. The estimations of the percentage of external knowledge acquisition (Models 2a and 2b) indicate this pattern. Moreover, it is noteworthy that, in this case, the model without control variables shows a stronger pre-trend (Model 2a) than the model with control variables (Model 2b). This highlights the importance of the covariates to correct for possible violation of the parallel trends assumption (Atanasov and Black, 2016).

The graphical representation of the lead-and-lag estimation provides a nice illustration of these effects (Fig. 1). The lead-and-lag graph for external knowledge acquisition from partners does not show a clear pattern of difference between treatment and control groups. The graph for innovation performance depicts parallel trends prior to the termination followed by a drop for the terminated group, while the estimation for the control group of non-terminated alliances remains stable. On the other hand, the graphs for the percentage of external knowledge acquisition and for technological diversity of innovation outcomes indicate not only a drop after the termination but also reveal potential pre-termination trends.

Table 5 shows the results for the conditional DID using the kernel matching and the bias corrected nn-matching. Similar to the earlier findings of the conventional DID estimation, we found a negative effect of alliance termination on innovation performance in support of Hypotheses 2a and partial support for Hypothesis 2b on the negative effect on innovation technological diversity. On the other hand, the positive and significant results for the percentage of external knowledge acquisition are in line with our previous results, thus leading to the rejection of Hypothesis 1b, which posits a negative effect. Finally, the non-significant results for partner knowledge acquisition also lead to the rejection of Hypotheses 1a.

4.2. Exploration of alliance and firm conditions

Previous research has discussed several alliance-specific and firm-specific conditions that could influence our analysis. Thus, in order to test the robustness and explore the heterogeneity of our results, we subsequently investigated several important potential moderating

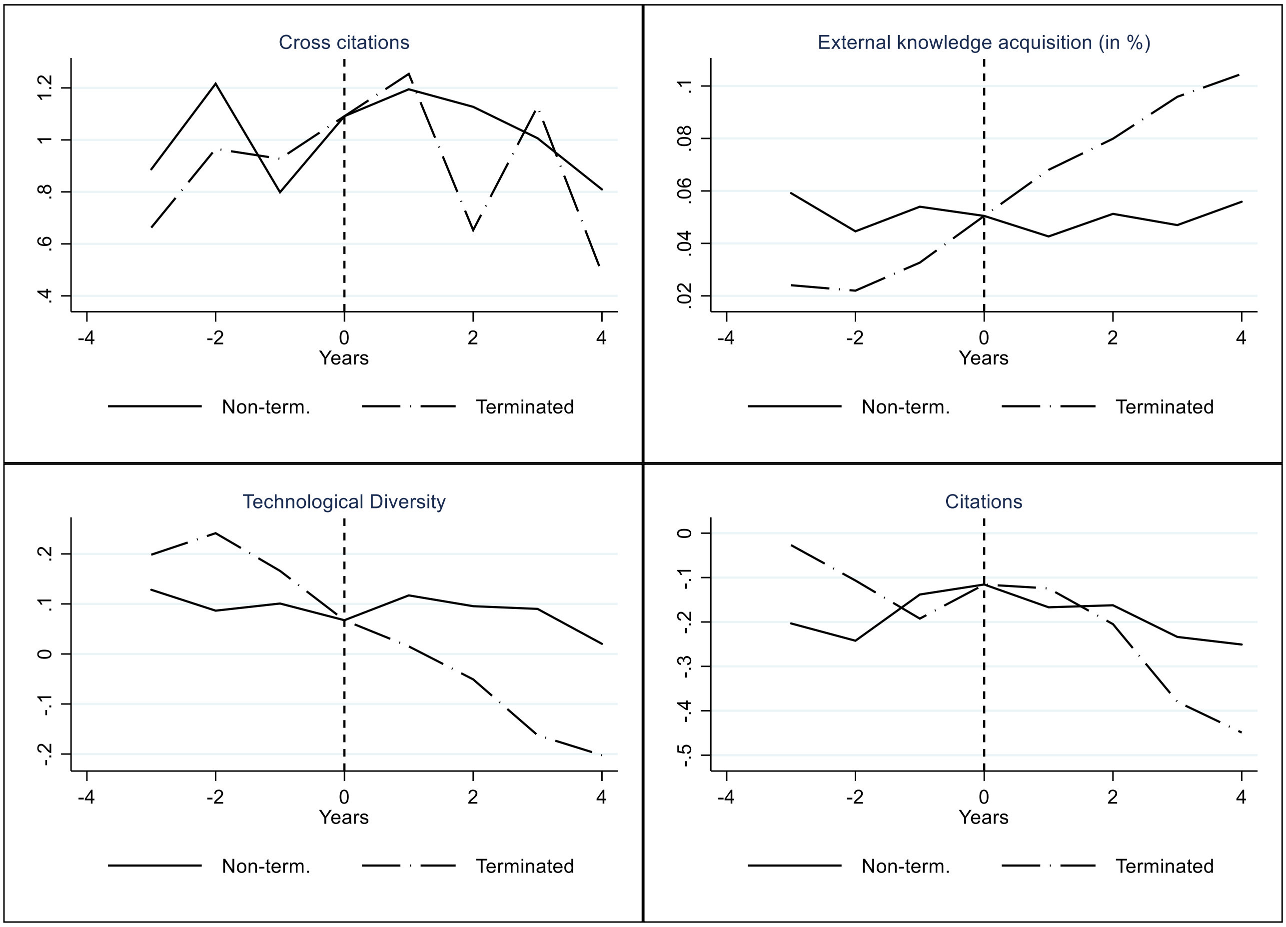

Fig. 1. Lead- and-lag graphs.

Table 5
Conditional DID.

Variable	Kernel matching		Nearest neighbor matching	
	ATT	St. Er.	ATT	St. Er.
	External knowledge acquisition			
Cross citations	0.000	0.000	0.000	0.000
Ext. knowledge in %	0.060***	0.007	0.062***	0.009
Innovation outcomes				
Citations	−8.151***	0.988	−13.662***	1.867
Tech. Diversity	−0.151***	0.013	−0.189***	0.023

Note: ATT = average treatment effect on the treated, matching variables and bias corrected: R&D expenditures, employees, sales, advertising expenses, cash flow, R&D alliances; non R&D alliances, technological distance, acquisition, alliance portfolio; nearest neighbor exact-match variables: JV governance, alliance duration; ***p < 0.01, ** p < 0.05, * p < 0.1.

conditions (Table 6):[13]

4.2.1. Alliance portfolio size

To understand the knowledge and innovation effects from a more dynamic perspective, it is important to incorporate the broader alliance strategy by considering firms' alliance portfolios. Given the limitations of firm resources and attention, firms cannot continue collaborating with an increasing number of partners. If some alliances are not terminated to form new partnerships, the firm would develop an increasingly broad and complex alliance portfolio that leads to decreasing returns (Laursen and Salter, 2006; Wassmer et al., 2017). However, Having a larger alliance portfolio may help protect against the shifts in knowledge acquisition and innovation outcomes arising from the termination of an individual alliance as firms will have continued access to diverse and external knowledge. Furthermore, additional partners might provide complementarities to previously acquired knowledge. Thus, we might expect a larger alliance portfolio to reduce the effects of alliance terminations.

4.2.2. Internal R&D

Several studies have explored the complementarity and substitutivity of internal R&D innovation strategies and external knowledge acquisition and find the activities to be substitutes under certain conditions (Cassiman and Veugelers, 2006; Hagedoorn and Wang, 2012). Overall, research shows that firms improve innovation performance by increasing external R&D activities up to a certain threshold, after which there is a decline in innovation outcomes (Berchicci, 2013). Furthermore, the substitution effect is larger for firms with greater internal R&D capacity, suggesting that the opportunity cost of forming additional alliances is higher for firms with a superior knowledge stock. Similarly, Hagedoorn and Wang (2012) show that internal and external R&D are employed as complementary inputs at higher levels of internal R&D, but as substitutes at lower levels of internal R&D. In the context of R&D alliance termination, the substitution or complementarity effects of internal and external R&D are important for determining the available inputs for knowledge recombination.

[13] JV governance and same-industry alliance were constructed as binary variables. JV: 1 = JV, 0 = contract alliance (e.g., Phene and Tallman, 2012). Same-industry alliance: 1 = same four-digit SIC code, 0 = different four-digit SIC code (e.g., Mowery et al., 1996). Geographic proximity was measured in Ln of kilometers, but results are robust to specification of kilometers without Ln and same country or state dummies (e.g., Rosenkopf and Almeida, 2003).

Table 6
Exploration heterogeneous effects.

Dependent variable	External knowledge acquisition				Innovation outcome			
	Cross citations		Ext. knowledge in %		Citations		Techn. Diversity	
Model	1a	1b	2a	2b	3a	3b	4a	4b
	Panel A: Alliance portfolio							
Alliance terminated	−0.261	−0.049	−0.013***	−0.029***	−0.072*	−0.112**	−0.059**	−0.062*
	0.163	0.232	−0.004	−0.010	0.040	0.049	0.023	0.034
Alliance terminated x treatment	0.043	0.271	0.065***	0.071***	−0.408***	−0.248**	−0.330***	−0.267***
	0.281	0.327	−0.007	−0.012	0.092	0.102	0.043	0.053
Alliance portfolio x alliance terminated	0.046**	0.014	0.006***	0.005***	0.007	0.007	0.009***	0.007***
	0.022	0.024	−0.001	−0.001	0.004	0.005	0.003	0.003
Alliance portfolio x alliance terminated x treat.	−0.014	−0.030	−0.007***	−0.006***	0.023***	0.022***	0.017***	0.012***
	0.037	0.031	−0.001	−0.002	0.007	0.007	0.004	0.004
	Panel B: Internal R&D							
Alliance terminated	–	−0.099	-	−0.044***	-	−0.068	-	−0.028
	–	0.177	-	−0.009	-	0.046	-	0.028
Alliance terminated x treatment	–	0.254	-	0.098***	-	−0.026	-	−0.233***
	-	0.301	-	−0.011	-	0.080	-	0.048
Internal R&D x alliance terminated	-	0.250*	-	0.073***	-	0.018	-	0.018
	-	0.130	-	−0.010	-	0.033	-	0.020
Internal R&D x alliance terminated x treat.	-	−0.156	-	−0.073***	-	−0.028	-	0.021
	-	0.112	-	−0.010	-	0.042	-	0.021
	Panel C: JV governance							
Alliance terminated	−0.113	−0.020	−0.001	−0.004	−0.052	−0.041	−0.020	−0.014
	0.155	0.164	−0.004	−0.008	0.046	0.035	0.019	0.023
Alliance terminated x treatment	−0.158	0.150	0.048***	0.055***	−0.511***	−0.058	−0.311***	−0.206***
	0.243	0.281	−0.006	−0.011	0.087	0.075	0.036	0.044
JV governance x alliance terminated	1.580***	3.195***	−0.009	0.012	0.095	−0.085	0.023	−0.015
	0.550	1.218	−0.012	−0.030	0.119	0.103	0.067	0.093
JV governance x alliance terminated x treat.	−1.184	−2.285	−0.013	−0.036	−0.137	0.010	−0.081	−0.057
	0.901	1.582	−0.015	−0.033	0.233	0.178	0.116	0.150
	Panel D: Geographic proximity (KM ln)							
Alliance terminated	−0.544	−0.037	−0.017	0.031	0.056	0.132	−0.023	0.023
	0.430	0.470	−0.011	−0.027	0.141	0.129	0.052	0.075
Alliance terminated x treatment	1.689***	0.865	0.079***	0.060	−0.708***	−0.141	−0.335***	−0.265**
	0.579	0.647	−0.018	−0.038	0.260	0.173	0.099	0.123
Geo. location x alliance terminated	0.070	0.001	0.002	−0.005	−0.014	−0.024	0.001	−0.005
	0.054	0.062	−0.001	−0.003	0.018	0.017	0.007	0.010
Geo. location x alliance terminated x treat.	−0.268***	−0.105	−0.004**	−0.001	0.029	0.013	0.005	0.010
	0.077	0.087	−0.002	−0.005	0.033	0.024	0.013	0.016
	Panel E: Same-industry alliance							
Alliance terminated	0.258	0.127	−0.005	−0.002	−0.004	−0.025	−0.021	0.000
	0.188	0.193	−0.007	−0.018	0.078	0.061	0.030	0.039
Alliance terminated x treatment	−0.283	−0.033	0.052***	0.056***	−0.728***	−0.240**	−0.324***	−0.224***
	0.295	0.334	−0.010	−0.021	0.129	0.108	0.055	0.066
Same-industry alliance x alliance terminated	−0.491*	−0.178	0.005	−0.002	−0.055	−0.031	0.006	−0.021
	0.291	0.324	−0.008	−0.020	0.094	0.073	0.038	0.047
Same-industry alliance x alliance terminated x treat.	−0.011	0.456	−0.009	−0.008	0.302*	0.258*	0.004	0.014
	0.465	0.540	−0.012	−0.024	0.164	0.139	0.071	0.084
	Panel F: Technological Distance							
Alliance terminated	0.060	0.290	0.004	0.010	−0.147*	0.088	−0.153***	0.027
	0.256	0.347	−0.004	−0.012	0.088	0.092	0.039	0.063
Alliance terminated x treatment	−0.214	−0.376	0.019***	0.037***	−0.271*	−0.221	−0.096	−0.392***
	0.362	0.416	−0.006	−0.013	0.143	0.135	0.065	0.088
Techn. Distance x alliance terminated	−0.125	−0.529	−0.012	−0.026	0.184	−0.245	0.241***	−0.073
	0.487	0.679	−0.008	−0.017	0.147	0.157	0.072	0.111
Techn. Distance x alliance terminated x treat.	−0.005	1.147*	0.048***	0.027*	−0.412*	0.274	−0.317***	0.318**
	0.598	0.624	−0.008	−0.016	0.213	0.221	0.097	0.138

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$; included control variables: Techn. distance, R&D expenditures, employees, sales, advertising, cash flow, R&D alliances, non R&D alliances, acquisition, alliance portfolio; counterfactual based on SOL sample. JV governance and same-industry alliance were constructed as binary variables. JV: 1 = JV, 0 = contract alliance; same industry alliance: 1 = same four-digit SIC code, 0 = different four-digit SIC code. Geographic proximity was measured in Ln of kilometers, but results are robust to specification of kilometers without Ln and same country or state dummies.

More specifically, with more internal R&D, firms may become more internally-oriented following an alliance termination and experience less of an impact on innovation outcomes, as these firms are potentially better able to compensate for the alliance termination due to their internal R&D base. Furthermore, extant research would predict that firms with high internal R&D capacity may benefit from reducing the complexity of their alliance portfolio (Berchicci, 2013; Hagedoorn and Wang, 2012).

4.2.3. JV governance

JV governance has often been shown to affect the knowledge acquisition and innovation outcomes of firms in alliances. Studies often highlight that interorganizational integration through closer contact and deeper collaboration, common in JVs, is a key factor fostering knowledge acquisition and innovation outcomes during the life of an alliance (e.g., Gomes-Casseres et al., 2006; Kogut, 1988; Mowery et al., 1996). Thus, terminating alliances with JV governance could lead to a greater impact on knowledge acquisition and innovation outcomes for firms. However, separating the alliance through JV governance may protect the firm from unintended spillover of knowledge unrelated to alliance activities (Oxley and Wada, 2009) and help isolate the firm from the disruption and changes in the post-alliance trajectory.

4.2.4. Geographic proximity

Studies also frequently address how geographic proximity interacts with the knowledge acquisition and innovation outcomes of alliances (e.g., Gomes-Casseres et al., 2006; Hohberger, 2014; Rosenkopf and Almeida, 2003) and conclude that proximity accentuates the positive effect of alliance formation. Thus, the main argument is that, if knowledge is embedded in the local context, geographic proximity facilitates the access and interaction between alliance partners that is necessary to support the exchange of tacit knowledge. Further, termination of a local alliance may have less impact on the relative external knowledge acquisition and the technological diversity of innovation outcomes, since the reduced access is to the same context in which the focal firm remains and could thus mitigate the change in firm knowledge acquisition and innovation outcomes.[14]

4.2.5. Same-industry alliance

The termination of alliances between firms in the same industry may be more damaging to leave, as such collaborations are more likely to be competitive in nature (Hamel, 1991). In turn, firms may seek to protect knowledge from these former partners resulting in a greater decrease in knowledge acquisition. However, research also suggests that firms competing in the same industry have a greater ability to understand and absorb partner knowledge (i.e., increased absorptive capacity (Lane and Lubatkin, 1998)), which would indicate that knowledge acquisition from the partner may persist post termination. On the other hand, the decline in innovation performance may be accentuated if competition intensifies and knowledge is more redundant. In a similar vein, alliances with partners outside of the firm's industry may lead to more diverse knowledge inputs. In this case, premature termination might further reduce knowledge diversity and drive the focus from external knowledge acquisition to internal knowledge.

4.2.6. Technological distance

Technological distance between partner firms is another alliance condition that has been shown to play an important role in the knowledge acquisition and innovation outcomes of R&D alliances (Gilsing et al., 2008; Gomes-Casseres et al., 2006; Rosenkopf and Almeida, 2003; Subramanian et al., 2018). For example, several studies show that lower technological distance between partners (meaning greater proximity in that partners have technological activities in similar domains), enhances knowledge acquisition and innovation related to existing firm knowledge (Almeida et al., 2003; Nooteboom et al., 2007; Schildt et al., 2012). Thus, the technological distance of partners may have an impact on the diversity of technological knowledge following premature termination. Specifically, greater technological distance likely implies that greater knowledge diversity is available during the alliance, which may suggest a greater reduction in knowledge diversity post termination compared to alliance partners who are technologically proximate. Moreover, research has revealed the challenges firms face when using alliance to acquire knowledge that is both distant and diverse (Vasudeva and Anand, 2011).

4.2.7. Results explorative analysis

We found relatively strong support for a possible heterogeneous effect of the alliance portfolio size and the impact of alliance termination (Panel A). The interaction effect is positive and significant for innovation performance (Model 3a and 3b) and technological diversity (Model 4a and 4b), and it is negative and significant for the percentage of external knowledge acquisition (Model 2a and 2b). On the other hand, we found only limited evidence of a moderating effect of the size of internal R&D activities (Panel B, Model 2b). The findings for the alliance-specific conditions also revealed only a very limited and inconsistent influence on knowledge acquisition and innovation outcomes post termination. In the case of geographic proximity, we found negative interaction effects only for the external knowledge acquisition variables and only in the case of the models without control variables (Panel D; Model 1a and 2a). We also found a weak ($p < 0.1$) positive effect for same-industry alliances, but only in the case of innovation performance (Panel E, Model 4a and 4b). In the case of technological distance, we found significant but inconsistent results (Panel F). Specifically, we found significant results for Models 1b, 2a, 2b, 3a, 4a and 4b, non-significant results for Models 1a and 3b, and sign changes between Models 3a to 3b and 4a to 4b. These mixed findings indicate that control variables, such as firm size and R&D intensity, are important in determining the interaction effect of partner technological distance on the diversity of innovation post termination, and therefore caution is required when interpreting Panel F in general.

5. Discussion

This study provides a test and exploration of the impact of premature termination of R&D alliances on knowledge acquisition and innovation outcomes. While previous research provides ample empirical evidence on the positive effects of alliance formation, we had scarce knowledge about the implications of alliance termination (e.g., Pangarkar, 2009; Singh and Mitchell, 1996; Zhelyazkov and Gulati, 2016), and even less about the impact on knowledge acquisition and innovation, although these goals often drive alliance formation. Overall, our findings show that alliance termination has an impact on external knowledge acquisition and innovation technological diversity and performance. However, the results reveal that the effects of termination are not always the opposite of alliance formation effects. Therefore, this study allows us to build a more complete and nuanced understanding of alliance activity, the associated innovation implications, and the underlying assumptions in the context of the KBV of the firm.

The results of our analysis show that premature termination of an R&D alliance reduces innovation performance post termination (Hypothesis 2a). This result is in line with previous research on the role of alliances as drivers or enablers of innovation activities (e.g., Baum et al., 2000; Jiang and Li, 2009; Stuart, 2000) and the idea that termination results in the opposite effect. Furthermore, our more detailed analysis also suggests that the rate of decay accelerates as the number of years that have passed since termination increases, and we found no pre-trend in innovation performance indicating that a decline in innovation was not driving the termination. Our results also show that premature termination of an R&D alliance decreases the technological diversity of the innovation outputs of a firm (Hypothesis 2b). Again, this result is in line with the KBV's theoretical expectation and previous empirical research on alliances. It supports the notion that R&D alliances are tools for accessing and acquiring external knowledge that is distinct from that of the firm (Grant and Baden-Fuller, 2004). Thus, removing the alliance reduces the diversity of knowledge inputs. It is noteworthy that this holds true when we control for same-industry

[14] It should also be noted that geographic proximity can also increase the competitive nature of alliances.

alliances, the technological distance of alliance partners, and the interaction of these variables with the termination event. In other words, even the termination of alliances with fairly similar partners, negatively impacts the diversity of innovation. This implies support for the idea from prior research that alliances generally allow for more diverse innovation activities, and that premature termination reduces this effect independent from the characteristics of the alliance.

However, contrary to our expectation in Hypothesis 1b, our results reveal that firms acquire more external knowledge (in relative terms) after premature termination. This goes against our initial hypothesis and the symmetry of alliance formation and termination. Similarly, we found weak and mixed results for the decline in the acquisition of knowledge from partners following premature alliance termination, suggesting that there is no clear reduction in the acquisition of partner knowledge. This finding is not aligned with our prediction within the KBV, in which one of the main motivations for forming alliances is the ability to acquire knowledge, and one would expect a reduction in this ability after a premature alliance termination. A possible explanation might be found in existing research on knowledge acquisition but outside the alliance space. Previous research on knowledge acquisition has argued that an organizational context might be necessary or at least helpful to create the social connections that enable knowledge exchange. However, even if the organizational context is removed, the social ties remain and continue to enable knowledge acquisition. For example, Corredoira and Rosenkopf (2010) found that, after losing employees, firms are more likely to subsequently cite the patents of firms hiring these employees, and they posit two different mechanisms supporting these effects. First, interpersonal relationships endure even after the contractual relationship ends and the connection allows for the communication and exchange of knowledge. The second mechanism is grounded in the Ocasio's (1997) attention-based view of the firm, suggesting that, even if an employee leaves an organization, her former employer is more aware of her activities. In turn, the former employer is more likely to acquire knowledge from her development even if she works for a new organization for which the knowledge is exclusively generated. This is also related to arguments from Agrawal et al. (2006) in the context of geographic distance. They argue that enduring social relationships determine knowledge flow patterns when inventors move to new locations and reduce the impact of social distance on knowledge acquisition. While the alliance context differs from these previous studies, the underlying mechanisms are potentially similar. As numerous previous studies show, and also central to our argument, an alliance provides a social context that enables knowledge acquisition (Almeida et al., 2002). However, while termination of the alliance brings the interorganizational context to an end, social ties can endure between individuals of the former alliance partners and thus enable and foster knowledge acquisition. Similarly, even after the termination of an alliance, a firm is probably more aware of and able to monitor the activities of the former partner firm, also potentially enabling and fostering knowledge acquisition.

It is interesting to note that the sustained acquisition of knowledge from former partners might also be a partial explanation to the unexpected results of Hypothesis 1b (percentage of external knowledge acquisition). On the one hand, the firm may increase its alternative external knowledge search after the premature termination of an alliance. The potential focus on alternative knowledge partners and sources might even be the motive for the alliance termination. At the same time, the organization is still able to acquire knowledge, although most likely at a lower level, from a former partner. Thus, the relative change of external knowledge acquisition is potentially lower than expected.

While we did not directly hypothesize on the constructs in our extended analysis, the results provide additional insight into the impact of premature alliance termination, which are worth discussing. Overall, we found no consistent impact of alliance conditions on knowledge acquisition or innovation outcomes post alliance termination. However, the importance of firm-level conditions is supported by our extended analysis. The results suggest that firm-level innovation strategies, particularly the size of the alliance portfolio, may have a positive moderating effect on the relationship between premature termination and knowledge acquisition and innovation outcomes. This supports the argument from previous alliance research that the alliance portfolio is an important resource for firm knowledge acquisition and innovation (Frankort et al., 2011; Lahiri and Narayanan, 2013; Wassmer, 2008). Alliance portfolio size seems to protect against declines in innovation output and mitigate the increase in relative use of external knowledge acquisition post termination. Moreover, firms with a larger set of partners are more likely to have continued access to diverse and external knowledge, as well as to additional previously acquired complementary knowledge from a larger alliance portfolio.

Finally, our study supports the KBV by offering empirical investigation into the tenets of the theory and demonstrating the breakdown of knowledge fostering mechanisms. We explain how the mechanisms proposed by the theory to promote knowledge acquisition and innovation outcomes are hindered in the context of premature alliance termination, reversing technological diversity and innovation performance outcomes. The revealed changes in knowledge acquisition patterns and innovation outcomes, including the unexpected increase in external knowledge acquisition, demonstrate the impact of both alliance formation and termination. Aligned with theory, we also show that alliance outcomes influence firm-level knowledge, although alliance conditions do not appear to have much impact on the reversal of alliance formation effects. This is an important boundary condition, as it shows that creating external paths for knowledge acquisition and innovation are more fine-grained processes that require specific dyadic conditions for success, whereas the removal of and changes to these paths depends on the larger firm context. On the other hand, the heterogeneous effects of firm-level characteristics, particularly alliance portfolios, corroborate the contingent relationship of termination outcomes and the importance of the portfolio lens for alliance research.

5.1. Managerial implications

Alliances have long been regarded as an important managerial mechanism for achieving strategic ends, especially those linked to knowledge acquisition and innovation (Chesbrough, 2006; Randhawa, et al., 2016; Hoang, H., and Rothaermel, 2016). Managers need evidence on the outcomes of termination in order to fully understand the value and impact of alliances and to better inform management decisions at the time of formation and throughout alliance and innovation management (e.g., Das and Teng, 2000). In this context, our study not only reveals the negative effect of the termination event on innovation outcomes, but also a non-finding for the decline in partner-specific knowledge acquisition post termination. This suggests that prematurely terminating an alliance agreement may not necessarily reduce knowledge acquisition opportunities across the partner firms. Thus, managers must be aware of this potential continued 'leakage' across firm boundaries and take steps to limit this if desired.

Similarly, while previous research may lead to the prediction that alliance characteristics determine the degree of spillover and innovativeness post termination (Mowery et al., 1996; Oxley and Wada, 2009), we did not find these characteristics had a strong impact. For example, JV governance did not protect firms from the decline in innovation performance post termination. Thus, these insights help to further reduce the uncertainty that firms face when terminating alliance agreements and when designing initial agreements. Specifically, when selecting partners and alliance design, firms should be aware that knowledge and innovation fostering characteristics are largely constrained to the alliance life.

5.2. Limitations

This study has several limitations, some of which point to avenues for future research. For example, our unique data collection efforts provide rare insight into the prevalent issue of premature alliance termination, on which there is a dearth of previous empirical research (often due to data availability). Although our data collection efforts are comparable to the limited number of related studies, not only is our sample relatively small, but it also does not cover all of the relevant termination events due to missing information. Furthermore, it would be worth exploring more fine-grained alliance termination and knowledge-related variables to shed more light on the implications of termination and to advance organizational theory. As with most archival alliance research, we cannot capture alliance formation motives or alliance strategies. We tried to account for this by focusing on R&D alliances within the life sciences, which are largely focused on knowledge access or exchange, and we explicitly excluded downstream, marketing, distribution, and manufacturing alliances without an R&D component from our analysis. While this allowed us to make a more credible assumption that knowledge acquisition and innovation is a significant motive for the alliances in our sample, it would be interesting to explore specific alliance motives and strategies and link these to the implications of premature termination. However, this more fine-grained analysis relies on more micro-level firm data—something that is difficult to obtain within an archival study and often requires survey or case study research approaches.

Related to the previous points, the relatively small sample size and specific focus of the study meant that we had to exclude several interesting conditions from our analysis (e.g., multi-partner alliances and alliance internalization). For example, existing multi-partner alliance research makes the credible claim that these alliances behave differently to dyadic relationships (Davis, 2016; Heidl et al., 2014), raising the issue for future research as to whether these effects hold in a multi-partner setting. The focus on premature dissolution also raises the questions as to whether the effects of planned alliance dissolution and internalization may reveal opposing effects given the distinct shift in firm boundaries.

Finally, although the application of the DID and conditional DID estimation (in combination with fixed effects and lead-and-lag analysis) significantly reduces the risk of misidentification and increases the confidence in a causal interpretation of the results, the procedure cannot completely rule out the possibility that time-varying alliance-specific effects influenced our results. Notwithstanding these limitations, our study demonstrates the importance of managing the temporal aspect of alliances to ward off any decline in innovation and undesired shifts in knowledge acquisition that accompany premature termination.

CRediT authorship contribution statement

Jan Hohberger: Conceptualization, Formal analysis, Methodology, Validation, Writing - original draft, Writing - review & editing. **Heidi Kruger:** Conceptualization, Investigation, Data curation, Writing - original draft, Writing - review & editing. **Paul Almeida:** Conceptualization, Resources, Writing - original draft.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.respol.2020.103944.

Appendix

Table A1.

Table A1
Indicator matching quality.

Indicator	Kernel matching		Nearest Neigbor matching	
	Unmatched	Matched	Unmatched	Matched
R2	0.053	0.005	0.097	0.006
χ^2	119.89	8.42	340.18	6.37
$p > \chi^2$	0.00	0.394	0.00	0.606
MeanBias	14.4	5.1	19.7	6.6

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