Is there life after death? Measuring the impact of strategic alliance termination on firm innovation and learning

Heidi Kruger  
ESADE Business School  
Strategy and General Management  
heidi.kruger@esade.edu

Jan Hohberger  
University of Technology Sydney  
Marketing Discipline Group  
jan.hohberger@uts.edu.au

Paul Almeida  
Georgetown University  
Strategy, Economics, Ethics, and Public Policy  
paul.almeida@georgetown.edu

Abstract  
The termination of a strategic alliance can be a disruptive event for organizations. However, research on alliance innovation and learning outcomes has paid little attention to alliance temporal nature and largely forgotten to account for learning after the active alliance life. This study address this gap and explores how alliance terminations in the life science industry are associated with subsequent firm innovation and learning in the period from 1990–2006. We apply a difference-in-differences estimation to a sample of terminated and surviving alliances to offer evidence that alliance termination significantly reduces innovation performance and impacts firm learning. We argue that these effects may be more abrupt than previously expected and show the rate of decay accelerates as time passes after termination. Firm learning becomes less diverse in knowledge sources, and unexpectedly, more external to firm boundaries following termination. We theorize on conditions that may influence the decline in innovation, shift in learning, and continuity of partner based learning, post termination. Our results are particularly relevant in dynamic environments where firms must constantly weigh alternative knowledge sources and innovation strategies. We discuss further implications of our findings for theory and practice on alliances, innovation and organizations.

Jelcodes:C21.C23
Is there life after death? Measuring the impact of strategic alliance termination on firm innovation and learning

ABSTRACT

The termination of a strategic alliance can be a disruptive event for organizations. However, research on alliance innovation and learning outcomes has paid little attention to alliance temporal nature and largely forgotten to account for learning after the active alliance life. This study address this gap and explores how alliance terminations in the life science industry are associated with subsequent firm innovation and learning in the period from 1990-2006. We apply a difference-in-differences estimation to a sample of terminated and surviving alliances to offer evidence that alliance termination significantly reduces innovation performance and impacts firm learning. We argue that these effects may be more abrupt than previously expected and show the rate of decay accelerates as time passes after termination. Firm learning becomes less diverse in knowledge sources, and unexpectedly, more external to firm boundaries following termination. We theorize on conditions that may influence the decline in innovation, shift in learning, and continuity of partner based learning, post termination. Our results are particularly relevant in dynamic environments where firms must constantly weigh alternative knowledge sources and innovation strategies. We discuss further implications of our findings for theory and practice on alliances, innovation and organizations.

Keyword: alliance termination; innovation; learning; knowledge; difference-in-differences
INTRODUCTION

A significant body of research has examined the key factors influencing alliance termination, including partner and alliance characteristics (e.g., Cui, Calantone, & Griffith, 2011; Hennart, Kim, & Zeng, 1998) resource configuration (e.g. Cui et al., 2011; Dussauge, Garrett, & Mitchell, 2000), competitive positions (e.g. Dussauge et al., 2000; Greve et al., 2010) and environmental uncertainty (e.g. Cui et al., 2011; Kogut, 1991; Xia, 2011). Given the likelihood of alliance termination and scholarly attention placed on alliance termination, it is surprising relatively little empirical evidence exists on the consequences of alliance termination (Zhelyazkov & Gulati, 2016). This is true for general performance consequences, and for innovation and learning related outcomes in particular. A few studies have helped shed light on the organizational consequences of termination. For example, Singh and Mitchell (1996) show that alliance termination has a negative impact on start-up survival that is mitigated by forming new partnerships. Other studies illuminate diverse effects of internalization and divestment of equity alliances on firm value (Kumar, 2005; Meschi, 2005; Reuer, 2001) and demonstrate termination experience improves future termination outcomes (Heimeriks, Bingham, & Laamanen, 2014; Pangarkar, 2009).

Still, scholars have not examined the influence of these events on the subsequent evolution of the firm. This paper addresses this gap and intends to contribute to the literature on alliances by exploring innovation and learning outcomes after alliance termination. Using a sample of 1,475 R&D alliances formed in life science industry from 1990-2004, we explore the innovation and learning post alliance termination in three different areas: innovation performance, firm learning, and partner based learning. The diversity of these measures enables us to capture the complex range of learning associated with R&D alliances. Additionally, we explore if and how alliance governance (i.e. joint ventures), geographic proximity and direct competitor alliances impact the change in innovation and learning following alliance termination.
We use a panel difference-in-differences design (DID) to show the impact of the alliance termination. Thereby, we estimate the effect of the treatment (i.e. termination of an alliance) on the outcome variables by comparing terminated and non-terminated alliances before and after the treatment. To account for the non-randomness and possible endogeneity of the alliance termination event, we conduct our analysis in three steps. First, we run the panel DID estimation with partner-alliance specific and year fixed effects to control for unobserved time invariant heterogeneity. Next, we use lead-and-lag regression and graphics to provide a detailed analysis of the parallel trend hypotheses to assess reverse causality and potential impact of unobservable shocks. Then we address the issue of possible differences between the treatment and control (selection bias) by applying conditional DID strategies (matching DID) (Heckman et al., 1997). While the combination of these three approaches cannot completely rule out that time-variant alliance specific shocks might influence our results, it reduces the risk of misidentification significantly and should increase the confidence in causal interpretation of the results.

The results of the DID estimations show that the termination of an alliance has a significant impact on innovation performance and firm learning. However, we do not find support for a significant negative effect of termination on partner based learning. This residual learning may indicate that social communities and other mechanisms aiding in building on partner related knowledge are sustained beyond the life of the alliance. The lead and lag analysis complements the main findings. It shows no pre-trend in the case of innovation performance but significant pre-trends in the case of firm learning. Additionally, the non-significance of joint venture governance, geographic proximity and direct competitor partnership variables indicates that the impact of these conditions on innovation and learning is limited to the active alliance period.
BACKGROUND AND HYPOTHESES

A significant body of work has uncovered the multitude of triggers for alliance termination including environmental uncertainty (e.g. Kogut, 1991; Makino, Chan, Isobe, & Beamish, 2007; Xia, 2011), firm characteristics such as size and performance (Cui, 2013; Hennart et al., 1998), alliance characteristics such as ownership structure (Chung & Beamish, 2010; Cui et al., 2011), the degree of competition between partners (Dussauge et al., 2000; Greve et al., 2010) and partner resource configurations (Cui et al., 2011; Dussauge et al., 2000). However, the consequences of alliance termination have received much less empirical attention and are typically assumed to be detrimental in theoretical discussion and research illuminating paths to termination avoidance. For example, Zhelyazkov and Gulati (2016) find negative relational and reputational consequences of VC syndicate withdrawal as the propensity to withdraw from deals reduces new deal formation. Further Heimeriks et al. (2014) find that codifying knowledge on the alliance termination process improves subsequent alliance performance (operationalized as future terminations and survey constructed performance measures). In a similar vein, Pangarkar (2009) discovers that past termination experience reduces the number of future alliance terminations. Illustrating how alliance termination may be particularly detrimental for start-ups, Singh and Mitchell (1996) found firm survival was negatively influenced by alliance termination although the effect was attenuated by forming new partnerships. Kumar (2005) found the value of JV dissolution and selloff was conditional on the reason for termination and market characteristics. In line, Meschi (2005) discover stock market reactions to JV selloffs are positive and conditional on the reason for termination. From the buyer perspective, Reuer (2001) finds the effect of JV internalization on shareholder wealth is positively related to R&D intensity and negatively related to cultural distance.

Hypotheses Building

Innovation performance. Research has uncovered a largely positive relationship between alliance activity and innovation and learning outcomes (e.g. Hess & Rothaermel, 2011; Stuart,
From a knowledge based view, the utility of interfirm alliances as a learning strategy is explained through the superior access to diverse knowledge for recombination (Grant, 1996; Grant & Baden-Fuller, 2004). Beyond access, improved innovation outcomes are supported by the overlapping knowledge bases and embedded context of alliances that foster knowledge recombination (Kogut, 1988; Rosenkopf & Almeida, 2003). Empirical studies have offered evidence that participation in different types of alliances impacts the exchange and access of knowledge and has a positive impact on innovation performance (e.g. Almeida et al., 2011; Stuart, 2000). For example, Gomes-Casseres et al., (2006) and Almeida, Song and Grant (2002) argue that alliances are superior in transferring knowledge than markets, and Hohberger (2014) argues alliances are particularly beneficial for emerging knowledge. Regarding innovation performance, Stuart (2000) shows that organizations with large and innovative alliance partners perform better than comparable firms without such partners. Similarly, Baum, Calabrese and Silverman (2000) examine strategic alliances formed by biotechnology start-ups and find that alliances enhance innovation performance by providing early access to information.

Theory may predict the reversal of these effects when the agreement is removed as the firm disengages from an external knowledge source. Without the superior access and platform for interaction afforded during the alliance period, firm innovation may decline as firms build on less diverse knowledge. Yang, Phelps and Steensma (2010) offer empirical evidence that a firm’s rate of innovation is greatest when they have access to large knowledge pools that are related to the firm internal knowledge base. Albeit limited empirical evidence, alliance termination research also supports the notion of detrimental performance consequences particularly for innovation. The account of the learning race (Hamel, 1991; Khanna, 1998) and common link of alliance termination to goal incompletion would suggest negative pressure on innovation performance for at least one of the partners. In addition to the drivers of alliance termination and removal of access to knowledge, the disruption of the termination itself may hurt innovation in the short-term as attention is redirected to managing the change. The empirical evidence of reduced start-up
survival of software firms following alliance termination (Singh & Mitchell, 1996) also supports the prediction that innovation is hampered by termination.

*Hypothesis 1:* Termination of an alliance agreement reduces firm innovation performance.

**Firm learning.** In knowledge-intensive industries with soaring R&D costs, alliances perform a particularly central role in diversifying risks and knowledge sources (Powell et al., 1996). The need to match a firm’s knowledge base to product domains may limit growth to single markets which often prevents full exploitation of firm knowledge (Grant & Baden-Fuller, 2004). To avoid this underutilization of knowledge, firms typically diversify into additional product domains through alliances and other mechanisms to further exploit firm knowledge. Alliances provide access to new complementary knowledge and a context to facilitate knowledge recombination (Rosenkopf & Almeida, 2003). Empirical evidence from Deeds and Hill (1996) supports this role of alliances as firm’s rate of new product development is a positive function of its alliance formations. Vasudeva and Anand (2011) show an inverted U shaped effect between firm knowledge utilization and technological diversity of a firm’s alliance portfolio substantiating diverse knowledge access through alliances and suggesting the maximization point for knowledge utilization also depends on knowledge distance.

Alliance termination may limit the scope of knowledge sourced and the potential for recombination by removing the interface for access and exploitation of complementary knowledge. The knowledge based view would predict less breadth of knowledge inputs as coordination mechanisms to recombine more diverse are impaired (Grant, 1996). Moreover, the narrowing of the scope of knowledge recombination aligns with a frequent driver of alliance termination, a change in strategic priorities (Reuer & Zollo, 2005) such as refocusing on core technologies. In line with these arguments, alliance termination reduces access to knowledge outside firm boundaries and may result in higher self-appropriation of internal knowledge as firms draw less from external sources. Increased self-appropriation may be intentional as
organizations shift to in-house knowledge production or a mere consequence of broken channels to external knowledge. For example, if alliances are often terminated in line with the predictions of the learning race where one partner no longer needs access to redundant partner knowledge absorbed during the alliance (Hamel, 1991; Khanna, 1998), these firms would likely shift to a more in-house intensive knowledge sourcing strategy post termination. From the partner perspective, the termination of the alliance could force the firm to focus more on internal knowledge as less external knowledge is available for recombination. Therefore, the reduction in access and recombination potential leads to complementary predictions that firm knowledge sourcing will become less diverse and more internal following alliance termination.

**Hypothesis 2a**: Termination of an alliance agreement reduces firm technological diversity.

**Hypothesis 2b**: Termination of an alliance agreement increases knowledge building on the firm’s internal knowledge base.

**Partner based learning.** One dimension of interfirm learning is the persistence of knowledge building related to former partner knowledge after the alliance agreement is terminated. Empirical evidence examining the impact of alliance formation demonstrates that firms are better able to build on external knowledge pools related to other organizations when they engage in formal strategic alliances (e.g. Gomes-Casseres, Hagedoorn, & Jaffe, 2006; Mowery, Oxley, & Silverman, 1996; Rosenkopf & Almeida, 2003). For example, Mowery, Oxley, & Silverman (1998) show increased partner related knowledge sourcing when firms form a joint venture regardless of the formation motive. Oxley and Wada (2009) evidence increased transfer of the knowledge covered in the scope of the agreement relative to knowledge not covered in the agreement. The empirical evidence on the formation of alliances suggests the formal alliance agreement is crucial for enhanced learning in another firm’s domain of knowledge, thus the termination may result in a reversal of these effects.
From a theoretical perspective, alliance agreements offer a degree of organizational embeddedness that may help individuals develop a shared identity and common language that facilitates the transfer of tacit knowledge (Kogut, 1988). The role of common knowledge is also central since the intersection of knowledge sets permits individuals to recombine parts of knowledge not shared between them (Grant, 1996). Alliance termination removes this context, the interface proposed to facilitate interfirm learning including face-to-face interaction (Rosenkopf & Almeida, 2003) and a shared identity. Moreover, the mechanisms proposed for integrating specialized knowledge: rules and directives, sequencing, routines and group problem solving (Grant, 1996) are no longer available to members of the terminated alliance to recombine knowledge.

Nevertheless, the argument for continued interfirm learning can be made as knowledge is embedded within individuals. Studies have shown that innovators rely on social relationships to access diverse social communities (e.g Fleming, 2001; Owen-Smith & Powell, 2004), typically united by common geographic, scientific, professional or organizational realms. A recent qualitative study examining the evolution of an R&D alliance shows how individual collaborations often transcend interfirm agreements (Berends, van Burg, & van Raaij, 2011). They observe the creation of social communities tied to the project that outlive the interfirm collaboration. These communities could be sustained by a professional identity linked to the disruptive innovative technology that was under development. Thus, the communities linked to the former R&D project, and individual social relationships built during the alliance, may remain intact following the alliance termination. Taken together, we predict that interfirm learning from former partner related knowledge is reduced upon alliance termination. However, evidence on mechanisms fostering learning would suggest a certain degree of persistence as some learning conduits are sustainable. Applying these arguments, we hypothesize a drop in continued learning from former partner related knowledge but also expect to observe a delay and some degree of residual learning.
Hypothesis 3: Termination of an alliance agreement reduces knowledge building on former partner related knowledge after the termination phase.

METHOD

Data and Variables

We test our hypotheses with a panel analysis of 1,478 R&D alliances in the life science industries formed from 1990 to 2004. An appropriate context to study alliance terminations, the life science industry has high rates of alliance activity and low success (Rothaermel & Deeds, 2004), in line with the high uncertainty, long development times, and above average investment and resources needs for the discovery and development of new drugs.

Alliances were identified from the SDC Platinum Database. To address the imbalance of termination literature restricted to joint ventures, we incorporate alliances of various governance forms including purely contractual relationships, alliances with equity stakes and joint ventures. To facilitate comparability and increase internal validity by assuring learning related alliance goals, we focus on R&D oriented alliances between for-profit firms with at least one participant firm based in the US or with US alliance activity. Alliances that were announced but not realized, multi-partner alliances, and those that upon closer examination were duplicate observations, strictly acquisitions of a patent or outside the life science industry were excluded. The sample was further reduced to R&D alliances and firms existing in the NBER patent database, which is appropriate given our interest in innovation and learning in knowledge intense industries. 1,475 R&D alliances met these characteristics.

Terminated alliances (Independent variable). The SDC database (or any other database to our knowledge) does not systematically and reliably track and report termination of alliances (Schilling, 2009), thus, we complemented the SDC data with detailed press and internet search (following Lavie, 2007; Park & 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 Web sites and Google searches. We read the full-text press releases and documents to identify the termination date and outcome (dissolution, buyout or acquisition). The termination year was identified through content analysis of the press releases rather than the date of the news itself when possible. We excluded cases where the termination outcome was a merger or acquisition of an alliance partners (35 cases) as full partner mergers are conceptually distinct from alliance terminations (Hennart et al., 1998) and would bias the interpretation of interfirm learning measures. For the same reason, alliances terminations evidenced by one firm entering bankruptcy or liquidation (9 cases) were also dropped from the sample. This procedure resulted in a sample of 363 terminated alliances.

We created two variables reflecting the termination event. First, *alliance terminated*, equal to 1 for each year the alliance in terminated, including the year of termination, and equal to 0 for the years the alliance was active. Next, we create the variable *termination year*, which counts the years before and after the alliance termination. Our analysis is based on the 3 years before and 4 years after the termination. This coding allows us to compare termination events across different points in time.

---

*Insert Table 1*

---

**Non-terminated alliances.** To conduct a DID estimation, it is necessary to compare the terminated alliances to non-terminated alliances. However, the termination event for the non-terminated alliances does not exist, thus, it is not possible to directly match terminated and non-terminated alliances on a termination date. Thus, we matched the alliances of the terminated alliance sample to a control group of non-terminated alliances based on a randomly generated termination event during the alliance existence. This approach has the advantage that it does not make prior assumptions about the alliance duration and how alliance learning changes during the life of the terminated alliances. To test robustness of these results we also created a sample, where the counterfactual of the non-terminated alliances is based on average observable alliance.
duration. The average alliance duration in the sample of terminated alliances is 3.3 years. This is within the range of alliance life span of 3 to 5 years of previous termination studies (e.g. Cui et al., 2011; Kogut, 1989; Park & Ungson, 1997). Thus, we estimate our model with an average termination period of three years. The advantage of this matching approach accounts for different possible trends of interfirm learning during the alliance period as it leaves the temporal pattern of the alliance intact, but ignores the different life spans of alliances in the control sample.

Sign-of-life: To improve the accuracy of the coding of non-terminated alliances we accounted for evidence of continued collaboration for alliances with no reported termination. In the case of the non-terminated alliances the previous coding assumes that no information of a termination event equals the persistence of the alliance. This coding can be inflated by alliances that are terminated but the termination is not announced or reported. To account for this possibility, we recorded the persistence of an alliance using press releases (Factiva, Lexis-Nexis). Then we created the variable, sign-of-life, equal to 1 in the years before and including the date of the last report of collaborative activity, and 0 after. The sign-of-life coding is particularly relevant for this study. It is important to have accurate measures of the existence versus the possible unobserved termination of the non-terminated alliances since these alliances build the counterfactual for our estimations.

Dependent variables. We follow earlier studies using patent, patent citations and IPC patent classes as a traceable indicator for firm innovation and learning activities (Gomes-Casseres et al., 2006; Rosenkopf & Almeida, 2003). Despite the various inherent limitations (e.g. Gittlemann, 2008; Alcacar & Gittlemann, 2006) patents and patent references provide one of the most accepted, and reliable sources to measure innovation and learning activities in large scale archival studies. Moreover, patents are a particularly appropriate measure of learning in the context of the life science sector given the widespread use in the drug industry as means of providing intellectual property protection. The patent data was obtained from the National Bureau of Economic Research (NBER) patent database.
Innovation performance: The raw patent count provides a first approximation of the innovation success of the firm. However, previous patent research has shown a high variance in patent value, thus we use the number of (forward) citations as an alternative 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. 2005; Harhoff et al. 2003; Jaffe et al. 2000). To account for the truncation of the citations measure we discount older citation counts with an exponentially decaying component: 

\[ e^{-\left(\frac{Y_t - Y}{5}\right)} \]

where \( Y \) is the patent publication year of patent in \( t \) and \( C \) is a constant of knowledge loss, which is set at 5 years (similar to Fleming, 2001).

Firm learning: We measure the ratio of self-citations to total citations to capture self-appropriation, the inward orientation of the innovation of the firm. To capture the technological diversity, 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 \( t \):

\[ D_t = 1 - \sum_{i=1}^{N} p_{it}^2 \]

A low value indicates a low level of technological diversity (high technological focus) and a high value suggests a high level of technological diversity.

Partner based learning: Partner based learning is measured by cross citations and common citations. Cross-citations, capture the relative extent to which a firm in a given dyad cites the other firm’s patents (similar to Mowery et al., 1998; Rothaermel & Boeker, 2008). It is measured as the sum of (backward) citations \( C \) of firm \( j \) to the patents of partnering firm \( i \) in a given year \( t \):

\[ = \frac{c_{t-i}^j}{c_j^j} \]

To control for the overall citations propensity of a firms we account for the total citations \( C \) of a firm \( j \) in year \( t \). This variable provides a proxy of how much of the knowledge a firm builds on originates from the former alliance partner. Common citations

---

1 We also used raw citation counts for the estimation, which lead to comparable results.
captures the degree to which a firm in a dyad draws from the same external technology base as
the former alliance partner (Mowery et al., 1998, Rothaermel & Boeker, 2008). It is measured as
the as sum of citations \( C \) from the patents of firm \( i \) to patents cited in firm \( j \) patents in year \( t \):
\[ \frac{C_{i,j}}{C_j} \]

**Estimation**

We apply panel DID with partner-alliance- and year fixed effects. The main empirical model is:

\[
E[Y_{it}] = \exp(\alpha(\text{Alliance terminated}_{it}) + \beta(\text{Alliance terminated}_{it} \times \text{Treatment}_i) + \\
\tau(X)_{it} + \delta_t + \mu_i)
\]

where \( Y_{it} \) is the one of the dependent variables, for alliance partner \( i \) in year \( t \). The year dummies
\( \delta_t \) and partner-alliance specific fixed effects \( \mu_i \) account for year specific variance and time
invariant partner specific effects of a firm in a specific alliance. The vector of control variables
\( X_{it} \) includes partner specific time variant controls for innovation and learning. The partner-
alliance fixed effects \( \mu_i \) subsume the classical treatment group dummy \( \text{Treatment}_i \). Different
to classical Panel DID estimation, the \( \text{Termination}_{it} \) is not subsumed in the model due to alliance
termination at different points in time. The DID effect is the \( \beta \) of \( \text{Alliance terminated}_{it} \times 
\text{Treatment}_i \). We adopt a Poisson quasi maximum-likelihood estimation with robust standard
errors clustered at the partner-level to allow for arbitrary serial correlation as it can be applied to
count data and to continuous non-negative data (Wooldridge, 1997). Following Bertrand, Duflo,
and Mullainathan (2004), we incorporated robust standard errors clustered at the partner-level to
address the potential serial correlations among observations of the DID-estimation.

**Control variables.** To account for the scale and performance at the firm level we control
for the R&D expenditures, number of employees, sales, advertising expenditures and cash flow.
We also account for the number of new R&D alliance formations as this likely affects the
resources and attention dedicated to the underlying alliance and creates alternative channels for external knowledge. In addition, numerous studies have demonstrated that proximity in firm technological positioning (low technological distance) also facilitates learning across alliance partners (Gomes-Casseres et al., 2006; Rosenkopf & Almeida, 2003). Thus, we account for the relative technological positioning based on the Euclidian distance between the patent portfolio of the partner firms based on IPC classes (Rosenkopf & Almeida, 2003), \[ \sqrt{\sum (p_{ikt} - p_{jkt})^2} \] where \( p \) represents the proportion of patenting activity for a firm \( i \) or \( j \) in a given patent subclass \( k \) in year \( t \).

**Endogeneity**

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

**Lead-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 & Black, 2015; Roberts & Whited, 2012). While this assumption cannot be directly observed, hence tested, we adhere to several recommendations offered in the literature on DID estimation (Atanasov & Black, 2015; Roberts & Whited, 2012). First, we use the leading indicators to measure whether innovation and learning impacts the likelihood of termination to determine the extent to which reverse-causality influences the coefficients. The leading indicators also serve to identify concerns of omitted changes in the alliance that precede the termination. Furthermore, the lagged indicators help discern the temporal dynamics of termination on innovation and learning including the speed of initial impact and rate of continued decay. This is important as the alliance termination might have a delayed impact. The model has the form:
Balancing & matching. Within DID estimation the treatment and control groups should be relatively similar along observable dimensions relevant for treatment, i.e., balanced (Roberts & Whited, 2012). Therefore, we examine the balancing and then apply the conditional DID (matching based DID) approach on the pooled pre and post termination samples. Conditional DID combines the strength of DID and matching approaches. It is perceived as superior to DID as it reweighs the observations according to the weighting function of the matching estimator and does not enforce linear functional form restrictions when estimating the conditional expectation of the outcome variable (Smith & Todd, 2005). From a matching perspective, it relaxes the assumption of conditional un-confoundedness as it allows for unobservable but time invariant differences in outcomes between participants and nonparticipants by comparing the conditional before and after outcomes of participants with those of non-participants (Heckman et al., 1997).

The general DID matching estimators average treatment effect on the treated (ATT) can be written as:

\[
E[Y_{id}] = \exp(a(Termination_{it-3}) + a(Termination_{it-2}) + … a(Termination_{it+i}) + \beta(Termination_{it-3} \times Treatment_i) + … + \beta(Termination_{it+i} \times Treatment_i) + \tau(X)_{it} + \delta_e + \mu_i)
\]

\[
\Delta^{MAT} = \frac{1}{N_t} \sum_{i \in I_t} [Y_i(1) - \sum_{j \in I_0} \omega N_0(i, j) Y_j(0)]
\]

where \(N_t\) is the number of cases in the treatment group \(I_t\) and \(I_0\) indicates the control group observations. The differences between matching estimators are based on the weights attached to the control group, where \(\omega N_0(i, j)\) is the weight placed on the \(j^{th}\) individual from the control group in constructing the counterfactual for the \(i^{th}\) individual of the treatment group (Heckman et al., 1997, Caliendo, 2009). Following the advice from Heckman et al. (1997) and Smith and Todd (2005) we opted for kernel matching, which is a nonparametric matching estimator that uses weighted averages of observations in the control group to construct the counterfactual outcome. Thus, one of 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 (Caliendo & Koepening, 2008). Additionally, bootstrapping is valid to draw inference for this matching method (Heckman 1997), which allows us to address the inference issues raised by Abadie and Imbens (2006). We use the Epanechnikov kernel in our estimation 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.\(^2\) As an alternative matching procedure we apply nearest neighbor (nn) matching estimation (Abadie & Imbens, 2002) with replacement and 3 comparison units. Thereby, we apply the bias-corrected matching, which adjusts the difference within the matches by the differences in their covariate values, and uses robust standard errors from the weighted regressions.

**RESULTS**

Table 2 shows the descriptive statistics for each alliance observation on the partner level. To make the variables comparable across different alliance termination years and alliance durations, we calculate the descriptive statistics based on the three years before the alliance termination. The results show that most variables are balanced with the exceptions of technological diversity and the alliance governance dummy.

---

Insert Table 2
---

Table 3 shows the results for the main DID coefficient\(^3\) for the different outcome variables based on the randomly generated control group for the non-terminated alliances. For each variable, we show the main DID coefficient with a) DID without control variables, and b)

\(^2\) The distribution of the propensity score is depicted in the Appendix, Figure A1. A visual analysis indicates sufficient overlap between the treatment and control group. We also show various matching quality indicators in Table A1 before and after the matching (i.e. mean standardized difference, pseudo R2, \(\chi^2\)-test). These indicators show satisfying results and suggest that the matching procedure was successful in balancing the covariates.

\(^3\) For space considerations, we only show the DID relevant coefficients, the full table can be requested from the authors.
DID with control variables, and without corrections for sign-of-life (panel A) and with corrections for sign-of-life (Panel B). Supporting Hypotheses 1 and 2b, we find a significant negative effect on the outcome variables of firm innovation performance (patents and citations) and firm learning as increased technological diversity. Contrary to Hypotheses 2a, we also find a significant negative impact of termination on self-appropriation suggesting firms actually draw less on internal knowledge post termination. We do not find conclusive support for Hypotheses 3 on reduced partner based learning as the results are mixed. We only find a significant drop for cross citations and common citations in the sign-of-life corrected estimations without control variables.4

Insert Table 3

Table 4 shows the results for the lead and lag estimation with the random termination year for the non-terminated alliances.5 The results are very much in line and confirm Table 3, with partially non-significant results for cross citations and common citations. However, more important in this analysis is the direction and significance of the coefficient along the time dimension. Significant negative effects after the alliance termination years $\geq 0$ and no significant effects before termination (termination years $<0$) would indicated a clear termination effect without anticipatory effects and without indication of reverse causality. The estimations of innovation performance with control variables are good examples of this pattern (Model 2a and Model 2b). On the other hand, estimations that show positive (or negative) decreasing (or increasing) significant effects for pre-termination period indicate violation of the parallel trend hypothesis and possible anticipatory effects or reverse causality. The estimation of patents and citations without controls, and the firm learning estimations display this pattern (Model 1a, 2a, 3a, 3b, 4a and 4b). It is noteworthy that in the case of patents and citations, only the models

4 The robustness test with the estimation for the average termination time for the non-terminated sample of $t=3$ with similar results.
5 We also conducted a lead and lags analysis for the estimation with assumed termination years of $t=3$. The results also confirm Tables 3 and 4 and can be requested from the authors.
without control variables show a pre-trend (Model 1a and 2a), while the models with control variables (Model 1b and 2b) do not show this pretend. This highlights the importance of the covariates to correct for possible violation of the parallel trend assumption (Atanasov & Black, 2015).

The analysis of lead and lags lends itself to graphical interpretation, thus, we also plot the lead and lag models for each variable. In the case of a “clean” leads-and-lags graph with no apparent pre-treatment trends, one can predict that potential shocks had insignificant impact (Atanasov & Black, 2015). The lead-lag graphs for common citations and cross citations do not show a clear pattern of difference between treatment and control groups. The graphs for patents and citations, depict parallel trends before the termination and a drop in the outcome variable for the terminated observations while the estimation for the control group of non-terminated observations remains stable. On the other hand, the graphs for self-appropriation and technological diversity show a drop after the termination, but also reveal strong pre-termination trends, thus violating the parallel trend assumption.

------------------------
Insert Table 4 & Figure 1
------------------------

Table 5 shows the results for the conditional DID using the Kernel matching and the Nearest-Neighbor matching. Supporting the earlier findings of the conventional DID estimation, we find a significant negative effect of the alliance terminations for innovation performance and firm learning, but not for partner learning.

------------------------
Insert Table 5
------------------------

**Exploration of Alliance Characteristics**

Our previous analysis controlled for time invariant alliance characteristics to better isolate the termination effects. However, following previous discussion in the alliance literature we now
explore three main alliance characteristics which could impact our average treatment effect of alliance termination.

**Alliance governance.** R&D alliance governance can range from unilateral contracts to equity based agreements and studies on the conditions fostering interfirm learning during the strategic alliance life have found a significant positive influence of joint venture governance (e.g. Chen, 2004; Gomes-Casseres, 2006; Mowery et al., 1996). The organizational embeddedness of joint venture arrangements is cited to better facilitate the transfer of tacit knowledge and create more opportunities for knowledge transfer (Kogut, 1988). The intense collaboration and embeddedness of joint ventures might lead to the persistence of social contact and relationships. Individual relationships that survive the termination of the alliance (Berends et al., 2011) would provide a channel for knowledge exchange and interfirm learning despite the removal of the alliance. Additionally, the close contact between firms during the joint venture may lead former partners to devote more attention to monitoring knowledge output of the other firm. Finally, former joint venture partners may have a relatively better understanding of the other’s knowledge after deep collaboration, thus enhancing learning from the partner knowledge base despite the termination.

On the other hand, the removal of the joint venture arrangements would strip the partners of the enriched mechanisms promoting increased learning between partners of joint ventures over contract alliances. Additionally, joint ventures can also be used to separate firms’ main activities from the alliance to protect the firm from unintended knowledge spillover beyond the alliance scope (Oxley & Wada, 2009). This implies that, while firms within a joint venture might have the enriched learning environment often described in the literature, they may also be more restricted to a specific knowledge area resulting in firms learning less about the other activities of their partner. Oxley and Wada (2009) provide evidence that joint venture governance positively impacts intended knowledge transfer while limiting spillover of knowledge outside the scope of the alliance. This finding would lead to the prediction that joint ventures will experience a sharper
decline in innovation and learning than contract based alliances as potentially unintended post-termination spillover may be more limited through the same mechanisms.

Similar to related studies on knowledge intense alliances (Oxley & Sampson, 2004; Phene & Tallman, 2012), we use the information from the SDC database to create a dummy variable, joint venture, to capture the alliance governance mode. This variable has value 1 if the alliance is a joint venture, and 0 for contract alliances. The variable enters the DID estimation only in the form of interaction effects with the dummy, alliance terminated, and the interaction with the DID estimator (interaction Alliance terminated. x treat. sample). The main effects of the joint venture variable is subsumed in the partner-alliance fixed effect.

Geographic Proximity. Various studies have examined the effects of geographic proximity on learning and knowledge exchange (e.g. Agrawal, Cockburn, & McHale, 2006; Singh, 2005). Fewer studies address how the geographic effect interacts with the formation of strategic alliances (e.g. Bell & Zaheer, 2007; Gomes-Casseres et al., 2006; Hohberger, 2014; Rosenkopf & Almeida, 2003) but arrive at the conclusion that geographic proximity accentuates the positive effect of alliance formation on interfirm learning. The argument follows that if knowledge is embedded in the local context, geographic proximity reduces the cost of access and increases the frequency of contact between alliance partners. Regarding the effect on termination and learning, since face-to-face interactions particularly promote tacit learning, the higher likelihood of personal contact between former partners located in the same geographic region suggests a reduction in the negative impact of termination. Increased frequency of personal contact between organizational members during the alliance period would also help build social relationships that are more likely to be resilient to the removal of interfirm agreements. Moreover, firms exploit regional relationships to access knowledge from other local firms, whether or not former partners (e.g. Almeida, Dokko, & Rosenkopf, 2003). Geographic context is

---

6 The interpretation of interaction terms in nonlinear models is often non-intuitive and more complex than in linear models (Ai and Norton, 2003), however, Puhani (2008) demonstrates that these concerns are not relevant for treatment effects in nonlinear difference-in-differences models.
relatively stable as it is not mere location that facilitates interfirm learning, but the more challenging process of establishing relationships in regional networks to become embedded (Saxenian, 1994). In sum, we expect partners embedded in the same regional cluster are better positioned to continue to monitor, understand and communicate with one another, thus reducing the impact of termination.

To account for geographic proximity, we created a binary variable to indicate whether the partner firms are located in the same geographic region. Following previous studies (e.g. Rosenkopf & Almeida, 2003) regions were defined as states within the United States and countries outside the United States. The only exception was New York, New Jersey, Connecticut, and Pennsylvania that was combined into one region. The focal and partner firm regional locations were obtained from the SDC database. If the alliance dyad participant firms were in the same region, the geographic proximity was set to 1, otherwise 0. As a robustness test, we also measured the geographic distance between the alliances partners in kilometers (km) and the logarithm of kilometers.

**Direct competitor alliance.** Innovation and learning studies have suggested that direct competitor alliances may hold increased opportunities for knowledge recombination afforded by the increased overlap of knowledge bases of firms competing in the same space. For example, Baum et al (2000) find the positive influence of R&D cooperation on innovation performance is strongest for partnerships between competitors. Christoffersen's (2013) review on alliance performance supports the positive influence of partner competition citing the ease of transfer of knowledge and resources for firms in the same industry. Research on alliance termination has pointed to the influence of partnering with direct competitors on both the achievement of knowledge outcomes and the propensity for termination (e.g. Hamel, 1991; Park & Russo, 1996). For example, Hamel (1991) suggests that the ease of learning generates instability as partners absorb knowledge and abandon partners. Cui et al (2011) finds direct-competitor partnerships have a higher termination propensity due to partner imitative activities that reduce the
uniqueness of alliance resources. Considering post-termination effects, organizational theorist predictions of detrimental effects of termination are often rooted in these potential dangers of coopetition. One may argue that when the incentive to collaborate is removed, as with the disbandment of an alliance, competitive dynamics prevail. Therefore, an organization may be more vulnerable to past partners’ absorption and appropriation of knowledge as it could be leveraged to compete in the same technologies and markets. Competition would then intensify following the alliance termination accentuating the impact on innovation and learning. Similar to Cui et al (2011), we accounted for cross-industry alliances using a dummy, which takes the value of 1 if the partner firm has the same primary SIC codes or 0 otherwise. The SIC codes of the participant firms were drawn from the SDC database.

Table 6 shows the results for the exploratory analysis of alliance governance, geographic proximity and competitor-alliances for the estimation with the random termination year for the non-terminated alliances. For space considerations, we only show the DID relevant coefficients corrected for the sign-of-life control estimations. We do not find significant differences between joint ventures and contractual alliances in terms of changes in innovation and learning patterns upon termination (Panel A). Similarly, the exploration of geographic location (Panel B) reveals only a limited amount of significant differences in the before and after comparison. We find negative significant results for cross citations (Model 6a) and self-appropriation (Model 4a and Model 4b). Finally, in the analysis of direct competitor alliances (Panel C), we find only weak significant results for cross citations and common citations (Model 2b and Model 6b). In summary, the results of the three additional alliance characteristics show only very limited influence on the impact of termination on innovation and learning outcomes.
DISCUSSION

This study provides initial exploration of innovation and learning following the termination of strategic alliances. Scattered empirical evidence on the consequences of exit from interfirm collaboration has demonstrated an impact of termination on dimensions of future organizational performance (e.g. Singh & Mitchell, 1996; Zhelyazkov & Gulati, 2016) but left open the examination of the implications on firm evolution in key domains such as innovation and learning. The answers provided herein have important implications for theory and practice on strategic alliances. From an organizational theory perspective, we uncover a shift in boundary decisions and resource configurations (knowledge sourcing), which are central to most theories of the firm. Moreover, our evidence supports the argument that termination is a key piece of the alliance puzzle often neglected by scholars that must be accounted for when measuring alliance activity and the net impact of alliances.

Our results show the removal of formal alliance agreements reduces innovation and technological diversity and suggest the rate of decay accelerates the more years that have passed since termination. We find no pre-trend in innovation performance indicating that a decline in innovation is not driving the termination. Some evidence of a pre-trend in firm learning measured as self-appropriation and technological diversity suggests that changes in the propensity to seek external and diverse knowledge also drive the decision to terminate an alliance as predicted by extant research on termination antecedents (Hamel, 1991; Nakamura et al., 1996). Nonetheless, the significant drop post termination and coefficients across time demonstrate an acceleration in the trend. The unexpected finding of a decline in self-appropriation post-termination, taken together with the decline in technological diversity, suggests that learning becomes more external and focused prior to and following termination, which may be highly relevant for firms in dynamic knowledge intense industries. The mixed results for the decline in partner based learning is also noteworthy as it demonstrates no clear reduction in building on partner related knowledge post termination. This likely signals partner based learning is more subject to the individual and
firm level mechanisms proposed as drivers of continued knowledge access and integration. The preliminary findings of a non-significant influence of alliance governance, geographic proximity and direct-competitor alliances suggest the impact of these factors on innovation and learning may be constrained to the active alliance life.

These findings relate to other studies that explore alliance termination consequences and interfirm learning. The high-level conversation on the link between termination and firm performance such as survival (Singh & Mitchell, 1996) and shareholder value (Reuer, 2001) is broken down to shed light on innovation and learning, which has been proven instrumental for firm performance (Powell et al., 1996; Stuart, 2000). The observed decline in innovation performance aligns with the assumption of termination as a downward driving force, reversing alliance facilitating impact. In line with research that shows the reciprocal influence of alliance termination on future alliance formation (Zhelyazkov & Gulati, 2016) and termination (Heimerick, 2014; Pangarkar, 2009), we illustrate more external and focused firm learning paths are forged following termination. These new learning paths are not only likely to influence subsequent firm evolution, but also new alliance formations and terminations. Our results also speak to the body of literature on innovation and learning outcomes in alliances by uncovering long term alliance effects and offering further evidence of the positive impact of alliance life exposed by its death.

Since innovation and learning involves building on existing and dispersed knowledge, the choice of knowledge sources is crucial for the pursuit of organizational learning. As firms consider alternative knowledge sources and innovation strategies, a more complete understanding of the net and long-term impact of strategic alliances is crucial. The temporal nature of hybrid organizational forms and the degree of permeability of boundaries are important for organizational outcomes as the costs of coordination, combination and communication of knowledge are key drivers of firm boundary decisions (Kogut & Zander, 1996). The termination of an alliance often signals a desire to intensify or reduce firm activities in a specific
technological or market space, and are here shown to produce shifts in the preference for different external knowledge sources such as technologically diverse knowledge. The abrupt negative impact of alliance termination on innovation performance corroborates concerns on the disruptive effects of termination. The non-significant decline in partner based learning post termination reiterates concerns of spillover after break-up (e.g. Park & Ungson, 2001), but also suggests useful former partner knowledge may be available for recombination (Yang et al., 2010) without the costly alliance structure.

**Limitations and Future Research**

This study bears several limitations that point to various avenues of future research. Future work should aim to further nuance the exploration of this effect by examining the underlying mechanisms that may drive the residual learning, such as individual scientific collaborations and mobility events, and by linking termination to changes in competitive positions. In addition, exploration of firm technological trajectories and connections to other dimensions of firm innovation strategy such as acquisitions may also prove helpful in elucidating the relationship between alliance termination, and innovation and learning.

Furthermore, the exploration of constructs related to embeddedness and networks, or contextual factors such as institutions and cultures, would further elucidate the implications of termination on innovation and learning and provide an opportunity to advance theory on organizations and their environment. Finally, our use of mostly secondary data and patent measures has some inherent weaknesses justified in this study by the advantages of non-subjective measures of innovation and learning. Still, future inquiry of this underexplored phenomenon would be well-suited for survey and qualitative research.
REFERENCES


http://doi.org/10.1057/jibs.2011.53


FIGURES

Figure 1: Lead- and lag graph

- Patents
- Citations
- Self Approp.
- Techn. Diversity
- Common citations
- Cross citations

Non-term. | Terminated
Table 1: Standardization of Alliance Termination Years

<table>
<thead>
<tr>
<th>Year</th>
<th>1997</th>
<th>1998</th>
<th>1999</th>
<th>2000</th>
<th>2001</th>
<th>2002</th>
<th>2003</th>
<th>2004</th>
<th>2005</th>
</tr>
</thead>
<tbody>
<tr>
<td>Termination year</td>
<td>-3</td>
<td>-2</td>
<td>-1</td>
<td>0</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
</tr>
<tr>
<td>Alliance terminated</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

Table 2: Descriptive Statistics Alliance Level

<table>
<thead>
<tr>
<th>Variable</th>
<th>Alliance (total)</th>
<th>Alliance (treatment group)</th>
<th>Alliance (control group)</th>
<th>Control-treatment</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>n</td>
<td>Mean</td>
<td>S.E.</td>
<td>Min</td>
</tr>
<tr>
<td>Patents</td>
<td>1603</td>
<td>29.55</td>
<td>61.86</td>
<td>0.00</td>
</tr>
<tr>
<td>Forward citations</td>
<td>1603</td>
<td>16.18</td>
<td>35.79</td>
<td>0.00</td>
</tr>
<tr>
<td>Self-citations</td>
<td>1603</td>
<td>0.08</td>
<td>0.14</td>
<td>0.00</td>
</tr>
<tr>
<td>Diversity</td>
<td>1603</td>
<td>0.28</td>
<td>0.21</td>
<td>0.00</td>
</tr>
<tr>
<td>Cross citations</td>
<td>1603</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
</tr>
<tr>
<td>Common citations</td>
<td>1603</td>
<td>0.01</td>
<td>0.03</td>
<td>0.00</td>
</tr>
<tr>
<td>R&amp;D expenses</td>
<td>950</td>
<td>1.19</td>
<td>17.67</td>
<td>0.00</td>
</tr>
<tr>
<td>Employees</td>
<td>918</td>
<td>0.02</td>
<td>0.03</td>
<td>0.00</td>
</tr>
<tr>
<td>Sales</td>
<td>954</td>
<td>22.43</td>
<td>493.18</td>
<td>0.00</td>
</tr>
<tr>
<td>Advertising</td>
<td>950</td>
<td>0.20</td>
<td>0.57</td>
<td>0.00</td>
</tr>
<tr>
<td>Cash flow</td>
<td>903</td>
<td>0.28</td>
<td>0.77</td>
<td>-4.29</td>
</tr>
<tr>
<td>Alliances</td>
<td>1603</td>
<td>1.09</td>
<td>1.37</td>
<td>0.00</td>
</tr>
<tr>
<td>Techn. Distance</td>
<td>1603</td>
<td>0.57</td>
<td>0.21</td>
<td>0.00</td>
</tr>
<tr>
<td>Alliance governance</td>
<td>1603</td>
<td>0.11</td>
<td>0.31</td>
<td>0.00</td>
</tr>
<tr>
<td>Competitor alliance</td>
<td>1603</td>
<td>0.69</td>
<td>0.46</td>
<td>0.00</td>
</tr>
<tr>
<td>Geographic location</td>
<td>1603</td>
<td>0.13</td>
<td>0.33</td>
<td>0.00</td>
</tr>
</tbody>
</table>

p-values in parentheses, * p<0.1, ** p<0.05, *** p<0.01
Table 3: DID Main Estimation

<table>
<thead>
<tr>
<th>Dependent variable</th>
<th>Model</th>
<th>Panel A: Not corrected for &quot;Sign of Life&quot;</th>
<th>Panel B: Corrected for &quot;Sign of Life&quot;</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Alliance term. x treat. n</td>
<td>Alliance term. x treat. n</td>
</tr>
<tr>
<td>Patents</td>
<td>1a</td>
<td>0.025 -0.399*** 7,564</td>
<td>0.027 -0.401*** 8835</td>
</tr>
<tr>
<td></td>
<td>1b</td>
<td>-0.470 0.000 -0.154* 4,025</td>
<td>-0.363 0.000</td>
</tr>
<tr>
<td></td>
<td>2a</td>
<td>-0.258 -0.054 -0.470 0.000 -0.363 0.000</td>
<td>-0.264 -0.044 -0.680*** 8306</td>
</tr>
<tr>
<td>Citations</td>
<td>2b</td>
<td>0.058 -0.217** 8,403</td>
<td>0.058 -0.310*** 4417</td>
</tr>
<tr>
<td></td>
<td>3a</td>
<td>0.117** -1.135*** 12,522</td>
<td>0.033 -1.052*** 6484</td>
</tr>
<tr>
<td></td>
<td>3b</td>
<td>-0.010 0.000 0.194*** -0.859*** 6,887</td>
<td>-0.541 0.000 0.131** -0.899*** 3667</td>
</tr>
<tr>
<td></td>
<td>4a</td>
<td>0.003 -0.353*** 17,489</td>
<td>0.036** -0.386*** 8282</td>
</tr>
<tr>
<td></td>
<td>4b</td>
<td>-0.849 0.000 -0.128 -0.017</td>
<td>-0.023 0.000 -0.128 -0.017</td>
</tr>
<tr>
<td></td>
<td>5a</td>
<td>0.033 -0.362* 2,822</td>
<td>0.178 -0.508** 1506</td>
</tr>
<tr>
<td></td>
<td>5b</td>
<td>-0.710 -0.083 -0.541 -0.437</td>
<td>-0.189 -0.029 0.117 0.037 956</td>
</tr>
<tr>
<td></td>
<td>6a</td>
<td>-0.057 -0.605*** 6,080</td>
<td>-0.016 -0.647*** 3180</td>
</tr>
<tr>
<td></td>
<td>6b</td>
<td>-0.358 0.000 -0.028 -0.213</td>
<td>-0.842 0.000 -0.028 -0.213</td>
</tr>
<tr>
<td></td>
<td></td>
<td>-0.733 -0.324</td>
<td>-0.627 -0.232</td>
</tr>
</tbody>
</table>

Note: *** p<0.01, ** p<0.05, * p<0.1, All models are performed with alliance-partner fixed effects and year fixed effects, model 1a-6a without control variables and full sample size, model 1b-6b with control variables and reduced sample size.
<table>
<thead>
<tr>
<th>Dependent variable</th>
<th>Model</th>
<th>Panel A: Not corrected for &quot;Sign of Life&quot;</th>
<th>Panel B: Corrected for &quot;Sign of Life&quot;</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Term. x treat.</td>
<td>Term. x treat.</td>
</tr>
<tr>
<td>Patents</td>
<td>1a</td>
<td>0.214***</td>
<td>0.156**</td>
</tr>
<tr>
<td></td>
<td>1b</td>
<td>-0.017</td>
<td>-0.044</td>
</tr>
<tr>
<td></td>
<td>2a</td>
<td>0.318***</td>
<td>0.300***</td>
</tr>
<tr>
<td></td>
<td>2b</td>
<td>-0.003</td>
<td>-0.040</td>
</tr>
<tr>
<td>Citations</td>
<td>3a</td>
<td>0.720***</td>
<td>0.664***</td>
</tr>
<tr>
<td></td>
<td>3b</td>
<td>0.549***</td>
<td>0.604***</td>
</tr>
<tr>
<td></td>
<td>4a</td>
<td>0.185***</td>
<td>0.184***</td>
</tr>
<tr>
<td></td>
<td>4b</td>
<td>0.081</td>
<td>0.123**</td>
</tr>
<tr>
<td>Self approp.</td>
<td>5a</td>
<td>-0.153</td>
<td>-0.014</td>
</tr>
<tr>
<td></td>
<td>5b</td>
<td>-0.320</td>
<td>0.097</td>
</tr>
<tr>
<td>Techn. Diversity</td>
<td>6a</td>
<td>-0.469</td>
<td>-0.267</td>
</tr>
<tr>
<td></td>
<td>6b</td>
<td>-0.726</td>
<td>-0.397</td>
</tr>
<tr>
<td>Common IPC</td>
<td>6a</td>
<td>0.230</td>
<td>0.239</td>
</tr>
<tr>
<td></td>
<td>6b</td>
<td>-0.381</td>
<td>-0.261</td>
</tr>
<tr>
<td></td>
<td></td>
<td>-0.475</td>
<td>-0.423</td>
</tr>
</tbody>
</table>

Note: *** p<0.01, ** p<0.05, * p<0.1, All models are performed with alliance-partner fixed effects and year fixed effects, model 1a-6a without control variables and full sample size, model 1b-6b with control variables and reduced sample size.
Table 6 Conditional DID

<table>
<thead>
<tr>
<th>Variable</th>
<th>Kernel matching</th>
<th>Nearest neighbor matching</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>n       ATT     St. Er.</td>
<td>ATT     St. Er.</td>
</tr>
<tr>
<td>Patents</td>
<td>865     -14.043 2.87***</td>
<td>865     -14.091 2.37***</td>
</tr>
<tr>
<td>Forward citations</td>
<td>865     -11.680 1.78***</td>
<td>865     -11.739 1.46***</td>
</tr>
<tr>
<td>Citations per patent</td>
<td>865     -0.310  0.03***</td>
<td>865     -0.344  0.02***</td>
</tr>
<tr>
<td>Self-citations</td>
<td>865     -0.068  0.01***</td>
<td>865     -0.080  0.01***</td>
</tr>
<tr>
<td>Diversity</td>
<td>865     -0.153  0.02***</td>
<td>865     -0.160  0.01***</td>
</tr>
<tr>
<td>Cross citations</td>
<td>865     0.000   0.00</td>
<td>865     0.000   0.00</td>
</tr>
<tr>
<td>Common citations</td>
<td>865     -0.003  0.00*</td>
<td>865     -0.001  0.00</td>
</tr>
</tbody>
</table>

Note: ATT = average treatment effect on the treated, matching variables & bias correction: R&D expenses, Employees, Sales, Advertising, Cash flow, Alliances; exact-match variables: Joint Venture, Direct Competitor alliance, Geographic location; number of comparison units: 3; * p<0.1, ** p<0.05, *** p<0.01
Table 6: Exploration alliance governance, geographic location and competitor alliances

<table>
<thead>
<tr>
<th>Variables</th>
<th>Patents</th>
<th>Citations</th>
<th>Self appropriation</th>
<th>Techn. Diversity</th>
<th>Cross citations</th>
<th>Common IPC</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model</td>
<td>1a</td>
<td>1b</td>
<td>2a</td>
<td>2b</td>
<td>4a</td>
<td>4b</td>
</tr>
<tr>
<td><strong>Panel A: Alliance governance</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Alliance terminated</td>
<td>0.020</td>
<td>0.035</td>
<td>0.025</td>
<td>0.055</td>
<td>0.029</td>
<td>0.153**</td>
</tr>
<tr>
<td></td>
<td>-0.530</td>
<td>-0.389</td>
<td>-0.534</td>
<td>-0.218</td>
<td>-0.617</td>
<td>-0.017</td>
</tr>
<tr>
<td>Alliance terminated x treatment</td>
<td>-0.394***</td>
<td>-0.152*</td>
<td>-0.670***</td>
<td>-0.316***</td>
<td>-1.073***</td>
<td>-0.934***</td>
</tr>
<tr>
<td></td>
<td>0.000</td>
<td>-0.062</td>
<td>0.000</td>
<td>-0.001</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>Alliance governance x alliance terminated</td>
<td>0.088</td>
<td>0.092</td>
<td>0.125</td>
<td>0.023</td>
<td>0.045</td>
<td>-0.236</td>
</tr>
<tr>
<td></td>
<td>-0.289</td>
<td>-0.400</td>
<td>-0.253</td>
<td>-0.830</td>
<td>-0.753</td>
<td>-0.264</td>
</tr>
<tr>
<td>Alliance governance x alliance terminated x treatment</td>
<td>-0.085</td>
<td>-0.032</td>
<td>-0.107</td>
<td>0.042</td>
<td>0.213</td>
<td>0.391</td>
</tr>
<tr>
<td></td>
<td>-0.630</td>
<td>-0.881</td>
<td>-0.668</td>
<td>-0.863</td>
<td>-0.360</td>
<td>-0.169</td>
</tr>
<tr>
<td><strong>Panel B: Geographic location (state)</strong></td>
<td>8835</td>
<td>4623</td>
<td>8306</td>
<td>4417</td>
<td>6484</td>
<td>3667</td>
</tr>
<tr>
<td>Alliance terminated</td>
<td>0.025</td>
<td>0.046</td>
<td>0.038</td>
<td>0.069</td>
<td>0.008</td>
<td>0.095</td>
</tr>
<tr>
<td></td>
<td>-0.431</td>
<td>-0.244</td>
<td>-0.338</td>
<td>-0.106</td>
<td>-0.885</td>
<td>-0.146</td>
</tr>
<tr>
<td>Alliance terminated x treatment</td>
<td>-0.388***</td>
<td>-0.166**</td>
<td>-0.655***</td>
<td>-0.316***</td>
<td>-0.961***</td>
<td>-0.807***</td>
</tr>
<tr>
<td></td>
<td>0.000</td>
<td>-0.042</td>
<td>0.000</td>
<td>-0.001</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>Geo. location x alliance terminated</td>
<td>0.021</td>
<td>-0.029</td>
<td>-0.022</td>
<td>-0.106</td>
<td>0.211</td>
<td>0.350**</td>
</tr>
<tr>
<td></td>
<td>-0.834</td>
<td>-0.847</td>
<td>-0.845</td>
<td>-0.499</td>
<td>-0.208</td>
<td>-0.031</td>
</tr>
<tr>
<td>Geo. location x alliance terminated x treat.</td>
<td>-0.122</td>
<td>0.095</td>
<td>-0.221</td>
<td>0.040</td>
<td>-0.738***</td>
<td>-0.700***</td>
</tr>
<tr>
<td></td>
<td>-0.547</td>
<td>-0.629</td>
<td>-0.388</td>
<td>-0.867</td>
<td>-0.007</td>
<td>-0.019</td>
</tr>
<tr>
<td><strong>Panel C: Competitor alliance</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Alliance terminated</td>
<td>0.015</td>
<td>0.073</td>
<td>0.033</td>
<td>0.070</td>
<td>0.045</td>
<td>0.103</td>
</tr>
<tr>
<td></td>
<td>-0.753</td>
<td>-0.259</td>
<td>-0.598</td>
<td>-0.362</td>
<td>-0.655</td>
<td>-0.396</td>
</tr>
<tr>
<td>Alliance terminated x treatment</td>
<td>-0.408***</td>
<td>-0.284***</td>
<td>-0.734***</td>
<td>-0.535***</td>
<td>-1.181***</td>
<td>-1.107***</td>
</tr>
<tr>
<td></td>
<td>0.000</td>
<td>-0.010</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>Competitor partn. x alliance terminated</td>
<td>0.018</td>
<td>-0.043</td>
<td>0.005</td>
<td>-0.017</td>
<td>-0.018</td>
<td>0.038</td>
</tr>
<tr>
<td></td>
<td>-0.773</td>
<td>-0.597</td>
<td>-0.952</td>
<td>-0.850</td>
<td>-0.884</td>
<td>-0.784</td>
</tr>
<tr>
<td>Competitor partn. x alliance terminated x treat. sample</td>
<td>0.012</td>
<td>0.191</td>
<td>0.080</td>
<td>0.322*</td>
<td>0.204</td>
<td>0.340</td>
</tr>
<tr>
<td></td>
<td>-0.923</td>
<td>-0.182</td>
<td>-0.614</td>
<td>-0.052</td>
<td>-0.270</td>
<td>-0.112</td>
</tr>
</tbody>
</table>

Note: *** p<0.01, ** p<0.05, * p<0.1. All models are performed with alliance-partner fixed effects and year fixed effects, model 1a-9a without control variables and full sample size, model 1b-9b with control variables and reduced sample size.
APPENDIX

Figure A1: Distribution of the propensity scores – Common Support

Table A1: Indicator matching quality

<table>
<thead>
<tr>
<th>Sample</th>
<th>Unmatched</th>
<th>Matched</th>
</tr>
</thead>
<tbody>
<tr>
<td>R2</td>
<td>0.018</td>
<td>0.005</td>
</tr>
<tr>
<td>$\chi^2$</td>
<td>34.17</td>
<td>8.38</td>
</tr>
<tr>
<td>p&gt; $\chi^2$</td>
<td>0</td>
<td>0.3</td>
</tr>
<tr>
<td>MeanBias</td>
<td>8.4</td>
<td>6</td>
</tr>
</tbody>
</table>

Note: Graph was generated using the STATA command psgraph