The Dynamics of Strategic Alliances: Theory and Experimental Evidence

August 2016

1 Introduction

Strategic alliances, broadly defined as voluntary cooperative inter-firm agreements with the goal of creating economic value (Gulati and Singh 1998; Agarwal, Croson, and Mahoney 2010), are used to pursue strategic aims that require input by multiple partners that all expect to benefit from the alliance (Gulati, Wohlgezogen, and Zhelyazkov 2012; Garrette, Castañer, and Dussauge 2009). Interestingly, many strategic alliances are formed among competitors within the same (or a closely related) product market. Examples for such competitive alliances include *Nissan* and *Renault* collaborating on the development of joint product platforms (Segrestin 2005), or the *Sony Ericsson Mobile Communications* joint venture that aimed, among other motives, at facilitating market access to the respective firms' home markets, Japan and Europe.

Strategic alliance research reports failure rates often well in excess of 50% (Kale, Dyer, and Singh 2002; Lunnan and Haugland 2008). Hence, despite their potential expected at the outset, alliances often produce disappointing outcomes (Kale and Singh 2009; Kogut 1989; Park and Ungson 1997; Park and Russo 1996; Reuer and Zollo 2005), which has led to extensive research studying the success and failure of strategic alliances. One broad stream of research examines the role of alliance configurations and governance for alliance success.[1] Within this stream, literature on the configuration of strategic alliances specifically focuses on the design of hierarchical structures in alliances (Gulati et al. 1998) and the choice of optimal alliance configurations conditional on the type of challenge faced by the alliance – transaction cost and opportunistic behavior, or coordination challenges (Gulati 1995; Baker, Gibbons, and Murphy 2008). A second extensive stream of research looks at the process of strategic alliances, i.e. how they are managed and how this generates long-term success (Ariño and De la Torre 1998; Doz 1996; Lokshin, Hagedoorn, and Letterie 2011; Malhotra and Lumineau 2011). Both lines of research differ in their focus while acknowledging that they interact – that is, alliance configurations are chosen to put mechanisms in place to manage the anticipated problems arising in specific alliances. Along similar lines, the management of alliances is influenced by the configuration parameters put in place at the start of the alliance.

Scholars of alliance governance often sidestep the process aspect of alliances because the contractual design and the subsequent hierarchical structure of an alliance puts in place a (static) set of rules that is then expected to persist over the entire alliance duration. Other aspects of alliance configurations, such as the number of alliance partners or the ease of leaving the alliance, might not matter when the alliance is going as planned, but they might have an impact on *how* the alliance is played, i.e. whether the alliance is likely to go as planned. For example, multiparty alliances appear very similar to bilateral alliances when they are successful, but multiple partners are more likely to have diverging interests or might form expectations about their partners' collective behavior differently. Similarly, if an alliance is going well, there is no need for a breakup option, but once cooperation breaks down, the cost of breaking up an alliance might well determine if it indeed dissolves or not. Moreover, this anticipated "off-equilibrium" behavior may in turn affect the likelihood of cooperation in the first place. Hence, alliance configurations, alliance dynamics and ultimately alliance success are intricately linked to each other.

[1] We define *alliance configurations* as the set of choice variables for an alliance as opposed to the narrower term *alliance governance*, which describes the "formal contractual structure participants use to formalize [an alliance]" (Gulati et al. 1998).

We capture some of the essential rules of interaction among alliance partners in unstructured collaborations, joint ventures and multi-party consortia. First, the key difference between an unstructured collaboration and a joint venture is the level of commitment involved: while an unstructured collaboration can be dissolved relatively easily and typically does not involve the setup of a new legal entity or alliance-specific investments, a joint venture involves just that, which in turn implies a more complicated process of dissolving a joint venture. We proxy for this difference as a breakup cost that is zero for unstructured collaborations and positive for joint venture. Second, we compare bilateral and multiparty alliances. Multi-party consortia can come in different forms: They could be relatively loose collaborations of a group of firms that can be dissolved easily, similar to an unstructured collaboration. A standard-setting organization or an industry network initiated to promote the diffusion of a new platform technology would be examples of that. On the other hand, multi-party joint ventures involve the co-investment of a larger number of partners, again making the dissolution more costly than for a multi-party unstructured collaboration.

In sum, we combine work on alliance configuration and alliance dynamics by studying the aggregate performance and dynamic behavior of different alliance configurations in two different environmental states, high and low product market competition. We identify the key challenges underlying the respective environmental states by means of a formal model and subsequently study different alliance configurations in a lab experiment. We use a $2 \times 2 \times 2$ setup (high/low competition, bilateral/multilateral, high/low commitment) capturing both competitive environment and alliance configurations and study both *alliance dynamics* as disaggregated measures of alliance stability and forgiveness and ultimately *alliance performance* as an aggregate measure over the entire course of the alliance. Observing behavior during an alliance – conditional on the alliance configuration – tells us about the effect of alliance configurations on alliance partners' behavior, and the aggregate outcomes of exogenously assigned alliance configurations inform us about the effects of key alliance parameters, specifically the number of alliance partners and the level of commitment of the partners, on alliance performance.

Fieldwork often faces the problem that alliance configurations are chosen conditional on environmental states and anticipated performance. In contrast, our setup lets us separate the alliance configuration choice from its expected performance implications — that is, in our experiment, we exogenously assign alliance configurations to different states of the competitive environment (Agarwal et al. 2010). Moreover, we can dig deeper into within-alliance dynamics, which typically requires detailed process data on individual alliances (Segrestin 2005; Ariño et al. 1998). In our setup, we have detailed information on a large number of identical (experimental) alliances. This lets us assess the impact of key alliance characteristics on different performance and behavioral metrics (Lunnan et al. 2008).

Our formal model shows that the relative importance of coordination problems and the danger of opportunistic behavior in an alliance can shift with a single parameter, the extent of competition in the product market. For relatively high levels of competition, opportunistic behavior is more important and strategic alliances will resemble a prisoner's dilemma. For low levels of competition, coordination considerations dominate and strategic alliances will be akin to a stag hunt game. Taking these two alliance environments (high and low competition) to the experimental data with our different alliance configurations, we find that the choice of alliance configuration matters greatly for alliance performance in high competition alliances, while low competition alliances perform at similar levels irrespective of the different alliance configurations. Regarding behavior in different phases of the alliance, we find that the strong differences in aggregate performance mainly stem corresponding differences in first-period behavior. Behavior in subsequent periods – most notably stability in cooperation, measured as the likelihood of continued cooperation in a successful alliance, and forgiveness, that is, cooperation following prior non-cooperation by alliance partners – shows similar qualitative patterns, but its importance in magnitude and significance is much lower than first-period behavior.

We contribute to the literature on strategic alliances in two important ways. First, we show that the impact of alliance configuration is conditional on the competitive environment the alliance partners encounter. Specifically, our two configuration elements, the number of partners and the level of commitment, matter greatly for alliances among close competitors, while they have a much more muted impact on the success of alliances among distant competitors. Second, we contribute to prior work on alliance dynamics by showing that first-period behavior determines long-term alliance success. Note that this result emerges from a setting in which the first and subsequent periods are economically no different, potential alliance benefits are well-known and actions easily observable and understandable. That is, even absent other factors that would render the early stages of an alliance more important does the first period play a disproportionate role in the success of an alliance.

2 Existing Literature

The literature on success and failure of strategic alliances is vast. Most relevant for our purposes, we identify three core themes in the literature: alliances among competitors, coordination challenges and opportunistic behavior, and alliance dynamics.

In strategic alliances among competitors, partners typically design safeguards or other mechanisms to reduce the detrimental effects of entering a close relation with competitors (Ariño et al. 1998; Dussauge, Garrette, and Mitchell 2000). Greve, Baum, Mitsuhashi, and Rowley (2010) report greater rates of alliance dissolution among closer competitors, suggesting that the degree of competition has a tangible impact on the performance of an alliance. Accordingly, firms aim to configure an alliance to offset these performance shortfalls, for example by creating a new collective identity (Segrestin 2005) or by requiring exclusivity from cospecialized alliance partners (Gimeno 2004). In experimental settings, Amaldoss, Meyer, Raju, and Rapoport (2000) and Amaldoss and Rapoport (2005) find that the division of post-alliance profits (proportional or equal, competitive or collaborative) matters for the degree of resource contribution to the alliance. Cui, Yang, and Vertinsky (2016) study the opposite causal direction, namely the effect of prior alliance behavior on subsequent competitive behavior. Along similar lines, Mitsuhashi and Greve (2009) study horizontal alliances in the liner shipping industry and quote one executive as saying that: "[t]he demerit of alliances is that they compromise our products.

Our historical strength through uniqueness becomes watered out because it is now available to everyone in the alliances." (Mitsuhashi et al. 2009: 982).

The key challenges in strategic alliances identified by practitioners and academic literature are the potential for opportunistic behavior and coordination problems (Gulati 1998). Early work on strategic alliances has emphasized alliance partners' concerns that their counterpart might appropriate much of the value (or knowledge) from an alliance through opportunistic behavior (Balakrishnan and Koza 1993; Pisano, Russo, and Teece 1988; Williamson 1991). This logic is reflected in work addressing mechanisms to overcome the threat of opportunistic behavior through repetition (Arend and Seale 2005) or trust (Das and Teng 1998). An alternative stream of research has focused on issues of coordination as key challenges to alliance success (Gulati 1995). More recently, however, these two views have been integrated and there is broad agreement that both problems and the corresponding solutions tend to be present in strategic alliances to varying degrees (Gulati et al. 1998; Agarwal et al. 2010; Kumar 2010a; Kretschmer and Vanneste 2016). Khanna, Gulati, and Nohria (1998) and Kumar (2010b) propose that it is the ratio of public to private benefits that determines the balance, a view formalized by Kretschmer et al. (2016) and Arslan (2016). Importantly, the literature agrees that opportunistic behavior and coordination problems can arise within the same setting and that their relative weight is a matter of degree rather than a strict separation.

Finally, in addition to the overall performance of alliances, there is a body of research that considers the dynamic properties, i.e. the alliance "behavior" rather than aggregate success. Much of this literature stream has focused on individual cases and/or on the dissolution of alliances. Regarding the former, Ariño et al. (1998) study the dynamics of a (failed) horizontal market-making alliance and find that there is a constant adjustment following alliance partners' actions and beliefs that contribute to reinforcing feedback loops – either positively or negatively (see also the review of the case-based literature on alliance dynamics by Majchrzak, Jarvenpaa, and Bagherzadeh (2015)). Further, there are some large-sample studies identifying the determinants of the dissolution of alliances in general and joint ventures in particular (Park et al. 1996; Park et al. 1997; Lokshin et al. 2011; Lunnan et al. 2008). Conceptually, Doz (1996) separates alliance behavior into two phases – the initial conditions and a learning phase. Doz (1996) illustrates how the two mutually affect each other, suggesting that alliance environment and configuration (i.e. the initial exogenous and endogenous conditions) impacts alliance dynamics. An emerging stream of research in this vein is the experimental literature studying repeated alliance games, often capturing a game-theoretical logic (Arend 2009). Fonti, Maoret, and Whitbred (2016) study multi-party alliances specifically, while Amaldoss and Staelin (2010); Amaldoss et al. (2000) and Agarwal et al. (2010) study two-player alliances.

Our study draws on all three perspectives. By developing a formal model in which an alliance can either be dominated by concerns over opportunistic behavior or coordination concerns depending on the degree of product-market competition, we take seriously the notion that both concerns can conceivably coexist in an alliance, depending on environmental (competition) parameters. Moreover, we explicitly combine product market competition and cooperative behavior in alliances, allowing us to address the interplay of competition and cooperation. We study both the overall success and the dynamic behavior within such alliances. Crucially, we isolate the behavioral aspects of alliances and abstract from issues of learning (Anand and Khanna 2000; Doz 1996; Khanna et al. 1998; Kale, Singh, and Perlmutter 2000), reputation (Arend 2009) or uncertain synergies (Segrestin 2005). That is, although in any given alliance these factors may plausibly make alliances more or less stable over time, we consider an alliance that stays unchanged from start to (an unspecified) finish to see if there are behavioral dynamics we need to consider.

3 Framework

We present a model of an alliance between two firms interacting and competing in the same product market over time. Our aim is twofold. We show first that the intensity of product market competition may affect the type of strategic interaction firms face within alliances. Indeed, in our framework, opportunistic behavior and coordination problems arise for "relatively strong" and "relatively weak" intensities of competition, respectively. Although we use a specific profit function of a demand-increasing alliance (e.g., a marketing alliance), these results hold in a more general setup with general profit functions and cost-reducing alliances, such as technology alliances (see Appendix B).

Our model also serves as a framework – and as a way to directly derive payoffs – for our experimental analysis, which focuses on the impact of two key features of strategic alliance configurations. As we describe below, we consider the possibility that the alliance involves some degree of commitment and the possibility that the alliance involves more than two partners. We use two representative levels of competition leading, respectively, to opportunistic behavior and coordination problems.

3.1 Basic Setup

We now describe the per-period actions and payoffs of two symmetric firms in a strategic alliance. Each of the two firms decides whether to "contribute resources" to the alliance (C) or not (nC) to increase demand for their products. C implies contributing to the alliance in the letter and spirit of the contractual agreement, nC means contributing to the alliance in the letter of the contractual agreement but not its spirit. For example, when contributing, a partner would staff its best personnel to the alliance, would actively promote the common brand to its customers, or would share its most up-to-date information with its partner. When not contributing, a partner would do none of these activities while still fulfilling the terms of the contract.

Synergies and full partnership value are only realized when both partners contribute resources (e.g. Hagedoorn 1993; Agarwal et al. 2010). In formal terms, the product market profits of each partner are given by $\pi\left(\widetilde{a}, m\right) = \widetilde{a} \cdot m$, where $\widetilde{a} > 0$ is the individual demand and $m > 0$ the per-unit price-cost margin, which decreases with the intensity of competition in the product market. Individual demand for each of the two partners is as follows:

$$\widetilde{a} = \begin{cases} a & \text{if none contributes} \\ a + k/2 & \text{if one contributes} \\ a + k + s & \text{if both contribute,} \end{cases}$$

where $a > 0$ is the baseline individual demand, $k/2 > 0$ are the (per-partner) gains of the individual contributions and $s > 0$ the (per-partner) "synergy" gains in excess of the individual contributions. The more dissimilar resources partners bring into the alliance, the more synergies s are present.

Alliance partners remain independent actors and retain control over their own resource contributions. We model this by assuming that each partner's decision to contribute resources requires a private cost of e monetary units. Decisions at each point in time are assumed to be taken simultaneously. Our model reflects thus the uncertainties resulting from difficulties in monitoring the behavior of alliance partners (e.g. Agarwal et al. 2010; Arend 2009). Indeed, many of the required "contributing " actions are simply too difficult to observe and describe in sufficient detail.[2] Action interdependencies make it even more difficult to measure separate contributions immediately (Gulati et al. 1998; Mesquita, Anand, and Brush 2008).

Figure 1a summarizes the payoffs of each firm as a function of both firms' choices within the alliance. As shown in the table, payoffs of a given partner depend not only on its own actions but also on its partner's actions.

[Figure 1 about here.]

In our model, partners benefit from the other's contributions. Indeed, the economic value created in alliances is shared, and alliance partners cannot be excluded from the benefits. We follow Dyer and Singh (1998: 666)'s concept of "complementary resource endowments" that "collectively generate greater rents than the sum of

[2]Some of these resource contributions may be contracted upon, but enforcing (near-)complete contracts is prohibitively expensive (Crocker and Reynolds 1993). For simplicity therefore, we assume resource contributions to be fully non-contractible.

those obtained from the individual endowments of each partner." Complementary resources have been widely discussed as a key factor in driving synergistic returns and the potential for rents from alliances.

3.2 Theoretical Results

We now show that the *degree of product market competition* affects the type of strategic interaction firms face within the alliance, and the resulting equilibrium actions (proof in Appendix A). Thus, competition will not only affect profits directly through margins, but also indirectly through resource contributions. We also compare the equilibrium outcomes to the Pareto efficient one.[3]

Proposition 1. There exist critical degrees of product market competition, represented by margins m_1^*, m_2^* and , m_3^*, such that alliances result in the following types of strategic interaction and equilibria:
(i) "*Prisoner's dilemma*" for $m_1^* < m < m_2^*$: no one contributing is an equilibrium, but it is Pareto-dominated by both contributing.
(ii) "*Stag hunt*" for $m_2^* < m < m_3^*$: there are two equilibria; both or no one contributing resources, whereby the former Pareto-dominates the latter.

If competition is strong and thus margins small (case (i)), there may be opportunistic behavior within the alliance. Rationally, firms should choose not to contribute resources, independent of what their partners do. Indeed, if competition is strong, firms gain from not contributing resources when their partners do so. However, it would be beneficial for each of them if they both contributed resources, because firms suffer a negative externality if their partner also chooses not to contribute.[4]

If competition is weak and thus margins high (case (ii)), contributing is better than not contributing whenever the other partner contributes as well. Alliances may

[3] We use thus the concept of *Pareto dominance*: a situation is Pareto dominant or Pareto efficient if it is impossible to make a partner better off without making the other worse off.

[4] There are two more strategic situations. First, if $m < m_1^*$, partners would not contribute resources nor would this be efficient. Second, if $m > m_3^*$, firms find it optimal to contribute resources independently of their partners actions, and it is efficient to do so. As both these situations pose no strategic challenges, we do not investigate these cases further.

as a result face coordination problems (Gibbons 1992; Gulati 1995). Although there is no real conflict of interest, partners may not be able to coordinate on the result where both contribute. Rationally, a partner will contribute resources if it believes the other does so as well. Note that the two partners may fail to achieve the potential gains of the alliance not because they have incentives to free ride off each other, but because they are uncertain about whether the other partner will contribute resources.

Consider the two parameterizations in Figure 1 (panels (b) and (c)), which also form the basis of our experimental analysis. In Figure 1b, we show a case of high competition and small margins, $m = 2/3$, whereas Figure 1c gives a case of low competition and high margins, $m = 1$. As the resulting threshold margins of Proposition 1 are $m_1^* = 0.55$, $m_2^* = 0.79$ and $m_3^* = 1.83$, these two levels of competition will lead to coordination problems and opportunistic behavior, respectively.[5]

3.3 Experimental Design

We now extend our setup to allow for dynamic interaction and the option to break up the alliance. In real-life alliances, alliance partners interact repeatedly, can change their decisions over time and react to partner's past choices. For example, a partner might start contributing resources but decide to stop doing so if its partner does not do so, or even decide to break up the alliance. Thus, we allow for a breakup option.[6]

Breakup option. In each period, the alliance can be broken up by any of the two firms (choose "B"). If any of them decides to do so, both of them obtain an outside option. In our baseline specification, breaking up the alliance is better than maintaining it if partners do not contribute resources. Specifically, we assume that

[5]As additional parameter values, we have taken a baseline demand of $a = 2.5$, gains of the individual contributions of $k/2 = 3$, synergy gains of $s = 4$, and private costs of contributing resources of $e = 5.5$ monetary units. All payoffs have been rounded to a multiple of 0.5 for the sake of clarity in the experiments.

[6]Moreover, this option makes it easier to compare our results with empirical papers; indeed, most of the empirical literature identifies an alliance's performance through its duration, as other measures are often unavailable. Perhaps surprisingly, we are aware of only one other theoretical/experimental paper on alliances that allows for firms to decide to be in or out of the alliance (Arend 2009).

the outside option of breaking up the alliance is equal to the profits of no resource contribution, $\pi(a, m)$. Maintaining the alliance, however, involves a fixed cost F to each partner, attributable to, e.g. buildings, machines, administration and other overhead needed to keep the alliance in place. We take $F = 0.5$, so that maintaining the alliance is better than breaking it up if partners contribute resources. Table 1 describes the resulting payoffs for each combination of actions.

[Table 1 about here.]

Dynamics. We model dynamics by considering an indefinite repetition of the decisions and payoffs described above, subject to an exogenous probability of termination at the end of each period. Alliance behavior then is equivalent to maximizing the discounted sum of stream of profits. We induce a discount factor of $\delta = 0.9$ by including an exogenous probability of termination of 0.1 at the end of each period. We modify this infinitely repeated setup slightly. We assume that if at least one partner breaks up the alliance in a given period (chooses B), the alliance ends and cannot be restarted later and both partners obtain the profits of the outside option from there on.[7]

3.4 Alliance configurations

Some alliance features may affect the strategic issues identified in Subsection 3.2. Some alliances involve greater degrees of commitment between alliance partners than others. Equity joint ventures, for example, are harder to break up and it is more difficult to step away than in "unstructured" alliances. Other alliances involve multiple partners. In "multilateral alliances", more than two partners are needed to generate the synergy gains. This section shows how we incorporate these alliance configurations into our framework.

[7] We also implicitly assume that per-period profits cannot be increased through cooperation in the product market. We do this to focus on the effects of repeated interaction within the alliance and not in the product market.

Commitment. We model the degree of commitment in the alliance through a one-off cost that both partners must pay if any of them decides to break up the alliance. We consider two treatments, one with a breakup cost of 0 ("low-commitment"), as described in the previous subsection, and another with a breakup cost of 10 ("high-commitment"). Taking into account the discount factor used, $\delta = 0.9$, a one-off breakup cost of 10 units is equivalent to an expected per-period breakup cost of 1 unit. Table 2 describes per-period expected payoffs of the "high-commitment" alliance in the low competition and high competition scenarios.

[Table 2 about here.]

Multilateral alliances. We distinguish between bilateral and multilateral alliances by analyzing alliances with two and three partners.[8] Synergies are realized only when all partners contribute resources. Individual demand of each of the three partners is as follows:

$$\widetilde{a} = \begin{cases} a & \text{if the alliance is terminated} \\ a + g \cdot k/3 & \text{if } 0 \leq g < 3 \text{ partners contribute} \\ a + k + s & \text{if the three partners contribute.} \end{cases}$$

Using the same parameter values as for two partners, Table 3 describes per-period expected payoffs for multilateral alliances with low and high commitment and in the low competition and high competition environments. Figure 2 summarizes the four different configurations, i.e. our combinations of commitment and number of players. We will use the following labels to identify our different alliance configurations. We label an alliance as BL when it is a bilateral low commitment alliance. Similarly, we use the labels BH (bilateral high commitment), ML (multilateral low commitment) and MH (multilateral high commitment).

[Table 3 about here.]

[Figure 2 about here.]

[8] To make the bilateral and multilateral treatments comparable, we augment each of the demand parameters at the aggregate level (baseline demand, gains of individual contributions and synergies), such that the individual demands for each combination of actions are comparable.

The experimental design outlined above gives us two alliance environments (high and low competition) and four alliance configurations outlined in Figure 2. We implemented this $2 \times 2 \times 2$ experimental setup at Melessa, the Experimental Social Sciences Laboratory at LMU Munich. All implementation details are given in Appendix C.

4 Results

We start by looking at the aggregate success of alliances, with a focus on *if* and *how* alliance configurations, i.e. levels of commitment and the number of partners, make a difference. We further investigate whether these have a differential impact depending on whether alliances are in low or high competition environments. We then study which dynamic decisions and decision rules by partners are affected by different environmental (competition) and configuration factors.

4.1 Alliance success

We consider two measures of aggregate alliance success, based on how often partners contribute resources and on whether alliances break up. Both dimensions are important in assessing alliance performance and of course easy to observe in a controlled experiment. First, we compute for each alliance the proportion of periods where all partners contribute. This measure indicates the success of an alliance relative to what could be obtained (if all partners contributed all the time). Second, we divide alliances into those that continue until the end of an interaction and those that break up prematurely.

Figure 3 shows levels of cooperation in low competition versus high competition alliances across our four different alliance configurations. It is clear that in general alliances where participants face low competition levels perform better than those where competition in product markets is high. The figure shows that the frequencies of cooperation in low competition alliances range between 75% (in the ML configuration) and more than 95% (in the BL and BH configurations). On the other hand, the fraction of cooperating high competition alliances is substantially lower and its range much wider: it goes from 12% (ML configuration), over 27% (MH configuration) and 63% (BL configuration), to reach almost 87% (BH). Interestingly, low competition alliances perform significantly better (with a 99% confidence interval as can be seen in the Figure) across all configurations, *except in BH alliances*. This last point is suggestive of a theme that will emerge strongly throughout our results: commitment has a strong effect on the success of high competition alliances; so much so that it can even level out the difference with respect to low competition alliances.

[Figure 3 about here.]

We now focus on how each alliance environment, i.e., low competition and high competition, performs across alliance configurations. Tables 4 and 5 summarize the results across alliance configurations and show non-parametric statistics that test for differences of these results across alliances configurations and environments; non-parametric test statistics are tests where we do not have to rely on assumptions that the data are drawn from a given probability distribution and are thus the most general type of tests one can perform. Panel (a) of Table 4 shows that for low competition alliances cooperation does not differ across different commitment levels, as can be seen in the Kolmogorov-Smirnov tests (K-S tests) in the right-most column.[9] The same panel (a) shows that cooperation levels are lower in multilateral than in bilateral alliances (see K-S tests in the bottom row). Panel (b) shows that for high competition alliances high commitment leads to more cooperation, whereas multiparty alliances do significantly worse; cooperation frequencies are much lower, dropping from an average of about 87% in the BH configuration to about 12% in the ML configuration, and all K-S tests of differences are significant.

[Table 4 about here.]

Panels (a) and (b) of Table 5 show a similar pattern for the frequency of breakups: for low competition alliances commitment makes no significant difference, whereas

[9] We have one value for each interaction and, hence, we can implement non-parametric comparisons of the entire distribution of cooperation across treatments by using the Kolmogorov-Smirnov test.

a higher number of partners leads to more frequent breakups (see χ^2 tests in the rightmost column and bottom row of panel (a)).[10] For example, bilateral alliances' breakup rates go from less than 4% in the BL configuration to exactly 2% in the BH configuration. Unsurprisingly, these differences are not significant. For high competition alliances, higher commitment leads to significantly less breakup. Indeed, the breakup frequency drops from almost 35% in BL alliances to about 5% in BH alliances and from almost 85% (ML) to less than 30% (MH) in multiparty alliances. The increase in breakups when going from two to more partners is equally pronounced and all differences are significant at the 1% level.

[Table 5 about here.]

In sum, commitment is a key factor in improving the performance of high competition alliances whereas commitment makes no difference in the performance level of low competition alliances. This leads us to the observation made above: Higher commitment improves high competition alliances' performance so much and low competition alliances' so little that their performance becomes virtually the same. When comparing bilateral and multiparty alliances – the other alliance configuration choice variable in our analysis – it shows that success is significantly lower as the number of partners increases from two to three. By all measures, multiparty alliances are significantly less successful than bilateral alliances.

The regressions reported in Table 6 summarize these results, while they allow us to further include control variables and take into account potential serial correlation within sessions. The first two columns of Table 6 show how our two measures of success – frequency of cooperation and probability of breakup – are determined by alliance configurations and level of competition. For the frequency of cooperation, we employ a simple OLS regression, whereas we estimate the probability of breakup via a logistic regression. Note that the coefficients of the logistic regression are expressed as odds ratios: a coefficient larger than 1 means that odds increase and a coefficient smaller than 1 means that the odds of breakup decrease. The baseline is a low

[10] Breakups are measured as frequencies across all interactions and, hence, comparisons are made using Pearson's χ^2 test.

competition BL alliance and coefficients should be measured against the success of this alliance environment and configuration.

[Table 6 about here.]

As can be seen from the first column of Table 6, higher commitment increases the frequency of success by 11%, having more partners in the alliance decreases it by almost 37% and being in a high competition alliance decreases it by 35%. Likewise, the second column shows that high commitment reduces the odds of breakup by about 97%, while being in a multiparty alliance increases the odds sevenfold, and operating a high competition alliance even by a factor of 12. All coefficients are significant at the 1% level.

When we include interaction effects (see columns three and four of Table 6), some interesting changes show up. Foremost, the main effect of a higher commitment disappears, but it is significant when interacted with high competition and its size effect increases. Column three shows a coefficient of 0.232 for cooperation frequencies in high competition high commitment alliances versus a general effect of only 0.11 of high commitment (see first column). Thus, commitment only influences alliance performance in high competition alliances. There is also an additional negative effect in high competition alliances of adding members for frequencies of cooperation (coefficient -0.316 in the third column, significant at the 1% level), but not for breakups. Other interaction effects are not significant.

4.2 Alliance Dynamics

We now dig deeper into the dynamics of alliance success to understand how different alliance environments (high or low competition) and configurations come to deliver the different aggregate success rates reported in the previous subsection. As a preliminary observation, Figure 4 shows first and foremost that breakup occurs earlier and more frequently for low commitment alliances, both for low competition and high competition alliances (panels (a) and (b), respectively). Further, when comparing high competition versus low competition, partners break up considerably earlier.[11]

[Figure 4 about here.]

We now divide the dynamic behavior of alliance partners into their initial phase – first period behavior – and their reactions to previous period outcomes. As we now look at reactions, we naturally make the individual choices the focus (as opposed to outcomes in the previous subsection).

4.2.1 First Period

As can be seen from panel (b) of Table 7, commitment significantly affects first period behavior in high competition alliances. Indeed, the distribution of actions has more C, less nC and less B (χ^2 tests in last column). These differences are strongest for bilateral alliances. On the other hand, there are no significant differences in the first period across different levels of commitment for low competition alliances (see frequencies of actions and χ^2 tests in panel (a)). The same patterns hold when comparing bilateral and multiparty alliances. As can be seen from the bottom rows of both panel (a) and (b), bilateral alliances perform better than multiparty alliances in the first period. This difference is more pronounced for high competition alliances; differences are significant at the 1% level whereas they are only significant at the 5% level for low competition alliances. In sum, the average effects identified in the previous section show up again very strongly in first-period behavior.

[Table 7 about here.]

4.2.2 Reactions: Stability and Forgiveness

We now focus on how partners react to previous outcomes. We consider two measures of *stability* and one measure of *forgiveness*. In terms of stability, we first look at how partners react after everyone cooperated in the previous period. This metric,

[11] These results also hold in a hazard rate regression with the different treatments and their interactions as explanatory variables for breakup occurrence and time (available from the authors).

therefore, looks at the stability of an alliance when it is going well, i.e. when everybody cooperates. Second, we look at breakup choices after one or two other partners chose to not contribute, whereas the focal partner did cooperate. This metric thus shows how stable an alliance is when it is vulnerable, i.e. continuation after one partner has not contributed. To capture forgiveness, we consider how likely the focal partner is to cooperate whenever one or more partners did not cooperate (but the focal partner did). This metric gives us insights on whether partners continue to cooperate even though their partner(s) cheated on them. While these are not the only reactions that can be studied, we feel that they are useful proxies for two behaviors of interest: keeping the alliance going and trying to get it working again. For completeness, although these are not discussed in the text, Table D.1 in Appendix D show frequencies of choices after all possible outcomes.

As can be seen from panel (a) of Table 8, for low competition alliances stability of cooperation is very high and above 99.6% in all cases. Moreover, both commitment and the number of partners have limited impact on whether partners continue to cooperate after everyone cooperated the previous period (see C choices and their corresponding χ^2 tests after $[C, C]$ or $[C, C, C]$).[12] Further, while we observe a higher breakup probability for lower commitment and multiparty configurations after (at least) one partner did not cooperate on the previous period, these differences are not significant (see B choices and corresponding tests). The same pattern can be observed for forgiveness: there is somewhat more cooperation after one of the partners cheated for high commitment and when being with less partners, but these differences are not significant. In sum, both stability and forgiveness do not differ substantially across alliance configurations when competition is low.

[Table 8 about here.]

When we look at high competition alliances (see panel (b) of Table 8), cooperation is somewhat less stable for multiparty alliances than for bilateral alliances, especially

[12]There are some significant differences at the 5% level, but these significance levels are due to having a very high number of observations and not because of any substantial differences in frequencies, which are between 99.6% and 99.9%

in a high commitment configuration: cooperation stability drops from 99.6% in BH to 97.9% in MH and this difference is significant at the 1% level. There is no difference in cooperation stability when comparing different commitment levels.

Moreover, there are substantially more breakup reactions in low commitment configurations after (at least) one partner did not cooperate, both for bilateral and multiparty alliances. For example, breakup frequencies jump from 6% after outcome $[C, nC, nC]$ in the MH configuration to 33.3% in the ML configuration (significant at the 1% level). High commitment alliances also generate more forgiveness for multiparty configurations (but not for bilateral alliances). For example, C is chosen 27% in MH alliances after outcome $[C, nC, nC]$ whereas it is only chosen with a frequency of 7.9% in ML configurations (significant at the 1% level).

Finally, when comparing breakup stability and forgiveness across the number of partners in an alliance, there are almost no significant differences. Interestingly, partners are more forgiving when not all other partners cheat. Indeed, C is chosen with a frequency of 58.8% after $[C, nC, C]$ but only 28.6% after $[C, nC]$ (significant at the 1% level) and 27% after $[C, nC, nC]$. In sum, high competition alliances show quite a bit of variation in terms of stability and forgiveness across alliance configurations.

Taken together, the results above suggest that first-period behavior strongly drives the performance of an alliance configuration in a specific environment. To investigate this further, we ran a mediation analysis to see how much of the effect of configuration parameters on alliance performance is mediated by first-period behavior. Table 9 summarizes total, direct, and mediated effects of high commitment and multilateral treatments on alliance cooperation, where first-period cooperation (0/1) is the mediating variable. The direct effects reflect our non-parametric results in 4. We find that where it is significant,[13] a sizable proportion of the effects of commitment and the number of alliance partners on overall success is mediated by first period behavior. Specifically, the proportion ranges from 62.1% for the number of partners in low competition alliances, over 69.7% for commitment in high compe-

[13]The direct effect of commitment on alliance cooperation in low competition alliances is not significant to begin with.

tition alliances, up to 78.2% for the number of partners in low competition alliances. That is, the effect of alliance configuration on first period behavior goes a long way towards explaining the effect on overall performance.

[Table 9 about here.]

5 Discussion

Our results on aggregate outcomes in section 5.1. suggest a powerful theme: alliance configuration matters when alliance partners are close competitors, while virtually nothing can go wrong in a strategic alliance among distant competitors. We dig deeper in section 5.2. to study different aspects of dynamic behavior by alliance partners: first, we look at first-period level of cooperation and find that the differences are pronounced and significant in high competition alliances and much smaller in magnitude and significance in low competition alliances. We then turn to alliance partners' reactions to their partners' behavior and find somewhat more differentiated results, although one finding that emerges is that commitment is especially suitable to induce stability and forgiveness in multilateral alliances among close competitors, and that adding a third alliance partner has an especially pronounced effect in the high competition case.

None of the baseline results are directionally unexpected: simple alliances (between two players) work better than complex ones, low competition alliances outperform high competition ones, and commitment can make alliance partners behave more cooperatively. However, what is interesting and novel is the fact that the expected effects are often contingent on the competitive environment and other alliance configuration elements. Specifically, we found that low competition alliances react much less to changes in alliance configuration, while the performance of high competition alliances is strongly contingent on their configuration. This relates to the few studies that have considered competition or partner rivalry in tandem with other environmental features as determinants of alliance success. Park et al. (1997) find that rivalry is a stronger predictor of alliance success than organizational factors, a view we confirm partially for low competition alliances, while we find that in high competition alliances aspects like safeguarding or mutual commitment may be needed to keep opportunistic behavior in check (Kale et al. 2000).

Another noteworthy finding is that across the different performance and behavioral metrics, first-period behavior corresponds most closely with overall performance, a result we confirm through a mediation analysis. That is, while there are some differences across our treatments in the stability of cooperation, the longevity of struggling alliances and the degree of forgiveness following non-cooperation by partners, the key differences in overall performance of alliance configurations stem from differences in first-period behavior. This corresponds to the findings by Doz (1996) and Ariño et al. (1998), who document a self-reinforcing process of alliance success and failure that consequently puts a high weight on first-period behavior. In other words, given the high stability of cooperation and the comparably minor differences in other behavioral aspects, initial differences are likely to persist over the duration of an alliance.

A useful feature of our controlled experimental setting is that we can rule out a number of possible explanations such as gradual learning about alliance benefits, or the changing shape of alliances over time. However, one possible and plausible mechanism is the development of within-alliance trust among alliance partners. Our results support a view where trust is built at the start of an alliance, not over time. However, contrary to Gulati (1995), who posits that trust is built through repeating alliances with the same partners, we find that even in our simple setting without repeating alliances with the same partners, the level of trust is established at the beginning of a particular interaction and persists through that interaction without a discernible trend up- or downwards (Vanneste, Puranam, and Kretschmer 2014). Our result is also in line with the finding that when the shadow of the future looms largest (i.e. in the early phases of an alliance), trust is most likely to be created (Poppo, Zhou, and Ryu 2008) .

Finally, we also offer some new insights for the emerging literature on multiparty alliances (Fonti et al. 2016). Our findings suggest that adding more firms to an alliance exacerbates cooperation problems independent of the level of competition. This informs emerging research on alliances in ecosystems (Eisenhardt and Hannah 2016) and standard-setting organizations (Ranganathan, Ghosh, and Rosenkopf 2016) where creating the full value depends on the behavior of multiple independent actors. Our results point towards a significant decrease in cooperative behavior as more actors are involved, and this may call for alternative organizational forms and even alternative ways of managing firms moving in social networks rather than dyads (Gulati 1998).

6 Conclusion

Alliances come in many shapes and forms (Baker et al. 2008; Gulati et al. 1998). We show in a simple formal model that alliances can resemble two broad types, depending on the degree of product market competition: Low competition alliances will resemble a stag hunt game in which contributing to the alliance is in the partners' interests. High competition alliances are akin to a prisoner's dilemma in which alliance partners have an interest in withholding effort, at least if the alliance game is played only once. We match these two alliance environments with different alliance configurations and vary the number of alliance partners and the level of commitment. We find that alliance configuration matters most in high competition alliances, while performance of low competition alliances is relatively unaffected by different alliance configurations. This points towards important contingencies for the choice of alliance configuration.

Our formal model and experimental implementation carry a number of limitations. In addition to the simplifications needed to generate a tractable model (two or three players, three actions, known payoffs) and the abstraction from real-world alliances to get the necessary statistical power and subjects' comprehension in the experiment, we also ruled out a number of alliance configuration features that could affect the performance of an alliance and dynamic behavior we studied. For example, pre- and within-alliance communication may help resolve coordination problems in low competition alliances more easily than opportunistic behavior in high competition alliances. Reputation buildup across alliances through a publicly known behavioral history might serve as a powerful disciplining device, especially for early phases of alliances among newly matched partners. Finally, varying the extent of resource contribution and the option of dynamic investment patterns so that today's investment affects tomorrow's baseline cost or demand would bring some added realism, especially for R&D alliances. Nevertheless, we are confident that by focusing on a narrowly defined strategic alliance and a small set of configuration variables and behaviors, we can uncover some interesting and relevant dynamics that will be at play in more complex settings too.

The managerial implications revolve around two main themes: First, behavior within an alliance is disproportionately affected by early-stage behavior. This suggests that even absent other, extraneous reasons to behave cooperatively early on like learning or cumulative investments, early cooperative behavior is likely to perpetuate throughout the alliance. Hence, managers should only enter an alliance when they are confident that they will be sufficiently knowledgeable and incentivized to cooperate in letter *and* spirit of the alliance. Otherwise, they can expect a downward spiral of lacking trust and non-cooperative behavior, leading to a breakup of the alliance. The second set of managerial implications revolves around the *choice* of alliance configurations depending on the product market in question. Our findings suggest here that alliances in highly competitive markets should be more restrictive, i.e. involve less partners, and feature built-in commitment devices to discipline alliance partners' behavior. That is, more due diligence should be exercised in highly competitive situations, not least because the incentives may be less aligned than in less competitive situations, but also because the choice of configuration is likely to have a much bigger impact on the eventual performance of the alliances.

Our research is an early step towards a deeper understanding of dynamic alliance behavior and the contingent impact of alliance configuration on alliance dynamics. Of course, it would be interesting to study many additional features of alliance configuration in an experimental setting that allows for a controlled variation of specific configuration parameters. Additionally, it seems especially promising to study some of our observations on dynamic alliance behavior in the field. For example, the importance of getting an alliance off to a good start or the link between commitment and forgiveness would be interesting to investigate in a sample of real-life alliances.

Table 1: Experimental Design. Bilateral, low commitment (BL).

(a) Low Competition

Partner 1	*Partner 2* *C*	*nC*	*B*
C	6.5 6.5	5 −0.5	2.5 2.5
nC	−0.5 5	2 2	2.5 2.5
B	2.5 2.5	2.5 2.5	2.5 2.5

(b) High Competition

Partner 1	*Partner 2* *C*	*nC*	*B*
C	2.5 2.5	3 -2.5	1.5 1.5
nC	-2.5 3	1 1	1.5 1.5
B	1.5 1.5	1.5 1.5	1.5 1.5

Table 2: Experimental Design. Bilateral, high commitment (BH)

(a) Low Competition

Partner 1 \ *Partner 2*	*C*	*nC*	*B*
C	6.5 6.5	5 −0.5	1.5 1.5
nC	−0.5 5	2 2	1.5 1.5
B	1.5 1.5	1.5 1.5	1.5 1.5

(b) High Competition

Partner 1 \ *Partner 2*	*C*	*nC*	*B*
C	2.5 2.5	3 -2.5	0.5 0.5
nC	-2.5 3	1 1	0.5 0.5
B	0.5 0.5	0.5 0.5	0.5 0.5

Table 3: Experimental Design. Multiparty.

(a) Low Commitment (ML). Low (left) and high (right) competition.

	2 cont.	*1 cont.*	*0 cont.*
C	6.5	0.5	-1.5
nC	6	4	2
B	2.5	2.5	2.5

	2 cont.	*1 cont.*	*0 cont.*
C	2.5	-1.5	-3
nC	4	2.5	1
B	1.5	1.5	1.5

(b) High Commitment (MH). Low (left) and high (right) competition.

	2 cont.	*1 cont.*	*0 cont.*
C	6.5	0.5	-1.5
nC	6	4	2
B	1.5	1.5	1.5

	2 cont.	*1 cont.*	*0 cont.*
C	2.5	-1.5	-3
nC	4	2.5	1
B	0.5	0.5	0.5

Notes: The matrices present the payoffs of partner i as a function of own choices and the number of other partners contributing resources to the alliance.

Table 4: Differences between configurations, Cooperation.

(a) Low competition alliances.

	Low commitment	High commitment	Difference test (K-S–Test)
Bilateral	95.3	95.2	0.018
Multilateral	75.2	81.0	0.089
Difference test (K-S–Test)	0.234**	0.175**	

(b) High competition alliances.

	Low commitment	High commitment	Difference test (K-S–Test)
Bilateral	63.4	86.9	0.249**
Multilateral	12.1	26.7	0.211**
Difference test (K-S–Test)	0.529**	0.667**	

Notes: Cooperation is defined as the percentage of periods where [C, C] or [C,C,C] is played, averaged across all interactions; * significant at the 5% level; ** significant at the 1% level.

Table 5: Differences between configurations, Breakup.

(a) Low competition alliances.

	Low commitment	High commitment	Difference test (χ^2)
Bilateral	3.8	2.0	0.89
Multilateral	18.3	9.8	2.87
Difference test (χ^2)	14.9**	7.3**	

(b) High competition alliances.

	Low commitment	High commitment	Difference test (χ^2)
Bilateral	34.7	5.1	42.0**
Multilateral	84.6	28.8	65.9**
Difference test (χ^2)	60.9**	28.1**	

Notes: Breakup is measured as a percentage across interactions; * significant at the 5% level; ** significant at the 1% level.

Table 6: Regression analysis of success measures.

Independent Variable	Success Measure Cooperation	Breakup	Cooperation	Breakup
Intercept	0.883^{**}	0.075^{**}	0.857^{**}	0.069^{**}
	(0.035)	(0.036)	(0.039)	(0.034)
Main Effects				
High competition	-0.354^{**}	12.007^{**}	-0.315^{**}	13.651^{**}
	(0.022)	(4.662)	(0.042)	(5.958)
Multilateral	-0.369^{**}	7.562^{**}	-0.200^{*}	5.702^{**}
	(0.023)	(1.853)	(0.070)	(3.074)
High commitment	0.110^{**}	0.131^{**}	-0.001	0.513
	(0.022)	(0.042)	(0.029)	(0.266)
Interaction Effects				
High comp. × Multilateral			-0.316^{**}	2.028
			(0.080)	(1.237)
High comp. × High comm.			0.232^{**}	0.193^{**}
			(0.050)	(0.117)
Multilateral × High comm.			0.058	0.927
			(0.120)	(0.699)
Three-way interaction			-0.144	0.724
			(0.138)	(0.634)
R^2 (pseudo)	0.352	0.327	0.422	0.342
Sample size	1009	1009	1009	1009

Notes: OLS regressions of Cooperation in each interaction on alliance environment and configuration, and odds ratios of logistic regression of Breakup on alliance type and configuration. We control for the interaction draw and interaction. All standard errors are robust for within-cluster covariance, clustered by session; * significant at the 5% level; ** significant at the 1% level.

Table 7: First period behavior.

(a) Low competition alliances.

	Low Commitment			High Commitment			
	C	nC	B	C	nC	B	Difference test (χ^2)
Bilateral	96.5	3.5	0	97.3	2.3	0.4	1.773
Multilateral	91.7	8.0	0.3	93.8	6.2	0	1.664
Difference test (χ^2)	6.828*			6.083*			

(b) High competition alliances.

	Low Commitment			High Commitment			
	C	nC	B	C	nC	B	Difference test (χ^2)
Bilateral	80.9	18.4	0.7	94.2	5.4	0.4	24.98**
Multilateral	51.9	46.5	1.6	61.5	37.8	0.7	6.600*
Difference test (χ^2)	55.92**			97.30**			

Notes: Choice values are in percentages. Pearson's χ^2 test of difference between the distribution of first period choices for low and high commitment alliances as well as bilateral and multilateral alliances; * significant at the 5% level; **significant at the 1% level.

Table 8: Responses.

(a) Low competition alliances.

	Outcome	Low Commitment C	nC	B	High Commitment C	nC	B	Difference test (χ^2) C choice	B choice
Bilateral	$[C, C]$	99.9	0.1	0	99.6	0.4	0	6.43*	–
	$[C, nC]$	60.0	24.0	16.0	66.7	30.8	2.5	0.07	2.18
Multilateral	$[C, C, C]$	99.6	0.3	0.1	99.6	0.4	0	0.00	0.00
	$[C, nC, C]$	64.4	30.8	4.8	61.8	35.3	2.9	0.06	0.11
	$[C, nC, nC]$	28.6	47.6	23.8	47.6	38.1	14.3	0.91	0.15
Difference test (χ^2). *Stability:*									
C choice after $[C, C]$/ $[C, C, C]$			5.14*			0.00			
B choice after $[C, nC]$/ $[C, nC, nC]$			0.08			1.42			
Difference test (χ^2). *Forgiveness:*									
C choice after $[C, nC]$/ $[C, nC, C]$			0.03			0.12			
C choice after $[C, nC]$/ $[C, nC, nC]$			3.36			1.35			

(b) High competition alliances.

	Outcome	Low Commitment C	nC	B	High Commitment C	nC	B	Difference test (χ^2) C choice	B choice
Bilateral	$[C, C]$	99.4	0.6	0	99.6	0.4	0	0.26	–
	$[C, nC]$	22.2	51.4	26.4	28.6	66.1	5.3	0.38	8.37**
Multilateral	$[C, C, C]$	98.3	1.7	0	97.9	2.1	0	0.05	–
	$[C, nC, C]$	34.6	46.2	19.2	58.8	40.1	1.1	14.5**	28.1**
	$[C, nC, nC]$	7.9	58.8	33.3	27.0	67.0	6.0	6.65**	19.1**
Difference test (χ^2). *Stability:*									
C choice after $[C, C]$/ $[C, C, C]$			4.04*			23.79**			
B choice after $[C, nC]$/ $[C, nC, nC]$			0.40			0.00			
Difference test (χ^2). *Forgiveness:*									
C choice after $[C, nC]$/ $[C, nC, C]$			2.57			14.47**			
C choice after $[C, nC]$/ $[C, nC, nC]$			3.54			0.00			

Notes: Choice values are in percentages. Pearson's χ^2 test of difference of the frequency of C choices and B choices; * significant at the 5% level; **significant at the 1% level.

Table 9: Causal mediation effects of configuration, through first-period behavior, on alliance cooperation.

(a) Low competition alliances.

	Treatment variable	
	Commitment (treatment = high)	Number of partners (treatment = multilateral)
Total effect	0.008	-0.171^{**}
Effect mediated by first period outcome	0.017	-0.106^{**}
Direct effect	-0.009	-0.065^{**}
Proportion mediated	–	$62.12\%^{**}$

(b) High competition alliances.

	Treatment variable	
	Commitment (treatment = high)	Number of partners (treatment = multilateral)
Total effect	0.201^{**}	-0.555^{**}
Effect mediated by first period outcome	0.140^{**}	-0.434^{**}
Direct effect	0.061^{**}	-0.121^{**}
Proportion mediated	$69.64\%^{**}$	$78.23\%^{**}$

Notes: First period outcome is measured as a dummy variable with value 1 if all partners choose C in the first period. Effects are computed from *outcome regression* and *mediator regression*, and inference is based on the bootstrapped distribution of effects. Outcome regression: linear regression of alliance cooperation on alliance environment and configuration and on first period outcome. Mediator regression: logistic regression of first period outcome on alliance environment and configuration. We control for the interaction draw and interaction; * significant at the 5% level; ** significant at the 1% level.

Figure 1: Payoff Matrices.

(a) Basic Setup.

Partner 1 \ *Partner 2*	***C***	***nC***
C	$\pi\,(a+k+s,m)-e$; $\pi\,(a+k+s,m)-e$	$\pi\,(a+k/2,m)$; $\pi\,(a+k/2,m)-e$
nC	$\pi\,(a+k/2,m)-e$; $\pi\,(a+k/2,m)$	$\pi\,(a,m)$; $\pi\,(a,m)$

(b) Basic setup, *low competition.*

Partner 1 \ *Partner 2*	C	nC
C	7 ; 7	5.5 ; 0
nC	0 ; 5.5	2.5 ; 2.5

(c) Basic setup, *high competition.*

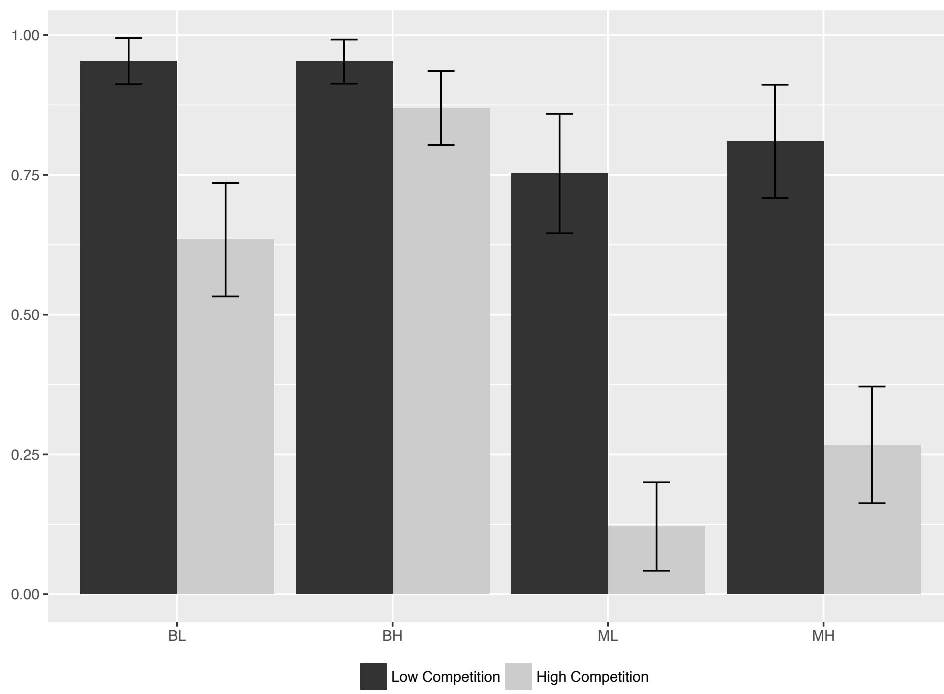
Partner 1 \ *Partner 2*	C	nC
C	3 ; 3	3.5 ; -2
nC	-2 ; 3.5	1.5 ; 1.5

Notes: Panels (b) and (c) are examples constructed with specific parameter values reflecting low and high competition.

Figure 2: Alliance configurations.

		Commitment	
		Low	High
# partners	Two	**BL** (Bilateral, low commitment)	**BH** (Bilateral, high commitment)
	Three	**ML** (Multilateral, low commitment)	**MH** (Multilateral, high commitment)

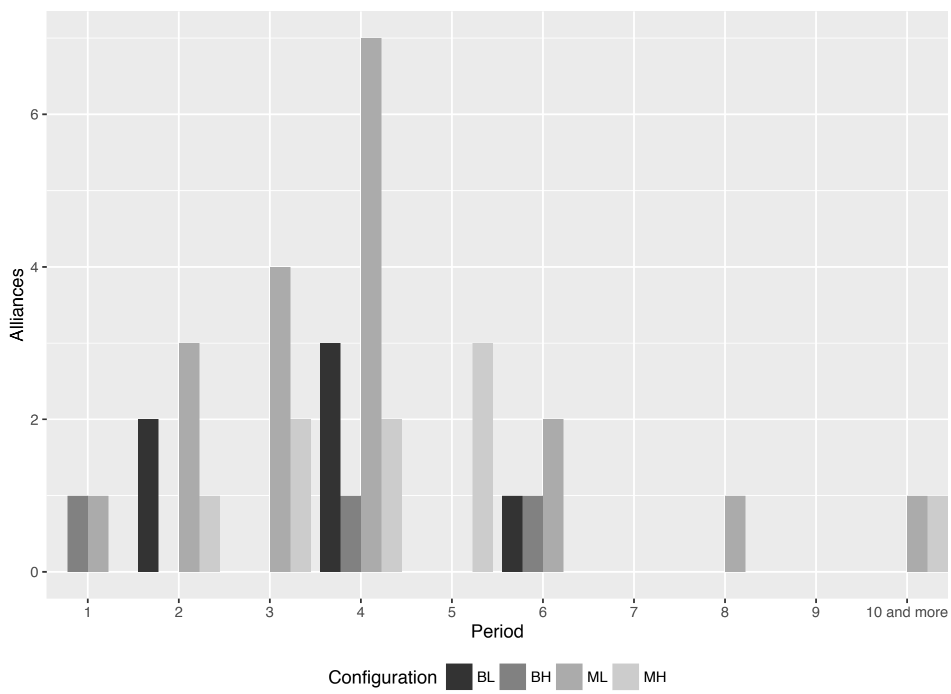
Figure 3: Cooperation by level of competition and alliance configuration.



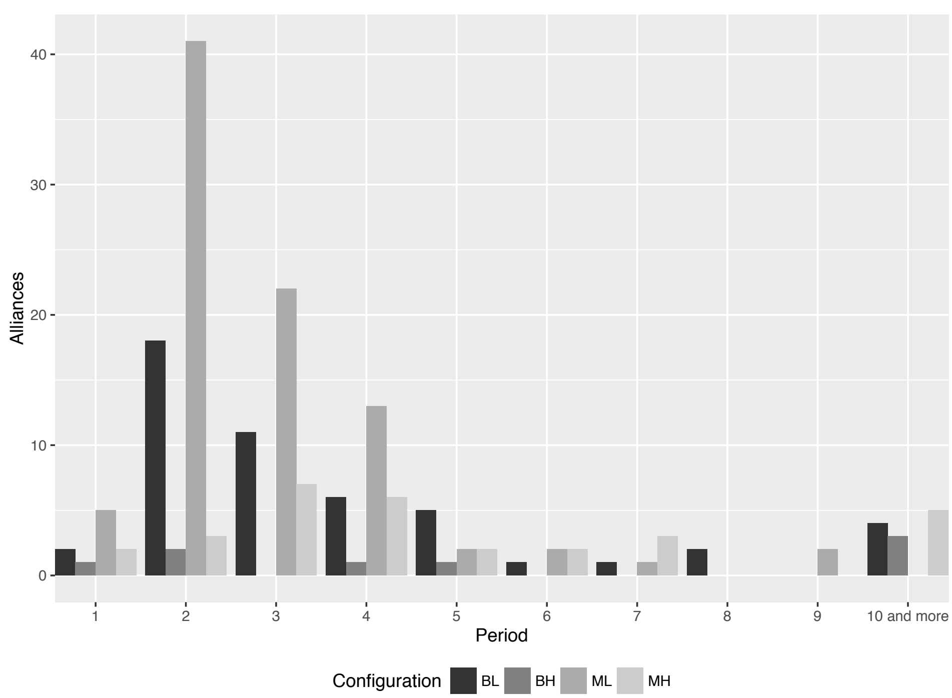
Notes: Cooperation is defined as the percentage of periods where $[C, C]$ or $[C, C, C]$ is played, averaged across all interactions. 99% Confidence intervals are displayed.

Figure 4: Period of termination by level of competition and alliance configuration.

(a) Low competition alliances.



(b) High competition alliances.



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