Rosencrantz and Guildenstern are Devalued?
How Alliance Announcements Change the Stock Market Valuation of Rivals

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Introduction

Over the last 20 years, the alliance has become an increasingly prevalent organizational form, particularly for technology development activities in knowledge-intensive industries. Academic literature on alliances has grown apace, as researchers seek to understand the mechanisms that link inter-firm collaboration to enhanced innovation and profitability. Early work on alliances posited a variety of benefits that could accrue to alliance partners, including learning, access to specialized resources, risk sharing, and shaping competition (Porter and Fuller, 1986). Over time, however, some of these hypothesized alliance benefits have received disproportionate attention in the literature, while others have been relatively neglected. Indeed, recent research on alliances has tended to focus almost exclusively on alliances as vehicles by which partners acquire or access new skills to become stronger competitors; it has become much less fashionable in strategy research to consider the potential for firms to use alliances to shape competitive interactions, possibly attenuating competitive intensity in the industry as a whole.

When looking for evidence of learning and other competitiveness-enhancing benefits of joint ventures and other alliances, researchers have typically turned to event studies, examining the stock market’s response to a firm’s announcement of a new alliance. Most find evidence that alliance announcements are, on average, accompanied by a positive stock market response,1 and that the magnitude of this response varies with the capabilities and experience of the partner (e.g., McConnell & Lantel 1985; Anand & Khanna 2000; Kale, Dyer & Singh 2002). These findings have usually been interpreted as supportive of the competitiveness-enhancing view of alliances, whereby an alliance raises a firm’s value by making it more competitive such that it can out-compete its product market rivals. However, positive abnormal returns to alliance partners are equally compatible with the competition-attenuation view of alliances.

In this study we seek to shed light on the different mechanisms underlying value creation in alliances by examining how alliance announcements affect the stock market’s evaluation of

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1 But see McGahan and Villalonga 2005 for contrary results.
allying firms’ rivals. If an alliance is expected to enhance the resource portfolio of partner firms, making them more fierce competitors, then this should lead to negative abnormal returns for rivals when the alliance is announced. If an alliance is expected to facilitate a reduction in competitive intensity, however, then this should lead to positive abnormal returns for its rivals as they will also benefit from the attenuation of competitive pressures (Eckbo, 1988). In addition, if alliances generate new resources that spill over to rivals or otherwise increase technological opportunity, this may also benefit rivals (Silverman & Baum, 2002; McGahan and Silverman, 2005).

We investigate the effect of firms’ alliance announcements on rivals’ stock market valuations through an event study analysis of R&D alliances announced in the telecommunications and electronics industries (SICs 366 and 367) in 1996 and 1997. Surprisingly, we find that the abnormal returns accruing to participating firms when a new alliance is announced are positively related to the abnormal returns accruing to these firms’ rivals. It is difficult to reconcile this finding with the idea that forming an alliance makes alliance participants more potent rivals. In addition, alliances linking competitors active in the same product markets – which are likely to be particularly conducive to "managing" or softening competition – are positively associated with rivals’ abnormal returns, at least in one of our samples of rivals. In contrast, cross-border alliances – which we argue are less conducive to managing competition and more compatible with efforts to access new resources – are negatively associated with rivals’ abnormal returns, indicating that such alliances generate greater competitive advantage for partners, vis-à-vis rivals.

Our paper makes at least one empirical and one theoretical contribution to the alliance literature, and another, broader contribution. Theoretically, our paper draws on literature in industrial organization and strategy and unpacks the alternative mechanisms by which alliances create value for partners – either by facilitating inter-partner learning and access to superior resources, such that the partners subsequently compete more fiercely with rivals, or by attenuating competitive intensity in the industry. Empirically, our study is the first examination
of abnormal returns accruing to rivals upon the announcement of an alliance. Although the preliminary results of this analysis provide few definitive answers as to the effects of alliance formation on industry dynamics, they highlight the need for care in interpretation of prior event studies of alliance announcements, and suggest that the exclusive focus on learning and resource accumulation through inter-firm alliances may be misplaced.

Finally, and more broadly, this study employs a methodology – examining the effect of one firm’s action on the abnormal returns earned by its rivals – that can usefully be applied to inform a wide range of strategic actions. To the best of our knowledge, this method has been used in a single prior study of stock market reactions to the announcement of new patents (Austin, 1993), and a conceptually similar study of the relationship between a firm’s Tobin’s q and the patenting of its rivals (McGahan & Silverman, 2004). But the methodology of analyzing abnormal returns to rivals has enormous potential use throughout the strategy field, particularly with respect to questions of competitive dynamics. We hope that this paper will encourage scholars to apply this method more broadly in the future.

Alliance motives and outcomes for participants and rivals

When inter-firm alliances emerged as a popular organizational form in the early 1980s, academic interest in alliances also took off. Early studies were primarily exploratory, examining the various benefits that may accrue to alliance partners, in an effort to better understand the increasing popularity of these collaborative arrangements. Porter and Fuller (1986), for example, posited a variety of benefits that could accrue to alliance partners, including learning, access to specialized resources, risk sharing, and shaping competition.²

Looking at the rich literature on alliance formation and management that has developed in the twenty years following these early taxonomic efforts, one cannot help being struck by the

² Contractor & Lorange (1988) and (Lorange and Roos) 1992, generate similar lists of alliance motives.
tight focus that has emerged around a conceptualization of alliances as vehicles for accessing and acquiring resources – particularly technological or other knowledge-intensive resources. Studies of inter-firm learning in alliances include practitioner-oriented studies (e.g., Hamel, et al, 1988; Hamel, 1991) and theoretically-motivated case studies (e.g., Inkpen & Dinur, 1992; Teece, 1992) as well as empirical studies employing large-scale datasets (e.g., Mowery, Oxley & Silverman, 1996; Lane & Lubatkin, 1998).

A basic (though often implicit) premise of these studies is that firms are motivated by a desire to acquire skills and resources from alliance partners, and that internalization of partners’ skills is an important indicator of alliance success, in addition to the creation of new resources. Several authors have nonetheless noted the potential instability of such learning alliances (e.g., Nakamura, Shaver & Yeung, 1996; Khanna, Gulati, & Norhia, 1998; Dussauge, Garrette & Mitchell, 2000), as asymmetric learning can upset the bilateral dependence that binds alliance partners together. These authors suggest that many alliances are designed not to promote knowledge sharing and inter-firm learning per se, but rather to facilitate co-specialization wherein partners continue to pursue their respective areas of specialization and the alliance serves as a vehicle for assembling complementary capabilities and resources without the need for significant technology transfer or sharing of proprietary knowledge. A classic example of this type of alliance is Airbus Industrie, the European producer of large commercial aircraft, in which member firms specialize in the design and manufacture of different components that are then brought together in the final aircraft (Mowery, Oxley & Silverman, 2002).

Despite their different implications for alliance dynamics, the learning and co-specialization alliances share the premise that successful alliances enable partners to augment their resource base, and so gain a competitive advantage over rivals. This premise also extends to
the risk-sharing or scale-based alliance motives common in resource exploration industries where the absolute size of the variance of returns for some activity is large in relation to optimal firm size in other activities, so motivating firms to share costs and hedge the risks of failure (Porter & Fuller, 1986, p. 325).³

In addition to such capability- or competitiveness-enhancing benefits of alliances, there also exists the possibility that alliances may play a role in shaping competition in an industry, however. Early theoretical work in economics on joint ventures and other alliances emphasized the potentially anti-competitive effects of cooperative ventures (e.g., Dixon, 1962), the hypothesis being that joint ventures could become a forum for more general discussions between competitors, that common sourcing could lead to common cost structures and identical pricing, and that joint ventures could be the mechanism through which emerging industries could be dominated by existing large firms in related industries (Porter & Fuller, 1986). This hypothesis has received little attention in the more recent strategy literature reflecting, in part, the emphasis in this literature placed on resource- and capability-based competition, as well as a general antipathy towards explanations relying on explicit collusion. Explicit collusion is not a necessary condition for alliances to dampen competitive intensity in an industry, however. As models of R&D cooperation in the industrial organization literature suggest, for example, (Katz, 1986; Katz & Ordover, 1990) R&D alliances can, in some circumstances, lead to a reduction in the level of R&D expenditure by alliance partners, so reducing R&D output which in turn has the potential to “soften” competition, even with rivals not involved in the alliance.

These two broad views of alliance motives and benefits generate conflicting hypotheses about the effect on rivals of a firm’s decision to form an alliance. Specifically, the

³ Similar motives are sometimes attributed to large-scale R&D alliances in high fixed cost industries such as semiconductors or pharmaceuticals, although pooling of complementary capabilities almost certainly plays an additional role in such alliances.
competitiveness-enhancement view implies that, ceteris paribus, an alliance will lead to lower future profits for rivals, while the competition-attenuation view implies that an alliance may lead to higher future profits for rivals. To the extent that capital markets accurately incorporate new information into the market values of publicly traded firms, the competitiveness-enhancement (versus competition-attenuation) view thus implies that the announcement of an inter-firm alliance should lead to a decrease (versus an increase) in the market value of rivals of the participating firms.

Beyond this fundamental divergence in the predictions regarding rival firms’ stockholders’ reaction to an alliance announcement, there are more nuanced predictions that may be derived by looking at the differential potential for competition attenuation that accrue to different types of alliances. For example, if we compare horizontal alliances – that is, alliances between firms that compete in the same industry – with vertical alliances that bring together firms active in different but vertically linked alliances, we might expect that horizontal alliances are more likely to be used to manage product-market competition and are therefore more likely to lead to an increase in the market value of rivals to the allying firms. Considering the geographic configuration of an alliance, a cross-border alliance seems more likely to entail the introduction and joining of new, complementary skills, and to be less suited to the type of product market coordination that could potentially benefit rivals. As such, the impact on rivals is more likely to be negative upon announcement of cross-border alliances. We explore each of these possibilities in the empirical analysis below, but first examine prior evidence on the stock market reaction to alliance announcements.
Event studies of alliance announcements

Event studies have become a quite popular method for examining the expected effect of an alliance on the value of participating firms. The basic idea behind the event study methodology is that an examination of “abnormal” changes in a partner firm’s stock price following an announcement of a new alliance gives a good indication of informed traders’ beliefs regarding the expected impact on future cash flows of the firm.⁴

Table 1 summarizes the theoretical and empirical focus and main findings for some of the most commonly-cited event study analyses of alliance announcements in the strategy literature. While not exhaustive,⁵ this sampling of studies captures the main flavor of findings to date: most of the studies find a positive abnormal return for partner firms following the announcement of an alliance, with average positive returns varying from less than 0.01% (Das, Pradyot & Sengupta, 1998) to 0.87% (Koh & Venkatraman, 1991). The one notable exception to this consensus regarding the positive stock market reaction to alliance announcements comes from a recent study by McGahan and Villalonga (2003) analyzing the stock market reaction in a comprehensive sample of deals by 86 members of the Fortune 100 from 1990-2000. As the authors point out, one possible explanation for this divergent finding is that the firms in the McGahan and Villalonga (M&V) sample are the largest in the economy and, as such they are likely to be almost always the larger partner in a their respective alliances; most prior studies have found that small firms benefit disproportionately from alliances and, as such, the returns to joint ventures and alliances may be obscured by the size of the firms in the M&V sample.

⁴ Details of the event study methodology can be found in the Methods section later in the paper.
⁵ For additional examples (also illustrating positive returns to alliance participants), see McConnell & Nantell (1985); Chan, Kensinger, Keown & Martin (1997); and Kale, Dyer & Singh (2002).
All of these prior studies associate the positive abnormal return to participants with enhanced value creation within the alliance; indeed several of the studies explicitly draw the inference that alliances are effective vehicles for knowledge acquisition (e.g., Koh & Venkatraman, 1991; Kale, Dyer & Singh, 2002). However, our earlier arguments suggest that such an interpretation may be premature, absent investigation of the effect of alliance announcements on the stock market reaction of rivals.

Data

Our empirical analysis examines the abnormal returns that accrue to rivals upon announcement of R&D-related alliances involving firms in the telecommunications equipment and electronics industries, (SICs 366 and 367) during 1996-1997. This is a useful setting for our study, as received wisdom suggests that profitability in this sector depends critically on firms’ abilities to create and commercialize new technologies quickly and efficiently (OECD, 2000). Furthermore, as the electronic and telecommunications equipment industries converged in the late 1980s, and a period of rapid growth and technological development ensued, firms began establishing R&D alliances at an unprecedented rate in order to spread the risks and costs of technology development and to gain access to new competencies; firms in these industries now frequently collaborate in their R&D activities (e.g., Duysters and Hagedoorn, 1996).

To compile our sample of alliances, we identified all firms active in SIC 366 and 367 in 1996 or 1997 from Compustat, and compiled information on all R&D alliance announcements involving these firms from Jan 1, 1996 through Dec 31, 1997 as recorded in the Securities Data
Company (SDC) Database on Alliances and Joint Ventures. Our initial sample totaled 470 alliances. Some of these alliances linked two or more firms active in SIC 366 and/or 367, while others linked one or more firms from within the sector with a firm (or firms) from other industries.

SDC reports announcement dates for all alliances recorded in the database, but these are not always accurate (Anand & Khanna, 2000). We therefore checked all announcement dates against multiple periodicals and wire services using the Dow Jones News Retrieval service. This process prompted us to revise the announcement date for 97 alliances and to drop 127 alliances for which we could find no reliable report of the alliance announcement, the actual announcement date was outside of our 2-year window, or the announcement related to ongoing alliance activities rather than to the initiation of a new venture. We also dropped alliances with greater than 2 participants to simplify the task of identifying rivals (see below); this further reduced our sample by 44 alliances.

A major concern in event study analysis is potential contamination by “confounding events” which may lead to abnormal returns to firms in the sample, but which are unrelated to the event of interest. To ensure that we could viably associate observed abnormal returns with specific alliance announcements, we excluded from our sample all alliance announcements that occurred within the event window surrounding the announcement of another venture in the same 4-digit SIC. We also need to make sure that, for each alliance participant or rival, abnormal returns are not contaminated by other major non-alliance events. We therefore exclude, on a firm-by-firm basis, all observations where a potential confounding event occurs within the event window.

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6 The SDC database is compiled from publicly available sources such as SEC filings, news reports, as well as industry and trade journals, and contains information on alliances of all types. SDC initiated systematic deal tracking around 1989 but coverage is still far from complete, as firms are not required to report their alliance activities. Nevertheless, this database currently represents one of the most comprehensive sources of information on alliances (Anand & Khanna, 2000; McGahan & Villalonga, 2003; Oxley & Sampson, 2004.)
These confounding events were identified by searching the Dow Jones News Retrieval service for references to the firm in question.

From SDC, we gathered data on several characteristics of the alliance: date of announcement; the identity of participating firms (with CUSIPs), whether the alliance involves cross-border activities or domestic activities; whether the alliance is organized as a JV, whether the alliance involved marketing or manufacturing activities in addition to R&D; and the four-digit SIC most relevant to the alliance activities. By marrying this data with Compustat, we were also able to obtain information on participant’s total assets ($million) and net sales ($million) for 1996 and 1997.

We identified rivals of allying firms using two approaches. For the “SIC rivals” we started with a listing of all firms in the Compustat database that had at least one active 4-digit SIC industry within SIC 366 or SIC 367 in 1997. This list comprised roughly 1100 firms. We then used overlapping 4-digit SIC industries to identify rivals: we assume that when an alliance is formed that involves a firm active in, say, SIC 3674, any firm that participates in SIC 3674 and that is not one of the partners in the alliance is a relevant rival.7

Our second approach to identifying rivals uses the 1998 edition of Hoover’s Handbook of American Business (Hoover’s 1998), which has profiles of 750 major U.S. companies. Each company profile includes a list of “key competitors.” According to Hoover’s, the universe of key competitors includes all public companies and all private companies with sales in excess of $500

7 Some participant firms are also in the rivals sample for alliances involving competitors from the same 4-digit SIC industry in which they themselves were not involved. Because we naturally exclude participant firms from the rivals sample associated with any given event, the set of rivals is not identical for each alliance within a given 4-digit SIC industry. In addition, where an alliance joins firms from more than one 4-digit SIC industry within SIC 366/367, we include observations for rivals from each of the relevant 4-digit SICs for that event. We have also experimented with a refinement of SIC rival measure, exploiting information on firms’ sales per segment, to determine the degree to which a rival was focused on the 4-digit SIC(s) in which the alliance partners operate. Preliminary analysis using a reduced sample of alliances suggest that this approach does not generate significantly different results to those reported here.
million. These include both U.S. and foreign companies. For each participant firm in our alliance sample that is included in the handbook, we identified a group of “Hoover rivals,” based on these profiles.

We searched for daily stock price data for each firm (both rivals and partners) along with the relevant daily benchmark local price index, from January 1, 1995 through January 31, 1998 using Datastream Advance. Because Datastream uses idiosyncratic firm identifiers rather than CUSIPS, this process required matching on firm names and nationalities; ambiguous or non-existent matches were dropped, resulting in additional sample attrition.

The final set of measures relate to the existing capabilities of partner firms and rivals. We use patent data for this purpose: A patent portfolio is a useful indicator of a firm’s areas of technological expertise. In order for a new technology to be patented (so allowing the inventor to claim exclusive rights over the product or process described therein) the invention must first pass the scrutiny of the patent office as to its novelty and improvement over existing technology. Extensive research has demonstrated the relationship between patents and other indicators of technological strength: Strong, positive relationships exist between patents and new products (Comanor & Scherer 1969), patents and literature based invention counts (Basberg 1982), and non-patentable inventions (Patel & Pavitt 1997). We therefore use counts of patent applications for partner and rival firms, as well as citation-weighted patent counts, as indicators of the strength of a firm’s technological strength (see below for precise measure).

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8 Because the firms in our sample come from a variety of countries, the relevant local price index (LI in Datastream) depends on the country in which the firm’s stock is listed. For most of the firms in our sample the relevant index is the S&P 500; other indexes used include the AEX, Affarsvalden, ASX, Bel 20, Dax 30, FTSE All Share, Hang Sen, India BSE, Israel TA 100, Jakarta SE Composite, Korea SE composite, Lima SE General, Mexico IPC (BOLSA), Milan COMIT global, OMX Copenhagen, Oslo SE OBX, S&P/TSX composite, SBF 120 index, Shanghai SE, Shenzhen SE, Swiss, Taiwan SE, and TOPIX.

9 We also dropped observations for firms that did not have daily stock price data over the entire estimation window of (-170, +3 days) around a given event date, as this represents the minimum data requirement for estimation of the market model and calculation of event CARs (see below).
In addition, when a patent is granted, the underlying technology is classified according to the US patent classification system. This classification system provides a means to identify the underlying technologies owned by each partner firm. From this, we can examine the extent of overlap among partner firms’ technological portfolios (Jaffe 1986), as well as between a rival firm and the technologically closest partner in the alliance (see below).

Methods

To assess the stock market’s estimate of the change in value accruing to partner and rival firms on the announcement of an alliance we use standard event study methodology. This involves implementing the following procedure for each firm-alliance pair:\(^{10}\)

(i) Estimating a market model of each firm’s stock returns during an estimation period prior to the event date, t=0. Following prior research (e.g., MacKinlay, 1997; McGahan and Villalonga, 2005), we use an estimation period of 150 days, beginning on day t =-170 and ending on day t =-21 and estimate the following equation for each stock:

\[
    r_{it} = \alpha_i + \beta_i r_{mt} + \epsilon_{it}
\]

Here, \(r_{it}\) denotes the daily return for firm \(i\) on day \(t\), \(r_{mt}\) denotes the corresponding daily return on the value-weighted S&P 500, or other local price index,\(^{11}\) \(\alpha_i\) and \(\beta_i\) are firm-specific parameters and \(\epsilon_{it}\) is distributed iid.

(ii) Using the estimated coefficients from this model (\(\alpha_i\) and \(\beta_i\)) to predict the daily returns for each firm \(i\) over the “event window” – i.e. in the days immediately surrounding the alliance.

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\(^{10}\) Because there are multiple alliance announcements in each 4-digit SIC industry in our sample, every rival experiences multiple events, and we have one observation for each firm-deal pair. For details of how this is implemented, see [http://dss.princeton.edu/online_help/analysis/multiple_event_dates.htm](http://dss.princeton.edu/online_help/analysis/multiple_event_dates.htm)

\(^{11}\) The relevant index is determined by the exchange on which the stock is listed – see footnote 9.
announcement. For our study we used three event windows: a 2-day window \([-1,0]\), a three-day window \([-1,+1]\) and a seven-day window \([-3,+3]\).

(iii) Computing the abnormal return (AR) for each firm \(i\) on each day of the event window by subtracting the predicted return from the actual return; and

(iv) Computing the cumulative abnormal return (CAR) for each firm \(i\) by adding the ARs over the event window.

This procedure yields the following measures, which we construct for each alliance participant and all relevant rivals:

- \(\text{CAR}2, \text{CAR}3, \text{CAR}7\) = the cumulative abnormal return (\%) experienced by a firm around an alliance announcement, over a 2-day \([-1,0]\), 3-day \([-1,1]\), and 7-day \([-3,3]\) window, respectively.

Other variables used in the empirical analysis are as follows:

- Average Partner CAR = average of the CARs for all partners in a given alliance
- Horizontal alliance = 1 if both alliance partners had their primary activities in the same 3-digit SIC industry, else 0
- Cross-border alliance = 1 if the alliance includes activities performed in at least two countries, else 0
- \(J\text{V} = 1\) if the alliance includes establishment of a stand-alone JV, else 0
- \(\text{R}&\text{D plus} = 1\) if the alliance involved marketing or manufacturing in addition to R&D, else 0
• Log Sales = Log of the value of net sales revenue (for the relevant participant or rival) in the year of the alliance announcement.

• Citation-Weighted Patent Count for each alliance partner and rival (and averages for partner firms in a given alliance) = total number of times that patents applied for by the firm in the four years prior to an alliance announcement are cited by other firms in the period up to and including 2004.

• Technology Overlap: To construct this measure, we first generate each firm’s technological portfolio by measuring the distribution across patent classifications of the patents applied for in the four years prior to alliance formation. This distribution is captured by a multidimensional vector, \( F_i = (F_i^1...F_i^s) \), where \( F_i^s \) represents the number of patents assigned to firm \( i \) in patent class \( s \). The extent of the overlap among two firms’ areas of technological expertise is then:

\[
\text{Technology Overlap} = \frac{F_i F_j}{\sqrt{(F_i^s F_j^s)(F_i^s F_j^s)}}
\]

where \( i \neq j \). Technology overlap varies from zero to one: a value of zero indicates no overlap in a pair of firms’ areas of technological expertise, while a value of one indicates complete overlap. We use the largest value of overlap between a rival firm and any of the partners in a given alliance as an indicator of relative absorptive capacity (Lane & Lubatkin, 1998; Mowery, et al, 2002).
**Estimation and results**

To establish a baseline result, and link to prior research, we examine the cumulative abnormal returns accruing to alliance participants (Table 2) before moving on to our analysis of rivals. Consistent with prior research (e.g., Koh & Venkatraman, 1991; Madhavan and Prescott, 1995; Anand & Khanna, 2000) we find that alliance participants indeed experience positive abnormal returns in the window surrounding the alliance announcement – this is true if we consider a sample that includes firms listed on both US and foreign exchanges (rows 1-3), or if we restrict the sample to include only S&P-500 listed firms (rows 4-7). Average 2-day cumulative abnormal returns to participants are 1.14% when we consider the complete sample of participants for which we have return data, and 1.69% for firms in the S&P 500. It is interesting to note that US investors appear to react more positively to alliance announcements than investors in other markets.

One way analysis of variance (not reported) does not reveal any significant differences in partner returns based on governance structure of the alliance – i.e., joint venture versus non-equity alliance, year of establishment, 4-digit SIC of alliance activities, domestic versus cross-border alliance, or horizontal versus vertical alliance. Simple bivariate regression does indicate, however, that partner returns are negatively related to firm size (significant at the 10% level), again consistent with prior research.

In contrast to alliance participants, rivals appear to experience negative abnormal returns when an alliance is announced (Table 3a), although the size of the effect is significantly smaller than for participants. Caution is warranted in interpreting these effects, however, given that the number of rivals per alliance varies widely – from 7 to over 100 in the SIC rivals sample,
depending on the 4-digit SICs of the alliance partners, and so there is likely to be significant correlation in the individual rival returns to a particular announcement which can lead to bias. When we repeat the estimates with clustering on alliance and robust standard errors (Table 3b), the significance of the negative returns to rivals is substantially reduced, going below the 10% level in some samples. However, on balance these preliminary correlations provide tentative support for the competitiveness-enhancing view of alliances, whereby investors expect participant firms to gain from alliance formation, and their rivals to be affected negatively.

Closer inspection of the relationship between rivals’ returns and alliance characteristics challenges this competitiveness-enhancing view of alliances, however. To better assess the significance and correlates of rivals’ reactions to alliance announcements, we follow standard event study methodology and use OLS estimation with clustering on the alliance, and report robust standard errors. Tables 4a and 4b present results of this analysis, focusing on 2-day returns: Table 4a focuses on the alliance characteristics that we argued may influence the probability of a competition-attenuating effect of alliance formation, and Table 4b provides supplementary analysis of rival firm characteristics.

Looking first at the results in Table 4a, model 1, we immediately see a result that, on its face, appears quite at odds with a competitiveness-enhancing view of alliances: the cumulative abnormal returns experienced by rivals are positively related to participant returns. In other words, the bigger the bump (or loss) that the stock market gives to participants in an alliance, the bigger the bump (or loss) that it awards to participants’ rivals. This is difficult to reconcile with the idea that forming an alliance makes alliance participants more potent rivals. This result is

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12 An alternate method of dealing with contemporaneous cross-correlation of rivals’ returns around a particular alliance announcement is to pool the rivals into one value-weighted portfolio. Our future plans include robustness checks using this method.
also robust to inclusion of other alliance characteristics. Several of the other alliance characteristics also have significant effects in a direction that is consistent with our arguments, but only in the sample of rivals identified by activity in the same 4-digit SIC industry.

Looking at the impact of different alliance types, we see that horizontal alliances (i.e., those that join industry competitors) are associated with more positive CARs for rivals than are alliances that join firms whose primary activities are in different industries – the coefficient on the dummy variable indicating a horizontal alliance (model 2) is positive and highly significant. Conversely, cross-border alliances, where the alliance covers operations in multiple countries, are less likely to generate positive returns to rivals (the coefficient on cross-border alliance in model 3 is negative and significant). This is consistent with prior research suggesting that cross-border alliances are associated with increased coordination difficulties (Oxley, 1997), and as such may be less effective vehicles for managing competition.

Evidence is more equivocal when it comes to the governance form of the alliance, and the inclusion of manufacturing and/or marketing activities within the scope of the alliance – both alliance features that arguably facilitate the coordination of production and investment plans that may in turn attenuate competitive intensity in the industry: As shown in models 4 and 5, the coefficients on JV and R&D-plus are both insignificant. In the fully specified model (model 6) the JV coefficient becomes significant and positive, as expected, but R&D-plus is actually negative and significant – the only effect that is inconsistent with our arguments in this sample. This is ironic, given that the potential for collusive outcomes in R&D alliances whose scope included manufacturing or marketing prompted the exclusion of such alliances from the National Cooperative Research Act (1984) for the first ten years of its existence.13

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13 The NCRA altered antitrust treatment of research alliances and consortia in two significant ways: First, it ensured that cooperative research ventures were subjected to rule of reason analysis rather than per se rules (i.e. their
The results regarding alliance characteristics should of course be treated as provisional, particularly given the lack of significance of any characteristic other than average partner CAR in the sample of “Hoover rivals.” They are nonetheless provocative and, at a minimum, call into question the almost exclusive current focus on learning and asset accumulation in alliances.

One additional explanation for a positive correlation between participant and rival returns upon announcement of a new R&D alliance is the possibility that investors foresee the prospect of development of new technology that will then spill over to rivals. While there are limits on the applicability of this explanation – it must of course also be the case that competition does not completely eradicate returns generated by the new technology – it is nonetheless an interesting possibility to investigate. We do this by looking at the relationships between rival CARs, participant CARs and rival characteristics, particularly as they relate to the “absorptive capacity” of rivals (Cohen & Levinthal, 1990). Table 4b presents the results of these analyses, which provide little evidence of spillover effects: Although a rival’s technological capabilities – as captured by citation-weighted patent count – is positive and significant in one specification (model 7 on the Hoover rival sample), absorptive capacity logically also depends on the extent of technology overlap between the rival and the alliance participants (Mowery, Oxley & Silverman, 1996; Lane & Lubatkin, 1998) and there is no evidence of any effect of technology overlap on rivals’ CARs. This reinforces the notion that the positive correlation between partner and rival CARs reflects the market’s expectation of competition-attenuation in an industry following alliance formation, at least in some instances.

procompetitive effects must be weighed against potential anticompetitive concerns). Second, the NCRA limited the liability of registered consortia participants to single rather than treble damages. The NCRA was later extended to allow joint manufacturing with the 1993 passage of the National Cooperative Research and Production Act (NCRPA). See Jorde and Teece (1993) for a more thorough analysis of the NCRA and the NCRPA.
Conclusions

This paper reports the first study to look at abnormal returns to rivals at the time that an inter-firm alliance is announced. Despite the challenges associated with implementing such a study, and the preliminary nature of the results, we find several patterns in the data that appear to be more consistent with a competition-attenuation view of alliances than with an asset accumulation or competitiveness-enhancing view, at least for a subset of alliances. We believe that the paper has the potential to make important contributions to the literature: First, if our empirical results hold up as we continue to investigate the data and perform additional robustness checks, then they present a challenge to the prevailing view that alliances are mostly - or at least only - about resource accumulation and improving competitive advantage vis-à-vis rivals. This in turn suggests that we should revisit issues about exactly where/when alliances serve this purpose, and where/when they serve a competition-attenuation purpose. Such investigation has clear implications for both managers and policymakers.

Second, going beyond the bounds of the current study, the method introduced in the paper opens up a new avenue for teasing out the motivations and consequences of alliances. Indeed, we believe that this method opens up a new avenue for testing a whole range of questions in the strategy field, relating to the competitive dynamics of almost any strategic behavior.
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<tr>
<th>Authors</th>
<th>Theoretical focus / hypotheses</th>
<th>Data</th>
<th>Main findings</th>
</tr>
</thead>
<tbody>
<tr>
<td>Woolridge &amp; Snow (1990)</td>
<td>Examines stock market reaction to many different strategic investment decisions including JVs to test basic relationship between shareholder expectations and managers’ investment decisions.</td>
<td>Announcements of investment decisions from WSJ for 1972-87; 767 announcements involving 248 firms in 102 industries</td>
<td>JVs produce positive abnormal return (0.80%).</td>
</tr>
<tr>
<td>Koh &amp; Venkatraman (1991)</td>
<td>Value of related joint ventures is greater than for unrelated ventures; applies to partner-venture relationship and relationship between partners.</td>
<td>175 JVs involving 239 firms in IT sector (broadly defined), compiled from WSJ joint venture announcements, 1972-86; CRSP returns; supplementary samples of tech exchange agreements, licenses, mktg agreements, supply agreements.</td>
<td>Mean 2-day CAR 0.87% for JVs; tech exchange agreements also generated positive return (0.8%), related ventures create more value than unrelated; smaller partner has higher returns than larger partner.</td>
</tr>
<tr>
<td>Das, Sen and Sengupta (1998)</td>
<td>Strategic alliances particularly valuable to small firms in technology alliances – resource accumulation rationale</td>
<td>119 non-equity alliances announced in 1987-91; bilateral alliances only; Data from ITSA, CRSP, Compustat</td>
<td>Significant 2-day CAR of 0.008%; insignificant return for marketing alliances.</td>
</tr>
<tr>
<td>Anand and Khanna (2000)</td>
<td>Firms learn from experience, so market reaction to alliances increases, the more alliances the firm does; greater learning associated with JVs than licenses and for R&amp;D JVs versus production or marketing JVs.</td>
<td>1976 manufacturing (SIC 20-39) joint ventures and licenses involving 147 firms, announced during 1990-93; data sources are SDC, CRSP, Compustat</td>
<td>Significant positive CARs for both JVs (0.78%) and licenses (1.78%); experience hypotheses confirmed.</td>
</tr>
<tr>
<td>McGahan &amp; Villalonga, (2003)</td>
<td>Mainly descriptive – interested in firm effects and ‘deal programs’ (pre-announced series of deals of one type).</td>
<td>7,714 deals announced by 86 members of Fortune 100 between 1990-1999; 7 types of deals distinguished; Data sources are SDC, CRSP, Compustat;</td>
<td>Average effect of all deal types is negative but small (2-day CAR is -0.053%); no significant difference among deal types; firm effects biggest contributor to variance; firm-governance choice interactions also significant – suggests importance of deal programs.</td>
</tr>
</tbody>
</table>
Table 2: Returns to Alliance Participants

<table>
<thead>
<tr>
<th>Alliances</th>
<th>Mean</th>
<th>Std Dev</th>
<th>Minimum</th>
<th>Maximum</th>
<th># of observations</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Partner CAR2 (%)</td>
<td>1.14**</td>
<td>9.56</td>
<td>-16.39</td>
<td>130.4</td>
<td>317</td>
</tr>
<tr>
<td>2. Partner CAR3 (%)</td>
<td>1.61*</td>
<td>15.01</td>
<td>-46.89</td>
<td>163.8</td>
<td>317</td>
</tr>
<tr>
<td>3. Partner CAR7 (%)</td>
<td>1.88**</td>
<td>15.72</td>
<td>-50.36</td>
<td>168.5</td>
<td>317</td>
</tr>
<tr>
<td>S&amp;P500</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4. Partner CAR2 (%)</td>
<td>1.69**</td>
<td>10.83</td>
<td>-15.12</td>
<td>130.4</td>
<td>233</td>
</tr>
<tr>
<td>5. Partner CAR3 (%)</td>
<td>2.31**</td>
<td>17.29</td>
<td>-46.89</td>
<td>163.8</td>
<td>233</td>
</tr>
<tr>
<td>6. Partner CAR7 (%)</td>
<td>2.34**</td>
<td>50.36</td>
<td>-50.36</td>
<td>168.5</td>
<td>233</td>
</tr>
</tbody>
</table>

*** = p < .01; ** = p < .05; * = p< .10 (for null hypothesis, mean=0)

Table 3a: Returns to Alliance Rivals

<table>
<thead>
<tr>
<th>Alliances</th>
<th>Mean</th>
<th>Std Dev</th>
<th>Minimum</th>
<th>Maximum</th>
<th># of observations</th>
</tr>
</thead>
<tbody>
<tr>
<td>SIC rivals, all alliances</td>
<td>-0.13</td>
<td>9.58</td>
<td>-77.25</td>
<td>116.4</td>
<td>4394</td>
</tr>
<tr>
<td>2. Rival CAR3 (%)</td>
<td>-0.51***</td>
<td>10.91</td>
<td>-95.88</td>
<td>129.5</td>
<td>4394</td>
</tr>
<tr>
<td>3. Rival CAR7 (%)</td>
<td>-1.50***</td>
<td>16.60</td>
<td>-262.86</td>
<td>191.2</td>
<td>4394</td>
</tr>
<tr>
<td>Hoover rivals, all alliances</td>
<td>-0.31**</td>
<td>4.81</td>
<td>-62.08</td>
<td>26.41</td>
<td>1338</td>
</tr>
<tr>
<td>5. Rival CAR3 (%)</td>
<td>-0.39**</td>
<td>5.85</td>
<td>-57.53</td>
<td>51.51</td>
<td>1338</td>
</tr>
<tr>
<td>6. Rival CAR7 (%)</td>
<td>-0.32</td>
<td>11.12</td>
<td>-99.13</td>
<td>137.1</td>
<td>1338</td>
</tr>
<tr>
<td>Hoover rivals, S&amp;P 500 only</td>
<td>-0.43**</td>
<td>5.42</td>
<td>-62.08</td>
<td>26.41</td>
<td>937</td>
</tr>
<tr>
<td>8. Rival CAR3 (%)</td>
<td>-0.52**</td>
<td>6.55</td>
<td>-57.53</td>
<td>51.51</td>
<td>937</td>
</tr>
<tr>
<td>9. Rival CAR7 (%)</td>
<td>-0.39</td>
<td>1.27</td>
<td>-99.13</td>
<td>137.1</td>
<td>937</td>
</tr>
</tbody>
</table>

*** = p < .01; ** = p < .05; * = p< .10 (for null hypothesis, mean=0)
Table 3b: Returns to Alliance Rivals; SE corrected for correlation within deals

<table>
<thead>
<tr>
<th></th>
<th>Mean</th>
<th>Std Error</th>
<th># of observations</th>
<th># of clusters (deals)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SIC Rivals, all alliances</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1. Rival CAR2 (%)</td>
<td>-0.13</td>
<td>0.26</td>
<td>4394</td>
<td>48</td>
</tr>
<tr>
<td>2. Rival CAR3 (%)</td>
<td>-0.51</td>
<td>0.35</td>
<td>4394</td>
<td>48</td>
</tr>
<tr>
<td>3. Rival CAR7 (%)</td>
<td>-1.50*</td>
<td>0.62</td>
<td>4394</td>
<td>48</td>
</tr>
<tr>
<td>Hoover rivals, all alliances</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4. Rival CAR2 (%)</td>
<td>-0.31*</td>
<td>0.19</td>
<td>1338</td>
<td>134</td>
</tr>
<tr>
<td>5. Rival CAR3 (%)</td>
<td>-0.39*</td>
<td>0.22</td>
<td>1338</td>
<td>134</td>
</tr>
<tr>
<td>6. Rival CAR7 (%)</td>
<td>-0.32</td>
<td>0.42</td>
<td>1338</td>
<td>134</td>
</tr>
<tr>
<td>Hoover rivals, S&amp;P 500 only</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>7. Rival CAR2 (%)</td>
<td>-0.51*</td>
<td>0.24</td>
<td>937</td>
<td>111</td>
</tr>
<tr>
<td>8. Rival CAR3 (%)</td>
<td>-0.47*</td>
<td>0.26</td>
<td>937</td>
<td>111</td>
</tr>
<tr>
<td>9. Rival CAR7 (%)</td>
<td>-0.45</td>
<td>0.54</td>
<td>937</td>
<td>111</td>
</tr>
</tbody>
</table>

*** = p < .01; ** = p < .05; * = p < .10 (for null hypothesis, mean=0)
Table 4a: Relationship Between Rival CARs, Participant CARs and Alliance characteristics

<table>
<thead>
<tr>
<th>Sample and Model #</th>
<th>Constant</th>
<th>Average partner CAR2</th>
<th>Horizontal Border</th>
<th>Cross-border</th>
<th>JV</th>
<th>R&amp;D plus</th>
<th>F-stat</th>
<th># of observations</th>
<th># of clusters (deals)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SIC Rivals, all alliances</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1.</td>
<td>-0.002 (0.003)</td>
<td>0.029** (0.013)</td>
<td>0.025*** (0.005)</td>
<td>-0.014** (0.003)</td>
<td>0.007 (0.007)</td>
<td>0.009 (0.008)</td>
<td>4.45**</td>
<td>4048</td>
<td>44</td>
</tr>
<tr>
<td>2.</td>
<td>-0.002 (0.003)</td>
<td>0.028** (0.012)</td>
<td>0.025*** (0.005)</td>
<td>-0.014** (0.003)</td>
<td>0.007 (0.007)</td>
<td>0.009 (0.008)</td>
<td>16.29***</td>
<td>3954</td>
<td>43</td>
</tr>
<tr>
<td>3.</td>
<td>-0.004 (0.003)</td>
<td>0.026*** (0.008)</td>
<td>-0.014** (0.003)</td>
<td>0.007 (0.007)</td>
<td>0.009 (0.008)</td>
<td>2.82*</td>
<td>4048</td>
<td>44</td>
<td></td>
</tr>
<tr>
<td>4.</td>
<td>-0.000 (0.003)</td>
<td>0.025* (0.013)</td>
<td></td>
<td></td>
<td>0.009 (0.008)</td>
<td>2.82*</td>
<td>4048</td>
<td>44</td>
<td></td>
</tr>
<tr>
<td>5.</td>
<td>0.000 (0.003)</td>
<td>0.025* (0.013)</td>
<td></td>
<td></td>
<td>0.009 (0.008)</td>
<td>2.82*</td>
<td>4048</td>
<td>44</td>
<td></td>
</tr>
<tr>
<td>6.</td>
<td>-0.002 (0.003)</td>
<td>0.015*** (0.005)</td>
<td>0.030*** (0.006)</td>
<td>-0.009* (0.005)</td>
<td>0.013** (0.005)</td>
<td>-0.016*** (0.004)</td>
<td>23.73***</td>
<td>3954</td>
<td>43</td>
</tr>
<tr>
<td>Hoover rivals, all alliances</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>7.</td>
<td>-0.004** (0.002)</td>
<td>0.072** (0.036)</td>
<td></td>
<td></td>
<td>0.009 (0.008)</td>
<td>2.82*</td>
<td>1563</td>
<td>135</td>
<td></td>
</tr>
<tr>
<td>8.</td>
<td>-0.004** (0.002)</td>
<td>0.074** (0.036)</td>
<td></td>
<td></td>
<td>0.009 (0.008)</td>
<td>2.82*</td>
<td>1563</td>
<td>135</td>
<td></td>
</tr>
<tr>
<td>9.</td>
<td>-0.004** (0.002)</td>
<td>0.066* (0.038)</td>
<td></td>
<td></td>
<td>0.009 (0.008)</td>
<td>2.82*</td>
<td>1563</td>
<td>135</td>
<td></td>
</tr>
<tr>
<td>10.</td>
<td>-0.004** (0.002)</td>
<td>0.073** (0.036)</td>
<td></td>
<td></td>
<td>0.009 (0.008)</td>
<td>2.82*</td>
<td>1563</td>
<td>135</td>
<td></td>
</tr>
<tr>
<td>11.</td>
<td>-0.003** (0.002)</td>
<td>0.072** (0.035)</td>
<td></td>
<td></td>
<td>0.009 (0.008)</td>
<td>2.82*</td>
<td>1563</td>
<td>135</td>
<td></td>
</tr>
<tr>
<td>12.</td>
<td>-0.004* (0.002)</td>
<td>0.067* (0.038)</td>
<td></td>
<td></td>
<td>0.009 (0.008)</td>
<td>2.82*</td>
<td>1563</td>
<td>135</td>
<td></td>
</tr>
</tbody>
</table>

Robust standard errors with clustering on deal
Std errors in parentheses; *** = p < .01; ** = p < .05; * = p < .10
Results for sub-sample of Hoover rivals listed on S&P 500 are essentially identical to Hoover rivals, all alliances
Table 4b: Relationship Between Rival CARs, Participant CARs and Rival characteristics

<table>
<thead>
<tr>
<th></th>
<th>Constant</th>
<th>Average partner CAR2</th>
<th>Citation-weighted Patent Count</th>
<th>Technology Overlap</th>
<th>Log Sales</th>
<th>F-stat</th>
<th># of observations</th>
<th># of clusters (deals)</th>
</tr>
</thead>
<tbody>
<tr>
<td>SIC Rivals, all alliances</td>
<td>-0.002 (0.003)</td>
<td>0.029** (0.013)</td>
<td>0.029** (0.013)</td>
<td>0.029** (0.013)</td>
<td>4.45**</td>
<td>4048</td>
<td>44</td>
<td></td>
</tr>
<tr>
<td></td>
<td>-0.000 (0.003)</td>
<td>0.018 (0.018)</td>
<td>0.018 (0.018)</td>
<td>0.018 (0.018)</td>
<td>1.04</td>
<td>2591</td>
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<td></td>
</tr>
<tr>
<td></td>
<td>0.005 (0.006)</td>
<td>0.010 (0.016)</td>
<td>0.005 (0.016)</td>
<td>0.005 (0.016)</td>
<td>1.64</td>
<td>2334</td>
<td>44</td>
<td></td>
</tr>
<tr>
<td></td>
<td>-0.006 (0.004)</td>
<td>0.031** (0.014)</td>
<td>0.031** (0.014)</td>
<td>0.031** (0.014)</td>
<td>4.21**</td>
<td>3750</td>
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<tr>
<td></td>
<td>-0.008 (0.012)</td>
<td>0.007 (0.018)</td>
<td>0.007 (0.018)</td>
<td>0.007 (0.018)</td>
<td>1.67</td>
<td>2159</td>
<td>44</td>
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<tr>
<td>Hoover rivals, all alliances</td>
<td>-0.004** (0.002)</td>
<td>0.072** (0.036)</td>
<td>0.072** (0.036)</td>
<td>0.072** (0.036)</td>
<td>4.12**</td>
<td>1563</td>
<td>135</td>
<td></td>
</tr>
<tr>
<td></td>
<td>-0.005** (0.002)</td>
<td>0.078** (0.031)</td>
<td>0.078** (0.031)</td>
<td>0.078** (0.031)</td>
<td>6.01***</td>
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<td>134</td>
<td></td>
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<tr>
<td></td>
<td>-0.000 (0.003)</td>
<td>0.072** (0.030)</td>
<td>0.072** (0.030)</td>
<td>0.072** (0.030)</td>
<td>3.69**</td>
<td>1113</td>
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<tr>
<td></td>
<td>-0.010 (0.007)</td>
<td>0.070* (0.040)</td>
<td>0.070* (0.040)</td>
<td>0.070* (0.040)</td>
<td>2.34*</td>
<td>1080</td>
<td>134</td>
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<tr>
<td></td>
<td>-0.003 (0.008)</td>
<td>0.068** (0.033)</td>
<td>0.068** (0.033)</td>
<td>0.068** (0.033)</td>
<td>1.58</td>
<td>873</td>
<td>132</td>
<td></td>
</tr>
</tbody>
</table>

Robust standard errors with clustering on deal
Std errors in parentheses; *** = p < .01; ** = p < .05; * = p < .10
Results for sub-sample of Hoover rivals listed on S&P 500 are essentially identical to Hoover rivals, all alliances