STRATEGIC ORGANIZATION Vol 6(4): 435–469
DOI: 10.1177/1476127008096365

http://so.sagepub.com

A cognitive model of stock market reactions to multi-firm alliance announcements

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Abstract

Previous studies of stock market reactions to alliance announcements assume that investors accurately detect and encode these public statements, evaluate them with stable, well-established preferences, and that the signalling value of an announcement is independent of the context in which it is conveyed. This article draws on behavioural decision theory to advance a cognitive model of stock market reactions to the announcement of complex, multi-firm alliances. The model predicts a U-shaped relationship between the diversity of partners comprising the alliance and abnormal stock market returns. An empirical analysis of multi-firm alliances announced in the US between 2000 and 2004 corroborates the model's prediction. Moreover, the study shows that a firm's size and analyst coverage moderate the relationship between its alliance partners' diversity and its abnormal returns. These findings suggest that attentional selection and subsequent encoding processes produce cognitive biases in the interpretation of announcements and the market moves towards greater efficiency for large or high-coverage firms. Managers should thus take the effect of the 'process of processing' into account when disclosing information to the investor community.

Key words abnormal returns • alliances • ambiguity aversion • categorization • signalling

Introduction

Strategic alliances have become one of the most important organizational forms for carrying out economic exchanges (Anand and Khanna, 2000), leading to a coinciding surge in studies on alliance outcomes. Researchers have attempted to gauge the value of these collaborations in a variety of ways, perhaps most notably through assessments of abnormal stock market returns (Das et al., 1998; Koh and Venkatraman, 1991; Park et al., 2004). Research of this type has examined the effects of partner size (Chan et al., 1997; Das et al., 1998; McConnell and Nantell, 1985), type of alliance activity (Chan et al., 1997; Das et al., 1998; Koh et al., 1991; Park and Kim, 1997) and environmental munificence (Park and Mezias, 2005) on the relationship between alliance announcements and abnormal returns.

Studies of abnormal returns treat an alliance announcement as a stimulus that prompts investors to reassess the expected return on the firm's securities. In formulating a response, investors are generally assumed to perceive and consider all information disclosed about the alliance (Madhavan and Prescott, 1995; Zajac and Westphal, 2004), and to ponder the hazards and value of the alliance as prescribed by theory (e.g. transaction costs, organizational learning), with theoretical predictions informing their decisions. If, in theory, the alliance is expected to create value for the firm, then it is also expected to create a market return.

This approach to stock market reactions has two important implications. First, decision-makers in financial markets are assumed to attend to alliance signals. This implies that investors detect alliance disclosures and actively seek ways to evaluate firms' persuasive arguments. Investors are thus viewed as capable of recognizing signals in their environment and motivated to interpret them. Furthermore, investors are presumed to have fairly stable and well-established preferences informed by theoretical arguments. When signals are received, decision-makers interpret them and reveal their preferences on the spot. Thus, the nature of an investor's response is determined by the match between the signal's persuasion cues and the investor's evaluation schemes. The investor decision process is infallible, and neither its requirements nor its characteristics matter. If managers have considered the correct decision inputs entering into an alliance, then investors will reward them. Second, and relatedly, the signalling value of an alliance is treated as independent of the context in which it is conveyed. Reactions to signals released in complex or volatile settings, and simpler or stable environments, are thus assumed to be the same. Situational factors do not intrude.

These implications portray a decision process that results in correct valuations and a decision-maker who is unaffected by cognitive biases. Both these characterizations, however, are inconsistent with evidence from studies of financial market behaviour in behavioural finance (see Hirshleifer, 2001 for a review) and sociology (Zajac and Westphal, 2004; Zuckerman, 1999, 2004), which demonstrate that investors frequently depart from economic conceptions of rationality. A host of cognitive biases and shortcomings arise in the formation of their expectations and in shaping their attitudes towards risk; investors over-extrapolate some information and under-react to other news (Hirshleifer, 2001; Hirshleifer et al., 2004).

In this article, we advance an alternative, cognitive model of stock market reactions to alliance announcements. To that end, we investigate the market returns to partner diversity in the context of multi-firm alliances. Multi-firm alliances are complex events that allow for and require investors to make more refined distinctions across signals. We focus on partner diversity as the primary explanatory variable for three reasons. First, partner diversity is a direct determinant of collaborative gains, costs and longevity (Park and Russo, 1996; Sampson, 2005) and, therefore, serves as a fundamental conditioning argument in investor evaluation of an alliance's economic worth. Second, diversity is a powerful cognitive categorization tool (Schwenk, 1984; Tversky, 1977). Alliance disclosures create incomplete decision situations in which investors are confronted by numerous, often ambiguous, information fragments on the basis of which they must assign economic value to an alliance. In this world, investors exercise choices with respect to limited, approximate and simplified models by categorizing discrete pieces of information (March and Simon, 1958). Third, there is scant empirical evidence on the relationship between partner diversity and abnormal returns, and the evidence that does exist is mixed, with Koh and Venkatraman (1991) reporting a negative relationship between partner diversity and abnormal returns, Balakrishnan and Koza (1993) and Reuer and Koza (2000) a positive relationship for joint ventures, and Merchant and Schendel (2000) no relationship.

Our study contributes to the literature on stock market reactions to corporate disclosures. In contrast to existing models, which are preoccupied with decision inputs, we consider the cognitive process by which investors make judgements as both influential in attitude formation and problematic for inference. We thus extend existing approaches by advancing a decision process model that outlines how decision-makers identify, extract, compile and process alliance signals. Our approach resonates with Stiglitz's (2000: 1471) call for the integration of economic explanations with cognitive research on 'how individuals process information, form expectations, and select among possible signals'.

Reviews of behavioural work on market responses to disclosures observe that most proposed explanations for errors in investor valuation tend to be expost rationalizations of the existence of a single, specific cognitive bias and are thus incomplete and limited in their predictive power. They rarely provide exante accounts of when one type of cognitive bias would dominate over others (Hirshleifer, 2001). In this article, we delineate stages (i.e. selection and encoding) and identify associated cognitive mechanisms (i.e. biases) that trigger discrepancies between the alliance's 'true value' and the stock market response. We develop predictions about the conditions under which such discrepancies are most likely to occur and validate them empirically. Furthermore, we shed light on factors that serve to mitigate errors in valuation, which complements extant research concerned with specifying when misvaluations might occur rather than under what circumstances they might not.

Our research emphasizes methodological caution to scholars who seek to use stock market reactions as a gauge of value creation in alliances. Research investigating returns to partner diversity in alliances has produced disparate findings. An explanation for the differences may be found in the information environment of the announcements and the cognitive processes evoked by the context.

Theory and hypotheses

Multi-firm alliances and partner diversity

Multi-firm collaborations are becoming increasingly common, yet in terms of traditional alliance queries, the terrain is virtually unexplored. These alliances differ from groups of dyadic alliances or a network of partners that maintain ties to a single focal firm. Though many of the differences between multi-firm and dyadic alliances are a matter of degree, multi-firm agreements have some idiosyncratic properties. These are intricate settings in which the behaviour of the focal firm is influenced by the entire set of other firms with direct stakes in the outcome. They require multilateral interactions between partners. Firms have little choice but to consider and rely upon the traits, motivations, actions and contributions of the other members of the group in crafting their behaviour (De Clerq et al., 2005; Lavie et al., 2007; Zeng and Chen, 2003).

Partner diversity is a central construct in the debate over collaborative costs and gains (Park and Russo, 1996; Sampson, 2007). The diversity of the organizations participating in an alliance can be measured in different ways. In this article, we employ industry diversity for two reasons. First, it is the most commonly used construct in studies of interorganizational networks and research on alliances. Industry diversity has been associated with heterogeneity in organizational routines and knowledge-bases, organizational experiences and information (e.g. Anand and Khanna, 2000; Beckman et al., 2004; Mowery et al., 1996; Oxley, 1997; Sampson, 2007). Managers from different industries hold dissimilar beliefs and diverse world views about their organizations and environments (e.g. Baum and Lant, 2003; Geletkanycz and Hambrick, 1997). Second, this measure is the most convenient for analyses of financial market behaviour as the social structure of the stock market hinges on an industry-based classificatory system. Security analysts are typically specialized by industry. Investors in stock markets value stocks in reference to their location in these industry-based categories and usually evaluate companies based on peer analyses (Jensen, 2004; Zuckerman, 1999, 2004).

Investor decision-making

Scholars have primarily used transaction cost economics (e.g. Balakrishnan and Koza, 1993; Koh and Venkatraman, 1991) and organizational learning theory (Anand and Khanna, 2000; Kale et al., 2002) to explain returns to alliance announcements. While these theories provide information about the costs and benefits of allying with diverse partners, they offer only a partial understanding of why the market reacts in specific ways to different types of alliance announcements. Market returns are the results of investors' buy–hold–sell decisions subsequent to the disclosure of an alliance, and are only indirectly determined by its value-creating properties. Thus, in order to explicate stock market reactions, we need to understand investors' decision-making processes.

The formulation of a stock market reaction to an alliance announcement is an intricate, inferential process. Investors often have incomplete information on firms' fundamentals and economic activities (Hirshleifer, 2001). Alliances themselves are complex arrangements resulting from myriad motives (Anand and Khanna, 2000). Moreover, most alliance information does not reach the decision-maker in convenient ways. For strategic reasons, firms may not disclose detailed information on the terms, structure or the content of an alliance. Additionally, decisions triggering alliances usually involve latent information not fully available to the market (Acharya, 1993). Expected alliance benefits might be framed in overly optimistic terms and the information contained in the announcement might be noisy and/or extraneous.

Alliances are also part of a broader context – organizational adaptation – to which investors must attend in enacting a decision. This is because the decision process embodies a probabilistic focus on the gains and also on the losses. Should the alliance fail, what the commitment means for the firm has to be taken into account. Alliance traits and aims must be weighed against organizational goals, priorities and recent actions. The omission of observable pre-event information for investors imputes a biased measure of the signal (Acharya, 1993).

Alliance announcements breach situational continuity and instigate efforts to construct a plausible sense of what is happening and what needs to be done (Weick and Sutcliffe, 2001). How investors respond depends on their identification and interpretation of alliance traits and other relevant cues under cognitive constraints and asymmetric information (Simon, 1957). Since potential pricing anomalies quickly dissipate, investors have to define and figure things out for themselves under severe time pressures, rendering efforts such as searching widely for information, conducting extensive analyses and engaging in feedback cycles difficult and costly (Frederickson and Mitchell, 1984). The decision process is one of an explicit effort of sense-making in a market in flux (Weick and Sutcliffe, 2001).

The complexity involved in multi-firm alliances and their contexts, combined with limited information and the need for fast decision-making, creates challenges for boundedly rational investors reacting to alliance announcements; challenges that, we contend, lead their interpretations of alliance benefits to vary as a function of alliance partner diversity.

Signals and categorization

Selective attention

Signalling theory holds that individuals do not immediately respond to signals. They first have to notice the signal, and research shows that signals are not all discerned equally (Hoffman and Ocasio, 2001). The mere identification of a signal requires attention. Only after identification is complete does activation of cognitive processing (e.g. categorization) occur. Thus, attention is necessary to invoke the 'enactment process' (Weick, 1979). However, individual attention is limited and often has to be split between competing signals and tasks, under time pressures. Hence, attention must be selective and requires effort.

Individuals do not randomly select where to deploy their attentional resources. Attentional selection depends on the results of temporally prior computational processes. These pre-attention processes are filtering mechanisms. They provide the informational as well as the motivational basis for attentional selection (Logan, 1992). The nature of these processes matters for our purposes because individuals trust in their validity and accuracy and, hence, their inputs weigh more heavily in subsequent interpretations and evaluations of the stimuli (Bargh, 1992). Evidence from signalling studies indicates that increases in the motivation to process signals influences the number of cognitive responses generated, with more positive cognitive responses and fewer negative responses generated (e.g. Chaiken, 1980; Petty and Cacioppo, 1986). Thus, we anticipate a positive bias in reactions to the alliance disclosures that gain investor attention.

Psychological research on attention process triggering highlights two properties of the information contained in signals. First, individuals tend to react to information that is salient. While several signalling properties may constitute salience, the critical one is the distinctive quality of the stimulus. Regardless of where their attention centres, individuals are still affected by distinctive stimuli (Nisbett et al., 1976; Taylor and Fiske, 1978). This is due to a crucial limitation of the pre-attention process, which is the inability to directly conjoin the properties of a stimulus; however, when its features are easy to discriminate, the target is detected very rapidly (Logan, 1992; Treisman et al., 1992). A distinct stimulus seems to dominate the sensory field and prompt the individual to notice unusual, differential or novel elements. Furthermore, the distinctiveness of the features increases the robustness of their combination in the face of disruption (by, for example, another signal) in subsequent processing. The signal becomes 'sticky' in the cognitive space (Bargh, 1992; Logan, 1992; Taylor and Fiske, 1978).

Familiarity is the second factor that seems to focus attention. Cognitively proximal targets (in a sensory, temporal or spatial sense) increase perceptual readiness and information-processing proclivities. They divert attention from the task at hand because the perception of familiarity increases the perception of relevance and affects the individual's motivation to use stored knowledge to interpret and integrate new information (Bargh, 1992; Logan, 1992; Nisbett and Ross, 1980; Taylor and Fiske, 1978).

In light of these two factors, we posit that high- or low-diversity multi-firm alliances are more likely than medium-diversity multi-firm alliances to be detected. Increasing diversity raises the distinctiveness of the signal's properties and allows for better integration in the pre-attentive phase. Alliance announcements involving highly diverse partners should stand out in the information environment, as they provide a sharp contrast with other stimuli in the same context. Reduced diversity increases cognitive proximity (especially for equity analysts who are specialized by industry [Zuckerman, 1999]) and, thereby, increases the chances of the signal being detected.[1] These screening effects diminish the quantity of intermediate-diversity alliance disclosures involved in cognitive processing and eventually curb trading based on the information supplied by them. This is likely to result in greater stock price stability of those firms involved in alliances of intermediate diversity.

Categorization, ambiguity aversion and overconfidence

Once a signal is detected, the individual begins encoding, which involves comparing and contrasting alternatives on the basis of some information-rich traits. Signalling theory asserts that as the set of alternative meanings of a signal declines, its clarity grows. A clear signal can be encoded quickly and allows for instant action. Unclear signals leave the receiver with uncertainties about the intentions and means–end relations (Heil and Robertson, 1991). Lack of clarity makes encoding more difficult, slower and less efficient (Jackson and Dutton, 1988). It calls for a 'piecemeal' process in which the assessments of each individual attribute must be cumulated to calculate an overall evaluation (Kulik, 1989). This strains the cognitive capacity. To cope, decision-makers resort to the organizing principles on which they structure their information environment. One powerful principle is categorization, which simplifies encoding by restricting attention to a limited set of variables (Baum and Lant, 2003; Tversky, 1977).

Categorization produces a reduction in ambiguity. However, inability to categorize a signal evokes a psychological bias known as ambiguity aversion. This results in either a negative evaluation of the signal or a deferral of reaction and, therefore, a preference for maintaining the status quo (Samuelson and Zeckhauser, 1988). Evidence abounds. Yates et al. (1978) found that decision-makers devalue alternatives that are partially described and incomplete in favour of clearly defined alternatives even though the partially described alternatives might score high on evaluation criteria. In studies of stock market reactions to managerial forecasts, investors have been known to interpret negatively the choice of a range forecast over a point forecast (Baginski et al., 1993). In analyses of consumer choice, consumers reveal a strong predisposition towards brand loyalty (status quo) under conditions of ambiguous information, e.g. multiple interpretations of product quality (Ha and Hoch, 1989). When the strategic characteristics are ambiguous, managers seem to be unwilling to draw firm conclusions about whether a particular issue is an opportunity or a threat (Jackson and Dutton, 1988). Likewise, executives of declining firms seem to increase their commitment to prior actions when confronted by ambiguous indicators of the effectiveness of a current strategy (Staw and Fox, 1977). More broadly, Weick and Sutcliffe (2001) observed that unless organizations have developed routines to handle weak signals, they are likely to ignore them or categorize them as irrelevant.

Many causal mechanisms have been invoked to explain this behaviour. The psychological state of decision ambiguity is cognitively painful, and so avoided (Curley et al., 1986). The less comprehensive an individual's understanding of a situation, the greater will be her or his feelings of incompetence and desire to avoid the situation in question (Heath and Tversky, 1991). Since default options are the outcomes of competent choices, an overconfidence bias towards the status quo will arise from less precise signals (Griffin and Tversky, 1992). Post-decision implications also contribute to ambiguity aversion. Signal clarity is negatively associated with expected post-decision disappointment (Harrison and March, 1984). The decision to stay with the status quo allows flexibility of future choice and avoids post-decision regret. It is difficult to justify decisions, and convince others that a good decision has been made, when the information available cannot be comprehended and documented precisely (Curley et al., 1986).

While individuals tend to be undersensitive to ambiguous signals, they also tend to be oversensitive to clear signals. An ambiguous signal inflates confidence in the default options, whereas a clear signal creates overconfidence in the sender's judgements. Overconfidence bias arises because individuals are economy minded – guided in their information processing by the least effort motive.[2] They are cognitive misers (Chaiken, 1980; Slovic et al., 1977; Taylor and Fiske, 1978). As a result, information that is easily retrievable weighs more heavily in human judgements than it should. Individuals attend too much to information strength and not enough to information weight, and so tend to overweight the probabilities of contingencies that are explicitly available for consideration (Griffin and Tversky, 1992; Slovic et al., 1977; Tversky and Kahneman, 1974).[3] For instance, greater precision in managerial forecasts leads investors to systematically overestimate the forecasts' accuracy (Baginski et al., 1993). Job seekers tend to make pessimistic inferences about the actual pay of jobs advertised with ambiguous information about pay (e.g. 'competitive salary'). When the actual salary is quoted, in contrast, they tend to find the advertised vacancy overly attractive (Barber and Roehling, 1993). Similarly, CEOs interpret clear media praise for past actions as a sign of confidence in their ability to create firm value (Hayward and Hambrick, 1997). More broadly, the literature on message comprehension has shown that individuals find clear, simple messages more persuasive (Chaiken, 1980; Ratneshwar and Chaiken, 1991).

In laboratory market studies, a clear signal does indeed create stronger market reactions than an ambiguous signal, in the form of higher closing prices (Nelson et al., 2001). Likewise, a stock trader appears to feel more comfortable investing in stocks with which she or he is moderately familiar when she or he is reminded of unfamiliar stocks, than when reminded of very familiar stocks (Fox and Weber, 2002). Hayward and Hambrick (1997) found that CEOs who have been the recent recipients of clear media praise pay larger premiums for subsequent acquisitions.

Implications for multi-firm alliance returns

Research on attention thus indicates that, in the face of cognitive constraints, individuals selectively attend to salient and familiar signals, leading us to expect pre-attentional sorting to limit investor attention to multi-firm alliance announcements of intermediate partner diversity. The screening process does not end with the signal being noticed, however. Encoding research highlights that clear signals are likely to generate more positive reactions than ambiguous signals as a consequence of ambiguity aversion and overconfidence. Consequently, among multi-firm alliance announcements that attract attention, those regarded as more (or less) ambiguous will tend to be evaluated less (or more) positively, as encoding unfolds. Table 1 summarizes our main theoretical arguments regarding partner diversity, as well as three mediating factors – firm size, uncertainty and analyst coverage – developed in greater detail below.

We contend that alliances of intermediate diversity represent ambiguous signals – and hence are subject to ambiguity aversion – whereas high- or low-diversity alliances constitute relatively clearer signals – and thus are subject to overconfidence bias. At the tails of the partner diversity distribution, a multi-firm alliance can be categorized as cooperative or competitive (Khanna et al., 1998), exploratory or exploitive (Koza and Lewin, 1998), local or non-local search (Zollo et al., 2002), or a link or scale collaboration (Kogut, 1988). At intermediate partner diversity levels, the alliance mixes these 'pure types' into a hybrid that suffers from lower standing (Carroll and Swaminathan, 2000), as individuals struggle to embrace the competing frames simultaneously embodied in it (Gilbert, 2006).

Zuckerman (1999) showed that security analysts evaluate firms more favourably when they are easily assignable to particular industry categories. They refrain from following firms that fail to establish themselves clearly as members of specific industry categories due to the difficulties of comprehending and evaluating them. Confusion over the categorical identity of a firm causes its equity to trade at a discount. Haunschild and Miner's (1997) study demonstrated that average past premiums paid by other firms consistently had no significant effect on an organization's choice of investment advisers, whereas very high and very low premiums affected their choices. Consistent with the preceding discussion, this pattern suggests that salient and detectable outcomes are particularly influential as signals. Taking account of these factors, we predict:

HYPOTHESIS 1 There is a U-shaped relationship between multi-firm alliance partner diversity and the abnormal stock market return following its announcement.

Moderating the effects of partner diversity on alliance returns

Certain variables, which affect the processes of both signal detection and encoding, might moderate these predicted relationships. We concentrate on firm size, firm-specific uncertainty and analysts' coverage. We consider magnitude effects as moderation outcomes: the degree to which firms that differ based on the

Table 1 Summary of theoretical arguments

Partner diversity main effect

Argument: Intermediate partner diversity alliances are less likely to be detected. Increasing diversity increases the distinctiveness of signals' properties, reducing diversity increases cognitive proximity.

Argument: Intermediate partner diversity alliances generate lesser returns than high- or low-diversity alliances. They trigger ambiguity aversion, whereas tails produce overconfidence bias.

Size as a moderator

Argument: The probability of detection is greater for the large firm's alliance signal than that of the small firm at all levels of partner diversity. Size affects familiarity, rate of information flow, signal clarity and alertness.

Argument: Small firm signals are more competitive at eliciting attention at high/low levels of partner diversity than intermediate levels. Source inputs exert less influence as signal becomes more discernable.

Argument: The probability of a positive market reaction is greater for a small firm alliance signal than that of a large firm at all levels of partner diversity. Size and returns to cognitive legitimacy are inversely related.

Argument: Overconfidence bias suggests that the difference in the probability of a positive market reaction between a small and large firm is greater at the tails than at intermediate partner diversity.

Uncertainty as a moderator

Argument: The probability of detection is greater for low-uncertainty firm's signal than that of the high-uncertainty firm at all levels of partner diversity. Uncertainty obscures signal clarity. It induces source derogation.

Argument: High-uncertainty firm signals are more competitive at catching attention at high/low levels of partner diversity than intermediate levels. The effect of source evaluation diminishes as signal's attention getting qualities improve.

Argument: The probability of a positive market reaction is greater for a firm experiencing high uncertainty than low uncertainty. Alliances signal that firm-specific issues are recognized and dealt with.

Argument: Overconfidence bias suggests that firms faced with more uncertainty garner greater returns than low-uncertainty firms at high or low levels of diversity.

Analyst coverage as a moderator

Argument: The probability of detection is greater for the high-coverage firm signal than low-coverage firm signal. Analysts enhance familiarity, narrow information asymmetry and reduce noise and ambiguity.

Argument: Low-coverage firm signals are more competitive at eliciting attention at high/low levels of partner diversity than intermediate levels. Source inputs exert less influence as signal becomes more discernable.

Argument: The probability of a positive market reaction is greater for a low-coverage firm than a high-coverage firm. Greater coverage implies greater market scrutiny and less momentum trading.

Argument: There should be less room for overreactions for high-coverage firm signals. Overconfidence bias should thus dominate low-coverage firm signals to a greater extent at high or low levels of partner diversity.

moderator earn differential returns given a certain level of diversity. We view these outcomes as the product of the probability of attentional selection and the probability of a positive response. The latter is conditional on the signal being detected. Any increase in the probability that the signal will be noticed increases the probability of a positive reaction. We structure our discussion accordingly.

Firm size

Firm size directly affects the attentional selection processes by increasing familiarity. Size and information availability are positively related. Large firms face greater pressure to disclose information voluntarily because their actions have a greater impact on their environments. They thus send more frequent signals. For this reason, large firms also attract more media attention, providing investors with more accessible and extensive information on their recent activities and fundamentals at lower cost (Pollock and Rindova, 2003). Since familiarity for the general public is closely related to the amount and duration of attention afforded to these firms by the media, the bigger the firm size, the greater is the motivation to process its signals.

In contrast, the search for information regarding small firms is more costly: fewer items are published in the business press, their actions are less visible and information about them travels slowly (Hong et al., 2000). Hence, small firm signals are more 'novel' and the information asymmetry between investors and managers is wider for small firms. The signals sent by small firms are also likely to possess less clarity. More frequent disclosure endows a firm with greater competence in the 'art' of disclosure. Unlike large firms, which usually maintain investor relations departments where communication experts manage information dissemination, few small firms have institutionalized the disclosure process (Rao and Sivakumar, 1999).

These observations suggest that a large firm's signals are more likely to be attended to than a small firm's signals at all levels of diversity. Familiarity with the sender increases the strength of the signal irrespective of its content (Taylor and Fiske, 1978). Repeated exposure results in individuals forming subconscious mental representations. It establishes memory traces of the outputs of a future attentional selection. It raises the individual's expectancy of encountering the target and is accordingly a positive determinant of 'alertness'. When the individual is highly alert, the reaction time to a stimulus is shorter (Cecil et al., 1984).

If investors are more likely to attend to the signals of large than small firms at intermediate levels of diversity, are they even more likely to do so as diversity departs from the intermediate level and the signal's attention-getting qualities improve? Existing evidence suggests the opposite. Although familiarity intervenes positively, its effect is diminished as the signal becomes more discernable, and the need for an individual to retrieve information stored through prior exposure from the memory reduced.[4] More generally, non-peripheral (source) stimulus inputs will exert significant influence on attentional choice when peripheral (signal) inputs lack diagnosticity. The background information will help individuals differentiate between alternatives that otherwise appear equivalent. Conversely, non-peripheral inputs such as perception of the source will influence attentional reactions less when peripheral cues are clear (Petty and Cacioppo, 1986). Small firms are thus more effective at competing for attention when the signal's content is perceptually easily identifiable. The signalling value of a marginal increase in analyst coverage (Hong et al., 2000; Pollock and Gulati, 2007), appointing a reputable outside director to the board (Deutsch and Ross, 2003) or a new product introduction (Chaney et al., 1991) – signals that are highly discriminable – is found to be greater for small firms.

Alliances award 'cognitive legitimacy' to small firms, and heighten their visibility and the market's awareness. In the eyes of financial evaluators, an alliance validates the resources and the capabilities of relatively unknown business organizations (Deeds et al., 2004; Jensen, 2004; Stuart et al., 1999). An immediate implication of this increased importance is the overconfidence bias in the expected future performance of small firms. For instance, there is evidence that salience-boosting signals, such as inclusion in the S&P 500 index (Denis et al., 2003), initiation of coverage by an analyst (Pollock and Gulati, 2007; Rao et al., 2003) and endorsements by lead underwriters (Higgins and Gulati, 2003; Stuart et al., 1999), tend to result in upward revisions in analysts' expectations of a small firm's earnings. This occurs because such signals inspire confidence (Higgins and Gulati, 2003; Stuart et al., 1999), and raise expectations that the firm's leaders will revise their own aspirations upward (Denis et al., 2003).

We reason that the marginal legitimacy effect of an alliance signal is greater for the small firm than for the large firm (Denis et al., 2003; Higgins and Gulati, 2003; Jensen, 2004; Rao et al., 2003). Thus, a positive bias should dominate the alliance encoding process to a greater degree for small firms than for large firms at all levels of diversity. Since small firm signals are relatively more competitive at eliciting attentional response at high or low levels of diversity and because it is also at those levels that overconfidence bias is postulated to be greater, we expect:

> **HYPOTHESIS 2** There is a negative relationship between firm size and abnormal stock market returns following a multi-firm alliance announcement; small firms' gains relative to large firms' will be smallest at intermediate partner diversity.

Firm-specific uncertainty

Decision-makers process signals in conjunction with available a priori information. High firm-specific uncertainty not only increases the information load, but also contaminates the information background and obscures the clarity of the signal. It implies many alternative evaluations, divergent opinions, dissimilar cues, random elements and substantial noise in the information environment, all of which increase the potential for negative post-decision surprises (Harrison and March, 1984) and raise fears of incorrect action (Curley et al., 1986). These conditions engender caution in selective attention.

Thus, at intermediate diversity, signals from high-uncertainty firms are less likely to attract attention than those from low-uncertainty firms. Justification for this expectation is provided by information-processing research, which suggests that, under strained processing conditions, rather than attempting to evaluate signal content, individuals may opt for source evaluation as a simplifying tactic. And, to the extent that the source appears to lack credibility, the signal will be discounted – a phenomenon known as source derogation (e.g. Chaiken, 1980). Since ambiguous signals demand greater cognitive processing, intermediate diversity is likely to induce substantial source-evaluation, and decision-makers to derogate high-uncertainty firms, resulting in less inclination to process their signals.[5] Moreover, just as the impact of size-produced familiarity, the effect of source evaluation should also diminish as the signal's attention-grabbing qualities improve. We therefore anticipate the difference in detection probabilities of signals of high- and low-uncertainty firms to decrease with signal clarity.

In the same way that small firms benefit disproportionately from alliances, so too do firms characterized by high uncertainty. Partnerships enhance the organizational ability to address issues that the firm has been unable to resolve effectively with the existing resources (Beckman et al., 2004). They signal to the external community that firm-specific issues are being recognized and dealt with (Beckman et al., 2004). The fact that a high-uncertainty firm has been able to join a multi-partner alliance lends legitimacy to its business fundamentals and managerial competence and raises performance expectations. The multi-partner alliance acts as an endorsement that influences external perceptions of the quality of the focal firm (Jensen, 2004; Stuart et al., 1999). Thus, following the overconfidence bias thesis outlined earlier, we expect high-uncertainty firms to garner greater returns from multi-firm alliance announcements than low-uncertainty firms at high or low levels of diversity.

> **HYPOTHESIS 3** There is a positive relationship between firm-specific uncertainty and abnormal stock market returns following a multi-firm alliance announcement; high-uncertainty firms' gains relative to low-uncertainty firms will be smallest at intermediate partner diversity.

Firm coverage

Security analysts are the market's most important intermediaries. They are highly credible sources of persuasion cues. They extract large amounts of data from various sources, identify key cues, develop judgements on firm values and expose firms' latent information. In doing so, they not only reduce the information asymmetry on the security and hence enhance investor familiarity; they also reduce 'noise' and 'ambiguity' in the market. For each analyst, there is a positive probability that he or she will discover some information not discerned by other analysts. Consequently, the more analysts cover a firm, the better informed will be the market about its equity. Furthermore, analyst coverage implies more stringent monitoring by the market, which forces firms to be more interactive with external stakeholders and to develop better competencies in information dissemination. For these reasons, empirical evidence generally confirms that analysts enhance the informational efficiency of markets (Hirshleifer et al., 2004; Hong et al., 2000; Rao et al., 2003). Thus, high coverage contexts should require lower cognitive processing costs and invite more attention at intermediate levels of diversity. We thus expect a greater fraction of low-coverage firm signals to fail to achieve attentional detection at these levels. This expectation is in line with source-evaluation reasoning that low analyst coverage implies low status in the market (Zuckerman, 1999) and, thereby, greater cognitive background for source derogation. Similar to our previous expectations, we predict the influence of analyst coverage on signal detection probability to be lowest when the signal is easily discernable. The peripheral cues will retain more attention than non-peripheral (e.g. analyst environment) inputs.

At high or low levels of diversity, we expect the overconfidence bias to be stronger for low coverage than for high coverage firms. On the one hand, similar to the case made for small firms, the positive legitimacy effect of a multi-firm collaboration must be greater for low-coverage firms. On the other hand, since greater coverage means greater market efficiency, by definition, there should be less room for overreactions. The increase in analysts' allocations of effort results in a more precise estimation of the firm's business fundamentals and increased professionally informed trading and, in turn, less volatile and more rational market reactions. For instance, studies of earnings expectations show larger variance in analysts' forecasts when the number of the analysts is small, suggesting greater potential for overreactions (Hirshleifer, 2001). More specifically, studies of momentum trading document that the magnitude of momentum profit is largest for low-coverage stocks. This, in part, is because stocks with lower analyst coverage, all else being equal, are those about which firm-specific released information moves more slowly across the investing public (Hong et al., 2000).

HYPOTHESIS 4 There is a negative relationship between analyst coverage and abnormal stock market returns following a multi-firm alliance announcement; low-coverage firms' gains relative to high-coverage firms will be smallest at intermediate partner diversity.

Methods

Sample

Our focus is on high-tech alliances, which are ideal for our purpose due to the frequency of multi-firm collaboration and the complexity of the information environment. We examine alliances announced between 2000 and 2004. The data were obtained from the Securities Data Corporation (SDC), which is a comprehensive source of information on alliances. The SDC allows the researcher to draw data exclusively on high-tech alliances. From these, we eliminated biotechnology alliances because of idiosyncratic industry properties (see Powell et al., 1996). Also, few biotechnology firms are listed on the stock markets. Non-equity alliances are most common in high-tech settings and, in addition, very few equity-based alliances involve multiple firms. These empirical conditions directed our focus to non-equity alliances. We further screened the sample by: (1) confining our analysis to multi-firm alliances; (2) focusing on firms listed on the NASDAQ and NYSE; (3) excluding joint ventures acting as alliance partners in the sample; (4) deleting multi-firm alliances with state agencies and non-profit organizations; and (5) eliminating firms that released other firm-specific information simultaneously with the announcement of the alliance, including unexpected dividend or earnings announcements, takeover bids, merger negotiations, changes in key executives, restructurings, major contract awards, significant labour disputes, liability suits and announcements of new products. To identify contaminated announcements, we searched LexisNexis for other firm releases and news over the three-day period (seven days for the extended event period in the supplementary analysis) surrounding the alliance announcement. Our final non-contaminated sample consisted of 173 multi-firm alliances comprising 269 observations.

Prior studies using the SDC database have reported occasional errors (Anand and Khanna, 2000). Once the sample was assembled, we therefore took two precautionary steps to ensure accuracy. First, we obtained all press releases through an electronic database search to validate the content of our data. Second, we cross-checked the assigned SIC codes with those reported in S&P Corporate Directories. These efforts led to the identification and correction of four errors, three misrecorded announcement days (from one to three days late), and one assignment of a parent firm's SIC code to an unrelated subsidiary.

Estimation

We employed event study methodology to gauge the firm valuation effects of announcements. Stock returns were gleaned from the Center for Research in Security Prices (CRSP) database.

Dependent variable: abnormal stock market return

Abnormal stock market return (AR) represents a critical measure of performance, as it determines the value of the firm and, in principle, dictates the cost of firm capital. It also signifies confidence in managerial decision-making. An announcement's impact on the stock price is calculated by regressing the rate of return on the share of firm i on day t (R_{it}) against the rate of return on a market portfolio (R_{mt}) on day t. To obtain estimates for α_i and β_i we use daily data on the stock market returns for each firm over a 100-day period 10 days prior to the beginning of the event period. We derive the estimates by ordinary least squares (OLS) regression of the actual return on the stock against the actual return on a market (CRSP) index:

$$R_{it} = \alpha + \beta_i R_{mt} + \varepsilon_{it}$$

where R_{it} denotes the daily returns for firm i on day t; R_{mt} denotes the corresponding daily returns on the CRSP value-weighted index on day t; α_i and β_i are OLS estimates of firm i's market model parameters, and ε_{it} is an idiosyncratic error term for security i on a given day. The abnormal return is computed for security i on day t as the error term (ε_{it}). For each firm i, abnormal returns are then cumulated over the announcement period to find the cumulative abnormal return (CAR).

A key issue in event studies is the choice of event period. Including time before the event helps to capture prior information leakage, whereas post-release time captures slow market responses. McWilliams and Siegel (1997) suggest that the event window should be as short as possible, as longer windows severely reduce the power of the test statistic. Short periods are also preferable in volatile sectors, because a short interval reduces potential noise. We chose the three-day period from day $t = -1$ to $t = +1$ to accommodate all these considerations (Koh and Venkatraman, 1991; Merchant and Schendel, 2000).

Independent variable: partner diversity

We formulated the partner diversity measure by tapping into the SIC code at the three-digit level (Zuckerman, 1999). We computed this measure as:

$$D_i = 1 - \sum (P_i / P_s)^2$$

where P_i is the share of the alliance partners in the same industry as the focal firm, and P_s denotes the alliance size. This measure takes into account the number of industries represented in the alliance and the relative importance of each in the total alliance composition.

Moderator and control variables

Prior research utilizes few control variables. Madhavan and Prescott (1995) used an industry-level variable and firm size as the only alternative explanations. Kale et al. (2002) controlled for industry effects, firm size and whether the alliance was equity or non-equity based. Das et al. (1998) tested only for the effect of alliance type and firm size. Park et al. (2004) imposed controls for the focal firm's alliance experience, age, size and business model. This narrow use of control variables assumes that other firm-specific pre-event information does not differ across firms, thereby also assuming that the market's inference of the value of information underlying an event is not conditional on information observable prior to an announcement (Acharya, 1993). In addition to our moderators, we employ several cross-sectional and inter-temporal controls.

Firm size: We include in our models the natural logarithm of annual sales.

Analyst coverage: To construct this variable, we drew on IBES (Institutional Brokers Estimates System). This variable includes the number of institutions that have covered the firm in the 12 months prior to the alliance announcement.

Firm-specific uncertainty: We operationalized this variable as the monthly volatility of the focal firm's stock in the year prior to the alliance announcement (Beckman et al., 2004). Monthly volatility is calculated as the coefficient of variation for firm *j*'s annual monthly closing price or:

$$\frac{\text{Standard Deviation (Firm's Monthly Closing Price, Year } i\text{, Firm } j\text{)}}{\text{Average (Firm's Monthly Closing Price, Year } i\text{, Firm } j\text{)}}$$

where $i = 1999,\ldots, 2003$. The index j represents each of the firms in the sample.

Performance: Even if firm size is a frequently used measure of familiarity, it is likely to capture performance as well, potentially confounding our findings. We therefore also control for performance defined as the average return on asset in the nearest four quarters.

Institutional ownership: Institutional investors tend to be much more sophisticated and seem to have different investment horizons and greater information-processing capacities than non-institutional investors. Thus, we account for their potential effects. We computed the proportion of outstanding shares owned by institutional investors based on the most recent reported data prior to the alliance announcement. We obtained these data from Thomson Financials.

Alliance size: We control for the number of partners in the alliance as alliance size might be negatively related to its performance (Zeng and Chen, 2003).

Alliance type: Different types of alliances may produce different stock market reactions (Das et al., 1998; Park et al., 2004). In line with prior studies, we created dummy variables for technology alliances and marketing and sales alliances, and alliances that involved both. We examined all the press releases to categorize these alliances and compared our results with the alliance SIC codes assigned by SDC, which showed a 98 percent correlation. The only differences were in relation to four alliances, which the press releases noted as both technology and marketing and sales alliances, whereas the SDC assigned them to one category only.

Alliance experience: Two different measures were used to capture alliance experience. General alliance experience is measured by the logged number of alliances a given firm has established in the five years prior to the alliance announcement (Kale et al., 2002). Partner-specific alliance experience may also influence the market reaction (Zollo et al., 2002). We measure this as the number of alliances formed with the same partner five years prior to the alliance announcement.

Alliance capability gap (ACG): Previous research on alliances suggests that alliance capabilities, which emerge out of previous alliance engagements, are the most important factor in alliance success (Anand and Khanna, 2000; Kale et al., 2002). Partners should be able to coordinate resources and tasks and manage interorganizational routines and conflicts effectively. An inability to do so will lead to the eventual demise of the alliance (Khanna et al., 1998; Zollo et al., 2002). For our purposes, in addition to the focal firm's alliance experience, we need to control for the degree of the heterogeneity of alliance partners' capabilities. To the extent that such capabilities are asymmetrically distributed, partners endowed with more will be likely to appropriate the economic rents of their less-advantaged partners (Park and Russo, 1996). We use the following measure:

$$ACG_{ij} = \sqrt{\sum_{k=1}^{n} 1 - \left(\frac{S_{ik}}{S_{\max_j}}\right)^2}$$

where in the alliance *j*; S_{ik} is the absolute difference in the experience counts of the partners *i* and *k* and S_{max} is the difference between the minimum and maximum experience counts in the alliance. Experience counts covered the last five years running up to the announcement date and include both dyadic and multi-firm alliances. We reason that the smaller is the value of ACG, the more partners are equal in their collaboration experience and thus alliance capabilities. Partners will make greater joint commitment to make the alliance work.

Partner interdependence: The extent of dependence among alliance partners in input or output markets might induce or alleviate transaction hazards (Balakrishnan and Koza, 1993; Oxley, 1997; Park and Russo, 1996) as well as increase or decrease organizational learning (Koza and Lewin, 1998; Sampson, 2005). By using the detailed Benchmark 2002 I/O tables (Use files) compiled by the US Bureau of Economic Activity, we constructed the following measures of dependence:

$$D_i = O_i * I_i, O_i = -\sum_{j=1}^{n}\left(\frac{P_{ij}}{S_i}\right) * \log\left(\frac{P_{ij}}{S_i}\right), I_i = -\sum_{j=1}^{n}\left(\frac{P_{ij}}{S_i}\right) * \log\left(\frac{P_{ij}}{S_i}\right)$$

where *i* indexes the focal firm's industry, *j* indexes the alliance partner's industry, *n* denotes the number of partners in the multi-firm collaboration (or alliance size minus 1), *S* represents the total final demand (in producer's prices) for the focal firm's industry and *P* represents the demand for *i* by the industry of its alliance partner (*j*). A high value of D_i suggests that partner industries are critical buyers. The focal firm's industry is highly dependent on its output market (O_i). The second construct is identical to the first in its operationalization, except that it measures dependence in the input market (*I*). *P* denotes the demand for *j* by the focal firm's industry (*i*) and *S* represents the total demand by *i*. A high value suggests that the focal firm's industry is a significant buyer of the output produced by the partners' industries. Interdependence (D_i) is the product of dependence in input and output markets.

As D_i increases, we expect the focal firm to be less vulnerable to opportunistic behaviour. At high levels, substantial mutualistic behaviour between collaborating partners should be observed. Further, high values of D_i signify greater absorptive capacity and existence of common organizational routines for capability transfer and joint learning. When D_i is low, parties should make significant commitments to build shared transaction specific assets, which augment the risk of hold up. There are strong competitive incentives to deviate from mutually agreed alliance objectives. We expect the multi-firm alliance to be most fragile in low-dependence situations.

Stock market: In the sample, some stocks are listed on NASDAQ, whereas others are traded on the NYSE. We control for a potential contextual influence with a dummy variable (Jensen, 2004).

Stock turnover: High turnover signifies the heterogeneity of traders and their incentives, while low turnover implies stability in the ownership base. Stability provides managers with discretion to engage in long-term, value-generating strategies. Such firms should be desirable alliance partners and should attract good partners, resulting in positive responses to their alliance announcements. We computed this measure by taking the 12-month average of the daily ratio of the number of traded stocks to the number of total outstanding stocks prior to the announcement.

Results

The correlation matrix and descriptive statistics are summarized in Table 2. Table 3 provides abnormal returns calculated for various event periods. In general, we found that multi-firm alliances received positive stock market returns. The average CAR for the event period was +1.15 percent. We assessed the effect using different event windows. Abnormal returns were positive and significantly different from zero in all event periods for a −2 to +2 day spectrum. Table 4 reports the models explaining the dependent variable. We use the Huber–White sandwich estimation method to correct for biases induced by possible heteroscedasticity. We use the cluster option to adjust the standard errors to account for non-independence. To address the potential for spuriousness resulting from time, we include time dummies. The first equation contains the control variables. In the second equation, we entered the diversity variable and its quadratic form. In the third, fourth and fifth models, we searched for moderating impacts. For reasons of space, we do not report the industry and time dummy coefficients.

As Model 2 in Table 4 suggests, there is strong support for hypothesis 1. Using the coefficients in Model 2, we can calculate the point of inflection for the curve at roughly −0.27 (see Figure 1). The results in columns 3–5 show that the relationship is moderated by firm size or analyst coverage, but not by firm-specific uncertainty. The interaction terms are statistically significant, which is our primary concern. Marketing alliances are more likely to generate positive returns.

Table 2 Descriptive Statistics and Correlation Matrix

		Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
1	Abnormal returns	.01	.06	1.00																		
2	Diversity	.00	.32	.02	1.00																	
3	Diversity SQ	.10	.14	.05	−**.81**	1.00																
4	Firm size[1]	.00	2.35	−.15	**.23**	−.07	1.00															
5	Uncertainty	.00	.24	.15	−.01	.00	−**.27**	1.00														
6	Coverage[1]	.00	.80	−.09	.05	−.00	**.36**	.05	1.00													
7	Performance	.01	.07	−.10	.05	−.06	**.31**	−.19	.12	1.00												
8	Firm age[a]	3.39	1.01	−.09	.19	−.06	**.69**	−.20	−.00	**.30**	1.00											
9	Institutional ownership	.39	.26	−.09	−.13	.05	−.22	−.12	.21	.02	−.18	1.00										
10	Partner experience	.99	2.22	−.01	.20	−.15	**.28**	−.07	.01	.03	**.22**	−.18	1.00									
11	Alliance experience[a]	2.59	1.51	−.09	**.23**	−.13	**.52**	−.09	**.45**	.15	.18	−.11	**.42**	1.00								
12	Alliance size	1.28	.25	−.07	.11	−.07	.12	−.07	−.02	.03	.13	−.09	.14	−.01	1.00							

(*Continued*)

Table 2 (Continued)

		Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
13	Technology alliance	.62	.49	−.17	.04	−.06	−.01	.06	.07	−.06	.04	.07	.05	.16	−.14	1.00						
14	Marketing alliance	.30	.46	.09	−.01	.03	−.02	−.06	−.07	.07	−.05	−.07	−.12	−.21	.12	**−.85**	1.00					
15	Tech. & mark. alliance	.07	.26	.15	−.06	.06	.04	−.00	−.01	−.01	.02	−.01	.13	.06	.04	**−.36**	−.18	1.00				
16	Interdependence	.05	.12	−.01	**−.37**	**.30**	.03	−.06	−.05	.03	−.04	−.11	.02	−.11	.22	−.21	**.26**	.10	1.00			
17	Alliance capability gap	1.25	.37	−.07	**.23**	**−.23**	−.03	.03	.02	−.06	.01	−.03	.12	−.11	**.38**	.04	.03	−.13	−.15	1.00		
18	Turnover	.01	.03	.01	.08	−.09	−.20	**.22**	.14	.01	**−.28**	.15	−.09	.04	−.02	.05	−.05	.01	−.08	−.03	1.00	
19	Stock market	.57	.50	2.07	2.01	.03	**.44**	**−.23**	−.02	.10	**.45**	−.06	−.12	−.12	.01	−.11	.10	.03	.13	.02	−.28	1.00

Notes: N = 269.

[a]Logarithm Correlation coefficients in bold are significant at a 5% level.

None of the industry dummies are significant in any of the models. Three-quarterly dummies are persistently positively significant in all the models. Model 6 is the full model including all six interactions. This specification has a higher VIF (Variance Inflation Factor), which makes the test more conservative. Results reveal a similar pattern found in the previous model: a non-linear relationship between diversity and abnormal returns that is moderated by analyst coverage.

Moderating effects

Our results demonstrate the moderating effects of firm size and firm coverage on the quadratic relationships between diversity and abnormal returns. We do not find any moderating impact of firm-specific uncertainty, which invalidates our prediction (H3) that at high or low levels of diversity, high-uncertainty firms would earn greater returns than low-uncertainty firms. We expected that as diversity moved towards the intermediate level, from either end point, this return differential would shrink. This was not corroborated.

To examine our remaining predictions (H2 and H4), we reduce the regression equations in Model 3 and Model 5 in Table 4 by substituting representative values for size and coverage (25th and 75th percentile means) and replacing all other predictors with their respective means. We plotted these reduced equations based on the variable range. Figure 2 is the graph of the diversity – abnormal return relationship for firms that are large and small, respectively. Figure 3 displays the diversity–abnormal return relationship for firms with high and low analyst coverage. Both graphs provide supportive evidence of our respective hypotheses. From Figure 2, it appears that for the most part, small firms tend to receive larger abnormal returns than large firms. However, around the inflection points, the relative cognitive advantage of being small is significantly reduced. Investors do not seem to respond differently to firms of different sizes at intermediate levels of diversity. Figure 3 shows that low-coverage firms attain greater returns than high-coverage firms except at around the intermediate levels.

Supplementary analyses

In a supplementary analysis, we shortened the interval for the experience variables from five to three years and the results remained substantively unchanged. We also experimented with new controls such as multi-firm alliance experience, closing stock prices on the day prior to the event or whether the alliance was international. There were no notable changes in the results.

Our sample consists of firms listed on US exchanges, but some firms are headquartered outside the US. To control for potential cross-border disparities in investor behaviour, we created a set of dummy variables distinguishing US, European and Japanese firms and firms from other regions. These variables correlated strongly with institutional ownership, indicating that institutions held greater control of US firms than European firms, which, in turn, had greater

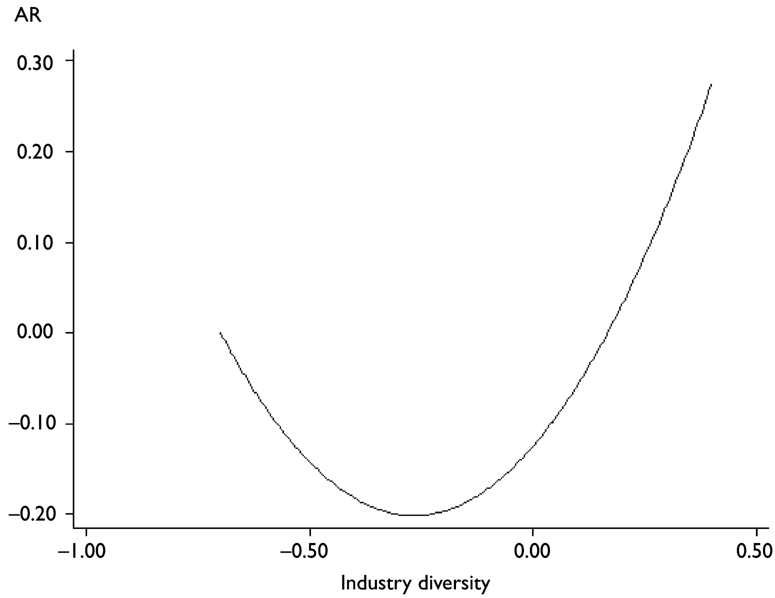

Figure 1 Industry diversity – abnormal returns (model 2)

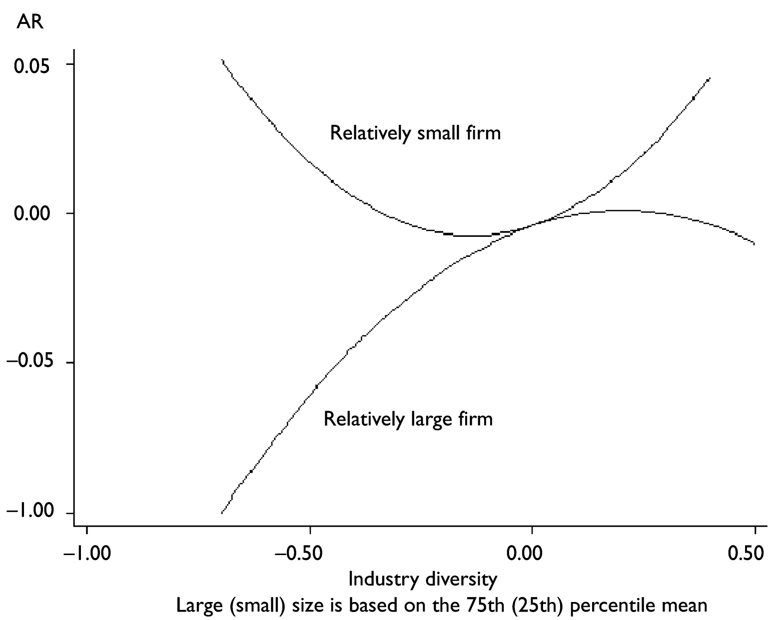

Figure 2 Graph of reduced regression equation by size (model 3)

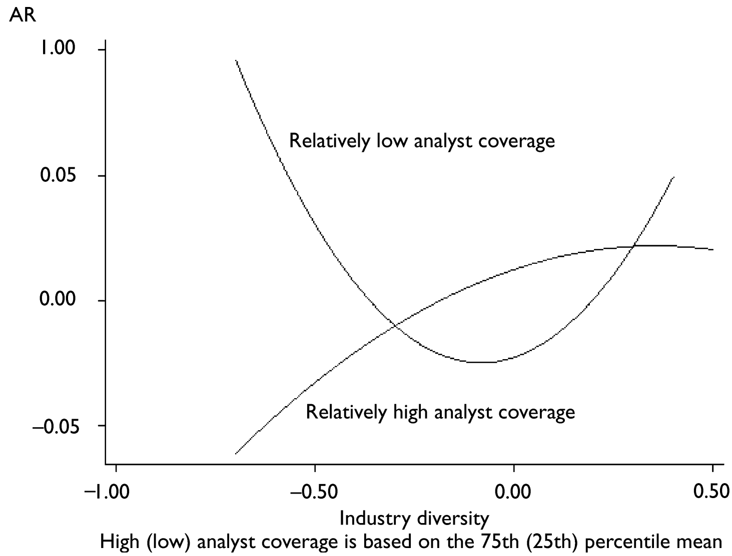

Figure 3 Graph of reduced regression equation by analyst coverage (model 5)

institutional ownership than Japanese firms. Replacing institutional ownership with nationality dummies produced substantively similar results. We also removed non-US firms from the sample and both the U-shaped relationship and the moderating effects persisted strongly. Although prior research has argued that the three-digit aggregation gives a more useful rendering of the analyst coverage structure (Jensen, 2004; Zuckerman, 1999, 2004), we tested the diversity–return relationship at the four-digit level, but found no significant relationship.

As a further robustness check, we computed a skills-based partner similarity measure, based on Farjoun's (1998) approach to diversification. The first step in this approach was to construct industry skill profiles based on the Occupational Employment Survey (OES) published by the US Department of Labor Statistics. The OES defines industries at the four-digit NAISC code and contains data on the percentage distribution of 480 occupations in all US industry. The occupational employment ratios indicate both the different types of skills needed in an industry and the extent to which they are required. We selected 149 major occupational categories. We computed partner skills similarity for a focal firm based on the inverse Euclidean distance (Baum and Lant, 2003) of its skill distribution to the respective mean values of the alliance or

$$S_i = 1 + \Big/ \left(1 + \sqrt{\sum (OC_{ij} - MOC_j)^2}\right)$$

where OC_j is the proportion of employees in the occupational category of the firm i and MOC_j represents the alliance mean of the ratios for the same category. Larger values for this variable imply greater similarity of the firm's skill base to that of its alliance partners. We should point out that the diversity and the similarity measures rest on alternative views of this categorization. In the former, we considered the SIC codes as the labels by which category membership is judged. The categorization is holistic. In the latter, we consider feature-by-feature correspondence with the alliance average and the target. Results using the similarity measures, which were strikingly similar to those reported in Table 3, are available upon request.

Discussion and conclusion

Why do some alliances create value when others destroy it? This question has attracted significant scholarly attention, making research on alliances one of the most vibrant and interdisciplinary branches. One stream of research seeks to measure alliance benefits by abnormal market returns. In these studies, explanatory variables are derived from general theoretical considerations in the alliance literature. It is assumed that abnormal returns indicate the quality of managerial decision-making with respect to the announced alliance. Shareholder value is treated as a proxy for the likelihood of the alliance's success or failure.

We suspect that these explanations are incomplete. Stock returns are conditional on the cognitive processing of information not the information itself. Investors are neither perfectly informed nor fully rational. There are limits to their cognitive abilities. They are subject to a host of cognitive biases (e.g. Hirshleifer, 2001; Jensen, 2004; Zuckerman, 1999). Their interpretations of the costs and the benefits of alliances might therefore produce outcomes that can be misaligned with the theoretical expectations. In this article, we provide a two-step process model that explains what might trigger these discrepancies, identifies the situations where they are most likely to occur, and makes theoretical and normative prescriptions for what needs to be done to close the gap. We chose a context

Table 3 Cumulative abnormal returns (CARs) over different event periods

Event windows	All alliances	Marketing alliances	Technology alliances
−3; +3	.0042	.0130	−.0039
−2; +2	.0079*	.0075	.0052
−1; +1	**.0115***	.0229*	**.0021**
−1; 0	.0111*	.0206*	.0027
0; +1	.0083+	.0098	.0046
−1; +2	.0116*	.0236*	.0021
−2; +1	.0099+	.0203†	.0024
−3; +1	.0087	.0130	.0030
−1; +3	.0070	.0235†	−.0048

Notes: $N = 269$, $^{+}p < .10$, $^{*}p < .05$, $^{**}p < .01$.
CARs are within the range of those observed in dyadic studies such as +1, 2 percent by Park et al. (2004), +1, 2 percent by Das et al. (1998) and +0, 87 percent by Koh and Venkatraman (1991).

Table 4 Industry diversity and abnormal returns

Variables	1	2	3	4	5	6
Constant	.05	.06	.06	.06	.05	.04
	(.04)	(.04)	(.04)	(.04)	(.04)	(.04)
Diversity		.06*	.05*	.06*	.05*	.05+
		(.03)	(.03)	(.03)	(.03)	(.03)
Diversity SQ		.11*	.08+	.10*	.10*	.09*
		(.05)	(.04)	(.05)	(.05)	(.05)
Firm size[a]	−.01	−.01	−.00	−.01	−.01	−.01
	(.01)	(.01)	(.01)	(.01)	(.06)	(.01)
Uncertainty	.03	.03	.03	−.01	.03	−.02
	(.02)	(.02)	(.02)	(.04)	(.02)	(.04)
Coverage[a]	−.00	−.00	−.00	−.00	.02*	.02+
	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)
Firm performance	−.06	−.05	−.06	−.05	−.04	−.04
	(.10)	(.10)	(.10)	(.10)	(.10)	(.11)
Firm age[a]	.00	.00	.00	.00	.01	.01
	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)
Institutional ownership	−.03	−.03	−.03+	−.03	−.02	−.03+
	(.02)	(.02)	(.02)	(.02)	(.02)	(.02)
Partner experience	.00	.00	.00	.00	.00	.00
	(.00)	(.00)	(.00)	(.00)	(.00)	(.00)
Alliance experience[a]	−.00	−.00	−.00	−.00	−.00	.00
	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)
Alliance size	−.02	−.03	−.03	−.03	−.03	−.04
	(.02)	(.03)	(.02)	(.03)	(.03)	(.03)
Marketing alliance	.02*	.01+	.02+	.02+	.01+	.02+
	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)
Tech. & mark. alliance	.04	.04	.04	.04	.04	.05
	(.03)	(.03)	(.03)	(.03)	(.03)	(.03)
Interdependence	−.00	.02	.02	.02	.02	.02
	(.04)	(.04)	(.03)	(.04)	(.04)	(.03)
Alliance capability gap	−.01	−.01	−.01	−.01	−.01	−.00
	(.02)	(.02)	(.02)	(.02)	(.02)	(.02)
Turnover	−.01	−.03	−.02	−.02	−.02	−.02
	(.11)	(.12)	(.12)	(.12)	(.11)	(.12)
Stock market	−.00	.00	.00	.00	.00	.00
	(.01)	(.01)	(.01)	(.01)	(.01)	(.01)
Firm size[a] * diversity			−.02			−.01
			(.01)			(.01)
Firm size[a] * diversity SQ			−.05*			−.00
			(.03)			(.03)
Uncertainty * diversity				.09		.07
				(.12)		(.12)
Uncertainty * diversity SQ				.43		.48
				(.29)		(.30)
Coverage[a] * diversity					−.06+	−.05+
					(.03)	(.03)

(Continued)

Table 4 (Continued)

Variables	1	2	3	4	5	6
Coverage[a] * diversity SQ					−0.21** (.06)	−.21** (.07)
r^2	.18	.20	.23	.22	.25	.27
Max.VIF	5.91	5.94	7.09	6.05	6.07	8.61

Notes: Determinants of abnormal returns – cluster (by firm) corrected and robust standard errors. All models include industry and time dummies, 269 observations.[a]

[a]Logarithm. $+p < .10$, $*p < .05$, $**p < .01$.

where decision-makers are likely to confront significant evaluative difficulties. We combined economic insights with those from cognitive research to develop alternative predictions to account for investors' decision-making processes. The core thesis of the model is that attentional selection and subsequent encoding processes produce biases in the interpretation of announcements. These biases must be factored into explanations of abnormal returns in order to reduce discrepancies between managerial expectations and actual outcomes.

Our results show that the signalling effects of an alliance announcement have an impact on the decision patterns in the investor community. In the first stage investors detect the disclosure. Selective attention in this stage results in a focus on highly distinct and highly familiar alliances, which initially eliminates other alliances. Investors subsequently encode the signal. In this stage, investment decisions about the detected alliances are subject to ambiguity aversion and overconfidence biases. Ambiguity creates a status quo bias or negative evaluation of the alliance's prospects. Clear actions are easy for investors to categorize, and allow them to utilize their established evaluative frameworks. In the alliance context, this implies that alliances with intermediate levels of partner diversity are subject to ambiguity aversion whereas low and high degrees of partner diversity enable categorization and promote overconfidence. This creates a U-shaped relationship between partner diversity and abnormal returns.

There are factors that moderate the relationships that we have identified. These findings call for more refined explanations. In accordance with our hypotheses, we find that firm size and coverage moderates the diversity–return relationship, making the overconfidence effect greatest for small firms and firms with low coverage. Interestingly, we find an inverted U-shape for large and high-coverage firms. We suspect that this is related to the market moving towards greater efficiency for large and high-coverage firms, which leaves less room for cognitive biases. Greater market efficiency implies better detection of announcements and improved encoding. It reduces the isolated effect of the 'process of processing'. We also find that the return to intermediate levels of partner diversity is higher for high-coverage than for low-coverage firms. This indicates that for high-coverage firms, the effect of ambiguity aversion disappears.

We do not find support for our hypothesis that alliance disclosures by high-uncertainty firms will generate greater returns than those from low-uncertainty firms at high or low levels of diversity. Our results show no relationship between returns to partner diversity and firm uncertainty, indicating that pre-alliance stock volatility plays no role in the decision-making process of investors in responding to an alliance announcement. One explanation for this surprising finding may be that firm-specific uncertainty does not have strong effects on the information environment of the firm in the specific context of our study. We concentrate on high-tech settings and it is possible that in dynamic environments, the role of historic stock market volatility is less pronounced.

Future research and limitations

Event studies have become central in the strategy and finance literatures (Oler et al., 2008). This underscores the importance of understanding the link between an event and the market's reactions. While it is well established that investor cognition matters for returns to corporate disclosures, more research is needed to advance our conceptions of how and under what conditions it matters. To that end, future research could address some of the limitations of this study. First, our examination of decision-making relies on theoretical rationales and prior empirical studies. In particular, following the findings from cognitive science, we make strong assumptions about cognitive processes. Future research could derive more precise insights into the actual decision-making processes of analysts and traders through interviews and observations. Second, we chose to focus on a complex decision setting – high-tech multi-firm alliances – to allow for refined distinctions across signals. This enabled us to tease out the effects of investor cognition on market reactions. Future research could examine the role of investor cognition in low complexity settings. This might tell us whether the magnitude of the effect of investor cognition increases with the complexity of the information environment or whether cognitive biases have different effects in different information contexts. Third, future research could untangle the joint effects of our two-stage model – selection and encoding on the outcomes. Fourth, our model does not consider ambient sources of effect such as stress or mood on cognitive processing. A refinement of our model along these lines would be a fruitful trajectory.

Another limitation concerns our exclusive focus on multi-firm non-equity alliances. Extension of our cognitive model into the domain of joint ventures (JVs) would be an important theoretical contribution. In building our model, we assumed a normal attentional condition: the investor is free to analyse the disclosure in any way that he or she chooses. Under these conditions, there is a tendency to analyse from the top-down so that the investor encodes the most global cues first. The disclosure is scanned broadly. We expect multi-firm JVs to represent a more directed attentional condition. Since these announcements often disclose investment or financial figures, the investor's attention will be explicitly and quickly directed to this part of the disclosure. The top-down approach will be bypassed (Modigliani et al., 1998). The financial commitment will constitute an anchor in decision-making (Tversky and Kahneman, 1974). Because these are concrete properties, the signal will have greater clarity. It will be perceived more immediately and by a broader investor base. Consequently, we predict more participation and greater trading volume on the news. In our view, there will still be room for decision biases; however, the extent of these will be less. The market will move closer to efficient processing and more so as the size of the focal firm's investment increases.

Despite these limitations, we hope that the cognitive turn that we offer will constitute a fruitful direction for research. Stiglitz (2000: 1453) wrote that: 'One of the key issues that firms today think about is how a particular action will be interpreted. What inferences will be made, for example, if a firm issues a different kind of security than it has previously issued.... The formal theory has little to say about this "out of equilibrium" behavior .' The main contribution of this article, therefore, is its integration of insights from the cognitive sciences and research on alliances to offer some understanding of one type of out-of-equilibrium behaviour.

Our study has implications for researchers and managers. Managers' actions tend to signal commitment to institutionalized beliefs and values (e.g. Rao and Sivakumar, 1999), and financial markets influence how managers choose organizational forms and practices and the types of organizational actions they furnish (e.g. Kock, 2005). Announcement of an alliance allows managers to release information to the market and receive feedback on the value placed on the alliance. The stock market functions as a test market or a domain for offline search. Organizational decision-makers' cognitive frames on alliance–outcome linkages are tested against the evaluation of the market (Gavetti and Levinthal, 2000). Since feedback from offline search constrains the direction of subsequent search (Gavetti and Levinthal, 2000), we have an interesting dilemma. If the feedback matches the managerial cognitive maps, then we should expect managers to continue with similar alliance choices. If there is a conflict, then managers might change their cognitive maps. When they do, subsequent alliance choices will be dramatically different. In this article, we demonstrated that when the signal is ambiguous, the market challenges the managerial cause–effect understanding. Our findings assert that managers might be thrown off a theoretically justified search trajectory by the market, and not because the market has superior information.

For managers, our findings underscore the importance of taking into account the cognitive limitations and biases of the investment community when disclosing information. To maximize shareholder returns, managers and investor relation units should proactively seek to eliminate noise and redundancy in the information environment. Efforts should be directed towards releasing clear signals that allow for detection and more accurate decoding.

Acknowledgements

We gratefully acknowledge helpful comments from Gautam Ahuja, Henrich R.Greve, Glenn Hoetker, Michael Leiblein, Ravi Madhavan, Jeffrey Reuer and Brian Silverman. We are particularly indebted to Joel Baum for advice and editorial assistance. An earlier version of this article received the Robert T. Litschert Best Doctoral Student Paper Award from the Business Policy Division at the 2006 Annual Meeting of the Academy of Management, Atlanta, USA. The usual disclaimer applies.

Notes

1 The detection probability of the signal may be further enhanced by two indirect mechanisms. First is the 'false recognition effect'. Since low diversity implies firms of similar category, any familiarity with one of the alliance partners will increase the investor's feeling of familiarity associated with the focal firm (Klinger, 2001). The second is the 'network effect'. Because information is structured in memory in a network of closely related concepts, activation of one concept (e.g. a partner firm) will lead to the activation of another (e.g. a focal firm) (Nisbett and Ross, 1980; Taylor and Fiske, 1978).

2 In our context, an additional impetus for overconfidence bias can be pinpointed, based on the agency view. Stock analysts tend to work at brokerage houses that make money by encouraging trading. Since every customer is potentially interested in buy rather than sell signals, optimistic forecasts are preferable (Hirshleifer et al., 2004).

3 Lau et al. (1991: 648) make a similar case for policy signals 'when voters are aware of only one interpretation of a policy proposal…most voters will simply accept the assertions of that interpretation. The single interpretation offers the only dimension of judgment on which to evaluate the proposal…. Since the interpretation will undoubtedly contain many easily understood "persuasion cues" as to how much better the advocated proposal is than competing proposals, many voters can become supportive of it without actively thinking about it. As a consequence, any agreement or disagreement between the assertions of the interpretation and the voters' general beliefs will be irrelevant.'

4 Brand names are good examples. Consumers rely upon brand names as attentional selection mechanisms to a greater degree, when they are unable to discriminate between product attributes (Ha and Hoch, 1989; see also cognitive research on advertising or price discounts). Similarly, one might conceive of the background effect as the 'base-rate' (Slovic et al., 1977; Tversky and Kahneman, 1974). People are more likely to ignore the base rate when the target of attention is concrete, vivid and salient and base rates are often used when outcome categories are hard to distinguish from one another (Nisbett et al., 1976; Slovic et al., 1977).

5 Source evaluation thesis is closely linked to the representativeness heuristic (Tversky and Kahneman, 1974). This assumption holds that decision-makers tend to generalize about a population of future outcomes based on a consistent pattern of recently observed outcomes. As a corollary, they over(under)react to a signal followed by a series of (in)consistent information signals (Hirshleifer, 2001; Hirshleifer et al., 2004). High firm-specific uncertainty is both a producer as well as an artefact of inconsistent signals. If investors exhibit the representativeness bias, at intermediate levels of diversity, we expect them to be more insensitive to signals from high-uncertainty firms than low uncertainty firms.

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