

THREE ESSAYS ON INVESTOR REACTION TO STRATEGIC ALLIANCE
ANNOUNCEMENTS

by

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ABSTRACT ESSAY 1

RAPID OVER-REACTION: PERCEIVED VALUE CREATION VIA ALLIANCE ANNOUNCEMENTS

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Under the Supervision of Professor Edward Levitas

The management literature has widely acknowledged the importance of studying and understanding the determinants of the market's reactions to the announcements of strategic alliances. With a focus on dyadic alliances, I ask what types of information signaled to the market by the alliance announcement influence the investors' perception of value. I hypothesize that the type of technical expertise, relationship expertise, and market expertise of each alliance partner, expressed as either explorative or exploitative, sends decodable signals to the investors, which in turn influences their reaction to the new alliance announcement. Using a sample of 927 alliances extracted from a unique biopharmaceutical dataset, I proxied investors' reaction to the alliance announcements by calculating the cumulative abnormal return during a three-day window around the alliance announcement. I found that while technical expertise does not appear to be a signal that investors consider when valuing firms involved in a new alliance, both relationship expertise and market expertise showed a statistically significant influence on the investors' perception of value.

ABSTRACT ESSAY 2:

REDUCING INVESTOR ANXIETY VIA ALLIANCE PARTNER SELECTION

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The management literature has recognized strategic alliances as an organizational form that has the potential to reduce uncertainty. One important step for alliances in order to achieve a reduction in uncertainty is selecting the right partner, one that enables the alliance to effectively address the specific type of uncertainty it faces. In this study, I specifically address the question of whether the perceived uncertainty of investors at the time of the alliance announcement is influenced by whether the skills and expertise of the two alliance partners are similar or complementary (diverse). I suggest that the level of technical expertise, expressed as either explorative or exploitative and interpreted as either similar or complementary, sends a signal to the investors, which in turn will impact their perception of uncertainty. In addition, I study whether this relationship is moderated by the level of exogenous uncertainty faced by the alliance. Using a sample of 927 alliances extracted from a unique biopharmaceutical dataset, I found that exogenous uncertainty in fact moderates the relationship between partner similarity/complementarity and investors' perception of uncertainty.

ABSTRACT ESSAY 3:

SPILOVER EFFECTS IN ALLIANCE RELATIONSHIPS

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Entering multiple simultaneous alliances is a common practice, especially in R&D intense industries. While this strategy may enhance the possibility of success by attempting to simultaneously unlock possible synergistic effects in multiple alliances, it also exposes the alliance partners to spillover effects created by their partners' alliances. In this study I will examine how one specific action of one partner, to enter a new alliance, affects the initial alliance partner. Specifically, given that firm A and firm B are in an existing alliance, how will the market react to the information that firm A has entered into a new alliance with firm C, and how will the market reaction affect firm B (the initial alliance partner)? I develop and test two sets of competing hypotheses using a unique biopharmaceutical dataset and find that the market reacts favorably to the new alliance as measured by the change in value of firm B's stock price. My goal is to contribute to the literature by testing how the signals sent by the alliance to the market affect the initial alliance partner and thus if investors monitor and react to post-alliance events.

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RAPID OVER-REACTION: PERCEIVED VALUE CREATION VIA ALLIANCE
ANNOUNCEMENTS

INTRODUCTION

Studies have shown that investors generally react positively to an initial alliance announcement (Dyer, Kale, & Singh, 2001; Shah & Swaminathan, 2008). However, these initial expectations are often not realized in that alliances fail to generate subsequent desired and expected returns (Kale, Dyer, & Singh, 2002). These findings point to the uncertainty faced by investors when making predictions as to how alliances will perform at the time of the alliance announcement, and how to assess the value of the partners. It is this investor reaction to the alliance at the time of the alliance announcement that is the focus of this study.

What causes investors to react to an alliance announcement, what signals are sent by the alliance, and how are these signals decoded by investors? With a focus on dyadic alliances, I specifically look at the skills and expertise of the alliance partners, which I suggest send signals to the investors. Specifically, I ask whether three specific types of signals that I have identified influence the investors' perception of value.

I investigate how the degree of technical, relationship, and market expertise of the two partner firms in the focal alliance sends a signal to investors, which in turn triggers the investor's reaction. Equally important, I examine how reactions vary along multiple components forming the explore/exploit dichotomy. Unlike previous research which has viewed exploration and exploitation along technological similarities, I will study the concepts of exploration and exploitation along many dimensions of the value chain. I chose the dimension of exploration and exploitation because I suggest that explorative and exploitative expertise send very rich signals to the investors, meaning that said signals carry information that investors decode and act upon. Exploration and

exploitation provide an effective base on which to assess investor reactions, since their definitions are premised on the degree to which firm activity diverges with previous activity and thus causes reassessment by investors at the time of the alliance announcement.

My research question is as follows: what information signaled to the investors by the alliance announcement creates a perception of value and subsequently triggers investor reaction as measured by the change in market value of one of the alliance partners? I will focus on three areas of partner and alliance expertise (technical expertise, relationship expertise, and market expertise) and state those in terms of exploratory or exploitative expertise. I will note that I am not considering the explorative or exploitative level of each individual firm, but rather that all three expertise, and the level of exploration / exploitation depend on the specific partner combination.

I code technical expertise as explorative or exploitative based on patent citation overlap. Explorative expertise is based on a low patent citation overlap (suggesting that the combined technical expertise by the partners is exploratory since the partner firms cite patents that are very different from each other), and exploitative expertise is based on a high value of patent citation overlap (suggesting that the expertise brought into the alliance by one partner is not that unique and new to the other partner as evidenced by a higher number of common patent citations). Relationship expertise is considered explorative when the two alliance partners have little or no, and possibly unrelated, prior experience in working with each other (e.g., if they have worked with each other but on a different type of alliance, or a long time ago, etc.). If they have relevant and/or recent work experience with each other, the relationship expertise would be considered

exploitative. Finally, market expertise refers to the alliance partners' documented experience and skill in bringing a new product to market prior to the focal relationship. Relatively little prior experience will be coded as explorative, while significant prior experience would be coded exploitative.

The basic premises of my hypotheses are that investors will decode and react to signals sent by the alliance. As such, these signals frame the investors' perception of value. The investors' reaction is based on the context in which exploration or exploitation occurs, as well as the investors' perception of how it will affect the future performance and returns of the alliance.

While exploration is usually associated with higher potential returns, I suggest that this does not always lead to higher value as perceived by investors when examined across all three constructs (technical, relationship, and marketing). Exploiting an existing competency could also lead to measurable returns. If investors display a preference for lower but more probable return over a more risky but potentially very high return, it will shape the investors' perception of value. Therefore, investors could theoretically react either positively or negatively to an alliance that focuses predominately on exploration or exploitation within two of the three dimensions that I have defined, while in the context of the third dimension (market expertise) I suggest that the investors' reaction is more predictable (although not certain).

This study contributes to the literature by furthering the understanding of determinants of investors' perception of value of alliance formations. This, I suggest, will increase our understanding of investor reaction to alliance formation which, given the many overvaluations at the time of the announcement, is needed. By studying what

factors may contribute to investors' (positive) reaction to the alliance announcement I aim to offer suggestions on which factors to further study. A linear mixed model regression analysis using a sample of 927 biopharmaceutical alliances will test my hypotheses.

The following section provides an overview of the literature and theory of alliance formation, leading to the hypotheses that I will test in this paper. Subsequent sections show the empirical analyses and discussion of the findings. The paper concludes with a discussion of the implications and limitations of this study.

THEORY AND HYPOTHESES

Alliances may be defined as formal cooperative agreements between two or more organizations involving the pooling or trading of resources, linked together with or without equity. Alliances differ along many dimensions, and one main difference is the purpose for which alliances are formed. This may include one or more of the following: facilitation of economic exchanges (Anand & Khanna, 2000), organizational learning (Mowery, Oxley, & Silverman, 1996), product marketing (Swaminathan & Moorman, 2009) or product innovation (Rothaermel, 2001a).

In addition to the purpose of the alliance, the literature has also recognized several levels on which alliances can help strengthen a firm's competitive position, such as by gaining access to new capabilities (Oxley & Sampson, 2004; Rothaermel & Boeker, 2008), access to new markets (Chen & Chen, 2002; Koka & Prescott, 2008), access to new assets (Huggins, 2010; Li, Eden, Hitt, & Ireland, 2008) including new knowledge

(Walter, Lechner, & Kellermanns, 2007), and enhanced reputation (Hitt, Dacin, Levitas, Arregle, & Borza, 2000), to name a few.

Because investors are looking for a way to recognize competitive advantages and future value, they are attempting to decode and interpret observable signals. In particular, explorative and exploitative signals lend itself for easier decoding and interpretation by investors because they each signal a distinct strategic direction of the organization.

Exploration and exploitation

March (1991) defines exploration as searching, risk taking, discovery, innovation, and experimentation. Others would associate exploration with investment, building new capabilities, and entering new lines of business (Koza & Lewin, 1999), and some would define it simply as the pursuit of new knowledge (Rothaermel, 2001b). The term exploitation on the other hand more commonly refers to refinement, efficiency, production, selection and implementation (March, 1991). Firms that engage in exploitation are thought of as entities that focus more on economies of scale, using existing processes and knowledge to refine a product or process, but certainly do not consistently take high risk and explore the unknown. Some scholars have suggested that the strategic decision to explore or exploit is a trade-off decision (March, 2006); within one firm, one might prevent the other (Benner & Tushman, 2002; Sull, 1999).

However, it has also been suggested that entities might have to possess relevant skill to engage in both, exploring and exploiting, in order to be consistently successful (e.g. the ambidexterity argument) (Zi-Lin He & Poh-Kam Wong, 2004). Because of this (perceived) need to do both, exploring and exploiting, an alliance might be the ideal organizational structure that allows each firm to mainly focus on exploration or

exploitation, while the alliance as an entity has the ability to focus on both. I therefore state my hypotheses in terms of the combined expertise of both alliance partners, which then equals the expertise of the alliance. I identified three overarching areas containing relevant exploration / exploitation variables for this study: technical expertise, relationship expertise, and market expertise.

Alliances are capable of producing both explorative and exploitative innovations (Dewar & Dutton, 1986). Both explorative and exploitative innovations have the potential to affect the valuation of an alliance, although this shift in value is realized differently. Explorative innovations, the more risky approach according to March (1991), seek to significantly shift the basis of competition within an industry (Ireland, Hitt, & Sirmon, 2003). In this regard, an explorative innovation could radically shift power within an industry and catapult a firm to the top. It is a risky strategy, and in some regards similar to an “all or nothing” approach. If successful it might positively affect the trajectory of profits for the foreseeable future.

Exploitative innovations on the other hand are designed to help maximize existing capabilities (Sheremata, 2004). As a result, this strategy is less risky, and it has almost no chance of significantly affecting the competitive position of a firm within an industry, either positively or negatively, in the short run. However, exploitation should not be interpreted as the less-desirable strategy but rather as a different strategic direction; this might appeal to some investors. Because of the differing potential outcomes between exploration and exploitation, I suggest that the investor reaction based on these signals sent by the alliance will differ.

Since exploration entails production of new knowledge and exploitation entails reuse, I examine how these approaches affect investor perceptions. Because alliances are designed to be able to engage in both exploration and exploitation, both may play a crucial part in a firm's overall strategic direction. Subsequently, investors may see this and base their initial reaction to the alliance announcement on their assessment of how well an alliance is prepared to take advantage of any synergistic effects for which it was created.

Previous work on performance perception of alliances has focused largely on the signals that firms send to other potential partner-firms before the alliance is formed (the partner selection process). Partner selection issues in alliances have been studied extensively (Beckman, Haunschild, & Phillips, 2004; Dollinger, Golden, & Saxton, 1997; Hitt et al., 2000; Kale & Singh, 2009; Shah & Swaminathan, 2008). However, the literature has not focused as much on the issue of partner-specific skill sets (i.e. the combined set of expertise and skills) and the subsequent investor reaction to the signals sent to exogenous entities (i.e., investors).

In an effort to more accurately predict the success of an alliance, prior studies have focused on several variables impacting alliance performance with a focus on resources that the partners bring into the alliance (Saxton, 1997). For example, alliance experience of a firm (Anand & Khanna, 2000; Dyer & Singh, 1998), reputation (Barney, 1991; R. Hall, 1992), or patent filings (Levitas & McFadyen, 2009), to name a few, have generally been viewed as predictors of future alliance success. Investors receive and decode signals in these variables. Therefore, once the alliance is announced, a desirable combination of partners can support the perception by investors that the alliance will act synergistically,

which would result in an increase in performance (Dyer et al., 2001). This in turn would explain the generally positive market reaction to alliance announcements.

Upon the announcement, investors identify, or at least believe that they have the ability to identify, the potential for future performance and reward the announcement with an appropriate reaction (positive or negative, depending on the investors' interpretation of the signals). However, even though alliance announcements are generally met with a positive market reaction (Shah & Swaminathan, 2008), alliances also carry a significant risk in the form of failure to generate the positive effects they were designed and expected to create (i.e., a product with market success that will generate positive cash flows). Research suggests that a significant number of alliances, in fact between 30% and 70%, fail or are prematurely terminated (Bamford, Gomes-Casseres, & Robinson, 2003; Lunnan & Haugland, 2008), leading to a destruction of shareholder value for the alliance partners (Kale et al., 2002). While alliance failure rates are not the focus of this study, these statistics underline the fact that because investors appear to positively over-react to the alliance announcements, more research into this subject is warranted. In other words, the question of what the alliance partners signal that gets the investors excited is relevant.

One of the main problems with evaluating the alliance at the time of the alliance announcement is the fact that the exogenous parties, the investors, have to overcome information asymmetry. The investors therefore rely on signals from the alliance (its member partners) before they, the investors, can react either positively or negatively to the announcement. Signaling theory (Spence, 1973; Spence, 1974) provides the

theoretical foundation for my study because it helps explain investor reaction to the alliance announcement in this environment of information asymmetry.

Exploration and exploitation affect the investors' perception of the alliance, and subsequently its value, very differently. On a very basic level, I suggest that exploration signals a willingness to take risks, to change the current norm, and to seek new discoveries. These attitudes communicate a willingness to change the status quo, which in turn may cause investors to re-assess their previous valuation of a firm. Exploitation, on the other hand, may allow for a more consistent valuation because of the lack of any drastic changes. Exploitation generally does not attempt to change a status-quo in the short term, but rather focuses on strengthening existing capabilities. Those are two very different strategic directions, and I suggest that the alliances' intention on which direction to take is signaled to the investors at the time of the announcements (when the partner-combination is revealed). The new partner combination then forces investors to react.

Signaling theory states that even though the exogenous entities (e.g., investors) might not be able to fully understand exactly what the new alliance will do (meaning that information asymmetry exists), they will receive and interpret signals sent by the alliance partners, and subsequently consider the signals' influence on the valuation of the alliance partners. This also suggests that alliance partners, knowing that investors may not be able to fully understand what the alliance will do (that is, how it will create value), have the opportunity to send very select signals that support a potential over-valuation at the time of the announcement. In this study, I will examine how the signals that I identified to be relevant are deciphered by the investors. I use the investors' immediate reaction around

the time of the alliance announcement ($t=[-1, 0, 1]$) as a proxy for their interpretation of the signals.

As mentioned above, finding the right partner is a critical step in leading an alliance onto a path toward future success. A significant number of studies have addressed the issue of partner selection, especially on partner skills and resource complementarity (Harrison, Hitt, Hoskisson, & Ireland, 2001; Ohmae, 1989). The concept of complementary skills specifically refers to *different* skills that partners bring into the alliance, with the assumption that one partner's different skills such as abilities, knowledge, organizational design, experience, etc., are then strategically used to offset possible weaknesses of the other partner. I am assuming that alliance partners make a strategic decision on which partner to choose, with the result that the corresponding partner combination of skills does not result by chance. Rather a conscious decision led to the specific combination. These decisions are observed, and the final selection of partners is then interpreted and acted upon by investors.

Technical Expertise

It has been suggested that inputs carry a signal to the investors about the potential future results of the alliance (Ahuja & Morris Lampert, 2001). The investors observe the inputs, come to a conclusion about potential outputs, and react long before potential outputs could lead to measurable profits. As a result, I create a variable that encompasses inputs of different dimensions of technical expertise of the two alliance partners.

In this study I will consider whether the technical expertise of the partners, proxied by the resources the partners bring into the alliance in the form of patents, are explorative or exploitative. Technical expertise refers to a firm's understanding of the technology

underlying its goods or services (Grant, 1996), and patents are a proxy for technical expertise. I will use the relative, partner specific, technological overlap of the combined inputs, the patent citations, as an indication of whether the technical expertise of the alliance is exploratory or exploitative.

However, it is not clear exactly how the investors interpret the signals. As outlined above, both exploration and exploitation can lead to value creation in the future, which would manifest itself through perceived value at the time of the alliance announcement (i.e. the investor reaction). The question becomes which type of value creation (explorative or exploitative) the investor is looking for, and how much risk the investor is willing to take. A positive reaction to an alliance featuring either exploratory inputs or exploitative inputs is possible, because the reaction is somewhat subjective. As a result, I suggest two competing hypotheses:

Hypothesis 1A: The higher the degree of combined explorative technical expertise of the alliance partners, the higher the investors' perception of value

Hypothesis 1B: The higher the degree of combined exploitative technical expertise of the alliance partners, the higher the investors' perception of value

Relationship expertise

When investors consider the specific partners involved in an alliance, they are interested in partner combinations that have the potential to reach explicitly stated or implied future performance goals (e.g., form an alliance with the goal of developing a cancer treatment). I identify three reasons that the degree to which alliance partners know each other may influence the achievement of a goal and subsequently the alliance performance, and thus will impact the investors' perception of the value creation of a new alliance at the time of the announcement.

First: *efficient knowledge transfer*. A stronger familiarity with the alliance partner increases the efficiency of knowledge transfer (Cohen, 2009; Kogut & Zander, 1992; Mowery, Oxley, & Silverman, 1998). In other words, certain alliance partner combinations signal to the investors that they, the alliance partners, have the potential ability to communicate and transfer vital information between each other efficiently.

Second: *knowledge of organizational routines*. Prior alliance experience can potentially reduce inefficiencies between the partners because the partners are familiar with, for example, each other's routines and culture, and can thus reduce transaction costs (Beckman et al., 2004; Parkhe, 1993). In other words, this combination of alliance partners has the potential to get the job done more efficiently, or without significant loss of resources.

Third: *trust*. Prior experience with each other increases trust, which in turn will reduce the firms' temptation to act unilaterally and, at the same time, increase the likelihood that partners will share crucial information with each other in a timely manner (Li et al., 2008). The question therefore is: do the partners know each other, and if so, how well?

Based on these relationship indicators, I suggest that the degree to which alliance partners know each other (and know how the other partner works) will trigger an investor response. Li et al. (2008) suggested that there are three different types of firms from which to choose an alliance partner, and which signal to the market whether the relationship is explorative (new) or exploitative (not new). Those categories of partners are: *close friend*, *acquaintance* or *stranger* (Li et al., 2008). Friends are firms with which the focal firm has worked in the recent past and has done so more than once. Acquaintances are partners with which the focal firm has worked before, but not recently

and not continuously. In the context of partner relationships, both friends and acquaintances may be categorized as exploitative partner choices. Strangers are partner firms with which the focal firm has not worked before, and as a result on which it has very limited (only secondary) information. Selecting a stranger as alliance partner would be considered an explorative partner choice.

In this study I will consider three specific variables that in their own way address the issue of relationships status. All three variables proxy the likelihood of information asymmetry between partners, which has the potential to lead to inefficiencies. The potential for inefficiencies may be viewed as a negative signal by investors at the time of the alliance announcement. *Number of prior partnerships* will address specifically how often the partners have worked together in the past. *Time proximity to last partnership* introduces a time component; if the partners have recently worked together it would suggest that organizational routines as well as the external environment have changed less than if the last time both partners worked together was well in the past. Time proximity would suggest that both partners would have to expend fewer resources to align organizational routines. Thus, the longer the time horizon since the last partnership, the greater the possibility that inefficiencies might occur. Third, since there are different types of alliances (e.g., marketing, R&D, etc.), the investors' reaction to the alliance announcement should consider the partners' relevant history in the type of the focal alliance. Therefore, the *alliance-type specific partner experience* is the third variable of consideration.

Exploitation, calculated across the three dimensions I suggested, would refer to a scenario where the partners know each other well and signal to the investors that there is

a potential for efficiencies based on a prior relationship. Simply put, the partners know each other well, have “done it” before, and are willing and able to capitalize on the potential synergies that the relationship offers. This could be interpreted as a positive signal, which would have the potential to trigger a positive investor reaction.

While it is true that firms are likely to call upon previous alliance partners (Gulati, 1995; Uzzi, 1997), this does not necessarily suggest that working with a new partner doesn't offer benefits as well. An explorative relationship can offer other benefits, such as the possibility of reducing inertial tendencies between partners (Sx & Rowley, 2002). Inertia between partners who have a history of working with each other might set in, and as a result the alliance partners might not be able or willing to implement necessary changes to, for example, the strategic approach to a given problem. Especially in industries like the pharmaceutical industry, breaking away from an existing relationship might carry benefits that the alliance would signal to investors. As a result, it might be the fact that an alliance consist of partners that have not worked together before (who would be categorized as *strangers*) that sends the desired signals to the investors.

Because alliances that are explorative with respect to relationship expertise, as well as those that are exploitative, have potential benefits and drawbacks, investors could potentially react positively to either partner choice. Either choice of partner carries a signal. Exploitative partner selection (close friends or acquaintances) signal efficiencies. Explorative partner (strangers) selection reduces the potential for inertia, which could also signal efficiencies. Because a reaction suggesting perceived value recognition by the investor could be triggered by either an explorative or exploitative partner choice, I suggest two competing hypotheses:

Hypothesis 2A: The higher the degree of combined explorative relationship expertise of the alliance partners, the higher the investors' perception of value.

Hypothesis 2B: The higher the degree of combined exploitative relationship expertise of the alliance partners, the higher the investors' perception of value.

Market expertise

Whereas in the biopharmaceutical industry technical expertise specifically refers to an alliance's ability to generate or create the desired therapy, the market expertise variable specifically addresses the alliance's ability to navigate the therapy through the process and into the market where, ultimately, profits are expected to be generated. Therefore, this area of expertise might also send a strong and relevant signal to investors, who are attempting to detect and forecast future profits.

One ultimate goal of an alliance may be to produce a marketable product that will positively affect future cash flows. In the pharmaceutical industry, any product has to be approved by the Food and Drug Administration (hereafter: FDA) before it can be marketed and sold in the United States. The FDA approval process is complicated and resource consuming. It is therefore critical that firms that plan to have a new patent approved for sale by the FDA understand the distinct FDA approval process. The process consists of six critical approval stages, each designed to expose a different sample to the drug¹. Along each stage, the firm has to prove that the drug actually does what it advertises; in other words, if a drug is said to reduce the risk for cancer, a study involving humans has to eventually prove this claim before the FDA would approve the drug.

¹ I divide the drug development process in to six stages: (1) preclinical stage, (2) the filing of an Investigational New Drug Application (or a Biologic License Application), (3) Phase 1, (4) Phase 2, (5) Phase 3, and (6) marketed

Organizational capabilities, such as learning, play a large role in generating superior performance (Nelson & Winter, 1982). The best way to learn the FDA approval process is by going through it and gaining expertise, or partnering with someone that has extensive experience in the process. The experience curve would suggest that efficiencies improve with experience; the direct experience is invaluable (Sampson, 2005). As a result, I suggest that alliance partners that have experience with the specific process will be more efficient in managing the process.

However, while the ability to manage the FDA approval process is absolutely vital, it is not enough to be successful. In other words, investors are looking for additional signals that would suggest that the alliance deserves a positive reaction at the time of the announcement. Complementary assets, defined as assets, infrastructure or capabilities vital to the success of a project, are needed to be successful; complementary assets can propel a firm from having failed despite experience in the FDA process, to having experienced success. Tripsas (1997) specifically states that commercial performance, which investors are interested in, hinges on the organizational structure's ability to use complementary assets. The alliance is again an organizational structure that allows for the relatively easy introduction of these assets into the partnership by simply choosing a partner that has the desired expertise.

In this study, I pay special attention to the degree of FDA approval process experience and FDA approval success by the partners. Process experience would suggest that a partner has at least tried to get a therapy approved and, therefore, has some experience with the bureaucratic and scientific hurdles that this process encompasses. Having had success in the FDA approval process, however, is rare; between 2003 and

2010 only about 10% of all drugs submitted were actually approved by the FDA (Business Wire, 2011).

Together, having all necessary assets to have experience and success, creates a construct that sends a signal to exogenous entities about specific FDA approval process experience. Rationally the investors should value experience in this category. However, to make sure I also test the scenario in which the alliance does not have experience in bringing a product to market:

Hypothesis 3A: The higher the degree of combined explorative market expertise of the alliance partners, the higher the investors' perception of value.

Hypothesis 3B: The higher the degree of combined exploitative market expertise of the alliance partners, the higher the investors' perception of value.

METHODOLOGY

Sample

I am using a sample of bilateral alliances that include biotech firms and pharmaceutical companies. I coded them as Client and R&D to indicate the relationship, where generally the larger pharmaceutical company represents the Client firm and the smaller biotech firm represents the R&D partner. I chose this industry because alliances are a very common organizational form, where partners are likely to work with each other numerous times. In addition, this industry relies heavily on patent protection for its products. As outlined above, patent citations send very rich signals about the technical expertise of the alliance partners.

All patent information was obtained from the National Bureau of Economic Research (NBER) Patent Citations database (B. H. Hall, Jaffe, Trajtenberg, & Centre for Economic Policy Research (Great Britain), 2001), and the United States Patent and Trademark Office's (USPTO) Cassis database. Additional data was taken from Compustat data files, the Center for Research in Security Prices (CRSP) U.S. stock database, the Recombinant Capital Biotechnology Database (ReCap), the IMS R&D Focus database, Spectrum Institutional Ownership files, and United States Securities and Exchange (SEC) proxy (DEF 14a) filings.

The initial sample included 28,470 biopharmaceutical alliances established between January 1st, 1989 and December 31st, 2008. I used the Wharton Research Data Services (WRDS), and specifically the Center for Research in Security Prices (CRSP) database, to determine which alliances include both biotech firms and pharmaceutical firms that were publicly traded at the end of the month of the event date. Because the initial data only indicated the month on which the alliance was announced, I further refined the event date (date of the alliance announcement) by performing a web search on each partner combination in the stated month. This search produced specific alliance announcements, which allowed me to define the exact date of the announcement. This date was then used to construct the three day window to measure the dependent variable. This data set includes 927 alliance events with exactly two partners that were both publicly traded at the time of the event date. Data availability constraints limited the final sample use in Model 2 of the analysis to 200 alliance events.

Measures

Dependent Variable

Cumulative Abnormal Return (CAR): The dependent variable is the sum of the abnormal stock returns (CAR) of the biotech firm around the time of the alliance announcement. CAR represents the deviation between the realized return, measured by the biotech firm's actual stock price movement, and the expected return of the biotech firm's stock performance. CAR has been used extensively as a performance measure in joint venture event studies (Gulati, Lavie, & Singh, 2009; Koh & Venkatraman, 1991; Park & Kim, 1997; Reuer & Koza, 2000) and as a dependent variable in alliance studies (Anand & Khanna, 2000).

I calculated the expected return by using a benchmark portfolio comprised of size-adjusted firms that match the 2-digit SIC code of the sample industry. I monitored the return during a three-day window [-1, 0, 1] around the alliance announcement of both the portfolio and the biotech firm (McWilliams & Siegel, 1997), and calculated the cumulative difference over the three days as the difference between the two cumulative returns. The short three-day window was chosen in an attempt to isolate the news of the alliance announcement and help prevent the inclusion of non-alliance related news in the movement of the securities [see for example Lee et al.(2000)], thus following the argument of market efficiency. I then matched the calculated CAR values by firm ID and date to the 927 alliance events in my sample.

Independent Variables

Technical Expertise: I measured the technical expertise held by the alliance partners as a ratio, indicating the level of the commonly held knowledge of the alliance. While prior studies have used R&D intensity as a measure of technological capabilities (Cohen & Levinthal, 1989; Mowery et al., 1996), Mowery et al. (1998) pointed out that R&D

intensity is an input measure while patents are an output measure that more accurately reflect technology-based capabilities.

Following Mowery et al. (1996) and their use of a cross-citation rate of patents, I am measuring the technological expertise of the alliance as:

$$\left(\frac{\text{Common citation of both partners}}{\text{Total citation of both partners}} \right)$$

where the *common patent citations of both partners* is the number of patents that *both* partners cite in their own patents, and *total citations of both partners* is the sum of the totals of both partners' citations. The result is a ratio of patent citation overlap that is an indicator of the technical expertise of the newly announced alliance.

The formula above should be interpreted as follows: a move toward a higher patent citation overlap relative to the total number of patent citations of both partners, indicated by an increase in the value of the ratio, suggests a greater technological overlap of the alliance partners because a higher percentage of the total patents (knowledge) of both partners cite the same previously patented technological expertise. The result is that an increase in the value of the ratio is a shift toward an exploitative technical expertise of the alliance since the alliance partners bring less patented knowledge into the alliance that is new to the other partner.

The opposite, a decrease in the value of the ratio suggests a move toward a lower patent citation overlap, indicating that the knowledge brought into the alliance by both partners overlaps less. This in turn suggests that the technological expertise of each

partner vis-à-vis the other is less redundant, and as a result the technical expertise of the alliance is more explorative.

To summarize, an increasing value of shared technical expertise suggests a move toward a more exploitative technical expertise, whereas a decreasing value suggests a move toward a more explorative technical expertise of the alliance.

Relationship expertise: I measure the degree to which the alliance partners know each other based on three firm indicators that the management literature suggests determine the type of relationship between two alliance partners: 1) prior alliance partner experience (Li et al., 2008; Sampson, 2005) , 2) recency of prior alliance experiences (Villalonga & McGahan, 2005), and 3) prior experience in the specific type of alliance (i.e. R&D, marketing, etc.) (Sampson, 2005).

In the following section I briefly outline each of these three indicators as well as how I coded the *Relationship Expertise* variable used in the analysis.

Prior alliance-partner relationship: This variable indicates whether the two partner firms have worked with each other in an alliance before, and if so, how often. The argument for inclusion of this measure is that a stronger familiarity with the alliance partner should increase the efficient transfer of knowledge (Cohen, 2009; Kogut & Zander, 1992; Mowery et al., 1998) and thus lead to a higher probability of inventive success.

I proxied the firm's alliance level experience with the partner by the number of previous collaborations, using the original dataset of 28,740 alliances. I calculated this variable as the cumulative sum of all *prior* alliances with the same partner. The variable

is a discrete quantitative variable expressed as the number of previous collaborations, not including the current alliance. The data revealed that the range in my sample is from 0 – 6.

An increase in this variable suggests that the partners have stronger familiarity with each other, whereas a decrease in this variable would suggest that the partners have less familiarity with each other. Consequently, an increase in this variable is a shift toward a more exploitative relationship since partners most likely will use previously established organizational relationships (Gulati et al., 2009), while a decrease in this variable is a shift toward a more explorative relationship.

Recency of prior alliance experience with same partner: This variable indicates how recent the partners' last cooperation was and is expressed in days. It is meant to capture the degree to which organizational structures may have changed since the last cooperative relationship between the partners, where it is assumed that a more intimate knowledge of the organizational structures of the alliance partner may lead to more efficiency.

This variable is expressed as a discrete quantitative variable in days since the last relationship, using the original dataset of 28,740 alliances. Many partner combinations have never worked with each other, which may be viewed as an extreme unfamiliarity with the partner's organization structures. I chose to assign an arbitrary value of 10,000 (days) to those alliances to reflect fact that the partners have no first-hand knowledge of working with each other. I chose to take the inverse ($1/X$) of the number of days since the last partnership. By doing so I transformed the variable into a smaller range (from 0 – 1), and I coded the variable so that an increase in this variable suggests a more recent

experience (which will be in line with all other indicator variables where an increase suggests an exploitative relationship with the partner).

The result is a variable that indicates the recency of the previous experience with the same partner, where an increase in the value of this variable suggests a more recent experience and consequently a more exploitative relationship. Conversely, a decrease in the value of this variable signals a shift toward a more unfamiliar relationship, which may be considered explorative.

Alliance-type specific partner experience: This variable is an extension of the previous two variables. It indicates whether the partner firms have worked together in the specific type of the focal alliance before. I define the different types as, for example, R&D alliances, marketing alliances, licensing alliance, supply alliance, etc.

I used the original dataset of 28,740 alliances and counted how often the two partners in a focal alliance worked together in the specific type of alliance. This is a discrete quantitative variable with a range from 0 – 5.

An increase in the value of this variable suggests a move toward a more exploitative relationship because the relationship becomes both less new and less rare. A decrease in this variable suggests a move towards a more explorative relationship because the type of alliance relationship is new or rare.

The final *Relationship Expertise* variable, which I used in my regression analysis, is the sum of the three relationship variables described above. I chose to use the sum because I found no evidence in the literature that one indicator ought to be weighted more heavily than another.

Market expertise: I measured two indicators that together represent the market expertise of the alliance: 1) the sum of the individual experience of the partners with the FDA approval process, and 2) the sum of the individual success of the partners in moving a product from one stage to the next (and subsequently closer to market approval).

FDA approval process experience: As mentioned earlier, the FDA approval process consists of six distinct stages through which the firm needs to move the therapy through before it can be marketed. FDA approval process experience can be gained on two dimensions. First, *experience over time in the same stage*. If a firm has had prior experience working with a therapy in, for example, the pre-clinical stage (stage 1), it influences the firm's action working with future therapies in stage 1 and should therefore be considered as expertise dealing with stage 1 of the FDA approval process.

Using the original data set with 28,740 alliances, I counted the number of times that each partner in each alliance has had a therapy in one of the six stages in the past (based on the alliance announcement date) and summed those up. As a result, each alliance partner in each alliance has a sum of prior experiences in each of the six distinct stages of the FDA approval process.

The second dimension is *the experience across stages*, and a decision as to how to add up the numbers representing the prior experience within each of the six distinct FDA stages had to be made. I tested for correlation between the six cumulative variables (stages) for each firm at each date, and found a high degree of correlation. In fact, all bivariate correlations were statistically significant at the 0.01 level (two-tailed test). Because the literature dealing with FDA approval stages does not indicate if one stage should receive a greater weight when creating an index, and because of the correlations I

found, I followed Grice (2001), who suggested using the factor scoring coefficients of a principle components analysis (PCA) as weights when creating an index. I performed a PCA to compute the factor scoring coefficients and used those as weights in computing the Market Expertise variable for each firm at each alliance date. Specifically, the weights are:

$$= (S1 \times 0.188) + (S2 \times 0.132) + (S3 \times 0.192) + (S4 \times 0.202) \times (S5 \times 0.188) + (S6 \times 0.196)$$

where S stands for the stage in the approval process. The result is one indicator of prior FDA approval experience for each firm. I then added up the values of the two partners, resulting in an indicator of prior FDA approval experience for the alliance. An increase in this indicator suggests more experience, making the experience exploitative, whereas a decrease in this indicator suggests a movement toward a newer experience, making the experience explorative.

FDA approval process success: This second indicator of market expertise indicates whether the alliance partners have previously had any success moving a therapy from one stage of the approval process to the next. Given the very small percentage of therapies that actually gain final FDA approval, and the large percentage of therapies that never moved beyond the initial stage, I coded any movement from one stage to the next as success, using the original data set of 28,740 alliances. Because success is rare, I assumed that when it happens, it significantly influences the firms' market experience. As a result, I did not restrict when in the past the success occurred. Next, I summed up all successful movements of the alliance partners in prior alliances.

The resulting indicator may be interpreted as follows: an increase in the *success* value suggests more previous success, which may be interpreted as exploitative (because

having success is then not as new to the firms). A decrease in the value of this variable suggests that success is a more a newer experience for the firms, which may be interpreted as a more explorative.

The variable used in the analysis, *Market Expertise*, is the product of *FDA approval process experience* and *FDA approval process success*. Given the amount of resources it takes to succeed in the FDA approval process, I chose to multiply the variables so as to assign a greater value to an alliance with partners that have experience and success. Additionally, by multiplying these two variables I recognize the rarity of success. This approach puts a greater quantitative distance between those who are not at all, marginally or very successful.

Control Variables

Firm size: I control for firm size because prior research suggests that firm size may explain R&D expenditures and firm performance (Levitas & McFadyen, 2009). R&D expenditures are especially relevant in this study because of this potential correlation with exploration and exploitation, and firm performance may be correlated to CAR. I used the natural log of the R&D firms' total assets as of December 31st of the year prior to the alliance date, which captures both tangible and intangible assets. Biotechnology firms often do not carry significant tangible assets but rather intangible assets (Rothaermel & Deeds, 2006), and patents are a form of intangible assets.

Industry environment: I created an industry index based on the Lerner Index (Lerner, 1994) as an indicator of the industry's willingness and ability to fund R&D projects in the biotech industry (Levitas & McFadyen, 2009). Willingness and ability to fund R&D projects greatly depend on the macroeconomic environment and industry outlook. There

is less funding available during economic downturns as companies and investors retract from engaging in risky endeavors, such as R&D. This retraction would then be measurable in this index; hence this measure is an appropriate proxy for the macroeconomic environment for the purpose of this study.

I calculated the index by using the month-end share price of common stock of a random sample of 12 biopharmaceutical companies from January 31st, 1989 to December 31st, 2008 and set January 31st 1989 to 1.000, resulting in a total of 240 industry values. I then matched those to the alliance date by using the industry index from the month ending prior to the alliance date.

Firm Age: To control for firm age is appropriate because the older the firm, the higher the probability that it had partnered with others in the past or had engaged in the patenting and FDA approval process. Therefore age influences many of the independent variables described above. Firm age is measured in years since the firm's founding (Rothaermel & Deeds, 2006), and I included the age of other partners in the analysis.

Number of current, active alliances: I used the original data set of 28,470 alliances and counted the total number of alliances for the Client firm in the two partner alliances. Because termination dates of alliances are usually not available, I only considered alliances that were three years or younger at the time of the event as active.

Model and Estimation

I tested the three sets of hypotheses using a linear mixed regression analysis that examines the effect of (1) the technical expertise of the alliance, (2) the relationship

expertise of the alliance, and (3) the marketing expertise of the alliance on the cumulative abnormal return (CAR) of the R&D partner in a two-firm alliance.

In addition to the three independent variables, I included a size variable, an industry index indicating the funding availability within the focal industry at the time of the alliance, an age variable, as well as a measure indicating the number of active alliances of the partner firms as control variables in the regression analysis.

In the sample of 927 alliances, 382 firms account for the $(2 \times 927 =)$ 1,854 partners involved in the alliances. 155 firms appear only once in the sample while one firm appears 53 times. Because of the unbalanced nature of the sample, as well as the likely presence of between-subject (firm) specific effects, a standard estimation method would not be appropriate.

To adjust for the characteristics of the sample, I used a linear mixed model design to execute the regression analysis that allows the subjects (firms) to differ from one another (Maxwell & Delaney, 2004). This approach allowed me to introduce random effects for each of the partner firms. Table 3 shows the fixed effects data estimation (within subject estimation) while accounting for the between-subjects firm effects. Parameters were estimated by the method of maximum likelihood using Proc Mixed in SAS 9.3.

RESULTS

I first tested for the presence of cumulative abnormal returns by testing whether the mean of the dependent variable is statistically different from 0. A T-Test confirmed that CAR is statistically significant different from 0 at $\alpha = 0.05$ (one-sample $t(456) = 5.155$, $p < 0.0001$) with a mean difference from 0 of 0.055, confirming previous studies (Dyer et

al., 2001; Shah & Swaminathan, 2008) that the stock market reacts positively to alliance announcements.

A close examination of CAR showed that the dependent variable and its residuals, are not normally distributed. As a result, I transformed the variable using a natural log (ln) transformation. I confirmed the successful transformation by visually inspecting the Q-Q plot as well as the P-P plot and deemed the dependent variable as well as the residuals approximately normal.

To assess the threat of collinearity I estimated the variance inflation factors (VIF) and found none to be great than 1.8. Prior studies cite different cutoff values, and I went with a conservative cutoff value of 10 (H. Y. Lee, 2011). As a result I conclude that no linear dependency among the independent variables exists.

Definitions of variables and the full model specifications are shown in Table 1. Descriptive statistics and the correlation matrix used in this study are provided in Table 2. The results of the linear mixed regression analysis are reported in Table 3, where Model 1 serves as the base model, including only the control variables, while Model 2 includes technical expertise, relationship expertise, and market expertise.

A likelihood ratio test, comparing model 1 to model 2, produced a chi-square statistic ($\chi^2 = 113.2$, 3 d.f.) above the critical value of 7.815. The resulting log likelihood ratio suggests that the addition of the three independent variables in Model 2 significantly improves the model fit.

Hypotheses 1A and 1B suggest that investors will react to an alliance's signal of technical expertise. I found no evidence of a statistically significant relationship between

the technical expertise of the alliance partners and CAR. As a result, I reject both hypotheses 1A and 1B.

Hypotheses 2A and 2B suggest that investors will react to the alliance's signal of relationship expertise. Specifically, hypothesis 2A suggests that investors react positively to the combined explorative relationship expertise of the alliance partners. The results provide statistical support for this hypothesis. The negative regression coefficient (-.000) indicates that as relationship expertise decreases (a shift towards exploration), investors' perception of value (proxied by CAR) increases ($p < 0.001$). As a result of hypothesis 2A being supported, I reject hypothesis 2B, which suggested that investors react positively to exploitative relationship expertise (which would have been evidenced by a positive regression coefficient).

Hypotheses 3A and 3B suggest that investors will react to the alliance's signal of market expertise. Specifically, hypothesis 3A suggests that there is a positive relationship between the combined explorative market expertise of the alliance partners and the investors' perception of value. For this to be the case, I would expect a statistically significant p-value with a negative regression coefficient, which is not the case (the regression coefficient is positive). As a result, I reject Hypothesis 3A.

Hypothesis 3B proposes that the combined exploitative relationship expertise of the alliance partners would positively affect the investors' perception of value. I did find statistically significant evidence to support hypothesis 3B. The correlation coefficient is positive (.000), indicating exploitation, and the p-value of 0.059 indicates marginal statistical significance at the 0.1 level.

DISCUSSION AND CONCLUSION

This study examined the causes of investors' reaction to alliance announcements. The underlying assumption of this study is that alliance announcements lead to an increase in stock market valuation of the participating firms, which then allowed me to investigate possible determinants. With a focus on the R&D partner, I confirmed that the sample in this study showed this characteristic, which allowed me to proceed and test three independent variables and their effect (signal) on the investors' perception of value.

The empirical portion of this study tested three sets of competing hypothesis that the management literature has not previously addressed. Interestingly, this study found no support for the first set of hypotheses that the technical expertise of alliance partners carries decodable signals to investors, as evidenced by the lack of statistically significant regression results (hypotheses 1A and 1B). Technical expertise in particular, which speaks to the ability of the alliance to create measurable results (in the form of patents) that could impact the future returns of the firm, should send rich signals to the investors. Especially in an environment of information asymmetry, I suggested that investors are eager to receive and decode signals that may allow them to more accurately predict the probability of future success of the alliance.

There may be several reasons for the lack of statistically significant findings, and, as such, implications for future research. First, given how potentially noisy this particular signal may be (given the vast number of patent citations that need to be coded to specifically match both firms), investors may simply not have enough time or the ability to decode this variable and then react in a timely manner to the alliance announcement. A

future study may consider isolating this variable and introducing a moderator so as to test whether this lack of statistically significant findings holds under different conditions.

Second, given the large number of alliance failures, investors may consciously choose not to consider this particular signal of technical expertise. Their internal evaluation model may have discredited this signal as unreliable as a predictor of future success.

The second set of hypotheses found that investors prefer alliance partner combinations with less previous work experience with each other (exploration) over alliances in which the partners have had a higher number of previous collaborations with each other (exploitation). These findings seem to contradict prior studies which suggest that efficient knowledge transfer (Cohen, 2009; Kogut & Zander, 1992; Mowery et al., 1998), knowledge of organizational routines (Beckman et al., 2004; Parkhe, 1993), and trust between partners (Li et al., 2008) are important indicators of organizational efficiencies, and thus may lead to a higher probability of success. Investors appear to value the possibility and benefit of reduced inertia between partners more highly than any other efficiencies that multiple collaborations would result in, as previous studies have suggested (Sx & Rowley, 2002).

In fact, the findings may suggest several things. First, could it be possible that investors believe that efficient knowledge transfer, knowledge of organizational routines, and trust between partners may not be positively related to the number of collaborations. Second, the findings suggest that investors like to take risk because an explorative relationship is by definition more risky than an exploitative relationship. One avenue for a future study would be to focus on the risk averseness of investors and introduce this concept into a follow-up study. Third, because exploration suggests a divergence from

previous activities, and because of the high failure rates of alliances, investors may interpret this signal as a firm-level reassessment of previous performance, and thus as a sign that firms are trying to correct previous strategic decisions that may have led to failures. This, then, would be in line with previous studies that suggest that firms get better by learning from previous experiences (Sampson, 2005), which in this case could mean to not work with the same partner again but rather focus on explorative (new) relationships.

The last set of findings pertaining to hypotheses 3A and 3B informs us about the investors' preference regarding the combined FDA-specific approval process experience and success. The analysis found that investors prefer alliances with more FDA approval process experience and success (exploitation) over alliances with less experience and success (exploration). These findings support prior studies that linked experience and learning to superior performances (Nelson & Winter, 1982). Given the high number of alliance failures, these findings support the notion that investors would value the process-specific experience and prior success of alliance partners.

Despite its contributions, this study is not without limitations. For example, the three-day window around the alliance announcement might not be enough time for investors to consider the patenting activity of each partner and the resulting combined technical expertise. A bigger window might possibly lead to different findings. However, a bigger window would also increase the possibility of non-alliance related events influencing the stock price of the focal firm (such as, for example, a dividend announcement, or a change in the top management team of the focal firm).

In conclusion, this study contributes to the field's understanding of determinants of investors' perception of value of alliance formations. The emphasis on technical expertise, relationship expertise, and marketing expertise, where each variable is coded along a continuum from exploration to exploitation, is a unique perspective that in this form has not been explored in the management literature.

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Table 1: Definition of variables and model specifications

Variable Name	Definition
CAR (R&D)	The Cumulative Abnormal Return (CAR) of the R&D partner, calculated using a portfolio of firms with the same 2-digit SIC code, adjusted for size and transformed (natural log) to adjust for non-normality of the data and the residuals.
Technical Expertise	An indicator of the technical expertise of the two partner firms in the focal alliance based on patent citation overlap. A low value indicates exploration, a high value indicates exploitation.
Relationship Expertise	An index describing the level of relationship experience between the two partners, calculated as = (Frequency) + (Recency) + (ATSPE); a low value indicates exploration, a high value indicates exploitation.
Frequency	The number or frequency of prior alliance relationships between the two firms
Recency	The recency (in days) of the last alliance relationship between the two. If the two partners have not worked before I set the value to 10,000
ATSPE	The alliance type specific partner experience, indicating if these two firms have worked together in this type of alliance before.
Market Expertise	An index describing the FDA approval process experience of the alliance partners at the time of the alliance date, calculated as ((C-MKT-Index + RD-MKT-Index) x (Alliance Success)). A low value indicates exploration, a high value indicates exploitation.
C-MKT-Index	The cumulative FDA approval process experience of the Client firm in each stage of the process and across all stages at the time of the alliance.
RD-MKT-Index	The cumulative FDA approval process experience of the R&D firm in each stage of the process and across all stages at the time of the alliance.
Alliance Success	The cumulative FDA approval success of the two partners.
Size (R&D)	Control variable, the natural log of total assets of the R&D firm
Industry Environment	Control variable, an industry index proxying the funding availability in the focal industry.
Age (Client)	Control variable, the age of the client firm from the firm's founding to the alliance date.
Age (R&D)	Control variable, the age of the R&D firm from the firm's founding to the alliance date
Active Alliances (Client)	Control variable, the number of current active alliances of the client firm as of the event date.
Hypothesis	Model Specification(s)
H1, H2, H3	CAR = (Technical Expertise) + (Relationship Expertise) + (Market Expertise) + (R&D Size) + (Industry Environment) + (Client Age) + (R&D Age) + (Client Active Alliances)

Table 2: Means, Standard Deviations, and Correlations

	Mean	S.D.	1	2	3	4	5	6	7	8	9
1 CAR	-.68	.29	1								
2 Technical Expertise	.42	.49	.080	1							
3 Relationship Expertise	-8704.14	3219.58	-.270**	-.064	1						
4 Marketing Expertise	509.82	1133.40	.120*	.068	-.038	1					
5 Size (R&D)	4.65	1.87	.018	.040	.027	-.037	1				
6 Industry Index	1.46	.31	.013	.042	.044	.007	.021	1			
7 Age (Client)	88.04	226.44	.000	-.008	-.042	-.036	.001	-.065*	1		
8 Age (R&D)	20.05	94.44	.004	.056	-.006	-.020	-.013	.015	-.002	1	
9 Active Alliances (Client)	28.45	28.29	-.016	.049	-.022	-.007	.214**	-.053	.006	-.020	1

** . Correlation is significant at the 0.01 level (2-tailed).

* . Correlation is significant at the 0.05 level (2-tailed).

Table 3: Maximum Likelihood estimates on CAR of Technical Expertise, Relationship Expertise and Market Expertise

Explanatory Variable	Model 1		Model 2	
	CAR		CAR	
Intercept	-0.674	(0.080)***	-0.966	(0.103)***
Technical Expertise			0.015	(0.033)
Relationship Expertise			-0.000	(0.000)***
Marketing Expertise			0.000	(0.000)†
Size (R&D)	0.005	(0.007)	0.007	(0.008)
Industry Index	0.001	(0.047)	0.077	(0.054)
Age (Client)	-0.000	(0.000)	-0.000	(0.000)
Age (R&D)	-0.001	(0.000)	-0.001	(0.000)*
Active Alliances (Client)	-0.000	(0.000)	-0.000	(0.000)
Log-likelihood ratio	87.5		-25.7	
Log-likelihood ratio vs. Model 1			113.2	***
Number of events	347		200	

Standard errors appear in parentheses

†p<0.10; *p>0.05; **p>0.01; ***p>0.001

REDUCING INVESTOR ANXIETY VIA ALLIANCE PARTNER SELECTION

INTRODUCTION

Alliances have held a prominent place in the management literature, and their importance has been widely acknowledged (Kale & Singh, 2009). A significant amount of research has focused on reasons for alliance formations, which include, among others, access to new capabilities (Oxley & Sampson, 2004; Rothaermel & Boeker, 2008), access to new markets (Chen & Chen, 2002; Koka & Prescott, 2008), access to new assets (Huggins, 2010; Li, Eden, Hitt, & Ireland, 2008) including new knowledge (Walter, Lechner, & Kellermanns, 2007), and enhanced reputation (Hitt, Dacin, Levitas, Arregle, & Borza, 2000). Additionally, studies have found that alliances can lead to more efficient facilitation of information transmittal between firms (Davis & Greve, 1997; Haunschild, 1993), or reduction in various forms of uncertainty (Beckman, Haunschild, & Phillips, 2004; Goerzen, 2007; Hamel, Doz, & Prahalad, 1989; Varadarajan & Cunningham, 1995). It is this last reason for, or benefit of, alliance formations, the potential for a reduction in uncertainty, that is the focus of this study.

Certain types of uncertainty create an environmental condition that has the potential to wreak havoc on the firm, which is why firms desire to proactively address and subsequently attempt to reduce uncertainty whenever possible. Uncertainty can loosely be described as being in a state of doubt, depending on chance, and being unsure of the future. What makes the concept of uncertainty difficult to address strategically is the fact that there are different types of uncertainty (e.g. market or systemic uncertainty, firm specific or unsystematic uncertainty) and that uncertainty can be experienced or perceived on several different levels (e.g., internal vs. external to the organization). Because of its complexity, uncertainty can negatively impact organizations' planning and

decision making processes (Jauch & Kraft, 1986; Pfeffer & Salancik, 1978), leading to a firm's attempt to avoid or reduce uncertainty. Forming an alliance is one way to proactively address uncertainty, rooted in the understanding that some levels of uncertainty can be managed by adapting the organizational design that best fits the environment (Williamson, 1981).

Alliances enable firms to deal with uncertainty better than a single firm because of the many synergistic effects alliances offer (Harrison, Hitt, Hoskisson, & Ireland, 1991). However, given the various types of uncertainty, I suggest that simply forming an alliance is not adequate to address uncertainty. Special attention should also be devoted to selecting a partner with the right skills. Previous studies have found that the degree to which alliance partners' specific skills and resources are similar or complementary matters (Harrison, Hitt, Hoskisson, & Ireland, 2001), and that firms search for alliance partners with this dimension in mind (Doh, 2000; Stuart, 2000). Similarity can reduce friction and can lead to efficiencies. On the other hand, a degree of complementarity (or diversity) may be necessary to meet unforeseen challenges imposed by uncertainty. Whether similar or complementary partners lead to a reduction of uncertainty is an interesting question, one that I will investigate further in this study. I examine how similarity or complementarity between partners interacts with current environmental conditions, how subsequently investors interpret the partner skill combinations and how this interpretation will affect uncertainty as perceived by investors.

In this study, I specifically examine how uncertainty as perceived by investors is affected by measuring components forming the explore/exploit dichotomy. Explorative and exploitative skills and expertise send very rich signals to investors, meaning that

these signals carry a lot of information which investors decode and react to. Exploration and exploitation are dimensions that, due to their ability to affect the trajectory of a firm, provide an effective base on which to assess investor reactions. I examine partner firms in order to observe partner combinations that can be considered as either similar or complementary. Firms are said to need distinctly different organization forms to successfully explore or exploit, making this dimension an ideal variable to distinguish between two partner firms.

Further defining my research setting, I am focusing on two-firm alliances in the pharmaceutical industry between a biotech firm and a pharmaceutical company. I will specifically focus on how exogenous uncertainty moderates the relationship between the alliance partners and endogenous uncertainty experienced by the biotech firm. My research question is as follows: Given different levels of exogenous (industry) uncertainty (high, low), should partner-specific skills within an alliance be similar or complementary so as to send the desired signal to investors and, as a result, reduce the uncertainty of the biotech firm as perceived by investors?

I will draw on signaling theory (Spence, 1973; Spence, 1974) to derive six total (four specific) hypotheses and suggest that strong signals that communicate the alliance's abilities to deal with different environmental conditions (e.g. different levels of exogenous uncertainty), based on the very specific combination of skills of the alliance partners, will lead to a positive (and desirable) reduction in firm-specific uncertainty as perceived by investors. I am extending the literature by focusing on the partner-skill combination of alliances in different environments defined by the level of exogenous

uncertainty. Empirical analysis using a sample of pharmaceutical alliances will test my hypotheses.

THEORY AND HYPOTHESES

The construct of uncertainty has been the subject of strong interest in prior management science studies, especially as it impacts strategic directions of the firm (Ambrosini & Bowman, 2009; Bourgeois III, 1985; Desarbo, Di Benedetto, Song, & Sinha, 2005; Jauch & Kraft, 1986; Mascarenhas, 2011). The general consensus is that, while some uncertainty is unavoidable (systemic), a reduction in unsystematic (firm-specific) uncertainty is possible and desirable but requires very specific, strategic action (Galbraith, 1973). Because of the negative impact internal and external uncertainty may have on firms, managers are encouraged to actively try to reduce uncertainty whenever and wherever possible (Daft & Lengel, 1986). One available strategic response to uncertainty is to make changes to structural arrangements as they pertain to organizational design (Williamson, 1981), one of which is to enter a strategic alliance (Goerzen, 2007).

Part of the process of forming an alliance is partner selection. I will explain later how I define effective alliance partner selection within the context of my research question, but would like to point out that the focus of this study is not on the process of selecting alliance partners. Instead I focus on how the combination of partners selected sends a signal to investors. The type of partner selected (in terms of explorative/exploitative skills) matters to the alliance, and as a result, matters to investors. Effective partners for the purpose of this study are those that create a partner-skill combination that lowers

firm-specific uncertainty as perceived by investors, given the level of exogenous uncertainty experienced by the alliance.

The next section will outline the two different types of uncertainty I consider in this study: firm specific uncertainty, which will directly influence uncertainty as perceived by investors (the outcome variable), and exogenous uncertainty experienced by the industry (the moderator).

Firm-Specific Uncertainty

As Beckman et al. (2004) pointed out, firm-specific uncertainties arise when firms experience some internal turbulence, such as entering a new market (Greve, 1996), purchasing another firm (Haunschild, 1994), experiencing high internal turnover (Carroll, 1984), experiencing information asymmetry between managers and shareholders, or doubting technical success (McGrath, 1997). I proxy firm-specific uncertainty by measuring the focal firm's stock price volatility, thereby conceptually following Lang and Lockhard (1990), who suggested that a firm's internal perception of uncertainty is positively related to financial volatility.

Examples of specific action to reduce firm-specific uncertainty can be found in the pharmaceutical industry. Firms may experience uncertainty when, for example, they know that a competitor is working toward a similar therapy (e.g. a cure for an illness). Increased investment by entering an alliance, which will provide access to new resources with the goal of eventually filing for patent protection before the competitor can do it, may be considered a strategic action taken to reduce firm-specific uncertainty. Therefore, firms in the pharmaceutical industries may deal with firm-specific uncertainty by entering into alliances, which is in line with McGrath's (1997) assessment of firm responses to

internal uncertainty as well as with Pindyck's (1993) suggestion that 'taking action' (entering an alliance, subsequently being able to focus on needed R&D, and filing for patent protection) can reduce internal uncertainty and lead to a higher probability of success.

In addition, firm-specific uncertainty in the pharmaceutical industry arises largely out of the complex and resource-consuming approval process set up and monitored by the Food and Drug Administration (FDA). Getting a new therapy approved may take upward of 15 years and costs, on average, over \$800 million (Pennings & Sereno, 2011). The process itself consist of six distinct approval stages, starting at the pre-clinical stage, Investigative New Drug (IND) application, three phases including testing on humans, and eventually the approval and market stage. Before a therapy moves from one stage to the next, it has to prove its effectiveness (as defined by each stage). These FDA hurdles are designed to prove effectiveness, and because success is not certain, they create uncertainty, which I suggest will be observed through the stock price volatility of the partner firms.

Because of the plethora of distinct skills and expertise, as well as other resources needed to move from one FDA approval stage to the next, a preferred organizational form to address the uncertainty that accompanies engagement in the approval process is the alliance. Entering into an alliance enables the partner firms to gain access to additional resources, which may reduce firm-specific uncertainty. The alliance announcement, therefore, might serve as a signal to the investors that firms are actively addressing internal uncertainty.

Next, I evaluate how the choice of combined skills and expertise of the partners affects investors' perception of uncertainty, followed by a test of how exogenous uncertainty moderates this relationship.

Skill combination of partners

It is understood that the search for an alliance partner has to go beyond simply choosing from the partner with the most resources, but rather involved choose a partner whose resources effectively complement or supplement those of the focal firm. Gaining access to the *right* resources, given the specific internal and external alliance environment, is a crucial managerial task (Shah & Swaminathan, 2008). The choice of partners, I assume, is a conscious strategic decision by the firm. This means that, assuming that each firm has options, the partner chosen may represent the partner that has the skills managers believe most efficiently offset any weaknesses of the other partner.

In this study, I frame the choice of partners along an exploration/exploitation dimension with regard to technical expertise. Exploration is defined as searching, risk taking, discovery, innovation, and experimentation (March, 1991). Exploration has also been associated with concepts like investment, building new capabilities, and entering new lines of business (Koza & Lewin, 1999), and some would define it simply as the pursuit of *new* knowledge (Rothaermel, 2001). Because pursuit of the unknown by definition creates uncertainty about which exact skills are needed to succeed, firms may decide on a strategy focused around economies of scope.

Exploitation, on the other hand, more commonly refers to refinement, efficiency, production, selection, and implementation (March, 1991). Here firms are said to focus

more on economies of scale, using existing processes and knowledge to refine a product or process, but certainly do not consistently explore the unknown.

The decision to characterize partner skills based on exploration and exploitation is based on the literature's acknowledgement that every individual firm, as well as the alliance in an aggregate, focuses to a degree on either or both of these activities (March, 1991). Therefore, exploration and exploitation play a part in a firm's overall strategic direction, and evidence of either should be found in any firm. Next, I will address these definitions as well as a justification for why I chose to express partner skills in those terms.

A basic premise of this study is that explorative skills will equip an organization to deal with environmental conditions that call for explorative responses, while exploitative skills prepare organizations to deal with exploitative environmental conditions. Because explorative and exploitative skills signal fundamentally different partner abilities, and because investors might be under-informed about what the firms and the alliance will actually do, investors will rely on very basic properties of these signals.

The dimensions of exploration and exploitation are well suited for this study because they signal fundamentally different strategic directions and possible future trajectories of the firm. This study centers on the question of what partner-skill similarity or complementary signals to investors, and how this signal affects uncertainty as perceived by investors. I will explore the concepts of skill similarity and skill complementarity in the next section.

Effective partner selection, i.e., creating a partner combination that reduces uncertainty as perceived by investors, is a critical step in leading an alliance onto a path

toward perceived value creation. Previous studies have addressed the issue of partner skills and resource complementarity (Harrison et al., 2001; Ohmae, 1989). The concept of complementary skills specifically refers to *different* skills that the partners bring into the alliance, with the assumption that different skills, such as abilities, knowledge, organizational design, and experience, etc., are then used strategically to offset possible weaknesses of the other partner. Skill similarity suggests that partners have similar types of skills (e.g., both have experience in the same type of therapeutic classes, both have guided a therapy through the FDA approval process, both have the ability to innovate).

Harrison et al. (2001) studied the question of resource similarity vs. complementarity and thus started this important conversation. Previous studies addressing skill similarity vs. complementarity have centered on the relatedness/performance hypothesis. Earlier research mostly suggested that relatedness should lead to higher performance (Singh & Montgomery, 1987). However, other studies found contradictory evidence and thus opened the door for additional research [see Harrison et al. (1991) for a review]. In the context of this study, higher performance should be achieved by creating lower internal uncertainty as perceived by investors. As a result I test the findings of previous studies by re-phrasing those terms of lower firm-specific uncertainty.

Hypothesis 1: High levels of skill complementary between alliance partners results in low firm-specific uncertainty of the biotech firm as perceived by investors.

Hypothesis 2: High levels of skill similarity between alliance partners results in low firm-specific uncertainty of the biotech firm as perceived by investors.

Exogenous Uncertainty

While firm-specific uncertainty is specific to the firm, exogenous uncertainty is the kind that every firm within an industry or group experiences. Because it is, to a degree, systemic to the industry or group, this type of uncertainty cannot be controlled at the firm level. Exogenous uncertainty is an independent construct from firm-specific uncertainty because it is possible for a firm to experience very low internal uncertainty while the industry to which the firm belongs may experience high uncertainty, or vice versa. For example, an industry might experience overall demand uncertainty, but the individual firm-specific demand might be stable. As a result, I will designate the industry environment as one of high exogenous uncertainty or low exogenous uncertainty at the time of the alliance announcement and measure how exogenous uncertainty moderates the relationship between the choice of alliance partners and firm-specific uncertainty of the biotech firm as perceived by investors. The next two hypotheses in this study are designed to test investors' perception of uncertainty under high exogenous uncertainty.

I suggest that high exogenous uncertainty calls for strategic approaches that broaden the resource level within the alliance. Because high exogenous uncertainty present at the industry level suggests that an alliance has to address a greater diversity of issues than an alliance operating under low exogenous uncertainty, resource complementarity could lead to the desired economies of scope (Harrison et al., 2001). By selecting a partner with complementary skills, the alliance partner firms would create some flexibility and put themselves in a position to be able to address a more diverse range of issues. This could lead to a subsequent reduction in uncertainty of the biotech partner as perceived by investors.

Choosing a partner with similar skills, however, equates to introducing more of the same resources and skills into the alliance. This would not be as desirable a strategy in an environment of high exogenous uncertainty because the alliance runs the risk of having excess unusable resources, while not possessing other, requites resources. The alliance is unable to use its existing resources to address and cope with exogenous uncertainty; more of the same would not be viewed as beneficial by investors. As a result I suggest two hypotheses:

Hypothesis 3: The level of exogenous uncertainty moderates the relationship between skill sets of alliances partners and firm-specific uncertainty of the biotech firm as perceived by investors such that under high levels of exogenous uncertainty, skill complementarity of the alliance partners results in low firm-specific uncertainty of the biotech firm as perceived by investors.

Hypothesis 4: The level of exogenous uncertainty moderates the relationship between skill sets of alliances partners and firm-specific uncertainty of the biotech firm as perceived by investors such that under high levels of exogenous uncertainty, skill similarity of the alliance partners results in low firm-specific uncertainty of the biotech firm as perceived by investors.

Hypotheses 4 and 5 will test the investors' perception of uncertainty (of the biotech firm) under low exogenous uncertainty. Low exogenous uncertainty suggests that the industry in which the alliance operates in does not experience a lot of turbulences but operates in a rather stable environment. This would suggest that firms have figured out what kinds of resources are needed to survive.

I suggest that under low levels of exogenous uncertainty, investors will react positively to alliances that appear to be aware of the general lack of this type of

uncertainty and thus focus on efficiencies as well as economies of scale. Given the nature of a stable industry environment with low uncertainty, firms have the luxury to carefully select a partner that will enhance their own capabilities by adding to those (e.g. more of the same). In the absence of high exogenous uncertainty, alliances can now afford to focus all of their efforts (meaning: all of the combined skills and expertises) on one goal: to either explore or to exploit. Therefore, alliances signal to investors that they are aware of the lack of exogenous uncertainty and that they are willing and ready to capitalize on this knowledge. Because of the lack of exogenous uncertainty companies do not have to take efficiency risks.

If, in this state of low exogenous uncertainty, alliances would comprise of firms with complementary skills, investors may critically question that partner combination because it may not lead to the desired maximum performance. The partner selection could signal that the partners are either not aware of the lack of exogenous uncertainty, or that no other partner was available or willing to enter into a partnership. Neither signal would be well received by investors because they signal some lack of external awareness. Low exogenous uncertainty would call for strategies that aim to capitalize on the opportunities for economies of scale. Investors observe this, and as a result I suggest that:

Hypothesis 5: The level of exogenous uncertainty moderates the relationship between skill sets of alliances partners and firm-specific uncertainty of the biotech firm as perceived by investors such that under low levels of exogenous uncertainty, skill complementarity of the alliance partners result in low firm-specific uncertainty of the biotech firm as perceived by investors.

Hypothesis 6: The level of exogenous uncertainty moderates the relationship between skill sets of alliances partners and firm-specific uncertainty of the biotech firm as perceived by investors such that under low levels of exogenous uncertainty, skill similarity of the alliance partners result in low firm-specific uncertainty of the biotech firm as perceived by investors.

METHODS

Sample

I used a sample of bilateral alliances that include biotech firms and pharmaceutical companies. I coded firms as Client or R&D to indicate the relationship where, generally, the pharmaceutical company represents the Client firm and the biotech firm represents the R&D partner. I chose this industry because alliances are a very common organizational form, where partners are likely to work with each other numerous times. In addition, this industry relies heavily on patent protection for its products which, as I outlined before, sends very rich signals about the technical expertise of the alliance partners.

All patent information was obtained from the National Bureau of Economic Research (NBER) Patent Citations database (Hall, Jaffe, Trajtenberg, & Centre for Economic Policy Research (Great Britain), 2001), and the United States Patent and Trademark Office's (USPTO) Cassis database. Additional data were taken from Compustat data files, the Center for Research in Security Prices (CRSP) U.S. stock database, the Recombinant Capital Biotechnology Database (ReCap), the IMS R&D Focus database, Spectrum Institutional Ownership files, and United States Securities and Exchange (SEC) proxy (DEF 14a) filings.

The initial sample included 28,470 biopharmaceutical alliances established between January 1st, 1989 and December 31st, 2008. I used the Wharton Research Data Services (WRDS), and specifically the Center for Research in Security Prices (CRSP) database, to determine which alliances included both biotech firms and pharmaceutical firms that were publicly traded at the end of the month of the event date. Next, I further refined the event date (date of the alliance announcement) by performing a web search on each partner combination in the stated month; this search produced specific alliance announcements which allowed me to define the exact date of the announcement. This final data set includes 927 alliance events with exactly two partners that were both publicly traded as of the event date.

Measures

Dependent Variable

Firm-Specific Uncertainty: I used the volatility of the focal R&D firm's stock price as a proxy for firm-specific uncertainty (Beckman et al., 2004). The management literature cites a high correlation between the managerial perception of (firm-specific) uncertainty and the volatility of the firm's stock prices (Bourgeois III, 1985; Lang & Lockhart, 1990), which justifies the use of stock prices to proxy firm-specific uncertainty.

Specifically, following Beckman et al. (2004) I operationalize an individual firm's level of internal uncertainty as the coefficient of variation for firm *j*'s annual stock closing price, or

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

where $i = 1988, \dots, 2007$, and the index j represents each firm in the sample.

By dividing the standard deviation by the mean, effectively calculating the coefficient of variation, measurements of uncertainty can be interpreted across firms with different price ranges (Beckman et al., 2004). I then matched this measure of R&D firm specific uncertainty to each alliance based on firm ID and alliance date, where I used the firm-specific uncertainty from the year prior to the alliance announcement.

Independent Variables

Partner Similarity (Technical Expertise): I measure technical similarity using patent citation counts of each partner. While prior studies have used R&D intensity as a measure of technological capabilities (Cohen & Levinthal, 1989; Mowery, Oxley, & Silverman, 1996), Mowery et al. (1998) pointed out that R&D intensity is an input measure while patents are an output measure that more accurately reflects technology-based capabilities.

I conceptually follow previous studies (Mowery et al., 1998; Rothaermel & Boeker, 2008; Vassolo, Anand, & Folta, 2004) that measured the degree of similarity/complementarity, between two firms by calculating dyadic patent or patent citation ratios for each partner combination and measuring the distance between the ratios as indicators of the degree of difference between partners. Specifically, I calculate the technological distance between alliance partners by taking the absolute distance between patent citation ratios of each firm (Rothaermel & Boeker, 2008), or

$$\left| \left(\frac{\text{Patent Citation Count (Client)}}{\text{Patent Citation Count (Client+R\&D)}} \right) - \left(\frac{\text{Patent Citation Count (R\&D)}}{\text{Patent Citation Count (Client+R\&D)}} \right) \right|$$

Each ratio represents the percentage of total technical expertise brought into the alliance by each partner. The absolute difference between the two ratios represents the difference in technical expertise brought into the alliance by each partner and thus represents a measure of technological similarity/complementarity within this dyadic relationship. A smaller distance would suggest that each partner contributed a more equal portion to the total technical expertise of the alliance (which suggests a higher degree of technical similarity of the alliance partners), whereas a greater distance suggests that the partners contributed a more unequal portion of the total technical expertise of the alliance (which suggests a higher degree of technical complementarity of the alliance partners).

I then transformed the difference value by taking (1 – value). As a result, an increase in this variable represents a move toward less distance between the partners, which may be interpreted as an exploitative partner combination. A decrease in this variable represents a trend toward greater distance between these variables, which would suggest an explorative relationship. I decided on this transformation to ensure a level of conformity to my related studies in which an increase in this value suggests a move towards exploitation, and a decrease suggests a move toward exploration.

Exogenous (Industry-Specific) Uncertainty: Following Levitas & Chi (2010) and Beckman et al. (2004) I operationalize industry uncertainty by calculating the annual coefficient of variation for the industry's monthly stock prices, thus proxying managerial uncertainty within an industry by creating a measure of industry volatility (Lang &

Lockhart, 1990). The fundamental approach and rationale to creating this variable is similar to the dependent variable in this study. I then matched the annual measure to the alliance data by using the coefficient of variation from the year prior to the alliance announcement.

Control Variables

Firm size: I control for firm size because prior research suggests that firm size may explain R&D expenditures and firm performance (Levitas & McFadyen, 2009). R&D expenditures are especially relevant in this study because of their potential correlation with exploration and exploitation. I used the natural log of the Client firm's total assets as of December 31st of the year prior to the alliance date, which captures both tangible and intangible assets. Firms in the biopharmaceutical industry firms often do not carry significant tangible assets but rather intangible assets (Rothaermel & Deeds, 2006), and patents are a form of intangible assets.

Industry environment: I created an industry index based on the Lerner Index (Lerner, 1994) as an indicator of the industry's willingness and ability to fund R&D projects in the biotech industry (Levitas & McFadyen, 2009). Willingness and ability to fund R&D projects greatly depend on the macroeconomic environment and industry outlook. There is less funding available during economic downturns as companies and investors retract from engaging in risky endeavors, such as R&D. This retraction would then be captured in this index; hence this measure is an appropriate proxy for the macroeconomic environment for the purpose of this study.

I calculated the index by using the month-end share price of common stock of a random sample of 12 biopharmaceutical companies from January 31st, 1989 to December

31st, and set January 1st, 1989 to 1.000, resulting in a total of 240 industry values (or one index per month). I then matched those to the alliance date by using the industry index from the month ending prior to the alliance date.

Firm Age: To control for Client firm age is appropriate because the older the firm, the higher the probability that it had engaged in the patenting. Therefore age may influences the variable partner similarity. Firm age is measured in years since the firm's founding at the time of the alliance announcement (Rothaermel & Deeds, 2006).

R&D Expenditures: This variable is used as an indicator of the firm's R&D commitment and intensity, which are likely to have an impact on knowledge creation and subsequently on patenting activity (Cohen & Levinthal, 1990; Leiponen & Helfat, 2010). I used the Clients' R&D expense at the end of the year prior to the alliance announcement.

Tobin's Q: Tobin's Q is a measure of intangible resources (Kumar, 2011) and as such an important factor to control for in a study that uses intangible assets (patents). It is calculated by dividing the market value of the Client firm (share price at the end of the year times the number of share outstanding) by the total year-end book value of the focal firm. I then matched Tobin's Q to each firm for the year ending prior to the alliance announcement.

Model and Estimation

I tested the hypotheses using a linear mixed model analysis that examines the effect of partner similarity and industry uncertainty on firm specific uncertainty of the R&D

partner in a two-firm alliance. In addition to the two independent variables I included described above in the regression analysis.

In the sample of 927 alliances, 382 firms account for the $(2 \times 927 =)$ 1,854 partners involved in the alliances. Further, 155 firms appear only once in the sample while one firm appears 53 times. Because of this unbalanced nature of the sample, as well as the likely presence of between-subject (firm) specific effects, a standard estimation method would not be appropriate.

To adjust for the characteristics of the sample, I used a linear mixed model design to execute the regression analysis that allows the subjects (firms) to differ from one another (Maxwell & Delaney, 2004). This approach allowed me to introduce random effects for each of the partner firms. Parameters were estimated by the method of maximum likelihood using the Proc Mixed procedure in SAS 9.3.

RESULTS

Definitions of variables and the full model specifications are shown in Table 1. Descriptive statistics and the correlation matrix used in this study are provided in Table 2. The results of the linear mixed regression analysis are reported in Table 3, where Model 1 serves as the base model, including only the control variables, Model 2 includes the independent variables, and Model 3 serves as the full model including the interaction term.

A close examination showed that the dependent variable *Firm Uncertainty*, as well as its residuals, is not normally distributed. As a result, I transformed the variable using a square root transformation. I confirmed the successful transformation by visually

inspecting the Q-Q plot as well as the P-P plot and deemed the dependent variable as well as the residuals to be approximately normal.

To assess the threat of collinearity, I estimated the variance inflation factors (VIF) and found none to be great than 1.227. Several prior studies cite different cutoff values, and I went with a conservative cutoff value of 10 (Lee, 2011). As a result I conclude that no linear dependency between the independent variables exists.

A likelihood ratio test, comparing Model 1 to Model 2, produced a chi-square statistic ($\chi^2 = 2.6$, 2 d.f.) below the critical value of 5.991. This suggests that the addition of *Partner Similarity* in Model 2 did not significantly improve the model fit from model 1. Due to this lack of overall explanatory power, and the fact that the regression coefficient for Partner Similarity in Model 2 is not statistically significant, I reject hypotheses 1 and 2, which suggested that the alliance partner combination in terms of similarity or complementarity has an impact on firm specific uncertainty as perceived by investors.

The likelihood ratio test comparing Model 1 to Model 3 (which I used to test hypotheses 3 – 6) produced a chi-square statistic ($\chi^2 = 8.6$, 3 d.f.) above the critical value of 7.815, suggesting that the addition of the three variables in Model 3 did significantly improve the explanatory power of the model.

Hypotheses 3, 4, 5 and 6 test the effect of partner similarity on firm specific uncertainty as perceived by investors under differing levels of exogenous uncertainty. Model 3 in Table 3 shows the regression results pertaining to these hypotheses, indicating significant findings. Figure 2 displays the relationship between partner similarity and firm specific uncertainty as perceived by investors under different levels of exogenous

uncertainty. Note that low partner similarity in the chart suggests partner complementarity.

Specifically, hypothesis 3 suggested that in an environment of high exogenous uncertainty investors favor partner complementarity over an alliance partner combination where the partners display similarity. This relationship is confirmed in Figure 2, which shows that under high levels of exogenous uncertainty investors prefer partner complementarity over partner similarity, as evidenced by lower firm specific uncertainty. Based on the statistically significant findings of Model 3 in Table 3, as well as the interpretation of the interaction effect in Figure 2, I accept hypothesis 3 and consequently reject hypothesis 4.

Hypotheses 5 and 6 focus on the relationship between partner similarity and firm specific uncertainty as perceived by investors under low levels of exogenous uncertainty. Specifically, hypothesis 5 suggested that under these low levels of exogenous uncertainty, investors favor partner complementarity over partner similarity. Model 3 in Table 3 again shows the statistically significant findings. Figure 2 shows that under low levels of exogenous uncertainty investors prefer similar partners over partners with complementary skills. As a result, I reject hypothesis 5 but conclude that I found statistically significant evidence to accept hypothesis 6, which suggests that under low levels of exogenous uncertainty, investors prefer partners with similar skills.

DISCUSSION AND CONCLUSION

The purpose of this study was to first investigate if the degree of similarity between alliance partners affects investors' perception of uncertainty, as indicated by stock price volatility. Second, if and how exogenous uncertainty moderates this relationship. I

focused on dyadic R&D alliances and used their technical expertise as an indicator of similarity/complementarity. Technical expertise has previously been used in the management literature as an indicator of partner similarity (see, for example, Ahuja et al. (2009) or Mari et al. (2010).

I used a linear mixed regression analysis to test the three sets of hypotheses. I found no support for the first set of hypotheses, which suggested that the degree of partner similarity should influence investors' perception of uncertainty. Considering the general business environment, the findings might actually make great sense in that no firm works in a vacuum. The external environment should always play a role in a firm's strategic decision making process (Larrañeta, Zahra, & González, 2013). As such, investors may not pay special attention to partner attributes, but rather consider those in context of the external environment. Hypotheses 3 to 6 specifically consider the external environment.

The results of the second set of hypotheses focused on the interaction between partner similarity and the level of exogenous uncertainty. I found support for the idea that, when faced with high levels of exogenous uncertainty, investors prefer alliances with partners that are less similar, or more complementary, to each other. The findings support the idea that under high levels of uncertainty, investors prefer alliances that offer greater flexibility to quickly adapt to a changing environment, which partners with different skills may be better equipped to achieve than partners with more similar skills. As such, the findings are in line with previous studies, for example Harrison et al. (2001) which suggested that resource complementarity, a form of resource broadening, is desirable under high levels of exogenous uncertainty.

The findings of this second set of hypotheses might suggest that investors pay close attention to this dimension of partner choice when a new alliance is announced. Because a diverse set of partners might be better equipped (meaning they may possess different skills) to quickly address a volatile external environment, one that demands different strategic responses to different environmental conditions, investors appear to send a positive signal to the market and the alliance. Specifically, as suggested by Shah and Swaminathan (2008), investors may reward the alliance for choosing the right resources given the external environment, which may signal managerial competence.

The third set of hypotheses investigated investors' perception of uncertainty under low levels of exogenous uncertainty. I found statistical support that in a less uncertain environment, investors prefer alliance partners that are more similar to each other (hypothesis 6). This might also point to managerial competence because managers have shown the ability to choose their alliance partners based on skills that match the needs of the firms in this environment. Specifically, the relative certainty of the external environment might present the firm with an opportunity to focus on economies of scale, which in turn might lead to higher efficiencies.

I realize, of course, that this study is not without limitations. First, I used a very specific dimension of the firm as indicator of partner similarity. Follow up studies might consider other dimensions on which to compare the partners and measure their relative distance to each other in an effort to create a more comprehensive indicator of similarity. Second, while stock market volatility is a common measure of firm and industry uncertainty, other measures using surveys exist as well. Future studies may want to consider using a survey method to gauge firm- and industry-specific uncertainty.

In summary, coding partner similarity and complementarity along a dimension of technical expertise and in terms of exploration and exploitation is a novel approach that has not been explored in the management literature. This paper and its findings represent a valuable contribution to the field of strategic management, and advance our understanding of investor reaction to alliance announcements.

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Table 1: Definition of variables and model specifications

Variable Name	Definition
Firm Specific Uncertainty (R&D)	The standardized monthly volatility of the R&D firm's stock price in the year prior to the alliance announcement. It is calculated as the natural log of the coefficient of variation for each R&D firm in the sample.
Exogenous Uncertainty	The standardized monthly volatility of the stock price of a portfolio of 13 biopharmaceutical firms in the year prior to the alliance announcement. It is calculated as the natural log of the coefficient of variation for the portfolio of firms.
Partner Similarity	An indicator of the uniqueness of the technical expertise of the two partner firms in the focal alliance based on patent citation overlap. A low value indicates exploration, a high value indicates exploitation.
Size (Client)	Control variable, the natural log of total assets of the Client firm
Industry Environment	Control variable, an industry index proxying the funding availability in the focal industry.
Age (Client)	Control variable, the age of the client firm from the firm's founding to the alliance date.
R&D Expenditures (Client)	Control variable,
Tobin's Q (Client)	Control variable

Table 2: Means, Standard Deviations, and Correlations

	Mean	S.D.	1	2	3	4	5	6	7	8	9
1 Firm Specific Uncertainty (R&D)	.58	.12	1								
2 Partner Similarity	.00	.49	.004	1							
3 Exogenous Uncertainty	.00	.03	-.014	.017	1						
4 Partner Similarity x Industry Uncertainty	.00	.02	.023	.009	.015	1					
5 Size (Client)	7.73	2.54	-.029	.034	-.015	-.058	1				
6 Industry Environment	1.46	.31	.259**	.038	.275**	.043	.021	1			
7 Age (Client)	88.04	226.44	.011	.009	-.050	-.006	-.057	-.065*	1		
8 R&D Expenditures (Client)	1233.94	1980.30	-.066	.034	-.094*	-.069	-.034	-.182**	.075	1	
9 Tobin's Q (Client)	180.98	734.08	.112	.091	.079	.064	-.026	.127*	-.009	-.063	1

** . Correlation is significant at the 0.01 level (2-tailed).

* . Correlation is significant at the 0.05 level (2-tailed).

Statistics estimated using centered values of variables involved in interaction

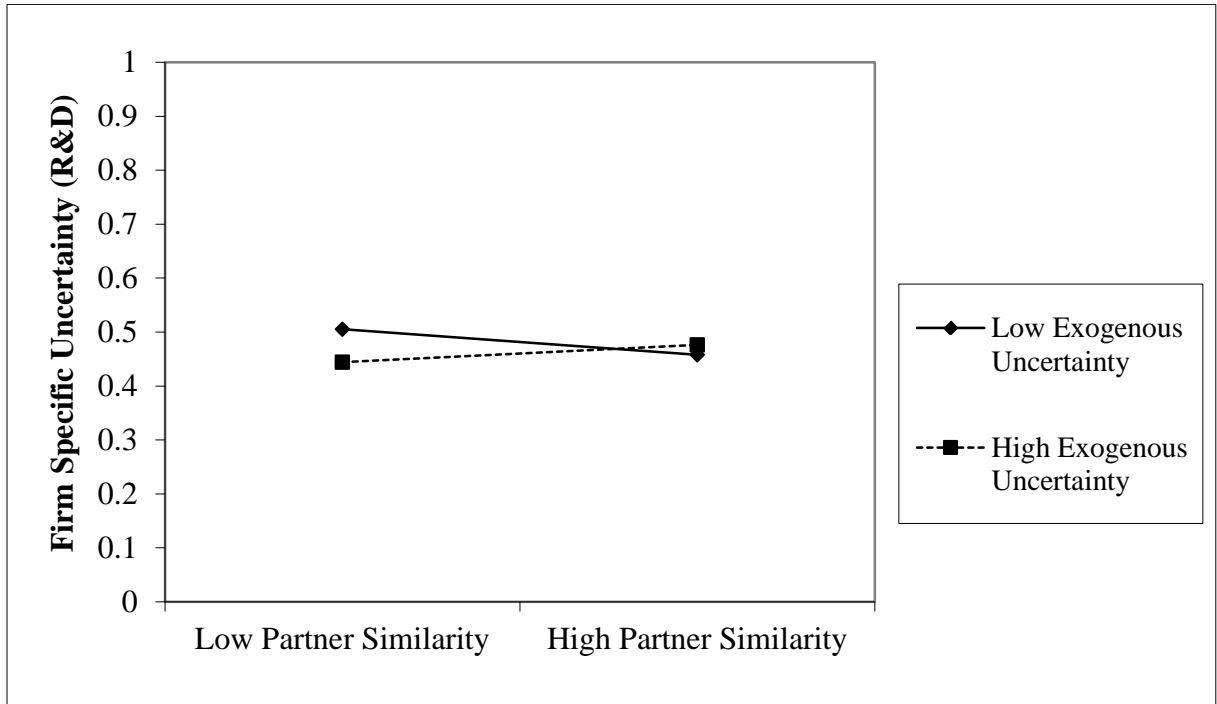
Table 3: Maximum Likelihood Estimates on Firm Specific Uncertainty of Technical Expertise Similarity

	Model 1 Firm Uncertainty (R&D)	Model 2 Firm Uncertainty (R&D)	Model 3 Firm Uncertainty (R&D)
Intercept	0.501 (0.053)	0.486 (0.053)	0.470 (0.053)***
Partner Similarity		-0.013 (0.018)	-0.007 (0.018)
Exogenous Uncertainty		-0.398 (0.280)	-0.358 (0.276)
Partner Similarity x Industry Uncertainty			1.350 (0.543)*
Size (Client)	-0.000 (0.003)	-0.000 (0.003)	0.000 (0.003)
Industry Environment	0.054 (0.029)†	0.065 (0.030)†	0.074 (0.030)†
Age (Client)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
R&D Expenditures (Client)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Tobin's Q (Client)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
Log-likelihood ratio	-261.4	-264	-270
Log-likelihood ratio vs. Model 1		2.6	8.6 *
N	183	183	183

Standard errors appear in parentheses

†p<0.10; *p>0.05; **p>0.01; ***p>0.001

Figure 1: Relationship between partner similarity and firm specific uncertainty under low and high levels of exogenous uncertainty (hypotheses 3 to 6).



SPILLOVER EFFECTS IN ALLIANCE RELATIONSHIPS

INTRODUCTION

We know that when firms enter alliances they do so in an attempt to unlock possible synergistically driven advantages, such as access to new markets (Chen & Chen, 2002; Koka & Prescott, 2008), access to new assets (Huggins, 2010; Li, Eden, Hitt, & Ireland, 2008), or to pursue an increase in legitimacy (Hitt, Dacin, Levitas, Arregle, & Borza, 2000), just to name a few. The skills and expertise of the partners are factors that determine the extent to which the alliance will be able to succeed. Alliances are formed at least partially because the partner firms are attracted to each other because of potentially synergistic effects achieved by combining their resources. However, inviting another entity into a formal cooperation connects the firms in such a way that both positive and negative actions by one partner may now spill over and affect the other partner.

In this study, I will examine how an action by one of the alliance partners - to enter a new, additional alliance while still engaged in the original base alliance - affects the other, original partner. The literature suggests that firms seek multiple alliance partners for two main reasons: 1) to maximize their influence within a network, and 2) to reduce uncertainty by maximizing their access to strategic capabilities (Burgers, Hill, & Kim, 1993). The question I ask here goes beyond the motivation for this behavior, but rather addresses how entering an additional alliance by one partner will affect the other, initial, alliance partner? I will focus on two-firm alliances in the biotech-pharmaceutical arena in which multiple simultaneous alliances are not uncommon, and examine how an additional alliance by one original partner impacts the stock price of the other original partner.

Ample resources have been devoted to study the stock market reaction to a new alliance announcement on the partner firms (Oxley, Sampson, & Silverman, 2009). Most, though not all, of the literature suggests that these alliance announcements trigger a positive stock market reaction (Anand & Khanna, 2000; Dyer, Kale, & Singh, 2001; Shah & Swaminathan, 2008). In addition, the complex nature of the innovation process in this industry may suggest that simultaneous engagement in multiple alliances to access new knowledge is a vital part of the firm strategy (Hess & Rothaermel, 2011). The combination of the positive stock market reaction and the desire to gain access to new knowledge in order to stay competitive may entice firms to enter multiple alliances, possibly without much regard to how this will affect older, yet still active, alliance partners.

My research question is as follows: Given that firm A and firm B are currently in an active alliance, how does the market react to the information that firm A has entered (or is entering) into a new alliance with firm C? Specifically, how does this information of a new alliance affect the market price of the initial partner (firm B)?

For early clarification purposes, I am focusing on two alliances: the base alliance (or initial alliance) and the new alliance. I define the pharmaceutical company currently in the base alliance as P_{Base} . This is the alliance partner that will enter into a new alliance. B_{Base} represents the biotech firm currently in the base alliance. This is the partner whose share price I will monitor to detect changes due to P_{Base} entering into a new alliance with B_{New} . B_{New} is the biotech firm that will enter into a new alliance with P_{Base} .

Because many factors may influence the market's reaction to the new alliance announcement, it is not clear whether the market's response to a new alliance

announcement will be positive or negative from the perspective of the initial alliance partner. To further study contributing factors, I will pay special attention to how the market considers one specific factor when valuing B_{Base} . Specifically, I hypothesize that whether the new alliance will operate in the same therapeutic class as the base alliance will have an impact on the valuation of B_{Base} . Using signaling theory (Spence, 1973; Spence, 1974) as theoretical foundation to derive my hypotheses, I suggest that the market could conceivably react positively or negatively, which results in two sets of competing hypotheses.

I aim to contribute to the literature by furthering our understanding of how the market interprets signals sent by one party, transfers the decoded information, and applies the new knowledge to other entities. By entering a new alliance, the partner P_{Base} may conceivably signal that the base alliance was not likely to generate the desired outcomes and, as a result, P_{Base} decided to move on and shift resources to a new alliance (which may result in a negative market reaction to B_{Base}). However, the same action of entering a new alliance could conceivably signal that the base alliance is in such an advanced stage and path toward success that it will thrive despite a now somewhat divided attention of resources by P_{Base} (which might result in a positive market reaction to B_{Base}). I am using a unique sample of biopharmaceutical alliances to test my hypotheses.

The following section provides an overview of the literature and theory of alliance formation, leading to the hypotheses that I will test in this study. Subsequent sections will show the empirical analyses and findings. I will conclude with a discussion of the implications and limitations of this study.

THEORY AND HYPOTHESES

Alliances have received a strong focus in the management literature. This organizational form may be defined as a formal cooperative agreement between two or more organizations, involving the pooling or trading of resources, with or without equity. The current study focuses fundamentally on market reactions to a new alliance announcement. Assuming that the investors have the ability to identify and decode signals sent by the involved parties, investors react to the announcement of a new alliance based on their interpretation of how this strategic action will impact the future performance of the involved parties.

Alliances are generally thought of as a performance catalyst for the partner firms. By inviting an independent entity (partner firm) to share resources, alliance partners signal that they believe that they might be able to generate synergistically driven outcomes (Harrison, Hitt, Hoskisson, & Ireland, 1991), which may ultimately lead to an increase in their market value. Several studies have focused on the direct, immediate stock market effect on the partner firms entering an alliance [see Burton (2005)].

In this study, however, I am looking beyond the direct effect on the partner firms announcing the new alliance (P_{Base} and B_{New}); I focus on how a new (additional) alliance announcement will affect an old, existing, initial partner (B_{Base}). Since the base alliance partners are still in an active alliance, I would suggest that the initial partner (B_{Base}), although not directly involved in creating the new alliance (between P_{Base} and B_{New}), will be affected by its partner's action to enter into a new alliance. How will investors react to the new alliance announcement, and thereby affect this initial partner?

Owners (investors) generally lack some knowledge of firm operations in comparison to managers, which exposes the investors to information asymmetry. Signaling theory (Spence, 1973; Spence, 1974) has been used to address issues concerning information asymmetry between owners and managers. The theory suggests that in the absence of perfect information, reading signals can reduce said information asymmetry, which would in turn impact the valuation of the firm or alliance by the investors. I suggest that by entering into a new alliance with a specific partner that will contribute certain expertise and experiences (here, experience in the therapeutic class), P_{Base} sends a signal to the market. The question is how the market will interpret these signals.

Because selecting the right partner is crucial to the success of an alliance, past studies have focused on issues surrounding the partner selection process (Beckman, Haunschild, & Phillips, 2004; Dollinger, Golden, & Saxton, 1997; Hitt et al., 2000; Kale & Singh, 2009; Shah & Swaminathan, 2008). Especially partner characteristics that may benefit the alliance are an important consideration when choosing the right partner, one that will help create synergistic effects and, possibly, the desired increase in value. The range of areas within the firms that could benefit from the synergistic effects of the alliance formation can include all functional areas of the firm. For example, as mentioned above, alliances generally create an initial positive shock to the partners' market value (Dyer et al., 2001; Shah & Swaminathan, 2008), thereby positively influencing the finance department of a firm. Other studies have found positive effects on operations (Anand & Khanna, 2000), marketing (Swaminathan & Moorman, 2009), or R&D (Rothaermel, 2001). Because synergistic effects can be created in different types of alliances, I am not

limiting this study to only one type, but rather include all types of alliances (e.g., R&D, marketing).

Because of these possible benefits to various functional departments, we have seen an increasing trend toward alliance formation in certain industries such as automotive, banking, or telecommunication (Garcia-Pont, 2006). Firms recognize the potential to reap the benefits of an increased market valuation, as well as an increase in long-term performance measures. Wanting to reach the maximum potential performance, managers may be inclined to enter into and actively work on several alliances at the same time. This is a form of diversification; especially in the pharmaceutical industry, in which the costs for a new approved therapy are high, but the potential (financial benefits) are even higher, firms may choose to work on several therapies at the same time so as to create several possible income streams.

Clearly, however, not all alliances succeed, and the threat of failure impacts investor perceptions. Research suggests that a significant number of alliances, in fact, between 30% and 70%, fail or are prematurely terminated (Bamford, Gomes-Casseres, & Robinson, 2003; Lunnan & Haugland, 2008), leading to a destruction of shareholder value of the alliance partners (Kale, Dyer, & Singh, 2002). This would suggest that investors ought to be cautious regarding how to react to a new announcement. While partner firms may enter the alliance with the desire to create synergistic effects, I note that entering into an alliance does not guarantee that the partners are able to take advantage of synergistic possibilities.

Some studies have noted that entering into additional alliances, while a form of diversification, may in fact impact the value of other, existing partnerships. For example,

Rothaermel & Deeds (2006) suggested an inverted U-shaped relationship between the number of R&D alliances in a firm's portfolio and the innovative output of said alliances. The authors attribute this relationship to the fact that managerial and financial resources are finite, and the more alliances a firm manages, the more strained the resources, leading to information-processing overload (Hitt, Hoskisson, & Kim, 1997; Zahra, Ireland, & Hitt, 2000). In other words, too many alliances might lead to a reduction in productivity, which in turn might be recognized by the investors. As a result, the investors might change the value of some or all involved firms.

I believe, however, that it would be an oversimplification to suggest simply that the latest (newest) alliances would always suffer the most from this decline in productivity. Partner firms might assign priority / importance to certain alliances regardless of the timing of their formation. Therefore, I note that the number of alliances is an important variable to consider, but to make a general statement concerning the resource allocation to the initial alliances, which might affect the productivity and, in turn, the valuation of the partner firms, might not be possible. For now, I note that entering into multiple alliances can have a positive or a negative spillover effect on existing alliance partners. I will now move on and introduce an additional dimension which I suggest is important to consider when predicting how investors will react to a new alliance announcement and subsequently change the valuation of B_{Base} .

The first set of hypotheses concentrates on a scenario in which the new alliance has a focus in the same therapeutic class as the base alliance. For example, if the base alliance with P_{Base} and B_{Base} is working on a cancer therapy, then I will analyze new alliances of P_{Base} that are also working on a cancer-related therapy and study the effect of the new

alliances on B_{Base} . Will the market be influenced by the fact that the old and new alliances operate in the same therapeutic class?

Several organizational capabilities can act as signals to the market as to whether the alliance might be successful or not. Learning is one of those capabilities (Nelson & Winter, 1982). With learning comes experience, and having alliance experience (including, for example, managing partners, managing resources, writing alliance contracts, having spent resources in a specific therapeutic class, etc.) that could make the alliance more efficient, leading, *ceteris paribus*, to a higher probability of success. Therefore, having relevant experience in the specific focus of the alliance should send signals that would impact the market's reaction to the new alliance announcement. In other words, experience might influence investors' perception of value if it is used as a decodable signal.

If the new alliance has a similar focus (defined as operating in the same therapeutic class) to that of the base alliance, then it could be suggested that the partners of the new alliance might benefit from the experience already developed by P_{Base} . I would expect that fewer resources will have to be employed to learn and generate experiences, which should lead to higher efficiencies and a higher probability of success for the new alliance. This might be a positive development for the base alliance in that P_{Base} could conceptually leave more resources in the base alliance, which would suggest that the base alliance might not be as negatively affected by the new alliance (and the potential corresponding resource drain). In fact, I suggest that this scenario might affect the base alliance positively in that the learning and experience from the new alliance might actually spill back to the base alliance, therefore benefiting said base alliance. I will

denote the new alliance partner of P_{Base} working on a therapy in the *same therapeutic class* as the base alliance as B_{NewSTC} . I suggest that it is possible that:

Hypothesis 1A: The announcement of a new alliance between P_{Base} and B_{NewSTC} operating in the same therapeutic class as the base alliance will positively affect the share price of B_{Base} .

However, if the new alliance operates in the same therapeutic class as the base alliance it might potentially signal to the market that the base alliance was either on a trajectory that P_{Base} does not believe will lead to the desired results (hence the action to enter into a new alliance and to start shifting resources toward a potentially more successful venture; the benefit of being able to diversify), or simply that B_{NewSTC} is a more desirable partner. It is beyond the scope of this study to analyze exactly why the market decodes this signal as negative, but I suggest that it is possible that the market decodes the action by P_{Base} to enter a new alliance as a signal that the base alliance was not believed to have the potential to create the desired success or that some firms are trying to play their partners off against each other. Any of these reasons might negatively affect the market value of B_{Base} , and in this case I would expect to see evidence that:

Hypothesis 1B: The announcement of a new alliance between P_{Base} and B_{NewSTC} operating in the same therapeutic class as the base alliance will negatively affect the share price of B_{Base} .

The second set of hypotheses focuses on a scenario in which the new alliance has a focus that is in a *different therapeutic class* than the base alliance, whereas I will denote the new alliance partner of P_{Base} as B_{NewDTC} . The signal that the announcement of a new

alliance sends could again be interpreted either positively or negatively as it pertains to the base alliance, and subsequently to B_{Base} , the focus of this study.

The same basic arguments used in developing the first set of hypotheses apply. However, with the new alliance operating in a different therapeutic class than the base alliance, any advantage that the market may have considered to be present in the first set of hypotheses is now not present; the benefits of the new alliance operating in the same therapeutic class as the initial alliance are non-existent. As a result, the market may look for additional signals to interpret. How will the new alliance impact B_{Base} ? For example, branching out and deciding to enter into an alliance which, from the outside, may have fewer positive spillover effects than the scenarios in hypotheses 1A and 1B (i.e., working on two therapeutic classes may have fewer synergistic aspects than working on two projects within the same therapeutic class in two different alliances), may also potentially send two different signals, one positive and one negative.

Let's start with the positive signal. A new alliance operating in a different therapeutic class may signal that the base alliance is on a path that allows P_{Base} to shift resources to the new alliance, despite the lower potential for positive spillovers due to the different therapeutic classes. Therefore, when P_{Base} enters into a new alliance that operates in a different therapeutic class than the base alliance, it may be an even stronger signal that the base alliance is on a path toward success and would be able to absorb the strain of P_{Base} dividing its attention and resources between the two alliances. Because investors won't have access to perfect information, they will have to rely on other signals and interpret them. Here, I suggest that P_{Base} entering into a new alliance will signal that the

base alliance is on a trajectory toward success, and I would consequently expect to observe that:

Hypothesis 2A: The announcement of a new alliance between P_{Base} and B_{NewDTC} operating in a different therapeutic class as the base alliance will positively affect the share price of B_{Base} .

The same signal, P_{Base} entering a new alliance focused on a different therapeutic class than the base alliance, may also be interpreted as a negative signal as it pertains to the base alliance and subsequently B_{Base} . Investors could potentially interpret this signal as a) that the base alliance has not made the desired progress toward a successful, marketable therapy; b) that B_{Base} is not a desirable partner; and/or that c) the base alliance does not have the necessary resources to successfully develop a new therapy in the focal class.

Generating a positive return on investment ought to be the ultimate goal of the alliance. Depending on the purpose of the alliance (e.g. R&D, marketing, etc.), success may be defined differently. It goes beyond the scope of this paper as it pertains to hypotheses 2A and 2B to define success. I merely suggest that investors who accept the fact that P_{Base} will enter into an alliance with a different focus than the initial alliance will potentially decode this signal as negative as it affects B_{Base} because it may delay or cancel any potential future success. As a result I suggest that:

Hypothesis 2B: The announcement of a new alliance between P_{Base} and B_{NewDTC} operating in a different therapeutic class as the base alliance will negatively affect the share price of B_{Base} .

METHODS

Sample

I used a sample of bilateral alliances that include biotech firms and pharmaceutical companies. The sample identified the firms as either pharmaceutical or biotech partner. Data were taken from Compustat data files, the Center for Research in Security Prices (CRSP) U.S. stock database, the Recombinant Capital Biotechnology Database (ReCap), the IMS R&D Focus database, Spectrum Institutional Ownership files, and United States Securities and Exchange (SEC) proxy (DEF 14a) filings.

The initial sample included 28,470 biopharmaceutical alliances established between January 1st, 1989 and December 31st, 2008. I used the Wharton Research Data Services (WRDS), and specifically, the Center for Research in Security Prices (CRSP) database, to determine which alliances included both biotech firms and pharmaceutical firms that were publicly traded at the end of the month of the event date. Next I further refined the event date (date of the alliance announcement) by performing a web search on each partner combination in the stated month; this search produced specific alliance announcements which allowed me to identify the exact date of the announcement; this date was then used to construct the three-day window to measure the cumulative abnormal return. Next, I identified all instances in which the pharmaceutical company entered into a subsequent alliance with a different biotech firm. I then used the therapeutic class as indicator of whether this new alliance operated in the same therapeutic class as the base alliance, or not. Data availability constraints limited the final sample used in this analysis to a total of 258 new alliances, of which 67 alliances did

operate in the same therapeutic class and 191 alliances did not operate in the same therapeutic class as the base alliance.

Measures

The variable used to conduct the test of difference between alliances based on their respective therapeutic classes is the sum of the abnormal stock returns (*cumulative abnormal returns*, or *CAR*) of B_{Base} around the time of the alliance announcement between P_{Base} and B_{New} . *CAR* represents the deviation between the realized return, measured by the biotech firm's actual stock price movement, and the expected return of the biotech firm's stock performance. *CAR* has been used extensively as a performance measure in joint venture event studies (Gulati, Lavie, & Singh, 2009; Koh & Venkatraman, 1991; Park & Kim, 1997; Reuer & Koza, 2000) and as a dependent variable in alliance studies (Anand & Khanna, 2000).

I calculated the expected return by using a benchmark portfolio comprised of size-adjusted firms that match the 4-digit SIC code of the sample industry. I monitored the return of both the portfolio and the biotech firm during a three-day window [-1, 0, 1] around the alliance announcement and calculated the cumulative difference over the three days as the difference between the two cumulative returns. The short three-day window was chosen in an attempt to isolate the news of the alliance announcement and help prevent the inclusion of non-alliance related news in the movement of the securities [see, for example, Lee et al.(2000)], thus following the argument of market efficiency. I then matched the calculated *CAR* values by firm ID and date to focal biotech firms.

Whether the future alliance operated in the same or a different therapeutic class as the base alliance is the variable that distinguishes the two different groups of *CAR* values in

this study. I only considered alliances in which the pharmaceutical company chose a different biotech partner than the base alliance. In addition I only included new alliances that were announced within three years of the announcement of the base alliance; alliances are generally thought-of as active for an average of three years. If the base alliance operated in the same therapeutic class as the new alliance, I coded the variable as 1, otherwise 0.

RESULTS AND DISCUSSION

Table 1 shows the descriptive statistics for CAR of B_{Base} at the time of the announcement of a new alliance between P_{Base} and B_{New} . Results of the t-test tests of differences in means of cumulative abnormal returns (CAR) of B_{Base} at the time of P_{Base} entering into a new alliance with B_{New} focusing on the same therapeutic class, or not, can be found in Table 2. I used a benchmark portfolio consisting of firms within the same 4-digit SIC code as the focal firm to calculate CAR.

I first tested for the presence of cumulative abnormal returns by testing whether the mean of CAR is statistically significantly different from 0 regardless of the therapeutic class. A t-test confirmed that CAR is statistically significant different from 0 at $\alpha = 0.05$ **(one-sample $t(257) = 4.223$, $p < 0.0001$) with a mean difference from 0 of 0.044.**

I next computed the mean for the subsample of CAR values for both a) instances in which the new alliance operated in the same therapeutic class as the base alliance, and b) instances in which the new alliance operated in a different therapeutic class as the base alliance.

The findings show that if the new alliance operates in the same therapeutic class as the base alliance, the mean cumulative abnormal return of B_{Base} at the time of the announcement of the new alliance is positive (0.044). As a result, I reject hypothesis 1B which suggested that the announcement of a new alliance would negatively affect the share price of B_{Base} . Next, I tested whether this positive mean difference is statistically significantly different from 0. A t-test showed that $t(67) = 1.822$, $p = 0.073$, suggesting that the positive difference between 0.044 and 0 is marginally statistically significant at the 0.10 level. As a result I accept hypothesis 1A which states that the announcement of a new alliance between P_{Base} and B_{NewSTC} operating in the same therapeutic class as the base alliance will positively affect the share price of B_{Base} .

The mean cumulative abnormal return for B_{Base} at the time of the announcement of a new alliance that is not operating in the same therapeutic class is positive as well (0.043). I therefore reject hypothesis 2B which suggested that the announcement of a new alliance in a different therapeutic class would negatively affect the share price of B_{Base} . The t-test showed that $t(191) = 3.926$, $p < 0.0001$, suggesting that the positive difference between 0.043 and 0 is statistically highly significant. I therefore accept hypothesis 2A which states that the announcement of a new alliance between P_{Base} and B_{NewDTC} operating in a different therapeutic class from that of the base alliance will positively affect the share price of B_{Base} .

As a result, the findings of the t-test support the hypotheses that investors react in a positive way to the announcement of a new alliance between P_{Base} and B_{New} . The result holds in both instances in which the new alliance operates in the same class and when it does not operate in the same class.

In addition to this appropriate test for the stated hypotheses I performed a post-hoc analysis (linear mixed regression) using the therapeutic class as a dummy variable in an effort to gain a better understanding of whether the therapeutic class of the new alliance matters to investors when they react to alliance announcements. Variable descriptions, descriptive statistics and the results of the linear mixed regression can be found in Appendix A. Table 3 shows the variable description, Table 4 shows the descriptive statistics and correlation matrix, and Table 5 shows the result of maximum likelihood estimates on CAR of therapeutic class. The findings provide marginal evidence at the 0.1 level that the therapeutic class does matter when investors react to the alliance announcement.

The fact that the market valuation changes upon the announcement of a new alliance involving P_{Base} is interesting for several reasons. First, it suggests that investors monitor events impacting firms that are not directly involved in an event (here, the announcement of the new alliance). Thus investors may consider spillover effects to be real and important.

Second, the investors appear to react more strongly to instances in which the new alliance operates in a same therapeutic class than the original alliance. P_{Base} entering into a new alliance with a different focus may signal to investors that the original alliance may have already or possibly will produce a marketable product.

Third, the fact that the new alliance announcement, although not directly involving B_{Base} , results in a positive market reaction regardless of the therapeutic class may provide additional evidence to prior studies that have found that the market usually reacts positively to new alliance announcements (Anand & Khanna, 2000; Dyer et al., 2001;

Shah & Swaminathan, 2008). An interesting follow-up study could focus further on how far beyond the directly involved partners this positive impact reaches.

I should point out some limitations in this study. First, while prior studies suggested that learning as an organizational capability may be closely tied to prior experience (Nelson & Winter, 1982), and thus represent a positive asset of the firm, failure of prior alliances may send a strong negative signal. My data did not contain any direct information on the success of (prior) alliances, which is very difficult to define and measure. Earlier studies have used indirect measures, such as previous alliance experience (Anand & Khanna, 2000). Future studies may focus on a way to measure and code success of alliances directly.

Second, the available data listed the therapeutic class, which clearly is a focus in this study, based on a press release at the time of the alliance formation. There is no guarantee that the focus (e.g. therapeutic class) did not change over time. As such, investors may in fact have more updated information than the available data contains.

CONCLUSION

The purpose of this study was to investigate whether investors monitor post-alliance events (i.e., the announcement of a new alliance), interpret the signal, and react to them. I derived hypotheses that suggested that investors react to post-alliance events, and that the focus of the alliance (i.e., therapeutic class) may matter. The statistical analysis suggests that investors do, in fact, react in a statistically significant way to the new alliance. The market valuation of the initial partner increases upon the announcement of a new alliance. A post hoc analysis also showed that the therapeutic class matters to investors. Further

analysis is needed to better understand when and how (in which context) the focus of the new alliance matters to investors when adjusting the market value of the initial alliance partners.

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Table 1: Descriptive Statistics

	N	Mean	SD	Std. Error Mean
CAR when in same Therapeutic Class	67	.044	.197	.024
CAR when NOT in same Therapeutic Class	191	.043	.152	.011

Table 2: One Sample T-Tests

	t	df	Test Value = 0			
			Sig. (2- tailed)	Mean Diff.	95% Confidence Interval of the Difference	
					Lower	Upper
CAR when in same Therapeutic Class	1.822	66	.073	.044	-.004	.092
CAR when NOT in same Therapeutic Class	3.926	190	.000	.043	.021	.065

Appendix

Table 3: Definition of variables

Variable Name	Definition
CAR (R&D)	The Cumulative Abnormal Return (CAR) of the R&D partner, calculated using a portfolio of firms with the same 2-digit SIC code, adjusted for size and transformed (ln) to adjust for non-normality of the data and the residuals.
Therapeutic Class	An binary variable, based on whether the therapeutic class of the base alliance is the same as the new alliance; 1 = indicates same as base alliance, 0 = not same as base alliance.
Technical Expertise	An indicator of the uniqueness of the technical expertise of the two partner firms in the focal alliance based on patent citation overlap. A low value indicates exploration, a high value indicates exploitation.
Relationship Expertise	An index describing the level of relationship experience between the two partners, calculated as = (Frequency) + (Recency) + (ATSPE); a low value indicates exploration, a high value indicates exploitation.
Frequency	The number or frequency of prior alliance relationships between the two firms
Recency	The recency (in days) of the last alliance relationship between the two. If the two partners have not worked before I set the value to 10,000
ATSPE	The alliance type specific partner experience, indicating if these two firms have worked together in this type of alliance before.
Market Expertise	An index describing the FDA approval process experience of the alliance partners at the time of the alliance date, calculated as ((C-MKT-Index + RD-MKT-Index) x (Alliance Success)). A low value indicates exploration, a high value indicates exploitation.
C-MKT-Index	The cumulative FDA approval process experience of the Client firm in each stage of the process and across all stages at the time of the alliance.
RD-MKT-Index	The cumulative FDA approval process experience of the R&D firm in each stage of the process and across all stages at the time of the alliance.
Alliance Success	The cumulative FDA approval success of the two partners.
Industry Environment	Control variable, an industry index proxying the funding availability in the focal industry.
Age (Client)	Control variable, the age of the client firm from the firm's founding to the alliance date.
Age (R&D)	Control variable, the age of the R&D firm from the firm's founding to the alliance date
Active Alliances (Client)	Control variable, the number of current active alliances of the client firm as of the event date.
Active Alliances (R&D)	Control variable, the number of current active alliances of the R&D firm as of the event date.

Table 2: Means, Standard Deviations, and Correlations

	Mean	S.D.	1	2	3	4	5	6	7	8	9	10
1 CAR	-.437	.211	1									
2 Therapeutic Class	.284	.452	.061	1								
3 Technical Expertise	.426	.494	.074	.035	1							
4 Relationship Expertise	-8666.106	3264.722	-.320**	-.021	-.080	1						
5 Marketing Expertise	510.110	1125.814	.086*	.074	.069	-.032	1					
6 Industry Index	1.465	.319	-.029	-.064	.093*	.057	.009	1				
7 Age (Client)	71.168	85.372	.019	.075	.046	-.008	-.004	-.057	1			
8 Age (R&D)	20.868	101.413	-.007	-.026	.061	-.007	-.020	.014	.009	1		
9 Active Alliances (Client)	28.529	28.511	-.005	.081	.047	-.039	-.005	-.079*	.087*	-.022	1	
10 Active Alliances (RD)	13.081	16.870	-.015	.101*	.059	-.004	-.026	.070*	-.025	-.007	.085*	1

** . Correlation is significant at the 0.01 level (2-tailed).

* . Correlation is significant at the 0.05 level (2-tailed).

Table 3: Maximum Likelihood estimates on CAR of Therapeutic Class

Explanatory Variable	Model 1 CAR	
Intercept	-0.693	(0.072)***
Therapeutic Class	0.042	(0.025)†
Technical Expertise	-0.005	(0.023)
Relationship Expertise	-0.000	(0.000)***
Marketing Expertise	-0.000	(0.000)
Industry Index	0.063	(0.039)
Age (Client)	-0.000	(0.000)
Age (R&D)	0.000	(0.000)
Active Alliances (Client)	0.000	(0.004)
Active Alliances (R&D)	0.000	(0.000)
Log-likelihood ratio	-146.7	
N	244	

Standard errors appear in parentheses

†p<0.10; *p>0.05; **p>0.01; ***p>0.001

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