Unmixed Signals:
How Reputation and Status Affect Alliance Formation

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Abstract
We analyze how incumbents in technology-driven industries are influenced by founders' reputation and status when considering strategic alliances with newly emerging firms. We theorize that reputation and status represent two distinct components of perceived quality that exert independent and interdependent effects on alliance formation. Using literature on impression formation processes to derive predictions of signal congruence, we argue that the independent effects of reputation and status are amplified when the two are congruent, and that the effect of negative congruence (both reputation and status are low) is stronger than positive congruence (both are high). We find support for our arguments based on panel data on alliances between pharma and biotech firms, using data on biotech scientists' research output (reputation) and university attended (status).

Introduction

The purpose of this study is to theoretically and empirically distinguish between the concepts of reputation and status. We argue that while related, reputation and status are two analytically distinct kinds of quality signals, exerting both independent and interactive effects on peoples' perceptions. We explore our premise by examining how and why reputation and status influence incumbents in technology-driven industries when considering strategic alliances with newly emerging firms. Signals, defined as 'activities or attributes of individuals in a market which by design or accident, alter the beliefs of, or convey information to, other individuals in the market'(Spence, 1974, p.1), have been shown to play an important role in numerous decision situations. For example, in hiring decisions, signals such as a job seeker's education credentials are likely to be perceived as an indicator of ability (Spence, 1974), and in buying decisions, price and warranty influence potential buyers' beliefs about a product's quality (Engers, 1987; Kihlstrom and Riordan, 1984; Nelson, 1974; Riley, 1975). At the organizational level, signals such as certification from credentialing agencies (e.g. Baum and Oliver, 1991; King, Lenox and Terlaak, 2005; Terlaak and King, 2006), placement in certification contests (Rao, 1994), media rankings (Rindova *et al*., 2005; Wade *et al*., 2006), and hiring of prestigious executives and directors (Chen, Hambrick, and Pollock, 2008) have all been shown to reduce uncertainty about firms' quality and future prospects in the eyes of key stakeholders.

Signals are especially important under conditions of uncertainty where information is scarce (Spence, 1974; Meyer, 1979). Uncertainty is typical of strategic decisions, particularly in technology intensive industries (Eisenhardt, 1989). A practice that has become widespread in such industries is the formation of alliances between incumbent firms and newly created companies. Since breakthroughs in technology intensive industries tend to originate with new entrants (Cooper and Schendel, 1976; Tushman and Anderson, 1986), alliances with newly created companies are a valuable means through which established firms engage in entrepreneurial activity (Stuart, Hoang, and Hybels, 1999), and thus highly attractive to incumbents. Yet this attractiveness is tempered by the significant difficulties incumbents face when attempting to evaluate the potential for collaborating with specific newly-created companies. Given the relative dearth of information available to incumbents regarding such small and new organizations, the decision to 'take the plunge' and form an alliance with a newly created firm is likely to be fraught with considerable uncertainty. Under such conditions, incumbents are likely to draw on signals of quality, or attributes that are thought to be causally related with the new company's ability to successfully develop and commercialize the technology for which it has been created (Burton, Sorenson, and Beckman, 2002; Stuart *et al.*, 1999; Podolny, 2005).

Recognizing the important role of signals in partner selection decisions, Pollock and Gulati (2007) explored different signals that may enhance an entrepreneurial company's ability to form strategic alliances. Their study examined how investors' reactions to entrepreneurial companies' initial public offering (IPO), analyst coverage, and affiliations with experienced venture capitalists and prominent underwriters, influence the companies' ability to form post-IPO alliances. In this study we extend this research in several important ways. First, not all entrepreneurial companies complete an IPO before forming alliances, and thus it is important to examine signals that are common to all newly created companies. In technology-based industries where product development is driven by basic scientific knowledge (Dasgupta and David, 1994; Pisano, 1994), a common denominator of all newly-created companies which has been shown to affect how competent such companies are perceived to be is their founding scientific team (Darby, Liu, and Zucker, 1999). In a longitudinal analysis of more than 300 U.S. biotechnology companies, Luo, Koput, and Powell (2009) found a positive relationship between the number of scientists working for a biotechnology company and its attractiveness to potential alliance partners. Yet while Luo *et al*. (2009) provide strong theoretical arguments and empirical evidence that potential partners pay much attention to a company's founding scientists when considering it as a partner, prior research suggests that the perceived quality of founding scientists may differ considerably across firms (Cohen and Dean, 2005).

Accordingly, in this study we focus on the signaling effects of founders' scientific capabilities on alliance formations between incumbents and newly-created companies. The dilemma, however, is that correctly evaluating scientific abilities has been shown to be a recalcitrant problem with no standard solution. Thus, while incumbents seek to reduce the considerable uncertainty they face in evaluating the potential of newly created companies as alliance partners by focusing on their founders' scientist capabilities, such capabilities are similarly difficult to evaluate correctly.

Perhaps not surprisingly, one major factor shown to influence people's perception of a scientist's abilities is his/her scientific credentials (Packalen, 2007). We suggest, however, that credentials encompass two kinds of signals: reputation signals and status signals. This distinction is important, because as Washington and Zajac (2005) have noted, while often conflated in prior studies, the two concepts are analytically distinct. Reputation is determined by the value or quality of one's previous actions, while status is determined according to a socially constructed ordering or ranking. In our study context, reputational signals would correspond to the research achievements of a scientist (i.e., publications and citations), while status signals corresponds to the prestige of the university from which the scientist graduated, independent of his/her research and publication achievements. While both concepts are associated with perceived quality, they may have independent effects on an incumbent's assessment of a newly-created company's probability of success. Thus it is vital to theoretically and empirically distinguish the two concepts. Accordingly, we introduce the theoretical distinction between a scientist founder's reputational credentials and his/her status credentials, and empirically differentiate the two concepts using a method for operationalizing the 'general impression halo.'[1]

A second major way in which we depart from prior research is by focusing on the contingent effects of signals. An underlying assumption in much of the literature on signals is that if a signal is provided, the appropriate actor will naturally attend to it. Recently, however, scholars have started to acknowledge that signals are not always equally valuable or useful. In some situations an additional signal provides significant uncertainty reduction and in other situations or contexts it only has a minimal impact (Higgins, Stephan, and Thursby, 2011). In this study we extend and support the contingency argument by considering the potential theoretical and empirical interdependencies between status and reputation. We advance the notion that when status and reputation are aligned, one will experience the strong effect of congruence. At the root of our view of congruence is the notion that the effects of status and

[1] This term stems from Balzer and Sulsky (1992), and is discussed in more detail in the methodology section.

reputation are contingent on the receiver's interpretation process. Congruent signals, we argue, lead to a category-based evaluation (Fiske, 1982) and, as a result, to an amplification effect (either highly positive or highly negative) on alliance formation. Incongruent signals, on the other hand, lead to piecemeal processing (Fiske and Neuberg, 1990) which does not generate an interaction effect.

Another way in which we depart from prior studies and contribute to the study of signals in management research is by focusing on the impact of negative quality signals. Literatures outside management studies suggest that negative quality signals may have considerable impact on the formation of quality perceptions (e.g. Madan and Suri, 2001; Lipe and Salterio, 2002). Nonetheless, management scholars have generally focused on positive quality signals and the benefits they can provide (e.g. Pollock and Gulati, 2007; Hsu and Ziedonis, 2008; Higgins *et al*, 2011), paying little attention to the role of negative quality signals. Based on the literature on negativity bias in impression formation (Fiske, 1980) we suggest that of the two amplification effects we predict, the negative amplification effect will likely be stronger than the positive amplification effect on alliance formation.

Our final contribution relates to our choice of dependent variable. Specifically, we use two dependent variables. First, for comparability to prior alliance research, our first dependent variable is the likelihood that an incumbent and a newly created firm will form an alliance. Then to further test our theoretical predictions and substantiate our results, we also examine how reputation and status affect the timing of the alliance. We do so using a large sample of alliances created between established pharmaceutical firms and newly-created biotechnology companies, a practice which has grown in popularity in the biopharmaceutical sector over the past decade (Kim and Higgins, 2007). In the biotechnology industry, the commercialization process takes place in a series of stages from the first discovery and early development of a new technology to the introduction of a product. Pharmaceutical firms can form an alliance with a biotechnology firm at any stage in this process. The earlier the stage in the commercialization process in which an alliance is formed, the greater the uncertainty regarding the product's commercial prospects, and hence, the greater the uncertainty as to the alliance decision. Having both the likelihood and timing of alliance formation as our dependent variables is therefore well-suited to our theoretical focus on how signals of quality affect the uncertainty an incumbent faces as it considers whether and when to form an alliance with a newly created company.

THEORY AND HYPOTHESES

Two key assumptions underlie our theoretical development: (1) in technology-intensive industry settings, incumbents face considerable uncertainty when considering alliances with newly formed companies; and (2) relying on founder/scientist credentials is an important mechanism by which incumbents reduce such uncertainty, enabling them to more confidently form strategic alliances with newly emerging firms. These assumptions are particularly valid in the biotechnology context.

The complex knowledge required to practice the innovations that underlie biotechnology has been traditionally retained by a small group of scientists who either recently left a university or remained on the faculty while establishing a small private business on the side (Powell and Brantley, 1992). These small startup companies, however, had lacked the knowledge and financial resources necessary for bringing products to market (Silverman and Baum, 2002). Conversely, traditional, chemical-based pharmaceutical firms had the necessary cash and expertise for conducting clinical testing trials, manufacturing, marketing, and obtaining federal regulatory approval, but were unable to internally create the capabilities necessary to adapt to the emergence of biotechnology as the new framework of drug discovery and development (Rothaermel, 2001). To overcome their lack of internal capabilities, biotechnology companies and pharmaceutical firms created over a thousand interfirm alliances (Powell, Koput, and Smith-Doerr, 1996; Higgins, 2007).

Choosing a partner from among hundreds of newly-created biotechnology companies, however, is a decision that must be made in the face of high uncertainty. The difficulty of attaining a reliable revenue and cost projections for the technology these companies typically offer, and the absence of a track record by which their ability to commercialize an emerging technology can be evaluated, prevent pharmaceutical firms from accurately forecasting the commercial viability of the technology offered by biotechnology innovators.

When decision makers do not have access to objective information by which they can estimate the worth of a company's quality they appraise the company based on conspicuous and readily available attributes (Stuart, 1998). As discussed above, given that biotechnology product development is driven by basic scientific knowledge (Dasgupta and David, 1994; Pisano, 1994), pharmaceutical firms' executives' evaluations are likely to be influenced by the scientific credentials of the biotechnology company's founding scientists when considering the biotechnology company as a partner. In this study we differentiate between two kinds of credentials: reputation credentials and status credentials.

Reputation signals

Fombrun (1996: 72) defined reputation as 'a perceptual representation of a company's past actions and future prospects that describes the firm's overall appeal to all its key constituents when compared to other leading rivals.' This definition suggests that a company's reputation is determined by the value or quality of its previous actions (Podolny and Phillips, 1996). But how is the reputation of a company that has yet to take any action determined? Past studies suggest that the reputation of such companies will derive from their founders' reputation (Cohen and Dean, 2005). Darby *et al*. (1999), for example, showed that biotechnology firms with ties to star scientists, identified by the number of articles they published, were more highly valued by investors. Deeds, Decarolis, and Coombs (1997) found a positive relationship between the total amount of capital raised by a firm through an IPO and the number of times the works of its top scientists had been cited. Higgins *et al*. (2008) found that biotechnology firms with an affiliated Nobel laureate succeeded in raising the value of their firms by more than $30 million during IPO compared to firms without a Nobel laureate. There are two important conclusions from these studies. First, while a newly created biotechnology company has no history by which its future prospects can be evaluated, its founders bring with them their own scientific reputations, which affect their company's appeal to investors. Second, while there are no clear criteria for appraising scientific work, simple proxies for evaluating research, such as publication counts and citation rates, play an important role in forming perceptions about the quality and value of a scientist's output, that is, in shaping scientific reputations. We maintain that these proxies are likely to influence newly created-companies' appeal to existing pharmaceutical firms in similar ways to how they influence IPO investor behavior.

Accordingly, we expect biotechnology companies that were founded by well-published and highly-cited scientists to be perceived as more capable of successfully developing the technology for which they have been founded, and hence, to gain the pharmaceutical firms' confidence more easily. More confidence in a biotechnology company's prospects, in turn, is likely to increase the amount of risk a pharmaceutical firm will be willing to accept, and consequently, the greater the likelihood of the biotechnology and the pharmaceutical firm forming a partnership, and the greater their likelihood of forming it earlier in the product's development process when uncertainty is higher about the biotech company's ability to move the product from the laboratory into the marketplace. Thus, we hypothesize:

Hypothesis 1a: The better a founding scientist's reputation, the greater the likelihood of an alliance being formed.

Hypothesis 1b: The better a founding scientist's reputation, the greater the likelihood of the alliance being formed early in the commercialization process.

Status signals

Similar to reputation, status may affect a company's perceived quality and expected performance, and thus impact its appeal to key constituents. Yet, while reputation is determined by the value or quality of an actor's previous efforts, status is determined by differences in social rank. As Washington and Zajac (2005: 284) explicate, status is a 'socially constructed, intersubjectively agreed-upon and accepted ordering or ranking of individuals, groups, organizations, or activities in a social system.' But how is an actor's relative rank within a stratification system determined? Sociologists have long argued that status is fundamentally a consequence of an actor's network of relations (Podolny, 2005). That is, an actor's status is ascertained by the status of its affiliates: the higher the status of an actor's affiliates, the higher the actor's status.

Several theories suggest that status may affect an actor's perceived quality and expected performance independently of the actor's reputation. Kiesler (1975), for example, introduced a process called 'actuarial prejudice' whereby the perceived probability of success of any one person is reduced (or increased) when the probability of success of the group to which the person belongs is lower (higher) than that of other groups. This cognitive bias suggests that the evaluation of a scientist's abilities is likely to be influenced by what is generally known about the group of scientists with whom s/he is affiliated. A similar phenomenon of inferences has been discussed in terms of 'status characteristics and expectation states' (Berger, Conner and Zelditch, 1972). Expectation-states theory focuses on the processes through which group members assign levels of task competence to each other and the consequences this assignment has for their interaction. The theory, which proposes that status characteristics serve as the basis for inferring individuals' capabilities and expected performance, and thus structure social interaction, has received strong support from extensive empirical research. A consistent result across studies is that a person higher in status than the other people being assessed is assigned a higher competence and probability for success than those who are lower in status (Berger *et al*. 1972).

These theories may help explain the positive relationship found in previous studies between founders and managers' affiliations with high status institutions and the amount of trust and confidence they receive from investors. Burton *et al*. (2002) for example, showed that the prominence of a new venture's founding team's prior employer has a positive effect on the odds of securing external financing at startup. Higgins and Gulati (2006) showed that the greater the proportion of a biotechnology company's top managers with affiliations to prominent pharmaceutical and healthcare institutions and/or to one of the top ten research organizations in a discipline related to biotechnology, the greater the number of quality institutional investors that invest in the company during IPO.

We suggest there is value in analyzing how founders' affiliations with high status institutions can influence industry incumbents' decisions to engage in strategic alliances with emerging firms. Specifically, we argue that scientists who are affiliated with high status groups of scientists will enjoy a higher perceived probability of success than scientists who are affiliated with lower status groups. While scientists may be affiliated with several scientific groups such as professional associations, or editorial boards, all scientists can be viewed as affiliated with the members of the university from which they graduated. The academic ranking of the university from which a scientist graduated is therefore a straightforward status characteristic that can be easily used to compare all scientists and impute expectation states.[2] The higher the status of the university from which a new firm's scientist/founder graduated, the higher the probability of success he or she will be assigned (independent of his/her research productivity); thus, we predict that the reliance of a pharmaceutical firm on this indicator of scientist status will increase its motivation to form an alliance, and generate a willingness to 'take the plunge' and form the alliance sooner in the commercialization process.

Hypothesis 2a: The higher a founding scientist's status (as evidenced by the status of his/her doctoral-granting university), the greater the likelihood of an alliance being formed.

Hypothesis 2b: The higher a founding scientist's status (as evidenced by the status of his/her doctoral-granting university), the greater the likelihood of the alliance being formed early in the commercialization process.

Reputation-status congruence

Our theoretical argument thus far has been additive, suggesting how reputation and status may independently affect this process. We now extend our theoretical argument to consider a multiplicative effect, i.e., we analyze how status and reputation signals may influence each other's effects. We begin our analysis by noting that the effects of status and reputation are contingent on the receiver's interpretation process. When signals are congruent we expect this interpretation process to result in a more predictable outcome; positive congruence (i.e., both reputation and status are high) will lead to an increased likelihood of JV formation, and an

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[2]A recent study of the management field supports this view, with evidence suggesting that the prestige of one's doctoral degree in management is an important predictor of a scholar's early and late career success (Bedeian, Cavazos, Hunt and Jauch, 2010).

increased likelihood that the JV will be formed early. Negative congruence (i.e., both reputation and status are low) will lead to a decreased likelihood of JV formation, and a decreased likelihood that the JV will be formed early.

Our prediction is based on a large body of literature on impression formation processes, which suggests that when people make an evaluative judgment of others they go through either one of two processes: they either classify the person into a particular category of people and make their evaluation on the basis of pre-existing beliefs and expectations about members of that category, or they piece together their judgment on the basis of the individual attributes of the person (Fiske, 1982; Fiske and Pavelchak, 1986; Fiske and Neuberg, 1990; Pavelchak, 1989). Fiske and colleagues suggest that the person's most salient attributes determine which evaluation process is used; category-based processes are used when the person's attributes are congruent with the attributes expected of members of a distinct category, whereas piecemeal processes are employed when the attributes are incongruent with such expectations. Their conceptual model has gained a substantial amount of empirical support in the psychology literature (e.g., Fiske, *et al*. 1987; Pavelchak, 1989).

Categories, in this line of work, are defined as cognitive structures of organized prior knowledge which contain category members that are perceived as similar or equivalent (Fiske and Pavelchak, 1986; Smith and Medin, 1981). When making an evaluative judgment of a new person, people will first try to categorize the person based on easily categorizable attributes (Fiske and Neuberg, 1990; Fiske and Pavelchak, 1986). When a category is selected, the evaluating person will check the fit between this category and other available attributes, on the basis of a category prototype or exemplar stored in memory (Fiske *et al*., 1987).

Given the substantial amount of research that has demonstrated the dominant impact of founding scientists' scientific credentials on the evaluations of newly established technology-based companies (Darby, Liu, and Zucker, 1999; Deeds, Decarolis, and Coombs, 1997), we believe that in our study context the most salient attributes associated with basic level categories are a founding scientist's scientific credentials (Packalen, 2007). The credential that is probably the most salient is the school from which a scientist graduated. A scientist's education credentials are usually listed first on the curriculum vitae and are publicly available. Hence, when making an evaluative judgment of a scientist who graduated from a highly ranked doctoral program, the managers of the pharmaceutical firm are likely to begin by categorizing him or her as a 'star scientist' (Higgins, Stephan and Thursby, 2011; Zucker and Darby, 1997; Zucker, et. al, 2002). The next step for the managers of the pharmaceutical firm would be to make a confirmation that the scientist is really a member of that category by considering his or her research output. A well-published and highly-cited scientist will meet the managers' expectations from a 'star scientist.' Because this type of category-based process is much more efficient than any other types of processes from a cognitive economy standpoint (Fiske and Pavelchak, 1986; Fiske and Taylor, 1991), even highly experienced executives would not feel the need to re-elaborate on the attribute information, unless they find anything different about the scientist.

In contrast, when the confirmation check reveals an incongruity between a scientist's attributes, that is, some credentials are congruent with a specific category but others are not, the pharmaceutical firm's managers will engage in piecemeal processing. Rather than using a category as the basis for their overall evaluation, they will evaluate the scientist in an attribute-by-attribute manner and integrate their attribute evaluations to reach a judgment (Anderson, 1974; Fishbein and Ajzen, 1975; Fiske *et al*., 1987; Pavelchak, 1989; Sujan and Bettman, 1989).

Whereas category-based processing of congruent signals are based on schemas stored in memory and thus lead to predictable judgments, piecemeal processing can render a positive evaluation, a negative evaluation, or may even result in a new category altogether that is neither conclusively positive nor negative (e.g. ‘average scientist’) and thus is likely to have less predictable outcomes than category-based processing. Accordingly, we propose the following hypothesis:

Hypothesis 3a: The effects of scientist reputation (H1) and status (H2) will be amplified when the two are congruent, thus increasing the likelihood of an alliance being formed when the congruence is high/high, and decreasing the likelihood of an alliance being formed when the congruence is low/low.

Hypothesis 3b: The effects of scientist reputation (H1) and status (H2) will be amplified when the two are congruent, thus increasing the likelihood of an alliance being formed early in the commercialization process when the congruence is high/high, and decreasing the likelihood of an alliance being formed early in the commercialization process when the congruence is low/low.

Having established our argument for the amplification effect of reputation-status congruity, we now turn to the possibility of asymmetry in the congruence hypothesis. Specifically, an established premise in the psychology literature is that negatives are more powerful than positives (Baumeister, *et al*., 2001; Rozin and Royzman, 2001). Studies have shown that people process negative information more thoroughly than positive information (Dreben, Fiske and Hastie, 1979), remember negative behaviors more accurately and vividly (Fiske, 1980), and agree more easily on who is unpopular (Newcomb, Bukowski and Pattee, 1993). But it is in the domain of impressions of persons that negative bias has its longest and fullest history in psychology (Rozin and Royzman, 2001). An enormous literature on impressions of persons has consistently demonstrated that people overemphasize negative data in impression formation (Falk and Fischbacher, 2006; Rozin and Royzman, 2001; Peeters and Czapinski, 1990;).

The particularly powerful effects of negatives in impression formation and evaluative judgment processes have also been documented in research on corporate leaders. Research provides strong evidence that executives and directors are likely to experience a strong negative impact on their professional careers when their companies perform poorly. They tend to be fired, suffer diminished employment prospects, receive lower pay, and those who are rehired tend to hold lower positions (Cannella, Fraser, and Lee, 1995; Semadeni, *et al*., 2008; Wiesenfeld, Wurthmann, and Hambrick, 2008). At the same time, there is much less evidence that the opposite case also occurs. That is, good performance records do not seem to provide CEOs and directors improved professional growth opportunities, better employment prospects, or higher wages (Tosi *et al*., 2000).

Based on this line of research, we expect a manager at a pharmaceutical firm to process a biotechnology company's founding scientist's status and reputation information more thoroughly when it is negative. The greater information processing may be reflected in paying more attention to a scientist's status and reputation, in elaborating them more thoroughly, and in remembering them more readily. Accordingly, we expect that:

Hypothesis (H4a): The amplification of reputation-status congruity (H3a) on the likelihood of alliance formation will be greater when the congruence is low/low, relative to when it is high/high.

Hypothesis (H4b): The amplification of reputation-status congruity (H3b) on alliance timing will be greater when the congruence is low/low, relative to when it is high/high.

METHODOLOGY

Sample and data collection

The hypotheses developed in this study were tested on a sample of 325 alliances created between 19 US public pharmaceutical firms and US biotechnology companies between 1990 and 2003. Data were drawn from a comprehensive list of all the 749 alliances that were created during these years between the 19 pharmaceutical firms and biotechnology companies for the purpose of developing a new product, purchased from Recombinant Capital (Recap). This list provided the names of the parties involved, the date the alliance was formed, the type of the agreement (i.e. development, distribution, manufacturing, etc.), and the stage at signing. Since the Recap data did not provide information about the biotechnology companies' founding chief scientists, each biotechnology company was contacted by mail, email, and telephone, and asked to identify its founding chief scientists and to provide a copy of their curriculum vita (CV)[3]. Biographical information was obtained for 250 founding chief scientists of 134 biotechnology companies, which were involved in a total of 325 alliances. Missing data reduced the sample to a total of 275 alliances.

To predict alliance formation, we compared biotechnology companies that did form alliances with those that could have formed alliances but did not. We supplemented the sample of alliances that were actually formed with a random sample of 300 potential alliances that might have formed but never did[4]. The risk set from which we sampled these 'potential alliances' was created as follows. First, we used the CorpTech Database to compose lists of all biotechnology companies in the US for each year from 1990 and 2003. These lists included both companies that

[3] A scientist associated with new biotechnology company may occupy one of the following organizational roles: scientific founder, member of the scientific advisory board, or the chair of the scientific advisory board (Audretsch and Stephan, 1996). We were therefore very careful to focus exclusively on the scientific founders by contacting each biotechnology company in our sample, asking for the name/s and CV of the scientific founder/s.

[4] This approach, in which a sample is formed by combining all observed events with a random sample of observations in which an event did not occur, yields results that are essentially identical to an analysis of a sample that contains all observed events plus the complete collection of non-events (Allison, 1995). The reason is that when the number of events is smaller than the number of observations in which an event did not occur, essentially no further information is added as more and more non-events are included in the sample (Allison, 1995).

were involved in alliances and all the ones that were not. Then we randomly sampled a year between 1990 and 2003, and from the list corresponding to that year, we randomly chosen a biotechnology company. Each of these biotechnology companies was randomly assigned a traditional public pharmaceutical firm as a 'partner.' Biographical information for the founding chief scientists of these biotechnology companies was obtained in the same way as it was obtained for the original companies, as described above. We then combined our original sample of 275 actual alliances with the sample of 300 potential alliances. Using discrete-time event history models, the ensuing sample of 575 alliances was utilized to estimate each alliance's likelihood of formation.

Dependent variable

The dependent variables examined here were alliance formation and alliance timing. The formation model predicted an alliance's likelihood of formation. Each dyad had a dummy variable indicating whether the incumbent and the biotechnology firm formed an alliance with each other in the given year. The timing model predicted the stage in the commercialization in which each alliance was formed. As discussed above, biotechnology commercialization takes place in a series of stages from the first discovery and early development of a new technology to the introduction of a product. Firms analyzing the biotechnology industry have divided the commercialization process into nine stages (Office of Technology Assessment, 1993) indicating the degree to which a technology has been developed. We obtained information about the stage of each product in each alliance from Recombinant Capital (Recap). Recap determines this information from press releases or the alliance's agreement, and when lacking, its analysts do their own research using sources such as the companies' websites and SEC filings. Our model treated the different stages as a set of ordered categories, predicting in which of these stages the alliance was formed.

Independent variables

We measured scientists' **reputation** using two key proxies employed by the academic community for evaluating its members: publication counts and citation rates. Publication counts involve the counting of scientific publications published by a researcher in reputable academic journals. Since each publication is likely to have been approved through a peer review system prior to acceptance for publication, and reviewers are assumed to be capable of evaluating the worthiness of the submission, publication counts have been traditionally viewed as a method for evaluating a researcher's scientific ability. Because CVs are not uniformly comprehensive we standardized the 'number of publications' variable as follows. First we sent out a survey to 40 scientists involved in biotechnology research in five different universities, asking them to identify the leading academic journals in biotechnology. Journals that were identified by more than one researcher were included in a list of leading journals, which comprised a total of 12 journals. Then, we calculated the number of publications each scientist in our sample published in these journals prior to the date in which a focal alliance was formed, using different online electronic databases such as Web of Science, ScienceDirect, and EBSCOhost web. For companies with more than one founding chief scientist Publications Count was the average number of publications.

While publication counts measure output, citation counts are considered to go one step further and address questions of quality and influence. The data being considered are the frequency with which a certain author is cited in other articles. The implicit assumption in regard to using citation counts to evaluate scientific work is that 'high quality' research will have a high impact on its target audience and will therefore become an important source of reference for other researchers and be cited more frequently (Sims and McGhee, 2003). Citation data were obtained from the Science Citation Index Expanded, and equaled the natural log of the total number of times a founding chief scientist was cited in other articles prior to the formation of a focal alliance. For companies with more than one founding chief scientist this was the average number of citations.

Publication counts and citation counts were highly correlated (r=0.65) so we could not use both in the same model. Therefore, we ran the analyses using different combinations of the two. First, we ran the models with each of the measures separately, once using publication counts to measure reputation and once using citation counts. Second, we created a reputation index out of the two measures by converting them to z-scores and adding them together using equal weighting. Third, we conducted factor analysis on the two measures using the principal factor method with promax rotation. As expected, the analysis yielded only one factor with an eigenvalue of 1.84. Loadings for each measure were greater than 0.5 on the factor, and less than 0.2 on the other factor. The three methods we used produced very similar results. The results reported below were obtained using the factor.

As explained above, while founding scientists' may be affiliated with several scientific groups, all the scientists in our sample are affiliated with members of the university from which they graduated. Hence, we measured scientists' **status**, using the academic status of the school from which he or she graduated with an advanced degree. With the rising popularity of college ranking surveys, academic rankings have become a key factor affecting judgments about scientific quality (Cicchetti, 1991). Every few years, <u>US News and World Report</u> publishes rankings of doctoral programs in the sciences based on the results of surveys sent to deans and department chairs in each discipline. Given that the majority of the scientists in our sample had a doctoral degree, we used the latest rankings available for each year of doctoral programs in biological sciences to measure the status of the institutions from which the founding chief scientist graduated. US News and World Report ranks doctoral programs from 1 to 30. We reversed coded these rankings so the higher a school's ranking the higher its status. For companies with more than one founding chief scientist this was the average ranking.

Using a large-scale survey as the one used by US News and World Report to measure status should be done with cautious though, because of potential respondent bias. Specifically, prior studies have shown that the perception of a company's status is influenced by its prior performance, resulting in a halo effect (Brown and Perry, 1994). Hence, before the doctoral programs' ranking described above could be used, this halo had to be removed. We did so following the method presented and validated in Brown and Perry (1994). First, we ran a preliminary multiple regression of the reputation variables on the status scores. The coefficients generated in this regression were used to build a 'predictive model' for status. Then, the model was subtracted from the observed ranking scores, producing halo-removed status ratings, which was used in the models presented below.

Control variables[5]

Biotechnology Company Controls. Firms that are led by scientists who engage in more 'basic' research will have a greater likelihood of forming alliances early in the commercialization process. Our conversations with people who have an inside working knowledge of the

[5] Two additional control variables which we included in the models but had to remove due to missing data were *therapeutical category* and *downstream operations.* The former controlled for whether the pharmaceutical firm worked in the same therapeutical category as the biotechnology company. The latter, for whether the biotech company was involved in R&D only or also had other downstream operations. In both cases data was available only for a small subsample of biotechnology firms. Secondary analyses performed on these subsamples confirmed that the inclusion of these variables did not alter the other findings.

biotechnology industry indicated that scientists who want to continue to conduct basic research tend to remain on the faculty of a research university while those who prefer more practical research tend to leave academia altogether. A **University Employee** dummy was therefore coded 1 if the founding chief scientist was a university faculty member at the time the alliance was formed and 0 otherwise. A founding scientist's reputation and status are not the only factors that may affect perceptions of quality and potential. We controlled for several other factors that may influence the evaluations of pharmaceutical firms' executives. Of the founding scientists in our sample 88 percent had a PhD. Not having a PhD may therefore seem odd and raise doubts about a scientist's abilities. **PhD** dummy was coded 1 if the founding chief scientist had a PhD and 0 otherwise. Industry experience may increase founders' access to pharmaceutical firms through prior encounters and enhance their understanding of how to lead biotechnology companies (Bruderl, Preisendorfer and Ziegler, 1992), so a dummy variable for **Industry Background** took a value of 1 if the founding chief scientist had any industry background and 0 otherwise, and **Time since Graduation** equaled the number of years since the founding chief scientist graduated. An important factor that may impact perceptions of capabilities and promise are previous technological achievements. We thus controlled for both **Founder Patents**, which equaled the log of the number of patents issued to the founding chief scientist prior to forming the focal alliance and **Biotech Patents**, which measured the number of patents issued to the biotechnology company in the twelve months prior to the formation of the focal alliance. These data were obtained from the U.S. Patents Database[6]. Likewise, we controlled for **Approved Products**, which equaled the number of products the biotechnology company had successfully commercialized in the past. A large founding team is likely to enhance confidence in a

[6] In separate analyses we also used the number of patents issued to the biotechnology in the prior two years, in the prior three years, the sum across all years in our dataset, and a weight that depreciated the value of patents across time. Results were remarkably similar.

biotechnology company's ability to successfully develop its technology by signaling a greater stock of knowledge, and by possibly having more connections to the pharmaceutical industry (Eisenhardt and Schoonhoven, 1996). Therefore **Number of Scientists** counted the number of scientists involved in the founding of the biotechnology company. Larger biotechnology companies may also gain more confidence because larger size may signal that they have been doing things right. **Biotech Size** was measured by the natural log of the number of employees the biotechnology company had in the year prior to the formation of the focal alliance. Using the log of deflated annual sales in the prior year instead produced similar results. Older biotechnology companies may gain more confidence regardless of their size (Singh, Tucker, and House, 1986), so **Biotech Age** was measured as the number of years that had elapsed from the year the company was founded. Previous investments in the biotechnology company by other firms may convey the fact that the biotechnology company has earned their positive evaluation (Stuart, Hoang, and Hybels 1999). Thus the number and the attributes of the firms that have previously invested in the biotechnology company should affect perceptions of quality. We therefore controlled for the number of **Previous Alliances** that the biotechnology has formed with pharmaceutical firms and for the average size of the pharmaceutical firms that formed alliances with the biotechnology company in the year prior to the formation of the focal alliance, measured by their deflated **Average Net Sales** in millions.

Biotechnology companies may vary in their opportunities and needs for forming alliances. Prior research has found that biotechnology companies located in areas with a high concentration of similar companies have greater access to information about cooperative opportunities (DeCarolis and Deeds, 1999). Therefore, we coded a dummy variable, **Geographical Location**, 1 if the biotechnology company was located in San Francisco, San

Diego, or Boston, which were previously identified as the top three biotechnology locations (splitting this variable to three dummies denoting the three separate locations did not change the results) (Gulati and Higgins, 2003). The earlier the stage in the commercialization process in which an alliance is formed the greater the percentage of future revenues that the biotechnology company may have to render to the pharmaceutical firm. Therefore, **Prior Investments,** which equaled the amount of money that the biotechnology company raised from venture capitalists and through an IPO prior to the formation of the alliance, was included to control for the biotechnology company's ability to hold off the alliance[7]. This information was obtained from the VentureXpert database. Finally, **CFS Present** dummy was coded 1 if the chief founding scientist was still present at the time the focal alliance was formed and 0 otherwise.

Pharmaceutical Firm Controls. Large pharmaceutical firms are likely to enjoy more slack resources, which may allow them to take greater risks and form alliances earlier in the commercialization process (Bourgeois, 1981). Hence, we included two variables to control for firm size and slack resources. **Pharma Sales** equaled the natural log of the total sales of the pharmaceutical firm in the year prior to the formation of the alliance, and **Pharma Size** equaled the number of employees it had in the year prior to the formation of the alliance. Finally, in models not reported here we used fixed effects to control for inherent differences in pharmaceutical firms' propensity to form alliances at certain stages in the commercialization process. The results did not change, so to conserve degrees of freedom, we estimated a piece-wise model using several dummies. We began with an exhaustive set of dummies, one for each firm, and collapsed categories as indicated by the magnitude and significance of these variables. This process yielded one statistically significant dummy variable: **Postponers**, which indicated

[7] When we split this amount into two separate variables, one equaling the amount of money that the biotechnology company raised from venture capitalists, and the other the amount it raised through an IPO, both variables had negative signs but did not reach significance. All other results remind the same.

six firms that had a tendency to form alliances late in the commercialization process. The remaining 13 firms were the omitted category.

Other controls. Prior research has shown that executives' decisions to form alliances are influenced by the observed actions of others (Garcia-Pont and Nohria, 2002). To control for the possibility that the imitation process also affects the decision when to form an alliance, we included two variables: **Social Cues**, which equaled the number of alliances created between pharmaceutical firms and biotechnology companies in the year prior to the formation of the focal alliance, and **Average Signing Stage**, which equaled the average stage in which these alliances were formed. Finally, as explained below, **Probability of Formation** controlled for selection bias in the timing models and was equal to lambda.

Analysis

While the data from Recombinant Capital (Recap) include relatively precise formation dates, Recap determines this information from press releases or the alliance's agreement, and when lacking, its analysts do their own research using sources such as the companies' websites and SEC filings. Given this coarse granularity, coupled with the fact that our predictors were recorded annually, we assessed formation on an annual basis.

These data limitations, however, do not change the fact that alliances were 'at risk' of formation throughout the entire year. The objective therefore was to recover what were actually continuous-time hazard rates. Discrete-time event history models that use a complimentary log-log function accomplish this by accounting for both the discrete nature of the available data, and the continuous nature of actual formation processes (Allison, 1995). Results of such analyses are essentially identical to those from continuous-time Cox models in which formations are assumed to occur either halfway through the year or, alternatively, with a uniform, random distribution throughout the year (Allison, 1995).

Finally, the timing analysis would suffer from sample selection bias if some of the same factors that influenced an alliance' likelihood of being formed (e.g. founders' scientific output) also affect the stage in which the alliance is formed (Stern and Henderson, 2007). We modeled and corrected for such bias using a generalization of the two-step procedure introduced by Heckman (1979). Specifically, as described by Lee (1983) and implemented by Henderson (1999) and others, we used parameters from the formation model to calculate each alliance's likelihood of formation and included it as a control in the timing analysis.

The second dependent variable, **Timing of Formation** takes nine different ordered values. Thus, in the timing analysis we used an ordered probit model to test the above hypotheses, clustering on the pharmaceutical firm to control for the possibility that the residuals for dyads involving the same pharmaceutical firm were correlated. The ordered probit model, also known as the cumulative probit model, estimates the effects of independent variables on the log odds of having lower rather than higher scores on an ordered, multiple outcome dependent variable (Borooah, 2001). One of the assumptions underlying ordinal probit regressions is the proportional odds assumption (the assumption that the relationship between each pair of outcome groups is the same). We examined the proportional odds assumption using both a likelihood ratio test and a Brant test. Both tests indicated that we have not violated the proportional odds assumption (i.e. tests were non-significant). In addition, to remove any further doubt we also ran a Logit model in which we predicted an early (as opposed to late) alliance formation by categorizing all alliances that were formed in stages 1 to 4 as 'early' and all alliances that were formed in stages 5 to 9 as 'late.'[8] Results were consistent with the results of the ordered probit regression.

RESULTS

Table 1 provides descriptive statistics for all variables. To ensure that multicollinearity had no material effect on our results we used matrix decomposition techniques to obtain condition indices (Judge, *et al.*, 1988). All computed indices were below the conservative upper threshold of 20, as recommended in the literature (Belsley, 1991), and the highest condition index in any model was 17.4, indicating no collinearity problems.

Insert Table 1 about here

Table 2 reports results of the discrete-time models of alliance formation rates (models 1-3) and the ordered probit models predicting stage at signing (Models 4-6). Model 1 and 4 contain the controls. Model 2 and 5 add the independent variables of Scientific Output and University Ranking, and Model 3 and 6 add the interactions relevant for hypothesis testing. Our theoretical arguments about signal congruence suggests that the independent effects of Reputation and Status on alliance formation are amplified when the two are congruent (Hypotheses 3a and 3b), and that the effect of negative congruence (i.e., both reputation and status are low) is stronger than positive congruence (i.e., both are high) (Hypotheses 4a and 4b). Since a simple linear interaction would not test such a relationship, we used a spline function (Greene, 1993: 235-238; Greve, 1998). A spline specification means that a variable coefficient can change at a predetermined point. We created splines by entering separate variables for reputation and status

[8] The average Stage at Signing is 3.14. Accordingly we ran two robustness tests. In one we classified stages 1-4 as 'early' and in the second we classified stages 1-3 as 'early.' Results were fairly similar. Other cutoff points produced much weaker results, suggesting that the cutoff point is somewhere between stages 3 and 4.

above and below the mean reputation and status of all founders in our sample, respectively[9]. Then we generated two interaction terms: 'Low Reputation X Low Status' equaled the multiplication of reputation and status for those observations that were below the average on both variables and zero otherwise, and 'High Reputation X High Status' equaled the multiplication of scientific output and university ranking when both variables were below the average and zero otherwise[10].

Insert Table 2 about here

The results reported in Model 2, provide support to both Hypotheses 1a and 2a that the better a founding scientist's reputation (H1a) and status (H2a), the greater the likelihood of an alliance being formed. Specifically, we observe that low reputation and status significantly decrease the likelihood of an alliance being formed, while high reputation increases the likelihood of an alliance being formed. The coefficient for High Status is positive, as expected, but does not reach statistical significance. Apparently, graduating from a high status university does not increase a founding scientist's likelihood of forming an alliance with a pharmaceutical firm, but graduating from a low status one significantly decreases that likelihood. This result, which is in line with the premise that negatives are more powerful than positives (Baumeister, *et*

[9] Given that the independent variables in our hypotheses are relative measures of reputation and status we were very cautious about the sensitivity of the results to the way in which low and high values were defined. Thus, we carried out the calculations for a considerable range of cutoff points. Results were similar, though a bit weaker, to the ones presented below when we used the median instead of the mean as well as different cutoff points ranging between 0.8 standard deviations below the mean to 0.7 standard deviations above it.

[10] Splines can also be made by entering Reputation and Status, an interaction variable of Reputation and Status, and an indicator when they are both below (or above) the mean (Greve, 1998). This method allowed us to investigate whether there is a difference between the interactions of 'low*high' and 'high*low.' No difference was found, as both interactions were insignificant. Altogether, the separate variables method and the interaction tests yielded very similar results. For simplicity of notation we report the separate variables method.

al., 2001; Rozin and Royzman, 2001), could have not been reached without separating the coefficients for high and low status[11].

Models 4-6 show the results of the models predicting the stage in the commercialization process in which an alliance will be formed between the pharmaceutical firm and the biotechnology company. Note that in accordance with our hypotheses, these models predict the probabilities that the levels of **Stage at Signing** will have lower values (i.e. occur at earlier stages). As shown in Model 5, the results support both Hypothesis 1b and 2b that the better a founding scientist's reputation (H1b) and the higher the founding scientist's status (H2b), the greater the likelihood of an alliance being formed early in the commercialization process. Specifically, low reputation and status significantly decrease the likelihood of an alliance being formed early in the commercialization process, while high status increases that likelihood. The coefficient for High Reputation is positive, as expected, but does not reach statistical significance. As before, this result, which could have not been reached without separating the coefficients for high and low status, demonstrates the powerful effects of negatives in impression formation and evaluative judgment processes.

Hypothesis 3a predicted that the likelihood of an alliance being formed will be amplified when Reputation and Status are congruent, i.e. increasing when they are both high, and decreasing when they are both low. Consistent with Hypothesis 3a, results show that when Reputation and Status are both low, the likelihood of an alliance being formed is decreased beyond the independent effect of each quality signal, as indicted by the negative and significant interaction between Low Reputation and Low Status in Model 3 in Table 2. On the other hand,

[11] Although we did not hypothesize about the shape of the relationship between status and reputation and alliance formation and timing, in contrast to prior studies which have assumed a linear relationship between a firm's quality signals and the way in which it is perceived, the results reported in Tables 3 and 4 suggest a nonlinear relationship. This is an interesting finding which we discuss further in the discussion section.

the interaction between High Reputation and High Status it is statistically insignificant (though positive as predicted), so Hypothesis 3a is only partially supported.

The statistically insignificant results obtained for the interaction between High Reputation and High Status make it impossible to test H4a, which predicted that the amplification of the congruence effect between Reputation and Status on the likelihood of alliance formation will be greater when the congruence is low/low, relative to when it is high/high. Nevertheless, although these null results cannot prove the absence of an effect, they support our thinking by providing evidence that congruence matters significantly when it is low/low, but, at least in our sample, has no effect when it is high/high.

Hypothesis 3b predicted that the likelihood of an alliance being formed early in the commercialization process will be amplified when Reputation and Status are congruent, i.e. increasing when they are both high, and decreasing when they are both low. As shown in Model 6 in Table 4, the results of the two interactions strongly support Hypothesis 3b: when Reputation and Status were congruent by being both below the mean Reputation and Status of all founders in our sample their interaction was *negative* and significant, and when they were congruent by being both above the mean, their interaction was *positive* and significant.

Hypothesis 4b compared the effects of the two quality signals when both are low to when they are both high on the likelihood of the alliance being formed early. In terms of the coefficient labels in Table 2, when all else is equal, the effects of Reputation and Status on the stage at signing are:

<u>When Reputation and Status are low</u>: b_1 (Reputation) + b_3 (Status) + b_5 (Reputation X Status)

<u>When Reputation and Status are high</u>: b_2 (Reputation) + b_4 (Status) + b_6 (Reputation X Status)

The parameter estimates (coefficients) for the interaction of Reputation and Status, reported in Table 2, suggest that the effect of Reputation and Status is stronger when both are low, thus supporting Hypothesis 2b. To test whether these effects are indeed different we performed a post-hoc F-test using the coefficients in Table 2, examining the following inequality:

$$|b_5 \text{ (Reputation X Status)}| > |b_6 \text{ (Reputation X Status)}|$$

This inequality proved to be true for all the different cutoff points used to classify Reputation and Status values as ‘low’ and ‘high’ (see above). For the cutoff points used in the models reported in Table 4 (i.e. means), $p = 0.0074$, thus supporting Hypothesis 4b.

DISCUSSION

The purpose of this study was to theoretically and empirically examine how and why incumbent pharmaceutical firms would be influenced by a biotechnology company’s founders’ scientific reputation and status when considering the formation of an alliance. We began by noting that prior research has generally failed to differentiate between these related but analytically distinct quality signals. One of our study’s major intended contributions was therefore the theoretical and empirical delineation of the two concepts, along with our notion that reputation and status congruence is also an important predictor of when alliances will form. We see our study as eliminating some of the confusion that has arisen from the interchangeable usage of the concepts of reputation and status; moreover, our independent and interdependent analysis of these two concepts has enabled us to make what we see as three contributions to the alliance literature.

First, this study documents the distinct roles of status and reputation in alliance formation decisions, suggesting that both are important factors that need to be incorporated in any model examining alliance formation. Second, it also reveals the importance of the congruence of status and reputation. When status and reputation are congruent they amplify each other’s impact (positively and negatively), rendering their cumulative effect more powerful than the sum of their separate effects. Additionally, we show that when reputation and status are both low, their amplifying effect is negative, thus decreasing the likelihood of an alliance being formed and its likelihood of being early. Finally, we show that these amplification effects are not fully symmetric, and that the double combination of low status and low reputation creates a particularly difficult situation for firms seeking alliances, as evidenced by a particularly retarding effect on alliance formation.

We see these findings as contributing to the considerable interest in the concepts of reputation and status in both the academic and practitioner literatures in recent years. This research has generally emphasized the potential benefits of having a positive reputation (Fombrun, 1996; Deephouse, 2000). A corollary to these studies is that the better the status and reputation of an organization or an individual, the greater the benefits they are likely to yield (Fombrun, 1996). While we do not call this notion into question, our findings suggest that the influence of status and reputation is not a simple linear function as these studies may seem to infer, but rather, that status and reputation interact in complex yet predictable ways. Hence, managing the status and reputation of individuals and organizations entails the consideration of their interaction and not only their independent effects.

A third contribution to the alliance literature is the study's dependent variable. In contrast to prior studies which generally only examined whether firms are likely to form an alliance, we also examined the timing in which an alliance is likely to be formed. The timing in which an alliance is formed is highly consequential to the partners, given that it typically can affect the distribution of future revenues between them and the relative ability of each partner to affect the alliance's evolution and progress (Lavie, Lechner and Singh, 2007).

Another contribution of this study is in recognizing differences in the findings across literatures regarding the interactive effects of signals. Our finding that the independent effects of quality signals on alliance formation are amplified when the two are congruent is consistent with previous research in marketing, sociology, and psychology. Research in marketing has shown that consistency across a brand's marketing mix is critical to its credibility and to customers' expectations (Erdem and Swait, 1998), and sociologists and psychologists have shown that when status attributes are consistent, the outcome of this process is straightforward; individuals whose attributes are consistent are perceived as having higher/lower abilities. But it is unclear, and still being disputed, how people form a perception when status attributes are inconsistent (Berger *et al.,* 1992).

On the other hand, our findings may seem at odds with studies that draw on the signaling literature in economics. Higgins, Stephan, and Thursby (2011), for example, have shown that the importance of having a Nobel laureate affiliated with a firm making an IPO diminish as other measures of firm quality become available. In an analysis not reported here we similarly found that the independent effects of both the reputation and status of the founding scientists in our sample diminished over time. Taken together, these results suggest an interesting question: when do quality signals amplify, and when do they diminish, each other's effects?

One possible answer to the above question is that when quality signals provide information of equal quality or relevance they amplify each other's effects, but once a signal reveals superior information, or more relevant information than has been provided by the first signal, it diminishes its effects. Note that in the marketing, sociology, and psychology studies discussed above quality signals were provided at the same time and there was no clear reason to believe that one was more indicative of the underlying quality being assessed than the other.

Conversely, the signals examined in the signaling studies emerged consecutively, and the latter signal always seems to be more closely related to the task at hand than the signals it surpasses. Future research should explore this premise in greater detail.

With respect to study limitations, we recognize that reputation and status may be especially important in the biotechnology industry, where product development is driven by basic scientific knowledge (McMillan, Narin, and Deeds, 2000), and such idiosyncrasies may limit the generalizability of our results. Additional studies in different settings are therefore needed to further clarify the relationship between the two signals. In addition, we took the perspective of the incumbent in our theorizing and hypothesis development, but our data do not allow us to know who actually initiated the alliance process. Future research should examine the decision processes that unfold as both incumbents and newly emerging firms engage in explorations with each other.

Of course, we also recognize that founding scientists, like all people, have multiple status and reputation characteristics. A scientist may have a reputation of being a good tennis player and a caring parent, for example, and status characteristics such as membership in a minority ethnic group and a certain marital status. While evaluators may establish their expectations on a number of reputation and status characteristics, they are likely to draw more heavily on characteristics that are task-relevant and salient (Berger and Zelditch, 1993). We therefore focused in this study on scientists' scientific reputation and status, which are both relevant and highly salient to incumbents when considering strategic alliances with a newly emerging firm. Future research, however, should examine additional status and reputation characteristics and the effects of congruence (or the lack thereof) between more than two status and reputation characteristics. Another promising avenue of research is to examine how other dependent variables, such as IPO valuations or organizational identity, are potentially affected by the congruence (or the lack thereof) of individual and organizational indicators of reputation and status. Addressing such issues can have a significant impact on our understanding of how firms see themselves, how others see them, and the consequences of such perceptions.

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Table 1: Means, Standard Deviations, and Correlations•

Variable	Mean	s.d.	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
1. Stage at Signing	3.14	2.84	1.00																								
2. Low Reputation	-0.23	0.63	-0.22	1.00																							
3. High Reputation	0.23	0.69	-0.28	0.12	1.00																						
4. Low Status	-1.92	2.90	-0.04	0.11	0.04	1.00																					
5. High Status	6.60	8.15	-0.24	0.08	0.01	0.54	1.00																				
6. University Employee	0.54	0.49	-0.20	0.19	0.37	0.11	0.09	1.00																			
7. PhD	0.88	0.32	-0.22	0.36	0.02	-0.07	0.02	0.00	1.00																		
8. Industry Background	0.61	0.48	0.24	-0.11	0.04	-0.11	-0.15	-0.07	-0.11	1.00																	
9. Time since Graduation	25.5	10.3	0.23	-0.20	0.02	-0.25	-0.14	0.12	-0.03	0.02	1.00																
10. Founder Patents	1.83	1.38	0.01	0.20	-0.06	0.13	0.38	-0.00	0.16	-0.08	0.01	1.00															
11. Biotech Patents	5.20	14.7	-0.00	0.08	0.11	0.07	-0.07	0.11	0.07	-0.06	0.13	0.02	1.00														
12. Approved Products	0.64	2.09	0.16	0.06	-0.05	-0.08	-0.20	-0.03	0.03	0.00	0.14	-0.21	0.33	1.00													
13. Number of Scientists	1.22	0.73	-0.08	0.04	0.11	0.12	0.02	-0.05	-0.00	0.08	-0.04	-0.08	0.06	0.13	1.00												
14. Biotech Size	4.41	1.55	-0.02	-0.03	0.04	-0.05	-0.00	-0.04	0.13	-0.04	0.19	-0.13	0.36	0.39	0.11	1.00											
15. Biotech Age	10.1	12.2	0.07	-0.05	-0.23	-0.23	-0.05	-0.15	0.05	-0.21	0.41	-0.00	0.23	0.31	-0.03	0.44	1.00										
16. Previous Alliances	1.81	1.06	0.05	-0.07	0.12	-0.01	-0.06	-0.03	0.12	-0.04	0.23	-0.11	0.33	0.43	0.03	0.68	0.29	1.00									
17. Average Net Sales	1.20	1.54	-0.13	0.10	0.17	0.08	0.04	-0.05	0.09	-0.03	-0.13	-0.03	0.18	0.16	0.02	0.14	-0.09	0.37	1.00								
18. Geographical Location	0.60	0.48	-0.12	0.13	0.33	0.01	0.03	0.06	0.02	0.07	-0.02	0.07	0.08	-0.08	0.11	-0.04	-0.18	-0.06	0.01	1.00							
19. Prior Investments	1.87	4.56	-0.05	0.02	0.17	-0.07	0.09	0.11	-0.12	-0.08	-0.08	0.03	-0.06	-0.07	-0.06	-0.05	-0.10	-0.18	0.05	0.13	1.00						
20. CFS Present	0.80	0.39	-0.07	0.02	0.17	-0.05	0.07	-0.01	-0.01	-0.06	-0.29	0.08	0.01	0.04	-0.05	-0.20	-0.13	-0.23	0.07	0.13	0.08	1.00					
21. Pharma Sales	9.18	1.19	-0.29	0.10	0.03	0.10	0.11	0.08	0.04	-0.01	-0.23	0.08	-0.03	-0.1	0.02	-0.19	-0.47	-0.13	0.08	0.08	0.15	0.05	1.00				
22. Pharma Size	49.4	24.8	-0.20	0.04	-0.02	0.02	-0.02	0.07	0.07	-0.00	-0.19	0.00	-0.01	0.03	0.04	-0.09	-0.22	-0.08	0.04	0.04	0.18	0.09	0.76	1.00			
23. Postponers	0.34	0.47	0.19	-0.12	-0.06	-0.05	-0.07	-0.13	-0.04	0.10	-0.02	-0.06	0.02	-0.04	-0.07	-0.03	-0.00	0.02	-0.01	-0.11	-0.05	0.02	-0.22	-0.21	1.00		
24. Social Cues	5.52	0.34	-0.15	0.04	0.06	0.05	0.07	0.04	0.08	-0.10	0.14	0.25	0.12	-0.05	0.03	0.05	0.06	0.07	0.05	0.02	0.11	-0.09	0.19	0.12	-0.08	1.00	
25. Average Signing Stage	3.99	0.88	0.30	0.08	-0.00	0.01	-0.07	0.07	0.04	0.15	0.02	0.02	-0.00	0.05	-0.03	-0.04	-0.03	-0.02	0.00	-0.00	-0.04	-0.00	-0.44	-0.21	0.06	-0.02	1.00
26. Probability of Formation	0.68	0.23	-0.13	0.17	0.12	-0.06	-0.08	0.35	0.02	-0.00	-0.01	0.24	0.08	-0.02	-0.06	-0.01	-0.25	-0.00	0.02	0.58	0.10	0.14	0.12	-0.06	0.02	-0.03	-0.08

• N = 275 Alliances. Statistics are reported for the sample used to predict stage at signing. Statistics for the sample used to examine formation were remarkably similar.

Table 2: Analyses of Alliance Formation Rates and Stage at Signing

	Alliance Formation			Stage at Signing		
Variable	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**	**Model 6**
Low Reputation		-1.004••• (0.306)	-1.236••• (0.362)		-0.460•• (0.151)	-0.483• 0.240
High Reputation		1.155••• (0.312)	1.863••• (0.421)		0.013 (0.181)	0.147 0.255
Low Status		-0.435• (0.202)	-1.112••• (0.320)		-0.296• (0.163)	-0.326• 0.164
High Status		0.352 (0.223)	0.902•• (0.348)		0.472•• (0.160)	0.425•• 0.160
Low Reputation X Low Status			-0.566•• (0.206)			-0.509••• 0.156
High Reputation X High Status			0.180 (0.207)			0.295• 0.155
University Employee	1.275••• (0.256)	1.632••• (0.314)	1.837••• (0.335)	0.783••• (0.200)	0.727•• (0.229)	0.697•• (0.232)
PhD	-0.326 (0.325)	-1.051•• (0.381)	-1.165•• (0.395)	0.535• (0.245)	0.584• (0.287)	0.374 (0.298)
Industry Background	0.007 (0.249)	0.273 (0.274)	0.241 (0.283)	-0.452• (0.206)	-0.572•• (0.214)	-0.652•• (0.219)
Time since Graduation	-0.004 (0.012)	0.012 (0.013)	0.005 (0.014)	-0.049••• (0.012)	-0.055••• (0.013)	-0.055••• (0.013)
Founder Patents	0.099 (0.078)	0.184 • (0.095)	0.212• (0.099)	-0.074 (0.067)	-0.094 (0.075)	-0.103 (0.076)
Biotech Patents	-0.029•• (0.011)	-0.025•• (0.011)	-0.028• (0.012)	-0.006 (0.006)	-0.003 (0.006)	-0.002 (0.006)
Approved Products	-0.050 (0.056)	-0.105 (0.060)	-0.105 (0.061)	-0.089• (0.042)	-0.041 (0.045)	-0.045 (0.045)
Number of Scientists	-0.228 (0.139)	-0.241 (0.157)	-0.195 (0.153)	0.118 (0.120)	0.152 (0.134)	0.161 (0.138)
Biotech Size	-0.017 (0.102)	0.040 (0.114)	0.087 (0.120)	0.080 (0.103)	0.052 (0.106)	0.027 (0.107)
Biotech Age	-0.055•• (0.021)	-0.073•• (0.024)	-0.070•• (0.024)	-0.007 (0.020)	-0.005 (0.021)	0.001 (0.022)
Previous Alliances	0.617••• (0.128)	0.564••• (0.141)	0.570••• (0.147)	-0.190 (0.140)	-0.261 (0.146)	-0.279• (0.148)
Average Net Sales	0.118••• (0.030)	0.143••• (0.034)	0.136••• (0.035)	0.247••• (0.071)	0.219•• (0.074)	0.243••• (0.077)
Geographical Location	2.079••• (0.282)	2.424••• (0.332)	2.634••• (0.355)	0.524• (0.215)	0.276 (0.229)	0.362 (0.231)
Prior Investments	-0.192••• (0.028)	-0.213••• (0.031)	-0.222••• (0.033)	-0.039 (0.024)	-0.049• (0.025)	-0.064•• (0.026)
CFS Present	0.263 (0.274)	0.580 (0.334)	0.611 (0.340)	-0.112 (0.273)	-0.049 (0.292)	-0.319 (0.318)
Pharma Sales	0.712 ••• (0.152)	0.768••• (0.171)	0.831••• (0.180)	0.275 (0.234)	0.280 (0.242)	0.221 (0.249)
Pharma Size	-0.011• (0.006)	-0.012 (0.007)	-0.014• (0.007)	0.002 (0.007)	0.004 (0.007)	0.004 (0.007)
Postponers	1.045••• (0.249)	1.141••• (0.282)	1.276••• (0.298)	-0.238 (0.196)	-0.234 (0.202)	-0.199 (0.203)
Social Cues	-0.364 •• (0.133)	-0.359•• (0.145)	-0.494•• (0.161)	0.717• (0.289)	0.647• (0.298)	0.569• (0.301)
Average Signing Stage	-0.126 (0.107)	-0.190 (0.126)	-0.147 (0.132)	-0.189 (0.148)	-0.219 (0.155)	-0.325• (0.160)
Probability of Formation				-0.530 (0.508)	-0.447 (0.533)	-0.787 (0.546)
-2 * log likelihood	232.722	206.189	196.319	572.855	541.745	526.456
Δ fit from prior model (χ^2)		26.533•••	9.87•		31.11•••	15.289••

• $p < 0.05$; •• $p < 0.01$; ••• $p < 0.001$; two-tailed tests