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# Contract Theory: Impact on Biopharmaceutical Alliance Structure and Performance

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**Abstract.** Alliances for new product development have been studied extensively in the operations management literature. Alliances between an innovator and a partner create value by utilizing their complementary capabilities. In this paper, we seek to understand what drives the alliance structure: the choice between *collaborative* alliances where the parties exert joint efforts and *sequential* alliances where, for the most part, the partner takes over going forward. Our analysis of a data set of over 2,000 biopharmaceutical alliances reveals our main finding: *a key role of operational choices is to address contract theoretic concerns faced by an alliance*. We also find that aligning the choice with predictions based on contract theory has consequences for performance. Therefore, our analysis not only has descriptive power about the drivers of alliance choice, but also provides valuable insight into the performance and eventual fate of alliances formed.

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**Keywords:** product development and design • technology management and process design • incentives and contracting • contract theory • private information • asymmetric information • holdup • risk aversion • signaling • alliances • biopharmaceuticals

## 1. Introduction

A dominant theme in the operations management (OM) literature on new product development (NPD) alliances is that parties to an alliance face at least one of several contract theoretic concerns. In this paper, we examine whether firms address these concerns by making better choices about the design of the NPD process that determines the structure of the alliance. We further explore the consequences of the choice for performance. To do so, we make use of data from the biopharmaceutical industry, where alliances play a major role.

The importance of the biopharmaceutical industry and of alliances within this industry is evident from various statistics. U.S. spending on biopharmaceutical products in 2015 was $424.8 billion. Three quarters of that value came from on-patent products recently approved by the U.S. Food and Drug Administration (FDA) (Aitken et al. 2016). Over half of all approvals, in turn, are given to alliances (Czerepak and Ryser 2008). Firms form alliances to realize benefits that arise from their complementary capabilities (Doz and Hamel 1998), and they clearly value them. According to our data set of over 2,000 alliances, the average deal value over 2008–2012 was $307 million (standard deviation, $434 million). This observation is consistent with the Thomson Reuters Recap Therapeutic Area Insights (2013), which covers the same period.

We refer to the party that holds the intellectual property rights to an innovation prior to the alliance as the *innovator*, and the party that gets involved once the alliance is formed as the *partner*. After committing such high stakes to an alliance, the two parties cannot afford to mismanage the operational implementation of the NPD process. Indeed, when implementing an alliance, Babler (2010, p. 146) states that the "structure of a relationship should be designed to address the needs of both parties." This view is echoed by Menzel and Xanthopoulos (2012), who suggest that assessing *how to deploy* the skills of both parties is a must for a successful alliance.

We classify the NPD process as either *sequential* or *collaborative*. This classification has implications for how the skills/efforts of the two parties are deployed. We call this set of sequential and collaborative settings the *alliance structure*. A sequential alliance structure refers to an alliance where predominantly an initial set of tasks carried out by an innovator is followed by further development or marketing by a partner such that only one party is exerting most of the efforts at any point in time. In contrast, a collaborative alliance structure implies that once an agreement is signed, efforts are exerted by the two parties concurrently on more equal terms. These are commonly found archetypes of alliance structures in biopharmaceutical alliances. Ionis Pharmaceuticals (2017), for example, describe two types of alliances. Regarding an alliance with Biogen, they state that their partner is "responsible for all global development, regulatory and commercialization activities and costs." Regarding another alliance with AstraZeneca they state "We and AstraZeneca are

also developing IONIS-STAT3-2.5Rx for the treatment of cancer."

Two leading drugs by sales volume provide examples of sequential and collaborative alliance structures respectively. Crestor, targeting high cholesterol, was initially developed by Shionogi of Japan and then licensed to AstraZeneca, who further developed and marketed the product. Plavix, for the treatment of heart disease, was initially discovered by Sanofi-Aventis and codeveloped by Sanofi-Aventis and Bristol-Myers Squibb after the latter joined Sanofi-Aventis as a partner. The annual global sales for the drugs were at $7 and $9 billion, respectively, at their peaks (PMLiVE 2016).

It is evident from these examples that both alliance structures have the potential to attain great success. At the same time, they show that any opportunities that are unnecessarily forgone may present a large opportunity cost. A quarter of alliances in our sample are eventually terminated. To demonstrate the negative impact a termination could potentially have, we provide anecdotal evidence of its share price implications. An alliance between Pfizer and Celldex Therepeutics aiming to develop a therapeutic cancer vaccine was terminated when Pfizer announced that the drug was no longer a strategic priority. Celldex' share price dropped by 26% as a result, despite their announcement that they would continue development on their own (Grogan 2010).

The alliance structure chosen is an important consideration at the formation of the alliance as it may have implications for the effectiveness of the subsequent operations of the alliance. Therefore, our first research question is the following: *What are the drivers of the alliance structure*? Specifically, we want to understand how an innovator and a partner choose to implement their alliance in terms of the NPD process. Do the two parties opt for a collaborative or a sequential alliance structure? And can this choice be informed by contract theory?

Our second research question is the following: *Do misalignments between predictions of alliance structure based on contract theory and the actual alliance structure chosen have an impact on performance*? We note that a focus on terminations as a performance measure presents a conservative test of contract theory predictions compared to other measures of performance. If deviations from contract theory predictions do increase the likelihood of an outcome as severe as alliance termination, they can also be expected to affect performance negatively in alliances that continue to exist.[1]

In this paper, we take a two-step approach in our empirical analysis of alliance structure and alliance performance. First, we develop a model that predicts the choice between collaborative and sequential alliance structures. This model provides insight into whether contract theoretic concerns influence the choice of alliance structure. Second, we investigate whether aligning alliance structure with the prediction of the model has consequences for performance. We do so by analyzing empirical models that predict which alliances are more likely to be terminated. To address endogeneity concerns in the second step of our analysis, we make use of coarsened exact matching (CEM). This is a method that creates a quasi-experimental setting and ensures that observations exposed/not exposed to a causal variable of interest have similar predispositions to the dependent variable.

We make two main contributions to the literature. First, much of the OM literature has focused on either a collaborative or a sequential NPD process but not the choice between the two. In contrast, we demonstrate that the choice between these processes, which determines the structure for an alliance, is consistent with predictions based on contractual hazards often studied in the OM literature: private information, holdup, and risk aversion. Notably, our focus on operational implementation decisions brings the alliance choice question to the operations management domain. Second, our findings also contribute to a growing body of literature in economics, which has found mixed evidence on whether contract choices, rather than operational choices, reflect the predictions of contract theory (Cohen and Siegelman 2010). Importantly, we go one step further than testing for conformity of decisions with contract theory predictions. We investigate the consequences of (mis)alignment between contract theory predictions and the chosen alliance structure on the subsequent performance of alliances. We find that deviating from contract theory predictions increases the probability of termination. Together, our findings suggest that *a key role of operational choices is to address contract theoretic concerns faced by an alliance*.

## 2. Literature Review

Our paper tests whether three contract theoretic concerns guide the choice between collaborative and sequential alliances and whether misalignment with contract theory predictions hinder alliance performance. In doing so, it relates to four streams of literature. First, it relates to the literature on NPD alliances in OM. These papers make use of contract theory to model the interaction between partners. Second, our work relates to papers in economics testing for behavior that is consistent with the presence of a contract theoretic concern. Third, our work relates to papers in strategy and management that study choices between different types of alliances. Fourth, our paper also relates to the literatures on alliance performance and the performance impacts of misaligned governance.

### 2.1. Contract Theory and NPD Alliances

Contract theory addresses concerns that arise as part of the strategic interaction between two parties (e.g., Bolton and Dewatripont 2005, Salanié 2005, Laffont and Martimort 2009). Our paper focuses on private (asymmetric) information, holdup, and risk-aversion concerns. Papers in the OM literature on NPD alliances each address a subset of the above concerns and moral hazard.[2]

Most papers model NPD as a sequential process, where different parties carry out different stages, akin to the sequential alliance structure we have described. Jensen and Thursby (2001) consider the licensing of university technologies to industrial partners and find that equity is more effective than royalties in addressing moral hazard. Savva and Taneri (2015) question why royalties coexist with equity and fixed fees. They show that the use of equity deems royalties a more effective tool against private information. Crama et al. (2008) show that upfront fees, milestones, and royalties can be used to address moral hazard concerns and private information about technical success probability estimates. In a sequential investment game where a provider invests in research effort and a client invests in development effort, Bhattacharya et al. (2015) show that milestones, along with a verifiable signal from the FDA, can address moral hazard, risk aversion, and the holdup problem. Crama et al. (2017) show that control rights, options, and alliance timing can be used to address moral hazard and private information.

Others model NPD as a parallel process, where two parties exert concurrent efforts, akin to the collaborative alliance structure we have described. Bhaskaran and Krishnan (2009) find that the interplay between the type of revenues generated and the type of uncertainties faced determines the choice between innovation sharing and investment sharing, both of which involve a double moral hazard problem. Savva and Scholtes (2014) show that codevelopment can mitigate the risk of inefficient abandonments (holdup) but introduces the risk of the innovator running out of capital. They show that an option to revert to licensing in such a scenario eases the latter concern. Modeling an innovator and a marketer that exert joint efforts in research and development (R&D) and marketing, Xiao and Xu (2012) find that royalty revisions alleviate moral hazard but heighten private information concerns.

In contrast to the prior OM literature, which has focused on addressing contract theoretic concerns within either a sequential or a collaborative framework, we test whether the choice between the two can address contract theoretic concerns.

### 2.2. Literature Testing Contract Theory

Literature in economics has been testing for behavior that is consistent with the predictions of contract theory with data from different sectors. Laffont and Matoussi (1995) find that pure rental agreements where all crop is kept by the tenant/farmer leads to higher yield. This shows evidence of moral hazard. Lazear (2000) also finds support for moral hazard; the introduction of incentive payments increases productivity at an auto glass manufacturer. Finkelstein and McGarry (2006) find evidence for private information along two dimensions: people who know that they have a high probability of needing a nursing home and people who know that they have a lower appetite for risk purchase insurance. However, empirical findings are not always in line with theory. For example, Cawley and Philipson (1999) find no evidence for asymmetric information in the life insurance market. This mixed evidence is also evident in a recent review of papers testing for the moral hazard and private information problems in various insurance markets (Cohen and Siegelman 2010).

Relatively few papers have tested the implications of contract theory in an R&D setting. They focus on the use of long-term versus short-term incentives. Lerner and Wulf (2007) find that long-term incentives for R&D heads have a positive impact on various measures of R&D outcomes, while short-term incentives have little impact. Azoulay et al. (2011) find that life science researchers at an institution that rewards longer-term productivity and tolerates early failure produce high-impact articles at a higher rate than researchers at another institution that has shorter review cycles. In a laboratory setting, Ederer and Manso (2013) also find that long-term incentives and tolerance for early failure induce innovation through exploration.

Our paper extends the literature testing contract theory in various dimensions. We test for multiple contract theoretic concerns with operational decisions in an R&D collaboration setting. We also go one step further by studying the impact of aligning alliance structure with contract theoretic concerns on performance.

### 2.3. Literature on Alliance Choice

Our study tests whether contract theoretic concerns can guide the choice between collaborative and sequential alliances. Choices between different forms of alliances have been studied more widely in the strategy and management literatures. Colombo (2003) finds that firms that are different in terms of technological specialization have a tendency to use equity. Oxley and Sampson (2004) study the choice between contracts and joint ventures and find scope to have an impact on alliance choice. They also study the impact of judicial efficacy and find no significant effect. Villalonga and McGahan (2005) focus on the choice between alliances and other forms of acquiring knowledge. Among others, they find ownership structure to be an important factor.

We add to the alliance choice literature, as the choices studied and the key drivers considered in the

previously mentioned studies are different from our emphasis on operational implementation and contract theory. We also draw on this literature when identifying control variables for our analysis.

### 2.4. Literature on Alliance Performance and Misaligned Governance

Other studies pertain to the performance of alliances. Schilling and Phelps (2007) find that firms embedded in alliance networks that exhibit dense local clustering and high reach have greater innovative output. Anand and Khanna (2000) find that more experience with alliances has an influence on alliance success, as measured by abnormal returns in the stock market. For biotechnology–pharmaceutical alliances, Hoang and Rothaermel (2005) find that the alliance experience of the biotechnology partner positively affects joint project performance, while, interestingly, partner-specific experience has a negative impact. Their performance measure is the launch of a product.

Various studies take a transaction cost economics perspective and find that misaligned governance leads to poor performance (see, e.g., Leiblein et al. 2002, Geyskens et al. 2006, Handley 2016). In the NPD domain, Sampson (2004) finds that deviations from predictions about the choice between equity joint ventures and pooling contracts leads to poorer performance in R&D collaborations. MacCormack and Mishra (2015) find a similar result for the choice between fixed price and time and materials/performance-based contracts.

We add to the alliance performance literature by investigating the impact of a different (mis)alignment: one between contract theoretic concerns and the choice of operational processes for new product development.

In summary, the OM literature on NPD alliances has made use of contract theory, each paper tackling a subset of concerns addressed by contract theory such as private information or the holdup problem. The models in these papers have typically modeled NPD as either a sequential or a collaborative process, but no attention has been paid to the choice between the two. Our study fills this gap in the literature by studying the choice between collaborative and sequential alliances. While the choice of different types of alliances (e.g., equity versus nonequity) has been studied in the strategy and management literatures, the type of NPD process adopted is an operational issue. This brings the alliance choice question to the operations management domain. Empirical research in economics has started to test some implications of contract theory. In an NPD setting, papers have shown better R&D output for long-term incentives. In other contexts, researchers have tested for the presence of contract theoretic concerns such as private information and found mixed evidence. We make three contributions to this literature. First, we test and find support for private information, holdup, and risk aversion. Second, we test whether risk aversion is more of a concern for smaller agents. Third, prior studies test whether decision makers deviate from the predictions of contract theory and provide the results as evidence for or against the presence of contract theoretic concerns. We go one step further. By studying subsequent terminations in addition to the choice of alliance structure, we test both whether decision makers deviate from contract theory predictions and what the performance implications of deviating from contract theory predictions are. This last contribution also adds to the literature on alliance performance and the literature on misaligned governance.

## 3. Hypothesis Development

In this paper, we seek to identify the drivers of alliance structure and alliance performance. Various papers have shown that frictions identified by contract theory such as private information (e.g., Xiao and Xu 2012), the holdup problem (e.g., Bhattacharya et al. 2015), and risk aversion (e.g., Crama et al. 2008) play important roles in NPD alliances.

Central to much of the contract theory literature is the concept of *asymmetric information*. When one party has *private information*, or is better informed than the other, it can use this information to its advantage. Relationships are often hindered by the presence of private information. In his seminal paper, Akerlof (1970) shows that the presence of private information can lead to the collapse of markets, destroying value for all parties involved.

A solution to the problem is proposed by Spence (1973). To address the problem, the holder of private information may be able to carry out an action that credibly conveys, or *signals*, the information it has to the other party. Signals are typically costly, but the cost depends on the type of information held. The party that incurs a lower cost to send the signal can do so and segment the market, thereby alleviating the problem.

Within the context of NPD, private information may be due to differing fields of expertise across firms. When this is the case, a partner may have a relative disadvantage in evaluating the quality of the innovator's research. As biotechnology companies typically have a narrow research niche that may be difficult for others to evaluate, we expect a nonbiotech partner to have concerns about private information—in particular, about the probability of success going forward.

The innovator can solve this problem by sending a credible signal of a high quality product candidate. For a signal to be credible it must cost less for the holder of one type of information compared to the holder of another type (e.g., an innovator with a higher versus lower success probability estimate). Collaborative alliances demand more resources from the innovator than sequential alliances where the partner takes over

going forward. The expected net cost of these additional resources is higher for low success probability innovators, who are less likely to recoup their further investment, compared to high success probability innovators. Therefore, a biotech innovator can signal the quality of its product candidate by continuing its involvement in the project through a collaborative alliance. The lower expected net cost for a high quality product creates a credible signal. In doing so, the innovator would ease the private information concerns of its partner. We therefore expect realized alliances between biotech innovators and nonbiotech partners to have a collaborative structure. This leads to our first hypothesis.

**Hypothesis 1** (Signaling Hypothesis) (H1). *If an alliance involves a biotech innovator engaging with a nonbiotech partner, the alliance will be more likely to adopt a collaborative structure.*

Another key problem addressed by contract theory is the *holdup* problem. This problem occurs when a party to a strategic interaction needs to make upstream investments in relationship-specific assets, while another party, who holds residual control rights, makes downstream decisions. Because the latter party cannot credibly commit to reimburse the former for their investment, the former rightfully worries about being *held up* and either does not make any investment or underinvests (Grossman and Hart 1986). This results in below-par performance.

Contract theory suggests that having the party with a comparative advantage make a relationship-specific investment and allocating residual control rights to them can alleviate the holdup problem (Hart 1995). On the one hand, if one party has a comparative advantage in making remaining investments, the investments should be made by that party, and control rights should be allocated to them. On the other hand, when the two sides have relative advantages in making remaining investments, then joint ownership of residual control rights is in order.

The holdup problem is likely to occur in new product development alliances in the biopharmaceutical industry where investments at any stage of development are relationship specific. For example, the recruitment of patients for clinical trials and the effort scientists put into drug development and the training of employees for the marketing of a specific product are all relationship-specific investments. They have little or no value outside the context of the alliance.

Biopharmaceutical products go through various stages of development starting from formulation, to clinical trials, through to marketing. At the embryonic stages of development, comparative advantage usually lies with the innovator who knows the specific product candidate best. At later stages of development, comparative advantage shifts toward the partner whom we can expect to have more experience with later stage clinical trials and marketing.

Typically, collaborative alliances allocate residual control rights to both the innovator and the partner, while sequential alliances allocate residual control rights to the partner. On the one hand, when an alliance is formed at an early stage of the NPD cycle, there are many steps down the road where either party can have a comparative advantage. On the other hand, when an alliance is formed at a late stage, comparative advantage lies with the partner. Thus, we would expect a collaborative alliance structure in the former case where both parties have control rights, and a sequential alliance structure in the latter where the partner is typically allocated control rights.

**Hypothesis 2** (Holdup Hypothesis) (H2). *The later in the NPD cycle an alliance is formed, the less likely that a collaborative structure will be adopted.*

Risk aversion is another concern addressed by both the general contract theory literature and the operations management literature on new product development (e.g., Bhattacharya et al. 2015). Typically, the agent is modeled as risk averse and the principal as risk neutral.

To address the issue, the principal must make an offer that appeases the risk concerns of the agent by limiting the agent's exposure to risk. Both Salanié (2005) and Laffont and Martimort (2009) show that the more risk aversion is a concern, the more the principal leans toward fixed payments. The degree of concern, in turn, depends on the level of risk and/or the level of risk aversion.

In the operations management literature, Crama et al. (2008) model the innovator as either risk averse or risk neutral, while the partner is assumed to be risk neutral. Similarly, Bhattacharya et al. (2015) model the innovator as risk averse and the partner as risk neutral. The argument they provide for risk-averse innovator firms is that partner firms are typically larger than innovator firms, which allows them to have a larger and more diversified R&D project portfolio. Indeed, Elton and Gruber (1977) show that the risk associated with a portfolio of $N$ assets is decreasing in the number of assets $N$ because of diversification. Having more diversified portfolios puts partner firms in a better position to absorb risk, leading to lower risk aversion. The relationship between firm size and risk aversion can also be inferred from the use of different discount rates to evaluate risky projects. Large pharmaceuticals use much lower discount rates than small biotechnology firms (Villiger and Bogdan 2005). The average partner in our sample is seven times larger than the average

innovator. Therefore, the average innovator may be risk averse when compared to the average partner.

Managers at biopharmaceutical firms have access to historical failure rates for drugs targeting different disease indications. For example, drugs targeting respiratory diseases are half as likely to succeed as those targeting gastrointestinal diseases (DiMasi 2001). The innovator's exposure to further risk can be limited through a sequential alliance, where most of the downstream outlay of efforts and cash are borne by the partner. In contrast, a collaborative alliance requires a higher resource commitment from the innovator, thereby increasing their exposure to risk. Therefore, we expect that alliances with a higher risk of failure will more likely be associated with a sequential alliance structure and will less likely be associated with a collaborative alliance structure.

**Hypothesis 3A** (Risk Hypothesis-A) (H3A). *A higher risk of failure will decrease the probability of a collaborative alliance structure being adopted.*

Hypothesis 3A essentially suggests that if innovators are risk averse, higher risk should lead to a sequential alliance structure. On the flip side, we should also expect that the more risk averse an innovator is, the stronger their preference for a sequential alliance structure will be.

As we can infer from the Elton and Gruber (1977) study, the number of projects in a firm's portfolio should decrease the risk in the overall portfolio. Larger firms, in turn, are more likely to have larger portfolios. Smaller innovators, who cannot diversify away their risk, should have a strong preference for sequential alliances. Larger innovators, who can diversify away their risk (much like their partners), should have a weaker preference for sequential alliance structures. Therefore, the size of the innovator firm should moderate the effect of risk.

**Hypothesis 3B** (Risk Hypothesis-B) (H3B). *The smaller the innovator, the more pronounced the negative effect of risk on the adoption of a collaborative alliance structure will be.*

We further note that papers in the OM literature on R&D alliances have adopted different approaches when modeling the utility of the innovator. While all papers agree that the partner should be modeled as a risk-neutral agent, there does not seem to be consensus about whether the innovator should be modeled as risk averse or risk neutral. For instance, both Bhattacharya et al. (2015) and Crama et al. (2017) model the partner as risk neutral. The former models the innovator as risk averse. The latter models the innovator as risk neutral. Testing Hypotheses 3A and 3B will therefore also inform modeling choices in the OM literature.

The first set of hypotheses are about the use of alliance structure to address contract theoretic concerns faced by the innovator and the partner. These hypotheses will be tested with a binary choice model predicting the outcomes collaborative (1) versus sequential (0). The actual choice may be the same as or the opposite of the predicted value.

So far, we have argued that the choice matters because the choice allows the parties to address a variety of concerns identified by contract theory. Consequently, our final hypothesis suggests that not aligning alliance structure with the contract theoretic concerns faced by the alliance should lead to poorer performance. In its most severe form, this should lead to the termination of the alliance.

**Hypothesis 4** (Structural Alignment Hypothesis) (H4). *When the choice of the two parties is different from the prediction of the proposed alliance structure model, the probability of a termination will be higher.*

## 4. Data Set and Variables

Our data set consists of 2,892, single-stage biopharmaceutical licenses for which the deal size was reported in the Reuters Recap Database. The analysis was limited to alliances that were formed between 1990 and the first quarter of 2014. We removed alliances that involve more than two parties, universities, hospitals, and nonprofit organizations. We were left with 2,435 data points. Of the remaining company-to-company alliances, we were unable to find some of the company-specific information for at least one of the two parties in 330 alliances. This left us with a final data set of 2,105 alliances.

Of the final data set, 984 alliances adopted a collaborative alliance structure and 1,121 adopted a sequential structure. Company-specific information such as the number of employees or ownership structure were obtained from official websites of companies, annual reports, and online company profiles (e.g., *BusinessWeek*, Bloomberg, *Financial Times*, or LinkedIn). Data on the strength of property laws in different countries are from a data set by the Heritage Foundation and the *Wall Street Journal*. All other variables are from the Reuters Recap Database. For both collaborative and sequential alliances, the database classifies parties forming an alliance as licensors and licensees. When we refer to innovators in our hypotheses or variables, this maps onto licensors in the database. The same is true for partners and licensees.

A description of the dependent and independent variables is given in Table 1, and summary statistics for the same set of variables are given in Table 2. We include a categorical variable, *partnerID*, for any partner that appears 25 times or more in the database. We label these 13 companies with the numbers 1 through 13 rather than list their names to avoid any inference about

**Table 1.** Dependent and Independent Variable Descriptions

| Variable | Description |
|---|---|
| *collaborative* (dependent variable) | Indicates whether an alliance has a collaborative alliance structure (1) or a sequential alliance structure (0). In addition to being classified as licensing agreements, the alliances that involve joint efforts by the two parties are listed as copromotion, comarketing, collaboration, or codevelopment agreements by the Reuters Recap Database. We classify all such alliances as collaborative (1) and others as sequential (0). |
| *terminated* (dependent variable) | Indicates whether the alliance was terminated (1) or otherwise (0) |
| *year* | Indicates the year when an alliance was formed |
| *deal_size* | The value, in U.S. dollars (millions), of upfront and milestone payments as part of the alliance |
| *exclusive* | Indicates whether an alliance involves an exclusive license (1) or a nonexclusive license, which allows the innovator to license out to other partners (0) |
| *worldwide* | Indicates whether an alliance involves a license with worldwide coverage (1) or otherwise (0) |
| *innov_size* | Natural logarithm of the number of people employed by the innovator |
| *innov_private* | Indicates whether the innovator is privately owned (1) or publicly owned (0) |
| *partner_size* | Natural logarithm of the number of people employed by the partner |
| *partner_private* | Indicates whether the partner is privately owned (1) or publicly owned (0) |
| *alliance_experience* | Gives the number of alliances that the partner has been involved with |
| *innov_law_score* | Gives the property rights score of the country where the innovator is based |
| *part_law_score* | Gives the property rights score of the country where the partner is based |
| *relative_industry_exp* | Year innovator was founded – Year partner was founded |
| *diff_country* | Indicates whether the innovator and partner are based in different countries (1) or otherwise (0) |
| *bio_to_other* (H1) | Indicates whether the innovator is a biotechnology company while the partner is not (1) or otherwise (0) |
| *npd_cycle* (H2) | The stage within the new product development cycle ranging from formulation (1) to approved/marketing (9) (scale: formulation (1), discovery (2), lead molecule (3), preclinical (4), Phase I (5), Phase II (6), Phase III (7), BLA/NDA filed (8), and approved/marketing (9)) |
| *risk* (H3) | The probability that the alliance fails in all therapeutic areas that it targets |

*Note*. BLA, biologics license; NDA, new drug application.

**Table 2.** Summary Statistics for Dependent and Independent Variables

| Variable | Mean | Std. dev. | Min. | Max. |
|---|---|---|---|---|
| *collaborative* | 0.467 | 0.499 | 0 | 1 |
| *terminated* | 0.201 | 0.401 | 0 | 1 |
| *year* | 2002.098 | 5.967 | 1990 | 2014 |
| *deal_size* | 129.738 | 314.249 | 0 | 6,900 |
| *exclusive* | 0.641 | 0.48 | 0 | 1 |
| *worldwide* | 0.477 | 0.5 | 0 | 1 |
| *innov_size* | 5.151 | 2.33 | 0 | 11.813 |
| *innov_private* | 0.256 | 0.437 | 0 | 1 |
| *partner_size* | 8.42957 | 2.825006 | 0 | 11.91839 |
| *partner_private* | 0.222 | 0.416 | 0 | 1 |
| *alliance_experience* | 24.85 | 30.276 | 1 | 108 |
| *innov_law_score* | 84.44656 | 5.742421 | 10 | 95 |
| *part_law_score* | 83.76722 | 7.445172 | 20 | 90 |
| *relative_industry_exp* | 38.51 | 71.848 | −344 | 342 |
| *diff_country* | 0.515 | 0.5 | 0 | 1 |
| *bio_to_other* | 0.537 | 0.499 | 0 | 1 |
| *risk* | 0.78 | 0.098 | 0.272 | 0.883 |
| *npd_cycle* | 4.051 | 2.322 | 1 | 9 |

**Table 3.** Summary Statistics for Cluster Variables

| Partner ID | Mean | Std. dev. | Min. | Max. |
|---|---|---|---|---|
| *partnerID = 1* | 0.0304038 | 0.1717365 | 0 | 1 |
| *partnerID = 2* | 0.0289786 | 0.1677863 | 0 | 1 |
| *partnerID = 3* | 0.016152 | 0.12609 | 0 | 1 |
| *partnerID = 4* | 0.039905 | 0.1957825 | 0 | 1 |
| *partnerID = 5* | 0.0513064 | 0.2206744 | 0 | 1 |
| *partnerID = 6* | 0.0247031 | 0.1552556 | 0 | 1 |
| *partnerID = 7* | 0.0137767 | 0.1165907 | 0 | 1 |
| *partnerID = 8* | 0.0123515 | 0.1104753 | 0 | 1 |
| *partnerID = 9* | 0.0228029 | 0.14931 | 0 | 1 |
| *partnerID = 10* | 0.015677 | 0.1242519 | 0 | 1 |
| *partnerID = 11* | 0.0223278 | 0.1477824 | 0 | 1 |
| *partnerID = 12* | 0.0266033 | 0.1609593 | 0 | 1 |
| *partnerID = 13* | 0.023753 | 0.1523148 | 0 | 1 |

the alliance performance of specific companies. Summary statistics for these 13 companies are provided in Table 3. As many companies appear repeatedly but not in all years, we note that we have an unbalanced longitudinal data set. We focus on the 13 partners that appear at least once a year on average, i.e., 25 times or more over the time span of the data set, and also note that many of these companies appear multiple times not just across years but also within years.

While the descriptions provided in Table 1 are self explanatory for most variables, we provide more detail on the variable *risk*. Based on U.S. marketing approvals, DiMasi (2001) reports typical success probabilities, $p_j$, for therapeutic areas $j$, where $j$ is one of the therapeutic areas anti-infective, antineoplastic, cardiovascular, central nervous system, endocrine, gastrointestinal, immunologic, respiratory, or miscellaneous. Alliances in our data set may target one or more therapeutic areas. For those that target a single therapeutic area, we

define a risk measure $f_j = 1 - p_j$, which gives the probability of failure for that therapeutic area. For alliances that target more than one therapeutic area, we use the risk measure $\prod_j f_j$ for all $j$ targeted by the alliance, which gives the product of the failure probabilities for each therapeutic area targeted, or the probability that the alliance fails for all therapeutic areas targeted, assuming that the failure probabilities across therapeutic areas are independent. We also note that DiMasi (2001) reports current and maximum possible success rates for each of the therapeutic categories. When the two are equal (due to no continuing development) we use the current value. When the maximum possible is higher (due to continuing development) we use the midpoint of the two probabilities reported.

We report pairwise correlation coefficients across the independent variables and their significance levels in the online appendix. None of the correlation coefficients are worryingly high.

## 5. Results

We split our results according to the two research questions: (1) What are the drivers of alliance structure and can contract theory inform the choice? (2) Does deviating from predictions of alliance structure based on contract theory have implications for performance?

### 5.1. Models for Alliance Structure

The dependent variable in the first step of our analysis is a binary outcome indicating whether the companies in an alliance opted for a collaborative or sequential structure, coded as 1 and 0, respectively. We use a mixed effects logistic regression model that allows for random intercepts for partner IDs. This multilevel approach allows for the analysis of alliances at a lower level, which are nested within aggregate clusters of observations for partners at a higher level. For multinomial choices, McFadden and Train (2000) show that the mixed logit model can approximate any choice model, while the reverse is not true. Indeed, likelihood ratio tests reveal that mixed effects logistic regression models are a better fit than logistic regression for all five models estimated in Table 4.

The sequence of models in Table 4 explains the choice of alliance structure. Model 1 includes a variable for trend only. Model 2 introduces control variables for innovator, partner, and deal characteristics. Model 3 introduces relative characteristics for the two parties and measures of property rights for the countries where they are headquartered. Model 4 introduces variables that test hypotheses regarding the implications of contract theory. Model 5 introduces an interaction term that allows us to test the moderating effect of innovator firm size on the effect of risk.

We first note that three of the control variables—*deal_size*, which gives the value of the transaction in millions of dollars; *exclusive*, which indicates whether or not the license is exclusive; and *partner_size*, which gives the natural logarithm of the number of people employed by the partner—are all consistently significant across all models. All three variables are positively associated with a collaborative structure. These results suggest that for more valuable alliances, the innovator continues to be involved, that innovators are more willing to grant exclusive licenses when they continue to be involved in further efforts, and that larger partners tend to be involved in collaborative alliances.

We now discuss hypotheses (H1, H2, and H3A) that test the implications of contract theory for alliance structure based on the results of Model 4 of Table 4. The first hypothesis suggests that differing R&D expertise across the two parties forming an alliance leads to asymmetric information. Asymmetric information will be more of a concern for alliances that involve a biotech innovator with highly specialized research skills interacting with a nonbiotech partner. Contract theory indicates that when this is the case, an informed party who incurs a lower cost to send a signal can do so and credibly convey their information. Collaborative alliances require further resources from the innovator but a high-success-probability innovator has a higher chance of recouping its investment, which makes the expected net cost lower. Such an innovator can signal the quality of its innovation by opting for a collaborative alliance structure. Therefore, when the innovator is a biotech while the partner is not, we expect that the alliance will more likely be structured as a collaborative alliance. The coefficient of the variable *bio_to_other* is positive and significant at the 1% level. This provides strong support for the first (signaling) hypothesis.

The second hypothesis is about the holdup problem. Contract theory suggests that the allocation of residual control rights to the party who has a comparative advantage in exerting efforts required going forward can alleviate the holdup problem. An innovator is likely to have a comparative advantage in early stage research, while a partner is likely to have a comparative advantage in larger scale, later stage confirmatory clinical trials and marketing. For an early stage alliance, all of these steps lie ahead, and it is beneficial for the two parties to share control rights. When the alliance is formed at a later stage of the NPD cycle and the product moves closer to market, the comparative advantage balance shifts toward the partner, and it becomes more beneficial to assign control rights to the partner. This indicates a collaborative alliance structure for earlier stages of the new product development cycle and a sequential alliance structure as one moves through stages. We find that the coefficient for the variable *npd_cycle* has the expected negative sign and is significant at the 0.1% level, providing strong support for the second (holdup) hypothesis.

**Table 4.** Models for Alliance Structure (Dependent Variable: *collaborative*)

| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 |
|---|---|---|---|---|---|
| *year* | 0.0257*** | −0.0045 | −0.0029 | 0.0111 | 0.0107 |
| | (0.0077) | (0.0090) | (0.0091) | (0.0095) | (0.0095) |
| *deal_value* | | 0.0025*** | 0.0025*** | 0.0027*** | 0.0027*** |
| | | (0.0004) | (0.0004) | (0.0004) | (0.0004) |
| *exclusive* | | 0.2492* | 0.2456* | 0.4285*** | 0.4255*** |
| | | (0.1086) | (0.1098) | (0.1168) | (0.1170) |
| *worldwide* | | 0.2891** | 0.3010** | 0.1038 | 0.1000 |
| | | (0.1041) | (0.1061) | (0.1127) | (0.1128) |
| *innov_size* | | −0.0441* | −0.0318 | −0.0062 | −0.2767 |
| | | (0.0212) | (0.0227) | (0.0236) | (0.1817) |
| *innov_private* | | 0.0891 | 0.0827 | 0.0399 | 0.0413 |
| | | (0.1101) | (0.1105) | (0.1125) | (0.1126) |
| *partner_size* | | 0.1551*** | 0.1329*** | 0.1137*** | 0.1143*** |
| | | (0.0243) | (0.0266) | (0.0282) | (0.0282) |
| *partner_private* | | 0.1345 | 0.1223 | 0.1106 | 0.1053 |
| | | (0.1195) | (0.1201) | (0.1222) | (0.1223) |
| *alliance_experience* | | 0.0005 | −0.0002 | −0.0012 | −0.0014 |
| | | (0.0051) | (0.0051) | (0.0052) | (0.0052) |
| *innov_law_score* | | | 0.0030 | 0.0041 | 0.0045 |
| | | | (0.0088) | (0.0090) | (0.0090) |
| *part_law_score* | | | 0.0085 | 0.0061 | 0.0062 |
| | | | (0.0071) | (0.0073) | (0.0073) |
| *relative_industry_exp* | | | 0.0020* | 0.0012 | 0.0011 |
| | | | (0.0009) | (0.0009) | (0.0009) |
| *diff_country* | | | 0.0935 | 0.0861 | 0.0868 |
| | | | (0.1011) | (0.1035) | (0.1036) |
| *bio_to_other* (H1) | | | | 0.3666** | 0.3715** |
| | | | | (0.1222) | (0.1223) |
| *npd_cycle* (H2) | | | | −0.1666*** | −0.1662*** |
| | | | | (0.0244) | (0.0244) |
| *risk* (H3A) | | | | −1.6947*** | −3.5037** |
| | | | | (0.5051) | (1.3078) |
| *risk* × *innov_size* (H3B) | | | | | 0.3471 |
| | | | | | (0.2309) |
| *_cons* | −51.1579*** | 7.1156 | 3.0414 | −23.1171 | −21.0085 |
| | (15.3499) | (18.0100) | (18.4427) | (19.0991) | (19.1937) |
| *N* | 2,105 | 2,105 | 2,105 | 2,105 | 2,105 |
| Log likelihood | −1411.7655 | −1311.2344 | −1307.7704 | −1275.4147 | −1274.2739 |
| $\chi^2$ | 11.2485 | 157.8733 | 163.4606 | 208.0863 | 210.0258 |
| Likelihood ratio test *p*-value | 0.0000 | 0.0008 | 0.0023 | 0.0027 | 0.0024 |
| Pseudo-$R^2$ [a] | 0.0423 | 0.1101 | 0.1126 | 0.1349 | 0.1357 |

*Notes.* Standard errors are in parentheses.

[a]Pseudo-$R^2$ values are not available for mixed effects models. We report values from corresponding logistic regressions.

*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

Hypothesis 3A relates to an inherent characteristic of one of the parties involved in the alliance. When the risk aversion of the innovator is of key concern, the innovator's exposure to further risk can be limited through a sequential alliance. Risk aversion will be more of a concern when the level of risk associated with the alliance is high. Therefore, the higher the risk, the less likely that we will have a collaborative alliance structure. Indeed, the coefficient for the variable *risk* has a negative sign and is significant at the 0.1% level, providing strong support for Hypothesis 3A.

Hypothesis 3B also relates to the effect of risk but introduces an interaction term to test for the moderating effect of innovator firm size. In Model 5, we introduce the interaction term *risk* × *innov_size* to test this hypothesis. We had argued that innovator firms are typically smaller than partner firms, and because smaller firms cannot diversify away their risk, innovator firms should exhibit more risk aversion than their partners. If this holds between an innovator and a partner, the level of risk aversion should also be different across innovators of different size. Rather than make

an argument about the level of risk, this hypothesis suggests that the more risk averse an innovator is, the more important the risk element of the alliance will be. While we should still expect risk to have a negative impact for the choice of a collaborative alliance structure, this effect should be moderated by the size of the innovator firm. This suggests that the variable *risk* should still have a negative sign, but the interaction term *risk* × *innov_size* should have a positive sign. We can see from Model 5 that both of these variables have the expected sign. In a review of studies employing interaction terms, Brambor et al. (2006) suggest that authors should (a) include the interaction term and the two constituent variables in their regressions, and (b) check the significance of meaningful marginal effects rather than the significance of the coefficients. In particular, they emphasize the analysis of marginal effects for the variable of interest (*risk* in our case) when holding the modifying variable (*innov_size* in our case) constant at different values. In Table 5, we report the marginal effects w.r.t. *risk* when *innov_size* is held constant at its mean, mean ± 1 standard deviation, and mean ± 2 standard deviations. We can make three observations from this table. First, the marginal effect of risk is negative for all five values at which the modifying variable is held constant. Second, the effect of risk is more pronounced for smaller innovators than for larger innovators. Third, the effect is significant at the 1% level when innovator size is at its mean or lower, but insignificant when innovator size is larger. Taken together, these findings provide support for Hypothesis 3B. Risk aversion, and therefore project risk, is a more important factor when forming alliances with smaller innovators.

Taken together, Hypotheses 3A and 3B also have implications for modeling choices of researchers. Some papers in the literature model both parties as risk neutral, while others model the innovator as risk averse. Hypothesis 3A suggests that innovators are indeed risk averse. Hypothesis 3B suggests that this risk aversion depends on firm size, with many innovators in biopharmaceutical alliances being risk averse but larger innovators not so.

The analysis in Table 4 only gives us directional effects. The marginal effects for the significant variables in Model 5 of Table 4 are reported in Table 6. They tell us how the probability of forming a collaborative alliance changes when one variable is varied (either from its own mean or from zero for a binary variable) while all other variables are held constant at their means.

First of all, note that all of the marginal effects are significant. We can see from these results that two binary variables have a large impact on the forming of collaborative alliances. When an exclusive license is involved, this increases the chance of a collaborative alliance, in absolute terms, by about 10%. Alliances that involve a biotechnology company as the innovator and a firm that is not a biotechnology company as the partner have a 9% higher chance of forming a collaborative alliance. Alliances that involve larger transactions in terms of money transfer from one party to the other are more likely to be collaborative; an additional $100,000,000 of value implies a 6% higher chance of a collaborative structure. We remind the reader here that the average deal size for our sample is about $130,000,000 with a standard deviation in excess of $300,000,000. In an alliance for which the risk of failure

**Table 5.** Marginal Effects: *collaborative* w.r.t. *risk* When *innov_size* Held Constant

| *innov_size* held constant at | *dy/dx* | Std. err. | *z* | $P > \|z\|$ | [95% conf. interval] | |
|---|---|---|---|---|---|---|
| Mean − 2 s.d. | −0.7800017 | 0.2829742 | −2.76 | 0.006 | −1.334621 | −0.2253826 |
| Mean − 1 s.d. | −0.5898632 | 0.1765074 | −3.34 | 0.001 | −0.9358113 | −0.2439151 |
| Mean | −0.4002549 | 0.1188998 | −3.37 | 0.001 | −0.6332943 | −0.1672155 |
| Mean + 1 s.d. | −0.2112243 | 0.1694498 | −1.25 | 0.213 | −0.5433399 | 0.1208913 |
| Mean + 2 s.d. | −0.0228182 | 0.2730681 | −0.08 | 0.933 | −0.5580219 | 0.5123854 |

*Note.* The table shows marginal effects calculated when all other variables are held constant at their means.

**Table 6.** Marginal Effects for Significant Variables: Model 5 of Table 4

| Variable | *dy/dx* | Std. err. | *z* | $P > \|z\|$ | [95% conf. interval] | |
|---|---|---|---|---|---|---|
| *deal_value* | 0.0006317 | 0.0000839 | 7.53 | 0.000 | 0.0004673 | 0.0007962 |
| *exclusive* | 0.099265 | 0.0275063 | 3.61 | 0.000 | 0.0453535 | 0.1531764 |
| *partner_size* | 0.0266615 | 0.0067017 | 3.98 | 0.000 | 0.0135263 | 0.0397966 |
| *bio_to_other* | 0.0866554 | 0.0284836 | 3.04 | 0.002 | 0.0308286 | 0.1424821 |
| *npd_cycle* | −0.0387596 | 0.0056655 | −6.84 | 0.000 | −0.0498638 | −0.0276554 |
| *risk* | −0.4002549 | 0.1188998 | −3.37 | 0.001 | −0.6332943 | −0.1672155 |

*Note.* The table shows marginal effects calculated when all other variables are held constant at their means.

**Table 7.** Classification Table for Model 5 of Table 4

| | Predicted | | |
|---|---|---|---|
| | Collaborative | Sequential | Total |
| Actual | | | |
| Collaborative | 600 | 384 | 984 |
| Sequential | 265 | 856 | 1,121 |
| Total | 865 | 1,240 | 2,105 |

is 10% higher in absolute terms, the chance of a collaborative alliance is 4% lower. Alliances that are formed one stage later in the new product development cycle are about 4% less likely to have a collaborative structure. A 1% increase in the number of employees for the partner leads to a 3% higher chance of a collaborative alliance structure.

Table 7 provides information on the predictive power of our model. We follow accepted convention and classify a prediction as collaborative when the predicted probability of a collaborative alliance is greater than 0.5 and as sequential otherwise. The overall probability of a collaborative alliance is 0.467, while the conditional probability that the actual alliance structure is collaborative given that the prediction is collaborative is $P(\text{col} \mid \text{pred\_col}) = 0.694$. Similarly, the overall probability of a sequential alliance is 0.533, while $P(\text{seq} \mid \text{pred\_seq}) = 0.690$. The overall probability of a correct prediction is 0.692. This is a 38% improvement over a model that allocates predictions based on the probabilities 0.467 and 0.533 for collaborative and sequential alliances, respectively.

### 5.2. Models for Alliance Performance

Our analysis so far indicates that companies should and often do align alliance structure with concerns addressed by contract theory. In this section, we test whether deviating from the "recommended" alliance structure has consequences for performance.

In addition to the type of alliance formed, Recap also lists whether alliances have been terminated. We want to know whether insisting on one type of alliance structure while our alliance structure model implies the other leads to more frequent termination of alliances. We assume that a termination is a negative outcome for three reasons. First, the risk of termination is accepted as a potential downside of working with a partner in the biopharmaceutical industry. Bogdan and Villiger (2008, p. 169) note that a partner, despite alliance benefits, adds the risk that "the project is halted even if there are no concerns related to safety and efficacy." Second, while an alliance can end because of an acquisition, these are indicated in the database with the acronym "acq," as opposed to "ter," which reassures us that terminations, as indicated in our database, are negative outcomes. Third, we observe anecdotal evidence that terminations lead to falls in share prices for public firms.

The dependent variable in the second step of our analysis is a binary outcome indicating whether a termination has been observed for an alliance. Alliances that were terminated are coded as 1, and others are coded as 0. The explanatory variable of interest, denoted by $D$, indicates whether the two parties chose the alliance structure indicated by Model 5 of Table 4 (0) or deviated from the suggested alliance structure (1). In the remainder of this paper, we call the group of alliances for which the variable $D$ takes on the value 1 the treated or treatment group and the remaining observations the control group. As the value of $D$ is a result of the two parties' choice, it is subject to an endogeneity problem that could lead to biases in estimates. We are interested in estimating

$$terminated(Y_i) = \alpha + \beta' X_i + \delta D_i + \epsilon_i,$$

and particularly the sign of the coefficient $\delta$, or the effect of the treatment on terminations.[3] The problem is that, with a simple binary choice model, the estimate for $\delta$ would be inconsistent and biased because $D$ is correlated with the error term $\epsilon$ (Kennedy 2008).

To address the issue, we make use of coarsened exact matching. This method nonparametrically balances the variables in $X$ across treated and control groups (Iacus et al. 2012, 2011). In doing so, the method drops observations from the sample of $X$ and $Y$ until the remaining distribution of $X$ is equivalent for both the treatment and control cases (Morgan and Winship 2014). This creates distinct strata for which treated and control groups are comparable on observable characteristics, which ensures that both the treated and control groups have similar predispositions to terminations. The impact of the treatment is revealed by comparing treated alliances with control alliances in the same strata. When sufficient balancing across the treated and control groups is achieved, the estimated effect, $\delta$, can be attributed solely to the effect of the treatment: a deviation from the recommended alliance structure in our case.

Making use of CEM as an effective method for addressing endogeneity is a recent trend across fields (e.g., Aggarwal and Hsu 2013, Azoulay et al. 2013, Feldman et al. 2016, Hallen et al. 2014, Kim and King 2014). In effect, CEM creates a quasi-experimental setting by sampling comparable treatment and control cases from a larger pool of data before running commonly accepted parametric analyses. The method has also been adopted in healthcare where, traditionally, randomized experiments are used to identify the effects of treatments. CEM has been used to analyze the effect of a treatment variable in cases where an analysis

was to be done ex post so a fully randomized experiment could not be designed. For instance, Obermeyer et al. (2014) analyze the impact of opting for hospice care on healthcare utilization and cost.

When choosing which explanatory variables to match the control and treatment groups across, one needs to make trade-offs between the number of variables chosen and the number of observations remaining. Matching across more variables creates a closer match between the control and treatment groups but reduces the number of observations remaining. Initially, we match control and treated cases across the following variables: (1) *year*, (2) *bio_to_other*, (3) *exclusive*, (4) *worldwide*, (5) *innov_private*, and (6) *npd_cycle*. These variables were chosen because they are either binary or ordered variables, which facilitates the matching process. The ordered variables are coarsened by the matching algorithm to create strata within which the treated and control groups match. We make use of the matching algorithm in Blackwell et al. (2009). As a robustness check, we also compare our results to models where continuous variables were coarsened and included in the analysis. This leads to very similar results as reported in the next section.

As the dependent variable, *terminated*, is binary, we use a logistic regression model with cluster robust standard errors and partner fixed effects to predict terminations. When analyzing matched data, observations are weighted according to the size of their strata (Blackwell et al. 2009). We note that the mixed effects logistic regression model cannot be used, as the associated Stata command does not allow for weights, while the command for logistic regression does.

Before reporting results, we note that drug development is a lengthy process, often taking about 10 years from lab bench to product launch. While our data set covers alliances formed as recently as 2014, terminations may happen long after an alliance is formed. To avoid censoring problems, we only considered alliances formed between 1990 and 2004. This gave us a total of 1,332 alliances, of which 320 (24%) were terminated. The effect of censoring was immediately apparent. For the remaining 773 alliances in the period 2005–2014, we observed 103 terminations (13%).

Models in Table 8 pertain to Hypothesis 4 on alliance performance. Models 1 and 2 are run with a matched sample, while Models 3 and 4 are corresponding models with the full sample and no matching. Model 1 includes only the treatment variable $D$ and partner fixed effects. Model 2 includes the treatment variable $D$ along with all other explanatory variables. The coefficient for the treatment variable is positive and significant at the 0.1% level, providing strong support for our structural alignment hypothesis. This suggests that deviations from the recommendation of Model 5 of Table 4 increase the risk that an alliance will be terminated. Furthermore, comparing these results to Models 3 and 4, we can see that the effect of the treatment would have been biased downward without matching. Combined with the previous hypotheses tested, the test of our final hypothesis shows that our analysis not only has descriptive power about the drivers of alliance choice, but also provides valuable insight into the performance and eventual fate of alliances formed.

**Table 8.** Logistic Regression Models for Alliance Performance (Dependent Variable: *terminated*)

| | Model 1 CEM | Model 2 CEM | Model 3 No CEM | Model 4 No CEM |
|---|---|---|---|---|
| *D* | 0.5568*** | 0.6835*** | 0.3340** | 0.3464** |
| | (0.1190) | (0.1390) | (0.1222) | (0.1181) |
| *year* | | −0.0239 | | −0.0703*** |
| | | (0.0151) | | (0.0131) |
| *deal_value* | | 0.0025 | | 0.0014 |
| | | (0.0026) | | (0.0009) |
| *exclusive* | | 1.5179*** | | 0.7494*** |
| | | (0.3593) | | (0.1511) |
| *worldwide* | | −0.5571* | | −0.3236* |
| | | (0.2789) | | (0.1272) |
| *innov_size* | | −0.1522 | | −0.1087 |
| | | (0.1802) | | (0.1071) |
| *innov_private* | | −1.1398** | | −0.6785*** |
| | | (0.3745) | | (0.1445) |
| *partner_size* | | 0.1216** | | 0.0618** |
| | | (0.0437) | | (0.0218) |
| *partner_private* | | 0.0267 | | 0.0531 |
| | | (0.1677) | | (0.1852) |
| *alliance_experience* | | 0.0061 | | −0.0018 |
| | | (0.0106) | | (0.0043) |
| *innov_law_score* | | −0.0139 | | −0.0044 |
| | | (0.0127) | | (0.0097) |
| *part_law_score* | | 0.0521** | | 0.0254 |
| | | (0.0175) | | (0.0140) |
| *relative_industry_exp* | | −0.0004 | | 0.0019 |
| | | (0.0018) | | (0.0015) |
| *diff_country* | | −0.3273** | | −0.0999 |
| | | (0.1256) | | (0.1305) |
| *bio_to_other* | | 0.8421*** | | 0.6084*** |
| | | (0.1733) | | (0.1318) |
| *npd_cycle* | | 0.1420** | | 0.1352*** |
| | | (0.0455) | | (0.0215) |
| *risk* | | −3.0874* | | −1.3040 |
| | | (1.2418) | | (1.3154) |
| *risk × innov_size* | | 0.0943 | | −0.0055 |
| | | (0.1562) | | (0.1134) |
| *_cons* | −1.5846*** | 43.3097 | −1.3927*** | 137.3896*** |
| | (0.0584) | (31.1774) | (0.0438) | (26.4330) |
| Partner FE | Incl. | Incl. | Incl. | Incl. |
| *N* | 734 | 734 | 1,326 | 1,326 |
| Log likelihood | −374.1942 | −310.1385 | −714.8290 | −644.9973 |
| Pseudo-$R^2$ | 0.0516 | 0.2140 | 0.0245 | 0.1198 |

*Notes.* Standard errors are in parentheses.
*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

**Table 9.** Marginal Effects for Significant Variables: Model 2 of Table 8

| Variable | *dy/dx* | Std. err. | *z* | $P > \|z\|$ | [95% conf. interval] | |
|---|---|---|---|---|---|---|
| *D* | 0.0921867 | 0.0179015 | 5.15 | 0.000 | 0.0571005 | 0.1272729 |
| *exclusive* | 0.2047171 | 0.0471409 | 4.34 | 0.000 | 0.1123227 | 0.2971115 |
| *worldwide* | −0.0751408 | 0.0374524 | −2.01 | 0.045 | −0.1485461 | −0.0017355 |
| *innov_private* | −0.1537181 | 0.0488456 | −3.15 | 0.002 | −0.2494537 | −0.0579825 |
| *partner_size* | 0.0163938 | 0.006013 | 2.73 | 0.006 | 0.0046085 | 0.0281791 |
| *part_law_score* | 0.0070205 | 0.0022949 | 3.06 | 0.002 | 0.0025226 | 0.0115184 |
| *diff_country* | −0.0441462 | 0.017185 | −2.57 | 0.010 | −0.0778281 | −0.0104643 |
| *bio_to_other* | 0.1135749 | 0.0227423 | 4.99 | 0.000 | 0.0690007 | 0.158149 |
| *npd_cycle* | 0.0191502 | 0.0063066 | 3.04 | 0.002 | 0.0067895 | 0.0315109 |
| *risk* | −0.352299 | 0.090945 | −3.87 | 0.000 | −0.530548 | −0.17405 |

*Note.* Marginal effects calculated when all other variables held constant at their means.

Table 9 lists the marginal effects for significant variables in Model 2 of Table 8. First and foremost, we would like to point out that deviating from the prediction of our model for alliance structure has substantial consequences. The average effect of a deviation when other variables are held constant at their means is a 9% increase in the probability of a termination in absolute terms. This is a noteworthy impact on performance considering that the probability of termination is 24% overall. Exclusive agreements are 20% more likely to be terminated, and the involvement of a privately owned innovator reduces the chance of termination by 15%. Our proxy for asymmetric information problems, an agreement where the innovator is a biotech while the partner is not, leads to an 11% increase in the probability of a termination. Worldwide agreements (as opposed to regional agreements) lead to an 8% lower probability of a termination. A 1% increase in the number of people employed by the partner leads to a 1.6% higher chance of termination, and each additional stage in the NPD cycle increases the likelihood of termination by about 2%. When the two firms are based in different countries, this decreases the likelihood of a termination by 4%. An alliance that has a 10% higher risk of failure is about 4% less likely to be terminated by the parties involved. Each point increase in the property rights score of the country where the partner is based leads to a 0.7% increase in the probability of a termination.

We can infer from Table 10 that the overall probability of a termination is 0.237, while the conditional probability that the actual alliance is terminated given that the prediction is terminated is $P(\text{terminated} \mid \text{pred\_terminated}) = 0.618$. Similarly, the overall probability of an alliance not being terminated is 0.768 while $P(\text{not\_terminated} \mid \text{pred\_not\_terminated}) = 0.807$. The probability of a correct prediction is 0.787. This is a 23% improvement over a model that allocates predictions based on the probabilities 0.237 and 0.763 of being terminated and not being terminated, respectively.

**Table 10.** Classification Table for Model 2 of Table 8

| | Predicted | | |
|---|---|---|---|
| | Terminated | Not | Total |
| Actual | | | |
| Terminated | 47 | 127 | 174 |
| Not | 29 | 531 | 560 |
| Total | 76 | 658 | 734 |

## 6. Robustness Checks

In Table A.1 in the appendix, we provide robustness checks regarding our model specification choices. For ease of comparison, Model 1 of Table A.1 replicates the main alliance structure model: Model 5 of Table 4. Model 2 is a random effects regression. We can see that the results are qualitatively very similar. Models 3 and 4 provide an alternative test of Hypothesis 3B. Instead of using an interaction term, these models analyze subsamples of small and large innovators, respectively. In Model 3, we run a model analogous to Model 4 of Table 4 for the most risk averse of our sample of innovators: those with less than 100 employees. In Model 4, we run a model analogous to Model 4 of Table 4 for the least risk averse of our sample of innovators: those with more than 500 employees. The coefficient for the variable *risk* has the expected sign and is significant for the former, while it is not significant for the latter group. This provides further support for Hypothesis 3B. We also carried out further robustness checks where we varied the employee cutoffs for most and least risk averse innovators to be 50 and 150 for small innovators and 400 and 600 for large innovators. The results are similar and available from the authors upon request.

In Table A.2 in the appendix, we provide further robustness checks of our results on alliance structure. These models test each hypothesis separately by including only the relevant variable(s) for the tested hypothesis and omitting those for the other hypotheses. Once again, for ease of comparison, Model 1 of

Table A.2 replicates the main alliance structure model: Model 5 of Table 4. Model 2 tests Hypothesis 1. Model 3 tests Hypothesis 2. Model 4 tests Hypothesis 3A, and Model 5 tests Hypothesis 3B. In each case, the results are consistent with our main model.

In Table A.3 in the appendix, we report robustness checks for the alliance performance model. Initially, we had matched control and treated cases across the following variables: *year, bio_to_other, exclusive, worldwide, innov_private*, and *npd_cycle*. In the first four models, we match over more variables, which reduces the sample size. In the final two models, we stop matching across one variable, which increases the sample size. In Models 1 and 2, we match across the initial set of variables as well as risk. In Models 3 and 4, we match across the initial set of variables as well as the innovator and partner employee counts. Finally, we match over fewer variables in Models 5 and 6 by matching over all previous variables except *npd_cycle*. The effect of the treatment variable $D$ is significant in all of these cases, providing further support for Hypothesis 4.

## 7. Discussion and Conclusion

In this paper, we argued that a key role of operational decisions is to address contract theoretic concerns faced by an alliance formed between an innovator and a partner. Specifically, we suggested that contract theory has a bearing on the NPD process that determines the structure of an alliance. The presence or extent of contract theoretic concerns should play a role in whether the two parties choose to exert further efforts concurrently through a collaborative alliance or pass efforts from the innovator to the partner through a sequential alliance. Moreover, we also argued that not aligning alliance structure with contract theoretic concerns would adversely affect performance.

We made three specific arguments for the implications of contract theoretic concerns on the choice of alliance structure. First, private information hinders the formation of strategic alliances but can be overcome by sending a credible signal. Innovators can send a credible signal by putting more of their own resources on the line through a collaborative alliance. Second, the holdup problem leads to underinvestment in relationship-specific assets and can be addressed by allocating control rights to the party or parties that have a comparative advantage going forward. In later stages, where comparative advantage shifts to the partner, a sequential alliance structure ensures that control rights are allocated to the partner. Third, partners, who are typically larger firms and are therefore better positioned to absorb risk, are assumed to be risk neutral in theory. Risk aversion can be addressed by transferring risk from the risk-averse party to the risk-neutral (or less risk-averse) party. For alliances that involve higher risk, the risk can be transferred to the partner through a sequential alliance. We tested these arguments with a discrete choice model predicting the choice between collaborative and sequential alliances for over 2000 biopharmaceutical alliances. Our results support all three arguments on the impact of contract theoretic concerns on alliance choice. However, our results also indicate that the last of these concerns, risk aversion, is context specific. Risk plays an important role in the choice for smaller innovators but not larger ones.

We also argued for a link between alliance performance and whether contract theoretic concerns were appropriately addressed. If contract theoretic concerns do indeed matter, not addressing them should lead to poor performance, and eventually to a termination as the worst case scenario. We tested this argument using a discrete choice model predicting whether or not an alliance would be terminated. The main predictor, a binary variable indicating whether alliance choice deviated from our prediction, leads to endogeneity concerns because it is a function of the result of previous analysis. We made use of coarsened exact matching, a method that alleviates the endogeneity problem by making sure that alliances in treatment and control groups have similar predispositions to terminations, to show that deviating from the alliance structure suggested by contract theory predictions significantly increases the probability that an alliance will be terminated. Our research contributes to the literature in several ways. We take a process design perspective by focusing on whether alliances should adopt a collaborative or sequential NPD process. This brings the alliance choice question to the operations management domain. The OM literature on NPD makes use of contract theory when modeling alliances. Our results support the theory developed, which suggests that risk aversion (e.g., Crama et al. 2008), the holdup problem (e.g., Bhattacharya et al. 2015), and private information (e.g., Xiao and Xu 2012) should play a role in alliances. The economics literature has found mixed evidence about whether the actions or contract choices of decision makers deviate from the predictions of contract theory. Our analysis tests and finds support for multiple contract theoretic concerns when decision makers make operational choices. We also go one step further and show that there are performance consequences of deviating from contract theory predictions by studying counterfactuals. Our analysis goes beyond confirming theory and also informs modeling choices in two ways. First, the OM literature addresses contract theoretic concerns within either a collaborative or a sequential NPD process. Our results show that it is also important to analyze the choice between the two. Second, some papers in OM assume the innovator to be risk averse, while others assume the innovator to be risk neutral. Our results show that risk aversion does play an important role and that this role is particularly important for smaller innovator firms that are less able to diversify.

**Table 11.** Trade-offs: How Preference Balance Shifts Between Alliance Structures for Low/High Levels of Different Considerations

| | Level | |
|---|---|---|
| Consideration | Low | High |
| Asymmetric information | Sequential | Collaborative |
| Extent of development | Collaborative | Sequential |
| Risk of failure | Collaborative | Sequential |

Our findings have two key managerial implications. First, different alliance structures are more effective in addressing different contract theoretic concerns. Second, ignoring the contract theoretic concerns faced by the alliance can hinder performance, eventually leading to a termination. Managers therefore need to make careful trade-offs to determine the alliance structure they should adopt. In making these trade-offs, managers should consider the level of asymmetric information, the extent of product development, and the level of risk associated with a project/alliance. We summarize how the presence and level of the different considerations tip the balance toward one alliance structure or the other in Table 11. When asymmetric information is high, e.g., because of differences in research specialization, innovators can signal quality by continuing to be highly engaged in the NPD process through a collaborative alliance. When the product under consideration is at an embryonic stage of development, collaborative alliances should be favored. For alliances with a high risk of technical failure, the partner, who is better able to absorb risk, can bring value to the table by taking on more of the risk through a sequential alliance structure. This last point is more important when dealing with smaller innovators who are likely to be risk averse.

Our study, of course, has various limitations. We were unable to cover some alliances because of lack of data on some companies' characteristics. While we had information on whether an alliance was terminated or not, we did not have information on when an alliance was terminated. Having the latter would have allowed further insight through survival analysis. Furthermore, our data set is limited to the biopharmaceutical industry. While this is a very important industry from the perspective of new product development alliances, further research should also test the implications of contract theory for NPD alliances in other sectors, such as electronics, where alliances are common but cycle times are much shorter. This would lead to further understanding of whether our findings can be generalized across different sectors or are specific to the biopharmaceutical industry.


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## Appendix. Robustness Check Tables

**Table A.1.** Robustness Checks for Models for Alliance Structure (Dependent Variable: *collaborative*)

| | Model 1 | Model 2 | Model 3 | Model 4 |
|---|---|---|---|---|
| *year* | 0.0107 | 0.0096 | 0.0062 | −0.0147 |
| | (0.0095) | (0.0096) | (0.0139) | (0.0217) |
| *deal_value* | 0.0027*** | 0.0027*** | 0.0030*** | 0.0034*** |
| | (0.0004) | (0.0004) | (0.0007) | (0.0008) |
| *exclusive* | 0.4255*** | 0.4359*** | 0.4375* | 0.2853 |
| | (0.1170) | (0.1176) | (0.1728) | (0.2678) |
| *worldwide* | 0.1000 | 0.1021 | −0.0384 | 0.0207 |
| | (0.1128) | (0.1135) | (0.1663) | (0.2671) |
| *innov_size* | −0.2767 | −0.2807 | 0.1069 | −0.0543 |
| | (0.1817) | (0.1822) | (0.0744) | (0.0827) |
| *innov_private* | 0.0413 | 0.0258 | 0.0683 | 0.0365 |
| | (0.1126) | (0.1131) | (0.1527) | (0.3137) |
| *partner_size* | 0.1143*** | 0.0936** | 0.1245** | 0.1597* |
| | (0.0282) | (0.0319) | (0.0433) | (0.0714) |
| *partner_private* | 0.1053 | 0.0997 | −0.0730 | 0.1594 |
| | (0.1223) | (0.1257) | (0.1825) | (0.2740) |
| *alliance_experience* | −0.0014 | 0.0109 | −0.0013 | −0.0111 |
| | (0.0052) | (0.0121) | (0.0073) | (0.0270) |

**Table A.1.** (Continued).

| | Model 1 | Model 2 | Model 3 | Model 4 |
|---|---|---|---|---|
| *innov_law_score* | 0.0045 | 0.0043 | 0.0047 | −0.0011 |
| | (0.0090) | (0.0090) | (0.0174) | (0.0135) |
| *part_law_score* | 0.0062 | 0.0066 | 0.0008 | 0.0182 |
| | (0.0073) | (0.0075) | (0.0086) | (0.0212) |
| *relative_industry_exp* | 0.0011 | 0.0010 | −0.0022 | 0.0004 |
| | (0.0009) | (0.0010) | (0.0015) | (0.0018) |
| *diff_country* | 0.0868 | 0.1258 | −0.0479 | −0.0133 |
| | (0.1036) | (0.1052) | (0.1546) | (0.2372) |
| *bio_to_other* | 0.3715** | 0.3844** | 0.4665* | 0.3127 |
| | (0.1223) | (0.1232) | (0.1858) | (0.2874) |
| *npd_cycle* | −0.1662*** | −0.1674*** | −0.1378*** | −0.1625** |
| | (0.0244) | (0.0245) | (0.0364) | (0.0530) |
| *risk* | −3.5037** | −3.4799** | −2.5575** | −0.9749 |
| | (1.3078) | (1.3138) | (0.7992) | (1.0764) |
| *risk × innov_size* | 0.3471 | 0.3467 | | |
| | (0.2309) | (0.2316) | | |
| Partner FE | | Incl. | | Incl. |
| *_cons* | −21.0085 | −18.6472 | −12.5250 | 27.4155 |
| | (19.1937) | (19.3334) | (28.0273) | (43.5867) |
| *N* | 2,105 | 2,105 | 951 | 497 |
| Log likelihood | −1,274.2739 | −1,257.2269 | −582.4038 | −267.0264 |
| $\chi^2$ | 210.0258 | 278.1836 | 87.4577 | 123.1568 |
| Likelihood ratio test *p*-value | 0.0024 | | 0.0096 | |

*Notes.* Standard errors are in parentheses.

[a]A *p*-value close to zero indicates that the mixed effects model is a better fit than the corresponding logistic regression model. When the mixed effects model is not a better fit than logistic regression (Model 4), we report the result of the corresponding logistic regression.

*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

**Table A.2.** Further Robustness Checks for Models for Alliance Structure (Dependent Variable: *collaborative*)

| | Model 1 | Model 2 (H1) | Model 3 (H2) | Model 4 (H3A) | Model 5 (H3B) |
|---|---|---|---|---|---|
| *year* | 0.0107 | −0.0011 | 0.0074 | −0.0020 | −0.0023 |
| | (0.0095) | (0.0092) | (0.0094) | (0.0092) | (0.0091) |
| *deal_value* | 0.0027*** | 0.0025*** | 0.0028*** | 0.0024*** | 0.0024*** |
| | (0.0004) | (0.0004) | (0.0004) | (0.0004) | (0.0004) |
| *exclusive* | 0.4255*** | 0.2417* | 0.4461*** | 0.2285* | 0.2261* |
| | (0.1170) | (0.1101) | (0.1161) | (0.1102) | (0.1103) |
| *worldwide* | 0.1000 | 0.3207** | 0.0913 | 0.3023** | 0.2974** |
| | (0.1128) | (0.1067) | (0.1117) | (0.1063) | (0.1064) |
| *innov_size* | −0.2767 | −0.0224 | −0.0140 | −0.0343 | −0.3032 |
| | (0.1817) | (0.0230) | (0.0232) | (0.0228) | (0.1781) |
| *innov_private* | 0.0413 | 0.0750 | 0.0567 | 0.0784 | 0.0793 |
| | (0.1126) | (0.1108) | (0.1118) | (0.1107) | (0.1108) |
| *partner_size* | 0.1143*** | 0.1083*** | 0.1386*** | 0.1335*** | 0.1346*** |
| | (0.0282) | (0.0279) | (0.0269) | (0.0266) | (0.0267) |
| *partner_private* | 0.1053 | 0.1171 | 0.1363 | 0.1077 | 0.1020 |
| | (0.1223) | (0.1205) | (0.1214) | (0.1204) | (0.1206) |
| *alliance_experience* | −0.0014 | −0.0001 | −0.0007 | −0.0006 | −0.0008 |
| | (0.0052) | (0.0052) | (0.0052) | (0.0051) | (0.0051) |
| *innov_law_score* | 0.0045 | 0.0022 | 0.0045 | 0.0031 | 0.0035 |
| | (0.0090) | (0.0087) | (0.0090) | (0.0088) | (0.0088) |
| *part_law_score* | 0.0062 | 0.0066 | 0.0075 | 0.0091 | 0.0091 |
| | (0.0073) | (0.0072) | (0.0072) | (0.0071) | (0.0071) |

**Table A.2.** (Continued).

| | Model 1 | Model 2 (H1) | Model 3 (H2) | Model 4 (H3A) | Model 5 (H3B) |
|---|---|---|---|---|---|
| *relative_industry_exp* | 0.0011 | 0.0016 | 0.0015 | 0.0020* | 0.0020* |
| | (0.0009) | (0.0009) | (0.0009) | (0.0009) | (0.0009) |
| *diff_country* | 0.0868 | 0.0672 | 0.1117 | 0.0939 | 0.0946 |
| | (0.1036) | (0.1018) | (0.1025) | (0.1012) | (0.1013) |
| *bio_to_other* | 0.3715** | 0.3463** | | | |
| | (0.1223) | (0.1202) | | | |
| *npd_cycle* | −0.1662*** | | −0.1584*** | | |
| | (0.0244) | | (0.0241) | | |
| *risk* | −3.5037** | | | −1.2756** | −3.0875* |
| | (1.3078) | | | (0.4907) | (1.2879) |
| *risk × innov_size* | 0.3471 | | | | 0.3454 |
| | (0.2309) | | | | (0.2266) |
| *_cons* | −21.0085 | −0.3841 | −17.2200 | 2.1089 | 4.2419 |
| | (19.1937) | (18.5104) | (18.9491) | (18.4924) | (18.5189) |
| *N* | 2,105 | 2,105 | 2,105 | 2,105 | 2,105 |
| Log likelihood | −1,274.2739 | −1,303.6258 | −1,285.2334 | −1,304.3605 | −1,303.1855 |
| $\chi^2$ | 210.0258 | 170.7609 | 192.5046 | 169.3756 | 171.3549 |
| Likelihood ratio test *p*-value | 0.0024 | 0.0020 | 0.0026 | 0.0027 | 0.0024 |

*Notes.* Standard errors are in parentheses.
*$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

**Table A.3.** CEM Robustness Checks for Models for Alliance Performance (Dependent Variable: *terminated*)

| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 |
|---|---|---|---|---|---|---|
| *D* | 0.8222*** | 0.7450** | 0.8648*** | 0.9792** | 0.3900** | 0.4351*** |
| | (0.2107) | (0.2785) | (0.2389) | (0.3029) | (0.1326) | (0.1278) |
| *year* | | −0.0383 | | −0.0549 | | −0.0761*** |
| | | (0.0501) | | (0.0318) | | (0.0227) |
| *deal_value* | | 0.0057 | | 0.0011 | | 0.0022 |
| | | (0.0035) | | (0.0025) | | (0.0016) |
| *exclusive* | | 1.2397** | | 1.2787*** | | 0.6321** |
| | | (0.4186) | | (0.3715) | | (0.1941) |
| *worldwide* | | 0.0419 | | 0.1852 | | −0.2523 |
| | | (0.3296) | | (0.3552) | | (0.1629) |
| *innov_private* | | −0.4705 | | −1.7357*** | | −0.8815*** |
| | | (0.4075) | | (0.2276) | | (0.1580) |
| *partner_size* | | −0.0818* | | 0.1278*** | | 0.0706*** |
| | | (0.0370) | | (0.0234) | | (0.0199) |
| *partner_private* | | −0.0115 | | −0.1088 | | 0.1907 |
| | | (0.4632) | | (0.1570) | | (0.1704) |
| *alliance_experience* | | 0.0023 | | 0.0005 | | −0.0080 |
| | | (0.0138) | | (0.0106) | | (0.0065) |
| *innov_law_score* | | −0.0240 | | −0.0536** | | −0.0062 |
| | | (0.0253) | | (0.0170) | | (0.0124) |
| *part_law_score* | | 0.1219*** | | 0.0602*** | | 0.0384*** |
| | | (0.0219) | | (0.0069) | | (0.0111) |
| *relative_industry_exp* | | −0.0001 | | 0.0027 | | 0.0016 |
| | | (0.0029) | | (0.0038) | | (0.0019) |
| *diff_country* | | 0.1078 | | −0.2238 | | 0.0610 |
| | | (0.4617) | | (0.3712) | | (0.1812) |
| *bio_to_other* | | 1.4448*** | | 0.9926*** | | 0.6855*** |
| | | (0.2131) | | (0.1841) | | (0.1270) |
| *npd_cycle* | | 0.2541** | | 0.2348** | | 0.1338** |
| | | (0.0918) | | (0.0813) | | (0.0442) |
| *risk* | | −5.9547 | | −9.0686 | | −1.6275 |
| | | (4.9819) | | (5.7177) | | (1.6280) |

**Table A.3.** (Continued)

| | Model 1 | Model 2 | Model 3 | Model 4 | Model 5 | Model 6 |
|---|---|---|---|---|---|---|
| *innov_size* | | −0.5841 | | −0.9566 | | −0.0495 |
| | | (1.0265) | | (0.8769) | | (0.1232) |
| *risk* × *innov_size* | | 0.6066 | | 1.0450 | | −0.0920 |
| | | (1.2270) | | (0.9975) | | (0.1492) |
| *_cons* | −2.0754*** | 69.8155 | −1.8390*** | 112.4477 | −1.3839*** | 148.1007** |
| | (0.1271) | (97.5320) | (0.1427) | (59.0125) | (0.0514) | (45.5080) |
| Partner FE | Incl. | Incl. | Incl. | Incl. | Incl. | Incl. |
| *N* | 324 | 324 | 304 | 304 | 1,202 | 1,202 |
| Log likelihood | −135.6686 | −112.7693 | −145.5538 | −113.5407 | −650.3062 | −574.0704 |
| Pseudo-$R^2$ | 0.0703 | 0.2272 | 0.0842 | 0.2856 | 0.0244 | 0.1388 |

*Notes.* Standard errors are in parentheses.
$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

## Endnotes

[1] We thank an anonymous referee for pointing out that our analysis presents a stricter test of alliance performance.

[2] Moral hazard occurs when an agent carries out nonobservable or nonverifiable tasks, which cannot be meaningfully written into a contract. The factors that are central to our paper (private information, holdup, and risk aversion) are explained in more detail in the next section.

[3] While we make use of nonlinear models we have chosen to express the model in linear form here for simplicity. The terms $Y$, $\alpha$, $X$, $\beta$, $D$, $\delta$, and $\epsilon$ are, respectively, the dependent variable (*terminated*), a constant, a vector of independent variables, a vector of coefficients, the treatment variable, the coefficient for the treatment variable, and the error term.

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