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Abstract

This study examines the performance implications of competition for access to the resources of a firm's alliance partners. Partner time and attention may be non-scale free resources, with their use in particular contexts constrained when applied across multiple relationships. Consequently, the other relationships in which a firm's alliance partners are engaged can influence the firm's returns to its alliance collaborations. Using a panel dataset of biotechnology start-ups I find that greater overlap in the R&D function between a start-up's alliances and its partners' other relationships can reduce start-up innovation output. I theorize that this stems from a reduction in knowledge spillovers from the partners, and I investigate the contingencies moderating this effect, as well as the conditions under which such effects may be less salient.

Key Words: Alliance Portfolios; Innovation; Start-ups.

INTRODUCTION

A large and growing body of literature developed over the past two decades has documented the beneficial consequences of strategic alliances for firm performance (e.g., Shan, Walker and Kogut, 1994; Singh and Mitchell, 1996; Reuer, 2004; Sampson, 2007). Alliances allow firms to access and recombine resources (Dyer and Singh, 1998; Lavie, 2006), acquire knowledge and information (Mowery, Oxley and Silverman, 1996), and generate signals of validation to external resource providers (Stuart, Hoang and Hybels, 1999). Such relationships are particularly valuable for resource-hungry, newly founded start-ups (Stinchcombe, 1965; Alvarez and Barney, 2001; Mosakowski, 2002), enabling such firms to commercialize new technologies, develop links with suppliers and customers, and obtain the knowledge and capabilities needed to develop and grow (Baum, Calabrese and Silverman, 2000; Stuart, 2000; Gans, Hsu and Stern, 2002).

Two prominent themes characterize many of the recent studies in the domain of strategic alliances. A first is the recognition that while alliances can confer important strategic advantages to participating firms, such relationships (particularly in a start-up context) occur under the shadow of significant competition, with each side balancing the desire to access resources and create value with the need to avoid appropriation of this value by their partner (Wadhwa and Kotha, 2006; Katila, Rosenberger and Eisenhardt, 2008; Dushnitsky and Shaver, 2009; Diestre and Rajagopalan, 2012). A second theme is an increasing focus on portfolios as the unit of analytical interest (e.g., Hoffman, 2007; Lavie, 2007; Jiang, Tao and Santoro, 2010; Vasudeva and Anand, 2011; Wassmer and Dussauge, 2011; Lahiri and Narayanan, 2013; Hoehn-Weiss and Karim, 2014). In a recent study, for example, Ozcan and Eisenhardt (2009, p. 246) write that "although a single tie can be useful, a firm's portfolio of ties is likely to be more crucial to the firm's performance, thus placing portfolios at the heart of strategic interest."

With this backdrop I seek to understand an issue that has thus far seen little attention in the extant literature: the implications of competition for the *resources* of a focal firm's partners (with such competition stemming from the partners' *other* relationships). This issue differs from market-based competition in that the dynamic of interest relates to *access* to an alliance partner's resources. Such competition is likely to be occurring since many of the resources of any given partner are constrained in their application across multiple uses (Levinthal and Wu, 2010). Since alliance relationships vary with respect to the functional purpose for which they are established, we would additionally expect variation in the effects of such resource competition as different alliance functions (e.g., R&D versus marketing) are considered together with different measures of performance.

In this paper I thus address the following inter-related questions: how do a firm's partners' partners influence the benefits of collaboration; and recognizing that alliances consist of differing functional activities, what is the specific role of competition within a given functional area over the partner's resources? Addressing these issues contributes to two streams of the extant literature. First, work on alliance portfolios has generally emphasized the composition of a firm's set of direct ties (e.g., Jiang, Tao and Santoro, 2010; Lahiri and Narayanan, 2013; Hoehn-Weiss and Karim, 2014); less well studied in this literature, however, is the contingent role of a firm's "indirect" ties.[1] This paper suggests that focusing on such effects can allow us to develop a deeper understanding of the effects of firms' alliance portfolios.[2]

[1] The term "indirect ties" refers to the focal firm's partners' partners. These are distinguished from "direct ties," which collectively comprise the focal firm's own alliance portfolio.
[2] Prior literature on alliance portfolios has recognized that partners beyond the interacting dyadic pair may be salient to understanding alliance benefits. Lavie (2007), for example, examines the role of multilateral competition in

A second, related literature examining inter-organizational ties from a networks perspective is distinguished by its priors emphasizing the *structure* of relationships within which the firm is situated (e.g., Gulati, 1998; Ahuja, 2000; Bae and Gargiulo, 2004). This paper contributes to this literature as well by highlighting the importance of taking into consideration tie *content* (through the focus on different alliance functions) versus just the structure of ties around the firm. This resonates with Ahuja, Soda and Zaheer's (2012, p. 444) call for future research in the domain of inter-organizational networks to "clearly specify the content that is expected or presumed to flow through the network."

To further illustrate how this study contributes to these literatures, Figure 1 presents a stylized example of two start-ups, each having established two alliances: one R&D and one marketing. The partners of the focal start-up in each panel also have their own relationships (taking on R&D and marketing functions); these partners configure their own portfolios differently in the left panel as compared to the right. Whereas an alliance portfolio perspective might emphasize just the direct ties of each focal start-up, which are the same in each panel (each start-up has one tie of each type), a networks perspective might ignore the distinction between tie types, emphasizing instead the structural similarity of the two panels. Taking into account the existence of indirect ties, as well as the content (the R&D versus marketing function) of the ties, however, suggests that each perspective is incomplete on its own: the start-ups in panels A and B may be quite different, with the start-up in panel A developing relationships with incumbent firms whose resources are potentially subject to greater competition as compared to the start-up in panel B, due to the existence (in panel B) of a larger number of relationships similar to those of the start-up's direct ties.

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influencing alliance value creation and appropriation. The focus in this stream of work, however, has generally been on value appropriation from the relationship itself, versus competition for the resources of the partner firm.

[Insert Figure 1 about here]

The primary focus of this paper is on the innovation performance implications of what I call *functional activity overlap*. For a given alliance type (e.g., R&D or marketing), this refers to the prevalence of the *same* type of alliance in the focal firm's partners' portfolios.[3] I theorize that the functional activity overlap construct proxies for the degree of competition over the focal firm's incumbent partners' time and attention resources within particular functional areas, and I argue that under certain conditions such competition can reduce the knowledge-related spillovers that are a precursor to start-up firm innovation. I focus specifically on R&D-related functional activity overlap, developing hypotheses around the main effect of this construct on firm innovation, together with two possible contingencies. As a final hypothesis I also consider *non-innovation* outcomes, theorizing that there are conditions under which functional activity overlap of a particular type (e.g., marketing) can benefit performance. I test the hypotheses using a panel dataset of biotechnology start-ups that I observe from their date of founding onwards.

THEORY AND HYPOTHESES

Innovation implications of competition from a firm's alliance partners' partners

Knowledge spillovers and strategic alliances. Innovation output is a key performance metric in the context of early-stage start-ups. Innovation can influence not only the degree of competitive advantage the firm obtains in its product markets, but can also serve as a signaling device to external resource providers (Hsu and Ziedonis, 2013), thereby reducing the barriers to assembling the financial and strategic resources necessary for survival. Knowledge is a critical precursor to innovation; access to diverse sets of knowledge, together with the capability to recombine this knowledge in new and interesting ways are key drivers of innovative output

[3] In Figure 1, for example, the start-up in Panel A has a high R&D activity overlap measure as well as a high marketing activity overlap measure, while the start-up in Panel B is lower (compared to Panel A) on both measures.

(Fleming, 2001; Dushnitsky and Lenox, 2005; Fleming, Mingo and Chen, 2007; Schilling and Phelps, 2007). The ability to acquire, process and realize value from diverse sources of knowledge, particularly across disparate domains, is thus central to the innovative performance of early-stage start-ups (Sosa, 2011; Hsu and Lim, 2014).

An important antecedent to a focal start-up's ongoing innovation output is the degree to which it can gain from the spillovers of knowledge from firms with which it interacts. Strategic alliances are an important mechanism through which young and resource-constrained start-ups access such knowledge-based resources (Shan et al., 1994; Mowery et al., 1996; Rothaermel, 2001). Alliances serve not only as signals of quality (Stuart et al., 1999), but also as pathways through which start-ups access external resources (Stuart, 2000; Ahuja, 2000; Katila et al., 2008). The knowledge-related benefits of alliances include direct access to information, as well as tacit knowledge regarding the knowledge recombination process (Dyer and Singh, 1998; Kale, Singh and Perlmutter, 2000; Lavie, 2006). Knowledge spillovers via strategic alliances thus provide the raw material for the innovation process, with regular and ongoing interactions between a start-up and its incumbent partners exposing the firm to new information and to new ways of recombining that information (Sampson, 2007; Hoang and Rothaermel, 2010; Yang, Zheng and Zhao, 2014).

Competition for access to a partner's knowledge resources. While alliances with incumbent partners are an important conduit for the start-up to gain access to new knowledge, the incumbent firm resources necessary for spillovers from the incumbent to the start-up to occur—namely the time and attention of the incumbent's technical personnel—may be subject to constraints on their use. This stems from the idea that many of a firm's resources are "non-scale free" (Levinthal and Wu, 2010) in that they incur opportunity costs in their application to one use versus another. Such resources are distinguished from those that are "scale free" and can be applied across multiple settings without diminishing their effect. The idea that partner time and attention are a key mechanism through which knowledge transfer occurs has its roots in prior literature. Sampson (2007, p. 366) suggests, for example, that the most important mechanism for knowledge transfer in alliances is "the mobility and/or contact between technical employees [of the partner firms]." Levinthal and Wu (2010, pp. 781-783) moreover point to human capital in particular as being a non-scale free resource, suggesting that "personnel with specific technical expertise" can face opportunity costs in the allocation of their time, with a key issue being the "best allocation of the time of a sales force, product development team, or top management group based on their opportunity costs."

As a consequence of the non-scale free nature of the incumbent firm's resources, there is likely to be competition over these particular resources from the partners' *other* alliances. Such competition of course differs from marketplace-based competition such as that which occurs directly between start-ups and incumbents. Marketplace-based competition has been studied from various perspectives in the prior literature (Alvarez and Barney, 2001; Katila, et al., 2008; Diestre and Rajagopalan, 2012), with a primary focus being the division of alliance value between a start-up and its partners. The perspective here, however, shifts attention specifically toward competition for access to the incumbent's resources, a viewpoint thus far relatively understudied in the literature.

The idea that resources such as the partner's time and attention can be non-scale free further resonates with the notion of individual decision makers in a firm being selective with respect to how they focus their time and attention (Simon, 1947; Ocasio, 1997), and to the concept of "relative standing" (Ozmel and Guler, 2013; Piezunka, 2013). In a contemporaneous study using the venture capital industry as the empirical context, for example, Ozmel and Guler (2013) find differences in the degree of attention a VC gives to particular portfolio companies after the investment relationship is formed. This suggests that the effects of intra-portfolio competition for resources can be substantial and relevant for start-ups allying with larger incumbent partners. A higher degree of competition over an incumbent's non-scale free resources would be likely to negatively influence the positive innovation output benefits to the start-up associated with the relationship; and all else being equal, greater competition is likely to arise with a larger number of partners competing for the same resources.

Knowledge-based spillovers are, moreover, likely to be a function of the *quality* of interactions the start-up has with a particular partner. In particular, deeper and more sustained ongoing interactions, facilitated by situations where there are fewer other firms vying for the partners' time and attention, are more likely to result in the types of knowledge-based spillovers leading to innovation benefits. Gulati, Lavie and Singh (2009) examine the value of partner-specific versus general partnering experience, finding that the former provides greater benefits in an alliance setting. While their definition of partner-specific experience relates to recurrent alliances among the same set of partners, an analogous argument can be made in the context of a single relationship: deeper relationships allow for a "consistent learning context" that leads to greater efficiency of learning, perhaps via increased relationship-specific investments.

Functional activity overlap and innovation performance. The degree to which competition over an incumbent's resources actually occurs is likely to vary as a function of the specific types of activities underlying the alliance. Recent work at the alliance portfolio-level underscores the idea that any given alliance can contain multiple functional activities, with the mix of activities having effects on outcomes such as firm-level knowledge acquisition and exit likelihood (Jiang, Tao and Santoro, 2010; Hoehn-Weiss and Karim, 2014). Identifying situations where competition over an incumbent's time and attention influences innovation output thus requires identifying the types of alliance activities (e.g., R&D, licensing or marketing) where knowledge spillovers are relevant in the first place.

Prior literature points to two dimensions of segmentation for alliance activities: technology versus commercialization (e.g., Mitchell, 1989; Tripsas, 1997; Lee, 2009; Sosa, 2009) and the possibly arms-length nature of the relationship (e.g., Oxley, 1997; Anand and Khanna, 2000; Aggarwal and Hsu, 2009). Taken together these dimensions allow us to characterize the salient differences between R&D, licensing and marketing activities: R&D and licensing relationships relate to an alliance's upstream technology focus, while marketing relationships relate to the alliance's downstream commercialization focus. R&D-oriented alliances, however, are less arms-length than licensing alliances, and are thus more likely to entail the types of reciprocally interdependent actions that lead to knowledge spillovers (Sampson, 2007; Yang et al., 2014).

It is in in the context of R&D-oriented alliances (as opposed to licensing and marketing relationships), where knowledge spillovers are most salient, therefore, that we would expect greater competition from the firm's partners' partners to influence the innovation-related benefits the focal firm receives from its alliances. The notion of "functional activity overlap" incorporates the distinction in the functional activities underlying the alliance; for any given alliance functional type (e.g., R&D), this construct reflects the relative prevalence of the *same function* in the alliance portfolios of those partners with whom the focal firm has an alliance of that type. Higher values of this construct for R&D activities thus proxy for situations where the start-up's portfolio of incumbent partners would face more demands for their non-scale free resources of time and attention in the R&D domain, because the firm's R&D partners have many other partners also involved in R&D relationships. Such a situation would likely reduce knowledge spillovers, and as a consequence reduce the positive innovation benefits stemming from the alliance. Thus, while alliances may be beneficial to start-up innovation on average, I predict that the positive innovation benefit of a start-up's alliance relationships will be reduced with greater R&D functional activity overlap.

<u>H1</u>: Greater R&D-related functional activity overlap stemming from a focal firm's alliance partners' partners will reduce the focal firm's innovation output.

Average deal scope and focal firm knowledge base as moderators

The core logical building blocks underlying the first hypothesis involve the spillover of knowledge from incumbent firms with which the focal start-up establishes alliances, together with the idea that the incumbent's resources of time and attention available to the start-up will be reduced when there is greater competition over these resources from the incumbent's other partners. The associated reduction in information and tacit knowledge flowing to the start-up under conditions of higher competition from the start-up's partners' partners will likely reduce the innovation-related benefits the start-up receives from the alliance. To further test the logic underlying this main hypothesis I develop two predictions that center on the conditions under which the effects in Hypothesis 1 are likely to be either enhanced or mitigated: the focal firm's average deal scope, and the size of the focal firm's established base of knowledge.

If knowledge-related spillovers from incumbents to the focal start-up are a precursor to innovation, with functional activity overlap in the R&D domain reducing the focal start-up's innovation output through its influence on such spillovers, we would expect the negative effects of the first hypothesis to be enhanced when such spillovers are the greatest. Put another way, functional activity overlap will have a more significant (negative) effect in situations where knowledge-based spillovers are more frequent, since competition from the focal firm's partners' partners will be most salient in such settings. One set of conditions where knowledge-related spillovers may be larger, and therefore more sensitive to functional activity overlap effects, is when the alliance in question encompasses a greater number of functional activities.[4] Such multi-function alliances, having a larger scope with respect to the functions over which partners collaborate, may be beneficial for the focal firm because they involve deeper and higher quality interactions that can lead to greater tacit knowledge transfer, and more generally to greater access to the incumbent firm's knowledge resources (e.g., Jiang et al., 2010; Hoehn-Weiss and Karim, 2014).

When a firm's alliances in the R&D domain also incorporate a larger number of other functional activities, it is thus likely that knowledge spillovers will also increase. Allying firms engaging in functional activities complementary to R&D (such as marketing or manufacturing) are likely to have a higher total level of ongoing knowledge flows amongst one another, relative to situations where the alliance is focused solely on R&D. Even if the other activities associated with the alliance do not directly entail a technology component, their complementarity with the firms' joint R&D activities will likely involve relationship-specific investments (Dyer and Singh, 1998) that would increase the total flow of knowledge between the allying firms. The negative effect of R&D-related functional activity overlap on innovation (i.e., the main prediction of H1) is thus likely to be amplified with a higher focal firm average deal scope.

<u>*H2*</u>*: The negative effect of greater R&D-related functional activity overlap on focal firm innovation (H1) will be amplified with a higher focal firm average deal scope.*

[4] Any given alliance consists of one or more activities; as Hoehn-Weiss and Karim (2014) note, "each alliance within a portfolio need not belong to a single function, but could consist of multiple functions … there may be an alliance within a portfolio in which the partners are collaborating both on R&D and marketing."

Whereas greater average alliance deal scope may enhance the negative effect of R&D-related functional activity overlap discussed in Hypothesis 1, there are also likely to be contingencies under which this effect is mitigated. I propose that the size of the focal firm's knowledge base is such a contingency. There are two sets of reasons why this might be the case. First, a firm's knowledge base serves as a proxy for its absorptive capacity, measuring its ability to capture, process, and assimilate unique and novel ideas via knowledge spillovers (Cohen and Levinthal, 1990; Vasudeva and Anand, 2011). Innovation involves a search for new (combinations of) ideas, and to the degree that a firm has a broad base of accumulated knowledge, the depth of its knowledge generation process can be enhanced (Katila and Ahuja, 2002). A deep knowledge base, moreover, offers a framework through which the firm can filter information received from its alliance relationships, enhancing its ability to identify and exploit insights and know-how from its partners. Such a framework, for example, would likely be particularly useful in accessing tacit knowledge in the context of R&D relationships.

A second set of reasons that a firm's knowledge base may be beneficial in counteracting the negative effects of R&D-related activity overlap is that a larger base of knowledge can reduce the relative opportunity costs from the perspective of the incumbent firm of allocating time and attention to the focal start-up. Because learning opportunities for the incumbent are potentially greater when the focal firm has a larger established knowledge base, it is more likely to view the focal firm as having a higher relative standing as compared to other affiliated (R&D) partners (e.g., Ozmel and Guler, 2013; Piezunka, 2013), and it will therefore be more likely to allocate its non-scale free capabilities of time and attention (Levinthal and Wu, 2010) toward the focal firm and away from competing firms. Taken together, these arguments suggest that a possible counteracting effect to competition over partner time and attention may occur in the context of R&D-related alliances when the focal firm has a higher established base of knowledge, providing a condition under which the main effect of Hypothesis 1 is reduced.

H3: The negative effect of greater R&D-related functional activity overlap on focal firm innovation (H1) will be reduced with a larger focal firm established knowledge base.

Non-innovation implications of functional activity overlap

The three prior hypotheses have focused on the role of R&D-related functional activity overlap in influencing firm performance, with innovation as the outcome metric of interest. The core logic for these hypotheses has accordingly focused on the precursors to innovation arising from strategic alliances—knowledge spillovers from the incumbent partners to the focal start-up, together with the conditions under which the effects of competition from the partners' other partners may increase or decrease such spillovers.

There are two important implications stemming from the focus on R&D relationships in the prior three hypotheses that are worth stating directly in order to frame the final hypothesis. The first is that functional activity overlap that is *not* R&D-related (e.g., marketing-related functional activity overlap) is not likely to have an impact on innovation. This is because the predicted impact on innovation is a function of knowledge spillovers, and in turn on the investment of time and attention of the incumbent's technical personnel. Because knowledge spillovers are less salient in alliance types such as marketing, there is no a priori reason to expect functional activity overlap in such relationships to have innovation-related effects. The second implication is that there may in fact be situations where a particular type of functional activity overlap does not result in competition for incumbent resources; that is, the presence of a partner's partners may not reduce the benefits flowing to the start-up as a consequence of the alliance relationship. This may occur, for, example, if the incumbent resources in question are relatively scale-free.

With this in mind, I thus focus the final hypothesis on the role that marketing-related functional activity overlap plays for *non-innovation* performance outcomes. As mentioned above, there is no reason to expect marketing-related functional activity overlap to have an effect on innovation. However, it may have an effect on alternative start-up performance metrics. I thus shift attention to a start-up's eventual exit outcome (e.g., IPO or M&A), arguing that greater functional overlap in the marketing domain (i.e., when the focal firm's marketing partners engage in a higher number of other marketing alliances) will *positively* affect the focal firm's ability to experience a high valuation exit outcome. If supported, this hypothesis would serve to further underscore the importance of considering the particular functions associated with an alliance when evaluating a focal firm's portfolio of relationships.

The logic linking greater marketing-related functional activity overlap to favorable exit outcomes rests on two inter-related building blocks. The first is the degree of resource competition generated by the presence of a partner's partners in the same functional area (marketing). Prior work on marketing alliances suggests that such relationships involve greater structure, with resources set aside and dedicated to the particular deal (Rothaermel and Deeds, 2004; Yang et al., 2014). Yang et al. (2014), for example, suggest that exploitation (e.g., marketing) alliances are beneficial for smaller firms because they offer returns that are relatively well defined. As such, in contrast with R&D relationships where incumbents must make explicit tradeoffs in time and attention, marketing relationships are less likely to entail such analogous tradeoffs. Competition over any non-scale free resources leading to more favorable exit outcomes is thus less likely to occur in such relationships.

The second building block of the final hypothesis involves the role of signaling in influencing the probability of favorable exit outcomes. Alliances have the characteristic of being effective signals (Spence, 1973) in that they are costly for the partner to engage in and they allow for a sorting of firms based on relative quality. Prior work supports the signaling role of alliances, pointing to implications for firm valuation (e.g., Chan et al., 1997; Reuer, Tong and Wu, 2012). This is particularly important when prominent (i.e., highly degree central) partners are involved (e.g., Stuart et al., 1999; Stuart, 2000; Higgins and Gulati, 2003). Thus, it is likely that the presence of other partners who are also engaged with marketing relationships with the focal firm, a situation that would increase the firm's marketing-related degree centrality, would benefit the focal firm. Taken together, this discussion suggests a positive link between marketing-related functional activity overlap and a favorable (high valuation) exit.

H4: Greater marketing-related functional activity overlap stemming from a focal firm's alliance partners' partners will increase the focal firm's probability of a high valuation exit.

EMPIRICAL ANALYSIS

Data and Sample

The industry setting for this study is biotechnology. This industry has the beneficial feature of being the context for several prior studies of the effects of alliances in start-up settings (e.g., Shan, Walker and Kogut, 1994; Stuart, Hoang and Hybels, 1999; Baum, Calabrese and Silverman, 2000), providing an anchoring point for comparison with insights from prior work. It is, moreover, a setting in which the high cost of complementary assets, together with strong IP protection, makes partnership the normative advice given to entrepreneurs (e.g., Gans et al., 2002).

I construct an unbalanced firm-year panel dataset, using as the sample the universe of 281 human biotechnology firms founded between 1990 and 2000 and present in the VentureXpert database, one of the largest commercial sources for data tracking venture capital investments. Using venture capital-backed firms drawn from a single industry is beneficial as it offers a degree of homogeneity with respect to firm quality, as well as a common set of metrics for innovation and long-run performance output, thereby facilitating inferences from the empirical analyses. The 1990 to 2000 time period ensures adequate coverage from the alliance data source, SDC, where data prior to 1990 is incomplete. This timeframe also ensures an adequate post-founding window to track start-up evolution. Each firm is tracked from founding through 2006, with data collected on the firm's alliances, venture capital funding, patenting, and exit outcomes.

Several archival sources are used: SDC Platinum and Factiva for alliance data; VentureXpert for venture capital funding histories; and the U.S. Patent and Trademark Office (USPTO) together with the IQSS Patent Network database (Lai et al., 2011) for patenting outcomes. Exit outcomes are identified from the SDC M&A database and Thomson One Banker, and are triangulated with Lexis-Nexis, Factiva and www.archive.org. Additional cross-checking is done using CorpTech, Compustat and SEC filings. Each measure has a maximum of 3,358 observations, representing the total number of firm-years across the sample of firms from founding through 2006. The focal firm's incumbent partners are those partnering with the firm as identified in SDC. Alliance data collection involves first identifying and coding all alliances for the focal firms, and then identifying and coding all alliances for partners identified in the first stage. The dataset includes 684 focal firm alliances, 11,389 incumbent firm alliances, and 6,554 patents issued to the focal start-up firms, which result in 19,408 forward citations. Measures are all aggregated to the focal firm-year level of analysis, and model estimation is done at the firm-year level.

Dependent Variables

Innovation output is measured using patent data; patents are a key metric for innovation in biotechnology (Levin et al., 1987), with prior work suggesting that innovation quality is best measured through citations (e.g., within a four-year window) to the firm's patents (Hall, Jaffe and Trajtenberg, 2005). I draw on the IQSS Patent Network database (Lai et al., 2011) to identify all patents associated with the sampled firms, extracting from this source all patents where the "assignee" name matches the current or former names of the focal firm. I collect all citations within a four-year window to the firm's patents; the innovation output measure, *forward citations*, represents the total number of citations within four years to current firm-year patents. The measure is further cross-checked with Google Patents to ensure completeness and accuracy.

The exit outcome measure, *high valuation exit*, is a dummy variable representing situations in which the firm experiences a favorable exit, defined as either an IPO or an acquisition where the valuation received by the start-up upon exit is higher than the median exit valuation. Favorable exits of this sort are an important performance metric in the context of venture capital-backed firms (Gompers and Lerner, 2004). I pool IPOs and acquisitions because each category by itself contains substantial heterogeneity. An acquisition, for example, may be the result of an asset (fire) sale, or alternatively a more successful purchase by an industry incumbent. Similarly, IPOs can occur at low valuations (e.g., the OTC market) or on an exchange such as the Nasdaq. Ultimately both exit options represent alternative mechanisms by which the focal start-up and its owners can achieve similar objectives (e.g., a liquidity event for the investors). As a consequence, a valuation-based measure seems the most appropriate method for differentiating between situations of favorable vs. unfavorable outcomes.

Independent Variables

Two sets of variables are of primary theoretical interest: (1) the main measures of functional activity overlap and (2) the contingencies (average deal scope and focal firm knowledge base). Four additional sets of variables are used to control for time-varying firm heterogeneity associated with the following characteristics: the focal firm's portfolio; the incumbent partners' portfolios; industry overlap; and firm-level development stage. Variables are all time-varying at the focal firm-year level. I discuss each set of variables in turn.

Functional activity overlap. These measures are the main variables of theoretical interest. For a given alliance relationship, these variables measure, for the particular function associated with the relationship (R&D, licensing, or marketing), the relative prevalence of that *same alliance function* employed in alliances other than that of the focal firm in the partner's portfolio. These therefore serve as a proxy for the relative degree of competition over the incumbent partner's resources related to the particular alliance function in question.

Part of the rationale for constructing the measures in this way is that, consistent with the theory development, we are concerned with the *quality* of interactions with an incumbent, versus just the *quantity* of resources assembled, as deeper and more sustained ongoing interactions between a start-up and its incumbent partners provide the conditions under which the knowledge-based spillovers underlying the benefits of alliances occur. Deeper relationships provide a "consistent learning context" (Gulati et al., 2009) leading to greater learning effectiveness on the part of the start-up. Thus, multiple, shallower investments are likely to be sub-optimal substitutes for fewer, higher quality interactions. An appropriate measure of the effects of a firm's partners' partners on the benefits of collaboration, therefore, relates to the *average quality* of the relationships in the start-up's portfolio. Such quality is afforded in situations where there is less competition for the incumbent partners' time and attention.

Defining a functional activity overlap measure involves first defining the relevant portfolios of alliances under consideration (both for the focal start-up as well as for its incumbent partners). The focal firm's portfolio is defined as the cumulative stock of all alliances it has developed since founding. Using a cumulative stock is important as start-ups typically have few alliance relationships with incumbent partners in their early years, and the relationships they do have can play an important role in shaping their ongoing evolution. The incumbent's relevant portfolio of partnerships is defined as all alliances created within a five-year window prior to the inception of the focal alliance, enabling a focus on the more active alliances of the incumbent that are likely to impact the competition for incumbent time and attention.

There are three functional activity overlap measures: *R&D overlap*, *licensing overlap*, and *marketing overlap*. *R&D overlap* and *marketing overlap* are associated with specific hypotheses (Hypotheses 1 through 3 for *R&D overlap* and Hypothesis 4 for *marketing overlap*). The *licensing overlap* measure is included mainly as a robustness check and control: licensing involves some technology-based collaboration, but given its arms-length nature is one in which knowledge spillovers are less likely to occur (as compared to R&D).

To construct each measure I first determine, at the focal firm-alliance level, whether the particular alliance involves the given activity (e.g., R&D). If so, I code a binary variable for that alliance-activity observation as 1 (and 0 if the activity is not associated with the alliance). Then, for the incumbent partner associated with the particular alliance, I determine the percentage of other alliances in the incumbent's portfolio where the particular activity is present. The overlap value at the alliance activity level is the product of the binary variable and the percentage variable. At the alliance level, therefore, a particular functional activity overlap measure represents the degree to which the incumbent's portfolio overlaps with the focal alliance *for the given activity in question*. When the activity is not associated with the focal alliance, the value is always 0 (since the binary variable is 0). When the activity is associated with the alliance, the value represents the incumbent firm's incidence of the particular activity within its alliance portfolio. In the boundary case where the focal alliance is the only alliance in the incumbent's five-year window at inception the activity overlap values are coded as 0.

Since the measures are aggregated to the focal firm-year level, values for each individual relationship are then aggregated across the start-up's portfolio of multiple relationships. Thus, the *R&D overlap*, *licensing overlap*, and *marketing overlap* variables are the average value of functional activity overlap across the focal firm's stock of prior relationships. Constructed in this way, these three variables proxy for the average quality of interactions (of different functional types) between a start-up and its portfolio of incumbent partners, with quality being influenced by the degree of competition from the focal start-up's partners' partners.

Contingencies: deal scope and knowledge base. To test the contingencies under which the impact of *R&D overlap* will be higher or lower with respect to its impact on innovation, I use the variables *focal average deal scope* and *focal established knowledge base*; these respectively represent the average deal scope associated with the focal start-up's alliances and the total stock of the focal start-up's patents. *Average deal scope* is constructed by first summing (for each of the alliances in the focal firm's portfolio) a set of 11 dummy variables representing different activity categories associated with the alliance; these values are then averaged across the focal firm's alliance portfolio for the firm-year.[5] To construct the *focal established knowledge base* measure I use the 1-year lagged stock of total patents issued to the firm, thereby measuring the firm's aggregate knowledge base. In the various specifications these variables are interacted with the main functional activity overlap variables above (with the interaction with *R&D overlap* being of primary theoretical interest).

Focal firm portfolio controls. I employ three variables to control for time-varying characteristics of the focal firm's portfolio of alliances. First, *focal portfolio size* is a count of the number of alliances the start-up has established since founding through the current firm-year. Second, *public firm percent* represents the percent of alliances in the focal firm's portfolio where the partner is a publicly traded firm. Third, *corporate investors* represents the count of unique corporate investors that have invested in the focal firm from founding through the current firm-year. Together, these three variables capture aspects of the focal firm's portfolio configuration that might influence the firm's innovation output or its high valuation exit probability. Together with the additional categories of control measures described below, these variables also address any time-varying changes in start-up quality that might not be captured by the start-up firm fixed effects used in the innovation specifications.

Incumbent partner portfolio controls. As a further means of controlling for the quality of the start-up's portfolio of relationships, I employ variables to capture characteristics of the incumbent partners' own portfolios. First, *incumbent portfolio size* measures the size of the incumbent's total portfolio of alliances, defined, as noted before, as the stock of alliances developed in the five-year window prior to the current firm-year. I also include the measure *first alliance percent,* which is the average percent of incumbent alliances where the focal alliance is

[5] These categories include various characteristics of the alliance, including R&D, licensing, marketing, computer integration, exclusive licensing, manufacturing, software development, joint venturing, funding, royalties, and technology transfer.

the first alliance in the incumbent's five-year prior history. These measures are both aggregated across the focal firm's multiple alliances, and are thus an average at the focal start-up firm-year level. In addition to these characteristics of the focal firm's incumbent partners' portfolios, I also control for characteristics of industry overlap, as I detail next.

Industry overlap controls. There are two industry overlap controls, which are designed to capture any variation that might result from industry overlap effects between the focal start-up and either its incumbent partners or its incumbent partners' partners. First, *industry overlap* is the percent of alliances in the focal start-up's portfolio where the focal firm and the incumbent partner are in the same industry, as defined by their 4-digit SIC code. Second, *industry overlap (focal firm-incumbent firm portfolio)* is used to capture the average share of the focal start-up's incumbent partners' portfolios of alliances with firms that are in the same industry as the focal firm. Note that this measure is different from the former in that it measures industry overlap between the focal start-up and its partners' partners (versus overlap between the focal start-up and its partners themselves).

Focal firm development controls. To further control for time-varying focal start-up characteristics that might influence start-up performance, I also include measures of the start-up's stock of total venture capital investments to date, its age, and whether it is publicly traded in the firm-year. Together with the previously mentioned focal firm portfolio measures, these proxy for factors that might drive matching between start-ups and incumbents of a particular quality type. *Equity stock* represents the total equity invested in the firm by all investors up to and including the current firm-year, following prior work which suggests that higher quality firms are more likely to obtain greater levels of financing from venture capital investors whose role in part is to screen for start-up quality (e.g., Gompers and Lerner, 2004). *Firm age* is defined as the number of years elapsed since firm founding, controlling for any life-cycle effects that might influence the firm's outcomes. Finally, *public dummy* controls for whether the firm is publicly traded, as such an ownership structure can influence the firm's innovative output (e.g., Aggarwal and Hsu, 2014).

In addition to these variables, I utilize both firm and year fixed effects, as discussed in the Model Specifications section that follows. Table 1 provides variable definitions and summary statistics, and Table 2 provides pairwise correlations between the independent variables.

[Insert Tables 1 and 2 about here]

Model Specifications

Innovation models. The dependent variable for the innovation specifications is *forward citations*, which is a count variable. For these specifications I therefore utilize a conditional fixed effects Poisson quasi-maximum likelihood model with robust (Huber-White) standard errors (Hausman, Hall and Griliches, 1984; Wooldridge, 1999). There are two important features of this model that make it attractive for use in this setting. First, it allows for the use of firm fixed effects, which, together with the time varying covariates described in the previous section provides a means of ruling out unobserved firm heterogeneity. As a consequence, the innovation specifications should all be interpreted as estimating within-firm effects.[6] Second, the use of robust standard errors allows for heteroscedasticity-consistent standard errors in a panel setting. In addition to the use of fixed effects and robust standard errors, I also employ year fixed effects by including indicator variables for each year in the main innovation specifications. The

[6] An important econometric issue is the possibly endogenous matching between start-ups and incumbents in the alliance formation process. To the degree that the end result of such a matching process is a pairing between start-ups and incumbents based on quality (i.e., the most attractive incumbents get matched with the highest quality start-ups), then conducting within-firm analyses, together with including in the specifications controls for time-varying firm characteristics, should make significant headway toward allaying such concerns. As noted in the variable descriptions in this section, I have aimed to include as many observable correlates of time-varying start-up quality as possible. I further discuss this issue in the Discussion and Conclusion section.

innovation specifications include firm-years where the firm has not yet been acquired or gone defunct; once an acquisition or defunct exit occurs, future firm-years are no longer observed. Firms that conduct an IPO remain in the sample, however, and I use the *public dummy* to control for effects associated with post-IPO firm-years.

High valuation exit models. To examine exit outcomes, I use the *high-valuation exit* variable. The specification used is a probit model with standard errors clustered by firm. This is essentially a discrete time survival model, which is necessary because there is (by definition) only one observed exit per firm. The covariates used in this set of analyses are essentially the same as in the innovation outcome analyses, with the exception of the *public firm* dummy. Firms without patents are not dropped, as the dependent variable is a high-valuation exit. However, all firm-years after which the focal firm has conducted any type of exit (high-valuation or otherwise) are dropped from the sample, as any such event removes the firm from the risk of undergoing a high-valuation exit event.

Empirical Results

I begin the analysis by examining start-up innovative output, measured by forward citation counts. The specifications in Table 3 use conditional fixed effects Poisson quasi-maximum likelihood specifications, with robust standard errors reported in parentheses. In addition to firm fixed effects, year fixed effects are included in all specifications; this helps rule out unobserved time-invariant firm-specific heterogeneity while also controlling for any time-based factors that could influence the results. The various characteristics of the start-up, its incumbent partners, and the nature of the alliances formed, aim to capture remaining time-varying effects that may not already have been captured in the firm and year fixed effects. The covariates are organized in the order of the categories listed in Table 1: the three measures of functional activity overlap; the contingencies of focal firm average deal scope and knowledge base; and the various controls (focal portfolio, incumbent portfolio, industry overlap, and focal firm development). Variables that are skewed in their distribution are log transformed.

Specification (3-1) includes the deal scope and knowledge base variables, together with the controls, excluding the functional activity overlap measures. *Focal portfolio size* and *equity stock* are positive and significant, consistent with prior literature on the benefits of alliances. *Incumbent portfolio size* is also positive, with this effect counter-balanced by industry overlap between the focal firm and its partners' partners (*industry overlap, focal firm-incumbent portfolio*). In addition, the *public firm dummy* is negative and significant, consistent with recent work suggesting a reduction in innovation output for post-IPO firms (Aggarwal and Hsu, 2014).

The next three specifications in Table 3 include the functional activity variables, variously coupled with the deal scope and knowledge base interactions. These three specifications, (3-2), (3-3) and (3-4), thus provide tests, respectively, of Hypotheses 1, 2 and 3. In specification (3-2), which includes the direct effects of the functional activity overlap variables, without the interaction effects, the *R&D overlap* measure is negative and significant. This offers strong support for Hypothesis 1, which suggests that R&D-related functional activity overlap will reduce the focal firm's innovation output. It is interesting to note as well that *licensing overlap* is also negative and significant (though with a smaller effect than *R&D overlap*). While I do not explicitly theorize about this variable, its effect is consistent with the mechanism of knowledge-based spillovers occurring in the context of technology-based collaborations. The lower effect of overlap in the context of licensing as compared to R&D collaborations is likely due to the more arms-length nature of licensing collaborations, which reduce the total effect of knowledge spillovers, thereby making overlap (which proxies for resource competition) along this dimension less relevant from the focal start-up's perspective.

The next two specifications then include the interaction effects used to further test the mechanisms underlying Hypothesis 1 (following the theory detailed in Hypotheses 2 and 3). In specification (3-3) I explore the interaction of the firm's average deal scope with the functional activity overlap variables. While the interaction between *R&D overlap* and *focal average deal scope* is of primary theoretical interest, I also include deal scope interactions with the other functional activity overlap variables for completeness. As this specification shows, the coefficient on the interaction between *R&D overlap* and *focal average deal scope* is negative and strongly significant, consistent with the theoretical prediction that greater average deal scope should amplify the negative effects of *R&D overlap*. The other two interaction effects in this specification are not significant (consistent with the absence of any theoretical predictions regarding their effects), and the effects of *R&D overlap* and *licensing overlap* continue to remain negative. This specification thus provides support for Hypothesis 2, and in so doing offers additional support for the mechanism of knowledge spillovers underlying Hypothesis 1.

In specification (3-4) I then explore the interaction of the firm's established knowledge base with the functional activity overlap variables. As with the prior specification, it is the interaction with *R&D overlap* that is of primary theoretical interest. The interaction between *R&D overlap* and *focal knowledge base* is positive and significant, consistent with the prediction of Hypothesis 2 that a higher focal firm base of established knowledge should serve to counteract the negative effects of activity overlap in R&D alliance settings. This hypothesis also provides further support for the theoretical mechanism underlying Hypothesis 1, as the prior theory development discussion suggests.

Figure 2 graphically illustrates the contingent effects of *focal average deal scope* and *focal knowledge base*. The figure shows the relationship between *R&D overlap* (on the x-axis) and the average predicted effect over all observations of the innovation output variable, *forward citations* (on the y-axis), graphed at low (minimum) versus high (maximum) levels of each of the two contingencies.[7] Consistent with the hypothesized effects, *focal average deal scope* enhances the negative relationship between greater *R&D overlap* and forward citations. Higher *focal knowledge* base on the other hand mitigates the negative effect of *R&D overlap*, with the firm's innovation output actually benefitting under the joint conditions of high *R&D overlap* and a high *focal knowledge base*.

In addition to the main and contingent effects, it is worth noting as well some of the results on the various control measures. *Focal portfolio size* remains positive and significant throughout the three specifications (3-2) through (3-4), suggesting that there is a consistently positive effect of having a larger portfolio of alliances from the focal firm's perspective. The negative effect of *first alliance percent* reflects the aggregate influence of the incumbents' alliance experience: while greater competition from the firm's partners' partners tends to have negative consequences for focal firm innovation, incumbents that are quite inexperienced with alliances may also have a negative impact on their start-up partners. Finally, the reduction in innovation associated with public firms is a consistent result throughout the Table 3 specifications.

Overall then, the results in Table 3 provide strong support for Hypotheses 1, 2 and 3. Hypotheses 2 and 3 are meant as tests of the theoretical mechanism underlying Hypothesis 1; together these three specifications thus offer results consistent with the idea that greater

[7] Hoetker (2007, p. 342), for example, recommends calculating the "average effect over all observations" in graphing and interpreting coefficients in non-linear models. I follow this approach in the graphs here.

competition within R&D-related functions stemming from a focal start-up's partners' partners will reduce the innovation benefits that accrue to the focal start-up due to capacity constraints on incumbent partners' time and attention.

[Insert Table 3 and Figure 2 about here]

Finally, I turn to the focal firm exit outcome specifications to test Hypothesis 4, which suggests that there are conditions under which functional activity overlap can be beneficial to the focal firm. As the theory suggests, this is likely to occur for marketing relationships, where a high valuation exit is the outcome of interest. Accordingly, Table 4 presents probit estimates of the dependent variable, *high valuation exit*. The covariates in this analysis are the same as in the innovation output analyses in Tables 3 and 4, except that the public firm dummy is not included (and in addition, since the dependent variable is a high valuation exit, post-exit years are not included in the sample over which the specifications are run). Specifications (4-1) and (4-2) are analogous to specifications (3-1) and (3-2), showing the effects on *high valuation exit* with and without the functional activity overlap variables. The main variable of theoretical interest is *marketing overlap*, which is significant and positive in specification (4-2), consistent with the prediction of Hypothesis 4.

[Insert Table 4 about here]

DISCUSSION AND CONCLUSION

This study has examined the performance implications of competition within particular functional areas for access to the resources of a firm's alliance partners. Central to the main argument is the idea that the time and attention of an alliance partner with respect to a given functional alliance activity may be non-scale free, with their effectiveness being constrained when applied across multiple alliances. As a consequence, the *other* relationships a firm's alliance partners have established can influence the firm's returns to its alliance collaborations. I develop the main hypothesis that greater levels of R&D-related functional activity overlap—i.e., when the start-up's incumbent R&D alliance partners have a higher incidence of other alliances with R&D activities in their alliance portfolios—will reduce the innovation performance benefits associated with the start-up's R&D alliance relationships. This effect stems from a reduction in knowledge spillovers from the incumbent to the start-up, an important input to the start-up firm's innovation process. I develop additional hypotheses regarding the role of deal scope and firm knowledge base, contingencies that respectively enhance and mitigate the negative main effect of greater R&D-related functional overlap, and that are predicated on the knowledge spillover-based logic underlying the main hypothesis.

Empirical analysis of a sample of biotechnology firms observed from their date of founding onwards provides supporting evidence for the hypothesized arguments linking R&D-related functional overlap (and its contingencies) to start-up firm innovation output. I find empirical evidence as well for the role of marketing-related functional activity overlap in positively influencing performance of a particular type (high valuation exits). Taken together, these results contribute to the alliance portfolios literature by demonstrating the importance of considering the resource competition effects of indirect ties, as well as to the networks literature by underscoring the importance of considering tie content (e.g., alliance function), an issue that has been relatively underemphasized in this literature due to the greater emphasis placed on issues of overall network structure.

Before discussing the implications of this study for future research, I briefly turn to the role that the precursors to relationship formation between start-ups and incumbents might play with respect to the dynamics examined in this study. In particular, there is likely to be an ongoing matching process taking place between start-ups and incumbents that influences relationship formation. Prior to tie formation both groups of firms are likely making decisions over the sets of relationships in which they engage, taking into account information available to them through various observable characteristics of their prospective partners. Such a process might raise endogeneity concerns if factors such as the start-up's underlying quality influence start-up performance outcomes and also influence the types of alliance relationships in which the start-up engages. There are two primary ways through which the empirical design of this study aims to mitigate any such effects: first, the use of start-up firm fixed effects in the innovation specifications to facilitate within-firm inferences and rule out unobserved (time invariant) heterogeneity; and second, the use of a broad set of covariates in all specifications that proxy for time-varying dimensions of start-up firm quality (e.g., the lagged measure of patent counts; the stock of venture capital investments; and the number of corporate investors in the firm).

The patent and equity investment measures are particularly helpful in controlling for the possibility of assortative matching based on start-up quality that may be occurring. Prior research suggests that factors such as homophily and network constraints lead better endowed and higher status actors to develop more favorable inter-organizational relationships (Ruef, Aldrich and Carter, 2003; Powell, White, Koput and Owen-Smith, 2005), leading to high-quality incumbents being matched with high-quality start-ups (consistent with the role of relationships with high-status partners as a credible signal of start-up quality [Stuart et al., 1999]). At the same time, the prior literature also suggests that venture capital and patent-based characteristics are observable signals used by prospective partners to assess the quality of early-stage start-ups (e.g., Gompers and Lerner, 2004; Hsu and Ziedonis, 2013). As a consequence, controlling for correlates of start-up quality, as is done in the specifications employed in this study, can help mitigate the effects associated with the typical forms of homophily and quality-based assortative matching discussed in the prior literature.[8]

In summary, this paper contributes to a deeper understanding of alliance portfolios by highlighting an important yet understudied dynamic: competition for access to partner firm resources. The idea that there is an inherent carrying cost of establishing multiple relationships that can then spill over to partnering firms injects a new dimension of analysis into the alliance literature that is of particular relevance to firms as they consider strategies for inter-organizational resource acquisition (Lavie, 2006; Gulati et al., 2009). There are several avenues for future research building on the insights of this study. First, expanding the study to other industry settings and considering performance metrics beyond innovation and exit outcomes could add further nuance to our understanding of competition for alliance partner resources. Second, more detailed process-oriented studies could provide a fuller understanding of the individual-level microdynamics of the knowledge spillover effects discussed here. Third, incorporating the role of distinct functional alliance activities into models explaining the emergence of network ties could offer a deeper understanding of the implications of inter-organizational networks. Finally, examining the resource allocation and organization design strategies used by incumbents and start-ups to mitigate the effects of non-scale free capabilities could further enrich our understanding of partner resource competition effects in alliances. This study thus helps shape the future direction for a set of emerging conversations in the literature on strategic alliances.

[8] An emerging stream of work on two-sided matching has sought to understand how factors beyond homophily and assortative matching can influence the partnering process (e.g., Mitsuhashi and Greve, 2009; Vissa, 2011; Mindruta, Moeen and Agarwal, 2013). While such processes are beyond the scope of the present study, the results here can inform future research on this topic, for example by highlighting the importance of incorporating resource competition effects into the preferences and interests of each side in the alliance formation process.

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Figure 1. Differing partner firm alliance portfolio configurations

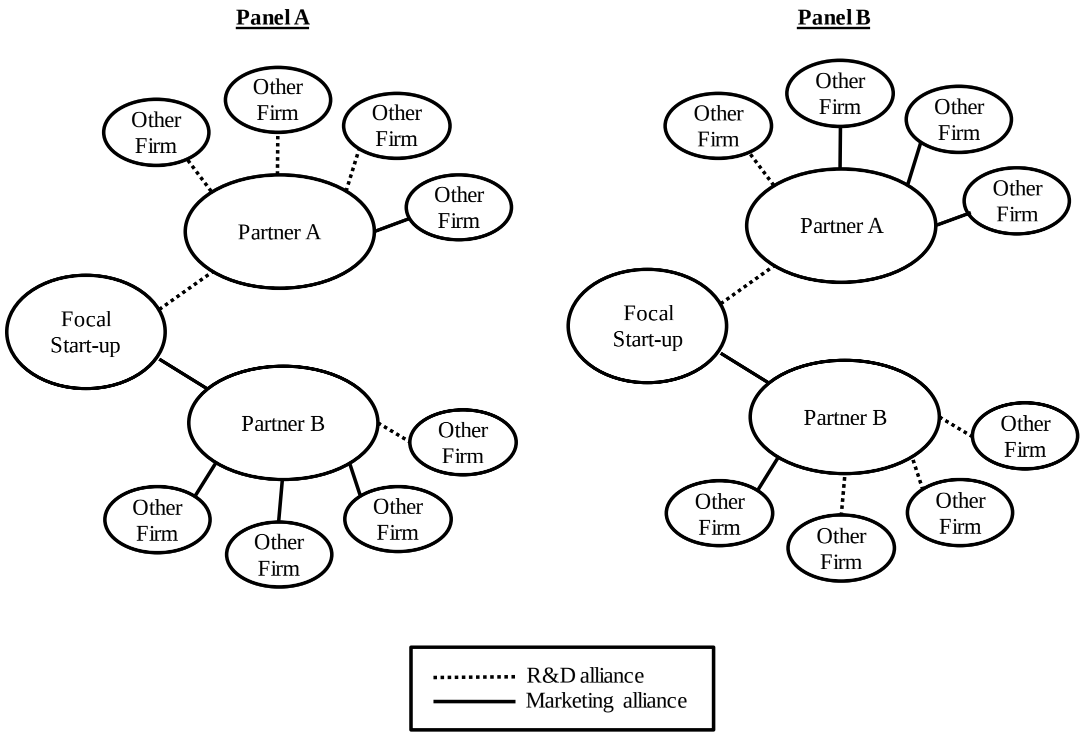

Figure 1 shows a start-up with two ties: an R&D alliance (dotted line) and a marketing alliance (solid line). The partners' alliance portfolio configuration differs in the two panels: the focal start-up's relationships in Panel A are with incumbents that have many other relationships containing the same function as the relationship with the focal firm (as compared to Panel B).

Figure 2. Effects of contingencies on innovation outcomes

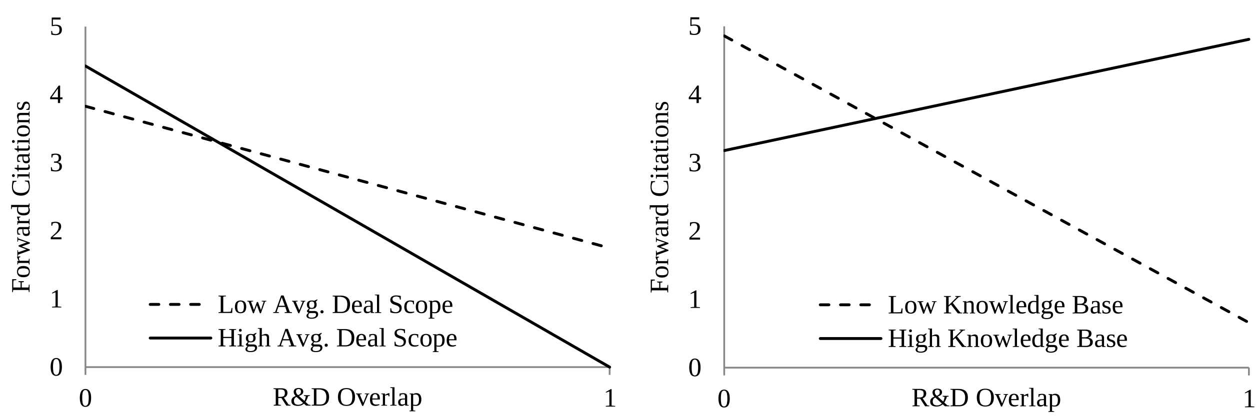

Figure 2 shows the average predicted count of forward citations as a function of R&D overlap, at low vs. high levels of the contingencies investigated in H2 and H3.

Table 1. Summary statistics and variable definitions, focal firm-year level of analysis

VARIABLE	DEFINITION	MEAN	SD
Dependent variables			
Forward citations	Total forward citations within a four-year window following the current firm-year to current firm-year patents	4.04	17.95
High-valuation exit	Dummy = 1 in firm-year if the focal firm exits through a high-valuation IPO or acquisition	0.02	0.14
Independent variables			
Functional activity overlap measures			
(1) R&D overlap	R&D overlap, focal firm-incumbent portfolio (see text)	0.31	0.31
(2) Licensing overlap	Licensing overlap, focal firm-incumbent portfolio (see text)	0.23	0.27
(3) Marketing overlap	Marketing overlap, focal firm-incumbent portfolio (see text)	0.09	0.18
Contingencies: deal scope and knowledge base			
(4) Focal average deal scope	Average number of distinct functional activities per alliance in the focal firm's alliance portfolio	0.25	0.79
(5) Focal knowledge base	Stock count of the focal firm's patents as of the prior firm-year	8.59	37.46
Focal portfolio controls			
(6) Focal portfolio size	Stock count of alliances established by the focal start-up from the date of founding up to the current firm-year	1.64	3.47
(7) Public firm percent	Percent of alliances in the focal firm's alliance portfolio with a publicly traded partner	0.34	0.37
(8) Corporate investors	Stock count of corporate investment relationships established by the focal start-up from the date of founding up to the current firm-year	0.51	0.86
Incumbent portfolio controls			
(9) Incumbent portfolio size	Average 5-year stock count of alliances in the focal firm's incumbent partners' alliance portfolios	16.69	34.51
(10) First alliance percent	Average percent of incumbent partners where the alliance with the focal firm is the incumbent's first such relationship	0.20	0.30
Industry overlap controls			
(11) Industry overlap	Percent of focal firm alliances where the focal firm and incumbent partner are in the same SIC code	0.25	0.35
(12) Industry overlap, focal firm-incumbent portfolio	Average percent overlap in SIC code between the focal firm and the incumbent partners' partners	0.15	0.26
Focal firm development controls			
(13) Equity stock	Stock of total venture capital investments into the focal firm from founding up to the current firm-year ($M)	31.13	48.48
(14) Firm age	Age of the firm in years (since founding)	5.85	4.02
(15) Public firm dummy	Indicator variable (=1) if the focal firm is publicly traded	0.03	0.16

Note: The natural logarithm of a variable, X, will be denoted L X.

Table 2. Pairwise correlation matrix of independent variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
(1)	1.00														
(2)	-0.23	1.00													
(3)	-0.27	0.36	1.00												
(4)	0.06	0.02	0.01	1.00											
(5)	-0.02	-0.03	-0.04	0.04	1.00										
(6)	0.10	-0.08	-0.08	0.28	0.46	1.00									
(7)	0.14	-0.12	-0.14	0.01	-0.01	-0.06	1.00								
(8)	0.22	-0.22	-0.12	0.05	-0.02	0.09	0.10	1.00							
(9)	0.03	-0.04	-0.05	-0.02	0.04	-0.04	0.17	0.04	1.00						
(10)	-0.39	-0.31	-0.21	0.00	0.04	0.01	-0.16	-0.13	-0.18	1.00					
(11)	0.11	0.18	0.10	0.02	-0.01	-0.04	0.09	0.09	-0.06	-0.04	1.00				
(12)	0.27	0.05	-0.10	0.02	0.02	0.04	0.08	0.08	0.03	-0.25	0.34	1.00			
(13)	0.15	-0.07	-0.07	0.09	0.07	0.10	0.08	0.34	0.12	-0.13	0.26	0.19	1.00		
(14)	-0.01	0.09	-0.01	-0.04	0.16	0.32	-0.08	0.22	-0.08	0.06	0.01	0.06	0.29	1.00	
(15)	0.06	-0.04	-0.02	0.14	-0.02	0.01	-0.00	0.07	0.04	-0.00	0.05	0.03	0.28	-0.01	1.00

Note: independent variable numbering corresponds to Table 1 numbering.

Table 3. Functional activity overlap and innovation output

Independent Variables	Conditional Fixed Effects Poisson QML Estimates with Robust Standard Errors Dependent Variable: *Forward Citations*			
	(3-1)	**(3-2)**	**(3-3)**	**(3-4)**
R&D overlap		-2.671*** (0.915)	-2.084** (0.920)	-4.197*** (1.126)
Licensing overlap		-1.567** (0.687)	-1.774** (0.722)	-1.651* (0.977)
Marketing overlap		2.379 (2.081)	2.319 (2.272)	3.533 (2.771)
R&D overlap * L focal average deal scope			-1.166*** (0.440)	
Licensing overlap * L focal average deal scope			0.073 (0.479)	
Marketing overlap * L focal average deal scope			0.684 (0.919)	
R&D overlap * L focal knowledge base				0.875*** (0.239)
Licensing overlap * L focal knowledge base				-0.220 (0.363)
Marketing overlap * L focal knowledge base				-0.628 (0.746)
L focal average deal scope	-0.053 (0.112)	-0.072 (0.115)	0.227 (0.236)	-0.132 (0.119)
L focal knowledge base	0.041 (0.116)	0.050 (0.117)	0.077 (0.117)	-0.172 (0.144)
L focal portfolio size	0.775* (0.455)	0.775* (0.441)	0.781* (0.427)	0.925** (0.424)
L public firm percent	0.877 (0.823)	0.984 (0.821)	0.818 (0.798)	1.076 (0.758)
L corporate investors	-0.222 (0.542)	-0.191 (0.546)	-0.257 (0.548)	-0.212 (0.548)
L incumbent portfolio size	0.525* (0.310)	0.127 (0.240)	0.252 (0.237)	0.202 (0.272)
L first alliance percent	0.043 (0.807)	-1.680* (0.876)	-1.492* (0.884)	-1.748* (0.917)
L industry overlap	1.560 (0.989)	1.342 (0.937)	1.370 (0.944)	1.642 (1.068)
L industry overlap, focal firm-incumbent portfolio	-2.766*** (0.782)	-1.507 (0.965)	-1.389 (0.917)	-0.175 (1.271)
L equity stock	0.334* (0.196)	0.270 (0.178)	0.280* (0.166)	0.177 (0.167)
L firm age	-0.184 (0.496)	-0.026 (0.469)	0.027 (0.461)	0.459 (0.582)
Public firm dummy	-0.599*** (0.199)	-0.620*** (0.196)	-0.635*** (0.195)	-0.641*** (0.209)
Year fixed effects	Yes	Yes	Yes	Yes
Firm fixed effects	Yes	Yes	Yes	Yes
Log pseudolikelihood	-3200.92	-3128.93	-3086.01	-3022.59
Num. Obs. (Firms)	774 (98)	774 (98)	774 (98)	774 (98)

*, ** or *** indicate statistical significance at the 10%, 5% or 1% level, respectively.

Table 4. Functional activity overlap and high valuation exit

Independent Variables	Probit Estimation with Standard Errors Clustered by Firm DV: *High Valuation Exit*	
	(4-1)	**(4-2)**
R&D overlap		-0.056 (0.379)
Licensing overlap		-0.978* (0.550)
Marketing overlap		3.302*** (1.147)
L focal average deal scope	-0.059 (0.175)	-0.023 (0.175)
L focal knowledge base	0.048 (0.096)	0.014 (0.102)
L focal portfolio size	0.306 (0.203)	0.337* (0.205)
L public firm percent	-0.188 (0.405)	-0.011 (0.433)
L corporate investors	0.016 (0.177)	0.064 (0.188)
L incumbent portfolio size	-0.026 (0.133)	-0.061 (0.149)
L first alliance percent	-0.811 (0.549)	-0.667 (0.620)
L industry overlap	0.656* (0.374)	0.955** (0.418)
L industry overlap, focal firm-incumbent portfolio	0.005 (0.693)	0.260 (0.741)
L equity stock	0.089 (0.084)	0.118 (0.080)
L firm age	0.430 (0.350)	0.661* (0.347)
Constant	-2.940*** (0.991)	-3.727*** (0.879)
Year fixed effects	Yes	Yes
Pseudo R^2 / Log pseudolikelohood	0.1528	0.1948
Num. Obs. (Firms)	438 (116)	438 (116)

*, ** or *** indicate statistical significance at the 10%, 5% or 1% level, respectively.

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