Resource Congestion in Alliance Networks: How a Firm’s Partners’ Partners Influence the Benefits of Collaboration

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Research summary. The network resources a firm can access through its strategic alliances are critical precursors to innovation: they provide the information and know-how needed to generate new knowledge. Yet prior literature has not directly considered the congestion of network resources stemming from constraints on their capacity to be applied without loss of value across multiple settings. I examine the degree to which this form of resource congestion influences the innovation benefits a focal firm realizes from its alliance portfolio. In a panel dataset of biopharmaceutical firms, I find that the knowledge-based resources of a focal firm’s alliance partners can be congested due to multiple claims on these resources from the firm’s partners’ partners. This insight bridges the network and resource-based perspectives on alliances and innovation.

Managerial summary. Strategic alliances are an essential tool for managers in knowledge-intensive settings: they allow firms to access diverse information and know-how which can be of critical importance as inputs to the innovation process. What managers may overlook, however, is that the knowledge-based resources of their alliance partners can be congested due to competing claims on these resources from the other alliances in which their partners are engaged. In such cases, firms may end up competing for resources such as partner time and attention with their partners’ other partners. Consequently, when engaging in alliances, managers should be attentive not only to the knowledge resources an alliance partner may hold, but also to whether these partner knowledge resources may ultimately be congested due to their partners’ other relationships.

Keywords: Alliance portfolios; networks; innovation; resource-based view; resource congestion

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INTRODUCTION

Innovation is a central competitive concern for firms in knowledge-intensive settings. Prior literature characterizes innovation as arising through the recombination of existing knowledge (Fleming, 2001; Galunic and Rodan, 1998; Hargadon and Sutton, 1997; Katila and Ahuja, 2002). As such, innovation requires access to diverse knowledge, which serves as a factor input to the process of new knowledge production. Much of the information and know-how used to produce new knowledge, however, resides outside firm boundaries (Ahuja, 2000; Rosenkopf and Nerkar, 2001). It is for this reason that alliances are often pervasive in knowledge-intensive settings: they facilitate the acquisition of knowledge and technological capabilities by firms from external sources (Mowery, Oxley and Silverman, 1996; Phelps, Heidl and Wadhwa, 2012; Reuer, 2004; Stuart, 2000).

A network-level perspective has been influential in shaping our understanding of the link between alliances and innovation (Ahuja, 2000; Gulati, 1998; Lavie, 2006; Schilling and Phelps, 2007). This perspective suggests that the network of alliances in which a firm is situated serves as the “locus of innovation,” (Powell, Koput and Smith-Doerr, 1996), allowing “knowledge, skills, and physical assets” to be shared among partners (Ahuja, 2000: 428). Direct (first-degree) and indirect (second-degree) ties allow firms access to knowledge and information from firms in the network, with more central network positions allowing for a richer inflow of information.¹

Empirical evidence points to tangible benefits of engaging in alliances and of being positioned centrally in knowledge networks (Baum, Calabrese and Silverman, 2000; Schilling and Phelps, 2007; Shan, Walker and Kogut, 1994; Shipilov, 2009), and scholars have accordingly extended

¹ The terms direct ties, indirect ties, network structure, and network centrality are commonly used in the networks literature (e.g., Wasserman and Faust, 1994). Direct ties are the number of connections a focal firm has to other firms in the network (e.g., the focal firm’s alliance partners). Indirect ties are the connections of the firm’s direct ties (the firm’s partners’ partners). Network structure is the overall pattern of connections in the network. Network centrality is measured in various ways: e.g., ‘degree centrality’ is the number of direct ties of a focal firm (Wasserman and Faust, 1994: 178).
the resource-based view (Barney, 1991) to recognize the role of network resources in competitive advantage (Gulati, 1999; Lavie, 2006).

Yet, while work bridging the network perspective on alliances with the resource-based perspective has been influential in directing attention to the role of network resources (e.g., Lavie, 2007; Wassmer and Dussauge, 2011), this work has sidestepped an important aspect of the resource-based view: namely, that certain resources may face opportunity costs when applied across multiple contexts (Helfat and Eisenhardt, 2004; Levinthal and Wu, 2010, Wu, 2013). Levinthal and Wu (2010), drawing on Penrose (1959), categorize firm resources into those that are “scale-free” in the sense that they are not limited by the extent of their application across different markets (e.g., a firm’s brand name), and those that are “non-scale free” in that they face opportunity costs when used in a particular setting (e.g., specialized human capital expertise). Multiple claims on the use of the latter category can diminish their efficacy in a specific context—in other words, such resources are capacity-constrained.\(^2\)

The literature on alliance networks has not directly incorporated the concept of capacity constraints into its view of network resources.\(^3\) Many of the purported benefits of being situated within a knowledge network, however, stem from resources that arguably face opportunity costs when applied across multiple settings. The transfer of specialized knowledge and expertise from a partner firm, for example, involves the time and attention of individuals (Devarakonda and Reuer, 2018; Howard et al., 2016), and multiple claims against such human capital resources likely diminishes their efficacy in any given setting. Explicitly recognizing the potential for congestion of certain knowledge resources held by a firm’s alliance partners (stemming from the

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2 This situation can also be characterized as exhibiting diseconomies of scope in the use of particular resources across multiple contexts (Panzar and Willig, 1981; Teece, 1982).
3 See Wadhwa, Phelps and Kotha (2016) for a notable example of a study that discusses resource capacity constraints in the context of investor cognitive limits in a corporate venture capital portfolio context.
capacity-constrained nature of the resources)\(^4\) may thus deepen our understanding of the innovation benefits to a firm from its alliance relationships.\(^5\)

In this study I examine the role of capacity-constrained resources in shaping the (innovation) benefits of alliance relationships. In alliance contexts, certain partner resources may become congested due to their capacity-constrained nature. The other relationships of a focal firm’s partners then become relevant considerations, as the focal firm’s partners’ partners influence the extent to which a focal firm can derive benefits from its network resources. I examine not only the average effect of this form of “resource congestion” in a firm’s network resources, but also the extent to which differential resource allocation on the part of a focal firm’s partners may diminish or amplify any resource congestion effects.

The empirical context is the biopharmaceutical industry, in which alliances among biotechnology and pharmaceutical firms are commonplace (Hagedoorn, 2002). This industry has served as the setting for prior studies addressing knowledge creation among partnering firms (e.g., Devarakonda and Reuer, 2018; Diestre and Rajagopalan, 2012; Rothaermel, 2001; Stuart, Hoang and Hybels, 1999; Vassolo, Anand and Folta, 2004), and is thus well-matched for the objective of understanding resource congestion in knowledge-intensive situations where there is a high-degree of intangible asset sharing. I assemble a firm-year panel of biotechnology firms, tracking each firm from its founding onwards, and collecting data on the firms’ alliances, their partners’ alliances, and other firm-level characteristics such as venture capital funding, patenting, and product development histories.

\(^4\) Knowledge flowing through a network likely contains a mix of codifiable information as well as more tacit know-how (Kogut and Zander, 1992; Polanyi, 1966). As discussed in the Theory and Hypotheses section, it is the tacit form of knowledge that is more likely to be congested.

\(^5\) Prior literature interchangeably uses the terms non-scale free and capacity-constrained (e.g., Levinthal and Wu, 2010; Wu, 2013). I use these terms to refer to a focal firm’s partners’ resources (or, more generally, capabilities) that diminish in effectiveness for the focal firm when faced with multiple claims on their use from the partners’ other partners. Partner resources of this type can be considered “congested” because of the presence of multiple claims on their use. Throughout this paper, I use the terms non-scale free, capacity-constrained, and congestible interchangeably in describing such resources. Note, in addition, that the terms scale-free and non-scale free are more general terms for categories of resources, whereas the terms codified and tacit are instances of such resources specific to knowledge-based settings. Underlying the notion of resource congestion is that there are constraints on a firm’s non-scale free tacit know-how to be applied without loss of value across multiple partners.
The core insight of this paper is that the congestion of alliance partner resources, arising from multiple claims on those resources from the focal firm’s alliance partners’ partners, can dampen the alliance-related innovation benefits flowing to the focal firm. This paper thus contributes to three distinct conversations in the strategy field. First, it expands our understanding of network resources (e.g., Gulati, 2007; Lavie, 2007) by strengthening the bridge between the network and resource-based perspectives. Whereas the networks literature suggests that indirect ties can act as channels for the flow of information, know-how, and other knowledge-based resources, this paper points to a tradeoff between such benefits and potential resource congestion. Second, this paper adds a new dimension to the conversation on capacity-constrained (i.e., non-scale free) capabilities. While prior work has focused on how a focal firm’s internal resources shape strategic outcomes (e.g., Levinthal and Wu, 2010; Wu, 2013), this paper addresses the implications of capacity-constrained resources for other firms (i.e., the implications a partner’s capacity-constrained resources have for the focal firm). Finally, this paper contributes to the growing literature on alliance portfolios in which a firm’s overall collection of alliances is at the forefront of efforts to understand the link between alliances and firm performance (e.g., Hoehn-Weiss and Karim, 2014; Jiang, Tao and Santoro, 2010; Lavie, 2007).

THEORY AND HYPOTHESES

Network perspective on alliances and innovation

Innovation arises through novel recombinations of existing knowledge (Fleming, 2001; Galunic and Rodan, 1998; Hargadon and Sutton, 1997; Katila and Ahuja, 2002). A firm’s ability to innovate is thus predicated on accessing diverse knowledge, which serves as raw material for recombination efforts (Balachandran and Hernandez, 2018; Dushnitsky and Lenox, 2005; Grigoriou and Rothaermel, 2017; Wadhwa and Kotha, 2006). Alliances are a key channel for knowledge sourcing (Aggarwal and Wu, 2019; Alvarez and Barney, 2001; Beckman and
Haunschild, 2002; Dyer and Singh, 1998; Rosenkopf and Almeida, 2003; Ro
taermel, Hitt and Jobe, 2006; Villalonga and McGahan, 2005), enabling the expansion and renewal of a firm’s knowledge base (Agarwal and Helfat, 2009; Capron and Mitchell, 2009; Hoang and Ro
taermel, 2010; Sosa, 2011). R&D alliances in particular allow firms to learn, to gain access to information they may not otherwise be able to access, and to develop crucial “know-how” that is of use in the innovation process (Ahuja, 2000; Hamel, 1991; Kale, Singh and Perlmutter, 2000; Schilling and Phelps, 2007; Singh et al., 2016; Vasudeva and Anand, 2011). These benefits span not only the context of the particular relationship in which firms are engaged, but spill-over to the broader set of firm activities: i.e., knowledge acquired in one context can facilitate knowledge creation efforts more broadly (Doz, 2017; Gambardella and Panico, 2017; Kale, Dyer and Singh, 2002; Khanna, Gulati and Nohria, 1998).

Our understanding of the link between alliances and innovation has been increasingly informed by scholars taking a network perspective (Ahuja, 2000; Ahuja, Soda and Zaheer, 2012; Brass et al., 2004; Greve, Rowley and Shipilov, 2013; Gulati, 1998; Owen-Smith and Powell, 2004; Powell et al., 1996). The network perspective recognizes that alliances are a key channel for information and knowledge access. Direct and indirect ties, together with tie scope, determine the firm’s available external knowledge-based resources (Ahuja, 2000; Gibbons, 2004; Gulati and Gargiulo, 1999; Madhavan and Prescott, 2017; Paruchuri, 2010; Phelps et al., 2012). Direct ties allow firms to draw on partners’ knowledge-related resources and to access information that can inform innovation-related choices, while indirect ties also serve as critical channels for ongoing knowledge spillovers (Ahuja, 2000; Lavie and Drori, 2012; Nerkar and Paruchuri, 2005). Inter-organizational networks thus confer firms with resources that can be employed toward achieving competitive advantage in knowledge-intensive settings.

Attempts to marry the network perspective with the resource-based perspective have been primarily motivated by the need to address a key limitation of the latter: namely, the focus only
on a firm’s internally held resources in explaining a firm’s ability to generate rents (Lavie, 2006).

By generalizing the resource-based perspective to account for the possibility that firm resources may span inter-organizational boundaries, the notion of network resources recognizes the role of partner resources in creating what Lavie (2006) refers to as “inbound spillover rents” for the focal firm. While factors such as deal scope and technology overlap shape the volume and diversity of knowledge flowing to a firm (Khanna, 1998; Oxley and Sampson, 2004; Schilling and Phelps, 2007), the networks literature broadly points to a world in which a higher volume of direct and indirect ties (together with the partner resources to which these ties provide access) endows a focal firm with higher levels of knowledge-related resources, and by extension, higher levels of innovation-related output.

**Resource congestion in the context of alliance networks**

Whereas the literature on network resources has sought to expand the resource-based perspective by highlighting the role of alliance partner resources, a separate stream of work in the resource-based tradition has deepened our understanding of the underlying characteristics of these resources, focusing on the contrast between resources (or alternatively, capabilities) that are non-congestible as a consequence of their relative inability to be impaired in value when applied in multiple settings, and those that do experience a reduction in value when applied in multiple settings (Levinthal and Wu, 2010; Wu, 2013). As Wu (2013: 1267-1268) explains, the former category can be viewed as “scale-free,” and encompasses capabilities such as knowledge and brand, which broadly resemble public goods because they are not subject to opportunity costs in their application. The latter, on the other hand, are “non-scale free” in the sense of being “capacity constrained [such that] their use in one activity at any point in time precludes their use in other settings.” In other words, “compared to the public good nature of scale-free capabilities, their non-scale free counterparts resemble congestible public goods.”
The distinction between capacity-constrained (i.e., non-scale free) capabilities and capacity-unconstrained (i.e., scale-free) capabilities, has roots in the prior literature. Work on inter-temporal economies of scope, for example, recognizes that capabilities can be redeployed across time periods to alternate uses (Helfat and Eisenhardt, 2004, Lieberman, Lee and Folta, 2017). In the absence of constraints on their use, of course, such a reallocation would be unnecessary. Work on capability replication, by contrast, points to the scale-free nature of some capabilities, where an Arrow core encapsulates the idea that “information is ‘non-rivalrous in use’ [Arrow, 1962]” and “… the fact that information has been used multiple times or […] is being currently used elsewhere in no way detracts from the availability of that information for further use” (Winter and Szulanski, 2001: 733). The idea of capacity constraints, which is anchored in the resource-based perspective, also bears a close relationship to the concept of diseconomies of scope (Panzar and Willig, 1981), which is anchored in the context of production economies. The congestible nature of resources, arising as a result of constraints on their capacity to be effectively applied across multiple settings, results in diseconomies of scope in production, and consequently creates opportunity costs for the application of these resources in a given context.6

Prior work has not explicitly considered the implications of capacity constraints for network resources. Work on knowledge networks paints a stylized view of network resources in which higher levels of direct and indirect ties increase access to knowledge-based resources. This work generally abstracts away from the question of whether these resources are congestible. It

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6 The central idea behind diseconomies of scope is that the “joint output of a single firm is less than could be achieved by separate firms when each produces a single product ... [which] could occur if the production of one product somehow conflicted with the production of the second” (Pindyck and Rubinfeld, 2013: 259). In elaborating on the idea of (dis)economies of scope, Panzar and Willig (1981: 269) link economies of scope to the existence of sharable inputs; as they put it, “inputs which, once procured for the production of one output, would be also available ... [for the] production of other outputs.” The Panzar and Willig discussion on this point highlights the link between the idea of (dis)economies of scope, which has as its focal concern production outputs, and the resource-based perspective, which has as its focal concern resource inputs. Sharable inputs—or as Teece (1982: 48) puts it, inputs that are utilized “without complete congestion,” underpin economies of scope, as they are available for use, undiminished in value, across multiple settings. Conversely, non-shareable inputs (those that are congestible when applied in multiple settings) underpin the existence of diseconomies of scope.
may be the case, however, that some partner firm resources may indeed be congestible and thus constrained in their capacity to be applied effectively across multiple relationships. For example, work examining the context of corporate venture capital (Wadhwa et al., 2016) suggests that having multiple similar investments within an investment portfolio may cause funds to run up against the cognitive limits of investors with specialized expertise. In an alliance context, the degree to which a firm’s partners’ resources are available for the focal firm’s use is thus likely to turn on the nature of network resources (specifically, whether or not they are subject to congestion), together with the sources of possible congestion (specifically, the other relationships of the focal firm’s partners).

**Congestible knowledge resources in R&D alliance networks**

Knowledge resources transferred via strategic alliances can take on two broad forms: on the one hand, some knowledge can be more explicit and codifiable, with an information-like character; on the other hand, some knowledge can take on a more tacit component, consisting of various sets of skills and know-how that are harder to more explicitly articulate (Ahuja, 2000; Oxley and Sampson, 2004; Polanyi, 1966).\(^7\) This distinction between “information” and “know-how” has roots in work on the knowledge-based theory of the firm (Kogut and Zander, 1992). Both forms of knowledge are important precursors of innovation. Singh et al. (2016), for example, point out that in order to innovate firms need not only highly explicit knowledge but also “combinatory knowledge,” which captures the ability to combine knowledge in new ways.

In an R&D alliance context, ongoing inter-personal interactions are a key mechanism through which knowledge resources are transferred. Howard et al. (2016), for example, find that in biopharmaceutical alliances, social interactions are crucial for transferring innovative know-how. Doz (2017: 27) points out that inter-partner learning in R&D alliances often involves

\(^7\) As Ahuja (2000: 428) notes, the former can be viewed as “discrete quanta of information that can be transmitted through simple communication in relatively complete form and without loss of integrity,” while the latter, which are more experience-based and reliant on tacit skills, can be relatively non-codifiable, with their transferability to the partnering firm more reliant on direct contacts among individuals.
“shared facilities, jointly performed tests and experiments, customer visits and so on,” together with “secondments, exchanges of personnel” or visits into to labs of the alliance partner. Hoang and Rothaermel (2010) make related observations regarding personnel exchanges in R&D alliances, while Kale and Singh (2017) stress that learning is critical to knowledge transfer in alliances. Knowledge transfer may occur through formal mechanisms such as steering committees and task forces (Devarakonda and Reuer, 2018), or more generally through other factors that promote communication and engagement, which in turn increases the likelihood of realized alliance gains (Agarwal, Croson and Mahoney, 2010).

In knowledge-based settings, individual time and attention, which serve to channel know-how among partners, are a key resource constraint (Fleming, Mingo and Chen, 2007; Hansen and Haas, 2001; Ocasio, 1997). Competing demands on individuals from multiple relationships can shape the availability of knowledge-based resources when multiple relationships require access the same sets of human capital resources. Different forms of knowledge (information and know-how) exhibit different levels of sensitivity to these time and attention demands. Tacit knowledge, for example, can be more difficult to transfer (Argote, 1999; Simonin, 1999; Szulanski, 1996; Zander and Kogut, 1995) due to the greater cognitive load it places on individuals. Given the importance of inter-personal interactions in knowledge-based alliances settings as discussed above, the time and attention of individuals with respect to the transfer of tacit know-how is likely to be subject to congestion. In other words, tacit know-how is likely to represent a capacity-constrained resource in knowledge-based settings.

**Capacity-constrained resource congestion and firm innovation**

Taken together, the arguments outlined above suggest that: (a) as a baseline, the network perspective on alliances posits that a firm’s direct and indirect ties are a means of accessing information and know-how held by partnering firms; (b) this view does not explicitly account for the possibility that certain resources may be capacity-constrained (i.e., congestible); and (c)
much of the knowledge-related resource transfer that occurs in alliances operates via individuals, with their tacit skills and experience representing an important category of knowledge resources, and in particular one in which there may be constraints on time and attention.

Given that information and know-how both constitute critical inputs to the knowledge generation process, I argue that a firm’s innovation output will be hindered when the innovation-related resources of its partners are subject to greater constraints on their use. These constraints will arise when there are spillovers in capacity-constrained resource demands from the firm’s partners’ other R&D relationships—i.e., when the same capacity-constrained R&D resources are shared across multiple partners. I predict that, on average, focal firm innovation will be reduced under conditions of higher R&D capacity-constrained resource congestion.8

**Hypothesis 1.** Greater capacity-constrained resource congestion of a focal firm’s R&D alliance partners (stemming from the focal firm’s partners’ partners), will reduce focal firm innovation output.

**Factors shaping partnering firm attention allocation**

The main hypothesis outlined above should be interpreted as an *average* effect, which implicitly assumes homogeneity in the nature of interactions between the partnering firm and each of its partners. Yet it is likely that R&D alliances do not receive equal levels of attention. Any given partner is likely making choices on an ongoing basis with regard to whom their capacity-constrained knowledge resources should be allocated. Accordingly, the next two hypotheses address the conditions under which partnering firms may differentially allocate attention to firms in their portfolio.

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8 Note that I am focused on the *average* effect of R&D capacity-constrained resource congestion. A focal firm’s partners, however, may be able to differentially allocate time and attention across the relationships in their portfolios. I investigate this issue in the moderating hypotheses below. In addition, note that a key assumption underlying this hypothesis is that the partner firm shares (at least some) R&D resources across its portfolio of alliances. I discuss the degree to which this may be the case in my description of this paper’s empirical setting. As I discuss in that section, insights from prior studies in the biopharmaceutical context, combined with field interviews of 15 executives in this industry, suggest that while in some cases there may be resources devoted to an alliance that are not shared across partners, the sharing of time and attention of individuals at the pharmaceutical partner across multiple alliances is indeed a significant and pervasive feature of biopharmaceutical alliances.
The idea that attention in organizations may be channeled selectively has its roots in the behavioral theory of the firm (March and Simon, 1958). The attention-based view (Ocasio, 1997) sparked renewed interest in this point, with scholars recognizing that attention is a scarce (and, in the context of this study, congestible) resource. Prior work has sought to understand the factors that shape both the antecedents and consequences of attention allocation in organizations (e.g., Hansen and Haas, 2001; Sullivan, 2010), with this work focusing on a broad range of environmental and organizational factors to explain selective managerial attention (Ocasio, 2011). I focus on two key factors that may shape partner attention in R&D alliances, and that can mitigate or amplify the R&D capacity-constrained resource congestion effect: (a) varying signals of ongoing productivity on the part of the focal firm; and (b) the relative distinctiveness of the focal firm with respect to its partners’ other partners.

With regard to signals of productivity, I argue that a focal firm may garner greater attention and higher levels of capacity-constrained knowledge resources from its R&D alliance partners when it displays visible signs of progress in early-stage product development. Such signals are particularly important in an R&D context because the extent to which the focal firm may be of value in ways that justify ongoing investment by the partner in knowledge-based exchanges is likely to be ex-ante unknown and only measurable with significant levels of noise (Hsu and Ziedonis, 2013; Spence, 1973; Stuart et al., 1999). Quality signals can thus shape the degree to which partner attention flows to one firm in an alliance portfolio versus another (Piezunka, Katila and Eisenhardt, 2019). In other words, beyond the initial decision to engage in an alliance, partnering firms will make ongoing decisions concerning how to best direct their attention, with time-varying signals of productivity in part driving these decisions.9 This

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9 The allocation of time and attention is generally at the discretion of each partner, and thus does not pose contractual issues. The field interviews in my empirical setting underscore the discretion of alliance partners in this regard.
attention rationing logic is consistent with evidence from other settings, such as venture capital (Ozmel and Guler, 2015).

In the empirical context of this study, anecdotal evidence points to an ongoing reassessment on the part of pharmaceutical firms with regard to how resources are allocated within an alliance portfolio. For example, pharmaceutical executives I interviewed noted that they continually reassess their portfolio with the objective of reallocating attention to areas of greater opportunity. One interviewee noted that attention paid to alternative projects “ends up being much more about the development stage and probability of success,” with progress through the development pipeline a highly visible example of the sort of observable outcomes often considered. Positive signals in this regard would indicate a higher potential for gain by the partner firm, resulting in more intensive engagement with the focal firm. I thus argue that stronger signals of early-stage productivity will shift more attention—and thus more congestible knowledge-related resources—toward the focal firm, mitigating the negative effect of R&D capacity-constrained resource congestion in Hypothesis 1.10

Hypothesis 2: The negative effect of greater capacity-constrained resource congestion of a focal firm’s R&D alliance partners (H1) will be reduced when the focal firm displays stronger early-stage R&D-related productivity signals.

A second factor shaping partner attention allocation in alliance settings is the distinctiveness of the focal firm vis-à-vis its partners’ other partners. Substitutability can influence the power a firm holds in an alliance (Bae and Gargiulo, 2004; Lavie, 2007). In situations where the focal firm is relatively less substitutable relative to other firms in its partner’s portfolio, the partner firm will likely be more engaged, thereby allocating a greater share of its capacity-constrained knowledge resources to the focal firm. This argument is consistent with work on the

10 Variation in focal firm knowledge may influence the extent to which partner knowledge can be used by the focal firm. Thus, I control for time-varying correlates of a firm’s knowledge in the empirical specifications.
development of partner-specific experience (Gulati, Lavie and Singh, 2009; Zollo, Reuer and Singh, 2002). As Gulati, Lavie and Singh (2009) argue, for example, firms need to balance the development of partner-specific experience with the need to explore and to gain exposure to more distinctive ideas. In R&D alliances a focal firm’s partners may view alliance partners through this lens. The opportunity to learn more may thus cause firms to channel a greater share of capacity-constrained knowledge resources to their more distinctive partners.  

The final hypothesis thus addresses the implications of industry-related overlap between a firm and its partners’ partners. I argue that such overlap, which will cause the focal firm to be more substitutable and less distinctive from the perspective of its partners, will amplify the resource congestion effect. Thus, higher substitutability (i.e., lower distinctiveness) of the focal firm will exacerbate the effect of R&D capacity-constrained resource congestion. 

Hypothesis 3: The negative effect of greater capacity-constrained resource congestion of a focal firm’s R&D alliance partners (H1) will be amplified when the focal firm has greater industry overlap with its partners’ partners.

EMPIRICAL ANALYSIS

Biopharmaceutical alliances

The empirical setting for this study is the biopharmaceutical industry, which has been used in a number of prior studies of alliances and innovation (e.g., Diestre and Rajagopalan, 2012; Mindruta, Moeen and Agarwal, 2016; Rothaermel, 2001; Ryu, McCann and Reuer, 2018). I

11 Redundancy in partner portfolios may have two additional affects. First, it may allow the partner to more effectively use knowledge in ongoing innovation efforts (Cohen and Levinthal, 1990; Weigelt and Sarkar, 2009). Second, it may shape the level of engagement by the focal firm with the partner. On the former, it is important to note that the central concern of this paper is with the focal firm’s own level of innovation output, which is likely to be impacted by the partnering firm’s lower level of attention due to intra-portfolio substitutability. On the latter, I control in the empirical specifications for a host of time-varying factors that likely correlate with firms’ levels of alliance engagement.

12 Greater distinctiveness may also imply that the firm draws on disparate sets of resources. Although this is unobservable given the study’s empirical design, this could be a possible mediator of the attention allocation effect. The field interviews, however, suggest that the bulk of human capital resource constraints stem from more generalized human capital (e.g., steering committees), which are likely to be less specific vis-à-vis a given industrial application. Thus, this particular mediator is less likely to be the primary mechanism driving attention allocation. Nonetheless, future work should examine the micro-mechanisms through which attention allocation occurs, together with the role of differences across industrial applications in this context.
focus in particular on R&D alliances, where innovation and knowledge-sharing considerations are a central concern (Aggarwal and Hsu, 2009; Arora and Gambardella, 1990; Sampson, 2007; Yang, Zheng and Zhao, 2014). Given the paper’s theoretical focus on knowledge-based resource exchanges, an appropriate setting is one in which there are (intangible and tacit) knowledge-based resources shared in the context of these R&D alliances.

To better understand knowledge-based resource exchanges in this setting, I conducted a series of 15 interviews with biopharmaceutical industry executives. The interviews, together with literature using this industry as a setting, point to a situation in which biopharmaceutical R&D alliance relationships occur against the backdrop of ongoing questions regarding the most effective allocation of specialized human capital. The resources of alliance managers, scientists, and other specialized R&D personnel are subject to opportunity costs, with spillover implications arising from the focal firm’s partners’ other relationships. Spillovers may be direct, such as in situations where individuals employed at a focal firm’s partners operate across multiple relationships, or they may be indirect in that the partners’ human capital allocation decisions are in flux and subject to considerations such as whether particular individuals may be more effectively allocated to other contexts. In brief, the opportunity costs of human capital allocation on the part of a focal firm’s partners are a salient factor in R&D alliances.

An executive at a U.S.-based S&P 100 global pharmaceutical company, for example, pointed to the role of steering committees in serving an oversight function on alliance collaborations. These committees involve three members from each side that contribute expertise and governance oversight by meeting, interacting, and discussing advances on a regular basis. The committee composition changes over time given the skills required at various points in the

13 The interviewees included individuals at large and established pharmaceutical firms, as well as at smaller biotechnology firms. In most cases, the interviewees were involved in the alliance (or more generally, corporate development) functions at their firm. The interviews ranged from more exploratory discussions aimed at understanding the nature of the partnering process to more detailed discussions aimed at understanding the ways in which R&D alliance relationships in the biopharmaceutical industry operate in practice.
development of the relationship, but can involve scientists and other R&D personnel. The committee is often complemented by a separate group of personnel with alliance-related R&D experience whose mandate can span up to six different projects. The interviewee noted that individuals often work on multiple alliances, and as such face constraints on the amount of time they can devote to each project. Individuals move from one committee to another, suggesting an internal allocation of resources that occurs on an ongoing basis depending on firm needs at various points in time.14

Beyond steering committees, the executives interviewed pointed to ongoing opportunities for knowledge exchange among individuals in the partnering firms. The interactions described echoed insights from Howard et al. (2016)’s discussion of collaboration between Eli Lilly and smaller biotechnology firms, where the authors note that a key channel through which biotechnology firms reap innovation-related benefits from pharma collaborations is via ongoing social exchanges. An executive at a large global pharmaceutical company pointed to the importance of face-to-face exchanges and joint social events, as well as the multitude of opportunities for R&D personnel on both sides to work jointly on co-development. Scientists and subject matter experts often work on multiple projects in parallel, though with alliance management having an eye toward resource allocation, given that “resources are always a battle.” Projects with higher growth possibilities may obtain more resources (e.g., scientists and individuals with specialized expertise), which can have negative implications for other projects. A biotechnology executive noted that across multiple partnerships there is often a mix of individuals, some of whom may be dedicated to a specific project, and others who may be

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14 Recent studies within the biopharmaceutical industry (Devarakonda, McCann and Reuer, 2018; Devarakonda and Reuer, 2018) underscore the role of steering committees in influencing the degree to which the transfer of tacit knowledge and the creation of new knowledge occur among partnering firms. Committees coordinate joint activities and put in place structures for communication that facilitate ongoing knowledge exchanges. In addition, there is often a regular movement of individuals from one alliance context to another, a point that resonates with the comments from the pharmaceutical executive. This often creates opportunity costs: as Devarakonda and Reuer (2018: 1916) note, “firms may have to redeploy productive employees from other projects to the focal alliance, thus creating a cost of foregone opportunity by way of loss in productivity in the original projects.”
working in parallel on multiple projects. In all cases, however, human capital allocation considerations occur against the backdrop of potential alternative allocations to other projects.

The interviews also suggested a potential source of tension between larger pharmaceutical firms and smaller biotechnology firms. A multinational pharmaceutical executive noted that their alliances with smaller biotechnology firms are ones in which scientists from both sides work together. Portfolio management plays a key role in this context, in particular by determining where to place key assets (i.e., individuals with specialized expertise). If a particular partnership is more successful, they may allocate more resources to it; and in some cases, they may share resources across multiple partnerships. An executive at a smaller biotechnology firm on the other hand pointed out that the portfolio management activities of their larger partners can create challenges in that they are often competing with their partners’ other partners for high quality staff. As she mentioned, it can be difficult “if [your partners] only have junior people [allocated to you].” From the perspective of the biotechnology firm, not only is it important to ensure that the time and attention of individuals at partnering firms is not substantially constrained, but also that the firm is allocated the most qualified human capital.

Sample and data sources

The dataset is an unbalanced firm-year panel of the universe of 281 human biotechnology firms founded between 1990 and 2000 and present in the VentureXpert database, one of the largest sources of data tracking venture capital investments. The 1990 to 2000 time period ensures adequate coverage from the alliance data source, SDC, where data prior to 1990 is incomplete (Anand and Khanna, 2000; Schilling, 2009), and also ensures an adequate post-founding window over which to track focal firm evolution. Each firm is tracked from founding through 2006.

I draw on several archival sources to assemble the dataset: 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. PharmaProjects and Inteleos are used to construct product pipeline data; and focal firm post-IPO status is identified from SDC and Thomson One. Additional cross-checking is done with CorpTech, Compustat and SEC filings. Alliance data collection involves first identifying and coding all alliances of the focal firms, and then identifying and coding all alliances for partners identified in the first stage. The firm-year dataset incorporates data on 684 focal firm alliances and 11,389 incumbent firm alliances,\(^\text{15}\) as well as 6,554 patents issued to the focal firms, which result in 19,408 forward citations.

**Dependent variable**

Innovation output is measured using patent data. Patents are a key metric for innovation in the biopharmaceutical industry (Levin *et al.*, 1987), with their economic value best captured through forward citations (Hall, Jaffe and Trajtenberg, 2005; Trajtenberg, 1990). A four-year window for citations is consistent with prior studies on patents and innovation (e.g., Hegde, Mowery and Graham, 2009), and is used to make meaningful comparisons of firm output in any given firm-year (without such a window there would be an artificial upward bias in favor of older patents).\(^\text{16}\) I draw on the IQSS Patent Network database (Lai *et al.*, 2011) to identify all patents associated with the sampled firms, extracting all patents where the “assignee” name matches current or former names of the focal firm. *Forward citations (4-yr)* captures citations within a four-year window to the focal firm’s patents in the firm-year. Cross-checks are conducted with Google Patents to ensure completeness and accuracy.

**Operationalizing capacity-constrained resource congestion**

To operationalize the idea of capacity-constrained resource congestion I consider the full alliance portfolio of the focal firms, together with the full alliance portfolio of the focal firm’s partners. Recent work points to alliance portfolios as a relevant unit of analysis (e.g., Hoffman, 2007; 2011).

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\(^{15}\) Descriptive statistics for the sample of alliances, including industry codes as reported in the alliance data, together with the propensity of particular functional areas within the sample of alliances, can be found in the Online Supplementary Material.

\(^{16}\) The results are robust to longer time periods over which to capture citation counts.
Lavie, 2007; Ozcan and Eisenhardt, 2009; Vasudeva and Anand, 2011; Wassmer, 2010), with portfolio configuration an indicator of the resources relevant to the firm’s alliances (Hoehn-Weiss and Karim, 2014) and an important predictor of performance (Jiang et al., 2010; Lahiri and Narayanan, 2013).

Figure 1 illustrates how R&D-related resource congestion is conceptualized. In each panel a focal firm (e.g., a small biotech firm) is engaged in two alliance relationships (e.g., with a larger pharma firm). In Panel A, for each alliance, the biotech firm’s pharma partners have many other alliances with the same functional purpose as the alliance with the focal (biotech) firm. Thus, the marketing relationship of the focal biotech firm in Panel A is with a pharma partner that has several other marketing alliances, and the R&D relationship of the focal biotech firm in Panel A is with a pharma partner that has several other R&D relationships. This stands in contrast with the biotech firm in Panel B, where for each alliance type there is a smaller proportion of “other” relationships of the same function as that in which the focal biotech firm and its pharma partner are involved. To the degree that the only difference between Panel A and Panel B is the set of functions associated with each alliance, Partner A in Panel A would face greater constraints on their R&D-related resources than would Partner A in Panel B: i.e., R&D-related resource congestion is higher in Panel A than in Panel B.

[Insert Figure 1 here]

There are three underlying assumptions of note in this conceptualization. A first assumption is that there are at least some resources of the focal firm’s partners that are shared across multiple alliance partners. This assumption concords with the empirical context I study. As discussed above, in biopharmaceutical alliances there are a number of ways in which human capital is directly or indirectly shared across an alliance portfolio. A second assumption is that of

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17 For illustration, these are single function alliances—one R&D alliance and one marketing alliance—though as prior work suggests (e.g., Hoehn-Weiss and Karim, 2014), any alliance may consist of multiple functions.
equal time and attention allocation by partner firms among all alliances. The resource congestion measure as conceptualized in Figure 1 should be viewed an average effect that is moderated by the set of contingencies—e.g., those described in Hypotheses 2 and 3. Finally, a third assumption relates to the window over which an alliance portfolio is defined. Consistent with the approach taken in a number of recent alliance studies (e.g., Bos, Faems and Noseleit, 2017; Cui, Yang and Vertinsky, 2018; Tyler and Caner, 2016; Van de Vrande, 2013; Yang, Lin and Peng, 2011), I use a five-year window to recognize that alliances continue beyond just the year in which they were established, but that they are at the same time finite in their lifespan.

To construct the measure of R&D resource congestion, I first determine, at the level of each focal biotech firm alliance, whether the particular alliance involves the R&D function. If so, I code a binary variable for that alliance observation as 1 (and 0 if R&D is not associated with the alliance). Then, for the pharma partner associated with the particular alliance, I determine the percent of other alliances in the partner’s portfolio where the R&D function is present. The overlap value at the alliance activity level is the product of the binary variable and the percentage variable. The resulting value thus represents the partner firm’s intensity of R&D activity within its alliance portfolio for the focal firm’s R&D relationships. Since the measure is at the focal biotech firm-year level, values for each alliance are averaged over the biotech’s portfolio of alliances (which captures alliances within a five-year rolling window) to arrive at the final measure of R&D capacity-constrained resource congestion. For conciseness I label the measure R&D resource congestion in the empirical discussion and tables.
Moderating and control variables

All variables are constructed at the focal biotechnology firm-year level. In addition to the R&D resource congestion variable described above (the core theoretical variable of interest) I construct two moderators of the main effect, together with a set of controls to capture focal and partner firm characteristics. All variables are time varying, and all analyses are run with focal firm fixed effects, as well as year and industry effects.

Moderators. Two variables serve as moderators of the main R&D resource congestion effect to test conditions under which capacity-constrained time and attention of the focal (biotech) firm’s partners will be more or less likely to be directed toward the focal firm. With Hypothesis 2 I seek to understand whether greater signals of early-stage R&D-related productivity will be more likely to attract partner attention in R&D settings, thereby reducing the negative effect of R&D resource congestion. In the biopharmaceutical context, products entering a preclinical trial stage (i.e., before human trials begin) are a key indicator of R&D success. I construct early-stage product pipeline, which is a count of products in the focal firm’s product pipeline that have entered preclinical trials. With Hypothesis 3 I argue that greater industry overlap between the focal firm and its partners’ partners will amplify the negative R&D resource congestion effect. In any given firm-year, focal-partners’ partners industry overlap is constructed as the average share of the focal firm’s partners’ portfolios involving alliances with firms in the same industry as the focal firm (as defined by their 4-digit SIC code).

Controls: alliance portfolio composition. I construct as controls a set of variables that capture characteristics of the alliance portfolios of the focal firm and its partners. To capture the focal firm’s overall level of alliance activity I construct focal portfolio size, a count of the number of alliances (all alliances, including non-R&D) in the focal firm’s portfolio (in a five-

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effect of capacity constraints is robust (and in fact stronger) for smaller (based on firm size) incumbents, providing further evidence consistent with the capacity constraints story.
year rolling window). This variable is consistent with measures of “degree centrality” in the networks literature, and thus serves as a baseline control for overall network resources. In addition, given that scope considerations are intertwined with alliance benefits (e.g., Hoehn-Weiss and Karim, 2014; Khanna, 1998; Oxley and Sampson, 2004), I construct focal average deal scope. This is constructed by summing (for each alliance in the focal firm’s portfolio) a set of 11 dummy variables representing different activity categories associated with the alliance, with the values then averaged across the focal firm’s alliance portfolio for the firm-year.20

Partner alliance portfolio size is a proxy for the focal firm’s indirect network ties—i.e., the focal firm’s partners’ partners, which is an important dimension of the focal firm’s network resources. Partner portfolio size measures the average size of the focal firm’s partners’ portfolios (in a five-year rolling window). In addition, to capture the extent of the focal firm’s partners’ knowledge base, I construct partner knowledge base, which is an average of partner patent stock across a focal firm’s alliance partners in each focal firm-year. A final partner characteristic is public firm percent, which proxies for the level of development of the focal firm’s partners, as well as the degree to which public status might influence engagement with the focal firm.

In addition to the R&D resource congestion measure discussed above, analogous measures for other alliance functions can be constructed. Recall that any given alliance can contain multiple functions (coding an alliance containing an R&D, marketing or licensing function, for example, does not mean that these functions are mutually exclusive). There may, however, be constraints on other types of incumbent resources—e.g., those specific to marketing or to technology licensing, that could influence the empirical results. I thus construct analogous controls for marketing resource congestion and licensing resource congestion.

20 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.
**Controls: focal firm quality.** A final set of controls captures time-varying characteristics of firm quality that could drive matching between biotechnology and pharmaceutical firms. To the degree that these variables are visible and credible signals of quality (e.g., Stuart et al., 1999), including them as (time-varying) controls (beyond time-invariant fixed effects) helps account for possible assortative matching among firms (e.g., Ruef, Aldrich and Carter, 2003). I construct measures that capture aspects of the firm’s knowledge base, its history of outside private capital investment, and its overall development stage.

*Focal knowledge base* is measured in each firm-year as the 1-year lagged stock count of total patents issued to the firm since inception. This is a visible signal of quality (Hsu and Ziedonis, 2013) as well as a measure of the firm’s overall absorptive capacity (Cohen and Levinthal, 1990). *Equity stock* captures the total equity invested in the firm by all investors from founding through the current firm-year, while *corporate investment stock* captures the stock of total corporate investment capital into the firm from founding through the current firm-year. These variables follow the prior literature which suggests that higher quality firms are more likely to obtain greater levels of early-stage financing (e.g., Dushnitsky and Shaver, 2009; Gompers and Lerner, 2004; Katila, Rosenberger and Eisenhardt, 2008). Finally, I include two time-varying characteristics of the focal firm’s overall development stage: firm *age*, the number of years since firm founding, and *public firm dummy*, which captures whether the firm is publicly traded, as ownership regime can influence innovation output (Aggarwal and Hsu, 2014).

In sum, the controls capture time-varying focal (biotech) firm quality characteristics that might not be captured by the firm fixed effects used in the model specifications. In addition, all specifications include industry dummies for the focal firm, year effects, and firm fixed effects.
Table 1 summarizes variables and definitions; Table 2 presents descriptive statistics; and Table 3 provides pairwise correlations of the independent variables.

Results and analysis

The dependent variable, *forward citations (4-yr)*, is a count. Because the data are over-dispersed, I employ fixed effects negative binomial specifications in all models (Allison and Waterman, 2002). Together with the various time-varying controls described in the previous section, the fixed effects model makes headway toward ruling out unobserved firm heterogeneity. Reported coefficients in Tables 4 and 5 are incidence rate ratios, which reflect the exponential of the coefficients of the negative binomial models, facilitating interpretation of economic magnitudes. For a unit increase in an independent variable, the reported coefficient implies that the incidence rate of the dependent variable should be multiplied by the value of that coefficient. Consequently, a coefficient value greater than one reflects a positive effect, while a coefficient value less than one reflects a negative effect.

Main effect results. In Table 4 I report results for the main effect of *R&D resource congestion*. All models include firm fixed effects, year effects and focal firm industry dummies. Variables are organized in the order listed in Table 1. Model (4-1) includes the full set of controls, while Models (4-2) and (4-3) add the main effect of R&D resource congestion and the direct effects of the two moderators.

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21 Because the sample is a panel structure, I report cross-sectional (between) standard deviations which are based on firm-level sample period mean values, as well as within-firm standard deviations. The within-firm standard deviation values are important because the inferences from the firm fixed effects regressions are driven by within-firm variation.

22 VIF estimates (e.g., 3.6 in the final model) suggest that multi-collinearity does not pose a significant concern.

23 An important econometric issue is the possibly endogenous matching between the focal firm and its partners in the alliance formation process. To the degree that the end result of such a matching process is a pairing among firms based on quality (e.g., the most attractive pharma firms get matched with the highest quality biotech firms), conducting fixed effects analyses, together with including in the specifications controls for time-varying firm characteristics, should make some progress toward allaying such concerns. I have aimed to include as many observable correlates of time-varying focal firm quality as possible. I return to this issue in the Discussion section.

24 Following guidance from Bettis *et al.* (2015), I report exact p-values in lieu of standard errors, and also omit the reporting of “stars” to indicate thresholds of statistical significance.
Turning first to Model (4-1), some of the control variable estimates are worth noting. *Focal portfolio size* is positive and significant (*p*-value=0.000), in accordance with our understanding of the positive innovation effect of alliances (e.g., Baum *et al.*, 2000; Paruchuri, 2010; Schilling and Phelps, 2007; Shan *et al.*, 1994). In addition, *focal average deal scope* is positive and significant (*p*-value=0.012), consistent with the idea that the strength of alliance ties matters because it allows for a more robust channel through which information can flow to the focal firm as an input to the innovation process (Bos *et al.*, 2017; Hoang and R ongoingal, 2010; Oxley and Sampson, 2004; Phelps *et al.*, 2012; Rota Meister and Deeds, 2004; Stuart, 2000). Beyond focal alliance portfolio size and scope characteristics, *partner knowledge base* is positive and significant (*p*-value=0.008), though with a small overall magnitude given the size difference between partner and focal firm patent portfolios. Finally, *equity stock* is positively related to innovation output (*p*-value=0.025), consistent with expectations given that this variable is a proxy for quality factors influencing innovation. Taken together, the control variables are consistent with expectations from the extant literature, suggesting that they collectively capture many of the network-based mechanisms influencing focal firm innovation output.25

Models (4-2) and (4-3) report the main result of the paper, which centers on *R&D resource congestion*. Model (4-2) adds only the *R&D resource congestion* variable to specification (4-1), while Model (4-3) includes the two moderators (to be further analyzed in Table 5). The main result of note is that *R&D resource congestion* has a negative and significant impact on focal firm innovation output: the coefficient has an incidence rate ratio of 0.498 in Model (4-2) and 0.508 in Model (4-3), in both cases with a significant *p*-value of 0.002. As these are incidence rate ratios, the interpretation is that this is a negative effect; more precisely, going from zero to full *R&D resource congestion* (i.e., shifting the value of the variable by one unit, among the two non-R&D resource congestion measures, *marketing resource congestion* and *licensing resource congestion*, neither is highly significant, though the *licensing resource congestion* variable gains some significance in subsequent specifications (and in Table 5). Of course, there is no a priori theoretical prediction regarding these variables, as the main focus is on the effects of *R&D resource congestion*. 

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25 Among the two non-R&D resource congestion measures, *marketing resource congestion* and *licensing resource congestion*, neither is highly significant, though the *licensing resource congestion* variable gains some significance in subsequent specifications (and in Table 5). Of course, there is no a priori theoretical prediction regarding these variables, as the main focus is on the effects of *R&D resource congestion*. 

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from zero to one), results in a 49.2% decrease in the dependent variable, *forward citations (4-yr)*, in Model (4-3). The *R&D resource congestion* effect remains stable and with a negative effect (i.e., with a coefficient of less than one) with the inclusion of the direct effects of the moderating variables. In addition, the pattern of effects of the various controls remains stable. Taken together, this table provides strong support for Hypothesis 1.

*Moderating effects results.* Hypotheses 2 and 3 suggest that the allocation of partner firm time and attention is likely to vary across alliances, differentially shaping the extent to which *R&D resource congestion* has negative implications. The models in Table 5 test these hypotheses. In Model (5-1), I test whether stronger signals of early-stage R&D-related productivity reduce the negative effect of *R&D resource congestion*, with a positive effect (incidence rate ratio greater than one) predicted for the interaction between *R&D resource congestion* and *early-stage product pipeline*. The coefficient value of 1.463 is significant at a *p*-value of 0.022, in support of Hypothesis 2. In Model (5-2) I test whether industry overlap between the focal firm and its partners’ partners will amplify the negative effect of *R&D resource congestion*. The prediction is a negative interaction effect (incidence rate ratio less than one) for the interaction between *R&D resource congestion* and *focal-partners’ partners industry overlap*. The interaction coefficient of 0.022 in Model (5-2), with a *p*-value of 0.001 is consistent with this prediction, in support of Hypothesis 3. In Model (5-3) I enter both interaction effects together with one another, with the effects stable in sign and significance.

In Figure 2 I plot the effects of the two factors that moderate *R&D resource congestion*. Panel A plots the effect of min and max values of *early-stage product pipeline* on the link between *R&D resource congestion* and innovation output (forward citations), while Panel B plots the effect of min and max values of *focal-partners’ partners industry overlap* on the link.
between R&D resource congestion and innovation output (forward citations). In both cases, the plots are based on the coefficient estimates in Model (5-3), with the data is plotted over the operational range of each variable (i.e., the min and max as reported in Table 2). Values of all other variables are kept at their means, while the y-axis reports the total number of forward citations (4-yr). As the graphs illustrate, R&D resource congestion is positively moderated by early-stage product pipeline and negatively moderated by focal-partners’ partners industry overlap, with the magnitude over the range of the data spanning approximately 2 forward citations in the case of the former and 1.25 citations in the case of the latter. For reference, the mean value of forward citations in the sample itself is 7.45, with an average cross-sectional standard deviation of 10.47 and within-firm standard deviation of 15.38.

[Insert Figure 2 here]

Finally, in the Online Supplementary Material I report a series of robustness checks in which I reformulate the R&D resource congestion variable to scale by partner firm revenue as opposed to number of partner firm alliances. The results in Appendix Table A2 show that the pattern of results is broadly similar to that in the main tables: a negative effect of R&D resource congestion, and positive and negative moderating effects, respectively, of early-stage product pipeline and focal-partners’ partners industry overlap.

DISCUSSION AND CONCLUSION

This study examines the role of capacity-constrained resource congestion in shaping the innovation performance benefits that firms derive from their alliance network resources. I argue that the conversation around network resources has sidestepped the role of constraints on the capacity of network resources to be used without loss of value across multiple contexts. Taking capacity constraints into account implies that the knowledge-based resources of a focal firm’s alliance partners may be congested when faced with multiple claims on their use by the focal
firm’s partners’ other partners. I find empirical support for this idea in the context of biopharmaceutical industry alliances.

This study has implications for several streams of the strategy literature. First, it contributes to research on alliance networks (Gulati, 2007; Lavie, 2006), which points to the importance of indirect ties through which information, know-how and other knowledge-related resources flow. I show that there is a tradeoff in that while indirect ties may provide access to knowledge-related benefits, they may also create the possibility of resource congestion. The potential for congestibility of certain partner resources has implications for how firms might evaluate the prospective benefits of alliance relationships. This study also advances our understanding of the role that opportunity costs play with respect to resource use. While to date this issue has largely centered on firm-level strategy considerations (e.g., the issue of related versus unrelated diversification), resource congestion in alliance networks suggests that partners’ opportunity cost considerations can spill-over to the focal firm. This expands our perspective on capacity-constrained resources beyond its single actor focus to one in which the broader network surrounding the focal firm is implicated. Finally, in recent years the strategy literature has adopted a portfolio-level view on alliances, arguing that scholars should shift attention to a firm’s full collection of alliances (e.g., Hoehn-Weiss and Karim, 2014; Hoffman, 2007; Jiang et al., 2010; Lahiri and Narayanan, 2013; Wassmer, 2010; Yang et al., 2014). This study injects into that conversation the insight that a focal firm’s partners’ portfolio choices can have implications for the focal firm, via their effects on the value (to the focal firm) of access to partner resources.

The theoretical arguments of this study focus on innovation as the outcome of interest, and on knowledge-based factors underlying partners’ resource capacity constraints. This presents an important boundary condition that should be explicitly noted: namely, that the results are relevant to knowledge-based settings in which there is a focus on the sharing of intangible assets.
that influence innovation. The setting of this study is one in which such intangible knowledge exchanges are important. Future work, however, may expand beyond the focus on knowledge-based settings to examine the congestibility of other categories of alliance network resources.

Before concluding with thoughts on avenues for future research, I briefly turn to the issue of the precursors to relationship formation. An ongoing matching process between biotech and pharma firms precedes relationship formation. Prior to alliance formation, firms make decisions regarding the relationships in which they choose to engage, taking into consideration information available through observable characteristics of prospective partners, and matching on factors such as quality, homophily, and potentially partner resource constraints (e.g., Piezunka et al., 2019). While I do not have an exogenous source of variation in such factors (which is difficult to find in real-world settings because managers choose alliance partners purposefully and experiments meant to replicate the setting are not available), the design of this study mitigates potential endogeneity concerns in two ways: first, fixed effects facilitate within-firm inferences; and second, a comprehensive set of observables control for possible assortative matching considerations.

The controls related to firms’ portfolio composition and focal firm quality are helpful in addressing the possibility of assortative matching. Prior research suggests that homophily and network constraints lead better endowed and higher status actors to develop more favorable inter-organizational relationships (Powell et al., 2005; Ruef et al., 2003), leading to higher-quality firms being matched with one another (consistent with the role of relationships with high-status partners as a credible signal of quality [Stuart et al., 1999]). At the same time, 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 firms (e.g., Gompers and Lerner, 2004; Hsu and Ziedonis, 2013). To the degree that assortative matching is indeed taking place in the market for alliances, it is likely that such a selection process would primarily happen
based on these various (controlled for) observable factors. As such, the “bandwidth” issue is likely to be second order. This point is supported by the extant literature. Work on networks, for example, argues for the benefits of network ties, but has not recognized the potential tradeoff with resource congestion. Thus, from a managerial perspective, resource congestion considerations are less likely to be salient “top-of-mind” considerations in the alliance formation process, as opposed to more readily observable factors such as firms’ total alliance count. This is supported by evidence from the field interviews, where executives noted the substantial degree of \textit{ex ante} uncertainty in the partnering process. Much of the learning about partner resources and capabilities occurs \textit{after} relationship formation; as such, it may be generally unlikely that factors such as resource constraints are fully considered in the matching process.\footnote{At the same time, I acknowledge there may be heterogeneity in the extent to which resource congestion is directly considered by firms when forming alliances. It may thus be the case that the negative effect of resource congestion could in some situations be partially due to selection, though it is unlikely to account for the entire negative effect. For selection to play a role, the effect would have to be net of firm fixed effects and the detailed set of focal firm and partner controls which together largely capture the set of factors observable to managers. Such situations may be rare. Future work, perhaps building on the literature on two-sided matching (e.g., Mindruta \textit{et al.}, 2016; Mitsuhashi and Greve, 2009; Vissa, 2011) and employing an appropriate causal method, could further inform our understanding of this issue.}

In summary, this paper advances our understanding of alliance network resources by showing that resource congestion can shape innovation outcomes in alliance networks. Future work might build on this study in several ways. More fine-grained process-oriented studies could provide a deeper understanding of the individual-level microdynamics that create network resource congestion in the first place. Additionally, incorporating resource congestion considerations into network models could offer a deeper understanding of network emergence and evolution. Finally, examining whether organization design strategies may allow firms to counter the effects of network resource congestion could further enrich our understanding of the interplay between networks and resources in competitive contexts. This study thus helps shape the future direction for a set of ongoing conversations in the literature on alliance network resources.
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A. Higher R&D resource congestion

B. Lower R&D resource congestion

Figure 1. Variation in R&D resource congestion due to partner alliance portfolio composition

Figure 2. Moderators of the R&D resource congestion effect
Table 1. Variables and definitions

| VARIABLE | DEFINITION |
|----------|------------|
| **Dependent variable** | |
| Forward citations (4-yr) | Total forward citations within a four-year window following the current firm-year to current firm-year patents |
| **Independent variables** | |
| **Main effect and moderators** | |
| (1) R&D resource congestion | Main effect of R&D capacity-constrained resource congestion (see text for full description) |
| (2) Early-stage product pipeline | Count of focal firm products in the firm-year in a preclinical stage of development |
| (3) Focal-partners’ partners industry overlap | Percent overlap in SIC code between the focal firm and the focal firm’s partners’ partners |
| **Controls: alliance portfolio composition** | |
| (4) Focal portfolio size | Stock count of all alliances (5-year window) established by the focal firm |
| (5) Focal average deal scope | Average number of distinct functional activities per alliance in the focal firm’s (5-year window) alliance portfolio |
| (6) Partner portfolio size | Average stock count (5-year window) of alliances in the focal firm’s incumbent partners’ alliance portfolios |
| (7) Partner knowledge base | Average stock count of the focal firm’s partners’ patents in the prior firm-year |
| (8) Public firm percent | Percent of alliances in the focal firm’s (5-year window) alliance portfolio with a publicly traded partner |
| (9) Marketing resource congestion | Control for marketing-related capacity-constrained resource congestion (see text for full description) |
| (10) Licensing resource congestion | Control for licensing-related capacity-constrained resource congestion (see text for full description) |
| **Controls: focal firm quality** | |
| (11) Focal knowledge base | Stock count of the focal firm’s patents in the prior firm-year |
| (12) Equity stock | Stock of total venture capital investments into the focal firm from founding up to the current firm-year ($M) |
| (13) Corporate investment stock | Stock of total corporate investment capital into the focal firm from founding up to the current firm-year ($M) |
| (14) Age | Age of the focal firm in years (since founding) |
| (15) Public firm dummy | Indicator variable (=1) if the focal firm is publicly traded |

**Note**: All models also include firm fixed effects, together with industry dummies and year effects.
| Variable Description | Overall Mean | Std. Dev. Overall | Std. Dev. Between | Std. Dev. Within | Overall Range Min | Overall Range Max |
|-----------------------|--------------|------------------|------------------|----------------|------------------|------------------|
| DV: Forward citations (4-year) | 7.45 | 18.52 | 10.47 | 15.38 | 0.0 | 244.0 |
| (1) R&D resource congestion | 0.48 | 0.33 | 0.28 | 0.21 | 0.0 | 1.0 |
| (2) Early-stage product pipeline | 0.43 | 1.02 | 0.61 | 0.82 | 0.0 | 8.0 |
| (3) Focal-partners' partners ind. overlap | 0.17 | 0.20 | 0.21 | 0.06 | 0.0 | 1.0 |
| (4) Focal portfolio size | 3.06 | 3.01 | 1.99 | 1.99 | 1.0 | 25.0 |
| (5) Focal average deal scope | 1.46 | 0.90 | 0.78 | 0.52 | 0.0 | 6.0 |
| (6) Partner portfolio size | 16.47 | 38.72 | 26.25 | 28.03 | 1.0 | 422.0 |
| (7) Partner knowledge base | 110.50 | 589.26 | 552.07 | 256.8 | 0.0 | 9572.0 |
| (8) Public firm percent | 0.53 | 0.40 | 0.37 | 0.23 | 0.0 | 1.0 |
| (9) Marketing resource congestion | 0.14 | 0.24 | 0.24 | 0.12 | 0.0 | 1.0 |
| (10) Licensing resource congestion | 0.31 | 0.31 | 0.29 | 0.16 | 0.0 | 1.0 |
| (11) Focal knowledge base | 17.90 | 63.98 | 31.46 | 47.2 | 0.0 | 771.0 |
| (12) Equity stock | 52.62 | 64.30 | 69.64 | 25.76 | 0.0 | 468.3 |
| (13) Corporate investment stock | 3.53 | 7.32 | 6.95 | 3.65 | 0.0 | 58.0 |
| (14) Age | 6.75 | 3.40 | 2.29 | 2.68 | 0.0 | 16.0 |
| (15) Public firm dummy | 0.06 | 0.23 | 0.08 | 0.22 | 0.0 | 1.0 |

**Note:** This table presents descriptive statistics for the dataset, which is a firm-year panel. The sample over which the statistics are calculated corresponds to that used in Model (4-1). The overall mean, standard deviation, and range is presented for each variable. In addition, the standard deviation is presented for between-firm (i.e., cross-sectional) and within-firm standard deviation.
Table 3. 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) | 0.02 | 1.00|     |     |     |     |     |     |     |       |       |       |       |       |     |
| (3) | -0.02| 0.13| 1.00|     |     |     |     |     |     |       |       |       |       |       |     |
| (4) | 0.07 | 0.08| 0.04| 1.00|     |     |     |     |     |       |       |       |       |       |     |
| (5) | 0.06 | -0.05| -0.05| -0.41| 1.00|     |     |     |     |       |       |       |       |       |     |
| (6) | -0.13| -0.02| 0.03| -0.05| -0.06| 1.00|     |     |     |       |       |       |       |       |     |
| (7) | -0.10| -0.05| 0.05| -0.06| -0.07| 0.56| 1.00|     |     |       |       |       |       |       |     |
| (8) | -0.22| 0.00| 0.24| -0.13| -0.02| 0.23| 0.12| 1.00|     |       |       |       |       |       |     |
| (9) | -0.03| -0.04| 0.04| -0.11| 0.43| -0.11| -0.08| -0.12| 1.00|       |       |       |       |       |     |
| (10)| -0.18| 0.09| 0.05| 0.00| 0.32| -0.10| -0.04| -0.23| 0.11| 1.00|       |       |       |       |     |
| (11)| -0.09| 0.02| 0.01| 0.23| -0.12| -0.02| 0.01| 0.00| -0.05| 0.03| 1.00|       |       |       |     |
| (12)| 0.03 | 0.03| 0.19| -0.12| -0.01| 0.08| 0.19| 0.24| -0.05| -0.11| 0.03| 1.00|       |       |     |
| (13)| 0.07 | 0.13| 0.04| 0.00| -0.15| -0.03| -0.01| 0.08| -0.05| -0.13| 0.02| 0.35| 1.00|       |     |
| (14)| -0.05| 0.06| 0.05| 0.02| 0.01| -0.12| 0.05| 0.07| 0.00| 0.07| 0.29| 0.30| 0.17| 1.00|     |
| (15)| 0.05 | -0.03| 0.03| -0.04| 0.03| 0.05| 0.08| 0.00| -0.01| 0.02| -0.04| 0.26| 0.04| -0.07| 1.00|

Note: independent variable numbering corresponds to Table 1 numbering.
Table 4. R&D resource congestion and focal firm innovation

| Independent Variables                          | Firm Fixed Effects | Negative Binomial Models | DV: Forward Citations (4-year) | Coefficients are Incidence Rate Ratios | Values in Parentheses are (Exact p-values) |
|-----------------------------------------------|--------------------|--------------------------|--------------------------------|----------------------------------------|------------------------------------------|
|                                               | (4-1)              | (4-2)                    | (4-3)                          |                                        |                                          |
| R&D resource congestion                       |                    |                          |                                |                                        |                                          |
|                                               | 0.498              | 0.508                    |                                |                                        |                                          |
| Early-stage product pipeline                  |                    |                          |                                |                                        |                                          |
|                                               |                    |                          |                                |                                        |                                          |
| Focal-partners’ partners industry overlap     |                    |                          |                                |                                        |                                          |
|                                               | 0.886              |                          |                                |                                        |                                          |
| Focal portfolio size                          | 1.116              | 1.124                    | 1.127                          |                                        |                                          |
|                                               | (0.000)            | (0.000)                  | (0.000)                         |                                        |                                          |
| Focal average deal scope                      | 1.274              | 1.344                    | 1.357                          |                                        |                                          |
|                                               | (0.012)            | (0.002)                  | (0.002)                         |                                        |                                          |
| Partner portfolio size                        | 1.002              | 1.001                    | 1.001                          |                                        |                                          |
|                                               | (0.173)            | (0.365)                  | (0.355)                         |                                        |                                          |
| Partner knowledge base                        | 1.000              | 1.000                    | 1.000                          |                                        |                                          |
|                                               | (0.008)            | (0.009)                  | (0.010)                         |                                        |                                          |
| Public firm percent                           | 1.414              | 1.277                    | 1.262                          |                                        |                                          |
|                                               | (0.062)            | (0.196)                  | (0.236)                         |                                        |                                          |
| Marketing resource congestion                 | 1.243              | 1.159                    | 1.178                          |                                        |                                          |
|                                               | (0.494)            | (0.649)                  | (0.611)                         |                                        |                                          |
| Licensing resource congestion                 | 0.731              | 0.574                    | 0.543                          |                                        |                                          |
|                                               | (0.198)            | (0.029)                  | (0.017)                         |                                        |                                          |
| Focal knowledge base                          | 1.000              | 1.000                    | 1.000                          |                                        |                                          |
|                                               | (0.831)            | (0.698)                  | (0.715)                         |                                        |                                          |
| Equity stock                                  | 1.003              | 1.003                    | 1.003                          |                                        |                                          |
|                                               | (0.025)            | (0.012)                  | (0.018)                         |                                        |                                          |
| Corporate investment stock                    | 0.999              | 0.998                    | 0.996                          |                                        |                                          |
|                                               | (0.953)            | (0.798)                  | (0.637)                         |                                        |                                          |
| Age                                           | 0.999              | 0.989                    | 0.980                          |                                        |                                          |
|                                               | (0.967)            | (0.756)                  | (0.578)                         |                                        |                                          |
| Public firm dummy                             | 0.714              | 0.719                    | 0.721                          |                                        |                                          |
|                                               | (0.123)            | (0.127)                  | (0.133)                         |                                        |                                          |
| Industry dummies                              | Yes                | Yes                      | Yes                            |                                        |                                          |
| Year effects                                  | Yes                | Yes                      | Yes                            |                                        |                                          |
| Firm fixed effects                            | Yes                | Yes                      | Yes                            |                                        |                                          |
| Log likelihood                                | -1399.69           | -1394.63                  | -1391.41                       |                                        |                                          |
| Num. Obs. (Firms)                             | 812 (112)          | 812 (112)                 | 809 (111)                       |                                        |                                          |

Note: Incidence Rate Ratios are reported; thus, a coefficient value greater than (less than) one indicates a positive (negative) effect. Exact p-values are reported in parentheses, in accordance with guidance from Bettis et al. (2015).
### Table 5. Moderators of R&D resource congestion

| Independent Variables | Firm Fixed Effects Negative Binomial Models |
|-----------------------|-------------------------------------------|
|                       | DV: Forward Citations (4-year)            |
|                       | Coefficients are Incidence Rate Ratios    |
|                       | Values in Parentheses are (Exact p-values)|
|                       | (5-1) | (5-2) | (5-3) |
| R&D resource congestion | 0.425 | 0.845 | 0.724 |
|                       | (0.000) | (0.524) | (0.236) |
| R&D resource congestion * Early-stage product pipeline | 1.463 | 0.022 | 1.555 |
|                       | (0.022) | (0.001) | (0.006) |
| R&D resource congestion * Focal-partners’ partners industry overlap | 0.935 | 0.845 | 0.724 |
|                       | (0.465) | (0.071) | (0.236) |
| Early-stage product pipeline | 0.891 | 0.845 | 0.724 |
|                       | (0.783) | (0.021) | (0.111) |
| Focal-partners’ partners industry overlap | 1.124 | 0.845 | 0.724 |
|                       | (0.000) | (0.000) | (0.000) |
| Focal portfolio size | 1.365 | 0.845 | 0.724 |
|                       | (0.001) | (0.001) | (0.001) |
| Focal average deal scope | 1.002 | 0.845 | 0.724 |
|                       | (0.323) | (0.192) | (0.142) |
| Partner portfolio size | 1.316 | 0.845 | 0.724 |
|                       | (0.165) | (0.239) | (0.159) |
| Partner knowledge base | 0.558 | 0.845 | 0.724 |
|                       | (0.024) | (0.016) | (0.021) |
| Marketing resource congestion | 1.000 | 0.845 | 0.724 |
|                       | (0.694) | (0.750) | (0.728) |
| Licensing resource congestion | 0.996 | 0.845 | 0.724 |
|                       | (0.680) | (0.813) | (0.856) |
| Corporate investment stock | 0.983 | 0.845 | 0.724 |
|                       | (0.641) | (0.658) | (0.764) |
| Equity stock | 0.721 | 0.845 | 0.724 |
|                       | (0.128) | (0.168) | (0.157) |
| Public firm percent | Yes | Yes | Yes |
| Marketing resource congestion | Yes | Yes | Yes |
| Licensing resource congestion | Yes | Yes | Yes |
| Focal portfolio size | Yes | Yes | Yes |
| Focal average deal scope | Yes | Yes | Yes |
| Partner portfolio size | Yes | Yes | Yes |
| Partner knowledge base | Yes | Yes | Yes |
| Industry dummies | Yes | Yes | Yes |
| Year effects | Yes | Yes | Yes |
| Firm fixed effects | Yes | Yes | Yes |
| Log likelihood | -1388.71 | -1385.76 | -1382.01 |
| Num. Obs. (Firms) | 809 (111) | 809 (111) | 809 (111) |

Note: Incidence Rate Ratios are reported; thus, a coefficient value greater than (less than) one indicates a positive (negative) effect. Exact p-values are reported in parentheses, in accordance with guidance from Bettis et al. (2015).