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CROSSING TECHNOLOGICAL BOUNDARIES: BROKERAGE AND THE EMERGENCE OF INNOVATION NETWORKS

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Firms face elevated levels of uncertainty in collaborations focused on new technologies. While third parties may foster such collaborations by reducing technological and relational uncertainties (i.e., *tertius iungens*), they might have competitive incentives to prevent such connections (i.e., *tertius gaudens*). Building on this theoretical tension, this study investigates how brokerage and incumbent technology network structure shape emergent technology networks. We argue that organizations in the position of knowledge brokers tend to facilitate tie formation between partners to help mitigate uncertainty in an emergent technology, yet this tendency is reversed when keeping the separation between partners allows them to secure competitively advantageous positions. We collect longitudinal data on research and development collaborations in the cancer therapy industry, and conduct in-depth interviews with scientists and industry experts. We test our theoretical framework through stochastic actor-oriented modeling by examining the emergence of technology networks after the technological breakthrough of monoclonal antibodies for cancer therapy. Our findings indicate that over time, the role of brokers in fostering or preventing triadic closure across technologies significantly impacts the structure of emergent technology networks.

Interfirm collaboration plays a critical role in the emergence of technological innovation (Ahuja, 2000a; Kumar & Zaheer, 2019; Powell, Koput & Smith-Doerr, 1996). However, firms face elevated technological and relational uncertainty in collaborations focused on new technologies (Anand, Oriani & Vassolo, 2010; Carson, Madhok & Wu, 2006; Furr & Snow, 2015). Knowledge brokers—that is, actors that span ties between two others—are central to the evolution of innovation networks (Burt, 1992; Reagans & McEvily, 2003; Waardenburg, Huysman & Sergeeva, 2022). Yet, these third parties face significant tension in such situations to balance collaboration and competition. On the one hand, they may seek to promote collaboration as a means to address uncertainty (Burt & Knez, 1995), in some cases facilitating new ties between their partners. Scholars have referred to this tendency as *tertius iungens,* the third who joins (Obstfeld, 2005). Alternatively, competitive concerns may lead network brokers to prevent collaboration, as a means to exploit their preferential position (Kumar & Zaheer, 2019)—a role referred to as *tertius gaudens*, the third who enjoys (Simmel, 1950; Zhelyazkov, 2018).

While prior research has provided convincing explanations for the preference of third parties to

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either foster or prevent triadic closure through these roles (Burt, 2021; Lee, Quintane, Lee, Ruiz & Kilduff, 2024; Obstfeld, Borgatti & Davis, 2014), it has not addressed these dynamics and their implications in the context of emerging technologies. Triadic structures have a profound effect on the evolution and outcomes of innovation networks (Balachandran & Hernandez, 2018). When new technologies are introduced, firms may engage in collaborative innovation among partners that span incumbent and emergent technology networks, and these bridging roles are critical in defining the broader network structure (Tatarynowicz, Sytch & Gulati, 2016). Existing structure and knowledge in incumbent technology networks might reduce uncertainty in forming ties in emerging technologies (Spencer, 2003). At the same time, competition for unique access to knowledge in emerging technologies might hinder collaboration (Rotolo, Hicks & Martin, 2015). Despite this documented tension between collaboration and competition across network actors, the decision of knowledge brokers to facilitate connections or ensure separation remains unclear. For that reason, our study addresses the following research question: *Under what circumstances do brokers within and across technology networks facilitate or inhibit collaboration between their unconnected partners?*

We introduce the concept of *multiplex technology closure* as transitive collaborations across incumbent and emergent technology networks.[1] We argue that whether the *tertius iungens* incentives outweigh the *tertius gaudens* incentives or vice versa depends on the nature of triads being uniplex or multiplex. For uniplex triads, where all ties focus on emerging technology development, brokers tend to prioritize uncertainty-mitigating arguments and thus promote triadic closure. For multiplex triads, which consist of emergent and incumbent technology collaborations, the asymmetry in firms' level of expertise in the emergent technology drives brokers' competitive incentives to hinder access to the new technology.[2] Figure 1 illustrates the study's uniplex and multiplex technology closure typology.

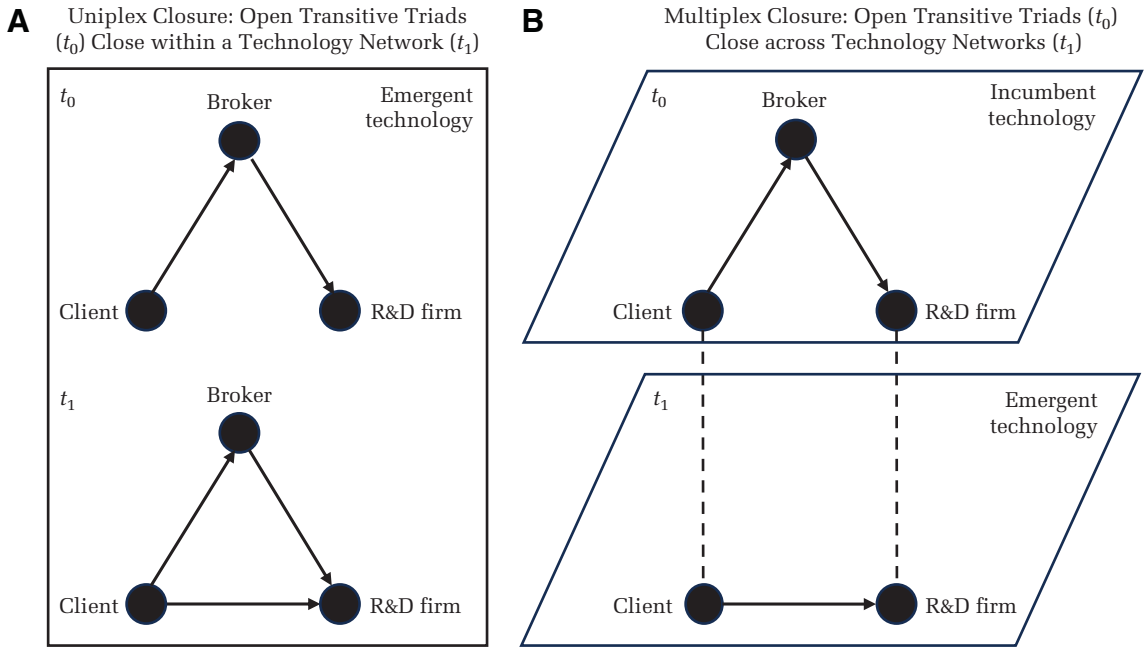
To test our theoretical arguments, we contextualize our research in the collaborative development between incumbent and emergent technologies that have been applied to cancer therapy in the last several decades. Enabled by the emergence of new technologies, groundbreaking innovations have been key in advancing cancer therapy to evolve from mainly surgery to radiotherapy, and chemotherapy to targeted therapy. The biotechnology revolution has spawned a wide variety of emerging technologies that challenge incumbent technologies for application in cancer therapy. In light of technological and relational uncertainty, established firms, especially large pharmaceutical companies, have sought access to different types of emergent technologies that were mainly driven by new entrants to the market. In our study, we examine the incumbent technologies of cancer therapy based on small-molecule technology challenged by the emergent technologies of biological monoclonal antibodies (mAbs).

Through in-depth interviews with industry experts, we sought to better understand the dynamics of collaboration and competition among these technologies. Collecting and analyzing data on the network evolution of cancer therapy research and development (R&D) collaborations from 2004 to 2020 using stochastic actor-oriented models, our findings demonstrate that tie formation in the emergent technology depends on firms' transitive collaborations in the incumbent technology (i.e., multiplex technology closure). Two firms are more likely to collaborate in the emergent technology if they share a common third party in the incumbent technology network. However, our findings also illustrate that third parties systematically discourage multiplex closure if they occupy positions with unique access to partner expertise in an emergent technology—underlining the enhanced tensions between collaboration and competition across incumbent and emergent technology networks.

[1] We conceptualize uniplex and multiplex technology *transitive* closure but use the terms *uniplex technology closure* and *multiplex technology closure* for simplicity. These triadic structures are comprised of directed ties, as the broker seeks knowledge from an R&D firm and provides knowledge to a client firm. In our theoretical framework, this particular form of triadic relationship is most relevant to the phenomenon of organizations seeking ties for access to knowledge and expertise regarding emergent technologies, as we discuss in more detail later in the paper.

[2] Our conceptualization of firms' involvement in the incumbent and emerging technology includes *relational* and *nodal* attributes. We envision incumbent and emerging technology networks as being based on the technological focus of the collaboration ties of which these networks are comprised (i.e., firms' R&D alliances). As such, the *relational* dimension constitutes our differentiation between *uniplex* and *multiplex* triads. Additionally, we consider the level of technological expertise in the emerging technology as a *nodal* attribute to assess the role of knowledge asymmetry between firms.

FIGURE 1
Uniplex and Multiplex Technology Open Triads and Closure



Note: Dotted lines in Figure 1b indicate that disconnected actors form a new tie in t_1 in different technology networks (i.e., multiplex technology closure).

Our work offers several significant contributions. First, while scholarship in collaborative innovation has acknowledged the central role of the social structure of interfirm collaboration in technological innovation (Khanagha, Ansari, Paroutis & Oviedo, 2022; Runge, Schwens & Schulz, 2022), we extend this research by shedding light on the paramount influence of the incumbent technology network on the evolution of new technology networks. We contribute to an emerging body of research on network dynamics (Ahuja, Soda & Zaheer, 2012; Chen, Mehra, Tasselli & Borgatti, 2022; Kalish, 2020) by adding to the understanding of how dynamics in one network influence the evolution of another network (Htwe, Lim & Kakinaka, 2020). Finally, we contribute to the literature on triadic closure in innovation settings (Obstfeld, 2005) by highlighting the role that the joint consideration of emerging and incumbent technology networks plays in resolving the *tertius iungens* versus *tertius gaudens* tension. We move beyond prior research on multiplex triads (Shipilov & Li, 2012) by theorizing and testing triadic multiplexity in node and tie characteristics in interorganizational technology collaborations.

THEORETICAL BACKGROUND

Interfirm networks are central to the production and dissemination of knowledge and innovation. Research provides substantial evidence that R&D collaborations can enable firms to be apprised of the most recent technological advancements (Anand et al., 2010; Rothaermel & Boeker, 2008) and increase firms' innovation productivity (Ahuja, 2000a; Howard, Steensma, Lyles & Dhanaraj, 2016). Triadic structures, including "open triads" in which two firms are connected to a common third party, are central to the evolution of innovation networks (Madhavan, Gnyawali & He, 2004; Sytch & Tatarynowicz, 2014a; Sytch, Tatarynowicz & Gulati, 2012). In situations of technology emergence in which multiple technologies coexist, brokers play central roles in controlling the flow of knowledge across technological boundaries. Established research highlights the agency of technology brokers in translating and sharing nonredundant knowledge among disconnected actors (Hargadon & Sutton, 1997). In that case, a shared third party is the receiver of knowledge for one actor and the transmitter of knowledge for the other.[3] Receiving the latest technological knowledge from one

[3] The idea that brokers have varying roles and incentives depending on group membership originates from Gould and Fernandez's (1989) seminal work. For instance, brokers can have buyer or client roles in triads (Shipilov & Li, 2012).

firm makes the third party an attractive knowledge provider to another firm, fostering the formation of transitive open triads in innovation networks (e.g., Gulati, 1999).

One of the core concepts of this literature stream is that third parties occupying intermediary positions make triadic closure (*tertius iungens*—the third who joins) between two indirectly connected actors more likely (Obstfeld, 2005). A central argument for why triadic closure occurs is that shared third parties mitigate uncertainty around the quality and behavior of actors (Burt & Knez, 1995; Simmel, 1950). The third party's referral increases trust among indirectly connected actors and makes "friend of a friend" ties more likely (Coleman, 1988; Gulati, 1995). Forging a connection between disconnected actors, the third party can strengthen relationships with both actors and create a common understanding that coordinates the exchange (Obstfeld et al., 2014; Tortoriello & Krackhardt, 2010).

At the same time, another theoretical perspective—*tertius gaudens*, the third who enjoys—proposes that common third parties have competitive incentives to separate disparate actors as they benefit from resulting brokerage rents (Burt, 1992; Simmel, 1950). Brokers occupying the *tertius gaudens* role face various demands to maintain the separation (Lee et al., 2024). As disconnected actors depend on the indirect exchange with the third party, the broker can charge brokerage rents for the mediation (Marsden, 1983; Ryall & Sorenson, 2007). Furthermore, maintaining the structural separation between actors allows brokers to control the flow of resources and information to their advantage (Burt, 2021). As such, brokers defend their information advantages (Burt, 2004) by discouraging direct connections between their otherwise unconnected partners (Soda, Mannucci & Burt, 2021; Zhelyazkov, 2018).

The pursuit of emergent technologies provides a context in which both the importance of brokers to network evolution and their stakes in making decisions to promote or discourage ties between existing partners are significantly heightened. The third party's tension between *tertius iungens* and *tertius gaudens* has been central to vivid debates around the social dynamics of triadic closure and brokerage, explaining innovation networks' structural evolution and productivity (Soda et al., 2021; Tatarynowicz et al., 2016; Ter Wal, Alexy, Block & Sandner, 2016). Yet, the interdependence between ties in an incumbent technology network and the tendency for triadic closure in emergent technology networks has received little attention. While firms in standard-setting competitions collaborate within technology networks to sponsor a preferred technology (e.g., Soh, 2010), situations in which multiple emerging technologies coevolve imply greater uncertainty around competition and collaboration across technological boundaries (Ansari, Garud & Kumaraswamy, 2016). As we will explain in more detail in the next sections, the tension between the broker's collaboration and competition incentives, to either foster or prevent cross-technology triadic closure (Ranganathan & Rosenkopf, 2014), is at the center of our theoretical arguments. Specifically, brokers foster triadic closure across incumbent and emergent technology networks due to their potential benefits of mitigating the enhanced technological and relational uncertainty that are characteristic of cross-technology settings (Li & Piezunka, 2020; Stovel & Shaw, 2012). At the same time, the competitive incentives of brokers in these boundary-spanning positions foster the separation of firms across incumbent and emergent technology networks (Gould & Fernandez, 1989; Simmel, 1950).

To study the joint consideration of incumbent and emerging technology networks and their influence on the *tertius iungens* versus *tertius gaudens* tension, we introduce the concept of *multiplex technology closure*. We differentiate between situations in which open transitive triads close within a technology network (i.e., *uniplex technology closure*) or across technology networks (i.e., *multiplex technology closure*). The *technological focus of the relationship* is the unifying element of the technology networks we study. Particularly, we differentiate between R&D collaborations focused on R&D development in an incumbent technology or an emergent technology.[4] We focus on a transitive structure "in which one actor mediates the flow of resources or information between two other actors who are not directly linked" as a common triadic structure in which knowledge flows through the intermediary (Fernandez & Gould, 1994: 1457; see also Gould & Fernandez, 1989). We argue that the joint consideration

[4] In line with previous research, we draw our network boundaries based on the type of relationships between actors. For instance, Ranganathan and Rosenkopf (2014) differentiate between firms' participation in alliance networks based on the objective of the relationship (knowledge generation vs. commercialization). We define the *incumbent technology network* as a network within the global innovation network in which R&D ties are formed to exchange knowledge on an industry-established technology. In contrast, the *emergent technology network* is comprised of ties formed to codevelop and transfer knowledge on a new technology that represents a groundbreaking industry change.

of emerging and incumbent technology networks in brokerage relationships contributes to a better understanding of the network dynamics in developing new technologies.

HYPOTHESES

Brokerage and Emergent Technology Tie Formation

Our study examines several situations in which resolving the *tertius iungens* versus *tertius gaudens* tension depends on considering actors' positions and expertise in incumbent and emergent technology networks. Our first premise is that third parties sharing collaborators exclusively in the emergent technology tend toward fostering uniplex closure due to the corresponding benefits of mitigating uncertainty—a function that is less critical with the more established technologies of the incumbent network. In this scenario, all three actors in the open triad have transitive collaborative ties in the emergent technology (Figure 1a).

Intermediaries play a central role in mitigating technological and relational uncertainties in emergent technology collaborative tie formation. These stem from uncertainties related to the success or adoption of the emergent technology and tie formation in the new domain (Gulati, 1995; Kapoor & Klueter, 2020, 2021). Contrary to incumbent technologies, emerging technologies are characterized by frequent setbacks and a high likelihood of failure. Particularly in domains where technological setbacks and failures have severe consequences for consumers, such as in the pharmaceutical sector, firms engaged in emerging technology collaborations face high levels of technological uncertainty (Kapoor & Klueter, 2021; Sosa, 2013). As a result, brokers may prove even more critical in knowledge exchange that may mitigate the uncertainty associated with emergent technologies.

Heterogeneity in the distribution of knowledge concerning an emergent technology may play an important role in its development. While the basic underpinnings and ultimate potential of technologies may be well understood in the incumbent technology network, this broad understanding would be lacking in the emergent network. Certain organizations have greater initial insights into the development and use of technologies as they emerge and diffuse (Compagni, Mele & Ravasi, 2015; Kapoor & Klueter, 2015), and will serve as more attractive partners for alliance formation. The diffusion of knowledge to the broker firm through this alliance enables further ties in which the broker serves as the relative source of knowledge (e.g., Gulati, 1999). In the context of an emerging technology, "alliance partners can provide trustworthy alternative interpretations of technical problems and solutions, allowing a firm with a central ego-network to compare and contrast these perspectives (Nonaka, 1994)" (Karamanos, 2016: 264).

Through their important role in the exchange of knowledge and their ability to facilitate ties that spur greater shared interpretation of new developments, brokers have both incentives and the ability to encourage beneficial collaboration. Allowing the flow of knowledge among firms by fostering triadic closure distributes the uncertainty involved in emerging technologies across the technology network. Fostering triadic closure increases the quality of innovation outcomes and enables coordinated innovation in the development of emergent technologies (Obstfeld, 2005). In their connecting role within the broader innovation effort, brokers are well positioned to directly benefit from this closure, receiving new insights and shared understandings that result from the direct interaction between previously separated partners. At the same time, restricting the flow of knowledge in the early development of a technology by separating firms might adversely affect the general development of the technology. However, in the uniplex setting, in which all parties are engaged in the emergent technology and have collaboration ties with that technology as their focus, brokers have less competitive incentives to prevent access to the emergent technology network. The incentives for *tertius gaudens* are lower in uniplex triads as all actors are already active in the same network. Rather, they benefit from fostering a closed network among actors already engaged in emergent technology collaborations.

In sum, we argue that brokers tend to close uniplex triads (i.e., *tertius iungens*) due to the brokers' benefits of reducing technological uncertainty in the formative stage of a technology compared to the brokerage incentives of maintaining the separation. In contextual terms, the benefits for a common third party to connect two firms in the emergent technology network lie in the enhanced knowledge flow of connected firms to solve technical problems in the emergent technology and outweigh the competitive disadvantages of losing the brokerage position.

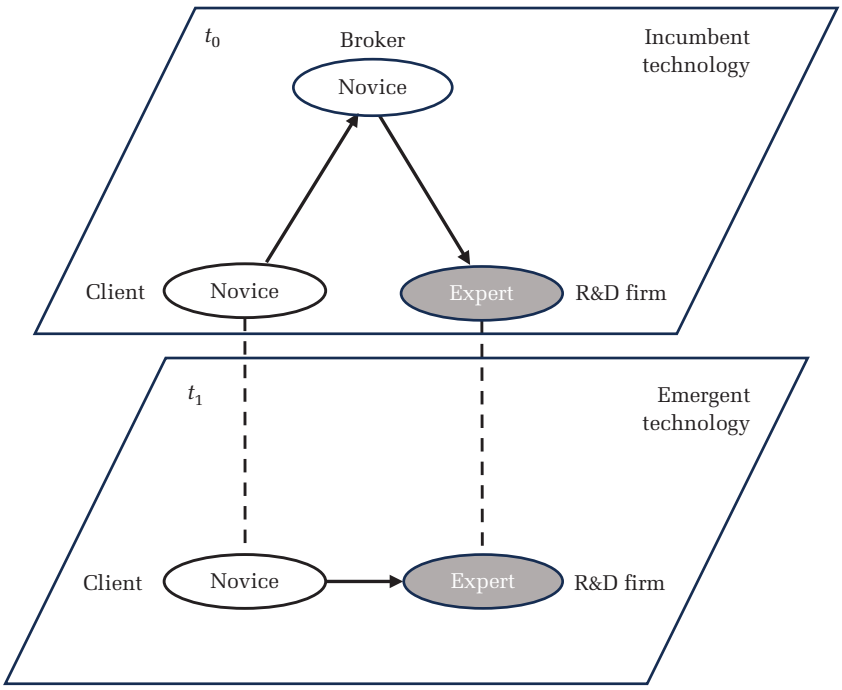
Hypothesis 1. Two firms are more likely to form an emerging technology alliance if they share a common third-party collaborator in the network of emerging technology alliances.

Turning our attention to the influence of incumbent network structure on the formation of collaborations in the emergent technology network, we argue that an open triad in the incumbent technology network will lead to multiplex closure in the emergent technology network (Figure 1b). In contextual terms, a common third party mediating the knowledge flow between two firms through R&D alliances in the incumbent technology will foster their collaboration in the emergent technology (i.e., *tertius iungens*). However, when the two unconnected firms have different levels of expertise in the emerging technology, the competitive incentives of the third party to maintain the separation increase (i.e., *tertius gaudens*).

In the former case of brokers spanning incumbent technology ties—that is, uniplex transitive relationships with the broker in one technology—the broker more convincingly fulfills the role of a nonpartisan mediator for collaboration in another technology. Neutral positions of the third party increase the credibility of referrals, while any biases toward one party would harm mediation across domains (Gould & Fernandez, 1989; Li & Piezunka, 2020; Stovel & Shaw, 2012). As a result, the broker may more freely share and translate information, even if anecdotal, about the emergent technologies through indirect ties, and is thus in a more neutral position to foster a new connection between two disconnected alters in the emerging technology. Furthermore, shared interests in the incumbent technology make joint agendas about the further trajectory of the emerging technology more likely. We argue that the technological commonalities mediated through brokers across actors in the incumbent technology build the necessary trust to venture into an emergent technology network—such as the trust that builds up in relationships between colleagues might support the formation of a friendship.

In the latter case, when heterogeneity of expertise in the emergent technology is apparent, we suggest that these dynamics will reverse. While the benefits to brokers in mitigating uncertainty across incumbent and emergent technology networks increase the tendency for *tertius iungens*, the shared third party may avoid forging that connection if the resulting collaboration damages themselves—for example, because it undermines their own competitive positioning. This is more likely when the incentives from *tertius gaudens*, or maintaining the separation between unconnected alters, increase. We argue that this is particularly true when brokers are both recipients and providers of knowledge to unconnected firms with asymmetry in the emerging technology expertise. Figure 2 illustrates the brokers' role in this

FIGURE 2
Boundary-Spanning Closure: Asymmetrical Firm Expertise in the Emerging Technology



Note: Dotted lines indicate that disconnected actors form a new tie in t_1 in another technology network (i.e., multiplex technology closure).

situation. Maintaining control of access to emergent technology will increase broker incentives for *tertius gaudens*.

In this situation, brokers are in a competitively attractive position of technology brokerage where they have access to knowledge in one technology network that is valuable but not accessible in another competing technology network (Ter Wal, Criscuolo & Salter, 2017). As such, brokers can determine "whether or not to grant access to an outsider" (Gould & Fernandez, 1989: 92).[5] It becomes clear that the boundary-spanning position granting the broker direct access to a firm with expertise in the emergent technology, with another firm indirectly accessing this expertise through the broker, provides relevant incentives for the broker to prevent a direct connection between the other two firms. Specifically, firms in the incumbent technology network will likely see great potential in receiving access to the new technology. Numerous studies, including that by Ahuja (2000a), have documented that firms with conventional technologies are willing to trade their social and financial capital for access to promising emergent technologies (e.g., Rothaermel & Boeker, 2008). Intermediaries in boundary-spanning roles will control the access to the emergent technology through their central position in the open triad, restricting information flow and exchange to inhibit unconnected firms from forming ties.

In sum, for brokers in the incumbent technology network, the benefit of reducing uncertainty generally increases the likelihood of *tertius iungens*, or multiplex technology closure, in the emergent technology network. However, as a boundary condition to that relationship, asymmetry in the expertise of the disconnected firms increases the broker's competitive incentives for *tertius gaudens*, further strengthening the separation of incumbent and emergent technology networks over time. This leads to the following hypotheses:

Hypothesis 2. Two firms are more likely to form an emerging technology alliance if they share a common third-party collaborator in the network of incumbent technology alliances.

Hypothesis 3. Two firms are less likely to form an emerging technology alliance if they share a common third-party collaborator in the network of incumbent technology alliances if only one of them has demonstrable expertise in the emergent technology.

[5] Gould and Fernandez (1989) mainly introduced two boundary-spanning brokerage roles: representative and gatekeeper. Formally, we analyze the representative role. The representative role in the Gould and Fernandez framework encompasses a third party representing the same group as a focal actor in an exchange with another actor belonging to a different group. Since we focus on the potential collaboration between the two indirectly connected firms, we do not differentiate between Gould and Fernandez's narrower boundary-spanning roles in our theorizing.

METHODS

Research Context

We test our hypotheses in the cancer therapy context, which is suitable for understanding collaboration across technologies for four key reasons.

First, cancer therapy has made enormous progress due to massive R&D activities. Cancer is the second most deadly disease in the world. However, we have seen a dramatic drop of 15% in age-standardized death rates from 1990 to 2019 (Ritchie & Roser, 2023). Cancer therapy has come a long way from surgery, when solid tumors were "chopped off"; to cytotoxic drugs in chemotherapy, limiting the growth of both cancerous and normal cells and thus having tremendous side effects; to targeted therapy, resulting in higher efficacy and fewer side effects; to immunotherapy. For some types of cancer these advances mean that instead of treating symptoms, a cure becomes possible. As an industry expert we interviewed put it, "the notion of curative versus palliative is something that you can't go back from." This advancement stems from massive R&D activities in oncology, but also from investments in chemistry and biology. Global spending on R&D in cancer therapy is expected to exceed USD 375 billion by 2027 (IQVIA, 2023).

Second, different technologies have coevolved in the race to provide cures for cancer. The therapeutic success in the last three decades can be largely attributed to advances in targeted therapy, which rely on two different technologies: small molecules and large molecules, specifically mAbs. Small molecules and mAbs are distinct technologies but also have commonalities. Small-molecule technologies underly 80% of all drugs. They have a low molecular weight and result from chemical synthesis (GlobalData, 2023). Starting with the discovery of genes that cause cancer (oncogenes), R&D in small molecules was linked to cancer therapy, immediately resulting in high investments from big pharma. The Food and Drug Administration (FDA) approved the first small-molecule cancer therapy drug (the tyrosine kinase inhibitor "imatinib") in 2001 (Zhong et al., 2021).

The development of small-molecule cancer drugs takes a rather long time, but the production is then inexpensive, and drugs can be administered orally, which allows treatment even from home. Given their chemical nature and the early investments from big pharma, small molecule technology is more accessible and thus relatively less innovative than mAbs at the stage of development captured in our study period.

Emergent mAbs technologies rely on naturally produced antibodies to attack foreign substances. mAbs are designed in the laboratory to recognize specific epitopes—that is, those expressed on cancer cells. Once they bind, the immune system attacks the cells and destroys them. mAbs are biological drugs with a large molecular weight, thus requiring injection. mAbs allow a targeted treatment, have a lower risk of toxicity and fewer side effects, and are also faster in time to market due to fewer safety issues in clinical trials. The rise of mAbs began in the 1980s with the first production followed by a setback phase, in which many major clinical candidates did not receive commercial approval or were even withdrawn after initial approval (e.g., *Centoxin*). The 1990s then saw several successful mAb approvals. The first mAb used for cancer treatment received approval in 1997 (*rituximab*), and advances in the production of humanized and fully human mAbs led to a strong preference for mAbs in therapeutic applications by the 2000s (Kapoor & Klueter, 2020). Unlike small molecules, mAbs did not receive big pharma investment initially, as they were originally not linked to value creation in the cancer therapy market. Instead, new entrants to the market developed this emergent technology for application in cancer drugs.

Given that the chemistry-based small-molecule development was driven by big pharma, while mAbs technology was spurred by new entrants to the market, this emphasizes the degree of uncertainty and new approaches beyond technological dimensions. An industry expert reflected: "Big pharma love[d] their small-molecule approaches until that was no longer enough," and explained, "[Biologicals] have so thoroughly pushed small molecule synthetics to the back of the bus."

Third, the biopharma industry in general and the cancer therapy market in particular are highly competitive. Cancer produces estimated annual healthcare costs of EUR 900 billion, and thus is a highly attractive market (European Commission, Directorate-General for Research and Innovation, 2020). Cancer refers to a group of more than 100 diseases, each with subtypes and many conditions under which one drug might be administered. However, despite this huge market potential, the costs of development are immense. Although the ultimate gold standard in drug success is its efficacy, developing the initial "first in class" innovation is central to driving greater return on investment (Kennedy, Gomez, Thovmasian & Chang, 2023). Nevertheless, this type of competition in cancer therapy does not lead to coalescence around a single dominant technology. The reasons for this include the fact that many different (sub)types of cancer require different medications, drug resistance often requires physicians to switch between medications and technologies, and the combinatory use of different medications may prove beneficial, which has, for instance, led to the development of antibody–drug conjugates. As an illustration of this coexistence of different treatment technologies, the list of top 10 breast cancer therapy drugs as measured by revenue includes both small-molecule (Imbruvica) and mAbs (Herceptin) drugs.

Fourth, R&D collaborations are a means to externally source access to new technologies. Due to competitive pressures, collaborations were not historically the norm in the cancer therapy market. However, biotechnological innovation disrupted the pharma market, altering how innovations are produced and forcing incumbents to acquire new biology-based competencies, often through strategic alliances (Kapoor & Klueter, 2015). Given the high failure rates of drugs along the R&D process, big pharma needs to spread R&D investments across different technologies. From the perspective of big pharma, R&D alliances fulfill the objective to increase the "shot on goals" or to cover "white space," as an expert on strategic alliances in biotech explained. On the other hand, new entrants also needed to collaborate with established actors to acquire competencies related to clinical trials (Kapoor & Klueter, 2015). R&D collaborations are also used to acquire competencies a company cannot yet access, especially for technological knowledge. Therefore, companies might have different links to other companies through which they seek or provide knowledge.

Insights from Interviews with Industry Experts

To better understand the mechanisms in cancer therapy and the biotech industry, we conducted 14 in-depth interviews with scientists, big pharma, biotech start-ups, regulatory officials, and other industry experts. Nine interviews informed our research

context, and aided in developing the research question and constructing our hypotheses. The remaining five were conducted post-hypotheses testing, and sought experts' sensemaking of our findings. The results complemented historical and scientific perspectives on the development of cancer therapy and clarified dynamics in interorganizational technology networks.

The experts seconded the notion of collaboration versus competition in oncology R&D, especially in terms of collaboration as a means for technological uncertainty mitigation:

> It's very important for the companies to be flexible, and to recognize that they can't develop everything in house, there's just too much […]. There's too much science, there's too many techniques, there's too many technologies, you can't do everything, you can't have the most brilliant scientists under your own roof all the time. (Industry expert)

Apart from covering the "white spots," collaboration can be a first step toward a later acquisition, which is described by big pharma as a "test before you invest" (Industry expert) strategy, whereas small biotechs describe that as both risk and chance (Biotech Startup_5). However, others mentioned that competitive threats may outweigh the benefits of collaboration:

> That's because you enter into alliances with many companies, but of course you also have to make sure that you don't get left behind and that you can hold your own against competitors with whom you don't enter into alliances. So it's a huge area of tension. (Scientific manager from a big pharma company)

When explicitly asked about the role of brokerage in the cancer therapy industry, all experts concurred with the notion that intermediaries have a unique competitive position and seek to protect that. An expert from a contractual research organization, for instance, commented: "As always in business, really, [the intermediaries, impeding triadic closure] want to make the profit themselves."

An interviewee emphasized the power of those with financial capital, typically big pharma, in selecting those actors eventually involved in (pre)-clinical trials: comparing the initiation of a collaboration to

> sending off proposals to a black hole, a very [opaque] process. The idea is very difficult to protect, and often there is a risk of the idea being discussed and further developed with more prominent or appropriate academic partners; in the end, one will only get a two-line rejection of the proposal. (Head of research institution)

Whereas both R&D firms and clients might theoretically approach potential partners for collaborations, the interviewees confirmed that the companies with technological expertise are usually approached by firms seeking access to the emergent technology, or the collaboration is created by intermediaries, which could be professional brokers or other network partners acting as brokers.

We conclude that this research context is ideal for testing our hypotheses on uniplex and multiplex technology closure. The cancer therapy market is marked by intense collaboration and competition, with higher technological and relational uncertainty linked to the emergent technology of mAbs, as opposed to the incumbent technology of small molecules.

Sample

We focus on firms involved in the development of new technologies applied to cancer therapy. Specifically, we capture all firms observed to participate in at least one R&D alliance focused on cancer treatment using targeted therapy (small molecules and mAbs) and other relevant technologies, such as gene therapy, during the study period of 2004 to 2020. This period captures the heightened collaborative activity in oncology research following the legitimacy and maturity of biopharma drugs (Kapoor & Klueter, 2020). Data on R&D alliances and their participants were obtained from BioSciDB, a comprehensive third-party peer-reviewed database on alliances in the biopharmaceutical industry that has been used in prior organizational research (e.g., Ceccagnoli, Higgins & Kang, 2018). Our final sample includes 453 firms.

Model Specification

Our hypothesized relationships examine the evolution of the network of ties formed between organizations collaborating in emergent or incumbent technologies, along with the interplay between the emergent and incumbent technology networks. As firms in these networks seek ties to gain access to new knowledge of the emergent technology, they are likely to observe and be influenced by the collaboration ties formed by others in the network (Rosenkopf & Padula, 2008). For that reason, the decision to form new ties violates the assumption of independence

between observations required for logistic regression or similar analytical techniques (Kim, Howard, Pahnke & Boeker, 2016; Wasserman & Faust, 1994). We overcome this limitation by using stochastic actor-oriented models (SAOMs) in our analysis (Kalish, 2020). SAOMs are a network analysis tool that allows for testing the evolution of networks over time and captures broader structural effects that may impact firms' decisions to form or dissolve ties. This method relaxes the independence assumption, as opposed to other social network analysis techniques (Snijders, 1996). We conduct our analysis using *RSiena* (Snijders, Van de Bunt & Steglich, 2010). This software program enables the use of SAOMs, along with the analysis of cross-network effects for the dynamics of multiple networks (Ripley, Snijders, Boda, Vörös & Preciado, 2023). This allows us to directly examine the interaction between network evolution dynamics in the incumbent and emergent technology networks. Over the 17-year time span of our study, sampled firms are not consistently active as organizational actors in the collaboration networks. New ventures may emerge, firms may be acquired or experience bankruptcy, and so on. *RSiena* provides a method for capturing the effects of nodes that may join or leave the network during the time of observation. We use the "sienaCompositionChange" function in *RSiena* (Ripley et al., 2023) to specify the years in which each sampled firm is active. This ensures that the SAOM analyses only consider the active firms as being at risk for tie formation.

Measures

Dependent variables. Our hypotheses address *collaborative tie formation between organizations in incumbent and emergent technology networks*. In constructing the data on network tie formation, we first identified all R&D alliances in the BioSciDB database associated with cancer therapy. We further segregated the data by distinguishing between alliance agreements focused on incumbent versus emergent technologies. Since the use of mAbs represents the emergent technology in our study, we isolated those deals in which "monoclonals" appears in the "technologies" field of the database. In follow-up conversations with the database vendor, we confirmed accurate categorization of alliances focused on mAbs and applied the same process to identify R&D alliances involving small molecules. Two life science scientists independently verified these categorizations provided by the database. We thus constructed the emergent technology network using interorganizational ties from cancer therapy alliances based on mAbs, and the established technology network based on small-molecule collaborations.

Our theoretical framework also addresses the dynamics of network evolution *between* technology networks, specifically in terms of multiplex closure effects proposed in the hypotheses. For that reason, we include tie formation in small-molecule technologies (representing the incumbent technologies applied to cancer therapy) as a simultaneous dependent variable. As a feature of SAOM analysis in *RSiena*, multivariate tie-formation outcomes can be modeled concurrently, allowing for tests of statistical inference on the evolution of networks resulting from influences and dynamics between different types of network ties (Ripley et al., 2023). Our network data (for both the emergent and incumbent networks) consist of directional ties. BioSciDB contains fields that identify the client firm seeking technology and the R&D firm providing it in the alliance agreement.[6] In our networks, ties point from the client firm to the R&D firm. Although our data lack formal records of alliance dissolution, we align with prior research indicating that biotech alliances typically last around three years (Pangarkar, 2003; Paruchuri, 2010), and we consider the alliances to be dissolved after that time period.[7]

Independent variables. To test Hypothesis 1, we model *Within-Network Uniplex Closure* using a geometrically weighted dyad-wise shared partner, "GWDSP," term in *RSiena*. This term captures the prior period's effect of shared third-party network connections on the likelihood of tie formation between two given network actors. While a greater number of shared third-party ties may have an increasing effect on tie formation, this term uses a geometrically decaying multiplier for each additional shared partner.[8] The *Cross-Network Multiplex Closure* effect in Hypothesis 2 is modeled using a

[6] We confirmed the division of alliance partners into knowledge source (R&D firm) and knowledge recipient (client) roles through interviews with BioSciDB staff, and also find this to be a typical structure in industry reports.

[7] We also conduct robustness tests in which the alliance duration is assumed to be five years; the findings are fully consistent with the baseline results.

[8] For example, while the second shared third-party partner may have a relatively strong influence on tie formation, the fifth, sixth, seventh, and so on are not likely to have a large incremental effect in the decision to form a network tie. Thus, this term accounts for the marginally declining effect.

mixed "$WW => X$ closure" term. This is similar to a triadic closure term in a univariate network, but in this case involves the presence of multiplex ties in the alternate technology network (e.g., two firms having small-molecule technology alliances with a common third party and subsequently forming a direct alliance in mAbs). Hypothesis 3 addresses the tendency of brokers, firms that occupy the boundary-spanning position between two unconnected collaboration partners, to resist allowing a direct tie to form between the two partners when one of them is an emerging technology expert. We test *mAbs Expertise Boundary-Spanning Closure* in *RSiena* using a "jumpWWClosure" model term based on mAbs patent expertise. Specifically, this term examines the tendency for mAbs alliance ties to form when the focal actor does not have prior emergent technology experience in terms of patented inventions in mAbs technology, the alter firm *does* have such expertise exhibited through prior mAbs technology patents, and the two firms are indirectly connected through an intermediary with which they share prior alliance ties in the incumbent (small molecule) technology. If our theoretical claims are correct, the third party will seek to maintain its advantageous brokerage position by resisting the alliance between emergent technology expert and nonexpert, leading to a negative coefficient for this network term in the SAOM analysis.

Actor-centric control variables. The centrality of a network actor is often predictive of the future likelihood of network tie formation (e.g., Maoret, Tortoriello & Iubatti, 2020). For that reason, we include *Focal Firm Indegree Popularity* and *Focal Firm Outdegree Activity* in our models. We draw from the patent record of the U.S. Patent and Trademark Office (USPTO) to construct a number of actor-centric control variables related to patenting. First, we undertake a disambiguation process to match the names of firms in our sample (i.e., the organizational names listed in BioSciDB) to the assignee names of patents in the USPTO record. Following prior research (Li et al., 2014), we implement a matching protocol to structure the text string data in both databases and then calculate matching scores using the "matchit" function in *Stata*. Nonmatches are dealt with manually. As the focal or "client" firms seek alliance ties with organizations that may provide them with valuable knowledge, we control for a variety of characteristics that may make potential partners more attractive to them. We include the number of *Alter* and *Focal Firm Patents* to reflect the overall knowledge stock of firms in the sample, as well as *Alter* and *Focal Firm Knowledge Quality*, the count of forward citations of the firm's patents. This is calculated based on the number of citations of the patents by external firms (i.e., excluding self-cites) over the five-year period following the year of application of each patent. This is often used as proxy for quality of knowledge demonstrated through the decision of objective, third-party organizations to build on the firm's patents (Wry, Greenwood, Jennings & Lounsbury, 2010).

Organizations with more employees allocated to innovative functions or with specific expertise in an emergent technology may attract greater interest as alliance partners. We control for *Alter* and *Focal Firm Number of Inventors*, measured as the count of unique active inventors appearing in patents on which the sampled firm is listed as the assignee. Having a greater number of inventors suggests that firms may hold greater capacity for knowledge development and technology collaboration. To assess firm expertise in the emergent technology, we identified the specific patent classification codes that are associated with mAbs technologies. Patents are organized through the system of Cooperative Patent Classification (CPC) codes to define unique technology categories, a system adopted by the USPTO in 2015 (and subsequently backfilled throughout the prior record of U.S. patents) to align with the categories implemented by the European Patent Office (Arts, Cassiman & Gomez, 2018). *Alter* and *Focal Firm Patents in mAbs* are calculated as count variables, reflecting the total number of patents using these primary CPC codes, on which the sampled firm is listed as an assignee, and summed through the year of observation. The knowledge stock reflected through this measure may directly influence a focal firm's tendency to be sought out for external R&D alliances in mAbs technologies.[9] We also account for the relative difference in expertise with mAbs patents by including *Focal–Alter Similarity in mAbs*, an *RSiena* term that captures how closely matched two firms may be in their count of mAbs patents. Finally, we include additional patent-based actor-centric controls, *Alter* and *Focal Firm Age of Technology*. This is calculated as the average age of the primary CPC codes appearing in the firm's patents, based on the number of years elapsed from the first occurrence of the CPC code in the U.S. patent record to the year of patent

[9] This measure also serves as the basis for differences in mAbs expertise factored into the "jumpWWClosure" network term described earlier that is used to test Hypothesis 3.

application. Whether firms are building on older or newer technologies may influence their attractiveness as potential partners.

Other indicators of knowledge and capabilities may be associated with collaborative network tie formation. For example, prior alliances involving later stage FDA approval process therapeutics may make firms more attractive network partners. Drawing from BioSciDB, we control for *Alter* and *Focal Firm Stage 3 FDA Trial Alliances in mAbs* and *Alter* and *Focal Firm Stage 3 FDA Trial Alliances in Small Molecule*. Similarly, we control for number of *Alter* and *Focal Firm FDA Drug Approvals* to reflect their success in commercializing new technologies.

Universities can be crucial in developing emergent technologies, as shown by our field interviews and previous research (Holmes & Smart, 2009). These organizations are typically dedicated to creating technology and treatments for the greater good and are, therefore, more active in sharing new technologies. To account for this, we include the control variables *Alter* and *Focal Firm Alliance Ties to Universities*, drawn from the categories in BioSciDB, capturing the total count of prior alliance ties between the firm and universities.

Dyadic control variables. We capture several dyadic effects that may contribute to tie formation in the alliance networks. Firms sharing a prior alliance tie in small-molecule technology may be more likely to form a mAbs alliance, separate from the hypothesized triadic effects. For that reason, we include *Small Molecule Multiplexity* as a control to capture this. Prior alliance research demonstrates that relative characteristics of knowledge held by potential partner firms may play an important role in collaborative tie formation. For example, firms that are more similar in their knowledge base may more easily share insights on new technologies (Lane & Lubatkin, 1998). For that reason, we include the variable *Focal–Alter Technology Similarity*. In each observation year, and in each firm pair in our sample, we calculate the distance between their patented knowledge. We first construct a vector representing the knowledge of each firm over the prior three years of their patent history. The primary patent classification codes listed on the firm's patents serve as the directional components of the vector, and the count of patents listing each of those primary codes are the corresponding magnitudes. Following prior work (Rosenkopf & Almeida, 2003), we then calculate the Euclidean distance between the vectors representing the two firms in the potential alliance dyad. This results in a distance measure ranging from 0 to the square root of 2; to ease the interpretation of this variable, we perform a linear transformation to set the range from 1 to 0, representing the technology similarity between firms. To address the potential curvilinear effects of this control, we also include the squared term for technology similarity in our models. Finally, we include *Focal–Alter Geographic Distance,* a factor shown to play an important role in interorganizational alliance partner selection (e.g., Reuer & Lahiri, 2014; Ryu, McCann & Reuer, 2018). This is implemented following the approach of Stuart and Sorenson (2003), geocoding the address of the headquarters location for each firm and then calculating the great circle distance between them.

With the dual dependent variable structure in our *RSiena* models, we include the same set of control variables applied to the analysis of tie formation and evolution in the small molecule technology network. We illustrate all SAOM model terms in Table 1.

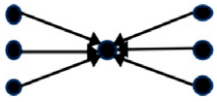
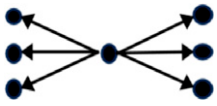
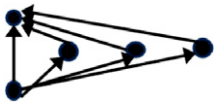
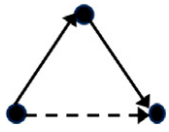
RESULTS

The characteristics of the cancer therapy R&D alliance networks (the context for tie formation as the dependent variables for our analysis) are provided in Table 2.

Our sample consists of 453 organizations that participated in R&D alliances involving mAbs and small-molecules cancer therapy technologies during the 2004–2020 observation period. Table 2 highlights network tie formation, network density, and change in the interorganizational alliance networks focused on mAbs and small-molecule technologies. Consistent with our fieldwork and assessment of key milestones in the development of the field, we do observe a substantial increase in mAbs alliances over the period of the study, with the alliance ties numbering over 100 by 2015. This likely corresponds to the desire of firms to seek knowledge of mAbs, given their increasing legitimacy and the realization of their tremendous potential for application in cancer therapy.

Table 2 shows the Jaccard indices for all between-year transitions in the network. The Jaccard index measures the similarity between two time periods' network structure, with values closer to 1 indicating little change and those closer to 0 indicating significant change (Jaccard, 1900). To support the stepwise change assumption required for SAOM analysis, gradual network change must be confirmed. Jaccard indices above 0.3 support gradual network change (Snijders et al., 2010). Our results align with this, with one exception: the mAbs network Jaccard index 2010–2011 was 0.26. As noted in the *RSiena* manual,

TABLE 1
SAOM Model Terms

Parameter	Diagram	Social Process or Control
Actor effects		
Alter (patents) Alter (knowledge quality) Alter (number of inventors) Alter (FDA approvals) Alter (FDA stage 3 in mAbs) Alter (FDA stage 3 in small molecule) Alter (network ties to universities) Alter (university or nongovernmental organization) Alter (patents in mAbs) Alter (age of technology)		Tendency of firms (R&D firms) with higher number of patents in mAbs, etc., to receive an R&D tie with another firm (client)
Dyadic effects		
Technology similarity Technology similarity^2 Geographic distance		Tendency of firms to form R&D ties with others of similar knowledge bases, due to geographic distance
Network structural effects		
Outdegree (density)		Baseline tendency for R&D tie formation
Focal firm indegree popularity		Tendency toward variation in the degree to which external actors pursue R&D ties with the focal firm
Focal firm outdegree activity		Tendency toward variation in the degree to which an actor pursues multiple R&D ties
Within-network uniplex closure (GWDSP)		Tendency for the closure of transitive triads
Cross-network multiplex closure (triadic closure)		See Figures 1 and 2 for detailed diagrams of triadic network structures.

a slightly lower index is not unusual in periods in which network evolution features the creation of new ties (Ripley et al., 2023).

Table 3 provides descriptive statistics and bivariate correlations for all study variables.[10] Table 4 presents the results of SAOM tests for the study hypotheses, including variable coefficients, standard errors, *p*-values, and *t*-ratios of convergence. Prior research indicates that acceptable *t*-ratios should be below 0.1, with overall model convergence in the range of 0.25 or lower (Howard, Withers & Tihanyi, 2017; Ripley et al., 2023; Snijders et al., 2010). Our results comply with these standards, with all variable convergence factors below 0.1 and model convergence values of 0.221 or lower.

Among the control variables, we note some interesting results of network tie evolution in the two networks. As is often the case in social network

[10] These statistics are modeled based on a dyad-year panel data structure used in our rare events logistic regression robustness tests described later in the methods section. A SAOM network analysis is not comprised of discrete panel observations, and this alternative structure offers intuition into the basic values and relationships between variables.

TABLE 2
Network Descriptive Statistics

Year	Number of Small-Molecule Ties	Small-Molecule Network Density	Small-Molecule Jaccard Index	Number of mAbs Ties	mAbs Network Density	mAbs Jaccard Index
2004	50	1.86E-04	—	45	1.27E-04	—
2005	46	1.86E-04	0.62	41	1.22E-04	0.7
2006	37	1.47E-04	0.31	29	1.03E-04	0.77
2007	41	1.86E-04	0.48	21	1.03E-04	0.4
2008	42	1.86E-04	0.55	20	9.77E-05	0.37
2009	32	1.37E-04	0.57	25	1.12E-04	0.72
2010	26	1.07E-04	0.47	20	8.79E-05	0.52
2011	37	1.71E-04	0.33	28	1.27E-04	0.26
2012	35	1.71E-04	0.52	35	1.71E-04	0.45
2013	76	3.71E-04	0.34	59	2.88E-04	0.49
2014	73	3.56E-04	0.39	85	4.15E-04	0.37
2015	106	5.18E-04	0.38	121	5.91E-04	0.49
2016	94	4.49E-04	0.51	131	6.40E-04	0.64
2017	89	4.25E-04	0.56	104	5.08E-04	0.58
2018	54	2.54E-04	0.39	77	3.76E-04	0.41
2019	46	2.25E-04	0.38	61	2.98E-04	0.44
2020	45	2.20E-04	0.36	54	2.64E-04	0.55

Note: Total sample nodes: 453.

research, outdegree activity plays a positive role in predicting tie formation for both mAbs and small-molecule alliances. Owing to the greater costs of travel and coordination, geographic distance has a negative effect on tie formation in both networks. Firms with more inventors and more FDA drug approvals are generally shown to be popular alliance partners in both networks, exhibited in the positive and significant coefficients of these terms in Model 1. Not surprisingly, focal and alter firms with prior alliances focused on stage 3 FDA trials in small molecule technology are positively associated with tie formation in that network.

Our theoretical arguments for Hypothesis 1 suggest that actors will engage in uniplex technology closure in the emergent technology network, tending to form ties with other network actors connected through a common third party. This is tested through the GWDSP term loaded into the *RSiena* model. As shown in Table 5, Model 2, this term is positive and significant ($\beta = 0.153$, $p < .05$), providing support for Hypothesis 1. We note that within-network uniplex closure is a marginally significant factor ($p = .055$) in the incumbent network, shown in the coefficient for the GWDSP term in predicting small-molecule tie formation. This may result from the more established basis for the technology; firms may not have as great a need for introduction through intermediaries to identify new alliance partners.

We include the cross-network multiplex closure terms in Model 3 of Table 4. Hypothesis 2 examines the role of multiplex triads, the behavior of network actors in three-party systems comprising different technology ties connecting the parties. In Hypothesis 2, we suggest that emerging network tie formation between the focal and alter firm is more likely when the focal firm is connected to a third party through an incumbent technology network tie, and this third party also has an incumbent technology tie with the alter firm. In line with our hypothesis, the *Cross-Network Multiplex Closure* term included in the *RSiena* model has a coefficient that is positive and significant ($\beta = 2.209$, $p < .05$) in the mAbs network. This supports Hypothesis 2, the notion that the broker allows for triadic closure and thereby enables collaboration linking the incumbent and emergent technology.

While our theoretical focus is on the formation of alliance ties in the emergent mAbs technology network, we also examined corresponding effects for the formation of ties in the incumbent small-molecule technology network. We tested the $WW => X$ multivariate triadic term in the small-molecule network, and it failed to achieve convergence, potentially indicating that this structure is not observed in or representative of the broader structure of the incumbent technology network (Ripley et al., 2023). We did, however, identify a similar multiplex triadic term in small molecules that did converge. The $XW => X$ term (testing the presence of one mAbs and one small-molecule tie leading to triadic closure through an additional small-molecule tie) was included. However, the coefficient of this term was

TABLE 3
Descriptive Statistics and Correlations

Variable		Mean	*SD*	1	2	3	4	5	6	7
1	mAbs network tie formation	4.30E-04	0.021							
2	Small-molecule network tie formation	3.93E-04	0.020	.116						
3	Within-network uniplex closure	5.98E-04	0.024	.384	.008					
4	Cross-network multiplex closure	4.77E-04	0.022	.039	.367	.066				
5	Focal firm indegree popularity	0.106	0.591	.032	.028	.043	.023			
6	Focal firm outdegree activity	0.002	0.121	.000	.000	.000	.000	−.003		
7	Focal–alter geographic distance (km)	5,688	3,890	−.004	−.002	−.005	−.004	−.006	.002	
8	Focal–alter technology similarity	0.210	0.301	.005	.003	.008	.008	.034	.019	−.052
9	Focal–alter technology similarity^2	0.135	0.216	.006	.003	.009	.009	.032	.018	−.046
10	Alter firm patents	7.726	15.548	.003	.007	.009	.016	−.001	−.001	−.023
11	Focal firm patents	2.898	10.114	.015	.010	.016	.012	.114	.009	−.038
12	Alter firm knowledge quality	15.097	45.294	−.001	.006	−.001	.010	−.020	−.001	−.039
13	Focal firm knowledge quality	5.602	28.855	.005	.005	.003	.007	.025	.003	−.041
14	Alter firm number of inventors	19.281	43.478	.001	.009	.006	.018	−.014	.000	−.002
15	Focal firm number of inventors	7.113	27.608	.018	.012	.015	.013	.092	.005	−.021
16	Alter firm FDA drug approvals	0.030	0.216	.002	.003	.008	.011	.005	.000	−.008
17	Focal firm FDA drug approvals	0.024	0.193	.022	.017	.018	.016	.173	−.002	−.007
18	Alter firm stage 3 trial alliances in mAbs	0.033	0.223	.017	.004	.008	.007	.001	.005	.001
19	Focal firm stage 3 trial alliances in mAbs	0.027	0.198	.028	.014	.011	.009	.045	−.002	−.004
20	Alter firm stage 3 trial alliances in small molecule	0.033	0.238	−.001	.017	−.001	.002	−.004	.002	.003
21	Focal firm stage 3 trial alliances in small molecule	0.025	0.195	.008	.023	.004	.004	.043	−.002	−.005
22	Alter firm alliance ties to universities	0.019	0.173	−.001	.000	−.003	.000	.005	−.002	−.002
23	Focal firm alliance ties to universities	0.019	0.182	−.002	−.001	−.003	−.001	−.011	−.002	−.004
24	Alter firm age of technology	31.604	8.151	−.003	.007	.001	.010	.018	.002	.017
25	Focal firm age of technology	12.001	16.211	.004	.003	.007	.006	.043	.019	−.046
26	Alter firm patents in mAbs	1.204	3.529	.012	.002	.016	.011	−.001	.000	−.029
27	Focal firm patents in mAbs	0.465	2.291	.015	.011	.015	.012	.146	.056	−.035
28	Focal–alter similarity in mAbs	0.036	0.186	.019	.001	.027	.002	.062	.023	−.021
29	Small-molecule multiplexity	0.001	0.066	.041	.210	.090	.728	.014	.000	−.004

Variable		8	9	10	11	12	13	14	15	16	17	18	19
9	Focal–alter technology similarity^2	.972											
10	Alter firm patents	.044	.061										
11	Focal firm patents	.347	.317	−.002									
12	Alter firm knowledge quality	.024	.036	.593	.001								
13	Focal firm knowledge quality	.242	.226	.002	.598	.022							
14	Alter firm number of inventors	.032	.051	.856	.001	.537	.017						
15	Focal firm number of inventors	.322	.303	.003	.870	.018	.551	.018					
16	Alter firm FDA drug approvals	.009	.013	.267	−.004	.081	−.009	.186	−.010				
17	Focal firm FDA drug approvals	.024	.022	−.004	.188	−.010	.060	−.010	.140	.003			
18	Alter firm stage 3 trial alliances in mAbs	.023	.022	.043	.004	−.014	−.001	.021	.002	.091	.002		
19	Focal firm stage 3 trial alliances in mAbs	.047	.041	−.003	.047	−.004	−.001	−.004	.030	−.001	.091	.015	
20	Alter firm stage 3 trial alliances in small molecule	.007	.007	.036	.002	.064	.005	.055	.002	.018	.000	−.013	.006
21	Focal firm stage 3 trial alliances in small molecule	.037	.034	−.002	.042	.004	.058	−.001	.054	.000	.051	.009	−.005
22	Alter firm alliance ties to universities	−.027	−.025	.042	−.003	.002	.000	.071	.004	−.015	−.005	−.016	−.011
23	Focal firm alliance ties to universities	−.027	−.025	.013	.008	.011	−.005	.024	.021	−.007	.034	−.013	−.003
24	Alter firm age of technology	.040	.036	.033	−.002	−.041	−.028	.006	−.032	.073	.018	.001	.017

TABLE 3
(Continued)

Variable		8	9	10	11	12	13	14	15	16	17	18	19
25	Focal firm age of technology	.824	.742	−.008	.358	−.015	.227	−.020	.320	.003	.037	.018	.038
26	Alter firm patents in mAbs	.049	.063	.606	.001	.381	.003	.556	.004	.251	−.002	.084	.004
27	Focal firm patents in mAbs	.249	.225	−.002	.652	.000	.400	.000	.602	−.004	.178	.006	.071
28	Focal–alter similarity in mAbs	.315	.336	.078	.212	.034	.117	.066	.190	.028	.037	.047	.059
29	Small-molecule multiplexity	.008	.009	.020	.010	.009	.007	.019	.010	.013	.011	.012	.008

Variable		20	21	22	23	24	25	26	27	28
21	Focal firm stage 3 trial alliances in small molecule	.007								
22	Alter firm alliance ties to universities	−.015	−.009							
23	Focal firm alliance ties to universities	−.008	−.013	.041						
24	Alter firm age of technology	.069	.011	−.097	−.064					
25	Focal firm age of technology	.007	.054	−.031	−.034	.050				
26	Alter firm patents in mAbs	.019	.002	−.003	−.001	−.047	.006			
27	Focal firm patents in mAbs	.002	.024	−.007	−.008	.004	.236	.001		
28	Focal–alter similarity in mAbs	−.003	.004	−.005	−.005	−.022	.222	.153	.298	
29	Small-molecule multiplexity	.002	.003	.000	−.001	.009	.006	.016	.008	.003

Notes: Correlations above .003 significant at the $p = .001$ level; values above .002 significant at the $p = .01$ level; values above .001 significant at the $p = .05$ level.

not significant in Model 2. Thus, we did not find evidence of a tendency either toward or away from multiplex closure in the incumbent technology network. This might indicate that tie formation in the incumbent network does not depend on intermediaries in the emergent technology, potentially due to lower levels of technological and relational uncertainty.

We test Hypothesis 3's arguments on the third party's incentive to separate unconnected firms across technologies by including the *mAbs Expertise Boundary-Spanning Closure* term in Model 3. The coefficient for this term is negative and highly significant in predicting mAbs network tie formation ($\beta = -126.659$, $p < .001$). This indicates that when two firms have a common third-party partner (broker) connected to each of them through a small molecule tie, and when one of them has emergent technology expertise demonstrated through creating mAbs patents but the other does not, the formation of a mAbs alliance between them is much less likely. We note that the magnitude of this coefficient is quite large in comparison to the other variables in the model. This is not unusual in SAOM models in which the network structure tested is exceedingly unlikely to occur in the observed data. Consistent with prior work (e.g., Howard et al., 2017), as long as the standard errors are not inflated and the convergence statistics are below the required levels, it is appropriate to interpret the findings. Consistent with our theoretical framework, this finding provides evidence that the broker firm may guard against multiplex closure when it enjoys a controlling position between one expert firm and one nonexpert firm. Because of the baseline tendency for multiplex closure (shown in the cross-network multiplex closure term) and for firms to seek out mAbs technology experts (shown in Model 1), this result suggests that the broker is playing a role in restricting the chance for connection between its shared partners.

We see a similar finding for mAbs patenting expertise as a factor in multiplex tie formation in the small-molecule network. Model 3 shows that the coefficient for *mAbs Expertise Boundary-Spanning Closure* is again negative and highly significant ($\beta = -14.957$, $p < .001$). When two firms have a common third-party partner connected to each of them through a mAbs tie, and when one of them has enhanced emergent technology expertise demonstrated through creating mAbs patents but the other does not, the formation of a small-molecule alliance between them is much less likely. The broker may seek to prevent the connection of ties between its partners, not only in the emergent technology network but also in the incumbent network. In other words, they may guard access to emergent technology expertise to such an extent that they resist any form of connection to this source of expertise, even

TABLE 4
Stochastic Actor-Oriented Models

Model Parameter	Model 1			Model 2			Model 3		
	β	*SE*	*T*-ratio	β	*SE*	*T*-ratio	β	*SE*	*T*-ratio
mAbs Network Tie Evolution									
Basic rate parameter (period 1)	0.182	(0.067)	.03	0.186	(0.069)	−.01	0.187	(0.071)	.03
Basic rate parameter (period 2)	0.118	(0.049)	.02	0.119	(0.051)	.01	0.119	(0.052)	−.01
Basic rate parameter (period 3)	0.418	(0.125)	.03	0.419	(0.123)	.02	0.422	(0.120)	−.01
Basic rate parameter (period 4)	0.467	(0.149)	.00	0.472	(0.137)	.01	0.473	(0.130)	.00
Basic rate parameter (period 5)	0.147	(0.059)	−.02	0.150	(0.057)	.01	0.150	(0.062)	−.02
Basic rate parameter (period 6)	0.279	(0.088)	−.04	0.285	(0.101)	.01	0.286	(0.091)	−.02
Basic rate parameter (period 7)	0.690	(0.173)	−.04	0.707	(0.158)	−.01	0.713	(0.213)	.02
Basic rate parameter (period 8)	0.504	(0.141)	.02	0.514	(0.127)	−.01	0.519	(0.142)	.02
Basic rate parameter (period 9)	0.728	(0.193)	−.02	0.732	(0.162)	.02	0.734	(0.181)	−.02
Basic rate parameter (period 10)	1.701	(0.370)	.00	1.685	(0.322)	−.01	1.686	(0.355)	−.02
Basic rate parameter (period 11)	1.361	(0.242)	.00	1.366	(0.218)	−.04	1.362	(0.224)	−.01
Basic rate parameter (period 12)	0.747	(0.120)	.01	0.745	(0.118)	−.01	0.744	(0.116)	.00
Basic rate parameter (period 13)	0.848	(0.125)	.03	0.840	(0.132)	−.01	0.838	(0.134)	−.05
Basic rate parameter (period 14)	1.212	(0.168)	.00	1.213	(0.170)	.02	1.213	(0.173)	.00
Basic rate parameter (period 15)	0.978	(0.159)	.00	0.979	(0.184)	.02	0.980	(0.180)	.00
Basic rate parameter (period 16)	0.593	(0.120)	.00	0.597	(0.131)	.01	0.597	(0.130)	−.02
Outdegree (density)	−9.201***	(0.131)	.01	−9.234***	(0.134)	.00	−9.238***	(0.136)	−.04
Focal firm indegree popularity	0.212	(0.500)	−.01	0.209	(0.465)	.00	0.216	(0.468)	.00
Focal firm outdegree activity	0.594***	(0.087)	.01	0.595***	(0.083)	.00	0.595***	(0.088)	−.03
Focal–alter geographic distance	−0.000***	(0.000)	−.03	−0.000***	(0.000)	.02	−0.000***	(0.000)	.00
Focal–alter technology similarity	−0.125	(1.174)	.02	−0.084	(1.164)	−.03	−0.060	(1.121)	−.02
Focal–alter technology similarity^2	1.055	(1.588)	.02	1.001	(1.575)	−.03	0.979	(1.529)	−.03
Alter firm patents	−0.055*	(0.024)	.00	−0.053*	(0.023)	−.02	−0.053*	(0.023)	.02
Focal firm patents	−0.016	(0.019)	−.02	−0.016	(0.019)	−.01	−0.016	(0.020)	−.01
Alter firm knowledge quality	0.001	(0.002)	−.01	0.001	(0.002)	−.01	0.001	(0.002)	.01
Focal firm knowledge quality	−0.007	(0.005)	−.03	−0.007	(0.005)	.00	−0.007	(0.005)	−.01
Alter firm number of inventors	0.010*	(0.005)	.01	0.009†	(0.005)	.00	0.009†	(0.005)	.02
Focal firm number of inventors	0.022†	(0.011)	−.01	0.022†	(0.011)	.00	0.022†	(0.012)	−.01
Alter firm FDA drug approvals	−0.406	(0.399)	−.01	−0.431	(0.388)	.01	−0.429	(0.381)	.02
Focal firm FDA drug approvals	1.489***	(0.438)	−.01	1.502***	(0.421)	.02	1.496***	(0.425)	−.02
Alter firm stage 3 trial alliances in mAbs	0.801***	(0.140)	−.03	0.688***	(0.158)	.00	0.689***	(0.159)	.00
Focal firm stage 3 trial alliances in mAbs	3.227***	(0.935)	−.01	3.271***	(0.869)	.00	3.257***	(0.862)	−.03
Alter firm stage 3 trial alliances in small molecule	0.053	(0.277)	.00	0.023	(0.268)	−.01	0.018	(0.265)	−.01
Focal firm stage 3 trial alliances in small molecule	0.986**	(0.315)	.01	0.985**	(0.311)	−.01	0.984**	(0.303)	.00
Alter firm alliance ties to universities	0.055	(0.427)	−.02	0.057	(0.409)	.00	0.059	(0.407)	.03
Focal firm alliance ties to universities	0.107	(0.434)	.01	0.117	(0.462)	.01	0.119	(0.446)	−.02
Alter firm patents in mAbs technology	−0.008	(0.102)	.02	−0.008	(0.094)	−.01	−0.008	(0.096)	.00
Focal firm patents in mAbs technology	−0.517	(0.517)	.00	−0.522	(0.493)	−.01	−0.521	(0.523)	.00
Focal–alter similarity in mAbs	−5.730	(4.233)	.00	−5.754	(3.869)	.00	−5.769	(3.994)	.00
Alter firm age of technology	−0.004	(0.009)	.00	−0.004	(0.009)	.03	−0.004	(0.009)	.00
Focal firm age of technology	−0.070	(0.227)	.01	−0.076	(0.215)	.01	−0.077	(0.223)	−.01

TABLE 4
(Continued)

Model Parameter	Model 1			Model 2			Model 3		
	β	*SE*	*T*-ratio	β	*SE*	*T*-ratio	β	*SE*	*T*-ratio
mAbs Network Tie Evolution									
Small-molecule multiplexity	2.940**	(1.006)	−.03	2.969**	(1.007)	.01	2.917**	(1.013)	−.01
Within-network uniplex closure (Hypothesis 1)	—			0.153*	(0.079)	−.01	0.155*	(0.078)	.01
Cross-network multiplex closure (Hypothesis 2)	—			—			2.209*	(1.015)	.01
mAbs expertise boundary-spanning closure (Hypothesis 3)	—			—			−126.659***	(10.442)	.10
Small-Molecule Network Tie Evolution									
Basic rate parameter (period 1)	0.467	(0.129)	−.01	0.464	(0.134)	.00	0.464	(0.120)	.01
Basic rate parameter (period 2)	1.325	(0.324)	.01	1.299	(0.332)	−.01	1.303	(0.322)	.01
Basic rate parameter (period 3)	0.840	(0.204)	−.02	0.821	(0.233)	−.01	0.815	(0.240)	−.01
Basic rate parameter (period 4)	0.676	(0.150)	.01	0.668	(0.175)	−.01	0.664	(0.173)	−.03
Basic rate parameter (period 5)	0.401	(0.114)	−.02	0.393	(0.111)	.01	0.393	(0.112)	.00
Basic rate parameter (period 6)	0.514	(0.135)	−.01	0.499	(0.153)	.00	0.499	(0.140)	.00
Basic rate parameter (period 7)	1.073	(0.296)	−.02	1.054	(0.288)	.00	1.054	(0.317)	.02
Basic rate parameter (period 8)	0.504	(0.120)	−.04	0.496	(0.121)	−.02	0.495	(0.130)	−.04
Basic rate parameter (period 9)	2.409	(1.125)	.02	2.315	(0.864)	−.01	2.325	(0.781)	.00
Basic rate parameter (period 10)	1.359	(0.245)	.02	1.330	(0.229)	−.02	1.328	(0.249)	.00
Basic rate parameter (period 11)	1.869	(0.352)	.04	1.985	(0.342)	.01	2.007	(0.361)	.09
Basic rate parameter (period 12)	0.930	(0.147)	−.01	0.940	(0.142)	.00	0.940	(0.144)	.01
Basic rate parameter (period 13)	0.795	(0.126)	.01	0.798	(0.126)	.02	0.799	(0.126)	.01
Basic rate parameter (period 14)	1.050	(0.172)	−.04	1.066	(0.169)	.03	1.064	(0.163)	−.01
Basic rate parameter (period 15)	1.013	(0.208)	.00	1.015	(0.202)	−.01	1.011	(0.179)	.00
Basic rate parameter (period 16)	1.071	(0.247)	.01	1.079	(0.229)	−.02	1.075	(0.245)	−.01
Outdegree (density)	−9.579***	(0.139)	.01	−9.548***	(0.135)	.00	−9.543***	(0.140)	.02
Focal firm indegree popularity	0.320	(0.693)	.00	0.323	(0.609)	.02	0.328	(0.626)	.00
Focal firm outdegree activity	0.670***	(0.089)	−.01	0.675***	(0.085)	.00	0.674***	(0.088)	.01
Focal–alter geographic distance	−0.000***	(0.000)	.03	−0.000***	(0.000)	−.01	−0.000***	(0.000)	−.01
Focal–alter technology similarity	−2.915*	(1.430)	−.04	−3.093*	(1.354)	.04	−3.077*	(1.323)	.02
Focal–alter technology similarity^2	3.739*	(1.864)	−.04	3.930*	(1.795)	.04	3.916*	(1.732)	.02
Alter firm patents	−0.040*	(0.016)	−.03	−0.042**	(0.016)	.01	−0.042**	(0.015)	−.02
Focal firm patents	−0.002	(0.014)	−.04	−0.001	(0.014)	.03	−0.001	(0.014)	.00
Alter firm knowledge quality	−0.002	(0.003)	−.05	−0.003	(0.003)	.02	−0.003	(0.003)	.00
Focal firm knowledge quality	−0.012*	(0.006)	−.01	−0.013*	(0.006)	.02	−0.013*	(0.006)	−.01
Alter firm number of inventors	0.018***	(0.004)	−.03	0.020***	(0.004)	.00	0.020***	(0.004)	−.01
Focal firm number of inventors	0.011*	(0.005)	−.04	0.011*	(0.005)	.02	0.011*	(0.005)	.00
Alter firm FDA drug approvals	0.480*	(0.212)	.03	0.618**	(0.224)	.02	0.615**	(0.220)	.00
Focal firm FDA drug approvals	1.269***	(0.244)	−.05	1.255***	(0.224)	.01	1.250***	(0.226)	−.01
Alter firm stage 3 trial alliances in mAbs	−1.732	(1.716)	.04	−1.592	(1.521)	.01	−1.612	(1.536)	−.01
Focal firm stage 3 trial alliances in mAbs	0.628†	(0.379)	.01	0.617†	(0.375)	.00	0.622†	(0.375)	.02
Alter firm stage 3 trial alliances in small molecule	0.778***	(0.130)	−.01	0.935***	(0.149)	−.01	0.935***	(0.163)	.01
Focal firm stage 3 trial alliances in small molecule	1.643***	(0.303)	.02	1.614***	(0.298)	.00	1.612***	(0.303)	.01
Alter firm alliance ties to universities	−0.729	(0.465)	.00	−0.790	(0.509)	−.01	−0.789	(0.512)	−.03
Focal firm alliance ties to universities	0.267	(0.279)	.00	0.265	(0.272)	.00	0.266	(0.270)	.01

TABLE 4
(Continued)

Model Parameter	Model 1			Model 2			Model 3		
	β	*SE*	*T*-ratio	β	*SE*	*T*-ratio	β	*SE*	*T*-ratio
Small-Molecule Network Tie Evolution									
Alter firm patents in mAbs	−0.031	(0.029)	−.02	−0.033	(0.029)	.01	−0.032	(0.029)	.01
Focal firm patents in mAbs	0.017	(0.035)	−.03	0.018	(0.035)	.03	0.017	(0.035)	−.01
Focal–alter similarity in mAbs	−0.032	(0.172)	.04	−0.038	(0.164)	−.01	−0.034	(0.166)	.00
Alter firm age of technology	0.048***	(0.009)	−.04	0.048***	(0.009)	.01	0.048***	(0.009)	.02
Focal firm age of technology	0.031*	(0.012)	.01	0.031**	(0.012)	.00	0.031**	(0.012)	.02
Within-network uniplex closure	—			−0.474†	(0.247)	.00	−0.483*	(0.240)	−.01
Cross-network multiplex closure	—			—			1.442	(0.928)	.01
mAbs expertise boundary-spanning closure	—			—			−14.957***	(0.054)	.05
Overall model convergence ratio	0.213			0.132			0.221		

† $p < .10$
* $p < .05$
** $p < .01$
*** $p < .001$

in cases of indirect spillover, when knowledge of the new technology may be casually shared between firms in an alliance explicitly focused on the incumbent technology.

Robustness and Goodness of Fit

We assessed the goodness of fit of our SAOM analyses by evaluating the characteristics of the modeled networks relative to the observed data. Specifically, we used the "sienaGOF" function in *RSiena* to compare the average values of auxiliary statistics across simulated models to the values in the actual data (Lospinoso & Snijders, 2019; Ripley et al., 2023). We chose to assess indegree distribution, outdegree distribution, and triad census (the count of specific types of triadic structures observed to form between sets of three nodes in the network) as auxiliary statistics. These statistics comprise important network structural elements that are descriptive components of the triadic effects we are studying (i.e., demonstrating a better fit with these statistics would suggest that our models are doing a good job of representing the nature of triadic sets of ties in the actual network). We provide the plots of our goodness of fit tests in Figure 3.[11]

The results are shown in violin plots, which are box plots combined with curved representations of the density distribution of values for a given auxiliary statistic (Hintze & Nelson, 1998). For example, the first graph in Figure 3 shows the distribution of the cumulative number of nodes in the network that have indegree centrality values of 0 through 7. The box plot and density distribution across trials in the Monte Carlo analysis can then be compared to the solid gray line, representing the actual values of the indegree centrality. As shown in the diagram, the actual values appear to fit within the distribution of modeled values for indegree. Additionally, the "sienaGOF" function provides a statistical test of model fit by calculating the Mahalanobis distance between the modeled and actual auxiliary statistics (Lospinoso & Snijders, 2019). In the case of indegree distribution, the *p*-value reported in Figure 3 is .147, which, at a 95% confidence interval, fails to reject the null hypothesis that the modeled networks appropriately match the data, thus indicating that

[11] We report the goodness of fit results for Model 3 of Table 4, as it includes the full set of study covariates. The results of the goodness of fit tests for the other models are the same or better in terms of their fit to the actual network data.

TABLE 5
Rare Events Logistic Regression Models

Model Parameter	Model 4 β	Model 4 *SE*	Model 5 β	Model 5 *SE*	Model 6 β	Model 6 *SE*
mAbs Network Tie Formation						
Focal firm indegree popularity	0.470***	(0.013)	0.295***	(0.023)	0.286***	(0.024)
Focal firm outdegree activity	0.301***	(0.091)	0.355***	(0.089)	0.332***	(0.091)
Focal–alter geographic distance	−0.000**	(0.000)	−0.000**	(0.000)	−0.000**	(0.000)
Focal–alter technology similarity	−0.287	(0.645)	0.535	(0.749)	0.588	(0.722)
Focal–alter technology similarity^2	0.423	(0.825)	−0.423	(0.984)	−0.463	(0.923)
Alter firm patents	−0.014	(0.011)	−0.009	(0.011)	−0.008	(0.010)
Focal firm patents	−0.011*	(0.007)	−0.019*	(0.008)	−0.017*	(0.007)
Alter firm knowledge quality	−0.003	(0.002)	0.001	(0.001)	0.000	(0.002)
Focal firm knowledge quality	−0.002	(0.001)	0.000	(0.002)	0.000	(0.002)
Alter firm number of inventors	−0.003†	(0.002)	−0.004†	(0.002)	−0.003†	(0.002)
Focal firm number of inventors	0.009***	(0.002)	0.010***	(0.002)	0.009***	(0.002)
Alter firm FDA drug approvals	−0.010	(0.192)	−0.256	(0.219)	−0.274	(0.218)
Focal firm FDA drug approvals	0.498***	(0.089)	0.490***	(0.107)	0.467***	(0.107)
Alter firm stage 3 trial alliances in mAbs	1.050***	(0.061)	1.034***	(0.081)	1.013***	(0.083)
Focal firm stage 3 trial alliances in mAbs	1.165***	(0.052)	1.220***	(0.064)	1.184***	(0.066)
Alter firm stage 3 trial alliances in small molecule	−0.064	(0.181)	−0.164	(0.205)	−0.172	(0.204)
Focal firm stage 3 trial alliances in small molecule	0.678***	(0.059)	0.733***	(0.067)	0.716***	(0.069)
Alter firm alliance ties to universities	−0.867	(0.499)	−0.477	(0.462)	−0.465	(0.461)
Focal firm alliance ties to universities	−0.591	(0.372)	−0.370	(0.361)	−0.368	(0.363)
Alter firm age of technology	0.016***	(0.003)	0.009***	(0.003)	0.009***	(0.003)
Focal firm age of technology	−0.003†	(0.003)	−0.006†	(0.003)	−0.006†	(0.003)
Alter firm patents in mAbs	0.126***	(0.029)	0.099***	(0.024)	0.091***	(0.024)
Focal firm patents in mAbs	−0.027	(0.012)	0.003	(0.014)	−0.002	(0.013)
Focal–alter similarity in mAbs	1.100**	(0.166)	0.555**	(0.202)	1.106***	(0.209)
Small-molecule multiplexity	0.535*	(0.034)	0.104*	(0.050)	−0.083	(0.080)
Within-network uniplex closure (Hypothesis 1)	—		6.905***	(0.101)	7.043***	(0.105)
Cross-network multiplex closure (Hypothesis 2)	—		—		1.121**	(0.396)
mAbs expertise boundary-spanning closure (Hypothesis 3)	—		—		−1.336***	(0.292)
Constant	−8.662***	(0.074)	−9.000***	(0.088)	−9.012***	(0.088)
Likelihood ratio χ^2	1,800.69***		5,218.96***		5,527.60***	

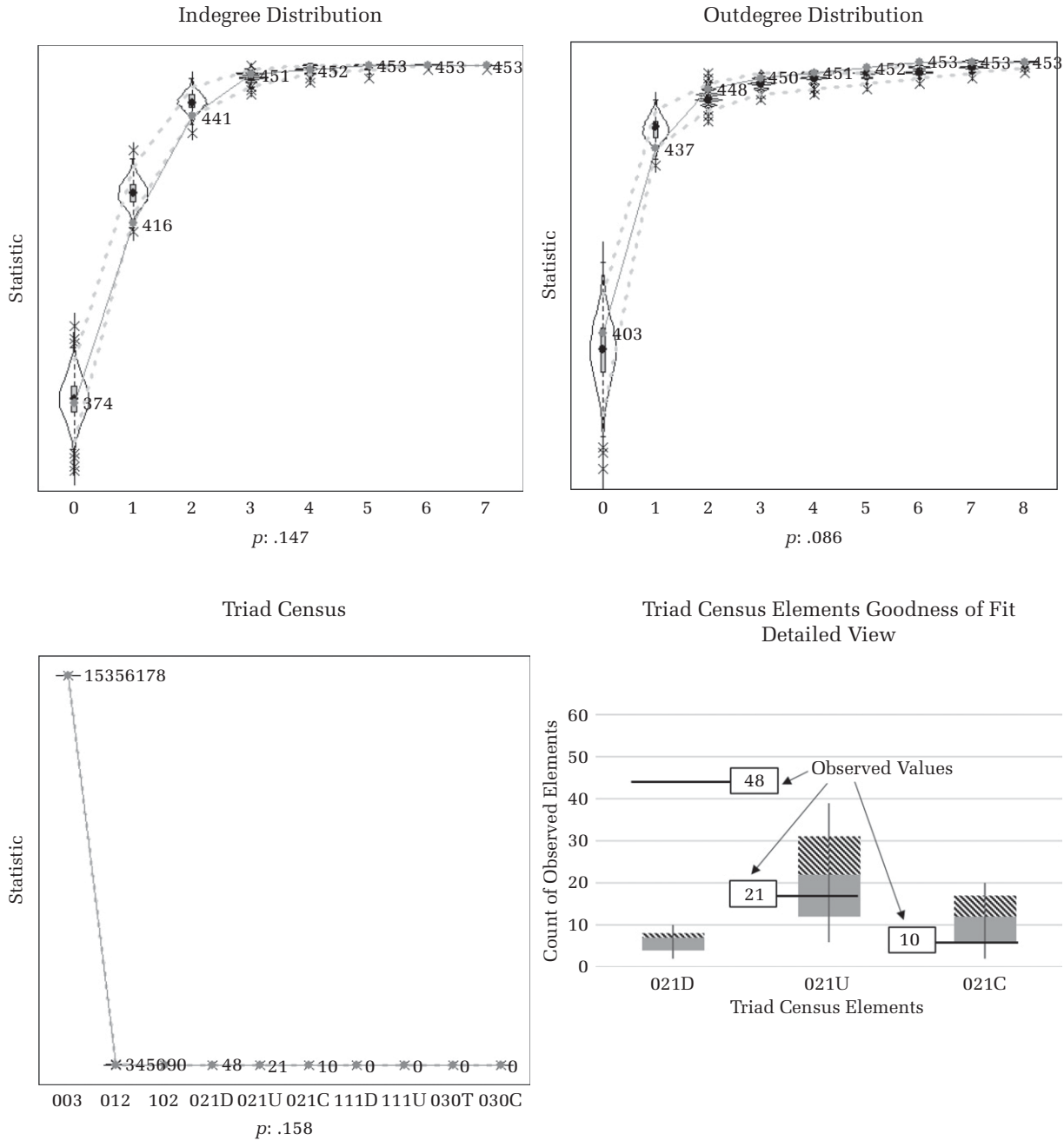
† $p < .10$
* $p < .05$
** $p < .01$
*** $p < .001$

the model has an acceptable fit. The remaining plots in Figure 3 show a similar result for outdegree distribution ($p = .086$) and triad census ($p = .158$).[12]

While the SAOM analysis of our baseline hypothesis tests offers advantages in relaxing the assumption of network tie independence, we tested the robustness of our results by modeling network tie formation through logistic regression. First, we restructured the data into a dyad-year panel comprised of observations of all pairs of sampled firms across all years in which both of them were active. This resulted in a total of 1.18 million dyad-year observations. We focused on

[12] The goodness of fit plots in the triad census graph appear to exactly match many of the triadic forms in the triad census. This is because many of these structures are extremely rare. The median value in the distribution of triadic terms listed to the right side of the plot equals zero (e.g., triadic terms 111D, 111U, etc.). Since the real data observations for the count of these triadic structures are also equal to zero, this shows an exact match in the plot. The same applies to the indegree and outdegree terms. The seemingly close match is also due to the scaling needed to display all structural terms in one plot, which reduces resolution for certain structures. For example, in the detailed view of the triad census shown in the final pane of Figure 3, adjusting the scale reveals that the observed values do closely fit within the distribution and error bars for two of the triadic structures (triadic forms 021U and 021C), but not the other (021D). Despite the misfit with 021D, the analysis overall supports the model's fit with the observed data for triadic terms.

FIGURE 3
SAOM Goodness of Fit Plots



tie formation in the emergent technology network (mAbs), with predictor and control variables matching those used in the SAOM analysis.

Though logistic regression tools cannot match the ability of *RSiena* in directly modeling network structural covariates, we constructed close equivalents to these terms in order to test effects of transitive tie closure. For the variable *Within-Network Uniplex Closure*, we counted the total number of shared mAbs alliance ties between the observed dyad pair in the year prior to observation. For *Cross-Network Multiplex Closure*, we followed a similar approach, counting the total number of shared small-molecule alliance ties between dyad firms. Finally, *mAbs*

Expertise Boundary-Spanning Closure was modeled as an interaction between the cross-network multiplex closure term and a binary variable to record instances in which the alter firm has prior mAbs patenting experience, while the focal firm does not. This interaction offers a reasonable approximation of the SAOM approach for testing the tendency of multiplex open triads to close when there is a difference in expertise between sampled firms.

Given the large number of observations in the dyad-year structure, using basic logistic regression may result in small-sample bias due to the very rare incidence of tie formation across dyads in the data panel. For that reason, we use rare events logistic regression, a technique developed by King and Zeng (2001) that corrects for the sample bias in such situations. Prior studies employing SAOMs have followed a similar approach in conducting robustness tests of network tie formation (Howard et al., 2017). We report the results of this test in Table 5.

Model 5 in Table 5 reports the robustness test of Hypothesis 1. The coefficient for uniplex closure within the emergent technology network is positive and significant ($\beta = 6.905$, $p < .001$), offering further support for Hypothesis 1. Model 6 tests the remaining hypotheses. The results for multiplex closure across the incumbent and emergent technology networks also agree with the SAOM results in providing evidence for Hypothesis 2, demonstrated in the positive and significant results for this variable ($\beta = 1.121$, $p < .01$). Finally, we test the interactive effect of cross-network shared ties with differences in emergent technology expertise between the focal and alter firms. This term is negative and significant ($\beta = -1.336$, $p < .001$), providing additional support for Hypothesis 3.

DISCUSSION

In our study, we investigated the joint role that incumbent and emerging technology networks play in resolving the *tertius iungens* versus *tertius gaudens* tension in new technology development. We introduced the concept of multiplex technology closure as the connection of firms in a triadic structure through collaborations centered on different technologies. Our results show that uniplex technology triads in an incumbent technology, over time, foster multiplex closure in the emergent technology network (i.e., *tertius iungens*). However, to defend their competitive positions in contexts in which they have exclusive access to expertise in an emergent technology, brokers maintain the separation and avoid multiplex closure (i.e., *tertius gaudens*). Together, these findings indicate that tie formation in emerging technologies depends on preexisting structures in the incumbent technology network, and brokers only foster multiplex closure across incumbent and emerging technology networks if their collaborative incentives of reducing technology uncertainty outweigh the competitive incentives of controlling the access to the emerging technology.

Theoretical Contributions

This study offers three significant theoretical contributions. First, we contribute to research on collaborative innovation. We build on prior findings that interorganizational collaborations are central to the emergence of technologies and innovation (Ahuja, 2000b; Kumar & Zaheer, 2019; Powell et al., 1996). Prior research highlights the tension between greater knowledge exchange versus withholding knowledge access as organizations craft collaborative strategies to pursue emergent technologies (Gulati, Sytch & Tatarynowicz, 2012; Runge et al., 2022; Tatarynowicz et al., 2016). Yet, most of this research has investigated such collaboration patterns within specific technology networks or broader industry networks, omitting potential interdependent social dynamics across technology networks. By deeply engaging with the cancer therapy market in interviews and archival data for our study, we highlight an important distinction between the nature of collaboration and competition in situations of technology emergence. While in standard-setting competitions, prior research has shown that firms collaborate within technological boundaries to support their preferred technology (Ranganathan, Ghosh & Rosenkopf, 2018; Soh, 2010), in settings of the coexistence of multiple technologies, collaborative efforts across technologies provide a competitive edge due to their combinatory potential. As such, our investigation enables a better understanding of the interwoven nature of technology and network evolution. We do so by studying firms' quest to cross technological boundaries, resulting in innovative combinations (e.g., such as antibody–drug conjugates) to treat cancer.

Second, our study builds on prior contributions that have significantly increased our understanding of how networks in technologically dynamic fields evolve (Powell, White, Koput & Owen-Smith, 2005; Tatarynowicz et al., 2016) and adds to an emerging body of research on network dynamics (Ahuja et al., 2012; Chen et al., 2022; Kalish, 2020) by increasing

knowledge of the complex and interdependent dynamics of network evolution. While prior research on network dynamics has shown that social relationships are subject to change (Kumar & Zaheer, 2022), to date there is only limited understanding of how the evolution of one network influences the evolution of another network (Htwe et al., 2020; Sytch & Tatarynowicz, 2014a). However, actors might observe tie formation in other networks and make their observations part of their tie-formation decision (Clough & Piezunka, 2020). Particularly, this study is one of the first to consider cross-network influences in the organizational context. We theorize and analyze how the formation of relationships in one network is influenced by preexisting relationships in another related network. From a dyadic standpoint, our empirical findings demonstrate that prior ties between two firms that are focused on the incumbent technology are associated with subsequent tie formation in the emergent technology. By applying SAOMs, we model network evolution as a dynamic process in which actor-centric, dyadic, and network structural attributes have effects across networks with two simultaneously dependent variables. Instead of treating other firms' network activities and the evolving network structure as independent from the decision to form new ties, we theorize and empirically measure how network dynamics on multiple levels over time influence tie-formation decisions in each network.

Third, by jointly considering the incumbent and emergent technology networks' role in triadic closure, our study extends existing theories on how brokers resolve collaborative (i.e., *tertius iungens*) and competitive (i.e., *tertius gaudens*) tensions in innovation settings. Our findings demonstrate how the classic "friend of a friend" relationship (Simmel, 1950; Ter Wal, 2014) facilitates tie formation in the emerging technology network. At the same time, we illustrate the boundaries of this social convention, offering evidence that multiplex technology triads involving asymmetric access to emergent technology expertise through third parties are not honored to create boundary-spanning connections (Gould & Fernandez, 1989); in fact, these intermediaries act for their own competitive advantage and appear to avoid them. Surprisingly, our findings show that brokers even prevent access to emergent technology expertise of unconnected alters if there is the potential for indirect spillover in an alliance explicitly focused on incumbent technology. While prior research draws clear lines between collaborative and competitive ties (Downing, Kang & Markman, 2019; Thatchenkery & Katila, 2021), we contribute to a better understanding of the simultaneous collaborative and competitive tensions brokers face in emergent technology settings. Particularly, we highlight how the unique access to emergent technologies can tip the scale from *tertius iungens* toward *tertius gaudens*.

Finally, we build on and extend research on multiplexity in triadic structures by introducing the concept of multiplex technology closure. While multiplexity research has primarily highlighted multiple relationships between two actors, only a few studies have transferred the concept to settings of triplets (Li & Piezunka, 2020; Shipilov & Li, 2012). Our empirical results align with the prior literature examining dyadic relationships—firms in our sample with prior ties in the incumbent technology do, in fact, have a greater tendency to form emergent technology ties. However, we center our core contribution on the broader, more complex system of triadic network relationships. While Shipilov and Li (2012) conceptualize multiplexity through vertical and horizontal relationships, we extend this research with our unique focus on different types of technology collaboration ties. Further, the significance of transitive structures throughout our findings hints at a hierarchical nature of emergent technology networks, in which the heterogeneous distribution of knowledge in the early stages of evolution establishes a structure of primary and more secondary or peripheral initial access to this knowledge. In the context of this transitive landscape, the conceptualization of multiplex technology closure in triads adds additional explanation to network mechanisms of brokerage and triadic closure, which is central to understanding the structural evolution of innovation networks (Gulati et al., 2012; Rosenkopf & Padula, 2008; Tatarynowicz et al., 2016).

Limitations and Future Research

Our study's limitations encompass opportunities for future contributions. First, while our study focuses mainly on how the evolution of one network influences the evolution of another network, it has implications for future research on the coevolution of networks. Research into the coevolution of networks implies two-way interdependencies between two or more different networks (Chen et al., 2022). In our methodological SAOM approach, we use both the incumbent and emergent technology networks as dependent variables, but we conceptually focus on the interdependent evolution of the emergent

technology network. Future research might draw inspiration from our methodological and conceptual approaches to study how different networks influence each other over time.

Second, our study has its limitations in generalizing the findings to other competitive situations of technology emergence. Since technological trajectories within or between industries might follow different dynamics, we need to be careful to simply transfer the findings to other contexts. Future studies can extend our findings by examining further nuances of technological progress. Our results suggest that triadic structures across technology networks become central in situations in which emergent and incumbent technologies coexist. The incentives for *tertius iungens* and *tertius gaudens* in our study are based on uncertainties and limited access to emerging technologies. However, technological breakthroughs (such as currently promising technological variants like CRISPR-Cas [a gene-editing system] in cancer therapy) might result in the establishment of dominant technologies. Accordingly, future research might investigate how the evolution of technology networks (and the role of brokers) changes when technological breakthroughs become new standards. Since our findings support the notion that technological competition influences the structural evolution of technology networks, further investigation into cyclical phases of the emergence of technologies (Anderson & Tushman, 1990) can improve our understanding of the coevolution between emergent and incumbent technology networks.

Third, we provide a novel perspective on the relationship between incumbent and emergent technology networks by focusing on the technological focus of interfirm collaborations. However, we know little about how our findings differ from applying a technology community approach defined through the distance of relationships (Wu, Adbi & Mahmood, 2023). As firms form multiplex technology triads, their relational distance to firms in other technologies might be shorter than to firms within the same technology network (Sytch et al., 2012). Accordingly, an interesting path for future research would be to investigate the role of multiplex technology closure in the coevolution of innovation communities (e.g., Sytch & Tatarynowicz, 2014b). How do broker dynamics of separating actors across incumbent and emergent technologies play out within and across communities? One of our theoretical contributions is to unveil the interdependent network dynamics across technology networks. Nevertheless, future research might take a closer look into the evolving network structures following these dynamics.

CONCLUSION

Our research addresses the role of brokers in fostering or preventing triadic closure (i.e., *tertius iungens* vs. *tertius gaudens*) within and across incumbent and emerging technology networks. We theorize the concept of multiplex technology closure as central to the evolution of emergent technology networks. Our findings suggest that the evolution of the emergent technology network depends on social dynamics in the incumbent technology network. Remarkably, while third parties generally foster triadic closure across incumbent and emerging technology networks, they play an active role in separating actors with different levels of expertise in the emerging technology. As research on cross-network dynamics is still in its infancy, we are hopeful that our study may encourage others to pursue the broad avenues available for future work in this area.

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