WHERE DO BEST IDEAS COME FROM?
THE EMERGENCE OF MOST VALUABLE IDEAS IN SOCIAL STRUCTURES

Spiro J. Maroulis*
School of Public Affairs
Arizona State University
411 N. Central Ave.
Phoenix, AZ 85004
Ph: 602.496.0464
Spiro.Maroulis@asu.edu

Maxim Sytch
Ross School of Business
University of Michigan
701 Tappan St.
Ann Arbor, MI 48109
Ph: 734.647.1055 Fax: 734.764.2555
msytch@umich.edu

*The authors contributed equally to this paper. The authors would like to thank Lindy Greer, Bill McEvily, Chris Rider, Michelle Rogan, and the seminar participants at the University of Michigan, the Academy of Management Conference, and the joint Arizona State–Hanyang University’s Data Analytics and Computational Modeling for Social Challenges Conference, and the Network Evolution Conference for helpful comments on this paper.
ABSTRACT
This study develops a theory of the emergence of the most valuable ideas in social structures. It does so by developing and analyzing a computational agent-based model that simultaneously tracks interactions of actors constrained by social structure, the idea development trajectories produced by those interactions, and the performance of the resultant ideas. Our theory establishes two distinct stages of idea development (1) “outside the last mile,” where ideas require significant novelty to develop into the most valuable idea and (2) “within the last mile,” where only incremental advancement is needed. It articulates how these stages interact with the processes responsible for exploring potential idea feature combinations (idea space infiltration), and the processes responsible for spreading ideas among actors (social infiltration), to produce the most valuable ideas in networked groups. Outside the last mile, idea space infiltration drives the likelihood of success, making the recombination of ideas the most potent action in producing the best idea. Inside the last mile, success is determined largely by social infiltration; recombinations can be counterproductive, whereas people searching independently for improvements and transferring existing ideas between network communities become most important for the emergence of the most valuable ideas.

INTRODUCTION
Where do valuable ideas come from? One powerful answer to this question emerges from studies of social structure. Indeed, network relationships become potent conduits that pattern the flows of knowledge and information throughout social systems. As a result, an actor’s network position can shape the knowledge and information inputs available to the actor and thus the actor’s subsequent idea production. More concretely, extant network research has produced two pertinent insights. First, brokers—actors who have connections to multiple network communities1—serve as wellsprings of valuable ideas. Underlying this finding is the notion that brokers’ unique position in the social structure equips them with access to diverse and heterogeneous information. Consistent with this belief, empirical research has revealed that

---
1 Network communities represent dense, non-overlapping structural groups within a network, in which actors are connected more to one another than to actors outside their group (e.g., Knoke, 2009; Sytch and Tatarynowicz, 2014; Clement, Shipilov, and Galunic, 2018). A network featuring multiple network communities represents a ubiquitous small-world topology that describes a wide range of social systems, including corporate boards; creative, academic and scientific collaboration networks; as well as a wide range of interorganizational relationships (Baum, Shipilov, and Rowley, 2003; e.g., Davis, Yoo, and Baker, 2003; Balconi, Breschi, and Lissoni, 2004; Uzzi and Spiro, 2005; Fleming, King, and Juda, 2007).
individuals in brokerage network positions generate better, more valuable ideas than non-brokers (Hargadon and Sutton, 1997; Burt, 2004; 2005: 58-92) and that organizations spanning multiple network communities engender more frequent and notable inventions (Vasudeva, Zaheer, and Hernandez, 2013; Sytch and Tatarynowicz, 2014).

Second, the processes of idea transfer and recombination are presumed to account for the brokers’ creative advantage. Both of these processes critically rely on the broker’s ability to see and access knowledge in disparate parts of the network, but they vary in how, exactly, the broker adds value. When engaging in transfer, the broker simply makes one network community aware of the insights residing in another community, thus supporting the export and import of existing ideas (Burt, 2004: 388; 2005: 62-63). When a broker recombines, however, the broker goes a step further by synthesizing bits and pieces of insights from different network communities to devise ideas that are both novel and valuable (Hargadon and Sutton, 1997; Burt, 2004: 349-350, 355; 2005: 64; Fleming, Mingo, and Chen, 2007).

While such theorizing is both useful and intellectually appealing, it can be advanced in substantive ways. To begin with, we have a limited understanding of how the processes of recombination and transfer can affect collective outcomes, such as the ability of a group to come up with the most valuable ideas that could be discovered. On the one hand, successful recombinations can benefit the collective by introducing all actors to novel and potentially better ideas. On the other hand, the transfer of ideas is known to homogenize the underlying knowledge landscape and squeeze requisite knowledge variety from the system. As the variety of inputs for innovations diminishes and the benefits of idea circulation supported by social structures decline, the entire collective could be worse off (Lazer and Friedman, 2007; Gulati, Sytch, and Tatarynowicz, 2012). This tension goes to the heart of the emerging debate regarding how
brokers, in addition to securing private advantage, shape collective outcomes, thus affecting those around them (Fernandez-Mateo, 2007; Burt, 2010; Galunic, Ertug, and Gargiulo, 2012; Stovel and Shaw, 2012; Clement, Shipilov, and Galunic, 2018). Consider, for example, a medical community aiming to discover the most effective vaccine for a given disease or an R&D group trying to produce the best-performing prototype of a given device. In these situations, knowing that scientists and researchers in brokerage positions are more likely to develop better vaccines or prototypes than their colleagues is only part of the answer. We also need to know just how good these ideas are relative to those that the group could have discovered.

Furthermore, processes of transfer and recombination assumed to underlie the actors’ creative advantage are rarely observed and hence only weakly understood. For example, in most empirical analyses, it is difficult to discern which of these processes, and to what extent, contributed to the emergence of valuable ideas (Burt, 2004; Sytch and Tatarynowicz, 2014; Kumar and Zaheer, 2019). Additionally, it is well-known that only “some fraction of the brokerage-spawned new ideas are good” (Burt, 2005: 59), and that brokers go through numerous “novel combinations of existing practice or opinion [that] are worthless” (Burt, 2010: 5). Conversely, not all good ideas come from brokers; indeed, novel and high-quality ideas can come from actors who do not have privileged access to multiple network communities. Extant research is relatively silent on why brokers could fail in their creative pursuits and how non-brokers generate novel and valuable ideas, despite the constraints imposed on them by the social structure.

Finally, against this backdrop, research on creativity and entrepreneurship suggests a more complex picture of actor behavior. Idea development is frequently a multistage and nonlinear process, which involves people searching for relevant inputs, then evaluating,
elaborating, and refining ideas (e.g., Amabile, 1996; Simonton, 1999; Maggitti, Smith, and Katila, 2013; Berg, 2014; McDonald and Eisenhardt, 2020). Networks can therefore be viewed as arteries supporting the continuous flow of ideas in a complex system of multiple interacting individuals. Enabled by networks, people concurrently develop many ideas in a social system, through numerous transfers and recombinations, which are likely to involve multiple – local and distant – contacts in the network. As ideas travel through the social structure, they can thus fuse with other ideas, supersede them, or be abandoned. Incorporating a more process-based view of idea development in social structures can illuminate how networks shape creative outcomes of social groups, as well as the heterogeneity in creative outcomes from individuals occupying the same structural positions in networks.

In this paper, we aim to advance the process-based view of idea development in networked collectives. More specifically, our goal is to develop theory connecting the idea emergence processes in social structures to the resultant collective outcome, which we define in this study as the quality of the best idea that any member of a collective discovers. To carry out this research, we combine insights from extant network research with computational modeling to systematically examine the trajectories of ideas as they interact with individuals in social structures. The point of departure for our research is a system of social interactions in which people both talk to their network contacts and ponder ideas individually. Some of these activities lead people to refine their ideas; others do not. People can recombine insights when pursuing valuable ideas by taking certain elements of others’ ideas; they can borrow others’ ideas in their entirety; or they can work individually to improve their current ideas. These different activities can occur in various parts of the network, sometimes spanning multiple network communities and at other times confined to just one community. More importantly, these activities are rarely
singular. Rather, they build upon one another, resulting in complex idea trajectories that reflect different types and volumes of activities occurring in different stages of development and in different sequences. As people interact, the resultant idea trajectories can become intertwined: ideas can fuse with other ideas, supersede previous ideas, or be abandoned.

Our model assumes a situation in which there is a well-defined problem or opportunity, whose nature is widely understood, and its importance shared by the collective. Importantly, people in a social group interact with the goal of finding an unambiguous best performing solution to the problem. As such, our study is more applicable to fields that are characterized by higher degrees of agreed-upon symbolic structure, logic, and outcomes, such as mathematics, engineering, or life sciences (e.g., Csikszentmihalyi, 1997).

Computational modeling is particularly useful for pursuing our goal for at least two broad reasons. First, computational modeling is especially valuable in developing and refining theory when the underlying theoretical logic is limited (Davis, Eisenhardt, and Bingham, 2007; 2009). Although we begin with the well-known theoretical constructs of network position, inter-network-community transfer, and idea recombination, the relationships among them are too weakly understood to warrant formulating specific hypotheses. Second, the data needed to draw inferences about the relevant processes and mechanisms would be extremely challenging, if not impossible, to obtain. An empirical endeavor intended to develop theory connecting idea development processes in social structures to the likelihood of generating the best collective outcome would need data on social structures, interactions in those structures, and records on how people updated their beliefs following those interactions, all over an extended period of time. It would also require knowing the universe of all possible discoverable ideas, which in the real world is unknowable. When faced with such data constraints, computational modeling
provides a key advantage by enabling us to model all of these critical components and to design controlled computational experiments (Harrison et al., 2007).

SOCIAL STRUCTURES AND VALUABLE IDEAS

Recombination and transfer as sources of private creative advantage
The notion that the idea generation process is largely a social enterprise, shaped by an individual’s network relationships, has received ample empirical support and has been widely accepted across the social sciences (e.g., Amabile, 1996; Burt, 2004; Hirst et al., 2015; Li et al., 2018). Supporting this view is research demonstrating that networks help direct social actors’ attention and provide access to private, tacit, and noncodified insights that would otherwise be difficult to locate and acquire (Argote, McEvily, and Reagans, 2003; Reagans and McEvily, 2003). In recent years, the socio-structural paradigm of brokerage has guided much of this research. This paradigm stipulates that brokers—actors who occupy privileged network positions by connecting diverse network communities—have an edge over other actors in producing valuable ideas. This is because ideas and insights within a given network community are assumed to be homogenous and, by spanning different communities, brokers are assumed to gain access to diverse ideas and knowledge as inputs into their own thinking (Burt, 1992; 2004; Zaheer and Soda, 2009; Clement, Shipilov, and Galunic, 2018).

Of central interest to the present study is how, exactly, such privileged network positions lead to the development of valuable ideas. The most theorized process in this respect is recombination, in which brokers combine bits and pieces of diverse ideas into novel and even more valuable ideas.\textsuperscript{2} The intellectual lineage of recombination can be traced to Parmenides’ \textit{ex}

\textsuperscript{2} Recombination has become so central in understanding creative outputs that some scholars proceeded to define creativity through recombinant processes. For example, Weick (1979: 252) defined creativity as “putting old things in new combinations and new things in old combinations.”
nihilo nihil fit\(^3\) and has been considered in various disciplines, including economics, sociology, and anthropology. In part because of its diverse genealogy, recombinant processes have appeared under an eclectic set of terms, including “recombination” (Galunic and Rodan, 1998: 1193-1194),\(^4\) “bridging” (Foster, Rzhetsky, and Evans, 2015: 889), “bricolage” (Lévi-Strauss, 1967: 17), “synthesis” (Burt, 2004: 355), “integration” (Li et al., 2018: 2221), and “second-order competence” (Rosenkopf and Nerkar, 2001: 289), among others. The brokerage paradigm has embedded the process of recombination into the patterns of concrete network relationships. It has made a compelling case that those actors who span multiple network communities—the brokers—hold a creativity edge against others who lack such access, by virtue of access to a broader and more diverse set of inputs for recombination.

The other main process presumed to underlie brokers’ valuable ideas is that of transfer, also known as “export-import” (Burt, 2004: 388), “bridging and learning” (Hargadon, 2002: 71), “borrowing” (March and Simon, 1958: 188), or “cross-realm transposition” (Powell, Packalen, and Whittington, 2012). This process is akin to information arbitrage, in which brokers can import ideas that are well-known in one network community to other social groups, yet again garnering recognition. Hargadon (2002: 44) succinctly describes this dynamic: “Individuals and organizations exploit this fragmented social structure by bridging multiple domains and moving ideas from where they are known to where they are not.” Similar ideas are reflected in work on the adoption of innovations, in which social actors adopt their contacts’ new practices and ideas in a way that could be traced to their social relationships with those contacts (Coleman, Katz, and Menzel, 1957; Davis and Greve, 1997; Rogers, 2003; Kilduff and Oh, 2006). In this line of

---

\(^3\) Parmenides’ philosophical dictum, translated as “nothing comes from nothing,” first appeared in Aristotle’s book *Physics* and subsequently in Lucretius’ poem “On the Nature of Things.”

\(^4\) Schumpeter (1934) is widely credited with being the first to discuss recombinant processes systematically with respect to creative function and output.
research, transfers represent not only the conveyance of the idea from one network community to another, but also the acceptance of the transferred idea by the receiving member, with greater emphasis placed on the latter.

Both the recombination and transfer processes have been theorized to support brokers’ creative advantage. Empirical evidence has been consistent with this claim, indicating that those who bridge multiple network communities indeed exhibit a greater capacity to generate valuable ideas (Burt, 2004; Zaheer and Soda, 2009; Sytch and Tatarynowicz, 2014; Li et al., 2018).

The Role of Recombination and Transfer in the Development of Best Ideas

The present study’s primary question concerns the processes that underlie a networked collective’s ability to generate the most valuable ideas. As aforementioned, this shift in focus away from private advantage and toward collective outcomes carries important theoretical and societal implications yet remains understudied. Indeed, work on brokerage has been near exclusively preoccupied with private advantage, indicating that brokers produce more valuable ideas than non-brokers. What remains unclear is just how good these ideas really are. Do brokers indeed enable the collective to discover the most valuable ideas that could be discovered? Or do they gain private advantage at the cost of constraining others’ ability to develop valuable ideas?

From a practical standpoint, this theoretical lacuna leaves us in the dark regarding a general class of problems for which developing the best possible solution is highly desirable. Such challenges could entail, for example, discovering the most effective vaccine or cure for a given disease, or creating a car that drives itself.

To elaborate this focus on a collective outcome, we aim to understand how the processes of idea recombination and transfer across network communities affect the collective’s ability to come up with the most valuable ideas. Our reading of the extant research leads us to believe that
most scholars would anticipate that between-network-community recombinations contribute positively to the emergence of the most valuable ideas in the collective. Most centrally, recombinations result in ideas that are both valuable and novel. It is therefore logical to infer that precisely such recombinations can help discover the most valuable ideas.

Two prominent lines of research support this reasoning. First, several studies look beyond the private advantage of brokerage by examining the benefits and costs accruing to those who are connected to the brokers (Burt, 2007; Clement, Shipilov, and Galunic, 2018), and how the socio-structural properties of the larger collaborative systems—spanning industries, regions, and organizational fields—shape the outcomes accruing to the actors residing in them (Owen-Smith and Powell, 2004; Uzzi and Spiro, 2005; Fleming, King, and Juda, 2007; Schilling and Phelps, 2007).

The preponderance of evidence across these studies has suggested that recombination across network communities is key to producing benefits that could enable others’ success (see Burt [2007] for a divergent result). For example, Clement, Shipilov, and Galunic (2018) unveiled how producers in the French television game show industry leveraged their relationships across multiple network communities to enhance the creative outcomes of their teams. In doing so, they theorized that “through shared community membership with hubs, creative directors may access creative elements emerging in other communities and recombine them with the elements they usually work with” (Clement, Shipilov, Galunic, 2018: 259) in order to maximize the projects’ uniqueness and ultimate creative success. In the words of one creative director, “You get ideas from everywhere, and you try to make up your own vision” (Clement, Shipilov, Galunic 2018: 258). Importantly, the creative directors who spanned multiple network communities in the television sector were associated with more successful shows. By the same token, when Fleming,
King, and Juda (2007) examined the inventive output of regions as a function of the small-worldliness of a region’s inventor networks, they emphasized the value of spanning multiple network communities as a way to connect inventors with “different sources and nonlocal perspectives” and that “without this exposure to new information and perspectives from others, inventors become insular and less creative” (Ibid: 941).

To be clear, the insights cited just above are consistent with theory and evidence explaining brokers’ private advantage. Studies of both private and collective advantage associate recombination processes with generating both valuable and novel ideas (Burt, 2004). The focus on collective outcomes adopted in the present study highlights the difficulty in ascertaining who is responsible for developing the most valuable ideas in networked collectives: Is it exclusively the broker, or others around the broker in part because of the broker’s recombinant ideas? It also highlights our limited theoretical understanding of the processes through which the most valuable ideas emerge within a network. It does not, however, call into question the direction of the relationship between recombination activities and the emergence of those ideas. Regardless of the relative attribution of credit, recombination of ideas from different network communities is assumed to increase the creative benefits accruing to the collective. It is important to note, however, that across all of this work, the process of between-network-community recombination is not observed but rather ascribed to actors connecting otherwise disconnected parts of the social structure. One notable exception in this respect is the work by Fleming, Mingo, and Chen (2007), who explicitly link the positions of brokerage in the social structure to the production of recombinant ideas.

Second, studies examining how recombinant efforts in the knowledge space affect the ultimate success of the resultant products provide further support for the positive connection
between recombinations and idea value. This work, while remaining agnostic to the underlying social structure, finds that ideas and inventions which span diverse knowledge domains are more valuable than those which do not (Rosenkopf and Nerkar, 2001; Carnabuci and Bruggeman, 2009; Foster, Rzhetsky, and Evans, 2015; Ferguson and Carnabuci, 2017). For example, Ferguson and Carnabuci (2017) demonstrated that patents that recombine insights from different technological domains garner a higher count of citations. By the same token, Foster, Rzhetsky, and Evans (2015) showed that highly cited publications examined pairs of chemicals that were rarely examined together.

All of the abovementioned research suggests that—while network communities incubate homogeneous conventions, paradigms, and perspectives—it is precisely between-network-community recombinations that can transform otherwise cloistered inputs into diverse and valuable outputs. Thus, we posit the following proposition that describes the current state of knowledge connecting processes on social networks and the generation of valuable ideas:

**Proposition 1:** *Recombination between network communities, by introducing novelty into the collective, contributes positively to the development of the best possible idea by the collective.*

Between-network-community transfers, in turn, facilitate the dissemination of valuable ideas. And while such transfers add novelty to the receiving network community, they do not add novelty to the collective. As such, although transfers can result in the brokers’ advantage (Burt, 2004), it is the advantage of a locally renowned genius (who is celebrated only by the members of the network community receiving the transfer of a given idea) or of an inventor who is really good at masking her sources. As a result, the translation of brokers’ private advantage from between-network-community transfers into collective outcomes is far from automatic. On the one hand, between-network-community transfers can facilitate the diffusion of valuable ideas, thus offering the rest of the collective better inputs for producing subsequent ideas. On the other
hand, the very same transfers can squeeze out the requisite diversity of ideas from the collaborative system, which is a critical edifice for creativity (Cohen and Levinthal, 1990: 134; Lazer and Friedman, 2007; Gulati, Sytch, and Tatarynowicz, 2012; Funk, 2014). In line with this logic, Gulati, Sytch, and Tatarynowicz (2012) associated the increased connectivity across network communities—and the implied enhanced knowledge transfer across communities—with the increased homogenization of the overall knowledge space. Uzzi and Spiro (2005: 449) similarly argued that “intense connectivity can homogenize the pool of material available to different groups, while at the same time, high cohesiveness can lead to the sharing of common rather than novel information.” The empirical evidence presented in the abovementioned studies is consistent with the homogenization of knowledge space. In a related line of thinking, Saxenian (1994: 36) observed how the Defense Department’s practice of second-sourcing—ensuring a backup supply of critical military components—facilitated learning and innovation by exposing multiple suppliers to new ideas and practices. And yet Saxenian (1994: 71, 81) also suggested that having young people in the semiconductor sector in Silicon Valley who did not know much about how to do business proved beneficial, because it encouraged the sector to experiment with previously unexplored alternatives. Saxenian’s (1994) inferences regarding the innovativeness of regions therefore parallel those of network research; namely, some transfer could benefit the collective’s creative potential, but excessive exposure to similar ideas and ways of thinking can limit the future production of good ideas.

These ideas collectively indicate that transfers across network communities exhibit conflicting pressures on the collective’s ability to develop the most valuable ideas. Transfers can enable the production of the most valuable ideas by offering more valuable inputs for future idea generation. However, they can suppress the quest for better and more valuable ideas by
propagating the recirculation of redundant information and thus constraining the diversity of
information available to actors for innovation. Hence, we articulate a second proposition
describing the current state of knowledge connecting processes on social networks and the
generation of valuable ideas:

**Proposition 2:** Transfers between network communities can contribute positively to the
development of the best idea by exposing actors to diverse knowledge, although high levels of
transfers between network communities can negatively impact the development of the best idea
by reducing the overall diversity of knowledge in a collective.

Although these propositions are logical extrapolations of the widely understood notions
regarding private advantage to the process of generating best ideas, several complications
remain. First, empirical evidence supporting these propositions is extremely scarce, raising the
question of whether the presumed relationships indeed describe the emergence of valuable ideas.
With few exceptions (Fleming, Mingo, and Chen, 2007), the streams of empirical research on
social networks and idea generation processes have evolved separately. The primary reason for
this is that tracking idea exchanges in networks and linking these exchanges to changes in social
actors’ beliefs, as well as the generation of new ideas and the quality of the resultant ideas, is
extremely challenging. As a result, the majority of extant network research links socio-structural
configurations to observed creative outcomes while only assuming the underlying idea-
generation processes (Burt, 2004; Zaheer and Soda, 2009; Balachandran and Hernandez, 2018).
Even work that connects changes in network configurations to changes in knowledge distribution
and flow, or to the features of the resultant creative product, is unable to pinpoint the processes
that originated that product (Reagans and McEvily, 2003; Fleming, Mingo, and Chen, 2007;
Sytch and Tatarynowicz, 2014; Clement, Shipilov, and Galunic, 2018).

The parallel stream of research exploring the details of the knowledge space and idea
generation processes has largely remained agnostic to the structure of the underlying social
interactions (Carnabuci and Bruggeman, 2009; Foster, Rzhetsky, and Evans, 2015). For example, Foster, Rzhetsky, and Evans (2015) identified clusters of knowledge communities in a network of chemical elements, which are jointly studied in publications. They subsequently explored how combinations of chemicals within and across such knowledge communities led to academic recognition. While this work revealed intriguing patterns of idea production, the patterns and role of collaborative relationships among the actors actually conducting this work—the scientists—remains unclear. Similar to network research connecting structural position to creative outcomes, many other knowledge and idea generation studies simply infer unobserved processes from the observed outcomes. In particular, the observation of a radically novel idea often leads to the assumption that the idea is a product of recombinant processes (see e.g., Hagardon [2002] for a discussion of this issue).

To complicate things further, assessing the value of the generated idea constitutes a formidable challenge in empirical work. Scholars typically have access to only relative comparisons of resultant ideas or the performance of actors to whom such ideas are attributed. While such comparisons elucidate relative performance advantage, they are unable to answer the question of whether social actors did the best they possibly could in leveraging the social structure and the underlying knowledge space. In other words, did the actors actually discover the best possible ideas that could have been discovered? As aforementioned, the emphasis on the best discoverable idea is important because it shifts the focus away from explaining individual private advantage and toward explaining collective outcomes in social systems.

A second problem related to inferring rather than observing the processes of recombination and transfer in social structures is that the relative contribution of each process to the emergence of valuable ideas is often unknown. Moreover, insights on idea development
processes suggest that ideas often have thorny development paths, which can involve multiple discussions, changes, transfers, and recombinations (Amabile, 1996; Simonton, 1999). Consider that many efforts are unsuccessful and lead to abandoned ideas. When do social interactions and associated idea generation processes combine into paths that result in producing valuable ideas rather than in idea decline and abandonment? Without observing these processes in real time, tracking the processes of idea emergence would prove challenging even to research that explicitly focuses on knowledge production (Fleming, Mingo, and Chen, 2007; Jones, Wuchty, and Uzzi, 2008; Carnabuci and Bruggeman, 2009; Foster, Rzhetsky, and Evans, 2015). Because the way social interactions and idea exchanges accumulate into valuable ideas remains unexplored, we may be losing the opportunity to understand how, exactly, actors contribute to the emergence of valuable ideas, even if they are not those who eventually come up with the ideas. These unsung heros could be critically supporting idea exchanges and idea generation processes, while not claiming the accolades for eventually produced valuable ideas. In this respect, research on knowledge creation consistently points to recognition accruing to ideas that combine a significant level of convention with some novelty (Jones, Wuchty, and Uzzi, 2008; Foster, Rzhetsky, and Evans, 2015). One possible explanation is that ideas that are too new and radical are not widely understood or accepted. A complementary lens may suggest that quite a bit of valuable idea generation could potentially occur in more proximate parts of the network, without necessarily spanning different network communities in the quest for significant levels of novelty.

Finally, without a better understanding of idea generation processes within social networks, extant social network research will have difficulty answering the question of why brokers frequently fail to generate good ideas, despite their superior positon to recombine and
transfer insights across different network communities. Relatedly, it remains unclear how non-brokers develop valuable ideas, even if less frequently than brokers, despite the socio-structural constraints on their ability to access and learn from different network communities (e.g., Ahuja, 2000; Burt, 2004).

The outlined complications indicate a pressing need for the development of theory about how people interact, borrow, and revise their ideas over time that combines (1) the understanding of social structures guiding interaction with (2) the underlying knowledge space in which those ideas grow and evolve. The process-based perspective on idea creation we aim to advance in the present study will help reveal how, exactly, the blood of new and old ideas, flowing through the veins of social structure, can give rise to the most valuable ideas. In doing so, the present study aims to advance current research by viewing social structures and knowledge spaces as distinct, albeit related, inputs into the idea generation process. The resultant theory will thus attend to the dynamic idea generation process that transpires with every interaction in the social structure.

METHODS

Model Description
To refine the theoretical propositions described above, we develop an agent-based model of an organization in which employees search for the best (most valuable) idea to solve a specific problem or pursue a particular opportunity. Illustrative examples could include a life science organization working to find the best drug to treat a particular condition or a technology company trying to create a product or service that best meets a market need. People in the organization are connected by social structures that shape who exchanges information with whom. As people share information with one another, they acquire, modify, copy, or abandon
Ideas and Idea Performance. Valuable ideas are comprised of multiple features that jointly determine the value of a given idea to the organization. We capture these properties in our model by representing ideas on a two-dimensional idea space, in which each dimension corresponds to a particular feature of an idea (see Figure 1a). Such features can represent any aspect of an idea over which the organization has control and can impact its performance. For example, one dimension might represent a decision related to the efficacy of a potential drug, while another is its safety. The resultant idea space is akin to—although admittedly simplified—the knowledge space in knowledge production research (e.g., Uzzi et al., 2013; Foster, Rzhetsky, and Evans, 2015). Moreover, the ideas that people hold are not static. They continuously move through social space in the process of discussion and imitation, being morphed, changed, and synthesized along the way (Owen-Smith, 2003; Colyvas and Maroulis, 2015). Positioning ideas on the two-dimensional idea space allows us to track their development trajectories over time.

To evaluate how valuable a given idea is, we introduce a performance landscape. The performance landscape maps the location of an idea in the idea space to a performance score. A key characteristic of the performance landscapes we used in this model is that the impact of a particular value of one idea feature depends on the value of the others (Kauffman, 1993). Such interdependencies between features are the hallmark of landscapes used to characterize
“complex” problems in organizational theory and strategy (e.g., Levinthal, 1997; Rivkin, 2000). The more complex the problem (i.e., the more interdependencies matter for performance), the more rugged the performance landscape; that is, it contains a greater number of performance peaks and valleys.

Each run of our model used rugged landscapes with one clear global peak to reflect a complex problem with an unambiguous winning solution (see Figure 1b for a representative performance landscape). The latter criterion is critical given the study’s focus on what leads actors to discover the best possible idea. Our primary outcome of interest—discovery of the best idea—is whether anyone in the organization discovers the idea whose location in the idea space corresponds to the global peak on the performance landscape. Such an outcome reflects the discovery of the best possible idea out of those that members of a collective could have discovered.

[Insert Figures 1a-1c Here]

_Social structure._ A _social network_ of information-sharing relationships governs the interactions among organizational actors in our model, as well the distribution of initial beliefs about the best performing ideas. Extant empirical research singles out the small-world network typology as one of the most ubiquitous in describing social structures (e.g., Burt, 2004; Moody, 2004; Uzzi and Sprio, 2005). We therefore set the network to have small-world properties, wherein 25 actors were distributed into 5 tightly interconnected network communities that are only sparsely interconnected to each other (see Figure 1b).\(^5\) Actors could interact only with

\(^5\) Identifying a small-world network formally relies on comparing the metrics of (1) clustering coefficients for the observed (C) to the random network of the same size and connectivity (C\(_R\)) and (2) average path length for the observed (L) and the corresponding random network (L\(_R\)). To satisfy a small-world condition, C/C\(_R\)>>1 and L/L\(_R\)~1. The network used in the present study satisfies these conditions.
direct network contacts. The network structure in Figure 1b was used for all runs of the model and remained fixed for the duration of a run.

Extant research also suggests that actors belonging to the same network community within a small-world network are likely to have ideas that are more similar to one another than actors belonging to different network communities (e.g., Burt, 1992; Gulati, Sytch, and Tatarynowicz, 2012; Clement, Shipilov, and Galunic, 2018; Maroulis, Diermeier, and Nisar, 2020). Thus, our starting condition initializes actors within a network community as having much more similar beliefs to one another than to the actors in other network communities. Figure 1c reflects this by showing how actors in the same network community are more proximate to one another in the idea space. Importantly, no actor or network community was initialized with a belief close enough to the global peak such that the actor could find the global peak just by virtue of their own thinking.

Idea Exchange and Improvement. The theoretical suppositions of prior research indicate that people can gain information and upgrade their ideas both independently and through collaboration. Independent improvement can occur through discovering new ideas by reading books or academic publications, searching the web, running experiments or reflecting on prior experiences in light of a given problem. For example, Hargadon and Sutton (1997) described how IDEO engineers would frequently rely on their past experiences in solving new design problems. Importantly, the reach of self-search is considered limited and would thus remain local with respect to the actor’s currently held beliefs about the highest-performing idea.

Information and idea improvements can also stem from collaborating with others. Such improvements can occur either by borrowing ideas from others (transfer) or by synthesizing elements of one’s own ideas with those from others (recombination). Studies expect brokers to

Informed by these observations from empirical research, in our model, each actor holds a view on the best-performing idea at any given point in time. This belief corresponds to a particular position of that idea in the idea space, which is based on the idea’s feature values. Furthermore, each idea has an associated performance score, which indicates the value of that idea and which actors attempt to improve in one of three ways. First, they can search the areas of the idea space close to their current beliefs on their own (self-search). Second, they can copy a higher-performing idea from a network contact (transfer). Third, they can create a new idea by recombining elements of their current beliefs with those of a network contact (recombination). Recombination occurs through a single-point genetic crossover of the bit string representations of actors’ beliefs (Holland and Order, 1995). The genetic crossover process yields a new location in idea space, whose performance each actor independently evaluates (see Technical Appendix A for the details and an example of recombination). Regardless of the mechanism through which a new idea is discovered initially, actors will update their beliefs if a higher performing idea is created or found.

**Model Dynamics**

Each time period of the model proceeds as follows:

1. One actor (ego) is randomly selected to act with uniform probability.

2. Ego chooses whether to collaborate with others or work independently (self-search). The probability that ego collaborates is given by the exogenously determined parameter $\text{collab}$; the probability of engaging in self-search is $(1 - \text{collab})$.

3. If ego engages in self-search, she evaluates the performance of all nearby locations in the idea space within a distance given by the exogenously determined parameter $\text{vision}$.
4. If ego decides to collaborate, she randomly (and with uniform probability) selects one network contact with whom to interact (alter). Ego will not consider choosing an alter with whom a previous attempt at interaction did not yield a change in either actor’s belief about the best performing idea, unless either ego or alter have updated their beliefs since the previous interaction.

5. If asked by the ego to interact, the alter chooses whether to participate. The probability that the alter participates in the interaction is $collab$.

6. If alter is willing to participate in the interaction, ego proposes either a recombination or transfer interaction. The probability that ego proposes a recombination interaction is given by the exogenously determined parameter $recomb$; the probability of transfer is $(1 - recomb)$.

7. If ego proposes a recombination interaction and alter responds affirmatively, ego and alter recombine their existing ideas. The probability that alter responds affirmatively is $recomb$.

8. If ego proposes a transfer interaction, ego learns the alter’s idea. Alter also has the opportunity learn ego’s idea during a transfer interaction. The probability that alter learns ego’s idea during a transfer interaction is $(1 - recomb)$.

9. Ego and/or alter adopt the highest-performing idea found or developed during the time period.

As the model repeatedly progresses through these steps, some ideas are initially held by actors and subsequently abandoned in favor of higher performing ones; some ideas contribute to local improvements of descendant ideas, which is reflected in new ideas moving incrementally beyond the previously held ideas in the feature space; and yet others catapult the actors far into new and previously unknown regions of the idea space. Importantly, each of the existing or newly formulated ideas is associated with a specific point on the performance landscape. Therefore, an idea that travels far in the feature space and is thus more novel with respect to its antecedent ideas—for example, as a result of between-network-community recombination—may or may not exceed the performance of its antecedent ideas. Technical Appendix A describes a sample run of the model in detail.

The model eventually reaches a steady state where the actors converge on one or more final ideas. This occurs when all actors have chosen an idea that is associated with a local or global
peak and no longer have any network partners with whom they have anything new to discuss. As stated previously, given the theoretical focus of the paper, the key outcome of interest is whether at least one of the actors in the collective discovered the idea that is associated with the global performance peak.

**Analytical Approach**

The primary purpose of the present study is to elaborate theoretically the processes by which actors embedded in social structures discover and develop the best performing ideas. To this end, analyzing our model consisted of two broad and iterative stages. The first stage, in which we examined the developmental trajectories of ideas, was largely inductive. To do so, we defined an action chain as the entire genealogy of an initial idea resulting from actors’ actions in the social structure, starting at the point of the idea inception, and including all of the idea’s subsequent change events. In particular, an action chain recorded all idea improvements through self-search, transfers, or recombinations experienced by the initial idea and its descendant ideas. An action chain would end when either all of its descendant ideas were abandoned, or when the model reached the steady state and at least some actors held a descendant idea as their final belief. We then qualitatively examined the action chains from a random sample of model runs, looking for insights regarding when and how action chains resulted in the actors’ discovering the most valuable idea.

To aid our comparisons of action chains, we developed a novel representation that simultaneously depicts social interactions in the network and changes to ideas as they traversed swaths of the social structure (Figure 2). Each interaction was recorded with the participating actors and the interaction’s specific location in the social structure (i.e., within or between network communities). Self-searches were similarly recorded with attributions to the actors.
undertaking that action. Importantly, each change event in the action chain was associated with a performance score of the resultant idea by positioning it on a rugged performance landscape, and whether the idea landed on a local or a global performance peak (See Figure 2 for an illustration of an action chain). As needed, our inductive, exploratory stage also included reproducing runs and walking step-by-step through the associated idea development processes. This speaks to one of the advantages of computational modeling: By examining and reflecting upon any retroactive run of the model, we gained a deeper understanding of how actors’ interactions in social structures translated into the various paths that ideas took on their way to ultimate success or failure. We describe these inductive insights predominately, although not exclusively, in the Exploratory Analysis of Key Processes section within our Results below. (Video of how an action chain unfolds on a social structure in a sample run of the model is available at https://anonymous.4open.science/w/bestideas-116C/video.html).

The second stage of our analysis was predominantly deductive. Having generated initial, albeit tentative, insights into how new and existing ideas become the best ideas, we tested the logical implications of our process-oriented, inductive learnings by analyzing action chains generated from more than 25,000 runs. More specifically, we assessed the probability of a particular action chain reaching the global peak (i.e., registering the highest attainable performance in a given model run) as a function of the number of each type of change activity occurring on the chain. The data’s quantitative analysis from a large number of runs enabled a

---

6 Except when stated otherwise, the trajectories presented and analyzed in the main text were generated from runs using values of $collab = 0.8$ and $recomb = 0.8$. These values represent a group that is both collaborative and innovative and resulted in a relatively high number of successes and large amount of variance in trajectories (26% of runs discovered the best idea under these conditions. See Technical Appendix B, Figure TA4). In testing the boundary conditions of our theory, we re-ran our analyses with alternative values of $collab$ and $recomb$. Doing so allowed us to explore the applicability of our findings to social groups that vary in their collaborative norms and propensities to innovate. The results of these analyses are reported in Technical Appendix B.
logical confirmation of theoretical Propositions 1 and 2 for which one would not normally have empirical data. It also enabled a more systematic examination of the social interactions and the resultant idea-generation processes, as well as the boundary conditions related to the qualitative insights.

It is important to note that action chains emanating from each actor in the model are apt to combine with one another, which made the comparison of action chain outcomes within the same model run difficult, if not impossible. To overcome this analytical challenge, in time period 1 of each model run, we changed the current belief of a randomly-selected actor to a random, higher performing belief in the idea space than the one they initially held. Doing so helped create the “focal” idea for each run, for which we tracked the emergent action chain. Each focal action chain incorporated anywhere from 0 to 157 change events, with a mean of 11.4. Our quantitative analyses are thus based on the comparison of a total of 25,000 unique focal chains (one for each run) that collectively incorporate 284,530 change events.

MODEL ANALYSIS AND INSIGHTS
Our analyses revealed two broad insights regarding the processes by which best ideas emerge within a networked collective. First, understanding the impact of actors’ actions — such as recombination and transfer — on a focal idea becoming the best idea requires considering the idea’s stage of development. In particular, action chains experienced two distinct phases of development—inside and outside the last mile. The distinction relates to whether incremental improvements are enough for an idea to become the best idea. For ideas inside the last-mile stage, incremental improvement is sufficient to reach the best idea; for ideas outside the last-mile stage, incremental improvements are not sufficient, and more novelty is required. While in practice this distinction is unlikely to be directly observable, the two stages of idea development
turn out to be crucial with respect to theoretically understanding the impact of actors’ actions on
the likelihood of an idea evolving into the best idea.

Second, social actors’ quest for best ideas can be reconceptualized as the product of two
fundamental processes: idea space infiltration and social infiltration. Idea space infiltration
describes the extent to which actors learn about potential combinations of idea features and the
performance they produce. The more feature combinations are tried and evaluated, the higher the
idea space infiltration. Social infiltration relates to the extent to which an idea (along with its
descendants) is held by the actors in the network. The greater the number of actors holding the
focal idea or its descendants as their belief, the higher the social infiltration. Considering the
extent to which actors’ actions infiltrate idea and social space helps explain variance in outcomes
that would not otherwise be understood, such as why some recombinations have more impact
than others.

In the remainder of this section, we elaborate on the analysis and computational
experiments leading to these insights. We also describe how they translate into specific
refinements to existing theory encapsulated in Propositions 1 and 2.

**Impact of Recombination and Transfer Depends on Idea Development Stage**

*Exploratory Analysis of Key Processes*

Our inductive analyses lead us to identify two qualitatively different stages of idea
development—inside-last-mile and outside-last-mile. Inside the last mile, incremental
improvements are sufficient to refine the current idea into the best possible discoverable idea for
a given problem; outside the last mile, more novelty is still necessary.\(^7\) For example, the

\(^7\) In terms of the computational representation, inside-last-mile stage of development refers to the set of ideas whose
features land it in the basin of attraction of the global peak of the rugged performance landscape. Outside-last-mile
describes the set of ideas whose features land it outside the basin of the global peak.
development of messenger RNA-based (mRNA) COVID-19 vaccines involved at least two strands of parallel development – one related to the production and properties of mRNA itself, and another related to a drug delivery system based on small “fat bubbles” known as lipid nanoparticles (Dolgin, 2021). One might consider the idea of an mRNA COVID-19 vaccine to have reached the last mile when those two strands of development combined into an influenza vaccine that could be tested in mice; and the subsequent modifications and improvements that further developed it into a highly effective mRNA COVID-19 vaccine for humans, as having occurred in the last mile.

Figure 3 illustrates the potential activity sequences and outcomes for a focal action chain both within and outside the last mile. All focal action chains started with an initial idea held by a randomly chosen actor. However, because the location of the focal idea was determined at random, it could begin its trajectory either inside or outside the last mile. As should be expected for an idea space representing a complex problem, most initial ideas (86%) began outside the last mile. These initial ideas then morphed through ideas chains, which involved a series of change events: self-search, transfer, and recombination. Importantly, the focal action chain tracks all descendants of the initial idea.

As social interactions within and between network communities took place and action chains unfolded, ideas could reach three different states at completion of their development trajectory, which are indicated with gray boxes in Figure 3. Ideas could be abandoned, in the sense that no actor held that idea or any of its descendant ideas. This means that no actor believed that the idea represented the best performing idea for the group. Ideas could settle on a local peak, meaning that at least one actor (or more typically a majority of at least one network community) considered the result of the action chain to be the best possible idea, but were
incorrect in their belief. The actors were simply not able to improve the idea beyond its current state. And finally, ideas could develop into the best possible discoverable idea, which is the primary outcome of interest in this study (17% of action chains).

Recombinations occurring outside the last mile could send an action chain on one of two paths. Most often, the idea remained outside the last mile and simply kept developing through a mix of self-search, transfers, and recombinations. Less frequently, the novelty of the recombination was enough to push it into the last mile of development. When an action chain was in the last mile, the predominant conclusion to its trajectory involved being refined through self-search activities into the best possible idea.

Interestingly, 29% of the action chains that reached the last-mile stage of development did not ultimately develop into the best discoverable idea. What could explain such outcomes? One reason an inside-the-last mile action chain was abandoned is because the only actor who held it, by virtue of transfer, adopted a higher-performing idea that was outside the last mile. Another reason is that actors have no way to know if their ideas are inside the last mile and only incremental advancement through self-search is needed. Consequently, they could pursue a recombination that created a higher performing idea outside the last mile, which when adopted, diminished their chances of reaching the already nearby best discoverable idea.

Interpreted in the context of current theory (Propositions 1 and 2), these qualitative observations of the model dynamics imply that the activity deemed crucial to producing the best idea—between-network-community recombinations—also has the potential to derail the collective’s progress as its most promising ideas approach the finish line, that is, in the last-mile
stage of idea development. Furthermore, between-network-community transfers, by spreading the last-mile idea to other areas of the social network, may be able to prevent such a derailment.

**Quantitative Analyses of Key Processes**

Informed by our exploratory analyses of the data, we estimated two logistic regression models. The first model predicted whether a focal action chain was the first chain in a given run of the model to enter the last-mile stage of development. It included only those focal chains that began outside of the last mile (21,572 focal chains). The second model examined whether the action chain was the first to reach the best idea after it had entered that last-mile stage of development. These models were based on 2,713 chains that entered the last-mile through one or more change events and 3,428 chains that were (randomly) initiated in the last mile at the inception of model runs (6,141 focal chains in total). The focus on being the *first* chain to enter the last mile or to reach the best idea was necessary because, once discovered, valuable ideas spread through the network quickly by virtue of others’ copying them. The present study’s theoretical interest lies in unveiling what network activities lead to discovering these valuable ideas in the first place.

In each of these models, we predicted the ultimate outcome of an action chain as a function of the number of each type of change activity (self-search, transfer, and recombination) that took place in the action chain. For the models predicting whether an action chain entered the last mile, we counted only those events that occurred in a given action chain until the time when either the focal or any other action chain in the model run reached the last mile. For models predicting whether an action chain in the last mile reached the best possible idea, we counted those events that occurred since the focal action chain entered the last mile. The event counter stopped when either the focal chain or any other chain in a given model run reached the global
peak (thus reaching the best performing idea) or when the model stabilized without any of the chains finding the best possible idea.

Table 2 summarizes the results by presenting the percentage-point change in probability corresponding to one additional change activity, calculated for a chain containing the median value of each variable (Model 2 in Tables TA1 and TA2 in the Technical Appendix B reports the full results of these models). The cell values in Table 2 can therefore be interpreted as representing the expected percentage-point difference between a “median” chain, and a chain with a one-unit increase for a given change activity.

[Insert Table 2 here]

These analyses revealed several important findings. First, and most critically for the present study, the effect of both between- and within-network community recombinations on the likelihood of an action chain reaching the most valuable idea is strong and negative for those ideas that reached the last mile of development (–5.8 and –10.9 percentage points, respectively). This result confirms early observations from our exploratory analyses that, once the action chain reaches the last mile, recombinations can become deleterious to reaching the most valuable ideas, because they can throw an idea out of the idea space region that is proximate to the best possible idea.

Second, both between- and within-network-community recombinations have a positive effect on the action chain entering the last mile. The within-network-community recombination effect is noteworthy because in much of the extant research, generating novel and valuable ideas through recombination is assumed to be an exclusive prerogative of brokers who interlink different network communities (e.g., Burt, 2004, Sytch and Tatarynowicz, 2014; Clement, Shipilov, and Galunic, 2018). This broker advantage is still evident in our model; the effect of
between-network-community recombinations is nearly three times as high as that of within-community recombinations (3.7 versus 1.3 percentage points). However, the positive coefficient on within-network-community recombinations indicates that these recombinations can also be beneficial on the path to finding the best ideas. Indeed, while the idea space within network communities is more homogeneous than between network communities, it is still not perfectly homogeneous, thus enabling recombinations among non-redundant insights and ideas.

Third, between-network-community transfers have a small positive effect (0.91 percentage points) on the likelihood that a given idea enters the last mile. Importantly, the magnitude of the positive effect of between-network-community transfers on reaching the best idea grows nearly 22-fold (to 19.8 percentage points) for those action chains that have entered the last mile. This quantitative finding is consistent with the exploratory insight that, once a given action chain enters the last mile, between-network-community transfers can greatly increase its survivability in the face of competing alternatives by allowing multiple network groups to work on it to potentially improve it further. Similarly, the small negative effect of within-network-community transfers on entering the last mile (–0.31 percentage points) turns strong and positive for last-mile ideas developing into best possible ideas (9.2 percentage points).

Finally, the impact of an additional between-network-community transfer in Model 1 (0.91 percentage points) is noticeably more modest than that of a between-network-community recombination (3.7 percentage points), even though both activities can lead to social infiltration of multiple network communities. This is because the coefficient on between-network-community transfer in Table 2 reflects a mixture of three different patterns of downstream idea development. Only two of the three patterns could successfully provide an idea to propel the chain into the last mile. One potentially successful pattern involved having an opportunistic
broker import an outside-the-last-mile idea from one network community into the broker’s own network community. The actors inside the broker’s network community then recombined this information into a new idea that sometimes propelled the action chain into the last mile. Another potentially successful pattern involved a broker acquiring an outside-the-last mile idea via a transfer from another network community. Before importing the idea into the broker’s own network community, however, the broker shared the idea with a member of a different subgroup, which then recombined that information in a manner sometimes resulting in a last-mile idea. Such a cosmopolitan broker then imported the last-mile idea into her own network community. These two patterns of opportunistic and cosmopolitan brokerage can be thought of as multistep equivalents to a single between-network-community recombination, in which both actors adopt the recombinant idea following their interaction. A final pattern never reached the last mile. This pattern involved additional transfer and self-search but no recombination.

Taken together, these results reinforce one of the primary insights from the qualitative analysis. Outside the last mile, recombinations help advance an idea toward the best performance, but once inside the last mile, a different dynamic gains salience. Spreading a promising idea to others through transfers and the idea’s incremental advancement through self-search become critical factors for an idea to reach its full potential. Indeed, recombinations within the last mile can actually suppress the collective’s ability to discover the most valuable idea. Recombinations, on average, produce ideas that are higher-performing and more attractive, but they divert the action chain from reaching the best possible idea. In short, the network activities that positively support an idea reaching its full potential change as the idea progresses through the distinct stages of development.

Impact of Recombination Depends on Interaction Partner Adoption
Action chains with similar numbers and types of recombinations could still lead to considerably different outcomes. Understanding this variance required attention to post-recombination activities. In particular, we discovered that one of the most important downstream determinants of the impact of the recombination was whether one or both of the actors that participated in developing the resulting idea adopted it. A recombination in which both interaction partners adopted the resultant idea was much more likely to contribute to an action chain reaching the last mile than one in which only one partner adopted.

Exploratory Analyses of Key Processes
As explicated above, ideas could be developed through recombinations. However, neither actor participating in a recombination was obligated to adopt an idea resulting from a recombination. In some instances, the new idea’s performance was better for both actors, so both adopted it as their highest-performing belief. In other cases, the resultant idea was better for only one actor, therefore only that actor adopted it. At still other times, the resultant idea was inferior for both actors, so neither adopted the idea resulting from the recombination. Importantly, the actors involved could have been from either the same or different network communities. Our exploratory analyses revealed that if (1) the two actors from two different network communities united to recombine an idea and (2) both ended up adopting the recombinant idea, then in addition to creating a novel idea from disparate pieces of information, the recombination also made it less likely that the idea would be abandoned.

Quantitative Analyses of Key Processes
To investigate the importance of the potential benefits of having both actors adopt an idea after a recombination more systematically, we conducted a computational experiment. Doing so was required because in prior analyses actors decided whether to adopt an idea based on whether the
performance of the idea was higher than that of their currently held ideas. It is therefore possible that the observation that both actors adopt is more beneficial than having only one actor adopt is spurious—ideas that both actors adopt could be simply of higher quality.

In the newly designed experiment, whether one or two interaction partners adopted the recombinant idea did not depend on the quality of the idea. As before, if the idea emerging from a recombination was not higher performing than an actor’s current idea, the actor did not adopt the new idea. The difference between these runs of the model and the previous runs occurred when the resultant recombinant idea was higher-performing for at least one of the actors. If the new idea was higher performing for a single actor, then that actor would adopt it. Departing from the prior analyses, whether the second interaction partner adopted the recombinant idea was determined randomly: the second actor was given a 50% chance of adopting. Similarly, if the new idea was higher-performing for both interaction partners, then whether one or both actors adopted was determined randomly, with each having a 50% opportunity. These experimental conditions effectively created a scenario in which the adoption of the recombinant idea was still related to its performance, but whether one or both of the actors adopted it was not. The other modeling conditions remained unchanged with respect to our prior analyses.

Similar to the approach used in the quantitative analyses reported above, we estimated a logistic regression model predicting whether an action chain entered the last mile using data from 5,000 runs of the model. To examine the effects of recombinations in which one or both interaction partners adopted the recombinant idea, for each action chain we included separate counts of the number of recombinations that were adopted by both participating actors, as well as those adopted by only one actor.
Table 3 summarizes the results of the four coefficients of interest by presenting the percentage point change in probability corresponding to one additional change activity in an action chain. That is, the cell values in Table 3 can be interpreted as representing the expected percentage point difference between a “median” chain and a chain with a one unit increase for a given change activity.

[Insert Table 3 here]

The results confirm the earlier exploratory observation that having both actors adopt a recombinant idea is an important factor that determines the ultimate success of the idea. The increase in the probability of the action chain entering the last mile corresponding to one additional occurrence of a within-network-community recombination adopted by both actors is more than twice the increase corresponding to one additional occurrence of a within-network-community recombination adopted by only one actor (2.1 percentage points versus 1.0 percentage points). The impact of both interaction partners adopting is even more pronounced when the adoption takes place across multiple network communities. When both actors adopted the resultant idea, the effect of each additional between-community recombination on the likelihood of the action chain entering the last mile was three times as high compared to when only one actor adopted (5.2 percentage points versus 1.6 percentage points).

**Actors’ Actions Infiltrate Both Idea Space and Social Space**

Taking a process-oriented view to the emergence of best ideas in a networked collective underscores that most actors’ actions have a rather indirect impact on a focal idea becoming the best idea. They do, however, have a direct impact on the extent to which the collective learns about potential combinations of idea features and the performance they produce – a concept we refer to *idea space infiltration*. Actors’ actions also have a direct impact on the extent to which
others in the social network favor the focal idea or its descendants over competing alternatives—a concept we refer to as social infiltration. The more combinations from more regions of the feature space that are tried and evaluated, the higher the idea space infiltration. The greater the number of actors and network communities holding the focal idea or its descendants as their belief, the higher the social infiltration.

Table 4 provides an overview of the extent to which different actors’ actions—self-search, transfer, recombination, and adoption of recombinations—infiltrated both the available idea space and the surrounding social space in runs of the model. Within-network and between-network transfers involved the copying of existing information from one actor to another, and therefore did not directly contribute to idea space infiltration. Instead, idea space infiltration occurred through self-search, within-network-community recombination, and between-network-community recombination. Self-search involved only a local exploration of idea space and therefore contributed the least to idea space infiltration of those actions. Within-network recombination often resulted in the infiltration the similar area of idea space as self-search. However, within-network recombinations produced more idea space infiltration than self-search, as they were able to take advantage of the heterogeneity of information available within network communities, especially early in the life of a model run. Recombinations occurring between network communities were more likely to result in significant leaps in the idea space, allowing actors to explore distant and previously unexplored feature combinations. Consequently, between-network recombinations contributed more to the idea space exploration of the collective than any other individual action. Transfers were the collective’s primary tool for social infiltration, with between-network-community transfers being particularly potent as they exposed
different network communities to a given idea. Intriguingly, recombination could also contribute to the social space infiltration of the collective. This occurred when both actors in an interaction adopted the recombinant idea.

Viewing action chains through the lens of idea space and social infiltration helps further explain the contingencies and variance observed in our earlier results. In particular, action chains reaching the last mile, but not leading to the best idea, did not achieve enough social infiltration to withstand the forces of idea space infiltration attempting to remove them. Stated differently, social infiltration of last-mile ideas can increase the survivability of a very promising—although not yet the best possible—idea, in the face of dynamics that could derail its development into the most valuable idea. The more people working to potentially improve a given idea, the longer it will take for it to be abandoned (if ever). In this sense, the social infiltration from between-network-community transfers were particularly beneficial in the last mile, because they potentially enabled multiple groups to pursue and improve a given last-mile idea. Similarly, we observed that recombinations where both actors adopted had a larger impact on the likelihood of becoming the best idea. This is because even if two recombinations equally increase idea space infiltration, the one where both partners adopt provides the additional benefit of increasing the social infiltration of the idea.

Translating these insights from our modeling into specific refinements to existing theory as encapsulated in Propositions 1 and 2 leads to the following:

**Proposition 1a:** The impact of both between- and within-network-community recombinations is contingent on the stage of idea development. Outside the last-mile stage of idea development, recombination activities contribute positively to best idea development by increasing the infiltration of the idea space; inside the last-mile stage, recombination activities risk impeding idea development. The infiltration of social space, rather than of the idea space, is a key enabler of success in this stage.
Proposition 1b: The impact of both between- and within-network-community recombinations is contingent on whether both interaction partners adopt the new idea that stems from their joint activity. Having multiple partners adopt amplifies the positive impact on best idea development, by increasing the infiltration of social space in addition to the infiltration of idea space provided by the production of a novel idea.

Proposition 2a: The impact of both between and within-network community transfers is contingent on the stage of idea development. Outside the last-mile stage of idea development, transfers are more likely to have a negative impact on the development of the best idea, by constraining idea space infiltration. Inside the last-mile stage, transfers contribute positively to the development of best ideas by increasing social infiltration and thus mitigating the risk of a promising idea being abandoned.

BOUNDARY CONDITIONS OF NEW PROPOSITIONS

In this section, we attempt to identify the conditions in our model for which Propositions 1a, 1b, and 2a no longer hold true. To conduct the analyses reported above, we had set the group’s collaboration and recombination propensities to fairly high levels. Specifically, the propensities to collaborate (collab) and recombine (recomb) were each set to 0.8. This means that actors operated in a highly collaborative and innovative environment. Actors ordinarily chose collaborating with others (80%) versus self-search (20%), and when the actors collaborated, they were inclined to recombine ideas 80% of the time and transfer 20% of the time. We subsequently explored whether the propositions developed above depended on the group’s average propensities to collaborate (collab) or recombine (recomb).

To do so, we re-ran all of our analyses using data generated from models in which actors had different propensities for collaboration and recombination: (1) a highly collaborative environment in which people are hesitant to innovate and are inclined to transfer instead (collab = 0.8, recomb = 0.3); (2) a weakly collaborative but innovative environment (collab = 0.3, recomb = 0.8); and (3) a weakly collaborative environment in which people are hesitant to innovate (collab = 0.3, recomb = 0.3). Across all of these environments, the primary results
relating to Propositions 1a and 2a remained consistent. On average, recombinations positively affected the likelihood of an idea entering the last-mile stage of development and negatively affected the likelihood of the idea developing into the best performing idea inside the last mile. The benefits of between-network-community transfers within the last mile, and their impact relative to between-network recombinations outside the last mile, were similarly robust across conditions (see Technical Appendix B, Table TA1). Thus, Propositions 1a and 2a do not appear to be bounded by the collaboration and innovation norms of the actors’ environment.

However, this is not to say that Propositions 1a and 2a are without limits. The salient boundary condition of Proposition 1a is that it does not apply to performance landscapes that do not lend themselves to the two stages of idea development. In practical terms, this means that Proposition 1a would not apply to simple problem spaces, in which the performance of an idea does not depend on the interaction of multiple idea features. The analogous situation in our model—which could be extended to all action chains for non-complex problem spaces—is when a focal action chain begins in the last mile. In such cases, we would simply expect the last-mile dynamics described above to prevail. For Proposition 2a, the salient conceptual limit is that the benefit of between-network-community transfers relies on the existence of some other activities that provide at least incremental novelty. While between-network-community transfers are potent social-space infiltrators, they do not enhance idea-space infiltration. In other words, in the extreme—and, in our opinion, highly unrealistic—scenario in which no other actors engage in at least a small amount of self-search or recombination (collab = 1, recomb = 0), the social infiltration benefits of between-network-community transfers in the last mile cannot be realized.

For Proposition 2b, given the importance of social infiltration into different network communities, we suspected that the benefit of having both interaction partners adopt the product
of a recombination may be sensitive to the behavior of actors around them. However, the benefit appeared robust across most conditions, with one important deviation: the advantage of both interaction partners adopting did not hold for the weakly collaborative scenario in which people hesitated to innovate (i.e., with low propensities for both collaboration and recombination) [see Technical Appendix B, Table TA2, Model 4]. An appropriately conservative interpretation of Proposition 1b, therefore, is that it is much more likely to hold in environments that are characterized by innovative behaviors—those that are characterized by multiple attempts to recombine—and not in environments in which actors do not pursue novelty through collaboration.

DISCUSSION
This study aimed to develop a theory regarding how social interactions among actors embedded in a social structure led to the emergence of most valuable ideas. This theoretical pursuit was situated in the joint examination of the social structures that pattern social interactions and the types of idea development processes that could stem from those interactions. Toward this objective, we employed agent-based modeling in which we simultaneously modeled social structures, interactions among social actors, the resultant idea exchanges, and the quality of the concomitant ideas that could have been discovered. It is essential to note that the present study focused on the relatively underexplored and yet societally important collective—rather than individual—outcomes, which were operationalized as the social group’s ability to discover the best possible idea that could have been discovered.

Our work produced two broad and interrelated theoretical advancements. First, we brought to light the importance of understanding idea development in social structures through the lens of two-stages: within the last mile and outside the last mile. Ideas within the last-mile
stage of development need only incremental novelty to develop into the best discoverable idea. Ideas outside the last-mile stage, in contrast, require significant novelty to develop into the most valuable possible idea. Second, we explicated the value of considering jointly the infiltration of idea space and the infiltration of social space. Idea space infiltration refers to the number of possible feature combinations in the idea space that have been explored by members of a collective and whose performance is understood. Social infiltration, in turn, describes the number of actors holding a given idea. The two-stage model of idea development puts into focus the fact that the very same processes underlying idea development—recombinations and transfers—can result in vastly different outcomes for the quality of the resultant idea, depending on the stage in which they take place. The dynamics of social and idea space infiltration, in turn, help us understand the mechanisms behind these outcomes.

Our theoretical development started with the logical extrapolations of the main precepts of current research to collective outcomes. In particular, our main point of departure was the proposition that between-network-community recombinations are expected to be the most potent driver of the most valuable ideas in a collective (Proposition 1). Indeed, it is precisely those social interactions that are expected to help actors stumble onto novel and valuable ideas by spanning distant points of the idea space (Burt, 2004; Zaheer and Soda, 2009; Tatarynowicz, Sytch, and Gulati, 2016; Balachandran and Hernandez, 2018). Moreover, extant research led us to expect that transfers of ideas across network communities could be beneficial, but only to a point (Proposition 2). A moderate amount of transfer activity could provide social actors with the raw materials for invention; whereas excessive transfers could debilitate the collective’s invention potential due to homogenizing the knowledge space and squeezing requisite variety
from the system (Uzzi and Spiro, 2005; Lazer and Friedman, 2007; Gulati, Sytch, and Tatarynowicz, 2012; Funk, 2014).

The dual theoretical lens of two-stage idea development and the infiltrations of social and idea space led to significant revisions of our initial propositions. Most centrally, we found that recombinations enhance an idea’s chances of developing into the best possible idea outside the last mile; in contrast, inside the last mile, recombinations should be expected, on average, to be detrimental to an idea’s chances of developing into the best possible idea (Proposition 1a). Recombinations are the most potent infiltrators of the idea space and hence have the unparalleled advantage of developing ideas so that they can enter the last mile. Moreover, their potency is amplified when both actors involved in the recombination decide to adopt the product of the recombination (Proposition 1b).

Inside the last mile, however, the same power of idea space infiltration can backfire, because continued recombinations can lead actors to pursue ideas more valuable at the time but with worse promise of subsequent development. In the last-mile stage of development, it is social infiltration rather than idea space infiltration that is largely responsible for determining whether the collective develops an idea into the best possible idea. The most potent tools for social infiltration at this stage are the between-network-community transfers. They enable members of multiple network communities to stay on a promising idea path, minimizing the chances that an idea trajectory will be abandoned or forgotten (Proposition 2a).

Importantly, note that the description of recombinations in the two-stage framework in the finding just above (and in the revised propositions) is not conditioned by the recombinations occurring solely between network communities. Although the effects of between-network-community recombinations are stronger than those of the within-network-community
recombinations, our findings indicate that both operate largely in the same way, and both aid the collective in producing the best possible idea. While the advantage of between-network-community recombinations may come with little surprise, the potency of within-network-community recombinant activity has been largely overlooked in extant research. It is true, of course, that the members’ idea space within the same network community is more homogenous than that of the members within different network communities. However, the idea space of a given network community is rarely—if ever—perfectly homogenous. The present study consequently revealed that even relatively modest levels of idea heterogeneity within network communities can enable recombinations that substantially contribute to a collective’s performance.

Taken together, our results highlight the importance of a closer conversation between the socio-structural perspective—the line of inquiry that links actors’ structural positions or global network properties to invention (Burt, 2004; Shipilov and Li, 2008; Sytch, Tatarynowicz, and Gulati, 2012)—with the dynamic lens on the process-centric aspects of idea development (Amabile, 1996; Cropley, 2000; Lubart, 2001; Berg, 2014). We believe that this discourse will prove to be generative. Socio-structural research can help understand how the patterning of social relations guides social interactions and shapes the distribution of raw material for invention across wider swaths of the social system. The dynamic, process-oriented lens can unveil, in turn, how the arteries of social structure carry ideas and knowledge and how, exactly, the concomitant social interactions can shape resultant ideas.

The present study established that the analysis of the actors’ structural positions in a network offers only a partial view into the development process of resultant ideas and the ensuing benefits to the social group. In particular, brokers—whose idea-generation potential is so
widely celebrated—can actually fail the group in terms of discovering the best possible ideas if they continue unabated recombinant activity and relentless infiltration of the idea space. One could see the parallel in this respect to the importance of slow learners in March’s (1991) seminal reasoning. More broadly, this finding again brings to the forefront the possible tension in private advantage accruing to the brokers and the benefits those around them reap (Fernandez-Mateo, 2007; Bidwell and Fernandez-Mateo, 2010). On the other hand, brokers who actively transfer last-mile ideas across different network communities and thus propagate social infiltration can greatly support the collective by enabling multiple shots on goal from different social groups. Such behaviors could conceivably come with less reputational luster and perhaps even invite criticism8 but nonetheless perform a crucially important collective function.

Furthermore, the combination of the socio-structural and process-centric lenses on invention may help identify numerous unsung heroes in idea development. Note that it is the process of incremental refinement (self-search in the model) that most frequently enables the idea to realize its full potential once an idea is in the last mile. Such activities are not at all limited to the brokers and, in fact, are more frequently carried out by non-brokers. The fact that brokers on average come up with better ideas than non-brokers can obscure that pedestrian, incremental refinement of the brokers’ ideas by non-brokers can often lead to significant value gains for the broader collective. By the same token, we may have been too quick to dismiss the inventive potential of non-brokers through recombination. Under the reasonable assumption of non-perfect idea space homogeneity within network communities, it appears that the idea space is plenty fertile for less impactful and yet far more frequent recombination.

---

8 Consider in this respect the famous cultural adages, such as Picasso’s “Mediocre artists borrow, great artists steal” (Hargadon, 2002: 54) and “The secret to creativity is knowing how to hide your sources,” attributed to Einstein. Both of these imply dubious reputational connotations of transfers for social actors.
The two-stage perspective on idea generation and development in social structures we advance in the present study can also prove fruitful for scholars studying the processes of idea development. Most models of creative process incorporate the stages of gathering relevant information and generating relevant responses (e.g., Guilford, 1950; Amabile, 1996; Lubart, 2001; Gupta and Khanna, 2019; Rao, Puranam, and Singh, 2021). Our research explicates how social structures—by patterning the recombinant and transfer activities among actors residing within and across network communities—can powerfully affect the efficacy of these stages for the quality of the eventual idea.

A limitation of our study, however, is that our theory remains agnostic to often thorny stages of problem identification, formulation, and evaluation of one’s ideas, all of which are featured prominently in the work on creative process (Isaksen and Treffinger, 1985; Amabile, 1996; Berg, 2014). Our theory, in contrast, is based on the existence of a well-defined problem or opportunity, whose nature is widely understood, and its importance shared by the collective. The evaluation process of idea value is similarly uncontested. While such evaluation dynamics are more representative of the fields that are described by higher degrees of agreement regarding symbolic structures, logic, and outcomes (e.g., Csikszentmihalyi, 1997), they are not broadly representative. Our expectation is that future research could extend the application of socio-structural dynamics to the broader spectrum of idea development processes. For example, it is conceivable that the same processes that result in varied solutions to problems—recombinations, transfers, and self-search—can also shape how these problems are defined in the first place, as well as how their solutions are eventually evaluated (Ocasio, 1997; Eggers and Kaplan, 2009; Li et al., 2013).
Another limitation is that our theory does not incorporate the possible cognitive heterogeneity among social actors. Psychological research has associated creative output with individuals’ openness to experience, divergent thinking, intrinsic and extrinsic motivation, and memory, among other factors (Feist, 1998; Furnham and Bacthiar, 2008; Amabile and Pratt, 2016). To the extent that such cognitive variations could correlate with individuals’ network positions and propensities for specific actions in search of better ideas, incorporating these elements can undoubtedly enrich the network- and process-centric perspective on idea development advanced in this study.

Our theory broadly applies to networked collectives — groups of social actors who could reside within or across organizational boundaries — thus potentially having implications for research on the creativity of organizations and organizational fields. A potential boundary condition for our arguments, however, is that they apply to collectives interlinked predominantly by collaborative network relationships. When competitive tensions substantively permeate the nature of information flows in network relationships, the ensuing implications for idea transfers, idea creation, and the resultant idea quality can be substantially more complex (Posen, Lee, and Yi, 2013; Cox Pahnke et al., 2015; Ghosh and Rosenkopf, 2015).

Of special note is the methodological advancements presented in the current study. We hope that the newly developed analytical framework and the computational approach that tracks actor interactions within the constraints of a social structure, along with the resultant idea genealogies, performance, and development trajectories, will prove valuable for future research. Considering our methodological approach, a critic may justifiably be concerned about the applicability of the two-stage idea development framework to empirical research. After all, these stages are unlikely to be easily observable in empirical data. We recognize this challenge, but
point out that for complex problems, these stages are likely to exist irrespective of our ability to cleanly delineate them. We are thus hopeful that the importance of the two-stage framework could lead subsequent research to search for and capture the observable indicators of the idea development stages. This could include elements such as idea maturity and quality, in conjunction with an analysis of the underlying performance landscape and culture of the collective in which individuals collaborate. Beyond that, the conceptual and analytical approach presented here can open broader avenues for future inquiry, including questions such as whether and to what extent the sequencing of various social interactions and associated idea changes can affect an idea’s eventual quality and ensuing collective benefits.
Figure 1. Idea space, performance landscape, and social network.

Figure 1a represents idea space and performance landscape. Possible ideas are defined by their location on a 32×32 grid (the performance landscape). Lighter areas of the performance landscape indicate higher-quality ideas; darker areas indicate lower-quality ideas. The top of the sharp peak on the left side is the best possible idea. Figure 1b reflects the social network structure used in computational experiments. White circles are organizational actors connected densely within, and sparsely across, five different network communities (A, B, C, D, and E). Figure 1c demonstrates a typical early time period of a model run. Each actor holds a belief about the features of an optimal idea that corresponds to a particular location of the performance landscape. Red squares are ideas that an actor has previously held. The trajectory of those ideas and their interaction with the social network is a focal point of our investigation.
Figure 2. Sample Idea Chains

Note: This figure represents the focal action chains resulting from actors’ interactions in the social structure from two separate runs of the model. One can view these chains as providing a residue of the ideas left behind as the actors search the landscape. Nodes are ideas, with node labels indicating the performance of the idea. Edges are change events connecting the ancestors and descendants of a given idea, with edge labels marking the network communities involved in the change event. Node colors describe the type of the change event that produced the idea (blue = self-search; red = between-network-community recombination; pink = within-network-community recombination; green = within-network-community transfer; yellow = between-network-community transfer; and brown = the starting idea). Node shape indicates the stage of development: circles designate last-mile ideas, in which only incremental improvements are sufficient to refine the current idea into the best possible idea; squares are outside-the-last-mile ideas for which a greater degree of novelty is required to reach the best possible idea. The largest circle represents the discovery of the best possible idea. The action chain on the right resulted in the best possible idea; the action chain on the left did not.
Figure 3. Phases and Final States of Idea Chain Trajectories
**Table 1.** System characteristics and their computational representation.

<table>
<thead>
<tr>
<th><strong>System Characteristics</strong></th>
<th><strong>Model Constructs and Assumptions</strong></th>
<th><strong>Computational Representation</strong></th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Ideas and Idea Performance</strong></td>
<td>The problem being solved is complex, in the sense that the impact of a particular value of one dimension of the feature space on performance depends on the value of the other. Novelty is required to find the best idea. Ideas can be built upon and refined or abandoned.</td>
<td>Ideas are represented as objects defined by their location in a two-dimensional feature space. The feature space of an idea maps directly to a randomly generated “rugged” two-dimensional (32×32) performance landscape, characterized by 5-15 local optima and a single, unambiguous global optimum (Figure 1b). The value of an idea is defined by its location on that landscape. Ideas that follow one another are networked together into action chains, which enables tracing their evolution.</td>
</tr>
<tr>
<td><strong>Social Structure</strong></td>
<td>Actors are embedded in a small-world network and interact only with those to whom they are connected. Initial ideas within a network community are much more similar to each other than ideas across communities.</td>
<td>Twenty-five actors are connected by a 45-edge network. The network is comprised of five tightly interconnected network communities, with each network community containing a broker who has connections to two other network communities (Figure 1a). This same network structure was used for all runs of the model, and it was fixed for the duration of a run. The network governs the initialization of actor beliefs. Actors in the same network community are assigned initial beliefs in locations of the feature space much closer to each other than to actors in other network communities.</td>
</tr>
<tr>
<td><strong>Idea Exchange and Improvement</strong></td>
<td>Actors hold a single belief about the best performing idea at any given point in time. They share the same perception of idea performance for a given combination of features.</td>
<td>Actors have a choice of whether to collaborate with others or work on their own, and if they collaborate, whether that will involve copying a better existing idea or recombining information to create a novel idea. The tendencies of actors to (1) collaborate and (2) to recombine are</td>
</tr>
</tbody>
</table>
number of ideas at any given point in time.

Actors can upgrade ideas by borrowing ideas from their contacts, synthesizing elements of their own idea with those from their contacts, or by searching for ideas independently (Hargadon, 2002; Burt, 2004; Fleming, Mingo, and Chen, 2007).

Collaboration is dyadic. Interactions between two actors can be repeated as long as one of them has new information since the previous interaction.

Actors will update their beliefs if a higher performing idea is created or found.

Collaborative interactions are exogenously determined by the parameters, \( \text{collab} \) and \( \text{recomb} \), respectively. They remain the same for all actors within a run of the model.

An actor can update their belief in three ways:

1. **Self-search**: Evaluate the performance of all locations in the feature space within their local vision and adopt the highest. Vision is an exogenously determined parameter and the same for all actors within a run of the model.

2. **Transfer**: Adopt a higher performing idea of another actor.

3. **Recombination**: Generate a novel idea through genetic crossover with another actor’s idea. The genetic crossover is accomplished by converting each actor’s idea into a bit string that corresponds to the idea’s location (see Technical Appendix A for additional details).
Table 2. Expected percentage point change in the probability of a given action chain reaching and completing the last mile corresponding to one additional change activity.†

<table>
<thead>
<tr>
<th>Action chain activity</th>
<th>Model 1</th>
<th>Model 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Within-network-community recombination</td>
<td>1.3</td>
<td>−10.9</td>
</tr>
<tr>
<td>Between-network-community recombination</td>
<td>3.7</td>
<td>−5.8</td>
</tr>
<tr>
<td>Within-network-community transfer</td>
<td>−0.31</td>
<td>9.2</td>
</tr>
<tr>
<td>Between-network-community transfer</td>
<td>0.91</td>
<td>19.8</td>
</tr>
<tr>
<td>Self-search</td>
<td>−0.88</td>
<td>22.9</td>
</tr>
<tr>
<td>No. of observations (chains)</td>
<td>21,572</td>
<td>6,141</td>
</tr>
</tbody>
</table>

Notes:
†Probability changes calculated for the median observation using logistic regressions in Technical Appendix B (Table TA1). The unconditional probability of success for the median observation is 8.0% in Model 1 and 59% in Model 2. †† Based on logistic estimation of a binary outcome: 1 if the action chain was the first in given model run to reach last mile and 0 if otherwise (Table TA1, Model 2). †††Based on logistic estimation of a binary outcome: 1 if the action chain was the first in a given model run to reach the best possible discoverable idea and 0 if otherwise (Table TA1, Model 6).

Table 3. Expected percentage point change in the probability of an action chain entering the last mile corresponding to one additional change activity, by the number of interaction partners adopting.

<table>
<thead>
<tr>
<th>Action chain activity</th>
<th>One partner adopts</th>
<th>Both partners adopt</th>
</tr>
</thead>
<tbody>
<tr>
<td>Within-network-community recombination</td>
<td>1.0</td>
<td>2.1</td>
</tr>
<tr>
<td>Between-network-community recombination</td>
<td>1.6</td>
<td>5.2</td>
</tr>
</tbody>
</table>

Notes: Probability changes are calculated for the median observation using the logistic regressions in Technical Appendix B (Table TA2, Model 2). The unconditional probability of reaching the last mile for the median observation is 6.3%. Wald-test-based comparisons between full and linearly restricted models reject the hypothesis that the one partner and both partner coefficients are equal (p < 0.0001 for both rows.)

Table 4. Magnitude of idea space and social space infiltration by actor activity.

<table>
<thead>
<tr>
<th></th>
<th>Self search</th>
<th>Within-network-community transfer</th>
<th>Between-network-community transfer</th>
<th>Within-network-community recombination</th>
<th>Between-network-community recombination</th>
</tr>
</thead>
<tbody>
<tr>
<td>One partner adopts</td>
<td>Idea space infiltration +</td>
<td></td>
<td>Idea space infiltration ++</td>
<td>Idea space infiltration +++</td>
<td></td>
</tr>
<tr>
<td>Both partners adopt</td>
<td>Social space infiltration +</td>
<td>Social space infiltration ++</td>
<td>Idea space infiltration ++ &amp; Social space infiltration +</td>
<td>Idea space infiltration +++ &amp; Social space infiltration ++</td>
<td></td>
</tr>
</tbody>
</table>
TECHNICAL APPENDIX A: MODEL DESCRIPTION AND IMPLEMENTATION

Our model features groups of actors, interlinked by a network of social relationships, who develop and search for valuable ideas. An overview of the model is provided in the main text. In this appendix we provide additional details on the implementation of the primary model elements and walk through a sample run of the model. The model was built and simulated in the widely used NetLogo Agent-Based Modeling Environment (Wilensky, 1999).

Primary Model Elements
The model contains five primary elements: ideas, actors and their behaviors, a social network, idea change types, and a performance landscape for the ideas.

1. Ideas have a multilevel representation. At the high level, they are defined by their location in a two-dimensional feature space. Each dimension contains 32 discrete integer values. At a lower level, each combination of features also corresponds to a 10-digit bit string representation of the integer location, which can be thought of as containing more detailed information on the elements of each idea. The bit string is a concatenation of the binary representations of the integers. For example, the 5-digit binary representation of the integer 17 is 10001, and for the integer 25 it is 11001. The 10-digit bit string representation for the location \{17, 25\} would therefore be 1000111001. As described below, the bit string representation is used to recombine ideas; the integer representation of an idea’s location the feature space is used to determine its performance.

2. Actors and actor behaviors. Actors hold a belief about what location in the idea space yields the highest performance. An actor can update their current belief with a higher performing belief in one of three ways. First, they can search the areas of the feature space close to their current belief on their own (self-search). The maximum radius an actor can search from their current belief is given by the parameter vision, which was set to 1.5 for all actors. Second, they can copy a higher performing belief from a network contact (transfer). Third, they can recombine elements of their current belief with those of a network contact.

Actors are also characterized by two general tendencies. One tendency, collab, is an actor’s tendency to collaborate with others. It governs the frequency with which the actor attempts to engage in collaboration (i.e., recombination or copying) as opposed to searching on their own. The second tendency, recomb, is the tendency to innovate when working with others. It governs the frequency with which the actor attempts to engage in recombination instead of copying, given that an actor has engaged in network search. In the results presented in the main text, collab and recomb were both set to 0.8 for all actors. Our boundary condition analyses, reported in the main text, explore the sensitivity of our results to varying levels of collab and recomb.

3. Social network. A social network of collegial ties governs the interactions between actors and the possible transfers and recombinations. The network takes the form depicted in Figure 1b in the main text: a small-world structure with five tightly interconnected network communities. Each network community contains a broker who has connections to two other network communities. This same network structure was used for all runs of the model, and it was fixed for the duration of a run.
The social network also governed the initialization of beliefs. Network communities were randomly assigned a different point in the feature space. The only restriction on that point was that it could not be a location from which an actor could find the global peak through only self-search. Actors within a network community were then randomly assigned a location on or near that point. Consequently, actors hold ideas much more similar to others within their network community than to those outside their network community when the simulation begins.

4. Idea change types. Actor behaviors interacted with the social network locations produce five different idea change types denoting the type of action that introduced the idea into the social system: (1) Self-search: actor learned about idea through local search; (2) Within-network-community transfer: actor learned about the idea from another member of her own network community; (3) Between-network-community transfer: actor learned about the idea from a member of a different network community; (4) Within-network-community recombination: actor developed the idea through a recombination with another member of her own network community; (5) Between-network-community recombination: actor developed the idea through a recombination with a member of a different network community

Recombination, whether between or within a network community, occurs through single-point genetic crossover of the bit string representations of their beliefs (Holland and Order, 1995). The genetic crossover process yields a new location in feature space, whose performance each actor independently evaluates. Regardless of the type of attempted improvement, if the new location discovered is higher performing, an actor will update her belief. Single-point genetic crossover is accomplished by picking a random point between two digits, where each string gets “cut,” creating two pieces—left and right—for each actor. The left half of Actor A’s string is then concatenated with the right half of Actor B’s, and the right half of Actor A’s string is paired with the left half of Actor B’s to create two novel bit strings.

For example, consider the case where Actor A’s current belief for the highest performing location in feature space is {17, 25}, which corresponds to a bit string representation of 1000111001; Actor B’s current belief is location {28, 30}, which corresponds to a bit string representation of 1110011110. Further assume that the model chose a cut point between digits 6 and 7. Crossover in this case would yield the following two new strings 10001110 and 1110011001. One of those two strings is then randomly selected (e.g., 1000111110) and reconverted into the corresponding integer values in the feature space {28, 25}.

5. Performance Landscape. The performance landscape maps the feature space location of an idea to the performance scores for that idea. A key characteristic of the types of performance landscapes we use in this model is that the impact of a particular value of one dimension of the feature space on performance depends on the value of the other. The more complex the problem (i.e., the more interdependencies matter for performance), the greater the number of peaks and valleys in the landscape; therefore, the easier it is to get stuck at local optima and not find the highest performing location (Levinthal, 1997). Each peak in the landscape has a unique basin of attraction, which is defined as the set of all locations that would lead to that peak if actors could engage only in self-search.
We generated a new performance landscape for every run of the model by picking five percent of the locations as starting points for diffusing performance to surrounding areas, and one additional location as a clear global peak. Figure 1a in the main text depicts a representative landscape. On average, the landscapes used in the model contained 9.5 total peaks (ranging from 5 to 15), and the highest peak of a landscape featured the level of idea performance that was 3.5 times as high as that of the second highest peak.

**Sample Run of the Model**

Please refer to the description of model steps in the main text. In the main analyses, collab is set to 0.8 for all actors; thus, the probability that self-search occurs in any given round is 0.2, and the effective probability that an interaction occurs in any given round is \((0.8) \times (0.8) = 0.64\). By the same token, since recomb is set to 0.8 for all actors in the main analyses, it implies that the effective probability that two actors engage in a recombination interaction in any given round is \(P(\text{interaction}) \times \text{recomb} \times \text{recomb} = (0.64) \times (0.8) \times (0.8) = 0.4096\). Similarly, the probability that two actors engage in a transfer interaction in any given round is \((0.64) \times (0.2) = 0.128\). Note that engaging in a search or interaction activity of any type does not mean that either actor changed his or her belief. Beliefs are updated only if a better-performing idea is developed or found.

Figure TA 1(a-c) below provides three snapshots of one randomly chosen run of the model at time steps 0, 200, and 1000. The cells of the grid represent the space of idea features. Each location on the grid (idea) is associated with a specific level of performance determined by the underlying performance landscape. On this performance landscape, lighter colors indicate higher-performing ideas; darker colors represent lower-performing ideas. The performance landscape is rugged, which is representative of complex problems, where idea features interact to determine performance. The ruggedness is evident in the lighter areas—which represent local performance peaks—being surrounded by darker valleys of lower-performing ideas. The bright white spot in the lower right corner is the global peak, indicating the best possible idea that can be discovered in the focal run of the model.

The social network of the collective features 25 white nodes, which represent actors who are interconnected by 45 white information-sharing relationships. The network is described by a small-world network topology with five densely interconnected network communities that are only sparsely connected across communities (Figure TA1). Importantly, the actors are placed on the location of the idea feature landscape in the way that corresponds to their initially held beliefs about the best-performing idea. As Figure TA1(a) illustrates, at \(t=0\), actors vary in their initial beliefs about which combination of idea features constitutes the best-performing idea, no actor is on or very near the global peak, and actors in the same network community are more similar to one another in their initial beliefs than to the actors located in other network communities.

As actors begin to interact with one another or engage in self-search, they progress in finding better-performing ideas. In the analytical representation of Figure TA1, they begin to make their way toward higher-performing (lighter) locations on the idea feature grid. See Figures TA1(b) and TA1(c). Regardless of the type of search in which the actors engage, some of the actors will inevitably end up converging on the same ideas. Such convergence may result from actors’ acquiring one another’s ideas through transfer or from actors jointly developing a new idea through recombination that is higher performing than either of their current ideas, with both
subsequently adopting it. Yet another possibility is that actors can converge on the same idea through self-search, especially if their ideas happen to be in the same basin attraction and thus tend toward the same peak.

**Figure TA1.** Illustrative Model Run

![Figure TA1(a). Model at $t=0$](image)

![Figure TA1(b). Model at $t=200$](image)

![Figure TA1(c). Model at $t=1000$](image)

In this run, the number of unique beliefs has decreased from 20 in time period 0 to 12 by time period 200. By time period 1000, the actors have converged on four unique ideas, each of which is associated with a different local peak on the performance landscape. In this particular case, no actor has discovered the best possible idea, as evidenced in the global peak (bright white cell in the bottom right corner) remaining unoccupied.

**TECHNICAL APPENDIX B: SUPPLEMENTARY RESULTS**

**Best ideas, idea value, and actors’ general tendencies to collaborate and recombine**

The two key parameters in our model are the actors’ general propensities to (1) collaborate with their network contacts in pursuing better ideas versus engaging in self-search ($collab$) and (2) to recombine their own ideas with those of others as opposed to merely transfer (copy) them ($recomb$). Conceptually, these parameters could be thought of as representing distinct environments that support collaboration and creativity to different degrees.

Before engaging in our main analyses, we ran models with various combinations of these parameters. Our goal was to identify a set of $collab$ and $recomb$ values that would produce variance in the key outcome of interest: the collective’s ability to discover the best idea. The results of these exploratory analyses are reflected in Figure TA4. Each cell reflects the fraction of model runs at specific values of $collab$ and $recomb$ in which actors have discovered the best possible idea. As stipulated in the main text, we have subsequently settled on an environment that is both highly collaborative and innovative ($collab = 0.8; recomb = 0.8$). This environment produced a fair amount of variance in the key outcome of interest: 26% of model runs reached the best possible idea. Note, however, that our examination of boundary conditions of our results
covered a broader range of environments with both high and low values of *collab* and *recomb* (see boundary conditions sections in the main text).

**Quantitative Analyses of Key Processes: Estimation of Conditional Probabilities**

This section presents the logistic regressions used to create Tables 2 and 3 in the main text, which report the probabilities of success for an action chain, conditional on the activities that occur in that chain. The primary unit of analysis, and hence the unit of observation in each model, is the focal action chain for that run. Coefficients in Tables TA1 and TA2 represent the change in the log odds of an outcome—whether the action chain was first to enter the last mile or first to reach the best possible idea—for a one-unit change in the corresponding predictor.

The data for Table TA1 come from fixing *collab* and *recomb* to four different pairs of specific values and collecting data on 25,000 model runs for each pair of values. The data for Table TA2 come from fixing *collab* and *recomb* to four different pairs of specific values and collecting data from 5,000 model runs for each pair of values. The model runs used for the logit analyses in Table TA2 used a modified model design described in the main text under the “both adopt” experiment. This design was used to eliminate the potentially confounding correlation between idea quality and both partners’ adopting.

Values in Table 2, Model 1, in the main text (reaching last mile) were calculated by converting the log odds to a probability change for a median observation using the coefficients in Model 2, Table TA1. The median observation in Table 2, Model 1, consisted of an action chain with 3 within-network community recombinations, 0 between-network community recombinations, 2 within-network community copies (transfers), 0 between-network community copies (transfers), and 5 self-searches. Such median observation had an 8.0 percent chance of reaching the last mile.

Values in Table 2, Model 2, in the main text (developing into the best possible idea) were calculated by converting the log odds to a probability change for a median observation using the coefficients in Model 6, Table TA1. The median observation in Table 2, Model 2, reflected an action chain with 1 within-network-community recombination, 0 between-network-community recombinations, 0 within-network-community copies (transfers), 0 between-network-community copies (transfers), and 1 self-search. Such median observation had a 59 percent chance of developing into the best possible idea.

Values for Table 3 in the main text (reaching last mile, both adopt experiment) were calculated by converting the log odds to a probability change for a median observation using the coefficients in Model 2, Table TA2. The median observation reflected an action chain with 2 within-network-community recombinations where one actor adopts, 0 between-network-community recombinations where one actor adopts, 1 within-network-community recombination where both actors adopt, 0 between-network-community recombinations where both actors adopt, 2 within-network-community copies (transfers), 0 between-network-community copies (transfers), and 7 self-searches. Such median observation had a 6.3 percent chance of developing into the best possible idea.
Figure TA4. Best ideas and actors’ general tendencies to collaborate and recombine

<table>
<thead>
<tr>
<th>Propensity to Collaborate (collab)</th>
<th>0.9-</th>
<th>0.8-</th>
<th>0.7-</th>
<th>0.6-</th>
<th>0.5-</th>
<th>0.4-</th>
<th>0.3-</th>
<th>0.2-</th>
<th>0.1-</th>
</tr>
</thead>
<tbody>
<tr>
<td>0</td>
<td>0.01</td>
<td>0.02</td>
<td>0.03</td>
<td>0.05</td>
<td>0.06</td>
<td>0.08</td>
<td>0.10</td>
<td>0.12</td>
<td>0.14</td>
</tr>
<tr>
<td>0</td>
<td>0.01</td>
<td>0.02</td>
<td>0.03</td>
<td>0.05</td>
<td>0.06</td>
<td>0.08</td>
<td>0.10</td>
<td>0.12</td>
<td>0.14</td>
</tr>
<tr>
<td>0</td>
<td>0.01</td>
<td>0.02</td>
<td>0.03</td>
<td>0.05</td>
<td>0.06</td>
<td>0.08</td>
<td>0.10</td>
<td>0.12</td>
<td>0.14</td>
</tr>
<tr>
<td>0</td>
<td>0.01</td>
<td>0.02</td>
<td>0.03</td>
<td>0.05</td>
<td>0.06</td>
<td>0.08</td>
<td>0.10</td>
<td>0.12</td>
<td>0.14</td>
</tr>
<tr>
<td>0</td>
<td>0.01</td>
<td>0.02</td>
<td>0.03</td>
<td>0.05</td>
<td>0.06</td>
<td>0.08</td>
<td>0.10</td>
<td>0.12</td>
<td>0.14</td>
</tr>
<tr>
<td>0</td>
<td>0.01</td>
<td>0.02</td>
<td>0.03</td>
<td>0.05</td>
<td>0.06</td>
<td>0.08</td>
<td>0.10</td>
<td>0.12</td>
<td>0.14</td>
</tr>
<tr>
<td>0</td>
<td>0.01</td>
<td>0.02</td>
<td>0.03</td>
<td>0.05</td>
<td>0.06</td>
<td>0.08</td>
<td>0.10</td>
<td>0.12</td>
<td>0.14</td>
</tr>
<tr>
<td>0</td>
<td>0.01</td>
<td>0.02</td>
<td>0.03</td>
<td>0.05</td>
<td>0.06</td>
<td>0.08</td>
<td>0.10</td>
<td>0.12</td>
<td>0.14</td>
</tr>
</tbody>
</table>

Note: Each cell reflects 500 model runs for which the actors’ general propensities to collaborate (collab) and recombine (recomb) were fixed at the corresponding values. For example, our main analyses were conducted in the environment that is both highly collaborative (collab = 0.8) and highly innovative (recomb = 0.8). The value in each cell represents the fraction of model runs that found the best possible idea. For example, for our main analyses (i.e., collab = 0.8; recomb = 0.8), 26% of model runs returned the best possible idea.
### Table TA1. Logit regressions predicting whether a focal action chain was the first to enter the last-mile stage of idea development (1-entered; 0-otherwise), and first to reach the best idea after entering the last mile (1-reached best possible idea; 0-otherwise).

<table>
<thead>
<tr>
<th></th>
<th>First to Enter Last Mile†</th>
<th>First to Reach Best Idea after Entering Last Mile††</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Within-network-</td>
<td></td>
<td></td>
</tr>
<tr>
<td>community recombination</td>
<td>0.571***</td>
<td>0.166***</td>
</tr>
<tr>
<td></td>
<td>(0.033)</td>
<td>(0.010)</td>
</tr>
<tr>
<td>Between-network-</td>
<td>0.589***</td>
<td>0.420***</td>
</tr>
<tr>
<td>community recombination</td>
<td>(0.031)</td>
<td>(0.023)</td>
</tr>
<tr>
<td>Within-network-</td>
<td>−0.064***</td>
<td>−0.043***</td>
</tr>
<tr>
<td>community transfer</td>
<td>(0.010)</td>
<td>(0.013)</td>
</tr>
<tr>
<td>Between-network-</td>
<td>0.094*</td>
<td>0.117***</td>
</tr>
<tr>
<td>community transfer</td>
<td>(0.050)</td>
<td>(0.033)</td>
</tr>
<tr>
<td>Self-search</td>
<td>−0.061***</td>
<td>−0.127***</td>
</tr>
<tr>
<td></td>
<td>(0.012)</td>
<td>(0.007)</td>
</tr>
<tr>
<td>Constant</td>
<td>−3.300***</td>
<td>−2.220***</td>
</tr>
<tr>
<td></td>
<td>(0.049)</td>
<td>(0.034)</td>
</tr>
<tr>
<td>No. of Observations</td>
<td>21,607</td>
<td>21,572</td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>−3,533.984</td>
<td>−6,694.709</td>
</tr>
</tbody>
</table>

**Notes:**
- *p<0.10  **p<0.05  ***p<0.01
- †Predictors are the number of each type of change activity on the action chain that occurred before the first chain in the model run reached the last mile. Data include only those focal chains that began outside of the last mile.
- ††Predictors are the number of each type of change activity on the action chain that occurred after the action chain entered the last mile. Data include only those focal chains that at some point reached the last mile or were initiated in the last mile.
Table TA2. Logit regressions for “both adopt” experiment predicting whether a focal action chain was the first to reach the last-mile stage of development (1-reached; 0-otherwise).

<table>
<thead>
<tr>
<th></th>
<th>recomb=0.3, collab=0.8</th>
<th>recomb=0.8, collab=0.8</th>
<th>recomb=0.8, collab=0.3</th>
<th>recomb=0.3, collab=0.3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Within-network-community recombination, one partner adopts</td>
<td>0.357*** (0.095)</td>
<td>0.150*** (0.026)</td>
<td>0.749*** (0.095)</td>
<td>0.972*** (0.206)</td>
</tr>
<tr>
<td>Between-network-community recombination, one partner adopts</td>
<td>0.877*** (0.130)</td>
<td>0.285*** (0.041)</td>
<td>1.292*** (0.136)</td>
<td>0.948*** (0.312)</td>
</tr>
<tr>
<td>Within-network-community recombination, both partners adopt</td>
<td>0.471*** (0.080)</td>
<td>0.218*** (0.054)</td>
<td>0.422*** (0.076)</td>
<td>0.892*** (0.093)</td>
</tr>
<tr>
<td>Between-network-community recombination, both partners adopt</td>
<td>0.688*** (0.126)</td>
<td>0.615*** (0.084)</td>
<td>0.809*** (0.130)</td>
<td>0.663*** (0.169)</td>
</tr>
<tr>
<td>Within-network-community transfer</td>
<td>–0.085*** (0.023)</td>
<td>–0.057** (0.027)</td>
<td>–0.236* (0.130)</td>
<td>–0.224*** (0.080)</td>
</tr>
<tr>
<td>Between-network-community transfer</td>
<td>0.093 (0.114)</td>
<td>0.058 (0.069)</td>
<td>–0.181 (0.121)</td>
<td>–0.077 (0.163)</td>
</tr>
<tr>
<td>Self-search</td>
<td>–0.043 (0.028)</td>
<td>–0.133*** (0.015)</td>
<td>–0.244*** (0.029)</td>
<td>–0.138*** (0.041)</td>
</tr>
<tr>
<td>Constant</td>
<td>–2.270*** (0.110)</td>
<td>–2.129*** (0.075)</td>
<td>–2.962*** (0.107)</td>
<td>–3.987*** (0.162)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>No. of observations</td>
<td>4,338</td>
<td>4,286</td>
<td>4,323</td>
<td>4,292</td>
</tr>
<tr>
<td>Log Likelihood</td>
<td>–682.894</td>
<td>–1,353.292</td>
<td>–696.861</td>
<td>–355.060</td>
</tr>
</tbody>
</table>

Notes: *p<0.10  **p<0.05  ***p<0.01.
†Predictors are the number of each type of change activity on the action chain that occurred before the first chain in the model run reached the last mile. Data include only those focal chains that began outside of the last mile.
References

Ahuja, G.
2000 "Collaboration Networks, Structural Holes, and Innovation: A Longitudinal Study."

Amabile, T. M.
1996 Creativity in context: Update to the social psychology of creativity: Routledge.

Amabile, T. M. and M. G. Pratt
2016 "The dynamic componental model of creativity and innovation in organizations: Making
progress, making meaning." Research in Organizational Behavior, 36.

Argote, L., B. McEvily, and R. Reagans
2003 "Managing knowledge in organizations: An integrative framework and review of emerging

Balachandran, S. and E. Hernandez
2018 "Networks and innovation: Accounting for structural and institutional sources of

Balconi, M., S. Breschi, and F. Lissoni
2004 "Networks of inventors and the role of academia: An exploration of Italian patent data."
Research Policy, 33: 127-145.

Baum, J. A. C., A. V. Shipilov, and T. Rowley
2003 "Where do small worlds come from?" Industrial and Corporate Change, 12: 697-725.

Berg, J. M.
2014 "The primal mark: How the beginning shapes the end in the development of creative ideas.

Bidwell, M. and I. Fernandez-Mateo
2010 "Relationship duration and returns to brokerage in the staffing sector." Organization
Science, Forthcoming.

Burt, R. S.
1992 Structural holes: The social structure of competition. Cambridge, MA: Harvard University
Press.

Burt, R. S.

Burt, R. S.
Press.

Burt, R. S.
2007 "Secondhand brokerage: Evidence on the importance of local structure for managers,

Burt, R. S.
University Press.

Carnabuci, G. and J. Bruggeman
2009 "Knowledge specialization, knowledge brokerage and the uneven growth of technology

Clement, J., A. Shipilov, and C. Galunic
2018 "Brokerage as a public good: The externalities of network hubs for different formal roles in

Cohen, W. M. and D. A. Levinthal
1990 "Absorptive capacity: A new perspective on learning and innovation." Administrative

Coleman, J. S., E. Katz, and H. Menzel
Colyvas, J. A. and S. Maroulis

Cox Pahnke, E., R. McDonald, D. Wang, and B. Hallen

Cropley, A. J.

Davis, G. F. and H. R. Greve

Davis, G. F., M. Yoo, and W. E. Baker

Davis, J. P., K. M. Eisenhardt, and C. Bingham

Davis, J. P., K. M. Eisenhardt, and C. B. Bingham

Dolgin, E.

Eggers, J. P. and S. Kaplan

Feist, G. J.

Ferguson, J. P. and G. Carnabuci

Fernandez-Mateo, I.

Fleming, L., C. King, and A. Juda

Fleming, L., S. Mingo, and D. Chen

Foster, J. G., A. Rzhetsky, and J. A. Evans

Funk, R. J.
2014 "Making the most of where you are: Geography, networks, and innovation in organizations." Academy of Management Journal, 57: 193-222.

Furnham, A. and V. Bachtiar

Galunic, C., G. Ertug, and M. Gargiulo

Galunic, D. C. and S. Rodan

Ghosh, A. and L. Rosenkopf

Guilford, J. P.

Gulati, R., M. Sytch, and A. Tatarynowicz

Gupta, B. and T. Khanna
2019 "A Recombination-Based Internationalization Model: Evidence from Narayana Health’s Journey from India to the Cayman Islands." Organization Science, 30: 405-425.

Hargadon, A. and R. I. Sutton

Hargadon, A. B.

Hirst, G., D. Van Knippenberg, J. Zhou, E. Quintane, and C. Zhu

Holland, J. H. and H. Order

Isaksen, S. G. and D. J. Treffinger

Jones, B. F., S. Wuchty, and B. Uzzi

Kauffman, S. A.

Kilduff, M. and H. Oh

Knoke, D.

Kumar, P. and A. Zaheer

Lazer, D. and A. Friedman

Lévi-Strauss, C. T. s. s. o. m. L. t. A. a., 101-18.
1967.

Levinthal, D. A.
Li, Q., P. G. Maggitti, K. G. Smith, P. E. Tesluk, and R. Katila

Li, Y., N. Li, J. Guo, J. Li, and T. B. Harris

Lubart, T. I.

Maggitti, P. G., K. G. Smith, and R. Katila

March, J. G.

March, J. G. and H. A. Simon

Maroulis, S., D. Diermeier, and M. A. Nisar

McDonald, R. M. and K. M. Eisenhardt

Moody, J.

Ocasio, W.

Owen-Smith, J.
2003 "From separate systems to a hybrid order: Accumulative advantage across public and private science at research one universities." Research Policy, 32: 1081-1104.

Owen-Smith, J. and W. W. Powell

Posen, H. E., J. Lee, and S. Yi

Powell, W. W., K. A. Packalen, and K. B. Whittington

Rao, H., P. Puranam, and J. Singh
2021 "Does design thinking training increase creativity? Results from a field experiment with middle-school students." Innovation Policy and the Economy: 1-18.

Reagans, R. and B. McEvily

Rivkin, J. W.

Rogers, E. M.

Rosenkopf, L. and A. Nerkar
Saxenian, A.

Schilling, M. and C. C. Phelps

Schumpeter, J. A.

Shipilov, A. V. and S. X. Li

Simonton, D. K.

Stovel, K. and L. Shaw

Sytch, M. and A. Tatarynowicz
2014 "Exploring the Locus of Invention: The Dynamics of Network Communities and Firms' Invention Productivity." Academy of Management Journal, 57: 249-279.

Sytch, M., A. Tatarynowicz, and R. Gulati

Tatarynowicz, A., M. Sytch, and R. Gulati
2016 "Environmental Demands and the Emergence of Social Structure: Technological Dynamism and Interorganizational Network Forms." Administrative Science Quarterly.

Uzzi, B., S. Mukherjee, M. Stringer, and B. Jones

Uzzi, B. and J. Spiro

Vasudeva, G., A. Zaheer, and E. Hernandez

Weick, K. E.

Wilensky, U.

Zaheer, A. and G. Soda