ADAPTATION AND LEARNING IN SOCIAL NETWORKS

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ADAPTATION AND LEARNING IN SOCIAL NETWORKS

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This dissertation broadly addresses the issue of learning in social networks. The dissertation builds on existing literature that leverages learning as a mechanism for predicting the performance effects of different network structures, and focuses on two competing structures: open networks in which none of an actor's partners are connected to each other, and closed networks in which all of an actor's partners are connected to each other. The dissertation examines these issues at both the inter-organizational and intra-organizational levels.

At the inter-organizational level, the dissertation addresses two related issues. First, prior network research has favored a simplistic view of learning, conceptualized as a firm's acquisition of information from its network partners. Second, in its focus on information acquisition, this work has prioritized a single informational characteristic—informational diversity. This dissertation uses formal simulation models to advance this literature by (1) accounting for learning not only as information transfer but also as a firm's ability to adapt in response to performance feedback, and (2) by demonstrating the importance of redundant rather than diverse information for learning from networks. It is shown that once these two issues are properly

accounted for, open and closed networks may each generate performance advantages in contexts thought impossible from the perspective of prior work.

At the intra-organizational level, prior work conceptualizes learning as an employee's process for developing expertise. However, the literature on expert development has ignored the importance of an actor's social network configuration for influencing whether the actor progresses from novice to expert. This dissertation advances the literature on intra-organizational networks by proposing a conceptual model which explains the importance of an actor's network structure for his or her development as an expert. These insights are then leveraged to propose organizational interventions that may be implemented to improve an employee's advancement toward expertise within the firm.

Overall, the dissertation advances existing research by bringing closer the disparate literatures on network structure and learning at the individual and organizational levels. Opportunities for future research are discussed.

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INTRODUCTION

How does *who* you know influence *what* you know? A core insight from network perspectives on organization is that an actor, be it an individual or organization, gains benefit from its network of relationships in large part because of how this network changes that actor's knowledge profile. Actors extract from their networks information that they would otherwise lack. Firms may use their network relationships to learn about new strategies, resources, and capabilities. Individuals may use their network relationships to learn about new ways of executing their tasks, and about opportunities to gain new experiences. One obvious implication is that an actor with a larger number of network connections will have more learning opportunities.

A more substantial contribution from the network literature focuses not on the number of ties an actor has, but instead on the actor's network structure—the pattern of relationships linking an actor's network partners to one another. The important argument from the literature is that the connections between an actor's partners will influence both (1) the extent to which an actor's network partners hold similar information (2) the likelihood that any one of an actor's network partners will be willing to share information. For instance, closed network structures are those in which all of an actor's network partners are connected to one another (i.e., Bob in Figure 1 below). In these networks, the focal actor's partners are likely to communicate directly with each other and therefore will hold similar pieces of information. However, since this network reflects a close knit community, each partner is highly likely to share the information they have with the focal actor. In contrast, open network structures are those in which none of an actor's network partners is connected to one another (i.e., Kathy in Figure 1). In these networks, the focal actor's partners are unlikely to communicate directly with each other and therefore will

hold diverse pieces of information. However, partners in these networks may lack the trust and social incentives to share the information they have with the focal actor. Thus even when two actors have the same number of network ties, varying the structure of relationships linking their partners leads to vastly different learning opportunities, by changing the quantity and diversity of information the actor can extract from these partners.

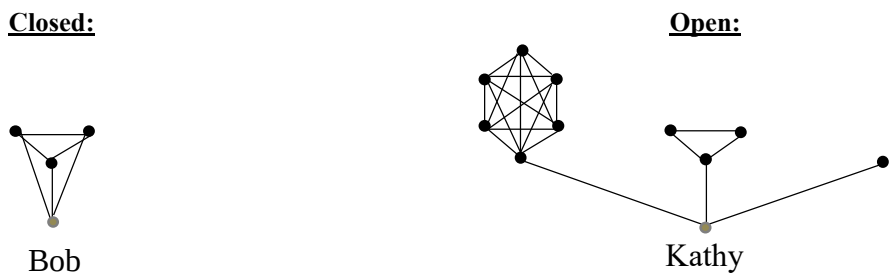

Figure 1. Comparing closed to open network structures

This dissertation adopts a structural perspective, placing focus on the configuration of relationships between an actor's partners, but contributes to this literature by accounting for novel aspects of learning that are traditionally ignored in this perspective. In particular, while learning is traditionally limited to the notion of information exchange between partners, this dissertation considers broader forms of learning such as learning from performance feedback (Chapter 1), processes for variation and selection within firms (Chapter 2), and the development of individual expertise through deliberate practice (Chapter 3). Each of these three forms of learning may be considered *adaptive* in that they reflect learning from experience, in contrast to the traditional focus on *social* learning, which reflects learning directly from one's partners. Thus, the core contribution of the dissertation lies in showing how an actor's processes for learning from experience provide new insights to network perspectives on organizations.

CHAPTER 1

EXPANDING THE ROLE OF ADAPTIVE LEARNING IN NETWORK THEORIES

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ABSTRACT

In network research, learning is considered a key mechanism through which network structure influences performance, but the conception of learning is reduced to information acquisition from the network. We contend that understanding how firms' network structures influence their performance demands treating firms and their alters as adaptive learners. We augment prior network models to better account for adaptive learning—incremental learning from performance feedback—and analyze this model using computer simulations. Our analysis centers on network closure and highlights three adaptive learning issues: exploratory search, competence development, and adaptive biases. The model produces several important findings. First, it predicts that even when open networks grant information advantages that enhance value identification—firms' processes for identifying valuable strategic practices—these networks impose a learning tradeoff by simultaneously reducing the rate at which firms develop competence with the very practices they identified as the most valuable. Second, it challenges prior theory by predicting that closed networks are superior to open networks for reducing uncertainty. Finally, it predicts that network closure can lead to superior performance even absent the relational advantages thought necessary in prior theory (i.e., trust). These findings demonstrate the importance of better accounting for adaptive learning in network structural arguments.

INTRODUCTION

Theoretical treatments of interorganizational relationships often portray social networks as conduits for organizational learning (Beckman and Haunschild, 2002; Powell, Koput, and Smith-Doerr, 1996). Networks, when properly structured, are thought to facilitate learning by

granting access to information that may better enable firms to identify valuable resources, opportunities, and strategic practices (Haunschild, 1994; McEvily and Zaheer, 1999). This perspective has stimulated a stream of research seeking to identify network structures that improve an organization's learning outcomes, with the expectation that network-driven learning may be consequential for enhancing organizational performance (Ahuja, 2000; Zaheer and Soda, 2009). This structuralist literature displays a serious limitation, however, in that it treats information acquisition from the network as its main learning mechanism, while failing to consider how the organization's internal adaptive processes may also mediate the relationship between network structure and organizational performance.

In contrast to the parochial focus on information acquisition from partners in the literature on network structure, a rich tradition in organizational learning characterizes firms as adaptive learners (Cyert and March, 1963). Adaptive learning centers on incremental learning from performance feedback (Levitt and March, 1988), and comprises a set of interrelated processes including boundedly rational search, and incremental competence development. Both search and competence influence firms' performance outcomes. Search may help firms identify more valuable strategies, while competence is needed to pursue them proficiently.

Nevertheless, we have very little systematic understanding of how a firm's network position may shape how these adaptive learning processes unfold. Prior work has considered the role of organizational search in explaining how network structures arise (Gulati and Gargiulo, 1999; Beckman, Haunschild, and Phillips, 2004), arguing that firms attend to performance feedback when deciding which new network partners to select (Shipilov, Li, and Greve, 2011). However, when arguing how existing network structures influence performance outcomes, firms'

adaptive processes have played only a peripheral role, acting at most as moderating conditions (Tsai, 2001), but more often ignored altogether.

For example, to explain how firms benefit from their existing network positions when selecting new strategic practices, prior work examined which network structures best enable firms to acquire information on practices from their network partners (McEvily and Zaheer, 1999). However, this literature has not considered whether a firm's network position may also influence whether it gains new information on the same practices from sources other than its network ties (such as from performance feedback), or whether its network position influences the proficiency at which it executes these strategic practices after selecting one to pursue. Thus, current theory omits many of the adaptive behaviors that may mediate performance outcomes.

One consequence of omitting these adaptive actions from network arguments is that doing so conceals how networks shape adaptive biases—adaptive behaviors that are performance enhancing in the short run but that undermine performance in the long run. While learning adaptively from performance feedback often leads to performance improvements, doing so may also subject the firm to adaptive biases such as competence traps and information restriction (Levinthal and March, 1993; Denrell and March, 2001). We know very little about how a firm's network structure may influence the extent to which these biases occur. Moreover, because a firm's network partners are also adaptive learners, the information a firm receives from its partners may already reflect the adaptive biases its partners hold. If these adaptive biases are in some ways determined by a firm's network position, then it is possible that current network arguments may be misspecified.

Our fundamental argument, therefore, is that underemphasizing adaptive learning in network models may result in erroneous theoretical predictions. To develop this argument, we augment extant network models to better account for adaptive learning, and analyze this model using computer simulations. Predictions from the model are compared to prior theory to assess (1) the potential for misspecified arguments in prior work, and (2) the model's potential for contributing novel propositions to the network literature. Since there is too large a number of network constructs to consider in a single paper, we focus on ego-network closure—the extent to which a firm is tied to partners who are also connected to each other. Closure plays a foundational role in network scholarship (Coleman, 1988; Burt, 1992), which allows for a detailed but impactful analysis. Its effects inform burgeoning network theories on topics such as network communities (Sytch and Tatarynowicz, 2014), network dynamics (Tatarynowicz, Sytch, and Gulati, 2016; Hernandez and Shaver, 2018), collective performance (Uzzi and Spiro, 2005), and brokerage as a public good (Clement, Shipilov, and Galunic, 2018). The model's key finding involves a learning tradeoff imposed by decreasing network closure. Reducing network closure enables firms to better identify valuable strategic practices, but simultaneously slows the rate at which firms develop competence with the very strategies they have identified as the most valuable. The mechanism behind this tradeoff centers on the unexpected finding that closed networks may reduce uncertainty, and this tradeoff leads us to predict novel conditions under which firms in closed networks can outperform those in open networks.

THEORETICAL MOTIVATION

Network scholars have long been interested in learning as a mechanism for linking a firm's external network configuration to its performance outcomes. Much of this work centers on

understanding how interorganizational linkages may help firms in deciding how to configure their internal resources, practices, and strategies (Haunschild, 1994; McEvily and Zaheer, 1999; Podolny, 2001). For instance, Haunschild (1994) theorizes that firms leverage information from their networks to decide which organizational procedures to employ when evaluating acquisition targets. To the extent that these strategic practices are important for deciding the firm's performance, we can say that the network's influence on learning is an important mechanism for understanding how network structures influence firm performance.

One limitation of this literature, however, is that it accounts for only a narrow subset of learning processes that may be important for theorizing performance effects. Organizational performance can be improved through two general processes: value identification and competence development. Value identification refers to the process through which firms determine which strategies and practices are the most promising. A firm's value identification process is more effective when the strategies and practices it identifies as the most promising are in fact the best available, and is therefore a function of the information that firms have on potential practices. Competence development refers to the process through which firms establish proficiency at implementing the key organizational routines that underlie a practice or strategy. Both processes are essential if the organization is to perform well, but both require adaptive learning in ways that have been ignored in network research. Network scholarship rarely attends to the actions firms must take become proficient at implementing practices internally. Further, while a firm's value identification process may be enhanced by any of its formal and informal procedures for gathering information on organizational alternatives, network scholarship considers only one—the acquisition of information from network partners.

Take for example the canonical debate on network closure. Scholars have debated whether more closed or more open networks are preferred for creating information advantages. Initially, some scholars argued that open networks confer an information advantage by connecting a firm to disconnected clusters in which it is more likely to find non-redundant information (Burt, 1992; McEvily and Zaheer, 1999). Other scholars later argued that closed networks confer an information advantage by engendering trust and cooperative norms which motivates information transfer (Coleman, 1988; Reagans and McEvily, 2003) and cognitive cohesion which makes information transfer feasible (Ter Wal, Alexy, Block, and Sandner, 2016).

This debate informs the learning and performance implications of network structures because the information flowing through the network may be used as an input in a firm's value identification process. Since open networks confer informational advantages under most conditions, these ideas lead to the proposition in the literature that open networks are superior to closed networks for enhancing value identification, and therefore performance, except in contexts where information flow in open networks is constrained by relational factors, such as a lack of trust or a need for shared cognition (Ahuja, 2000; Burt, 2005; Ter Wal, et al. 2016).

This theoretical account depicts a limited view of learning, however, in that it treats firms as passive consumers of information from the network, and merely assumes that a firm will have the ability to implement the strategic practices discovered through the network. In contrast, a rich tradition in organizational learning research has shown that firms are not prisoners of existing information from external sources, but instead are capable producing information internally through exploratory search (Levitt and March, 1988). Thus, internal search and external ties represent distinct sources of the information a firm can use to enhance value identification. In

addition, while most network models have omitted competence development altogether, the organizational learning research demonstrates that firm level competencies are slow to develop and are not easily transferable across firms (Nelson and Winter, 1982). Thus, to fully understand the learning mechanism through which network structure influences performance, we must consider how the network structure may shape exploratory search and competence development.

Accounting for Network Effects on Exploratory Search

Exploratory search refers to a conscious choice to deviate from practices that hold the highest expected values when evaluated using existing information, in order to gain information on different organizational alternatives experientially (March, 1991). Most network research that examines exploratory changes have treated these changes as ends in themselves, while ignoring their informational consequences (Kraatz, 1998). What little work considers the informational consequences of exploration has suggested that a firm may seek novel information by searching for new partners who can provide information beyond that provided by existing partners (Gulati and Gargiulo, 1999; Beckman, Haunschild, and Phillips, 2004; Shipilov, Li, and Greve 2011). However, in these accounts, a firm's pursuit of novel information is still mediated by network relationships. We emphasize a distinct way in which firms use exploratory search in attempts to gain new information, not by seeking new external sources of information, but by producing new information internally. When a firm engages in exploratory search it implements a practice that is not seen as preferable when judged on the basis of existing information. However, because the firm observes performance feedback from the practice after it is implemented, the firm gains novel information on the practice that may not be reflected in network information.

This informational value of internal exploration may inform network arguments in two ways. First, even if closed networks expose firms to less valuable information from the network, the information gained during exploratory search may feed into the firm's value identification process and allow such firms to discover valuable strategic practices. This may neutralize the information advantage of open networks. Second, even if information in open networks leads firms to identify more valuable strategic practices, if a firm chooses to engage in exploratory search rather than implement the identified practice, then it may not actually gain a performance advantage on the basis of the superior information from the network.

While network research generally does not attend to the informational value of firms' internal changes, this literature does suggest that network structure influences exploration. The traditional argument is that information from the network increases a firm's propensity for exploratory change simply by exposing the firm to more alternatives (Burt, 2005; Battilana and Casciaro, 2012). We add a second, more nuanced, argument centered on the link between adaptive learning and uncertainty. A firm's network structure influences the amount of uncertainty it will perceive while making decisions regarding organizational resources, practices, and strategies (Podolny, 2001). This may lead to different patterns of exploratory search across network positions, since firms facing greater uncertainty are more likely to engage in search by deviating from their existing practices (March and Simon, 1958; Greve and Taylor, 2000). These two arguments are not necessarily compatible, since the network structure that increases exposure to alternatives may differ from the structure that increases uncertainty. Nevertheless, both arguments suggest that a firm's network structure will influence its exploratory behavior.

Accounting for Network Effects on Competence Development

The performance implications of a firm's network structure may also reflect different patterns of competence development across network positions. Competence is important for linking network structure to performance since even if a given network configuration aids the firm in identifying valuable strategic practices, the firm will profit from this advantage only when it can execute these practices proficiently. Nevertheless, we know very little about how external networks influence a firm's development of internal competencies. What little work has considered competence at all has generally done so by focusing on external competencies. For instance, Powell, Koput, and Smith-Doerr (1996) highlight that a firm's network position may grant it an advantage in developing competence at managing external network relationships. The question that remains, however, is whether external network structures may influence the speed at which firms develop competence not only at managing external partnering relationships, but also at implementing key practices and strategies within the firm.

We propose that network structural effects on competence may follow from the effects on exploratory search that we have argued for above. A firm's competence with a strategic practice is a function of the experience it accumulates with that practice over time (Nelson and Winter, 1982; Argote and Epple, 1990). Competence improves through more exploitative forms of search (March, 1991), as the firm repeatedly makes minor organizational adjustments that refine the core routines underlying a practice (Levinthal and Marino, 2015). However, competence declines when firms depart from these routines, due to negligence or to resource constraints (Haunschild, Polidoro, and Chandler, 2015). Such is the case when firms engage in exploratory search, since

the firm's choice to deviate from the current practice prevents it, at least temporarily, from further enhancing its competence at that practice.

Accounting for Partners' Adaptive Biases

A final reason to include adaptive learning in network models is because failing to do so ignores the potential for adaptive biases among partners, and therefore may lead us to ignore some pitfalls inherent in learning from the network. The information a firm receives from a partner will reflect that partner's prior adaptive trajectory. This includes the partner's prior attempts at exploration, the partner's prior competence development, and the partner's adaptive biases. If partners display an adaptive bias, then the information acquired by the focal firm from these partners will be biased also. For example, a partner may display the "information restriction" bias, which refers to when an actor responding to performance feedback gathers too little information on a practice to make reliable inferences about its true value (Denrell and March, 2001). Yet this partner may still make recommendations to the focal firm regarding the practice. Current theory does not consider how adaptive biases embedded in network information may harm a focal firm's ability to benefit from its network position. For example, we do not know whether information in open networks, while more diverse, may also be more reflective of these biases. Thus, without better accounting for adaptive learning, we may misunderstand the relative costs and benefits of acquiring information from the competing network structures.

THEORETICAL MODEL

The verbal arguments above suggest the importance of including adaptive learning in network models, but do not offer precise predictions for network effects on firms' adaptive behaviors and performance outcomes. In this section, we formally augment existing network

models to incorporate adaptive learning, and analyze the implications of this new model in the next section. The development of a formal model is an exercise in theory construction, and the findings produced by analyzing the model using simulation methods may be regarded as theoretical predictions (Harrison, Lin, Carroll, and Carley, 2007). Simulations are especially useful when the conceptual model underlying a theory involves path dependent processes or complex interactions among agents (Davis, Eisenhardt, and Bingham, 2007). Our model involves both: a firm's adaptive trajectory is subject to path dependent outcomes that include adaptive biases (Denrell and March, 2001); and each firm's adaptive trajectory is influenced by its partners'. Thus, a simulation analysis is ideal for theory construction in this paper.

Modeling the Network Structure

We start by describing the networks in our model. Extant network models conceptualize the defining feature of network structure as "clusters of dense connection linked by occasional bridge relations between clusters" (Burt, 2005: 12). We adopt this conceptualization. To implement it we initialize a disconnected caveman graph, which comprises a set of fully connected cliques such that no ties exist across cliques (Watts, 1999). Next, we follow prior work by randomly rewiring a proportion of the ties in this disconnected caveman graph to create interconnected clusters (Reagans and Zuckerman, 2008; Fang, Lee, and Schilling, 2010).

We operationalize the network to reflect broadly the characteristics of empirically observed networks. In particular, networks in the model are generated using an initial disconnected caveman structure with 100 firms networked in 20 fully connected cliques, where each clique has five members. Ties are then rewired with a probability of 0.125. This process produces graphs with properties that reflect key characteristics of the empirical networks

observed by Davis, Yoo, and Becker (2003); Schilling and Phelps (2007); and Tatarynowicz, Sytch, and Gulati, (2016). The simulated networks have an average degree of four, an average density of 0.04, a measure of community structure averaging 0.70, and an average clustering coefficient of 0.40. Figure 2 displays a representative network from the model.

Our independent variable of interest is the degree of network closure. We follow prior

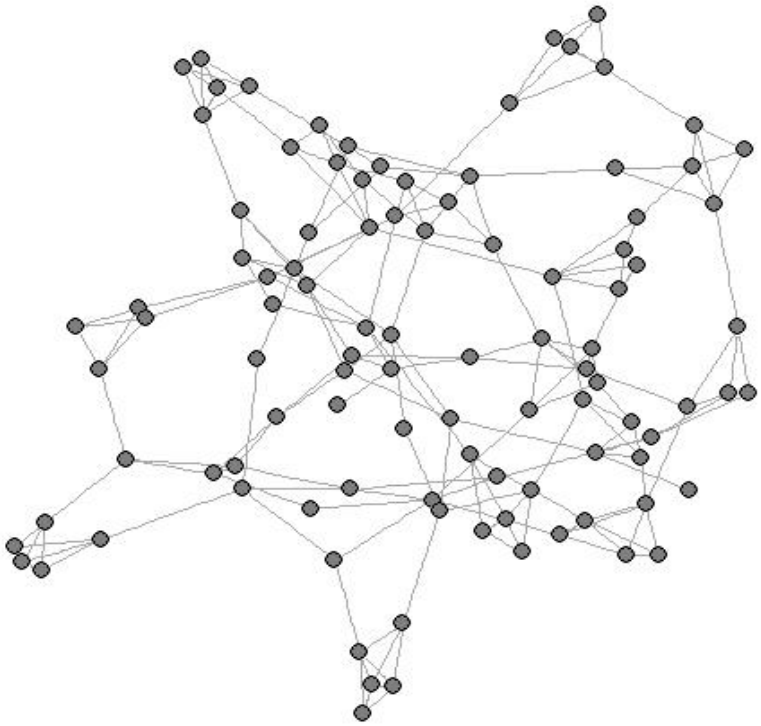


Figure 2. Representative simulated network

work by measuring closure as ego-network density (Reagans and Zuckerman, 2008; Gargiulo, Ertug, and Galunic, 2009), computed as the number of ties that exist between the firm's partners divided by the total number of possible ties that could exist between these partners.

Modeling the Task Environment

In this section we describe the task environment in which firms in the model operate. We base our conceptualization of the task environment on Haunschild's (1994: 391) assertion that

the critical organizational problem from network perspectives is the process through which a firm's interorganizational linkages influence its "practices, structures, and major strategic decisions". We therefore ground our description of the model in a firm's choice of which strategic practice to pursue in a given period. For example, consider a firm deciding on a growth strategy. There will be numerous strategic options, only some of which may be known to the firm. For instance, the firm may be aware of several acquisition strategies it could use, but may be less knowledgeable of organic growth strategies. The firm may learn of new strategies by communicating with its network partners or by engaging in exploratory search. Finally, the firm's performance in each period is jointly determined by the potential value of the strategy it pursues and its competence at implementing that strategy.

Formally, we assume a task environment in which there are *N* potential strategies. Each firm may pursue one strategy in each period. At the start of the simulation, the existence and values of the potential strategies are unknown to the firm. For each strategy *n*, there exists some maximum performance level that can be attained with the strategy given the industry specific opportunity structure. The potential value v_n of each strategy is randomly assigned at the start of the simulation from a symmetric beta distribution. Specifically,

$$v_n \sim beta(2,2). \tag{1}$$

This distribution displays a unimodal shape resembling the normal distribution, but takes its mean at 0.5 and is bounded between zero and one.

While the potential value of a strategy is determined by industry constraints, the value the firm actually realizes from using that strategy will vary. First, there will exist some variation in returns from the strategy across different time periods. Second, there will exist some variation in

returns due to differences in firms' competence in pursuing the strategy. Formally, let e_{nt} represent the firm's realized return from implementing strategy *n* at time *t*. Then,

$$e_{nt} = \theta_{nt} v_n, \tag{2}$$

where θ_{nt} is the random component. In line with prior models (Levinthal and March, 1981; Denrell and March, 2001), we assume that the mean of the random component increases with competence, while the variance of the random component decreases with competence. Formally, let c_{nt} represent the firm's competence with strategy *n*. Then, the random component θ_{nt} is given by a draw from a beta distribution with mean c_{nt}, and standard deviation $\frac{1}{10}(1 - c_{nt})$. We choose the beta distribution because it bounds θ_{nt} between zero and one, restricting the maximum return from a strategy to its potential value.[1]

Modeling Competence Development

Competence develops through experiential learning (Argote and Epple, 1990). Each time a strategy is used, competence may be built as the firm engages in exploitative experimentation to implement new micro-practices and routines that might better align with the strategy (Levinthal and Marino, 2015). However, competence may also deteriorate, during periods in which the organizational routines that underlie a strategy aren't maintained (Nelson and Winter, 1982; Argote and Epple, 1990). For instance, a Silicon Valley tech company may become more competent at implementing an organic growth strategy over time, as it incrementally improves its tactics for recruiting from local universities. But devoting organizational resources to university

[1] Because a beta distribution is not traditionally stated directly in terms of its mean and variance, specifying the exact distribution required a transformation.

outreach simultaneously detracts from the firm's ability to pursue acquisition-based growth strategies in future periods, since the resources used to develop recruiting skills could have been used to build skills at evaluating acquisition targets instead.

Based on this intuition, we assume that competence improves in periods that the firm chooses to use the strategy, but deteriorates in periods the strategy is not chosen. Formally,

$$c_{nt} = c_{nt-1} + \varphi(1 - c_{nt-1}) \quad \text{if the firm chooses strategy } n \text{ at time } t\text{, and} \tag{3}$$

$$c_{nt} = (1 - d)c_{nt-1} \quad \text{if it does } \textit{not}. \tag{4}$$

The parameter φ represents the learning rate, and the parameter d represents the rate at which competence deteriorates when a strategy is not pursued. The learning rate φ will be lower in contexts where core production technologies are either not well understood or are constantly changing, but higher when production technologies are simple and stable. The deterioration rate d will be higher in contexts where strategic routines are harder to maintain, such as when turnover is high or when the effectiveness of routines depend on many actors who must execute interdependent subtasks. Both parameters may take values ranging from zero to one. This model of competence building and deterioration is analogous to standard learning and forgetting curves (Argote and Epple, 1990), and broadly reflects models of competence development in prior formal work (Denrell and March, 2001; Rhee and Kim, 2015).

Modeling Value Identification

In each period, the firm selects a strategy to pursue. In depicting the organization's decision process, extant network models typically assume that a firm will attempt to selected strategies that best allow it to achieve its goals. In our model, this amounts to assuming that a

firm will generally select the strategy it believes will best enhance organizational performance. These beliefs are shaped by the firm's value identification process, which we detail here.

Extant network models hold that a firm will attempt to identify which strategy is the most valuable by forming estimates for known strategies using information from its network partners (McEvily and Zaheer, 1999). Uncertainty plays a key role in deciding how much weight firms assign to social information when forming these estimates. Firms are more likely to rely on social information when perceiving higher uncertainty (Haunschild, 1994; Podolny, 2001), but are more likely to rely on their own internal estimates as uncertainty is resolved (Rao, Greve, and Davis, 2001; Strang and Macy, 2001). We leave this assumption intact, but add the insight from organizational learning research that the firm's internal estimate will reflect performance feedback from its historical experiences with the alternative (Cyert and March, 1963). Therefore, to augment extant models we assume that the firm's evaluation of each alternative is formed (1) socially by incorporating information acquired from its network partners, and (2) experientially through trial and error learning. Formally, the firm's overall estimate for each alternative is calculated as a weighted average of the experiential and social elements of learning, where the weight given to each element is contingent on the degree of uncertainty u_t experienced by the firm at the time. Formally, for each time period *t*, let TE_{nt}^{i} represent firm *i*'s overall estimate of the value of the nth alternative. Then,

$$TE_{nt}^{i} = (1 - u_t)E_{nt-1} + u_t S_{nt}, \tag{5}$$

where E_{nt-1} represents the experiential portion of learning, and S_{nt} represents the social portion. We explain in detail each element of this equation in the paragraphs that follow.

The experiential portion, E_{nt-1}, reflects the firm's sense-making process that evolves through the use of performance feedback (Levitt and March, 1988). As its experience with a strategy accumulates, the firm gains knowledge concerning its potential value. In line with this intuition, we calculate the firm's experiential estimate for a strategy as the mean return from all prior periods in which the strategy was chosen (Posen and Levinthal, 2012). If the firm has no experience with the strategy then E_{nt-1} is zero. Note that the firm observes only the realized value of the strategy but not its potential value. Since the realized valued is subject to various sources of randomness, ambiguity concerning the strategy's true potential may persist overtime.

The social portion, S_{nt}, reflects the role that social information plays in shaping how the firm evaluates a strategy. This component is formed as the firm seeks out advice from its network partners. In each period, the firm randomly selects one partner and records the partner's estimates for all strategies that the partner is aware of. This may expose firms to new strategies, or to additional information on known strategies. Over time, the firm may collect information from multiple partners concerning the same strategy. If so, the firm forms its social estimate for the strategy by averaging the most recent estimate received from each partner. Formally,

$$S_{nt} = \frac{1}{|K|}\sum_K TE_{nt^*}^k, \tag{6}$$

where K is the subset of the firm's network ties that have given the firm information on strategy *n*, and $|K|$ represents the cardinality of K. Finally, t^* represents the most recent time period that the focal firm received information from partner *k*. When K is empty, S_{nt} is 0. Note that partners do not consider the focal firm's network position prior to transferring information. Thus, our model is operationalized for contexts where structural correlates of trust do not determine

information transfer. This is desirable since it allows us to ensure that common explanations based on trust do not drive the performance benefits of network closure derived in the model.

Firms give greater weight to social information when perceiving higher levels of uncertainty u_t. Existing network models are concerned with forms of uncertainty involving organizational questions such as which resources to employ, which markets to enter, and which strategies to enact (akin to what Podolny calls egocentric uncertainty). Uncertainty is thought to be higher when firms are less able to identify an ideal course of action. Podolny (2001: 37) provides an example using an automobile manufacturer, arguing that uncertainty is higher when the producer is unable to decide "which hiring decisions, supplier relations, and production choices will result in a vehicle that is perceived by some set of buyers to provide considerable value". Podolny's (2001) depiction of uncertainty centers on the agent's struggle to optimize over its choice set, highlighting that uncertainty is lower when it is clear which decisions "will *best* enable the producer to realize" market opportunities (pg. 37)(emphasis added). We adopt this conceptualization and assume, therefore, that a firm perceives a lower level of uncertainty to the extent that the estimated value of one strategy appears to be higher than others. Formally,

$$u_t = 1 - [\max(TE^i_{nt-1}) - mean(TE^i_{nt-1})]. \quad (7)$$

Modeling Strategy Selection (Accounting for Exploratory Search)

Extant network models assume that a firm will select the strategy it estimates to be the most valuable at the time (McEvily and Zaheer, 1999). We augment this assumption to account for the notion of exploratory search in the organizational learning literature. The organizational learning literature concedes that firms show a strong preference toward selecting the strategy believed to be the most lucrative (Cyert and March, 1963; Tripsas and Gavetti, 2000). This literature adds,

however, that when existing information provokes doubt in the decision problem, firms may pursue strategies with lower expected returns to learn via exploratory search (Greve and Taylor, 2000). To capture this intuition, we employ the Softmax algorithm (Posen and Levinthal, 2012; Stieglitz, Knudsen, and Becker, 2016). This specification assigns to each strategy a probability of selection proportionate to the perceived value of that strategy *relative* to others in the current period. Strategies with higher perceived values are more likely to be selected, but all strategies have a nonzero probability of selection. Formally, the probability p_{nt} that the firm selects alternative *n* in time *t* is

$$p_{nt} = \frac{\exp(25TE_{nt}^{i})}{\sum_{N}\exp(25TE_{nt}^{i})}. \tag{8}$$

A larger coefficient of TE_{nt}^{i} reflects a stronger propensity to select the strategy with the largest expected value. The coefficient 25 indicates moderately strong preference for implementing the strategy with the highest expected value. This choice is consistent with prior work which typically operationalizes the Softmax equation with coefficients ranging from one to 100.

MODEL ANALYSES AND PREDICTIONS

We now present simulation analyses of the model. The analyses are displayed in three parts. First, we report predictions from the model relating network closure to competence development and value identification, and consequently to overall performance. Second, we analyze the model to uncover the mechanism underlying these relationships. Finally, we present contingencies affecting the size and duration of performance advantages in closed networks.

Each set of analyses reflects average measures across 1,000 runs of the simulation model, where each run uses a different randomly generated network. A simulation run lasts 100 periods, which we found to be sufficient to characterize the model's behavior. Firms begin the simulation

without information on any of the strategic alternatives, and are randomly assigned an initial strategy to pursue. The firm's initial competence with this strategy is randomly drawn from the interval [0.02, .98]. The firm's competence with all other strategies is initialized as zero. In the base analyses, the learning rate (φ) is set at 0.1 and the competence deterioration rate (d) at 0.05. These parameters are later allowed to vary.

For ease of exposition, we term the strategy a firm estimates to be the most the valuable in its awareness set at a given time as its *identified strategy*. For example, a firm may be aware of two growth strategies, one organic growth strategy and one acquisition strategy. If the firm estimates the organic growth strategy to be worth $100 million, and estimates the acquisition strategy to be worth $50 million, then the organic growth strategy is the firm's identified strategy. Since each firm is randomly assigned one strategy at the start of a simulation run, this initial strategy is by default the firm's identified strategy at the beginning.

The Conflicting Effects of Closure on Value Identification and Competence Development

Our main findings concern a learning tradeoff inherent in network closure between value identification and competence development, and the performance implications of this tradeoff. Prior work has focused on how open networks facilitate learning by granting firms access to information that may enhance value identification (McEvily and Zaheer 1999; Podolny, 2001). Our findings extend beyond this work. We predict, in line with prior theory, that open networks enhance value identification, but add that the same network structure may simultaneously restrict competence development, undermining a firm's ability to benefit from the very strategy it identifies as the best. Thus, reducing network closure involves the tension between learning

which strategic practices are the most valuable and learning how to implement them effectively. This learning tension is demonstrated in Figure 3.

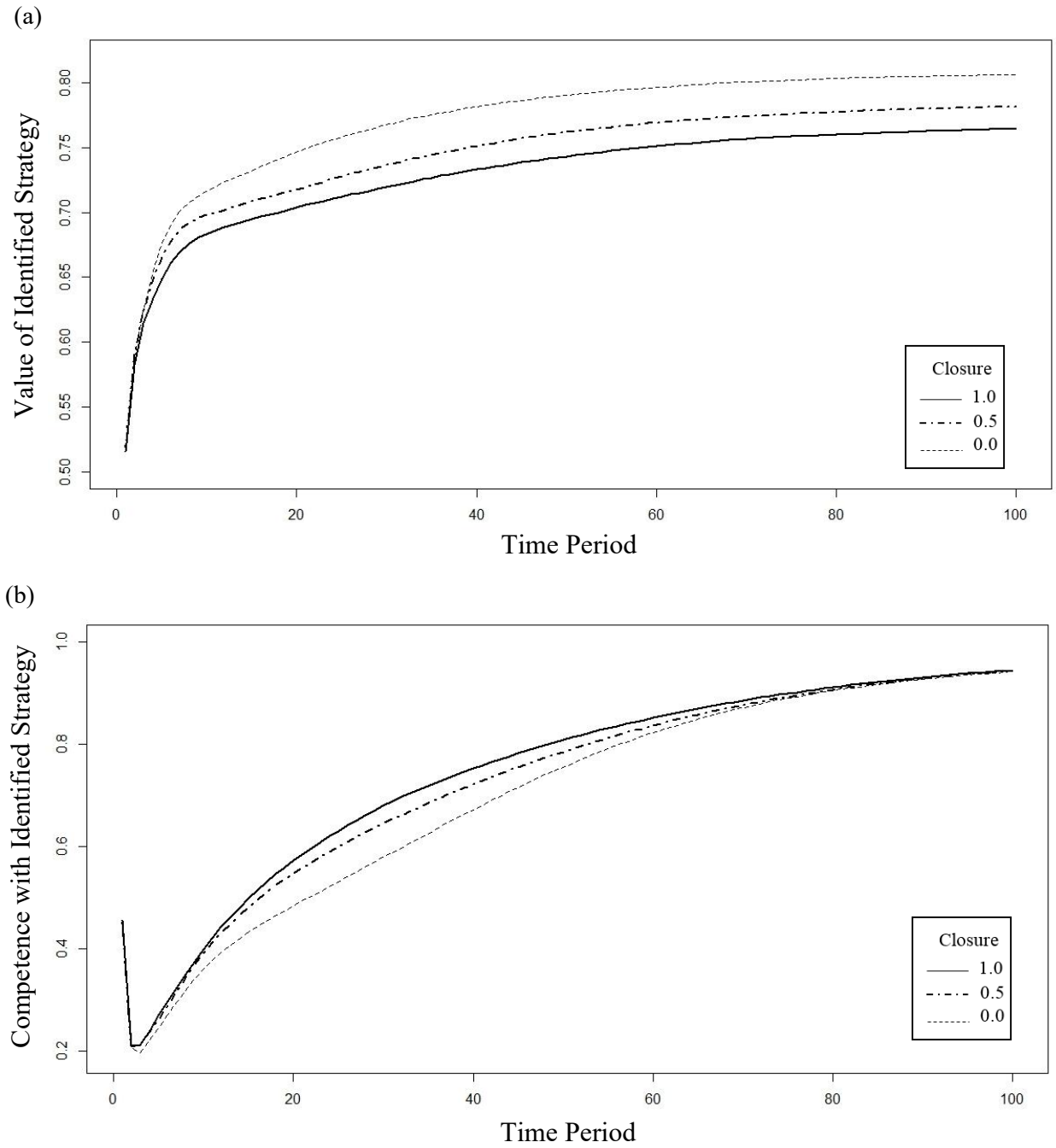
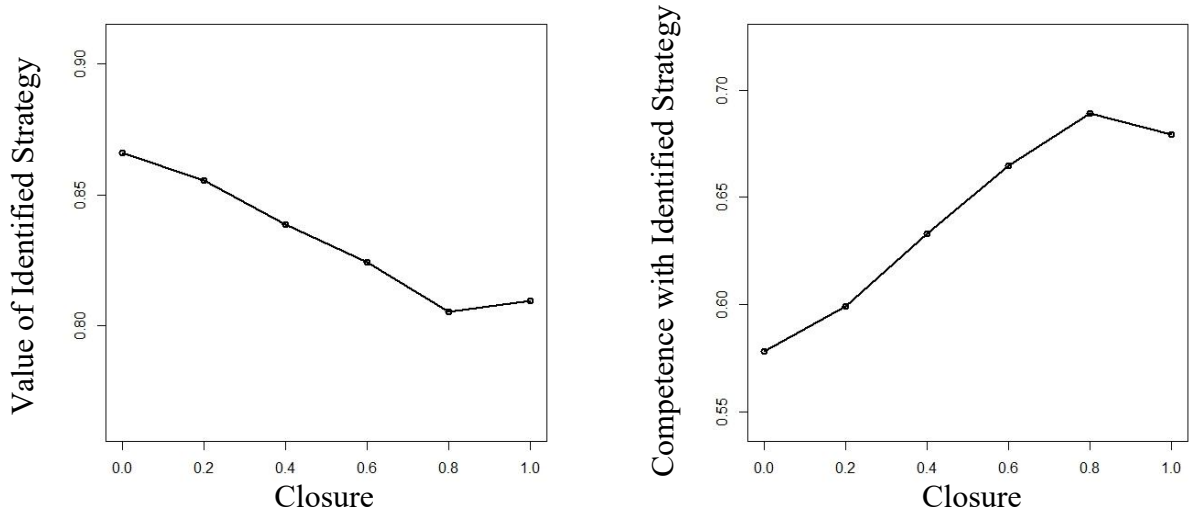


Figure 3. Effects of network closure on competence development and the efficacy of firms' value identification processes

Figure 3a depicts the relationship between closure and the efficacy of firms' value identification processes. Since a firm may observe performance benefits from a strategic practice without knowing its true value, the critical aspect of value identification is whether the practice a firm believes to highly valuable is actually one of the more valuable alternatives. We, therefore, measure the efficacy of a firm's value identification process as the true potential value of the firm's identified strategy. Figure 3a shows that open networks enable firms to identify more valuable strategies, while closure correspond to less efficacious value identification. Figure 3b plots the relationship between closure and firms' competence with their identified strategies. The figure shows that firms in open networks display slower competence development for the strategies they have identified as the most effective.



* The random generation of networks occasionally produces closure measures with too few observations to construct reliable estimates. To account for this we round each firm's closure to the nearest 0.2 prior to producing the graphs.

Figure 4. Effects of network closure on competence development and the efficacy of firms' value identification processes (t = 30)*

For example, at t=30 (see Figure 4), firms in open networks demonstrate an average competence of 0.57 at the strategies they've identified as the most effective, while firms in closed networks demonstrate an average competence of 0.68 at the strategies they have identified to be the most effective. This represents a 19 percent increase in competence. Thus, while prior literature may be correct in arguing that open networks facilitate more effective value identification, it may be erroneous to assume that this leads to superior performance, since firms may be unable to competently pursue the very strategies upon which this performance advantage is thought to depend.

Figure 5 displays these performance consequences, plotting the average period performance for firms in the model. The results show that, on average, firms in closed networks outperform those in open networks until about period 56. While open networks eventually gain a performance advantage, the results suggest that the competence advantage of closed networks supersedes the value identification advantage of open networks during the early periods.

This finding suggests that the narrow focus on informational advantages in current network theory may be inappropriate. Prior theory predicts that closed networks outperform open networks only when relational factors transfer the information advantage from open networks to closed networks (Aral and Van Alystne, 2010). Examples include cases such as when partners refuse to communicate with actors in open networks due to a lack of trust (Ahuja, 2000), when partners lack the motivation to transfer information in the absence of cooperative norms (Reagans and McEvily, 2003; Vasudeva, Zaheer, and Hernandez, 2013), or when cognitive differences across social boundaries make information transfer and interpretation arduous (Ter Wal et al., 2016). Since the model was operationalized to reflect contexts where these factors do

not disrupt information flow in open networks, our findings show that once adaptive learning is accounted for, closure can lead to superior performance in spite of an information disadvantage.

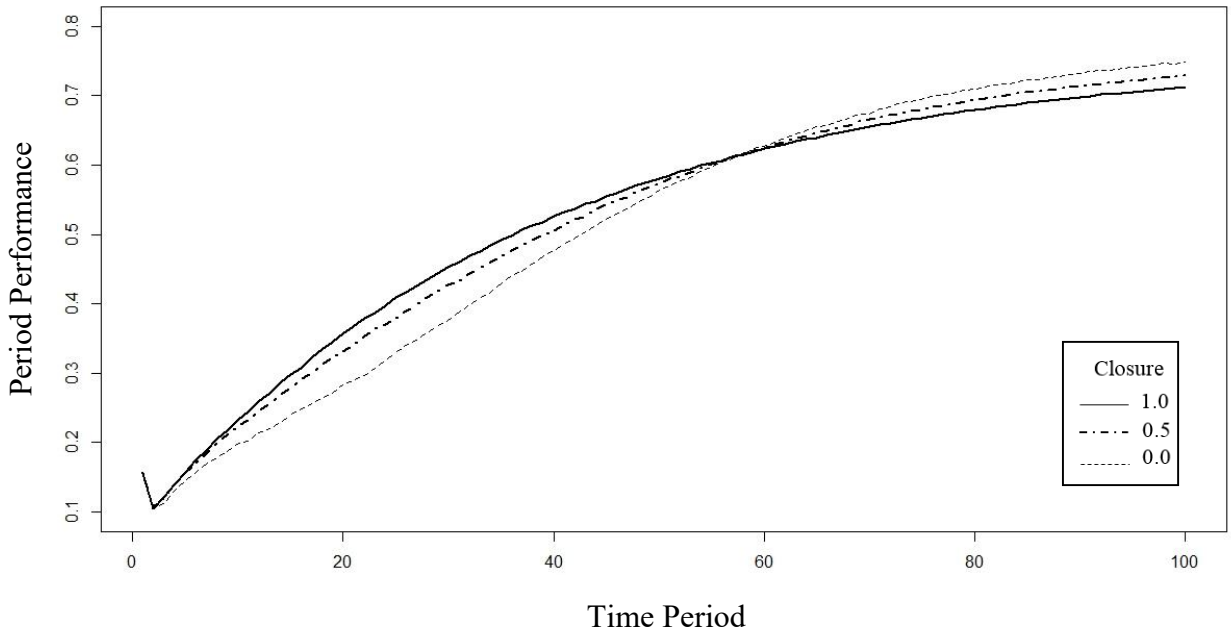


Figure 5. Network closure and period performance

Understanding the Underlying Adaptive Mechanism

In this section, we explain the mechanism producing the learning and performance effects discussed above. Since the effect of closure on the efficacy of a firm's value identification process is well understood, we devote the analysis to understanding the novel effect of closure on competence, and focus on the role that adaptive learning plays in producing this effect. In sum, because of how the network shapes adaptive biases, firms in open networks are less likely to believe they have identified the best strategies, even when they have, and are therefore less likely to execute these strategies with the consistency needed to move quickly up the learning curve.

Closure and uncertainty: The role of partners' adaptive biases. To begin, our model predicts that increased closure leads to lower perceptions of uncertainty (see Figure 6). This finding suggests that although firms in open networks more accurately identify which strategies are the best, these firms hold weaker conviction in their estimates. This finding contradicts prior theory, which predicts that open networks should reduce uncertainty (Podolny, 2001).

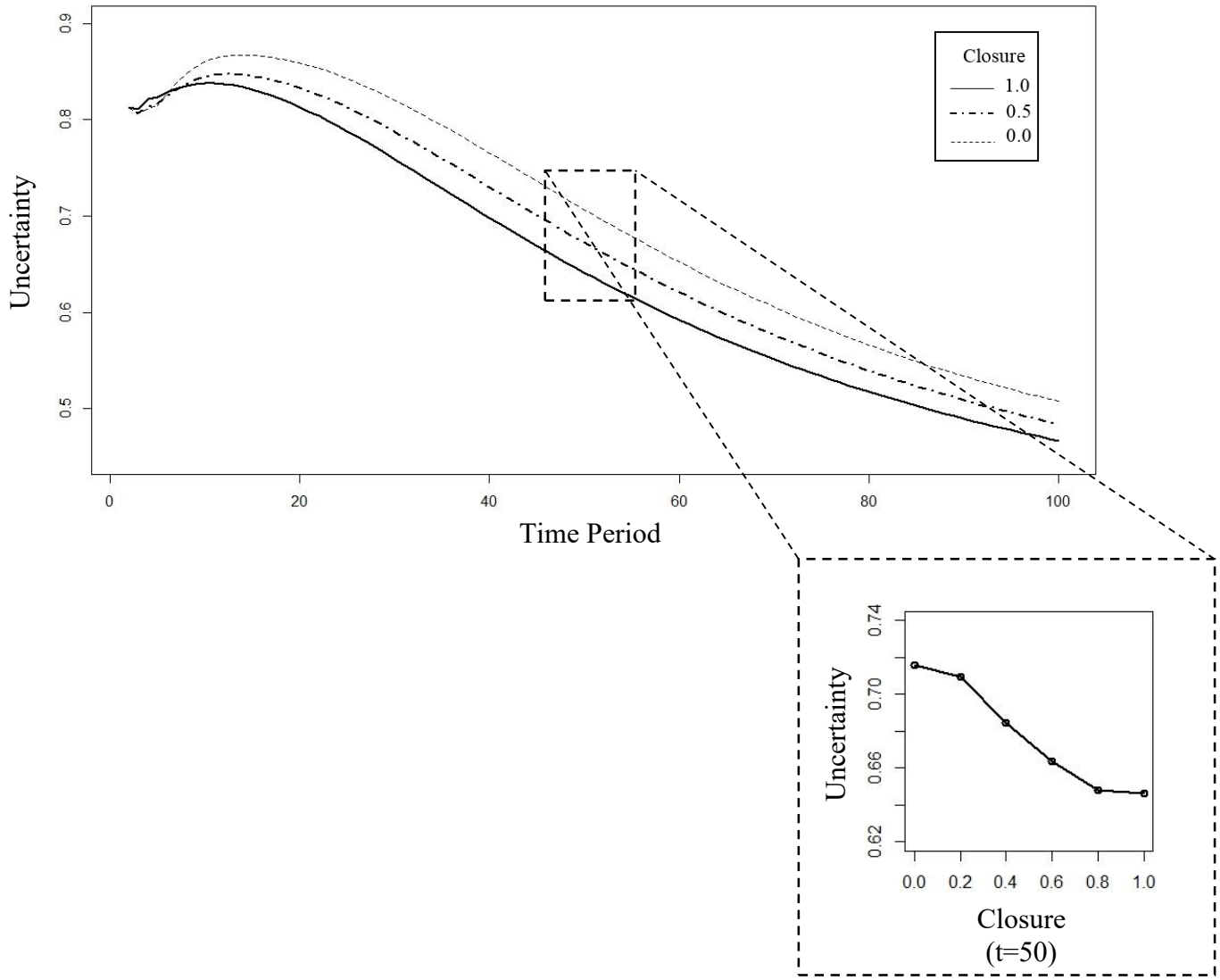


Figure 6. Network closure and uncertainty

The explanation behind this effect relies on organizational adaptation in ways that have not been incorporated in network theorizing. Prior network research has approached the issue of uncertainty from a purely cognitive perspective, thinking only of how firms may synthesize network information to engender confidence in their strategic choices (Podolny, 2001). In contrast, the learning literature holds that uncertainty is resolved not only by analyzing information, but also through organizational action (Cyert and March, 1963). Organizational action produces the information creating the perception of uncertainty, and organizational action produces the information used to resolve it (March and Simon, 1958; Weick, 1979). Moreover, since a firm's perception of uncertainty is shaped by the information provided by its alters, we must attend not only to the focal firm's adaptation, but also to the adaptive paths that partners traverse in producing the information that is ultimately relayed to the firm.

The simulation results reflect this logic, suggesting that open networks foster uncertainty because they allow the adaptive biases held by a firm's partners to persist over time. A firm will perceive less uncertainty in its task environment when it holds a relatively high estimate for its identified strategy—the strategy to which it assigns its highest valuation. Thus, a firm's perception of uncertainty will be higher when it obtains information from partners that underestimate the value of this strategy. Information from such partners promotes uncertainty by preventing the firm from building confidence that the strategy it has identified is in fact the best. In mathematical terms these partners put downward pressure on the firm's estimate for its identified strategy, making the firm's estimate for this strategy less distinguishable from its estimates of less valuable alternatives (see Equation 7 for the mathematic intuition).

The simulation results show that a firm is more likely to be connected to partners that underestimate its identified strategy when the firm is embedded in a more open network. Figure 7 illustrates this effect, plotting the average estimation error by partners for the focal firm's

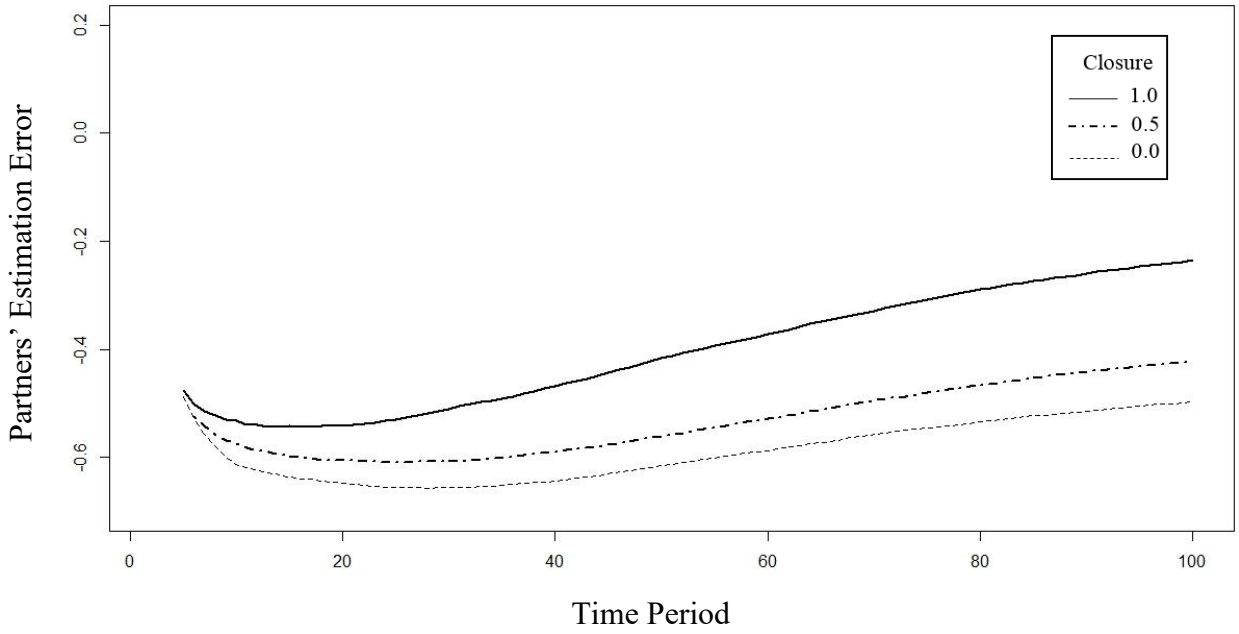


Figure 7. Partners' estimation errors for the focal firm's identified strategy

identified strategy. This estimation error is calculated as each partner's estimate for the strategy minus the true value of the strategy, averaged across all the firm's partners. The figure shows that partners' estimates typically fall below the true value of the strategy[2], and that the degree of underestimation tends to be much higher in open networks.

[2] Some partners may overestimate the strategy. However, overestimation tends to be self-correcting, while underestimation is not (Denrell and Le Mens, 2007). Thus, on average, the effect yielded by partners with underestimation biases is more pronounced.

Of course, uncertainty can be attenuated if partners underestimating the firm's identified strategy increase their estimates for this strategy. However, since these partners are also adaptive learners, if left to their own devices these partners are unlikely to gain new information that will cause them to revise their estimates. When an adaptive learner holds a low estimate for an alternative, it rarely experiments with the alternative any further (Denrell and March, 2001; Denrell and Le Mens, 2007). Thus, for these partners to update their estimates for the strategy, they must be compelled to gain new information on the strategy by an outside force.

Closed networks are more effective than open networks for ensuring that this condition is met. To see why, consider a partner firm, B, that underestimates the focal firm's identified strategy. Each time the focal firm increases its estimate for its identified strategy, B will increase its estimate also (because the focal firm's estimates are included in B's social estimate as detailed in Equation 6). This effect is amplified in closed networks since the focal firm exerts additional influence on B's estimates through shared third parties. When the firm relays its increased estimates to a shared third party, this party is also inclined to increase its own estimate of the strategy, and may relay its new estimate to B. The more shared third parties linking the focal firm to B, the larger the upward adjustment in B's estimates.

This is enough to create temporary differences between open and closed networks in uncertainty. However, over the long term, it is not enough for a partner to obtain positive social information on the focal firm's identified strategy. For changes in uncertainty due to social influence to last, partners such as B must resample the strategy for themselves. This is because B will use social information to inform its estimate of the focal firm's identified strategy only to the extent that B also faces high uncertainty in choosing a strategy (Rao, Greve, and Davis, 2001;

Strang and Macy, 2001) (see also Equation 5). When B's uncertainty is reduced, this partner will rely more on its experiential estimate of the strategy, and this estimate is what will be relayed to the focal firm. A crucial point, therefore, is that because closed networks enable a rapid increase in the positive information that a partner holds for the strategy, these networks better ensure that partners like B resample the strategy before becoming less susceptible to social influence.

Sampling (or resampling) the strategy generally increases such partners' experiential estimates. Since the partner underestimates the strategy, regression to the mean is enough to ensure that resampling the strategy will lead on average to higher estimates. Thus, closure leads to reduced uncertainty because partners underestimating the focal firm's identified strategy are more likely to upwardly adjust their experiential estimates by sampling the alternative for themselves. In contrast, open networks foster uncertainty because they allow the adaptive biases held by partners with low estimates for the focal firm's identified strategy to persist over time.

Uncertainty, exploratory search, and competence. Partners' adaptive biases then lead the focal firm to maladaptive action. Because firms in open networks experience greater levels of uncertainty, these firms are more likely to engage in exploratory search. Even though a firm identifies a strategy to be the most valuable, the firm may not always implement this strategy, but may instead engage in exploratory search, deviating from the strategy believed at the time to yield the highest returns (March, 1991). Figure 8 plots the proportion of firms engaging in exploratory search in each period. We measure exploratory search as each instance in which a firm identifies one strategy to be the most valuable but pursues another strategy instead. Figure 8 shows that firms in more open networks were more likely to engage in exploratory search.

This proposition in some ways reflects the expectations of traditional network thinking, which suggests that open networks expose firms to a larger number of alternatives, allowing these firms a greater possibility of experimentation (Burt, 2005; Battilana and Casciaro, 2012).

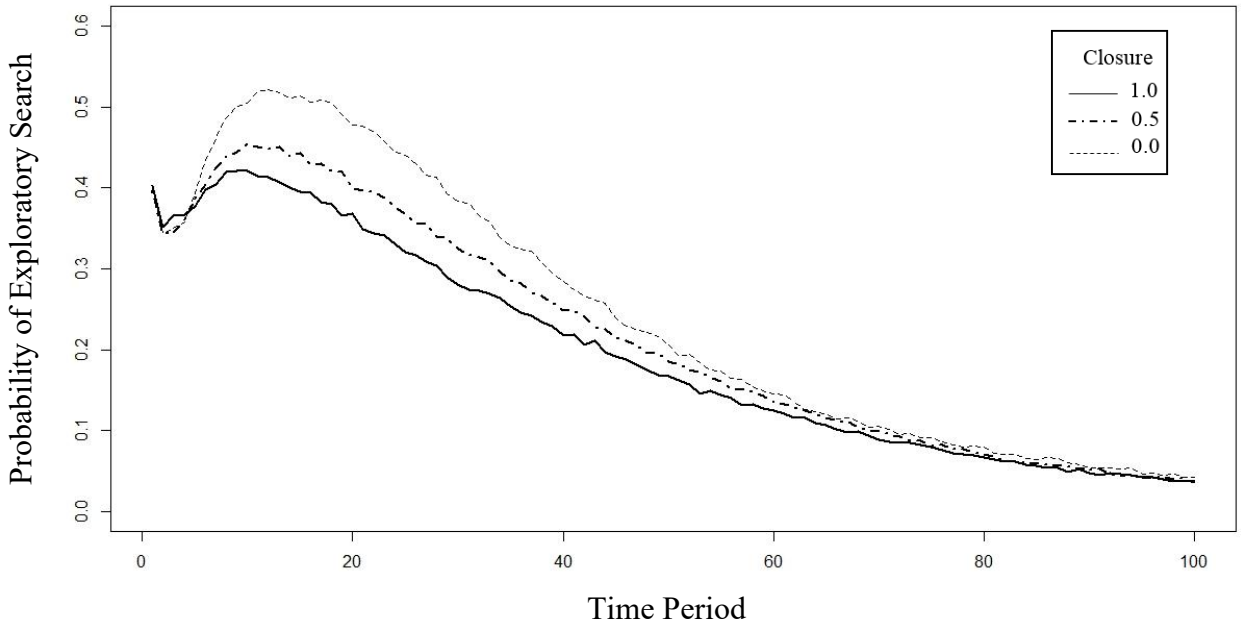


Figure 8. Network closure and exploratory search

However, the effect we propose is distinct in both its causes and its consequences. First, exploratory search in our model is driven more by uncertainty than by exposure to alternatives. In analyses not displayed here, we find very little difference in exposure to alternatives across levels of network closure past period 20. Thus, the differences in exploratory search beyond this period cannot be attributed to differences in exposure to alternatives. Instead, these differences are attributable primarily to greater perceptions of uncertainty by firms in open networks.

Second, the consequences of experimentation in our model are more problematic than prior network thinking has suggested. Existing theoretical accounts view experimentation in open networks as a positive, with very little downside. However, from an adaptive learning

perspective, exploratory search is a double-edged sword (Rivkin and Siggelkow, 2003). Exploratory search may increase the likelihood that a firm discovers highly valuable alternatives, but may be harmful when it causes the firm to deviate from highly productive alternatives to experiment with inferior ones (Siggelkow and Levinthal, 2003).

Figure 9 investigates which of these consequences emerges in our model, and suggests that exploratory search is generally unproductive beyond the first few periods, particularly for firms in open networks. The y-axis of Figure 9a plots the difference between (1) the potential value of the strategy the firm estimates to be the best at the time, and (2) the potential value of the strategy the firm implements during a period of exploratory search. This figure shows that, after the first five periods, when firms deviate from the strategies they have identified as the best, the alternatives they select tend to hold much lower potential values (shown as larger losses in value). Consequently, exploratory search rarely leads firms to change their beliefs concerning which strategy is the most effective (see Figure 9b). Comparing Figures 8 and 9b shows that firms are much more likely to engage in exploratory search than to actually change which strategies they believe to be the best (their identified strategies), and this effect is more pronounced for firms in open networks. These results are important because they suggest that network information and exploratory search act as substitutes in the firm's value identification process. A firm need not use both. Thus, the propensity for firms in open networks to engage in higher levels of exploratory search may be seen as an adaptive penalty paid for occupying these network positions, rather than as a benefit.

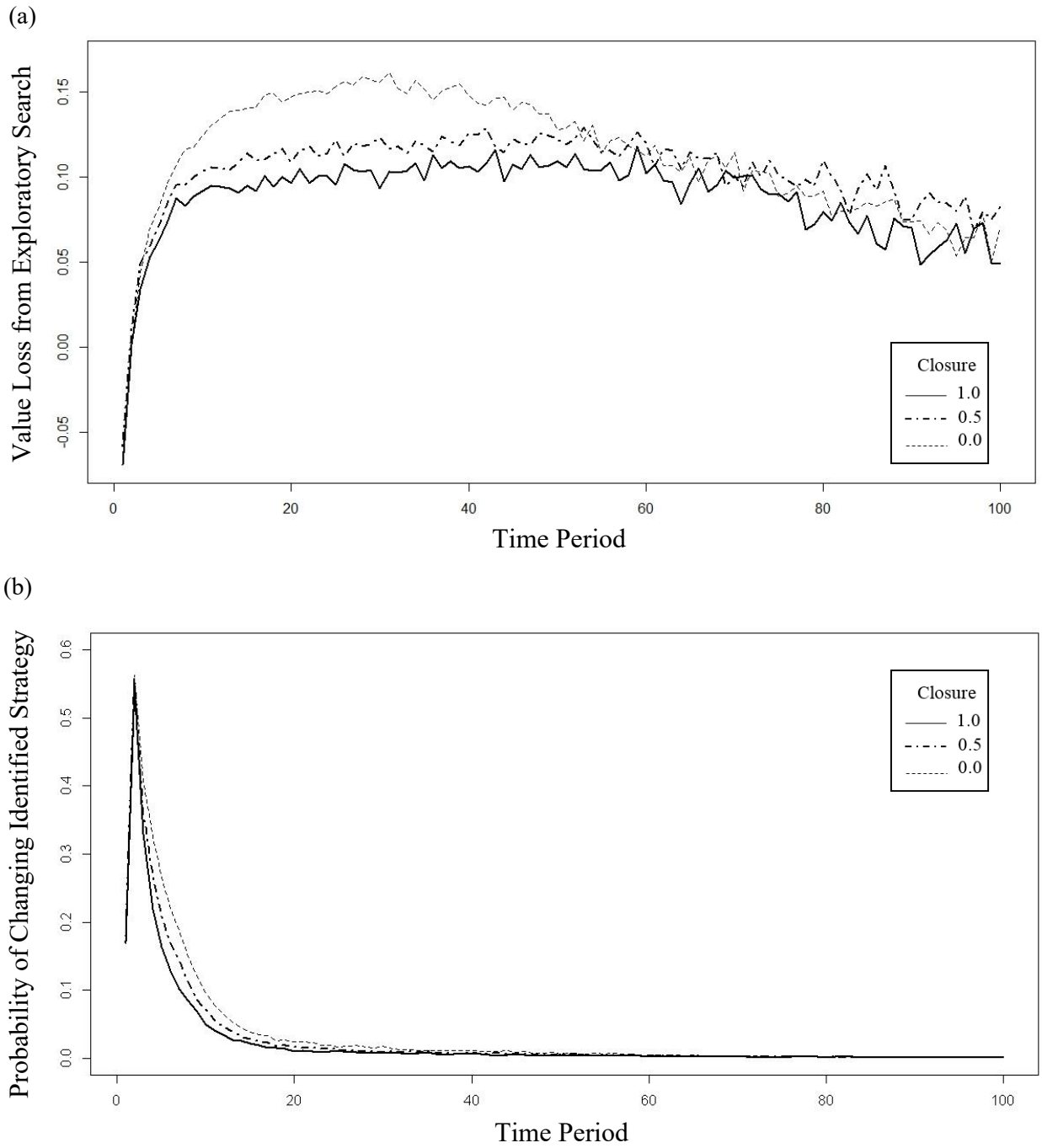


Figure 9. Implications of exploratory search

Firms in open networks pay another penalty for engaging in more exploratory search: they develop competence at a slower rate than firms in closed networks (as demonstrated in Figure 3b). Since firms in open networks are more prone to deviate from the strategies they have identified as the best, these firms are unlikely to implement the identified strategy with the repetition needed to move quickly up the learning curve. This leads firms in open networks to display lower levels of competence at the very strategies that should enable superior performance, resulting in performance advantages for firms in closed networks.

Non-Relational Moderating Effects for the Closure-Performance Relationship

The mechanism identified above also helps us to uncover a novel class of moderating variables in the relationship between network closure and organizational performance. Prior work centers moderating conditions on features of the relational environment in which firms are embedded, focusing on whether the context prioritizes trust and whether shared cognition is needed and present. However, the mechanism discussed above suggests that in addition to these relational factors, the relationship between closure and performance may also be contingent on firms' adaptive learning processes, particularly those features that determine the extent to which exploratory search inhibits competence development. The more detrimental exploratory search for competence development, the stronger and more durable the performance advantage of closed networks should be. We examine this relationship below.

In the model, the influence of exploratory search on competence is reflected in the learning (φ) and deterioration (d) rates (see Equation 3). If we increase the competence deterioration rate d, while holding constant the learning rate, with each instance of exploratory search the firm observes larger losses in competence with its identified strategy. In contrast,

increasing the learning rate, while holding constant the deterioration rate, allows firms to easily regain any competence losses suffered during periods of exploration. Since the performance advantage of closed networks in this paper reflects greater competence losses in open networks due to more frequent exploratory search, we should observe a stronger and longer lasting performance advantage for closed networks when φ is lower or d is higher.

For an intuitive example of this moderating effect, consider the case when d reflects the turnover rate for employees within a firm. When personnel turnover is higher, maintaining competence at key practices requires the constant transfer of organizational knowledge between incumbents and newcomers. Since actors in the firm are more likely to attend to knowledge regarding the firm's current practices (Ocasio, 1997), deviating from a strategic practice will result in greater losses in the firm's competence with that practice when personnel turnover is higher. Thus, higher turnover corresponds to a larger value of d. Network closure should be more beneficial in these contexts. Since firms in open networks are more likely to engage in exploratory search, incumbents in these firms will often transfer to newcomers knowledge regarding more transient strategies. When the firm later executes a different strategy, its employees may lack the organizational knowledge needed to do so proficiently. In contrast, since firms in closed networks are less likely to engage in exploratory search, prior to leaving the firm, incumbent personnel can transfer to newcomers information regarding strategic practices that the firm continues to use in future periods, allowing competence with these practices to be maintained despite higher levels of turnover. Thus as turnover rises, the gap in competence, and therefore in performance, between firms in open and closed networks should increase.

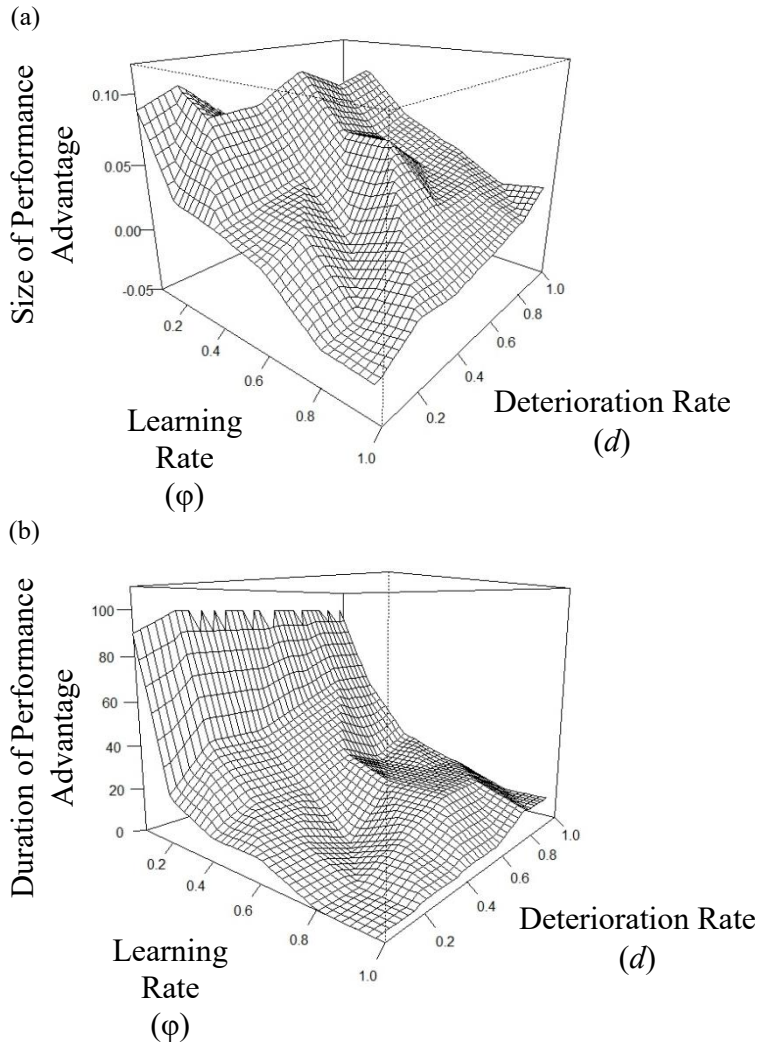


Figure 10. The size and duration of performance advantages for closed networks

Figure 10 shows how this relationship plays out in the simulations. Here, *d* may reflect the turnover rate, or any other variable that when increased results in greater breakdowns in a firm's competence for strategic practices that are not implemented. Likewise, φ may reflect any variable that when increased results in faster competence improvement as a strategic practice is implemented. The y-axis of Figure 10a plots the maximum performance advantage for closed

networks over the course of a simulation run. To measure this advantage, let AP_t^C and AP_t^O represent the average performance at time *t* for firms in closed and open networks respectively. Then size of the maximum performance advantage for closed networks is given by $\max_t(AP_t^C - AP_t^O)$. The y-axis of Figure 10b plots the duration of the performance advantage for closed networks, measured by recording the first time period for which firms in open network outperform those in closed networks (on average).

Figure 10 shows that as the learning rate decreases, or the competence deterioration rate increases the performance advantage of closed networks (1) increases in magnitude, and (2) lasts longer. One exception occurs when learning during periods of exploration is extraordinarily difficult (when φ is low). Since there exists some minimal level of productive exploration needed for performance improvement, increasing the cost of exploration (by increasing *d*) when the learning rate is low leads all firms to perform worse. This results in smaller performance differences between any two firms, and consequently in smaller performance advantages for firms in closed networks. Nevertheless, the general pattern is that increasing the cost of exploration typically leads to larger performance advantages for firms in closed networks. This finding points to a class of learning variables that systematically moderate closure-performance relationships independent of relational considerations.

DISCUSSION

This paper was motivated by the observation that although the literature on interorganizational networks holds learning as a mediating mechanism for the establishment of performance advantages, structuralist perspectives have generally reduced the notion of learning to information acquisition from partners. Current theory underemphasizes the broader set of

adaptive behaviors that constitute organizational learning, and largely ignores how the configuration of a firm's external network influences internal adaptation. Our paper addresses this oversight, and augments prior network models to better account for firms as adaptive learners. In doing so, this paper produces several insights.

Each insight is derived directly from the simulation findings, and therefore can be regarded as a prediction or proposition based on our model (Harrison et al., 2007). First, our model predicts a novel learning tension underlying closure-performance relationships, by highlighting closure's countervailing effects on value identification and competence development. Prior research has assumed that any learning advantages in closed networks must stem from factors that allow for superior information transfer in closed networks. This thinking has led scholars to concentrate efforts on theorizing relational correlates of network structure—such as trust, norms of cooperation, and shared interpretive schema—that are critical for successful information transfer to occur. Although rarely subject to empirical investigation, the conclusion drawn from this work is that closure produces performance advantages only in contexts where these factors play a significant role. Our model suggests that this view is incomplete. Closure promotes competence development, and thus may lead to performance advantages even when information flow in open networks is not restricted.

Second, our model challenges the traditional argument relating network closure to uncertainty. Podolny (2001) argues that open networks are superior to closed networks for reducing uncertainty. While Podolny was unable to test this argument, the analytical precision of our formal model and simulation allows us to investigate the logic of this claim directly and predicts the contrary: open networks are more likely than closed networks to foster uncertainty.

This finding highlights a major implication of our work: understanding the effects of network structure requires accounting for the adaptive trajectories of both the firm and its network partners. Our prediction on uncertainty differs from Podolny's because, while Podolny considers only the information available to the focal firm, we consider also the adaptive paths that partners traverse in producing the information that is eventually passed to the firm. Our focus on partners' adaptive trajectories is in line with recent work in organizational learning that considers how the path dependencies of external actors may influence a focal firm's learning outcomes (Denrell and Le Mens, 2007, 2017; Theeke, Polidoro, and Fredrickson, 2018). However, this learning literature has yet to consider how this influence depends on the network structure connecting external actors to the focal firm. In our model, the path dependencies of network partners are what sustain uncertainty for firms in open networks. In closed networks, partners that underestimate the focal firm's identified strategy are likely to resample the strategy and update their assessments. In open networks, these partners are less likely to obtain new information on that strategy, and instead continue to communicate their low assessments to the focal firm, causing the focal firm to remain uncertain of the value of its identified strategy.

The prediction from our model on uncertainty reflects Burt's (2005: 18) characterization of open networks as fountains of "ambiguous, or distorted information" that expose actors to "contradictory variation." However, Burt makes this point in passing without fully considering its implications. Our model suggests that this idea needs to be taken more seriously because its behavioral consequences may undermine the theorized advantages of open networks. One immediate consequence is a different interpretation of why exploratory search is more frequent in open networks. While the traditional view is that firms in open networks are more likely to

engage in search because of exposure to more alternatives, our simulation findings suggest that search in open networks is also increased due to uncertainty. This is important since, while firms in open networks gain faster access to information, this information may eventually disperse through the network such that actors in open and closed networks are aware of the same number of strategic alternatives. Under such conditions, prior theory expects that the level of exploration in open and closed networks should be equal. Our model suggests that this is not the case. Because uncertainty is higher in open networks, actors in these networks continue to show higher rates of exploration under these conditions, even when further exploration is unproductive.

The third key prediction from our model is that closure can lead to persistent performance advantages under certain conditions. The novelty in this prediction is that these conditions need not depend on relational factors, which suggests a new class of moderating variables for closure-performance relationships. Our model predicts that firms in open networks will observe an advantage when competencies require little in the way of time and effort to develop. In contrast, the model predicts that closure will lead to stronger and more durable performance advantages when competencies are difficult to develop, requiring more time for firms to realize the benefits of their strategic choices. These advantages hold even when firms in closed networks discover less valuable alternatives. Thus, network scholars may turn attention toward gaining empirical traction on unearthing moderators to the closure-performance relationship that center on the relative ease or difficulty of developing organizational competencies. Such moderators may include a variety of factors that extend the learning curve, including technological complexity, decentralized decision structures, organizational turnover, and environmental dynamism.

Our analysis focused on network closure, but may inform network theories more broadly. Here we give two examples. First, the model may speak to the burgeoning literature on brokerage as a public good. This research asks whether alters may benefit (collectively) from their relationships to a broker. Clement, Shipilov, and Galunic (2018) expose a tension underlying this question: brokers may enhance alters' performance by granting these alters access to novel information, but may harm alters' performance by shirking from group activities that require the broker's commitment. Our model suggests a second tradeoff involving brokerage as a public good, which might arise even when the broker's commitment can be guaranteed. Group performance may be undermined not only when members display a lack of effort, but also when coordination failures emerge because interdependent agents cannot predict one another's actions (Puranam, Raveendran, and Knudsen, 2012). Our model suggests that brokers may constrain a group's coordination efforts, since brokers are more likely to vary how they perform their core activates (e.g., due to exploratory search). This inhibits coordination, even when brokers are fully committed to the group, since the broker's changes must be constantly anticipated by (or communicated to) other group members. The conceptual implication is that forming theoretical predictions regarding brokerage as a public good may require considering how the broker's adaptive tendencies align with coordination demands of the group's tasks.

Second, our model informs work on collective learning in social networks. Work in this domain emphasizes the importance of network configurations that enable the dispersion of information and behaviors across the entire network, but also posits that this dispersion should occur at a moderate rate to preserve diversity in the system and prevent early convergence on suboptimal solutions (Uzzi and Spiro, 2005; Lazer and Freidman, 2007). This work typically

treats brokerage ties as structural devices that increase the speed of convergence to a solution (Fang, Lee, and Schilling, 2010). Our model adds to this literature by suggesting that brokerage ties may also slow the rate of convergence to a solution. While brokerage ties increase the rate at which exposure to solutions spreads across the network, these ties may also slow the rate at which the entire network comes to share competencies in enacting solutions. Differences in competences can result in different returns to the same practice across actors, leading to the possibility of continued search for alternatives. Since brokerage ties may both introduce and limit practice diversity in the system, our model may help scholars gain a deeper understanding of how these countervailing effects influence collective learning outcomes.

As with all theory development, our predictions depend directly on the applicability of the model's assumptions. However, to reduce the likelihood that the findings are particular to the minutiae of the model's construction, we examined the sensitivity of our results to a number of alternative modeling specifications and parameter settings. First, we used Burt's (1992) constraint measure as an alternative measure of closure. Second, we tried different distributions for the values of alternatives from which firms choose (see Equation 1). Third, we employed a fractional updating approach that allowed firms to weigh recent performance more heavily, rather than assuming that firms weigh all prior performance feedback equally (as is implied by a simple average). Fourth, we tried different coefficients for Equation 8 that are consistent with the assumption that firms are more likely to implement alternatives with higher expected values. Finally, we examined the model using a number of different network generating processes. In each of these additional specifications, the results lead to the same general conclusions.

Our model produces new insights concerning the linkages between network structure, adaptive organizational learning, and firm performance. These insights suggest a new path for research to further elaborate the performance implications of network structure and internal organizational adaptation. Ultimately, our paper points to a network theory that better reflects the adaptive learning processes of network actors, and thus provides a foundation for better understanding how a firm's network structure influences its performance outcomes.

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CHAPTER 2

NO BANDWIDTH, NO PROBLEM: CLARIFYING INFORMATIONAL MECHANISMS IN NETWORK STRUCTURAL THEORIES

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ABSTRACT

Informational advantages play a central role in explanations linking actors' network positions to their performance outcomes. This paper assesses two widely held assumptions regarding the informational characteristics underlying network based performance advantages. In particular, network theories often hold the assumption that information from the network is more useful when more diverse, and when acquired at a faster rate. Using a simulation analysis that formalizes extant network models, this paper presents evidence that highlights gaps in this logic. First, this paper finds that actors in open networks who are exposed to redundant information may outperform actors in similar networks that are exposed to more diverse information. Second, this paper finds that a large subset of actors in open networks benefit more from network information when this information is acquired slowly rather than quickly. The consequence of these two results is that the strongest long run performance advantages from open networks may occur in precisely the social contexts thought most incompatible with open networks, strong bandwidth tradeoff context—contexts where small increases in structural openness result in large decreases in tie bandwidth because relational factors such as trust and shared cognition are strong preconditions for information transfer between partners.

INTRODUCTION

Social network arguments often begin with the assumptions that information from the network is more beneficial for an actor's economic performance when it is more *diverse* and when the actor can acquire novel information *faster*. This assumption is central to Burt's (1992) seminal argument that an actor can increase its performance by arranging its ties in more structurally open ego networks—networks in which fewer of the actor's network partners are

connected to each other. The rationale here is that a pair of connected actors will generally hold similar bits of information. Thus, an actor can optimize its exposure to diverse information, thereby optimizing its performance, by structuring its social connections to partners who are not themselves connected (Burt, 2005).

While this logic has served as the foundation for scores of empirical studies across the organizational sciences, recent work has questioned the first part of Burt's traditional logic—that more open structures offer more rapid access to diverse information. While Burt's original argument emphasized the *sources* of information, more recent literature focuses on the *bandwidth* of ties connecting an actor to a given information source (Burt, 2005; Aral and Van Alstyne, 2011). Bandwidth refers to the amount of information that is likely to flow through any one network tie in a given time interval. A growing body of research suggests that crafting structurally open networks creates a bandwidth tradeoff (Ahuja, 2000; Tortoriello, Reagans, and McEvily, 2012; Reagans, Singh, and Krishnan, 2015). On one hand, a more open network may connect the focal actor to more diverse sources of information, putting upward pressure on the total amount of diverse information the actor extracts from its network. On the other hand, however, a more open network simultaneously limits the bandwidth of each tie, putting downward pressure on the total amount of diverse information the actor can acquire from any one network partner.

These recent arguments suggest that the link between structurally open networks and diverse information, and therefore performance, may be highly contingent. Burt's original proposition is expected to hold when the bandwidth tradeoff is weak—when even large increases in structural openness results in relatively minor decreases in tie bandwidth. However, when the

bandwidth tradeoff is strong (such as when information is proprietary demanding trust, or highly complex demanding shared cognition, for information transfer to occur), an actor is argued to gain faster access to diverse information from its network partners in a closed rather than an open network (Burt, 2005; Aral and Van Alstyne, 2011). The consequence for performance is that Burt's original proposition is refined to predict that more open structures will enhance performance when the bandwidth tradeoff is weak, but more closed structures will enhance performance when the bandwidth tradeoff is strong (Ahuja, 2000; Aral and Van Alstyne, 2011).

This paper presents a simulation model which demonstrates that even this refined version of Burt's (1992) original proposition may be limited. The existing logic disproportionately prioritizes informational diversity when explaining the informational mechanism through which network structures confer performance advantages. Yet, while informational diversity increases variation in the organizational alternatives a firm is exposed to, informational redundancy may be needed to help firms select from the expansive pool of alternatives. The simulation analysis offers evidence that suggests the need to attend to both uses of information. The model requires no additional assumptions beyond those used in extant network arguments. The model assumes a network structure reflecting Burt's (1992, 2005) stylized depiction of social networks, and adopts the recent conceptualization of network actors as problem solving agents (Shore, Bernstien, and Friedman, 2015; Knoben, Oerlemans, Krijkamp, and Provan, 2018). The simulation analysis produces novel insights by highlighting some unrecognized consequences of existing assumptions, and carefully examining the informational qualities of the highest performing network positions, in a manner that would be difficult in an empirical study and that would not be tractable using verbal arguments alone.

The analysis offers several findings that sharpen our understanding of informational mechanisms in network research (see Table 1 for a summary). The main finding from the model is that, contrary to current thinking, structurally open networks *in the long run* produce their strongest advantage over closed networks when the bandwidth tradeoff is strong, rather than when the tradeoff is weak.

Table 1. Conceptual contributions from the model

Prior Thinking	Finding from Current Model
The benefit of structural openness will be greatest in *weak* bandwidth tradeoff contexts	In the long run, the benefit of structural openness will be greatest in *strong* bandwidth tradeoff contexts
Information from the network is more useful for performance when it is more *diverse*	Actors in open networks that obtain more *redundant* information from their networks outperform actors in similar network structures obtaining diverse information from their networks
The network structure that enables *quicker* access to novel information will be best for performance	Many actors in open networks benefit when the inflow of novel information is *slower*

In explaining the mechanisms producing this finding, the simulation analysis generates two additional insights of equal importance to network thinking. First, the model predicts that actors in open networks perform best when exposed to more redundant information. This finding is important since very little network research acknowledges the importance of redundancy. The little work that does has focused on the need for redundant cognitive schema in the information transfer process, while maintaining the assumption that the actual information being transferred is most beneficial when more diverse (Ter Wal et al., 2016). Second, findings from the model suggest that firms in open networks benefit most from diverse information when this information

is acquired slowly. This lies in contrast to existing network research, which prioritizes fast access to novelty (Aral and van Alstyne, 2011).

THEORETICAL MOTIVATION

Current theory linking an actor's network position to its performance outcomes centers on the bandwidth tradeoff. This section briefly summarizes the literature informing the bandwidth tradeoff, and its shortcomings. To summarize the argument, recent network research improves our understanding of the contextual factors that determine whether open or closed networks grant faster access to informational diversity. However, this work remains limited in its ability to form precise performance predictions in that it focuses overwhelmingly on factors that increase variation in the ideas and practices a firm is exposed to (informational diversity), while overlooking the factors needed to enable selection from this more diverse pool of alternatives (informational redundancy).

The Bandwidth Tradeoff in Prior Literature

The bandwidth tradeoff reflects the recognition that crafting structurally open networks connects a firm to more unique sources of information but simultaneously reduces likelihood of information transfer between the firm and its partners (Aral and van Alstyne, 2011). The tradeoff emerges because, while disconnected partners tend to think and behave differently, the lack of social closure in these networks often results weak ties which may strain information flow (Uzzi, 1996). In other words, the bandwidth tradeoff arises due to relational impediments to information transfer in open networks.

The flow of information may be impeded in open networks for several reasons. The first is a lack of trust. An actor's network partners may resist transferring information to the actor,

either out of fear of opportunism or because incentives for the actor to behave cooperatively are absent (Ahuja, 2000; Vasudeva, Zaheer, and Hernadez, 2013). In such cases, closed networks better facilitate information transfer because they are more likely to engender trust, and to induce the social norms needed to motivate cooperation (Gulati and Gargiulo, 1999; Reagans and McEvily, 2003). Second, the flow of information may be impeded in open networks by interpretive barriers. Information transfer across social boundaries often requires translation (Bechky, 2003; Reagans and McEvily, 2003). Closed networks are more likely to induce the shared perspectives needed for the receiver to translate and interpret the diverse information relayed by the sender (Hansen, 2005; Carnabuci and Diószegi, 2015; Ter Wal et al., 2016). Each of these arguments suggests information exchange benefits for closed networks.

The tension between increasing the diversity of an actor's information sources and increasing the information accessed from any one tie is a general property of network structure (Uzzi, 1996; Burt 2005). However, its importance for predicting whether structural openness allows for more novel information transfer will depend on whether the bandwidth tradeoff is strong or weak (Aral and van Alstyne, 2011). The bandwidth tradeoff is stronger in contexts where small increases in structural openness leads to large decreases in tie bandwidth, such as when trust, social norms, and shared cognition are more important for successful information transfer to occur. For instance, the bandwidth tradeoff may be weak in industries and countries where intellectual property rights are well developed and enforceable. In these settings, a partner need worry less about whether a broker will opportunistically expropriate value from the information exchanged in that relationship, and therefore will be more likely to share information with actors in open networks (Liebeskind, Oliver, Zucker, and Brewer, 1996; Jones, Hesterly,

and Borgatti, 1997). Absent these protections, the bandwidth tradeoff is strong, since firms in open networks would face a harder time convincing partners to share any valuable information.

As a second example, the bandwidth tradeoff may be weaker in industries where technological standards boards encourage a common language for codifying and communicating new developments. In such cases, a shared mental model is less required for information exchange across partners (Hinings, Gegenhuber, and Greenwood, 2018; Dougherty and Dunne, 2011). Absent these standards, firms in open networks are disadvantaged in the information exchange process since these networks may hinder the emergence of a common language and interpretive schema (Dougherty, 1992). To summarize, in settings where the bandwidth tradeoff is weak, open networks should confer access to more diverse information, but in contexts where the bandwidth tradeoff is strong, closed networks are predicted to allow for more novel information transfer than open networks.

Performance predictions are expected to follow directly from this logic, such that the performance benefit of structural openness is thought to be contingent on the strength of the bandwidth tradeoff (Ahuja, 2000; Burt, 2005; Vasudeva, Zaheer, and Hernadez, 2013; Ter Wal et al., 2016). For instance, Ahuja (2000) attributes the poor performance of structural brokers in the chemicals industry to the strong bandwidth tradeoff active in this industry at the time. Ahuja argues that, because competitive intensity in the chemicals industry was high, firms in open networks were unlikely to acquire information from partners who would fear misuse on the part of the focal firm, and that this information deficit was reflected in inferior performance. Thus, Burt's original proposition is refined in light of the bandwidth tradeoff to predict that open

structures enhance performance when the bandwidth tradeoff is weak, but more closed structures enhance performance when the bandwidth tradeoff is strong (Aral and Van Alstyne, 2011).

Reconsidering the Link between the Bandwidth Tradeoff and Performance

Despite the intuitive appeal behind the performance predictions above, these predictions may be limited, in that they consider only one type of informational advantage important for linking a firm's network structure to its performance outcomes. The bandwidth tradeoff accounts for arguments favoring both open and closed networks, which both emphasize informational characteristics that increase variation in the pool of ideas and practices that firms are exposed to. However, neither perspective accounts appropriately for the process through which firms select from this expanded pool of ideas and practices. A main point of this paper, therefore, is that network research overemphasizes the importance of variation enhancing processes (informational diversity), while paying insufficient attention to selection enhancing processes (informational redundancy).

Consider, for example, a software company positioned in an open network in a weak bandwidth tradeoff context. Let us say the firm has a history of producing programs that fill important market needs, but also a history of producing programs plagued with bugs. To fully realize the performance benefits of its software releases, the firm needs an organizational solution for better discovering bugs in code prior to issuing new releases. The firm may leverage information from its network to learn about potential solutions. Since the example assumes that the bandwidth tradeoff is weak, we should expect that the firm is exposed to a larger number of potential solutions than it would be exposed to in a more closed network. However, not all of these solutions will be valuable; some may be worse than the firm's current process. Further, the

firm has no guaranteed way of knowing which solution is best ex-ante. While information from the network may help, the increased exposure to informational diversity may be both a blessing and a curse. The firm, because of its open network, is exposed not only to a greater number of solutions, but also to more varied beliefs concerning the viability of any one solution. This allows for the possibility of "contradictory variation" across partners (Burt, 2005:18). So how does the firm effectively select one from the large number of potential solutions?

This example suggests that the logic implied by the bandwidth tradeoff is incomplete. Simply arguing which network structure exposes firms to greater informational diversity is insufficient for proposing relationships between network structure and performance. If a firm is exposed to more alternatives without a compensating mechanism for choosing from these alternatives, then it is conceivable that the firm will wind up performing worse rather than better (Burgelman, 1991; Barnett and Burgelman, 1996; Siggelkow and Levinthal, 2003). Thus, to form precise predictions relating network structure to performance, we must attend not only to the importance of informational diversity for increasing variation in the practices that firms are exposed to, but also to mechanisms for internal selection amidst increased variation.

Attending appropriately to the selection problem in network predictions suggests the importance of informational redundancy. A wide breadth of organizational research has demonstrated the importance of redundancy in selection processes. Centola and Macy (2007) argue that even after an actor is exposed a new practice, the actor is unlikely to adopt the practice until there is redundant usage of the practice across the actor's network partners. In addition, prior work has shown that firms are favored in selection processes when displaying more redundant performance across time periods (Levinthal and Posen, 2008), when showing

redundancy in organizational form relative to the dominant population of firms in the industry at the time (Carroll and Harrison, 1993), or when displaying greater redundancy in the product categories they produce for (Zuckerman, 2001). This list captures just a sampling of the many approaches for examining selection processes. Regardless of approach, however, prior work demonstrates that an organizational alternative is more likely to be selected when it is characterized by some degree of redundancy.

The simulation analysis presented in this paper demonstrates that informational redundancy is one key selection criterion influencing network outcomes. The model shows that failing to account for the importance of informational redundancy in network structural arguments leads to imprecise performance predictions. In particular, the extant prediction that the performance benefit of structural openness decreases in strong bandwidth tradeoff contexts may hold only in the short run. The model shows that, in the long run, firms in open networks observe their strongest advantages over firms in closed networks when the bandwidth tradeoff is strong. Importantly, this finding does not require importing new assumptions into network models, but reflects instead the unexamined implications of informational redundancy in extant models.

MODEL

Modeling Strategy

Because networks involve complex interactions between social actors, verbal theorizing may overlook important implication of what appear to be simple theoretical assumptions (Macy and Wiler, 2002). Problematically, when these oversights occur, they may go undetected by empirical research, since examining informational mechanisms in network arguments requires gathering all the communications occurring between large numbers of actors over time.

Opportunities to acquire such robust data rarely arise. Simulation modeling offers a means of overcoming these analytical and emperical difficulties, since it allows us to assess the logical validity of complex network arguments through the use of controlled computational experiments (Harrison et al., 2007). Thus the approach taken in this paper is to (1) formalize the assumptions used in extant network arguments, then to (2) simulate the model to determine whether key logical implications of these assumptions have been overlooked in prior work.

The model treats firms as problem solving agents, and the network as a means of acquiring information on potential solutions. A firm's performance is a stochastic function of the underlying value for the solution it has implemented, and firms may share their experience with prior solutions with their network partners. This process is discussed in detail below.

Problems and Solutions

One way of characterizing a firm's value creating activity is to consider the firm's processes for matching organizational problems to solutions. Examples of organizational problems may include the firm's selection of its core strategies, resources, technologies, and product positioning (McEvily and Zaheer, 1999; Podolny, 2001). Implementing poor solutions to these problems generally constrains the firm's productivity, whereas implementing better solutions generally leads to increased performance. Thus, this problem-based approach is broad enough to speak to a wide array of critical organizational decisions that influence the firm's performance outcomes (Nickerson and Zenger, 2004).

Following prior network research, therefore, the model treats firms as agents in search of solutions to an organizational problem (Shore, Bernstien, and Lazer, 2015; Knoben, Oerlemans, Krijkamp, and Provan, 2018). In the model, the firm faces a problem for which there exists N

potential solutions. The returns that the firm receives when enacting a particular solution depend on the underlying value of the solution (v_n) and a stochastic component capturing randomness that may occur across time and across firms (e_{int}). Formally, let r_{int} represent the return that firm *i* observes when selecting the nth solution in period *t*. Then,

$$r_{int} = v_n + e_{int} \tag{1}$$

The expected value of each solution (v_n) is assigned at the start of each simulation run as random draw from the *beta(2,2)* distribution. This distribution takes a unimodal shape resembling the normal distribution, but takes its mean at 0.5 and is bounded between one and zero. The stochastic term e_{int} is determined by a draw from a normal distribution with mean zero and standard deviation 0.05, but the results are robust to different distributional assumptions.

Criteria for Selecting Solutions

In each period, a firm selects what it has evaluated to be the most valuable solution at the time.[3] However, firms lack full knowledge of all the potential solutions or their values. For simplicity, I assume each firm in the model begins with knowledge of one of the potential solutions, which it implements in the first period. This solution is randomly assigned and may differ across firms. Thus, firms will typically begin with relatively poor performance.

The Evaluation of Solutions

A firm may improve its performance as it discovers and selects for implementation a more valuable solution than the one it is currently implementing. However, since the firm lacks

[3] As an alternative specification, to capture the potential for actors to engage in exploratory search, I also model choice as a probabilistic function, where a solution is more likely to be selected the higher its expected value relative to other solutions. This is operationalized using the canonical softmax algorithm, $p_{nt} = \frac{e^{TE_{nt}/(\tau/10)}}{\sum_N e^{TE^i_{nt}/(\tau/10)}}$. The results are robust to this alternative specification.

perfect knowledge concerning the value of potential solutions, these values must be estimated. Network arguments, like most social treatments of choice, assume that an actor evaluates potential choices by attending to both (1) its prior idiosyncratic experiences (experiential information) and (2) to the information and beliefs relayed by other actors in its local social context (social information)(Emirbayer and Mische, 1998). The weight given to each type of information is thought to be contingent on uncertainty (Mizruchi and Stearns, 2001). Actors are more likely to rely on social information when facing greater levels of uncertainty (Haunschild, 1994; Podolny, 2001), but are more likely to rely on their own experiences as uncertainty is resolved (Rao, Greve, and Davis, 2001; Strang and Macy, 2001). I assume, therefore, that the firm's estimated value for each solution is formed (1) experientially through trial and error learning, and (2) socially by incorporating information acquired from its network partners. The firm's overall estimate for each solution is then calculated as a weighted average of the experiential and social elements of learning, where the weight given to each element is contingent on the degree of uncertainty u_t experienced by the firm at the time. Formally, for each time period *t,* let TE_{nt}^{i} represent firm *i*'s overall estimate of the value of the nth solution. Then,

$$TE_{nt}^{i} = (1 - u_t)E_{nt-1} + u_t S_{nt}, \tag{2}$$

where E_{nt-1} represents the experiential portion of learning, and S_{nt} represents the social portion. Each element of this equation is explained in detail in the paragraphs that follow.

The experiential portion, E_{nt-1}, reflects the firm's sense-making process that evolves through the use of performance feedback (Levitt and March, 1988). As its experience with an organizational solution accumulates, the firm gains knowledge concerning the solution's

potential value. In line with this intuition, I calculate the firm's experiential estimate for a potential solution as the mean return from all prior periods in which the solution was implemented (Posen and Levinthal, 2012). This reflects the insight in extant network models that the performance effects of open and closed networks will reflect a firm's "accumulation" of knowledge over time (McEvily, Jaffee, and Tortoriello, 2012). If the firm has no experience with the solution then E_{nt-1} is zero.

The social portion, S_{nt}, reflects the role that social information plays in shaping how the firm evaluates each potential solution. This component is formed as the firm seeks out advice from its network partners in each period. (The exact quantity of information the firm receives from each partner is discussed below). Over time, the firm may collect information from multiple partners concerning the same solution. When this occurs, the firm forms its social estimate for the solution by averaging the most recent estimate received from each partner. Formally,

$$S_{nt} = \frac{1}{|K|}\sum_{K} TE_{nt^*}^{k}, \tag{3}$$

where K is the subset of the firm's network ties that have given the firm information on solution *n*, and $|K|$ represents the cardinality of K. Finally, t^* represents the most recent time period that the focal firm received information from partner *k*, where $t^* \leq t$. When K is empty, S_{nt} is 0. The amount of information that the firm acquires from a partner in a single period is determined by the structure of ties linking the firm to the partner, and the strength of the bandwidth tradeoff. When the bandwidth tradeoff is weak, information flows easily through the network regardless of the local network structure. When the bandwidth tradeoff is strong, the amount of information that can flow between actors in a single interaction is contingent on the number third party ties the actors share (Aral and Van Alstyne, 2011; Reagans, Singh, and Krishnan, 2015). I assume

therefore that, in each period, each network partner transfers only a proportion of its information to the focal firm[4], and that this proportion is a stochastic function of the number of shared ties between them. In the model this means that, in each period, the partner may transfer information on some solutions but not on others. Formally, let β represent the strength of the bandwidth tradeoff. Then, for any solution *n*, the probability that *j* transfers to *i* information on that solution in period *t* is given by,

$$p\_tran_n^{ij} = (1-\beta)^{1-\frac{s_{ij}}{\max(n_i, n_j)}}, \tag{4}$$

where s_{ij} represents the number of shared ties between firms *i* and *j*, and n_i and n_j represent the number of network ties possessed by *i* and *j* respectively. When β=0 the bandwidth tradeoff is weak, and partners transfer all information regardless of the local network structure that surrounds the relationship. As β increases toward one the bandwidth tradeoff strengthens, and successful information transfer becomes more contingent on the number of shared ties between two partners. This formulation reflects all sources of difficulty in information transfer within open networks under high bandwidth tradeoff contexts, including the issue of interpretation. In this specification, information that cannot be interpreted is not transferred at all. This is consistent with the notion that the difficulty of interpretation is correlated with an actor's motivation to engage in the transfer in the first place (Reagans and McEvily, 2003), and with the idea that information that is communicated to an actor but not interpreted is simply lost in translation (Bechky, 2003).

[4] This proportion may include zero, so it is possible that a partner does not transfer any information to the firm.

Firms give greater weight to social information when uncertainty u_t is high. Uncertainty is higher when firms are less able to identify the most valuable solution based on their current estimates. As an example, firms may be aware of several alternative technologies that can be used in a new manufacturing plant, but may find it difficult to determine which technology would lead to the greatest returns. This conceptualization of uncertainty aligns with prior network research. For instance, Podolny (2001: 37) notes that uncertainty is higher when a firm faces difficulty in deciding which resource in a set of known alternatives will "best" enable it to capitalize on market opportunities. Following this intuition, I assume that firms perceive lower levels of uncertainty when there exists one solution that is clearly superior to most others. Formally,

$$u_t = 1 - [\max(TE^i_{nt-1}) - mean(TE^i_{nt-1})], \tag{5}$$

The Network Structure

While all actors may seek out information from their network partners when discovering and selecting solutions, actors will have access to different information based on the network structure that connects them to other agents in the social structure. In modeling network structure, the key aim was to capture the standard view that the defining feature of social structure is "clusters of dense connection linked by occasional bridge relations between clusters" (Burt, 2005: 12). To do so, I initialize a disconnected caveman graph, which comprises a set of fully connected cliques such that no ties exist across cliques (Watts, 1999). Next, I follow prior work by randomly rewiring a proportion of the ties in the disconnected caveman graph (Reagans and Zuckerman, 2008; Fang, Lee, and Schilling, 2010). In specifying the proportion of ties to rewire, the main aim was to operationalize the network to broadly reflect the characteristics of

empirically observed networks. Thus, networks in the model are generated using an initial disconnected caveman structure with 100 firms networked in 20 fully connected cliques, where each clique has five members. Ties are then rewired with a probability of 0.125. This process produces graphs with an average degree of four, an average density of 0.04, a measure of community structure averaging 0.70, and an average clustering coefficient of 0.40. For empirically observed networks with similar characteristics see Davis, Yoo, and Becker (2003); Schilling and Phelps (2007); and Tatarynowicz, Sytch, and Gulati (2016). Figure 11 displays a representative network from the model.

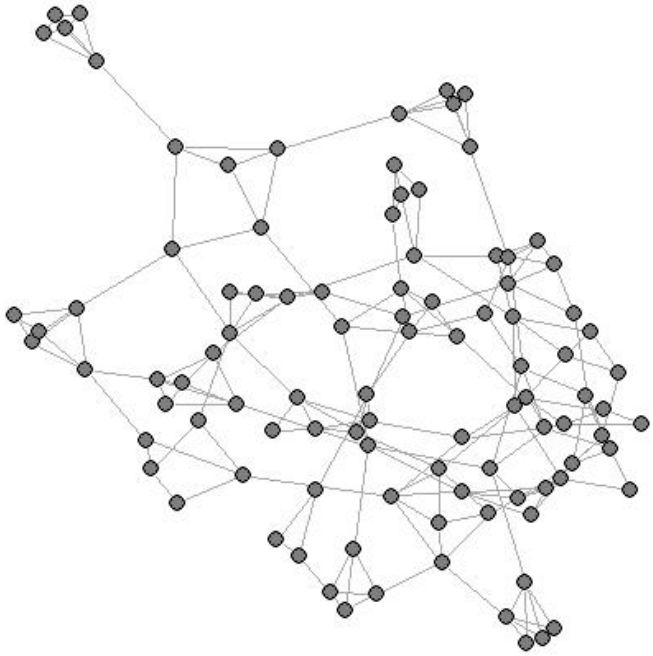


Figure 11. Representative Simulated Network.

MODEL ANALYSES AND PREDICTIONS

In this section, the model is operationalized and the simulated output analyzed to better understand the informational mechanism that links network structure to firms' performance

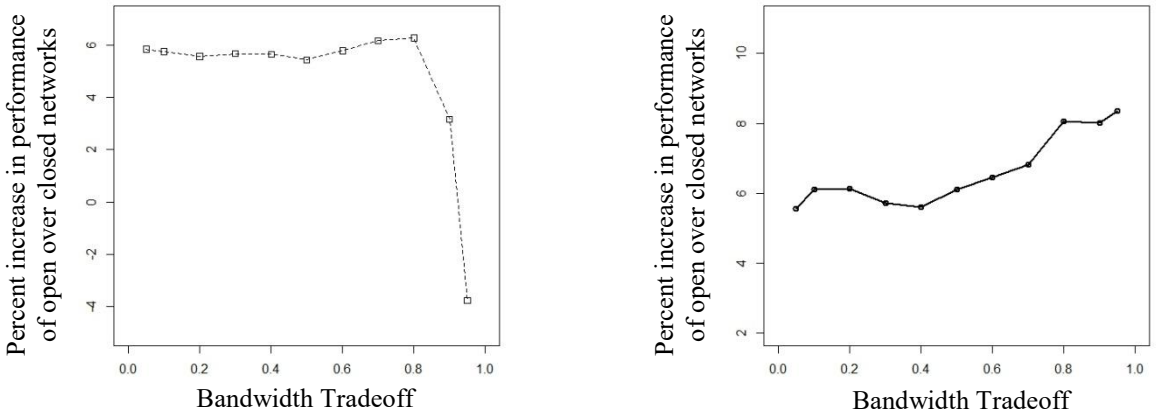
outcomes. Before proceeding, however, it is important to operationalize the measures for the key independent and dependent variables in the in the analysis. The main dependent variable is performance. Each actor's performance at time *t* is given simply by the returns that actor earns in the period (r_{int} in Equation 1). The main independent variable is the degree of structural openness displayed in a firm's ego-network. Structural openness reflects the degree to which a firm's partners are disconnected from each other. I follow prior work by measuring structural openness as a function of ego-network density (Reagans and Zuckerman, 2008). The structural openness measure is calculated as follows. First, I the calculate the firm's ego-network density, computed as the number of ties that exist between the firm's direct contacts divided by the total number of possible ties that could exist between these contacts. I then calculate the firm's structural openness as one minus the firm's ego-network density.

Result 1: The Long Run Benefit of Structural Openness Increases as the Bandwidth Tradeoff is Strengthened

Current theory holds that open networks will be most advantageous for organizational performance when the bandwidth tradeoff is weak (Ahuja, 2000; Burt, 2005; Aral and Van Alstyne, 2011). Findings from the model suggest that this might not be so straightforward. Instead, the model predicts that in the long run open networks are most advantageous in precisely the context where access to information is most constrained.

This effect is demonstrated both graphically and in a regression of the simulation results. To demonstrate this effect graphically, Figure 12 plots the strength of the bandwidth tradeoff on the x-axis, and on the y-axis plots the percentage difference in performance between (1) firms in fully open networks and (2) firms in fully closed networks. Figure 12a shows the short run

relationships, taken at *t = 10.* This result shows that, in the short run, the expectation of prior theory holds. The advantage of open networks decreases, and in fact becomes negative, as the strength of the bandwidth tradeoff increases. Figure 12b demonstrates the long run relationship, taken at *t = 100*. Figure 12 shows that in the long run, as the strength of the bandwidth tradeoff increases, open networks confer a stronger performance advantage. When the bandwidth tradeoff is weak, firms in structurally open networks outperform those in closed networks by about 5.5% on average. However, when the bandwidth tradeoff is strong, firms in structurally open networks outperform those in closed networks by about 8.25% on average. Thus, where prior theory expects a decreased advantage of structural openness, the model predicts an increased advantage.



(a) *t = 10* (b) *t = 100*

Figure 12. Performance Advantage of Open Structures by Bandwidth Tradeoff

The graphical results are corroborated by a regression analysis of the simulation data in Table 2. Each regression is run using output data from 1,000 simulation runs. In each of the 1,000 simulation runs used in the regression analysis, the strength of the bandwidth tradeoff (β) is randomly assigned. It is important to note that the simulated data embody the logical consequences of the modeling assumptions, rather than inputs for empirically testing theory.

Therefore, regression is used here as a means of interpreting the patterns of the relationships that arise from the model, and the regression coefficients are suggestive of the theoretical relationships predicted by the model, rather than as an empirical test. In that regard, the regression analyses complement the graphical analysis. While the graphical analysis only compares the two most extreme levels of structural openness, the regressions allow for comparison across all levels possible in the simulation, helping to ensure that the result is not particular to the extreme values. In agreement with the graphical analysis, the second regression (R2) in Table 2 demonstrates that, in the short run, the positive effect of structural openness decreases as the strength of the bandwidth tradeoff increases. In contrast, the fourth regression (R4) demonstrates that, in the long run, the positive effect of structural openness increases as the strength of the bandwidth tradeoff increases.

Table 2. Linear Regression of Closure-Performance Relationships in the Simulation

Variables	Performance *t=10* (R1)	Performance *t=10* (R2)	Performance *t=100* (R3)	Performance *t=100* (R4)
Intercept	0.732***	0.725***	0.722***	0.730***
Direct Relationships				
Structural openness	0.038***	0.052***	0.041***	0.038***
Bandwidth Tradeoff	-0.036***	-0.022***	-0.022***	-0.007***
Moderating Relationship				
Structural openness × Bandwidth Tradeoff		-0.027***		0.018***

Prior work offers little insight for understanding the model's long run prediction that open networks are more advantageous when the bandwidth tradeoff is strong. This suggests that there may exist informational mechanisms that have yet to be recognized by network scholars. The next two results from the simulation offers some insight to how this effect arises. After

discussing each result separately, the two results are integrated to form an explanation for the increasing advantage of open networks in strong bandwidth tradeoff contexts.

Result 2: Informational Redundancy Aids in Selecting Valuable Solutions in Open Networks

The second key result involves the importance of acquiring redundant information from unshared ties in open networks. The core insight is that while social information may be more valuable in open networks, firms only benefit from access to this information when they implement (select) the solutions suggested by their partners. Redundant information is important for this purpose since firms are more likely to implement a socially suggested solution when receiving more consistent information from partners in favor of this solution. This dynamic is examined graphically for weak bandwidth tradeoff contexts below, but this key result holds in both weak and strong bandwidth tradeoff contexts.

First, the model shows that in weak bandwidth tradeoff contexts, the information acquired in open networks general points to more valuable solutions than does the information in closed networks. Define the solution with the highest average estimate among a firm's partners as the *socially suggested solution*.[5] The y-axis of Figure 13a plots the true value of the socially suggested solution for different levels of structural openness. By the last period of the simulation run, the average value of the socially suggested solution for firms in open networks is about 0.8,

[5] Note that the socially suggested solution may differ across firms. Since each firm can have a unique set of partners, the solution emerging from the local social context of any two firms may differ.

and for firms in closed networks is about 0.72. Based on this, open networks should facilitate a performance advantage, as is suggested by prior theory.

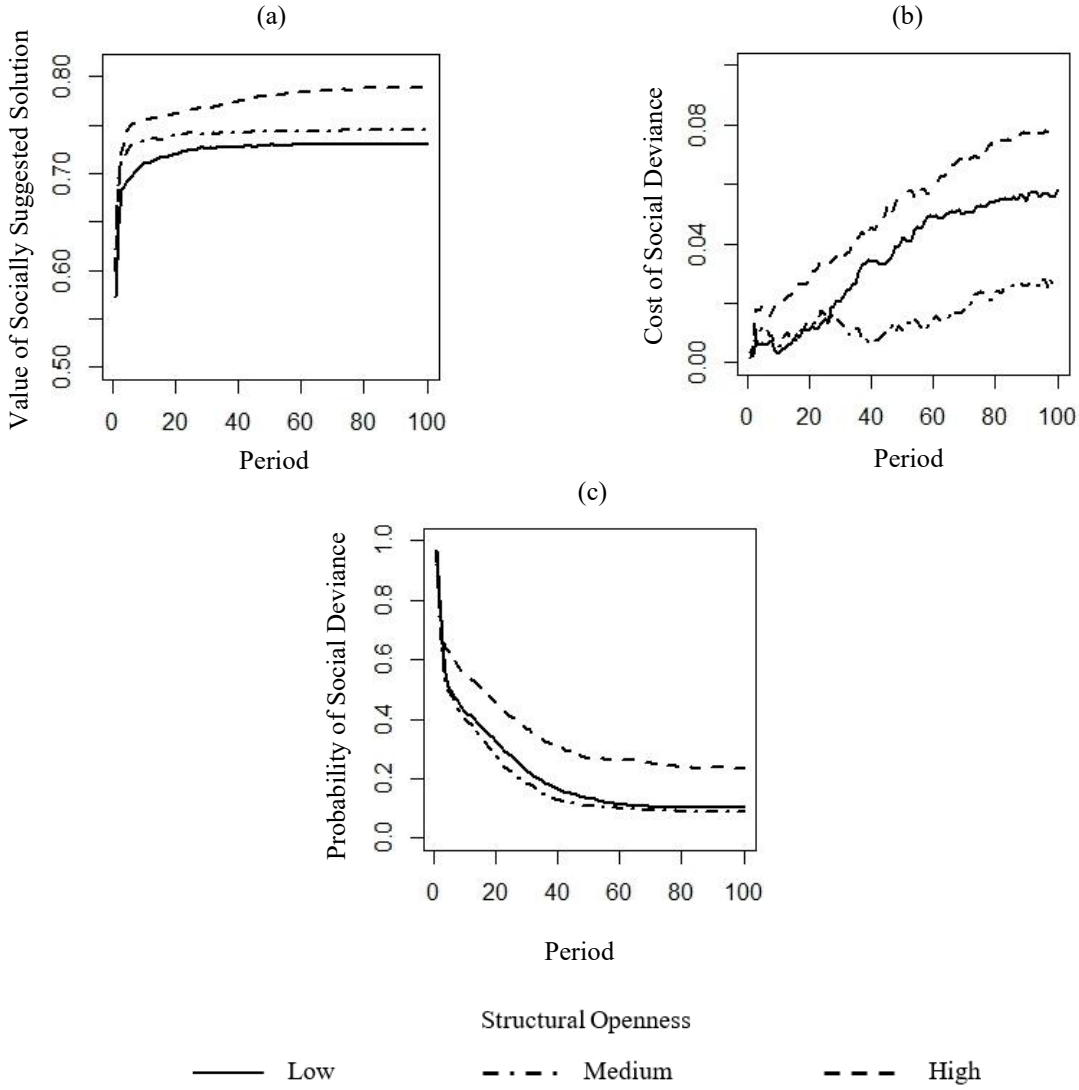


Figure 13. Cost and Likelihood of Social Deviance under a Weak Bandwidth Tradeoff

However, this advantage is captured only by firms that actually select the socially suggested solution for implementation. Firms in the model that deviate from this solution tend to implement alternatives that are much less valuable. Figure 13b demonstrates this effect. The y-axis of Figure 13b plots the average performance loss for implementing a solution that differs

from the socially suggested solution, which is calculated as the absolute difference between the value of the socially suggested solution and the value of the solution that the firm actually implements. The figure shows that firms on average face losses when deviating from the socially suggested solution across all network configurations.[6] However, this penalty is substantially larger in open networks, where firms face losses nearing 0.08 performance points. Thus, firms that do not implement the socially suggested solution struggle to locate equally valuable solutions on their own, and this is particularly true of firms in open networks.

A key insight from the model is that a firm is much more likely to select the socially suggested solution when receiving redundant information from its partners regarding this solution. Figure 14 compares actors that implement the socially suggested solution to those actors that deviate from this solution. For each type of actor, Figure 14 reports the diversity of partners' estimates for this solution, measured as the variance in estimates for this solution across the firm's partners. The results show that the actors that tend to implement the socially preferred solution are those that observe less diversity in their partners' estimates for this solution. This is true for firms at all levels of structural openness, but the effect is stronger for firms in open networks, and more problematic since the overall level of reduce in open networks is lower.

The intuition behind this finding is that more diverse evaluations for a solution often means that some partners hold a high valuation for the solution while others hold a low valuation. Consequently, even though some of a firm's partners relay high estimates for the

[6] This finding is in accordance with findings from research on the "wisdom of the crowd" (Galton, 1907). While closed networks lead actors to implement lower performance solutions than they would have in open network, firms in closed networks still tend to implement solutions that outperform those they implement when acting on their own.

solution, if other partners provide negative estimates for the same solution, the solution may appear unattractive in the eyes of the focal firm. Thus a lack of agreement among the firm's partners regarding the solution makes the firm less likely to implement it.[7] Since actors perform better on average when implementing the socially preferred solution, this suggest that actors in open networks generally benefit when partners display more redundant estimates for the socially preferred solution.

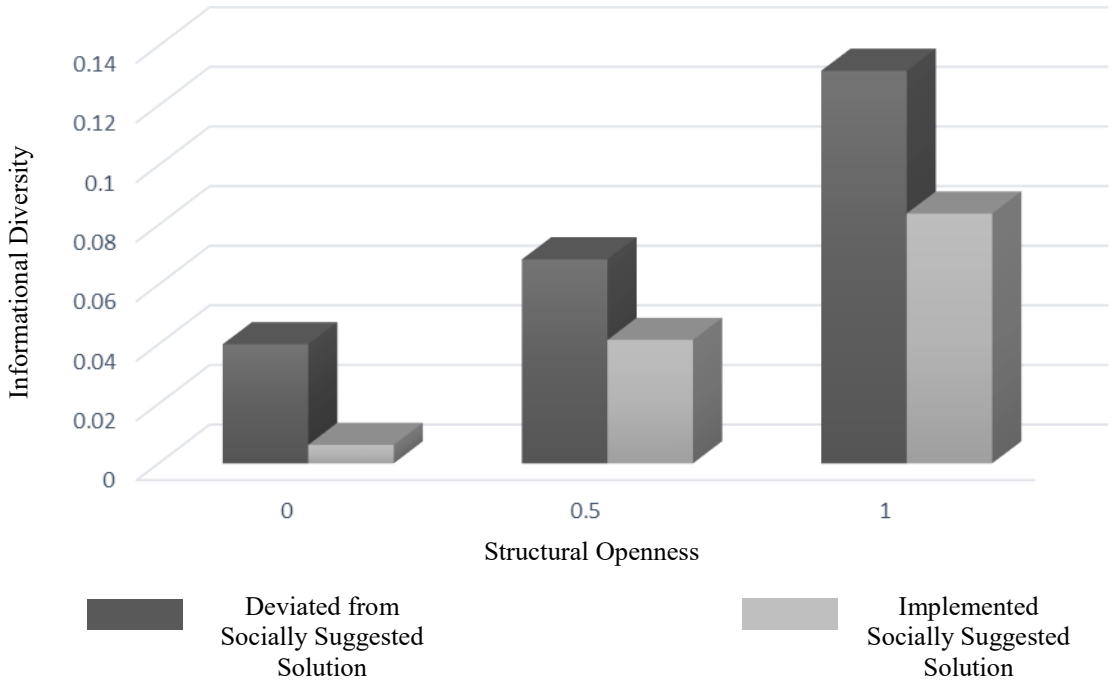


Figure 14. Informational Diversity and Deviance from the Socially Suggested Solution

[7] This effect arises here in a purely mathematical sense. Lower estimates by some partners lead to a lower average estimate for the solution in Equation 6. However, a lack of agreement may also create an aversion to implementing the solution for more sociological reasons, since firms may stray away from solutions causing high levels of cognitive dissonance, and those lacking social legitimacy.

Result 3: The Cost of Social Deviance is lower under a Strong Bandwidth Tradeoff

The findings above suggest that when firms are exposed to more diverse information, these firms may be reluctant to select the solution suggested by the network information these firms receive. However, the penalty paid for deviating from network information is not equally severe for all firms. The results so far suggest that firms face different penalties for deviance across different networks structures. Figure 13b in the previous section showed that firms in more structurally open networks faced greater performance losses when failing to implement the socially suggested solution. This section focuses on a second but perhaps more critical contingency, showing that firms face different penalties for deviance depending on the strength of the bandwidth tradeoff in their social contexts.

Figure 15 demonstrates this effect among firms in the simulation. This figure is analogous to Figure 13 but displays results for strong bandwidth tradeoff contexts. Comparing Figures 13b and 15b shows that across weak and strong bandwidth tradeoff contexts firms in closed networks pay a similar penalty for deviating from their socially suggested solutions. However, the penalty for firms in open networks decreases significantly when moving from weak to strong bandwidth tradeoff contexts. One way of interpreting this finding is that, when occupying open networks, firms are able to select high quality solutions despite deviating from socially preferred solutions in strong bandwidth tradeoff contexts, but are not able to do so in weak bandwidth tradeoff contexts.

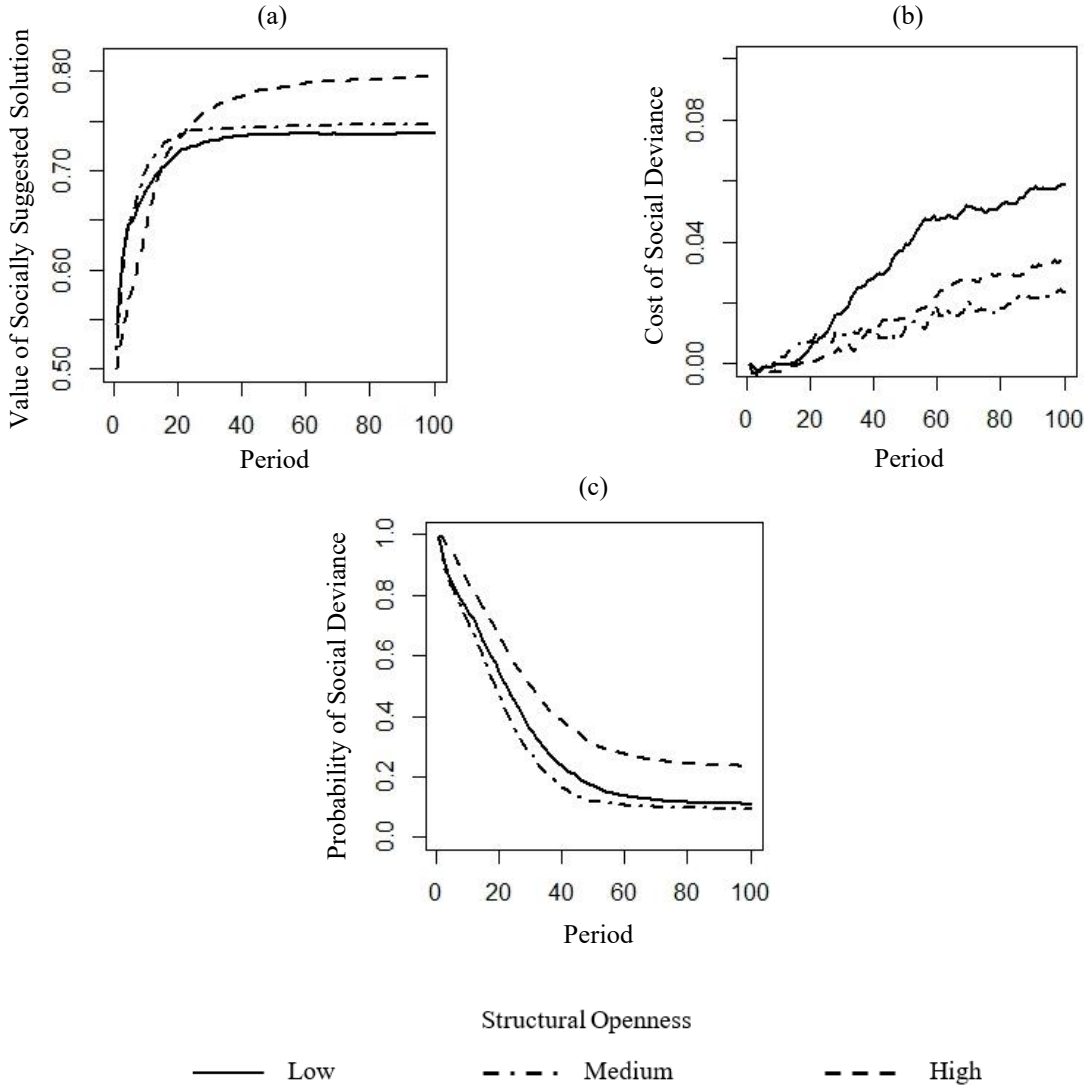


Figure 15. Cost and Likelihood of Social Deviance under a Strong Bandwidth Tradeoff

But why? The intuition behind this effect is that, in the early periods, a firm occupying an open network typically has information from only one partner on each potential solution. Simulation results for strong bandwidth tradeoff contexts showed that at *t=20* a firm in an open network averaged only 1.413 information sources for each known solution. This number

remained under two until period 36 on average, meaning that until period 36, firms in open networks typically held information from only one partner on each known solution.[8] This reduces the opportunity for conflict across partners in open networks, making it more likely that the firm will implement a solution that a partner highly recommends during these early periods. In later periods, as contradictory information from other partners arrive, a firm's experience with the solution helps to guard against the potential detrimental effects that these contradictions may pose. By then, firms are able to co-examine experiential and social information regarding a single solution, allowing for the selection of reasonably effective solutions, even when these solutions differ from those most recommended by network information.

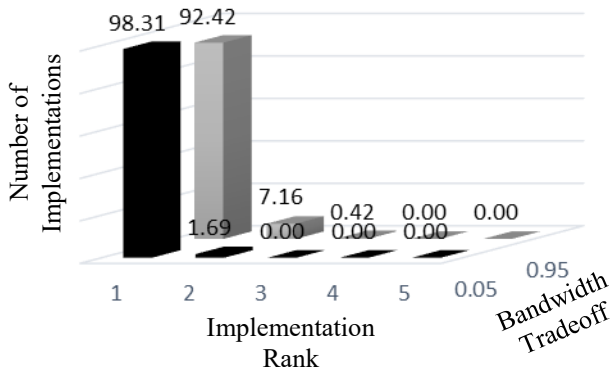
This dynamic is evidenced in the simulation results. Firms in open networks implemented 45.13% more solutions when the bandwidth tradeoff was strong than they did when the bandwidth tradeoff was weak. Further, when the bandwidth tradeoff strengthened, firms increased not only the number of solutions they implemented, but also the amount of times they implemented transient solutions.

Figure 16 rank orders each solution by the number of times the firm implements it, and plots on the y-axis the average number of implementations for each of the five most implemented solutions. As the bandwidth tradeoff was strengthened in the simulations, firms' implementations became more evenly distributed across different solutions, allowing firms to gain more accurate estimates for a larger number of solutions. This was particularly true for

[8] To compare, in weak bandwidth tradeoff contexts, firms in open networks held information from at least two partners on each known solution by $t = 5$. Further, by $t = 20$, these firms held information from an average of 3.251 partners for each known solution, allowing for greater conflict across partners in their estimates for these solutions.

firms in open networks, who displayed a more evenly dispersed distribution of implementations. This increased experience with multiple solutions benefited all firms in open networks, in the sense that they all became more likely to choose the best available solution. However, this benefit was particularly strong for social deviants in open networks, who increased their probabilities of selecting the best available solution from 0.061 to 0.205 (non-deviants increased from 0.268 to 0.312).

(a) Closed Networks



(b) Open Networks

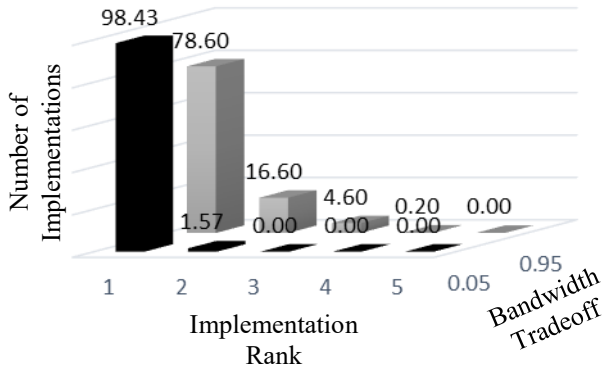


Figure 16. Distribution of Implementations across Solutions

These findings suggest novel insights into how the speed of information acquisition influences whether actors benefit from their network positions. Prior work emphasizes that faster information acquisition should be a primary advantage of open networks. In contrast, we see here that there are distinct benefits to slowing the inflow of information in open networks. In particular, when actors in open networks gain information slowly because the bandwidth tradeoff is strengthened, they are better able to select high quality solutions, even when disagreement across partners causes these firms not to implement the socially suggested solution.

Summary: Why is Structural Openness more Beneficial under a Strong Bandwidth Tradeoff?

Results from the previous two sections can be combined to form a succinct explanation for why open networks confer a more pronounced long run performance advantage when the bandwidth tradeoff is strong. While the information found in open networks tends to point firms to more valuable solutions, occupying these networks nevertheless carries hazards caused by the lack of informational redundancy. First, a lack of redundancy surrounding estimates for the socially suggested solution causes a large proportion of firms to ignore this solution, even though the solution tends to be valuable. Second, a lack of redundancy surrounding estimates for remaining solutions restricts the firm's pursuit of high performing alternatives to the socially suggested solution. The consequence is that while some firms in open networks perform exceptionally well, others perform exceptionally poor, driving down the average performance of firms in these networks when the bandwidth tradeoff is weak. Table 3 shows that, in simulations of weak bandwidth tradeoff contexts, firms in open networks that deviate from their socially

suggested solution perform poorly, observing even lower performance than firms in closed networks that adopt their socially suggested solution (0.693 vs. 0.734).

Table 3. Comparing the performance of deviants to non-deviants (t=100)*

	Structural Openness		
	0	*0.5*	*1*
Weak Bandwidth Tradeoff (β = 0.05)			
Non-Deviants	0.734	0.742	0.781
Deviants	0.696	0.737	0.693
Strong Bandwidth Tradeoff (β = 0.95)			
Non-Deviants	0.733	0.748	0.783
Deviants	0.678	0.707	0.742

Increasing the strength of the bandwidth tradeoff mitigates the second of these two hazards. Specifically, by slowing the rate at which firms in open networks access information, a stronger bandwidth tradeoff allows those firms deviating from the socially suggested solution to find high performing alternatives. In simulations of strong bandwidth tradeoff contexts (see Table 3), firms in open networks that deviate from the socially suggested solution perform reasonably well, improving their average performance from 0.693 in weak bandwidth tradeoff context to 0.742.

Comparing Figures 13 and 15 highlights how this dynamic unfolds in the simulation. First, firms in the simulation that implement the socially suggested solution show similar performance, across different bandwidth tradeoff contexts (compare Figure 13a to Figure 15a). Second, in the simulations, firms in open networks are no more likely to implement the socially preferred solution as the strength of bandwidth tradeoff increases. By comparing panels (b) from Figures 13 and 15, we see that firms in open network deviate from the socially preferred solution

about 22% of the time in weak bandwidth tradeoff contexts and about 24% of the time in strong bandwidth tradeoff contexts. Finally, the only change across bandwidth tradeoff contexts is the performance penalty that results when deviating from the socially preferred solution. By comparing panels (c) in Figures 13 and 15, we see that the cost of deviance decreases from 0.08 performance points in weak bandwidth tradeoff contexts to about 0.03 performance points in strong bandwidth tradeoff contexts. Thus, as the strength of the bandwidth tradeoff increases, open networks better enable firms to select high performing solutions, whether these solutions reflect those directly suggested by network information or not.

DISCUSSION

This paper adds to our understanding regarding the informational mechanisms underlying network effects on performance. While the existing network literature assumes the importance of rapid access to diverse information, this paper demonstrates the limitations in this perspective. In doing so the paper produces several insights. First, the analysis suggests that actors in open networks benefit more when receiving redundant (rather than diverse) information regarding leading solutions in the network. In open networks, the solution held in the highest regard among a firm's partners tended to be highly valuable, whether partners held consistent estimates for this solution or not. However, firms were much more likely to actually implement the solution when partners' estimates are more similar. Thus, redundant information is important for ensuring that actors actually pursue the most valuable information they are exposed to in their networks.

This insight is important since prior work has mostly emphasized the benefit of diverse information in open networks. The little work that has considered redundancy at all has focused on the need for redundant interpretive schema, while maintaining the assumption that the actual

information passing through the network is most beneficial when more diverse (Ter Wal et al., 2016). From this perspective, the benefit of diverse information is limited only by an actor's ability to interpret it. In contrast, the analysis in this paper suggests that it is precisely in contexts where interpretation between ego and alter is least problematic that firms in open networks suffer most from a lack of informational redundancy. Firms in the model paid a higher penalty for a lack of exposure to redundant information in context where prior work theorizes that interpretation is least problematic—when the bandwidth tradeoff was weak (Aral and van Alstyne 2011; Ter Wal et al., 2016). This is because an actor that can fully interpret the information from disconnected alters may be more likely to perceive deeply rooted contradictions across these partners' beliefs, making it harder to act on the information.

These findings suggest an opportunity for network scholarship to leverage insights from evolutionary perspectives of organizing. Evolutionary perspectives hold that performance increases require both variation and selection mechanisms (Levinthal and Marino, 2015). While it is important for firms to be exposed to a variety of organizational solutions and practices, this variation may be unproductive, and potentially harmful, if the selection mechanisms necessary for subsequently choosing from the available options are absent or muted. Thus far the focus in network theory has been lopsided, favoring network mechanisms that increase variation, but ignoring networks mechanisms that aid a firm in its selection of alternatives. This paper suggests the need for more theoretical balance in this regard, and highlights that redundant information may be one such selection mechanism. Future research may build on this result by examining other network mechanisms that may support internal selection.

To reconcile the importance of informational redundancy observed here with the intuited importance of informational diversity in prior thinking, network theorists may need to consider the possibility that there may be conflicting performance effects of different types of informational diversity among network partners. There may exist more than one type of informational diversity among an actor's network partners. On one hand, partners may be diverse in their knowledge of solutions; different partners may be aware of different solutions. On the other hand, partners may be diverse in their beliefs concerning a single solution; some partners may view a solution positively, while other partners view the same solution negatively. While prior work has acknowledged these distinct types of informational diversity (Shore, Bernstien, and Friedman, 2015), the performance implications of these differences as it relates to actors' network positions have not been thoroughly examined. The findings of this paper demonstrate the benefits of redundant information regarding partner's estimates for a single solution. Thus, it is possible that firms benefit from informational diversity as it relates to knowledge of different solutions, but benefit from redundant information as it relates to partners' evaluation of any one solution. Future work should test this hypothesis empirically, and carefully examine its theoretical implications.

A second key insight from the model lies in recognizing the value of slow access to information in open networks. Prior network research has privileged fast access to information. For instance, Burt (2005: 16) notes that beyond the diversity of information, "early access to that information" is a core advantage of open networks. The analysis in this paper suggests otherwise. This is because when information trickles in slowly, actors in open networks gain experience with a wider number of solutions than they do when information is acquired quickly. This

increased breadth in experience enables the actor to select better solutions, even when the actor's choice of solution deviates from those that are more highly regarded among the actor's partners. These ideas are consistent with work in organizational learning research that has long demonstrated that fast learning often leads to suboptimal performance (March, 1991). Nevertheless, network scholars have grossly ignored the potential advantages of slow information acquisition.

One may resolve the finding from this paper that slowly acquiring information in open networks is advantageous with the ideas from prior work suggesting the benefits of fast access to information by carefully constructing boundary conditions for the benefits of each. The problems caused by rapid access to information involve actors making suboptimal organizational decisions when information is acquired quickly. This suggests two cases where faster access to information from the network may be preferred. First, expedient action is sometimes more important for performance than appropriate action (Lieberman and Montgomery, 1988). Thus, when first mover advantages are strong enough to override losses in performance from otherwise poor strategic choices, actors in open networks may benefit from fast access to information. However, when obtaining satisfactory performance is highly contingent on the actor's ability to find high quality solutions to strategic problems, the fast access to information in open networks may be detrimental. Second, in some contexts, an actor may acquire information with no intention of directly employing this information, but instead seeks to benefit by trading this information with others (Burt ,1992). In this case, fast access to information may be preferable, since the information does not directly inform the actor's strategic choices.

The final key insight from the paper regards new propositions that help us to understand how relational features of an actor's social context help to moderate the relationship between structural openness and performance. Prior work has shown that in strong bandwidth tradeoff contexts—relational contexts emphasizing trust, cooperative norms, and shared cognition—closed networks become more advantageous than open networks for acquiring diverse information from one's network partners. The intuition for performance predictions is that open networks should also be less beneficial for performance in these contexts. This paper suggest that this prediction may hold only in the short run.

In the long run, actors in open networks benefit from slow access to information, and therefore may demonstrate higher performance in strong bandwidth tradeoff contexts than they do in weak bandwidth tradeoff contexts. One implication of this finding is that we may need to rethink prescriptions for actors seeking to gain the benefits of open networks while reducing the cost of doing so. Prior intuition would prescribe that actors in open networks invest resources in building strong relationships with their partners to mollify obstructions to the flow of information in strong bandwidth tradeoff contexts. This paper suggest that this may not be the necessary. To the extent that crafting strong relationships is costly, firms in open networks may do better by doing nothing. The passage of time may be enough to transform the slow acquisition of information to performance benefits, without any additional relational investments. Of course, if network structures evolve somewhat rapidly the short run conclusions from prior theory may be sufficiently accurate for practical purposes. Whether or not this is the case, improving the long run accuracy of the theory is important for conceptual purposes, since doing so may shed

light on the dynamics of the informational mechanisms which also govern short run outcomes (such as the importance of redundant information).

CONCLUSIONS

This paper demonstrates that some taken for granted ideas about information in the production of network effects on performance may be inaccurate. While the prevalent intuition for when and why open networks may produce performance advantages centers on the notion of rapid access to diverse information, this paper shows that slow access to information and redundant information may both play a critical role in allowing actors to benefit from open network positions. The consequence is that, in the long run, open networks may be most beneficial in relational contexts where prior work expects these networks to be least beneficial. Future network research may benefit from these ideas by continuing the search for novel causal pathways through which an actor's network position may influence its ability to select high performance solutions to strategic and organizational problems.

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CHAPTER 3

HOW TO MAKE AN EXPERT: THE SOCIAL NETWORK DRIVERS OF EXPERT DEVELOPMENT

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ABSTRACT

This paper adopts a network approach to organizational design to explain how firms may implement structures and policies that facilitate the development of its employees from novices to experts. The theory is one part descriptive and one part prescriptive. First, the paper uses social network theory to explain why very few actors will naturally progress to the expert stage of development. Second, the paper provides insights as to how organizations can help individuals to overcome these difficulties by focusing design efforts on developmental bottlenecks—stages in the expert development processes that are disproportionally responsible for impeding an actor's progression toward expertise. The paper concludes by discussing implications for value creation within firms.

INTRODUCTION

In the last 30 years, organizational effectiveness has come to depend increasingly on intellectual work. This has led to a proliferation of conceptual perspectives that elevate the importance of organizational knowledge, with the expectation that a firm's ability to remain competitive is limited in large part by the expertise of its employees (Simon, 1991; Felin and Hesterly, 2007; Polyhart and Moliterno, 2011).Thus, a firm's knowledge creation, and therefore value creation, potential is thought to reflect its structures and processes for managing the expertise of its employees (Grant, 1996; Galunic and Anderson, 2000).

Yet, while there exists substantial scholarly recognition that organizational performance may depend on the presence of individual expertise within the firm, there exists little understanding of how a firm's structures and policies may enhance or detract from the development of experts internally. Organizational research on expertise has given more attention

to how organizational structures such as hierarchy (Nickerson and Zenger, 2004), and organizational processes such as turnover (Campbell, Coff, and Kryscynski, 2011; Polyhart, Nyberg, Reilly, and Maltarich, 2014), influence the composition of experts within the firm. In these perspective experts are acquired or hired, but not made. Less understood is how a firm's structures may be designed to facilitate an actor's progression from novice to expert.

The study of expert development has a much richer tradition in the broader social sciences (Simon and Chase, 1973; Dreyfus and Dreyfus 1986; Aristotle, 2000; Feltovich, Prietula, and Ericsson, 2006). The canonical debate in this literature amounts to a discussion of nature versus nurture: to what extent are experts born versus made? Scholars generally advocate the side of nurture, and prior literature has shown that expert development is an outcome of deliberate experience—where the actor gains experience with a problem while consciously attending to how the problem can be solved better (Ericsson and Charness 1994; Ericsson, 2006). This perspective is promising for organizational scholarship since it suggests that there are actions a firm may take to strategically produce experts internally.

However, applying the deliberate experience perspective in organizational settings is made difficult by the fact that experience alone is not enough to move an actor from novice to expert. Indeed, the deliberate experience approach has come under attack for its failure to fully explain the emergence of experts (Camerer and Johnson, 1997; Ullen, Hambrick, and Mosing, 2016). In the deliberate experience approach, all that prevents advancement to the expert stage is motivation (Ericsson, Krampe, and Tesch-Romer, 1993). Yet, prior work suggests that there are more individuals who wish to become experts than there are experts (Zucker and Darby, 1996; Beane, 2018). Further, even proponents of deliberate experience acknowledge that actors

advance quickly from the novice stage to display competence, but that substantial improvement beyond this point is rare (Ericsson and Lehmann, 1996; Ericsson, 2006).

The contribution of this paper lies in explaining these difficulties in developing expertise, and proposing an organizational design approach for overcoming them. First, the paper produces a theory to explain the difficulties in expert development, using insights from the literature on social network structure. This paper begins by recognizing that the struggle in explaining expert emergence may arise from a limited view of "nurture" in the deliberate experience perspective. What is meant by "nurture" is that the individual must cultivate her talents by gaining experience, perhaps under the guide of a teacher or mentor (Ericsson, 2006; Hunt, 2006). Absent, however, is a systematic understanding of how aspiring experts are nurtured by their broader social context. In contrast, network structural perspectives hold that, in many domains, critical resources tend to be scattered across social space (Lin, Ensel, and Vaughn, 1981; Coleman, 1988). Therefore, an actor's outcomes depend not only on individual motivation, or on the presence of dyadic network ties, but also on how the configuration of her network ties facilitates access to these critical resources (Granovetter, 1973; Burt, 1992; Kilduff and Brass, 2010).

This perspective is useful for explaining the difficulties individuals face in developing expertise for two reasons. First, experience itself might be a scarce resource to which few individuals have direct access (Lin and Dumin, 1986). The deliberate experience perspective has taken for granted that an aspiring expert will have the autonomy to access experience building opportunities. Yet in many organizations, the problems that the aspiring expert must solve to gain experience are guarded by gatekeepers, who decide which individuals get to solve which problems (Katz and Tushman, 1981; Beane, 2018). Second, expert development depends on the

presence of cognitive resources, which may also be functions of an actor's social network configuration. Even when an actor has opportunities to build experience, acquiring expertise requires that the actor demonstrate a cognitive transformation in how she mentally represents potential problems and solutions in the domain (Newell, 1973; Hinsley, Hayes, and Simon, 1978 Dreyfus and Dreyfus, 2005; Feltovich, Prietula, and Ericsson, 2006). This cognitive transformation is greatly aided by non-tangible resources such as diverse perspectives and the intellectual freedom to reimagine existing problems (Dane, 2010). Yet, these cognitive resources may also be considered forms of social capital that derive from the aspiring expert's network position (Liebeskind, Oliver, Zucker, and Brewer, 1996; Burt, 2005; Perry-Smith and Mannucci, 2017). Thus, individuals with network configurations that do not facilitate all the resources needed for advancement will struggle to progress through the expert development process.

The paper's second key contribution lies in explaining how organizations may design structures and policies to account for difficulties that individuals face in becoming experts. The key insight is that, while there are multiple stages in the expert development process (Dryfus and Dryfus, 2005), the needs of some stages can be met with simple network configurations, while the needs of other stages require conflicting network structures. Thus, there will exist bottlenecks that naturally emerge in the expert development process—actors will naturally pass through some stages of development easier than they pass through others. The paper unites this insight with Baldwin's (2014) argument that firms create value when centering design rules on bottlenecks in key processes, to argue that firms can best aid in the development of experts internally when focusing design efforts on bottlenecks in the expert development process.

DEFINING EXPERTS

Experts are generally considered actors with high levels of domain-specific knowledge, which allows them to demonstrate extraordinary performance in a particular domain (Ericsson, Krampe, and Tesch-Romer, 1993; Dryfus and Dryfus 2005; Feltovich, Prietula, and Ericsson, 2006). Since the topic of expertise is approached from a variety of perspectives in the literature, this paper takes a problem-based view of expertise, which allows the integration of ideas from across the social sciences (Davidson and Sternberg, 2003). In this section, I highlight an actor's ability to solve domain-specific problems, and use this problem-based view to define expertise and expert performance, as well to contrast experts and novices.

A problem exists when there is a (task related) goal that is not being met, or when there is reason to believe that the goal will not be met in the future (Simon, 1975). An actor's performance in the domain reflects the extent to which the actor is able to move the state of affairs away the undesirable starting condition and closer to the goal state (Newell and Simon, 1972; Sweller, 1988). To accomplish this, the actor must recognize that a problem exists, form an adequate cognitive representation of the problem, then discover and implement a solution for the problem (Pretz, Naples, and Sternberg, 2003). The manner in which each of these three steps is executed is what differentiates experts from novices in a domain.

Problem recognition involves discerning a gap between a current state of affairs and the goal state. Research suggests that experts are superior to novices in their abilities to recognize problems (Barley, 1996; Pretz, Naples, and Sternberg, 2003). One reason novices find it difficult to recognize problems is that they do not always understand precisely what the desired goal state is (Harpaz, Honig, Coetsier, 2002; Corley and Schinoff, 2017). In many domains the goal state is

socially constructed by a community of practitioners over time. Thus, learning what the goal state is often requires some degree of socialization into the domain. A second reason novices fail to recognize problems is that perceiving gaps between a current state of affairs and the goal state often requires an actor to apprehend nuanced signals from the environment (Camerer and Johnson, 1997; Schenk, Vitalari, and Davis, 1998). In an ethnography of technicians across multiple professions, Barley (1996: 425) found that expert technicians had the "ability to make sense of subtle differences in the appearance of materials and the behavior of machines … where novices and even professionals saw no information at all." In sum, because experts are more socialized into the domain and have the ability to sense nuances in the environment, these actors are better able to recognize problems in the domain.

Problem representation involves creating a cognitive model to mentally organize the information known about the problem. Due to cognitive limitations, and potentially to a lack of information, actors rarely perceive problems as they truly exist. Instead actors must form cognitive representations of a problem before attempting to solve it (Simon, 1975). Pretz, Naples, and Sternberg (2003: 6) note that problem "representations are composed of four parts: a description of the initial state of the problem, a description of the goal state, a set of allowable operators, and a set of constraints." Prior work has shown that experts use bottom up processes to craft problem representations by directly synthesizing problem related information, whereas novices use top down processes by applying available heuristics when forming representations (Groen and Patel, 1985; Feltovich, Prietula, and Ericsson, 2006).

In addition, an expert's representation of a problem is typically more detailed than a novice's (Sweller, 1988; Dane, 2010), containing a larger quantity of information for each of the

four subcomponents of a representation. For instance, an expert may be more aware of potential constraints imposed by a problem. Likewise, an expert's problem representation tends to contain a larger number of interrelations linking different pieces of information (Schenk, Vitalari, and Davis, 1998; Dane, 2010). For example, Holden and Klinger (1988) compared the processes through which experienced and novice nurses diagnosed why a baby is crying. They found that experienced nurses were more likely to collect the most critical piece of information (the baby's age), and were able to make a diagnosis using fewer pieces of information, suggesting that experienced nurses had better developed cause-effect schema for the crying-baby problem.

Problem solving involves implementing ideas for reducing the distance between an undesirable state and the goal state. For some problems, solutions are evidenced in changes to the observable reality. For example, in medical treatment, a problem exists when a patient is sick, and the problem is solved when the patient is no longer sick. Thus a solution to the problem is reflected in an observable change in the patient's health. For other problems, solutions do not involve altering the observable reality, but instead altering existing understandings of reality. For example, in medical diagnosis, a problem exists when we do not know why a patient is sick. This problem is solved once we have an understanding of why that patient is sick. However, solving the diagnosis problem does not require making the patient well. In either case, experts differ from novices in that the actions taken by experts tend to be more effective, and tend to receive the desired results with greater consistency (Camerer and Johnson, 1997; Schenk, Vitalari, and Davis, 1998; Feltovich, Prietula, and Ericsson, 2006; Norman, Young, and Brooks, 2007).

To summarize, performance in a domain will reflect an actor's ability to solve problems, by transforming undesirable existing states into more desired goal states. Experts will differ from

novices in that they will find a way to meet each of the three conditions of problem solving (problem recognition, representation, and solution) with a high degree of proficiency. From this perspective, I define an expert as an actor that is able to consistently and satisfactorily recognize, represent, and solve problems in a given domain.

THE FIVE STAGE MODEL OF EXPERT DEVELOPMENT

The section above describes experts, and details how experts and novices differ. However, this paper is concerned with explaining why some novices become experts while others do not. To aid in this goal, it is helpful to consider the stages of expert development that fall in between the novice and expert stages, and to consider the resources needed to proceed through each stage. For this I rely on Dreyfus and Dreyfus's (2005) five stage model of expert development, which distinguishes the abilities and developmental needs of actors in each phase. The five stages comprise novice, advanced beginner, competent practitioner, proficient practitioner, and expert. A main takeaway from this section is that in each intermediate stage of development the actor moves closer to expertise, by improving a different problem solving element (problem recognition, representation, or solution). Table 4 encapsulates the arguments from this section, relating each stage to a different problem solving element, and different resource needs for advancement.

Three caveats are in order. First, while some actors may in practice lack the motivation to progress through all five stages, this paper focuses on explaining difficulties in expert development beyond mere motivation. The paper, therefore, assumes motivation. Second, while the progress toward expert status is described as occurring across five clearly identifiable stages, in practice the boundary separating each stage may be blurry, since an actor may show signs of

being in multiple stages simultaneously. Finally, while I describe a linear process, most domains of practice do not officially label and regulate progression through these stages. Thus, in practice actors may display some characteristics of more advanced stages before displaying some characteristics of a preceding stage. Nevertheless, this stylized model of expert development characterizes the progression as followed by most candidates, with sufficient realism to allow for productive theoretical advancement.

Table 4. Aspects of Expert Development

	Novice	Advanced Beginner	Competent Practitioner	Proficient Practitioner	Expert
Acquired Skill	Rule Execution	Problem Recognition	Problem Representation	Problem Solving	Problem Reevaluation
Needs for advancing through the stage	(1) Access to simple rules (2)Controlled environment	Access to Conditional Rules	(1) Access to diverse frameworks (2) Room to fail	Opportunities for Micro-Experimentation	Disconfirming Evidence
Facilitating network structure	Strong Ties	Closure	(1) Brokerage (2) Closure	Network Range	Centrality

Stage 1: Novice

The journey to expertise begins with the novice stage. The novice stage commences when the actor makes her first attempts to become active in the domain. Upon entering the domain, the actor is confronted with overwhelming complexity. She enters with little knowledge of the domain, and is mostly unaware of the domains core questions and problems. To advance through this initial stage, the novice requires two things. First, the novice requires simple and concrete rules for action (Dreyfus and Dreyfus, 2005). Simple rules aid the novice by presenting solutions to problems in the form of general principles to guide action (Groen and Patel, 1985; Norman,

Young, and Brooks, 2007). Second, the novice must gain experience in a controlled environment, stripped of the complexities that practitioners in the domain would actually face (Dreyfus and Dreyfus, 2005; Issenberg et al., 2005). For example, data scientists begin as novices by working with fictitious data, medical professionals begin by evaluating medical dolls rather than real patients, and computer programmers begin by working on simple issues that could easily be addressed using existing point and click prompts. The novice begins to develop expertise by concentrating on how well the rule is implemented. Assuming the learning environment is stripped of complexity (as it must be for progress to be realized in this stage), better implementation of the simple rule leads to improved task performance.

Stage 2: Advanced Beginner

The second stage of expert development is the advanced beginner stage (Dreyfus and Dreyfus, 2005). While the novice shows improvement by implementing simple rules in a controlled environment, progression beyond the novice stage is limited by the lack of realism in the novice's tasks. Because of this lack of realism, novices do not gain experience recognizing when problems are present, crafting unique representations of problems, or crafting solutions to problems. The experience gained by the novice orients the actor to the domain, but does not sufficiently prepare the actor to manage problems that real practitioners face. Thus, if the actor is to develop further toward the expert level, she must be exposed to problems rich in complexity, with the ability to recognize these problems as they are typically encountered in the domain.

The advanced beginner stage commences when the actor confronts real problems for the first time (Dreyfus and Dreyfus, 2005). Think for example of a medical doctor's ascension from medical student to resident. Having mastered simple rules in the novice stage, the advanced

beginner has gained some understanding of the domain. However, because must solve real problems, the advanced beginner quickly learns that employing the simple rules will not suffice. Instead, to progress through this stage, the advanced beginner needs access to conditional rules that allows the actor to recognize problem characteristics that must be confronted for the first time (Goldstein and Gigerenzer, 2002; Dreyfus and Dreyfus, 2005).

Conditional rules facilitate problem recognition, enabling an advanced beginner to recognize and respond to problems in the domain. Conditional rules dictate which environmental stimuli to attend to, and how to respond to those stimuli (Gigerenzer and Goldstein, 1996). For example, Fischer et al. (2002) present a conditional rule diagnosing pneumonia in children (see Figure 17 below). The rule directs a clinician's attention to only two pieces of information that are both easy to collect and interpret, while predicting positive cases with 72% accuracy (compared to accuracy of 73% for logistic regression models). Conditional rules, such as this one, bound complex problems into manageable chunks by enabling an actor to assess whether key characteristics of known problem are present or not (Marewski and Gigernzer, 2012). In this sense conditional rules embody established problem representations. However, these problem representations are implicit in the rule and need not be acknowledged by the advanced beginner for the rule to be recognized and used. This allows advanced beginners to solve problems with reasonable success without exceptional knowledge or skills in the domain.

Actors progress through the advanced beginner stage when exposed to a manageable number of conditional rules for addressing a problem. Any one conditional rule will be incomplete by its nature. The rule displayed in Figure 17, for instance, is useful when both conditions detailed in the rule are met, but is rather useless otherwise. If a clinician is presented

with a sick child whose fever has lasted more than two days, but who is younger than three years old, then this conditional rule is ineffective for uncovering the cause of the sickness. Thus, an advanced beginner that is aware of only a few conditional rules is prepared to address only a small number of problems in the domain. Accessing a larger number of conditional rules increases the breadth of problem characteristics the actor can sense and respond to. However, acquiring too many conditional rules is counterproductive in that doing so reintroduces complexity into the problem, by forcing the advanced beginner to attend to more problem characteristics than she is prepared to deal with. Thus actors that operate with a moderate number

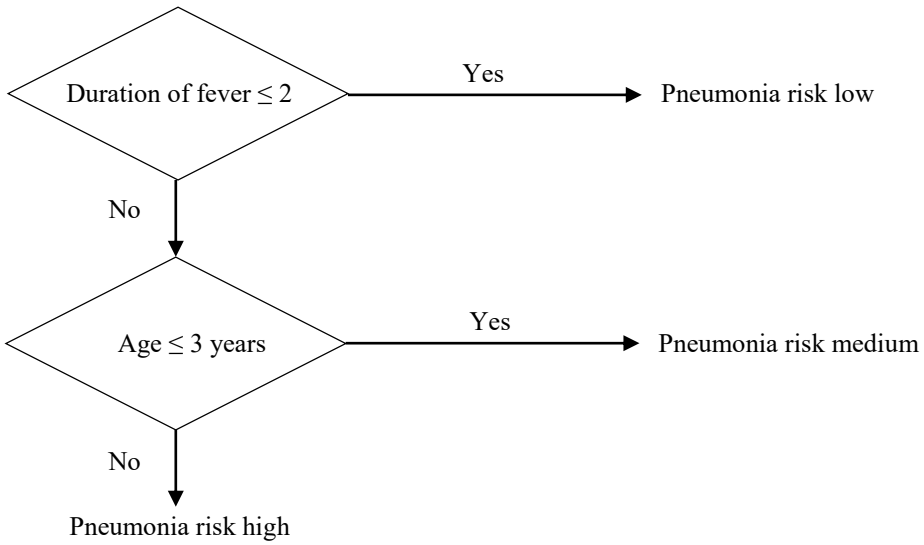

Figure 17. Example of a Conditional Rule for Diagnosing Pneumonia

of conditional rules will best progress through the advanced beginner stage.

Stage 3: Competent Practitioner

The third stage of expert development is the competent practitioner phase (Dreyfus and Dreyfus, 2005). Leveraging conditional rules is important for progressing through the advanced beginner stage, but relying on these rules eventually limits the actor's development toward

expertise. Conditional rules are applicable for very unique types of problems (Gigerenzer and Goldstein, 1996). First, conditional rules address problems for which the conditions to be examined rarely occur in the absence of the problem. For instance, it is unlikely that a child above the age of three will have a fever lasting over two days when not stricken with pneumonia. Second, conditional rules are likely to emerge only for problems that occur frequently enough to allow this concurrence to be recognized and encapsulated in rule form. Absent both criteria, an actor must assess and address problems without the aid of a rule. The ability to do so begins when the actor starts to build proficiency with crafting problem representations on her own.

The competent practitioner stage focuses on problem representation, and begins when the actor first begins to judiciously abandon rules when cognitively assessing problems (Dreyfus and Dreyfus, 2005). Like the advanced beginner, the competent practitioner attends to environmental stimuli when approaching problems. Unlike the advanced beginner, however, the competent practitioner does not depend on rules to know which problem characteristics to look for. The competent practitioner understands that each problem she encounters may have unique combinations of characteristics that must be attended to for a satisfactory solution to be found. Thus, the competent practitioner engages in representation crafting—the bottom up process of forming a unique mental representation of a problem—rather than depending on conditional rules to provide top down problem representations for her (Groen and Patel, 1985).

The actor's move to representation crafting makes advancing through the competent practitioner stage more involved than advancing through the previous stages. First, to advance through the stage the actor needs access to different frameworks (Dreyfus and Dreyfus, 2005). To manage the process of representation crafting, the competent practitioner employs general

frameworks to guide her decision making. Representation crafting demands deciding on a case by case basis which aspects of a problem must be reflected in a solution, and which can be ignored. Frameworks provide the tools for examining a problem from different perspectives in the process of breaking it down to its essence (Goffman, 1974; Benford and Snow, 2000; Thorton, Ocasio, and Lounsbury, 2012; Maitlis and Christianson, 2014). Access to different frameworks is important because, like rules, no one framework is able to govern all situations (Dougherty, 1992; Leonardi, 2011; Besharov and Smith, 2014). Unlike with rules, however, the competent practitioner is not seeking to find the perspective that "works", instead she uses different perspectives as tools to help her shape how she evaluates environmental stimuli when crafting her representation of the problem (Swidler, 1986). She picks up frameworks as she needs them and discards them when she does not. She may use multiple frameworks in the process of crafting a problem representation, but in the end, the representation she has crafted is her own, and not a deterministic output of which frameworks were used (Swidler, 2001; Pache and Santos, 2013). For this reason, access to more perspectives is better, since this gives the competent practitioner more tools in the representation crafting process.

Second, to advance through this stage the actor needs room to fail (Dreyfus and Dreyfus, 2005). The competent practitioner blindly follows neither rules nor perspectives. This independence entails a risk however, for both the actor and other stakeholders in the problem, since it means that her decisions are no longer based on socially legitimated rules for action (Ford and Gioia 2000; Scott, 2008). Any action taken by the practitioner may result in failure, which may cause tremendous losses for critical stakeholders. When such failures occur, actions that conform to legitimated rules are easier to defend than actions that do not (Ouchi, 1977;

March and Olsen, 2004). Nevertheless, improvement at representation crafting requires that the actor gain experience creating novel assessments of problems encountered in the field. This means that if the competent practitioner is to observe further advancement towards expertise, managers and supervisors (who hold the power to restrict access to the problem) must be willing to allow the actor room to fail (Katz and Tushman, 1981; Tierney and Farmer, 2002). For instance, Beane (2018) reports that surgical trainees were encouraged to use traditional surgical methods, but were often barred participation in novel robotic surgical procedures. This restriction ultimately impeded these actors' progression toward expertise.

Stage 4: Proficient Practitioner

The fourth stage of expert development is the proficient practitioner phase (Dreyfus and Dreyfus, 2005). While the start of the competent practitioner phase is signaled by representation crafting, the start of the proficient practitioner phase is marked by solution crafting. The competent practitioner deviates from known rules when assessing a situation to evaluate a problem, but this actor attempts to solve the problem by finding the best existing solution. The proficient practitioner progresses beyond this, crafting not only unique problem representations and but also crafting unique solutions to solve these problems.

To advance through the proficient practitioner stage, the actor needs repeat access to similar problems. It is rare that an actor can craft a highly effective solution to any substantial problem in a single attempt (Thomke, 1998). More often solution crafting involves first identifying a general approach, then fine tuning the approach iteratively to narrow in on the most productive means of solving the problem (Newell and Simon, 1972; Rudolph, Morrison, and Carroll, 2009). This suggests that to become especially proficient at crafting solutions for a

particular type of problem, an actor must engage with the same problem often enough for this iterative process to unfold.

Stage 5: Expert

Upon the final stage of development, the actor enters the expert phase. However, even after becoming an expert there is room for the actor to develop further by increasing and maintaining her flexibility for responding to change in the domain (Dane, 2010). The expert phase begins when the actor observes consistent success at both crafting problem representations and solutions (Ericsson and Charness, 1994; Dreyfus and Dreyfus, 2005). This consistent success is born in the repeat exposure to the same problem, which allows the actor to perfect a solution. While this repetition is crucial for the development of expertise, a downside is that such repetition encourages the expert's mental representation of the domain to calcify (Dane, 2010). This cognitive entrenchment reduces her ability to solve problems that do not conform to the ones for which she gained her expertise (Chi, 2006), and is the reason why experts' performance tends to decrease dramatically (more starkly that novices' performance) when critical assumptions in the domain are altered (Nelson and Irwin, 2014; Almandoz and Tilcsik, 2016). For example, Nelson and Irwin (2014) found that expert librarians were slow to respond to the emergence of electronic search engines because of their cognitive embeddedness in non-internet search methodologies.

To further develop after reaching the expert phase, the actor must gain access to unique cases that force her to reevaluate taken for granted beliefs that harden over the course of the expert development process (Dane, 2010). Exposure to these unique cases does not guarantee that the actor attends to these nuances, and thus do not guarantee that the expert retains cognitive

flexibility (Chi, 2006). However, exposure to unique cases act as a necessary condition for retaining cognitive flexibility, since confronting only belief consistent problems further enforces the associative links in the expert's existing mental model of the domain.

SOCIAL NETWORK CHARACTERISTICS AND EXPERT DEVELOPMENT

The five stage model discussed above provides an overarching logic for understanding the differing needs for advancement in each stage of expert development. However, some of the resources needed to advance through the expert development process may be located in the social structure surrounding the actor, rather than in the actor's possession. Thus, even if the actor is fully motivated to gain expertise through deliberate experience, progress is dependent on the actor's access to those key resources. Since the extent to which these resources are accessible may depend on the structure of ties connecting the actor to resource holders, this calls for examining how an actor's progress toward expertise is shaped by her network structure. Building on this logic, this section forms a theory, and presents a set of propositions, that match each stage of expert development to one or more facilitating ego-network configurations (see Table 4).

Network Structure for Progressing through the Novice Stage

Our discussion of the five stage model suggests that to advance through the novice stage the actor needs access to set of simple rules and a controlled environment in which to gain experience executing the rules. The challenge for the novice is not necessarily locating the simple rules, but rather gaining experience in a manner that enables the actor to recognize errors in rule execution (Kruger and Dunning, 1999). In many domains, simple rules for beginners are accessible through public sources, such as in popular press books, or posted on websites (Chan and Ngai 2007). The problem for novices is that they lack enough knowledge of the field to

know when they are implementing a rule incorrectly, and to know what adjustments they should make to correct these execution errors (Caputo and Dunning 2005; Ehrlinger et al., 2008). Thus, a novice acting autonomously will often fail to acquire the domain's most fundamental skills.

Help from an advisor allows the novice to recognize implementation mistakes early, and make adjustments enabling better enactment of the simple rules (Pennequin, Sorel, Nanty, and Fontine 2010; Miller and Geraci, 2011). This argument suggests that network connections to other practitioners who are further along in the expert development process will aid the focal actor's progression through the novice stage. However, not all ties will work equally well for this purpose. Nurturing a novice requires a substantial commitment from the mentor (Ragins and Scandura, 1999). Helping a novice to observe and correct errors requires time and energy, which undermines a mentor's ability to engage with her own work (Wanberg, Welsh, and Hezlett, 2003). Many potential mentors will be unwilling to incur these costs, since a novice lacks the skills to reciprocate, leaving little benefit in the transaction for the potential mentor. Prior work has shown that strong ties (relational embeddedness) lead individuals to incur costs in both time and material resources that they would wholeheartedly avoid in more arms-length relationships (Hansen, 1999; Uzzi and Lancaster, 2003). This suggest that an actor is more likely to convince a potential mentor to aid in her development toward expertise if the actor already has a strong, relationally embedded, tie with this individual.

> ***Proposition 1****: Strong (relationally embedded) ties to individuals with better developed expertise in the same domain will facilitate an actor's progression through the novice stage of expert development.*

Network Structure for Progressing through the Advanced Beginner Stage

The five stage model of expert development suggests that to progress through the advanced beginner stage the actor needs access to an array of conditional rules. As was argued for the novice stage, locating rules is not itself a problem. More problematic for the advanced beginner is finding a set of rules that is large enough to equip the actor to solve problems, but a set that is small enough to prevent reintroducing the complexity that the conditional rules are intended to reduce in the first place. This suggest that an advanced beginner will benefit from a network structure that produces a manageable set of conditional rules that the actor can adhere to.

Based on this logic I argue that (ego)network closure should facilitate progress in the advanced beginner stage. Network closure at the ego level reflects the extent to which an actor's network ties are connected to each other. Prior work has shown that closed networks facilitate the production of rules to which actors embedded in that network cluster are expected to adhere (Granovetter, 1985; Coleman, 1988). At the same time, there is reason to expect that closure imposes an upper limit on the number of rules that will be transferred from actor to actor. Specifically, closed networks act as echo chambers, which tend toward circulating a small set of relatively redundant information (Nahapiet and Ghoshal, 1998; Burt, 2005). Even, when there is initially a reasonable degree of content diversity in a closed network, actors in these networks converge on discussing only a subset of the information initially in the system (Lee, Bachrach, and Lewis, 2014). Thus, it is reasonable to expect that closed networks will expose the advanced beginner to rules for action in the domain, but that these networks will bound the actor's attention to only a subset of conditional rules. Therefore, I predict the following:

Proposition 2*: Closed ego-networks will facilitate an actor's progression through the advanced beginner stage of expert development.*

Network Structure for Progressing through the Competent Practitioner Stage

The five stage model of expert development suggests that to progress through the competent practitioner stage the actor requires both access to diverse frameworks and room to fail. The need for exposure to diverse frameworks suggests that an actor's advancement through this stage of development may be facilitated by more open ego networks—networks where fewer of an actor's network ties are connected to each other. Shore et al. (2015) find in an experimental study that actors in closed networks tend to discuss problem relevant information from the lens of only a few frameworks, whereas actors in open networks tend to share different frameworks for interpreting problem related information. This evidence is consistent with Burt's (2005) theory that open networks facilitate creative thought by exposing actors to diverse perspectives.

Proposition 3*: Open ego-networks will facilitate the acquisition of diverse frameworks, which aid an actor's progression through the competent practitioner stage of expert development.*

It is important to note here that open networks are proposed to grant access to only one of the two needs required for advancing through the competent practitioner phase. In addition to the diverse frameworks granted by open networks, actors in this stage of development also require the room to fail while learning how to craft problem representations.

This second need is more likely to be filled for actors in network positions with higher levels closure. An actor's access to problems is often buffered by intermediaries who act as gatekeepers that decide who will be allowed to address problems and who will not (Katz and Tushman, 1981). These individuals must be willing to bare the risk associated with the focal actor deviating from known rules by attempting to craft novel problem representations (Tierney

and Farmer, 2002). Closed networks facilitate trust and reputational benefits, which make it more likely that these gatekeepers will accept the risk (Reagans and McEvily, 2003). Closed networks act as echo chambers not only for information regarding problems, but also for reputational information regarding the characteristics of actors in the network, including their skills and abilities (Burt, 2005; Sorenson, Rivkin, and Fleming, 2008; Argote Aven, and Kush, 2018). This means an actor who is connected to a gatekeeper through a closed network is more likely to be recognized by the gatekeeper for her burgeoning abilities in the domain than when this actor is connected to the gatekeeper through an open network.

To be sure, even though closed networks make the gatekeeper more aware of the actor's skills, this alone may be insufficient to compel that gatekeeper to acquiesce to the actor's need to deviate from domain specific problem solving rules. This is because, in the competent practitioner stage, the actor's skill level may not be refined enough to secure the buy-in of a gatekeeper on merit alone. In a closed network, however, the gatekeeper may feel compelled to take a risk on the competent practitioner despite this skill gap, due to the social expectation that individuals act cooperatively when working with other members of the closed network (Coleman, 1988). To violate the norms of cooperation in a closed network, the gatekeeper risks not being able to secure the cooperation of any others in that network when their assistance is needed by the gatekeeper at a future date (Gargiulo, Ertug, and Galunic, 2009). Thus, in closed networks, gatekeepers are not only more likely to be aware of an actor's progress toward expertise, but also more likely to cooperate with the actor despite any remaining reluctance to accept the consequences of errors should the actor make a mistake. Therefore, I predict the following,

Proposition 4*: Actors in more closed networks are more likely to be granted room to fail, which aids their progression through the competent practitioner stage of expert development.*

Network Structure for Progressing through the Proficient Practitioner Stage

I argue that network range in the actor's ego-network aids advancement through the proficient practitioner stage. Network range is the extent to which an actor has network ties to different knowledge pools (Reagans and McEvily, 2003). The proficient practitioner needs repeated access to similar problems to allow the micro-experimentation and fine tuning needed to craft effective solutions. The challenge in gaining opportunities for micro-experimentation is that many practitioners, due to the nature of their work, may be unable to focus exclusively on a single type of problem. Thus, the precise problem for which an actor is attempting to develop expertise may not reoccur with the regularity needed for the actor to master the process of crafting solutions to the problem. For example, clinical cardiologists carry out a range of tasks in treating a single patient, such as interpreting blood tests and exercising stress tests. Because they must complete an array of tasks for each patient, a typical cardiologist may have limited opportunities to accumulate experience with special procedures, such as echocardiology (which involves interpreting cardiac ultrasounds). Thus, even if a cardiologist is motivated to do so, she may have little opportunity to develop deeper specializations.

Network range may help the actor to overcome this challenge. Network range is helpful for the proficient practitioner in that it may allow the actor to trade problems with other specialists. When the actor has ties to others with diversified knowledge backgrounds, some of these individuals may be better at solving problems that require that focal actor's attention. This is useful when solving the traded problem would not contribute to the focal actor's area of

budding expertise. For example, a cardiologist may tradeoff problems with her peers, sacrificing opportunities to diagnose congenital heart conditions, in favor of gaining opportunities to interpret cardiac ultrasounds. Potential partners are incentivized to engage in such trades since the proficient practitioner has the skill to make trading problems beneficial to both parties, allowing both actors to accumulate the experience needed to move more quickly through the expert development process (Wegner,1987; Argote Aven, and Kush, 2018).

Of course, this argument requires two conditions be met. First, it is important that the partner works in a domain sufficiently proximate to the focal actor's area of specialty that each actor has problems worth trading with the other. Second, it is important that the partner's expertise be sufficiently developed, as evidenced by a track record of success, for the focal actor to trust that partner with taking over a problem assigned to the focal actor (Borgatti and Cross, 2003). However, assuming that these two conditions are met, I propose the following.

> ***Proposition 5****: Network range in the actor's ego-network will facilitate progression through the proficient practitioner stage of expert development.*

Network Structure for Progressing in the Expert Stage

I argue that network centrality aids development in the expert stage. The challenge upon reaching the expert stage of development lies in maintaining cognitive flexibility. This challenge is more likely to be met when the actor is exposed to a healthy dose of evidence to disconfirm some of her taken-for-granted beliefs about problems in the domain (Dane, 2010).

An actor in a more central network position is more likely to be exposed to such disconfirming evidence for two reasons. First, central actors sit at the crossroads of information flows (Brass, 1985; Ibarra, 1993; Borgatti, 2005). Thus, when an especially difficult problem arises somewhere in the network, a central actor is more likely to hear about the problem, which

provides an opportunity for the actor to rethink her previous conceptualization of problems in the domain. Second, the actor's central position makes her an attractive partner for others struggling with unique problems (Podolny, 2001; Rossman, Esparaza, and Bonacich, 2010). The combination of high past performance and high network centrality makes the actor highly visible as a domain expert (Oldroyd and Morris, 2012; Sterling, 2015). When other practitioners in the domain encounter problems that require the assistance of someone more knowledgeable, the focal actor is likely to be seen as a viable option (Borgatti and Cross, 2005). This is important for the actor's continued development, since it is precisely these unique problems that may encourage her to reformulate her views of problems in the domain (Dane, 2010). Less central practitioners, with similar levels of expertise, may not be afforded this opportunity, allowing their domain schema to calcify. Therefore, I propose the following.

> ***Proposition 6****: Network centrality will facilitate an actor's progression through the expert stage of expert development.*

ORGANIZATIONAL DESIGNS FOR FACILTATING EXPERT DEVELOPMENT

The theory and propositions presented in the section above offer a descriptive theory of how social networks facilitate and impede an actor's progress toward expertise. This section builds on those insights to explain how organizations, by attending to the network challenges involved in expert development, may design structures that increase the chance that an employee becomes an expert. It is argued, in particular, that the competent practitioner stage acts as a bottleneck in the expert development process, and therefore that this stage should be the focus of a firm's design efforts.

A bottleneck refers to a point of congestion, or more generally to a component in a complex system that significantly limits the performance of the system as a whole (Goldratt,

1984; Baldwin, 2014). The imagery of a bottleneck suggests that system inputs flow relatively smoothly until reaching a certain point, and relatively smoothly after escaping that point, but that progress at the point is restricted.

Such is the case for the expert development process (see Figure 18 below). Propositions 1- 6 suggest that actors will (1) progress rather smoothly through the novice and advanced beginner stages, (2) face tremendous difficulties advancing through the competent practitioner phase, then (3) progress rather smoothly through the proficient practitioner phase to expert level. Progressing from the novice stage to the start of the competent practitioner stage requires that the actor's ego-network evolve from one comprising strong dyadic ties to a closed network where the actor's partners are connected to each other. This is feasible since a triad comprising a pair of strong but disconnected ties will show a natural tendency toward closure (Granovetter, 1973; Krackhardt and Kilduff, 1999). Even if an actor does nothing to purposefully facilitate an introduction between two of her disconnected strong ties, these partners are likely to meet simply due to their propensity to frequently interact with the focal actor (Granovetter, 1973; Kossinets and Watts, 2006). Thus the network needs in the novice and advanced beginner stages are compatible. Likewise, advancing in the proficient practitioner stage requires high network range, while progressing in the expert stage requires high network centrality. These network structures, while distinct, are compatible in that one network structure does not preclude the other. Thus from a social network perspective, it is feasible for actors to progress rather smoothly both in the stages preceding and in the stages succeeding the competent practitioner phase.

The point of obstruction in the expert development process comes in the competent practitioner phase. Comparing propositions 3 and 4 suggests that the competent practitioner stage

requires conflicting network structures to provide the two distinct needs in this stage. Thus, an actor occupying either one of these network configurations exclusively will be able to fulfill one need but not the other, halting advancement toward expertise. Therefore, I propose the following.

> ***Proposition 7****: The competent practitioner stage acts as a bottleneck in the expert development process.*

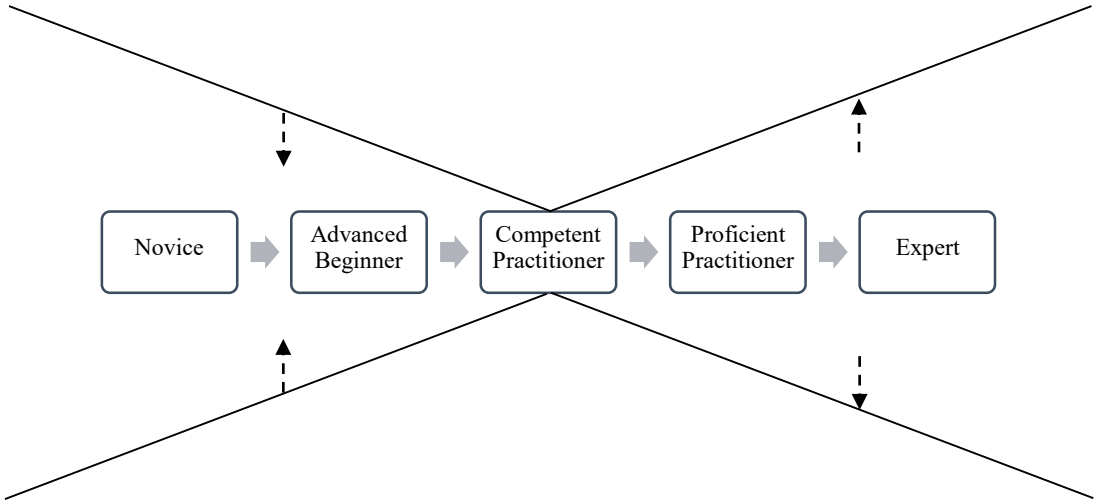

Figure 18 The Developmental Bottleneck

Note that this proposition provides an explanation for the empirical puzzle that many actors advance from the novice to competence stage, but few actors show further development once reaching competence (Ericsson and Lehmann, 1996; Ericsson, 2006; Beane, 2018). The bottleneck proposition adds deeper insights. Whereas the prior intuition attends to the feasibility of progress in the stages preceding competence, the bottleneck proposition emphasizes also the relative feasibility of progress in the stages succeeding the competent practitioner stage.

The implication for organizational design is that firms should concentrate developmental efforts on the competent practitioner stage of development. Many organizations will have limited

material and attentional resources (Ocasio, 1997), and therefore will struggle to successfully implement design efforts across every stage of the expert development process. Even firms that possess these resources may still wish to avoid imposing structures and procedures in every stage to avoid overstructuring the expert development process (Davis, Eisenhardt, and Bingham, 2009). Thus, a firm's efforts to design the expert development process may be limited in scope either by force or by choice. Since firms must be judicious in implementing design choices, it makes sense to concentrate the firm's design efforts where these efforts will have the most impact. Accordingly, Baldwin (2014) argues that firms should focus design rules on bottlenecks in organizational processes. The intuition is that, the functionality at the bottleneck will serve as an upper limit on the performance of the entire system. As it applies to expert development, this argument points to the recognition that in all stages excluding the competent practitioner stage, the emergent processes through which networks influence expert development will help to push actors through the process even without the firm's involvement. Thus, centering design efforts on assisting actors through the competent practitioner phase maximizes the marginal return for each design choice implemented. Therefore, I propose the following.

> ***Proposition 8****: Organizational design choices will lead to the largest positive influence on expert development when focused on the competent practitioner phase.*

While presenting an exhaustive list of design options is not the focus of this paper, it is useful to propose one salient design approach to help firms develop experts internally. Recent network research suggests that actors can gain the benefits of both open and closed networks by engaging in network oscillation (Burt and Merluzzi, 2016; Kumar and Zaheer, 2018). The primary insight from this work is that, because both open and closed networks provide actors

with critical but distinct resources (Burt, 2005), actors with stable ego-networks (be they open or closed) may underperform similar actors who oscillate from one network configuration to another over time. In the case of advancement through the competent practitioner phase, open networks provide actors with the diverse frameworks used to craft unique problem representations, and closed networks provide actors with the room to fail when applying novel problem representations in practice. Therefore, oscillation across these networks structures may allow actors to acquire both needs for advancing through the stage.

However, for many actors, continuously restructuring one's ego-network is not feasible (Ahuja, Soda, and Zaheer, 2012). While network structures are capable of change, individual actors have very little control over how network structures evolve (Mayhew, 1980). This is because the network configuration that materializes depends on the actions taken to add and remove ties by both the actor (which she controls) and her network partners (which she does not control) (Buskens and van de Rijt, 2008). Thus, most actors will have few opportunities to engage in the wholesale restructuring of their networks implied by moving strategically from a highly closed to a highly open network, or vice versa.

Organizations may implement design choices to overcome this individual level difficulty. Organizations yield control over the networks that emerge among employees, as the formal organizational structure may require relationships that would not otherwise exist (Tichy, Tushman, and Fombrun 1979; Dow, 1988; Clement and Puranam, 2018). Prior work has found that network relationships are more consistent and durable when reinforced by the formal structure and more episodic when emerging outside of formal arrangements (Klienbaum, Stuart, and Tushman, 2013; Clement and Puranam, 2018). This suggests that firms have some control

over which dyadic ties will be weak ties allowing for open networks, and which will be strong ties encouraging closed networks. For instance, a firm can open an actor's network by moving the employee from a traditional team setting to a boundary spanning position that coordinates work across a set of disconnected units, work groups, or external actors. After the employee spends some time in this position, the firm can again close the actor's network by moving her back to a traditional team role. Thus, while the actor would on her own accord struggle to engage in the wholesale restructuring needed to oscillate her network, the firm can design opportunities that allow the actor to move across open and closed networks by changing her formal role in the organization. This may help the actor to advance through the competent practitioner phase, where she would have otherwise struggled. Therefore, I propose the following:

> ***Proposition 9****: An organization may facilitate an actor's progression through the expert development processes by oscillating the actor's network between closed and open structures during the competent practitioner phase.*

DISCUSSION

This paper was motivated by the need to better understanding how firms may design structure that encourage the emergence of experts by examining how the structure of relationships surrounding an actor informs the potential for that actor to develop from novice to expert. While several organizational theories recognize the importance of internal expertise for organizational performance, there is little guidance as to how such expertise can be produced internally. The deliberate experience perspective on expert development provides a useful starting point to draw from. However, the perspective is limited in its ability to speak to organizational research in that it tends to view actors as atomistic agents, while ignoring the influence of the social structure surrounding the actor. Thus, by presenting a theory of how

network structures may facilitate an actor's progress toward expertise, this paper is able to contribute to both the literature on expert development and to the broader literatures on value creation within firms.

Contributions to the Literature on Expert Development

The literature on expert development generally proposes that an actor's progression toward expertise is a direct reflection of the amount of deliberate experience the actor has gained with a problem. While this perspective has been broadly validated in empirical research, it remains difficult to explain the relative dearth of experts in most domains. More specifically, there is no clear explanation for the empirical regularity that actors seem to advance to the competent practitioner phase with relative ease, but rarely show progress beyond this stage. This paper adds to the expert development literature by providing an explanation for this empirical regularity. In most stages of development actors require a single key resource that can be supplied by a single network structure. Further, for the most part, the network structure required by successive stages of development tends to be complementary. The one exception is the competent practitioner phase. Actors require two distinct needs to progress through this stage of development, and these two needs are supplied by conflicting network structures. As a result, the competent practitioner stage acts as bottleneck in the expert development process.

This bottleneck proposition provides two unique insights to the expert development literature. First, the expert development literature has viewed the actor's motivation for gaining deliberate experience as the key driver of expert development. The bottleneck proposition demonstrates the importance of considering the propensity for conflicting needs in the development of expertise. When the needs of a developmental stage conflict, the actor may

struggle to advance through the stage no matter how motivated. Second, the paper adds a more nuanced view on the finding that actors stall at the competent practitioner level. The view supplied by prior research is that the stages proceeding the competent practitioner stage are practical to traverse, and that the road to expertise is arduous thereafter. In contrast, the bottleneck proposition suggests that progress is feasible both in the stages proceeding, and the stages succeeding, the competent practitioner phase. This distinction is important since it suggests that the most efficient means for assisting actors through the expert development process lies in centering organizational efforts on helping actors in the competent practitioner phase, rather than also spreading these resources across proficient practitioner and expert stages.

Contributions to the Literature on Value Creation within Firms

Beyond its contributions to the literature on expert development, this paper speaks directly to two perspectives on value creation within firms. First, the problem-solving perspective of the firm views value creation as reflective of the firm's ability to create new knowledge internally (Nickerson and Zenger, 2004). In the problem-solving perspective, new knowledge is created as organizational problems are solved. A manager's role is to discover problems and then structure the organization in a manner that enables effective search for a solution. In this view the core organizational hazard lies in a manager's propensity to expropriate value from a firm by accumulating and applying knowledge for individual rather than organizational level benefit. However, additional hazards may exist, in that this perspective takes for granted the manager's ability to recognize and represent problems. The theory in this paper suggests that a manager may not be able to perceive problems, nor properly represent them. As a consequence, a manager with insufficient expertise may choose to peruse problems that do not create value, and choose

the wrong structure for finding solutions to these problems. Importantly this hazard applies even if incentives are implemented to alleviate the propensity for knowledge expropriation.

A second contribution to the problem-based perspective lies in suggesting the need to expand the role of the organizational structure. In extant literature the role of the organization's design efforts lies in coordinating the search for solutions, rather than developing an agent's ability to search. However, an actor's ability to search for solutions is reflective of her expertise in the domain. Thus, in the problem-based perspective, the role of organizational design in enhancing value creation is contingent on the pre-existence of experts in the firm. From this perspective, however, if actors capable of search (experts) are not present, then the organizational design does not matter. This paper suggests, in contrast, that the role of organizational design in the problem-solving view should comprise two stages, (1) designing to develop agents capable of search and (2) designing the search process. Thus, this paper expands the role of organizational structure, thereby expanding the opportunities for strategic value creation in this view. This raises interesting questions, such as whether the designs needed to develop search agents always cohere with the design needed for effective search processes, and whether the need and ability to develop experts internally changes the firm's boundary choices from a problem-solving perspective.

Second, this paper speaks to value creation as viewed from the literature on strategic human resources. This literature is traditionally pitched at the organizational and unit levels, which allows scholars to circumvent individual development to focus on how hiring process and turnover can shift a unit's strategic human capital. However, recent shifts in this literature call for a sound theory that explains the organization's strategic role developing individual expertise.

In particular, the emerging "human capital resource" perspective has re-emphasized the role of individual experts, arguing that individual expertise is the fundamental building block of unit level human capital (Polyhart, Nyberg, Reilly, and Maltarich, 2014). Thus far, however, this literature has focused theoretical effort on understanding the organizational structures and policies that productively recombine existing expertise within the firm. This paper suggests the need for human resource policies that enhance the emergence of experts in the first place. For instance, in addition to policies for motivating actors to develop expertise, job rotation policies may help actors to progress through the competent practitioner phase.

CONCLUSIONS

Experts are important for knowledge creation within firms. It is important, therefore, that we develop a sound understanding of the role a firm's internal structures play in deciding whether its employees develop as experts. This paper suggests a design approach firms can take in persuing this goal. The core insight is that an actor's social network helps to determine when acquiring the resources needed to develop expertise will be easy and when it will be difficult. By accounting for these difficulties this paper provides guidance as to how firms may shape an actor's social network at critical stages in the expert development process to enhance the likelihood that the actor advances from novice to expert.

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CONCLUDING REMARKS

This dissertation presents three essays that help to shift the way learning is conceived in social network research. Prior work conceptualizes learning as the acquisition of information from one's network partners, with the assumption that information is most beneficial when more diverse and when acquired at a faster rate. This dissertation shows the added importance of experiential learning for network theory.

Chapter 1 shows the importance of exploratory search and competence development within firms for understanding the performance consequences of network structure. Both exploratory search and competence development represent adaptive learning from performance feedback. This paper shows that a firm's network structure influences not only the information the firm extracts from the network, but also the information the firm gains experientially through its search efforts. Firms in open networks face greater uncertainty and are therefore more inclined to engage in exploratory search even when the information gained during search merely repeats the information gained in the network. Consequently, these firms lag in their progress up the learning curve, thereby displaying slower competence development. This account gives new insights into how closed networks can lead to performance advantages over open networks.

Chapter 2 examines the tension between variation and selection in networks. Prior work has considered the importance of networks for heightening exposure to variation—in the form of diverse practices, strategies, and resources. However, this work has ignored the mechanisms necessary for selecting from this expanded pool of practices. This paper creates greater balance by accounting simultaneously for network mechanisms that increase variation (diverse information) and network mechanism that aid selection (redundant information). The paper

shows that in contexts where open networks confer rapid access to diverse information, many firms fail to benefit because they lack a mechanism for selecting from this diversity. In contrast, in contexts where access to diverse information in open networks is slowed, selection is aided by the firm's ability to match its experiential information on a given practice with the network information on that practice.

Chapter 3 moves the level of analysis from the firm to the individual, and highlights the role of networks in the development of individual expertise. This paper speaks to the deliberate practice perspective on expert development, which argues that an actor's progression toward expertise in a domain is a direct reflection of the amount of experience that actor has accumulated in the domain. Social networks contribute to this literature by showing that opportunities for an actor to build experience with a problem are not a given. Because problems are often guarded by gatekeepers, the structure of relationships linking the actor to those gatekeepers helps to determine how experience will be accumulated. This paper provides deeper insights into how firms may help its employees to develop expertise by accounting for network influences on experience accumulation.

Each of the three papers sheds light on how an actor's network structure influence learning from experience, and how this in turn influences the effects of network structure on organizational outcomes such as performance and individual outcomes such as expert development. As a collective, this work helps to push the network literature forward by pointing to novel mechanism through which network structural effects arise.

BIOGRAPHICAL SKETCH

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- **Ayenda Kemp**, J. Richard Harrison, and Zhiang (John) Lin. "Expanding the Role of Adaptive Learning in Network Theories"– ***Under Second Round Review at Administrative Science Quarterly*** (dissertation paper)
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