Strategic Management Journal
Strat. Mgmt. J., **35**: 974–994 (2014)
Published online EarlyView 28 June 2013 in Wiley Online Library (wileyonlinelibrary.com) DOI: 10.1002/smj.2142
Received 22 April 2010; Final revision received 1 April 2013

WHEN HUBS FORGET, LIE, AND PLAY FAVORITES: INTERPERSONAL NETWORK STRUCTURE, INFORMATION DISTORTION, AND ORGANIZATIONAL LEARNING

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The interpersonal network structure of an organization directly influences the diffusion and recombination of ideas and can thus facilitate or impede organizational learning. Most interpersonal networks have 'hubs'—individuals who have significantly more connections than does the average member. This raises important questions about how hubs influence organizational learning outcomes. Does the presence of hubs improve or impair performance? What happens if hubs forget or misrepresent information that is transmitted through the network? Using simulation models, we find that moderately hubby networks outperform both very hubby and democratic networks. We also find that moderate amounts of information omission or misrepresentation can be surprisingly beneficial to performance, though the patterns of their effects are strikingly different.

INTRODUCTION

One of the primary reasons that firms exist is their ability to create and exploit knowledge (Connor and Prahalad, 1996; Grant, 1996; Kogut and Zander, 1996). Many forms of learning and knowledge transfer only take place through close and frequent contact and the development of shared routines. The firm provides both a venue and an incentive system for such learning and knowledge transfer to take place. The repository of knowledge, routines, and recombinatorial capabilities that emerge are often the basis of competitive advantage (Argote and Ingram, 2000; Lippman and Rumelt, 1982; McEvily and Zaheer, 1999; Uzzi and Lancaster, 2003).

A significant body of research has highlighted the influence of organization structure on organizational learning (Cohen, 1991; Stinchcombe, 1990). The early work in this area tended to focus on formal organization structure and routines (e.g., Cyert and March, 1963; Daft, 1983; Lawrence and Lorsch, 1967). This stream includes, for example, research on the effect of task decomposition (Burton and Obel, 1984), reporting structures (Carley and Lin, 1997), autonomous subunits (Bower and Christensen, 1995), incentives (Kretschmer and Puranam, 2008), and hierarchy (Siggelkow and Levinthal, 2003), as well as governance choices (Nickerson and Zenger, 2002). Another line of work has focused on the structure of interpersonal networks within the organization (e.g., Borgatti and Cross, 2003; Hansen, 1999; Miller, Zhao, and Calantone, 2006), examining, for example, the effect of centrality (e.g., Krackhardt

Keywords: interpersonal networks; organizational learning; scale-free networks; recombinant search; exploration; exploitation
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and Hanson, 1993), weak ties (e.g., Hansen, 1999), and cohesion (e.g., Reagans and McEvily, 2003).

Despite the volume of works linking organizational structure and organizational learning, however, the available evidence on the association between structural configurations and organizational learning is still rather limited (Argote, McEvily, and Reagans, 2003; Reagans and McEvily, 2003). Our paper focuses on two very significant omissions in this line of work—the prominence of 'hubs' (individuals who are much more connected than the average individual) in the interpersonal network of an organization, and the concomitant influence of their ability and willingness to transmit accurately information to their contacts.

Hubs are ubiquitous in both formal and informal interpersonal networks (Barabási, 2002). Many studies have shown that both formal and informal social networks very often exhibit skewed degree distributions, meaning that there are a few individuals in the network who have significantly more connections than does the average member of the network. In social networks, for example, some individuals are much more inclined or able to build and maintain a very large number of acquaintances. Individuals can become hubs in the interpersonal network by virtue of their role within an organization, exceptional performance, propensity for social exchange, among other reasons.

Because they are connected to a great many other individuals, hubs provide shortcuts between many pairs of individuals. A hub is also in a position to capture a disproportionate amount of the information and other resources that travel through the network and can exert great influence over whether, how, and to whom information and other resources are transmitted (Dhanaraj and Parkhe, 2006). This raises some important questions about how hubs in an interpersonal network influence organizational learning. Do organizations that have 'very hubby' interpersonal networks learn better and attain higher performance? What happens when hubs are voluntary or involuntary bottlenecks in the diffusion of information? Furthermore, what happens if and when hubs deliberately withhold or misrepresent information?

Building on recent advances in graph theory, our paper complements existing research by studying how organizational learning is influenced by a spectrum of interpersonal network configurations that range from those with an extremely skewed degree distribution to those where hubs are much less prevalent. Each of the network configurations we explore has numerous real-world analogs. For instance, the interpersonal email network of the Linux community has been shown to be scale free (Ebel, Mielsch, and Bornholdt, 2002). On the other extreme, in the friendship networks of high school students it is extremely rare to find individuals who have significantly more or fewer links than the average (Fararo and Sunshine, 1964). Though formal reporting hierarchies might be deliberately structured to avoid hubs (to reduce the information burden of individuals), evidence suggests that the interpersonal networks, as represented in patterns of communication among individuals in the organization, are typically quite 'hubby'. For example, in a study of the complete record of email communications and scheduled meetings among 30,328 people in a large information technology firm from October through December 2006, Kleinbaum, Stuart, and Tushman (2013) found that the distribution of both the number of messages sent or received by individuals and the number of correspondents of individuals have very long right tails: while the mean employee exchanged 385 single-recipient emails with 15 other employees of the organization, some individuals sent as many as 14,000 emails and maintained more than 200 correspondents.

Examining the impact of such hubs on learning empirically, however, poses a significant challenge because real world networks seldom present us with opportunities to disentangle the influence of network structure from a host of other confounding variables such as network density (i.e. the total number of connections), network size and individual characteristics. To overcome this challenge, we develop a simulation model of organizational learning that systematically tunes the network configurations. Our model builds on March's (1991) learning model but incorporates interpersonal learning and a network structure that varies in its degree of 'hubbyness'. We are able to examine the effect of hubs on diffusion and learning, and we are able to incorporate the possibility of hubs omitting or misrepresenting information (i.e., the effect of hubs forgetting, lying, and playing favorites).

The organization of this paper is as follows. In the following section, we review the relevant literature. We then develop an organizational learning model that focuses on how learning is conditioned

DOI: 10.1002/smj

by the pattern of interactions in the interpersonal networks of organizations. We tune the degree of 'hubbyness' of a network with a single parameter that systematically varies the dominance of hubs. We then examine how organizational learning is further complicated by the omission or misrepresentation of information by hubs. Lastly, we discuss our main findings and their implications for future research as well as practice.

INTERPERSONAL NETWORK STRUCTURES AND ORGANIZATIONAL LEARNING

Network structure

An interpersonal network consists of a set of individuals and of the links among them. Links may represent a wide range of connections, such as friendship, advice and information seeking, communication, and material transfers. Most physical and social real world networks can be classified into three distinct classes according to the distribution of the links or connections (Amaral *et al.*, 2000). First, networks are scale free when their degree distribution (i.e., the distribution of the number of links per node) follows a power law. This means that hubs with many more connections than the average node are relatively common. Many empirical studies over the last decade have shown that real world networks are often characterized by scale-free or fat-tailed connectivity distributions (Amaral *et al.*, 2000; Barabási and Albert, 1999).

The existence of such 'hubby' networks is often explained by a preferential attachment process (Barabási and Albert, 1999), in which new nodes arrive and connect to nodes that are already well connected. As the network expands, the rich get richer as early nodes receive disproportionately more links and eventually become hubs (Barabási and Bonabeau, 2003). This preferential attachment process is likely to describe fields where status, reputation, or power is salient (Gould, 2002; Wagner and Leydesdorff, 2005).

The second class of networks exhibits a relatively large number of well-connected hubs, but fewer *extremely* well-connected hubs, than would be expected in strictly scale-free networks. In other words, its connectivity distribution has a power law regime followed by a sharp cutoff in the tails of the distribution. For instance, the movie actors' collaboration networks are truncated scale-free networks (Amaral *et al.*, 2000). The truncation implies that the biggest hubs do not get bigger and 'richer' *indefinitely* but rather are subject to growth constraints that hinder the preferential attachment process. For instance, people only have enough time, energy, and interest to befriend so many others (Watts, 2003). We refer to these networks as 'moderately hubby'.

The third class of networks represents the other extreme and is characterized by a *democratic* distribution of links: nodes have more or less equal number of links, and it is very rare to observe nodes with many connections. Thus, the connectivity distribution has a fast-decaying tail, such as exponential or Gaussian in log-log scale. In these networks, cultural and social constraints may encourage equality and egalitarian distribution of resources. Many deliberately structured networks are explicitly democratic (e.g., a phone tree), as are those in which the formation of a link is extremely costly or excludes the possibility of forming another link (e.g., the family tree network created by mapping marriages and births).

Performance implications of various interpersonal network structures

The structure of the interpersonal network within the firm has direct and important implications for organizational learning. One of the key ways that individuals learn is through sharing ideas with others embedded in the same networks. When individuals interact, they pool, exchange, and recombine information, resulting in the creation or refinement of the ideas and knowledge possessed by each individual (Argote, 1999; Brown and Duguid, 1991; Larson and Christensen, 1993). In this recombinant view of learning, it is easy to assume that the rapid diffusion of ideas will facilitate learning by increasing the pool of ideas that individuals can access and utilize. Consistent with this, both the research on innovation and managerial practice typically emphasize mechanisms that increase the exchange of information throughout the organization such as cross-functional teams, personnel rotation, liaison roles, and knowledge management systems (Brown and Eisenhardt, 1995; Nobel and Birkinshaw, 1998). Intriguingly, however, other research has suggested that when ideas diffuse too quickly through a population, the result

DOI: 10.1002/smj

can be premature convergence around a popular, though suboptimal, set of ideas. An initially better performing idea can out-compete seemingly inferior ideas, causing variety to be extinguished. Since the number of recombinatorial possibilities available to individuals is a direct function of the diversity of knowledge they have access to (Beckman and Haunschild, 2002; Damanpour, 1991; Fleming, 2001; Taylor and Greve, 2006), the loss of 'requisite variety' in a population's knowledge stocks can thwart long-run learning.[1] In March's seminal (1991) paper on organizational learning, he finds that 'slow learning', though less efficient, allowed the organization to preserve more diversity of knowledge and to explore a wider range of possible combinations of beliefs. Thus the quality of organizational knowledge in the long run is higher. Michael Eisner (former CEO of Disney) illustrated an intuitive understanding of this when he emphasized the importance of diversity and conflict in Disney's creative process: 'If [an idea] is just sliding along with no friction, you get the easy solution; you get mediocrity' (Eisner and Wetlaufer, 2000:118).

Breakthroughs in network simulation and analysis methods have spurred the growth of a young-but-growing body of research that models interpersonal learning as a network process (e.g., Fang, Lee, and Schilling, 2010; Miller *et al.*, 2006; Rodan, 2005, 2008; Tang, Mu, and MacLachlan, 2008). For example, the Fang *et al.* (2010) study built on March's original result by showing that when an organization's interpersonal network is subdivided into semi-isolated subgroups, the organization's long-term learning performance is significantly higher than when the network is not divided into subgroups or when subgroups have many cross-group links. They conclude that the semi-isolation of groups fosters the diversity of ideas, thereby enhancing long-run learning outcomes. Like the majority of work in this area, however, their study models a uniform degree distribution (i.e., each individual has the same number of information exchange partners) and assumed that all individuals transmit their information completely and accurately. In many real-world organizations, these assumptions break down in important ways. First, organizations have individuals who possess many more connections than the average due to factors such as their position, tenure, status, social tendencies, etc., which significantly affects the structure of the interpersonal network. Second, these hubs may be prone to overload or agency, suggesting that they may not transmit all of their information completely and accurately to all of their contacts. Each of these issues is discussed further below.

Hubs and network structure

Like random connections or individuals in 'brokerage' roles (brokers are individuals who connect groups of individuals that would otherwise be disconnected), hubs dramatically shorten the path length of a network and are thereby likely to accelerate diffusion. However, hubs are very different from random connections and brokers. First, hubs are organizationally far more likely as they arise through the very common formal and informal processes described earlier. Random connections and brokerage connections are, almost by definition, atypical connections. Furthermore, while individuals with random connections or in brokerage roles may have access to information that is more diverse than that available to the average member of the organization, a hub has access to a greater quantity, a greater diversity of information, and is in a position to aggregate and compare information from many sources simultaneously. If, for example, a hub could only learn from the same number of sources as a typical individual, the solution to a problem would be no better or worse, on average, than that of other individuals in the network. Even if a hub might be able to broadcast its solution widely, this solution might not propagate through the network because it has only an average likelihood of dominating other solutions. By contrast, when a hub can learn from many individuals, the solution might be more likely to exhibit traits of the best solutions that exist at that point in time in the network. Though other better solutions might have emerged later on, the hub's solution may achieve early dominance: when a hub broadcasts this solution, it propagates through the network quickly. It should thus be clear that hubs are not merely shortcuts in the network.

[1] The term 'requisite variety' generally refers to Ashby's (1956) Law of Requisite Variety that states, 'the available control variety must be equal to or greater than the disturbance variety for control to be possible.' This axiom is widely used to explain the need for variety to ensure evolvability in any entity subject to selection pressure (e.g., species diversity).

Information distortion

Even more importantly, hubs have disproportionate influence over the flow of information through the network and, by virtue of their exceptional connectivity, may be more prone to overload or agency than the average individual. The typical conception of a hub as a shortcut in the network relies on an implicit assumption that hubs (and nodes of the network more generally) are perfect relays that transmit information perfectly, accurately, and immediately. In reality, however, the individuals in a social network are constrained in their capacity to process and transmit information and are likely to act with agency that is influenced by a myriad of competing incentives (Davis, 2010). Because hubs have a great many more connections than others in the network, they may be significantly more likely to be sources of information distortion in the network, for reasons we discuss below.

First, because hubs have many connections, they are likely to be especially prone to overload (O'Reilly, 1980). A considerable body of research posits an inverted U-shaped relationship between information quantity and diversity and managerial performance (Eppler and Mengis, 2004). On the one hand, having access to a wide variety of information expands the opportunities and resources of managers, enhancing their creativity (Rodan and Galunic, 2004) and even helping them further develop their information processing capacity (Eppler and Mengis, 2004). On the other hand, having an overly heavy information load can also cause an individual to become confused, possibly forgetting the information and making it difficult for the individual to determine the relevance or priority of the information (Schick *et al.*, 1990). The individual might choose to ignore large amounts of information (Sparrow, 1999), take longer to reach a decision (Jacoby, 1994), and/or make decisions of poor accuracy (Malhotra, 1982). Hubs might thus fail to transmit all of their information to some or all of their contacts or may transmit inaccurate information. Second, because hubs are in a position to capture a disproportionate amount of the information and other resources that travel through the network and to exert great influence over whether, how, and to whom information and other resources are transmitted (Dhanaraj and Parkhe, 2006), it is possible that hubs might intentionally withhold or manipulate information. Hubs might thus deliberately transmit false information to all of their contacts or to all but their preferred contacts. All of these mechanisms can cause hubs to become deliberate or involuntary bottlenecks in the network.[2]

It is difficult, ex ante, to know what effect each of these possibilities would have on organizational learning. While it is typical to assume that forgetting information, misrepresenting information, and playing favorites are undesirable behaviors that might hinder learning in the organization, they might also create or preserve requisite variety in the organization, helping to sustain long-term learning. It is not uncommon, for example, for a manager to assign two teams to develop solutions for a particular problem and to intentionally withhold information from each team about the solutions being developed by the other team. By not transmitting this information across the two teams, the manager ensures that the teams are not prematurely contaminated by the other's solution set, freeing them to pursue their own ideas. This is the basis of much of the work on 'skunkworks'. It is also closely related to Lingo and O'Mahony (2010)'s finding that, during some phases of record production, music producers keep some parties to the creative process apart in order to avoid premature evaluation. Finally, it is entirely plausible that a manager might deliberately mislead a team about another team's performance or approach in order to avoid premature convergence on a single solution. Furthermore, there could be differences in how different forms of distortion (selective or unselective omission or misrepresentation) influence learning outcomes.

To systematically explore these possibilities, we first build a baseline model that tunes the 'hubbyness' of the interpersonal networks, ranging from completely democratic to scale-free. We then explore the effect of hubs forgetting, misrepresenting, or playing favorites, by incorporating selective and nonselective incomplete transmission and distortion.

[2] Consistent with this, Reagans and Zuckerman (2009) show that when actors (1) are not motivated to pass on valuable information without receiving information in return or (2) cannot transmit all that they know in a single interaction, they become bottlenecks in the interpersonal network.

A BASELINE MODEL

To examine how the 'hubbyness' of an interpersonal network influences organizational learning, we extend the classic March (1991) model in two ways. First, we incorporate interpersonal learning. This is a major point of departure from March's (1991) model, where individuals do not learn directly from each other. Rather, they learn from an organization code. Second, we generate the interpersonal networks with varying degrees of 'hubbyness', building on Xulvi-Brunet and Sokolov (2002) and Barabási, Albert, and Jeong (1999). Following March (1991), our model has three main entities: *organization, external reality and individuals*.

Organization

To model the genesis of ties and formation of different network configurations, we build on models by Xulvi-Brunet and Sokolov (2002) and Barabási *et al.* (1999). Xulvi-Brunet and Sokolov (2002) modify the preferential attachment algorithm detailed in Barabási *et al.* (1999) to model a broad range of network configurations. Xulvi-Brunet and Sokolov (2002) begin with an assumption of preferential attachment and incorporate a distance penalty such that when the penalty is low, a node forms links with other nodes without respect to their distance (thus it is influenced solely by preferential attachment), and when the penalty is high a node greatly prefers to form links with nodes that are close neighbors. The benefits of this model are twofold. First, one can generate network topologies of varying 'hubbyness' by tuning only a single parameter α ($0 \leq \alpha$), which represents the sensitivity towards distance as the network grows. Second, using the distance penalty ensures that the alternative to connecting to a hub is connecting to a proximate neighbor (rather than a random connection). This results in a much more sociologically realistic network with local clustering.

Specifically, we start with a one-dimensional ring lattice of L sites, with each site identified by a unique location index running from 1 to L. At $t = 0$, we start with n_0 number of initial nodes. We spread these nodes uniformly in this ring lattice, with each node being connected to its two closest neighbors (one on its left and the other on its right). Thus, at $t = 0$, every node has exactly two links. Visually, the network resembles a closed ring of nodes, with some sites on the lattice occupied by an initial set of nodes (see Figure 1a), and the remaining sites vacant. In this ring lattice, we measure distance between any two nodes i, and j, as below:

$$Dist_{i,j} = \min\left(L - |L_i - L_j|, |L_i - L_j|\right) \quad (1)$$

where L is the total number of sites and L_i is the location index of node i. For instance, the distance between two nodes that are located in 50th and 10th sites, respectively, in a 100-site ring lattice is calculated as the minimum of two numbers: (1) 100—(50–10) and (2) (50–10). Thus, the distance is 40, which is the shortest distance between these two nodes.

In each subsequent period, one new individual node arrives in the organization until the network reaches a size of n individuals. When a new node arrives, we first locate it at a randomly chosen, unoccupied site. Next, we connect the incoming new node to Z number of existing individuals. However, not all existing individuals are equally likely to attract a new link. The probability of any existing node i to get a link from the new node k is determined by both the number of links i already possesses and the distance between i and k. Specifically, we denote $LinkNum_i$ as the number of links an existing node i has and $Dist_{i,k}$ as the shortest distance between nodes i and k as measured by the number of sites between node i and node k in the lattice. Therefore, we can express the probability of node i getting a new link from node k as a function of (1) $LinkNum_i$, (2) $Dist_{i,k}$, as well as (3) the parameter α:

$$P(i,k) = \frac{LinkNum_i * \left(Dist_{i,k}\right)^{(-\alpha)}}{\sum_j \left[LinkNum_j * \left(Dist_{j,k}\right)^{(-\alpha)}\right]} \quad (2)$$

The parameter α is a real, nonnegative number that tunes the penalty associated with distance. When α is 0, there is no penalty associated with distance. The probability of an existing node getting a link from a new node is proportional to number of existing links alone, independent of distance. The higher the number of existing links (regardless of distance), the higher the probability of attracting a new link. The model

DOI: 10.1002/smj

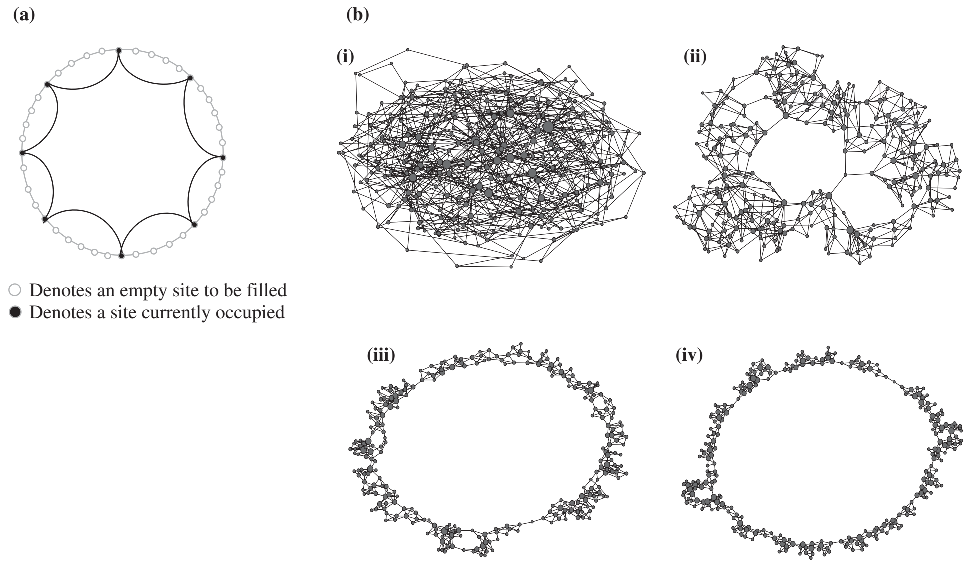

Figure 1. (a) Ring lattice with n_0 initial nodes[3], (b) Spring embedded graphs for different interpersonal network structures[4]. (i) Very hubby; $\alpha = 0$. (ii) Moderately hubby; $\alpha = 2$. (iii) Mildly hubby; $\alpha = 3$. (iv) Democratic; $\alpha = 5$.

in (2) reduces to the same preferential attachment algorithm as that in Barabási and Albert (1999). Nodes that initially attain an advantage in their number of links (because, for example, new nodes were randomly placed near to them) will come to possess more and more links. As such, the rich get richer, as a function of initial luck and age. These nodes grow dramatically to become 'hubs' (i.e., nodes with a many more connections than the average for the network). A very hubby network eventually emerges, with many long links or shortcuts connecting distant sites.

As the penalty associated with distance, i.e. the parameter α, increases, existing nodes that are located far away from a new node become less likely to get a new link. While the number of links of an existing node still counts, the probability of attracting a new node is also proportional to distance. The further the distance between the existing node and a new node, the more penalty the existing node suffers and, therefore, the lower the probability of its attracting a new link. When α is very large, the probability of connection between two distant nodes becomes very small. Even if an existing node has a lot of links, it will not get connected to an incoming node if the distance between them is large. Nearly all nodes are now locally connected. The longest connections in the network are the original connections, made when the network was sparse (i.e. at the beginning of the network formation process). The younger connections, in contrast, get shorter and shorter since a newly introduced node is almost always connected to someone nearby. The network thus has a more egalitarian distribution of links.

Figure 1b plots spring-embedded graphs of a selection of these interpersonal networks that vary in the distance penalty parameter α (other parameters are set as follows: the total number of individuals in an organization $n = 280$, the initial number of individuals $n_0 = 80$, the total number of sites $L = 10{,}000$, the number of links an incoming new node creates $Z = 3$). As shown, when the distance penalty α is 0, the network is very hubby because nodes with a lot of existing links attract more and more incoming nodes. As the distance penalty increases, however, the network becomes more locally clustered and democratic.

External reality and payoff function

We describe reality as having m dimensions, each of which has a value of 1 or -1. The probability that any one dimension will have a value of 1 (or

[3] For simplicity of presentation, the graph here depicts a ring lattice with far fewer nodes than those used in our actual simulations.
[4] The sizes are scaled by relative degree, and specific to each archetype.

DOI: 10.1002/smj

−1) is 0.5. An individual's performance is determined by a generalized payoff function (detailed in the online Appendix S1), which translates individuals' beliefs into a performance score according to its correspondence with reality (c.f. March, 1991). This payoff function tunes the interdependence of a search problem with a single parameter s. The greater the value of s, the more interdependent a search problem is. For example, if $s = m$, the search problem is maximally interdependent: even if an individual's belief matches the reality in every dimension except one, her payoff is zero. On the other hand, when $s = 1$, the search problem becomes completely independent. An individual's payoff is exactly the number of dimensions that match with reality. Similar to the NK model (Kauffman, 1993; Levinthal, 1997; Rivkin, 2000; Siggelkow and Levinthal, 2003), this payoff function is not only capable of dealing with the complexity of a search problem, but also reduces the computational burdens (Fang *et al.*, 2010). An organization's performance is measured as the average performance across all individuals in the organization.[5]

Individuals

There are n individuals in an organization. Each of them holds m beliefs about reality at each time step. Each belief has a value of 1, 0, or −1. These individual members interact with each other according to their ties. Furthermore, following March (1991), we model organizational learning as the accumulation of knowledge over time as individual members interact with each other. When individuals first join an organization, they start with idiosyncratic sets of beliefs that are heterogeneous across individuals. Each dimension of an individual's belief set is determined by assigning a value randomly drawn from 1, 0, or −1. She then interacts with her contacts within the organization, comparing the performance of her own belief sets to those of her contacts. The interaction pattern is specified by the structural configuration of the interpersonal network, which ranges from scale free to democratic according to the network generation algorithm described in (1) and (2). She updates her beliefs to imitate the beliefs of 'superior performers'—those contacts whose performance is superior to her own. Notably, though the individual knows *what* the beliefs of her contacts are and what their performance is, she does not know *how* each belief contributes to the contact's performance. Since these superior performers may not have the same beliefs on each of m dimensions, the focal individual adopts probabilistically the dominant belief (or the majority view, as used in March, 1991) on any particular dimension. That is, each individual adapts to each dominant belief on m dimensions with probability $p_{learning}$. Two features of this learning rule are worth noting. First, when there are ties (i.e., the number of superior performers who believe in −1 is equal to that of those who believe in 1), she keeps her existing belief.[6] Second, if a superior performer has a belief of 0, it signals that the individual has no definitive belief. As such, a belief of 0 is ignored when the focal individual computes the majority view. To summarize, individuals in an organization learn by interacting with others according to the structure of the interpersonal network. Over time, superior beliefs diffuse throughout the organization, accelerating the increase in overall performance. Eventually, organizational performance reaches a plateau because all members converge on a similar set of beliefs and there is no one with superior performance.

Results of the baseline model

In Figure 2a, we report organizational performance over time across four archetypes of organizational structure ($\alpha = 0$, 'very hubby'; $\alpha = 2$, 'moderately hubby'; $\alpha = 3$, 'mildly hubby'; and $\alpha = 5$, 'democratic'). To obtain organizational performance, we follow two steps. First, we create different organizational structures by growing the interpersonal networks according to Equations (1) and (2). Other parameters are set as follows: $n = 280$, $n_0 = 80$, $L = 10{,}000$, $Z = 3$. After an organization structure is created, we then start the interpersonal learning process for subsequent time periods and measure organizational performance as the average of all individuals' performance. We continue this process of learning for 2,000 periods, until no further

[5] Following other models of organizational learning and design (Lenox, 2002; Levinthal, 1997; Rivkin, 2000; Siggelkow and Levinthal, 2003, 2005; Siggelkow and Rivkin, 2005, among others), we model a generalized search problem where each dimension is equally important in determining performance.

[6] We also examine the effect of resolving the ties with a coin flip, as discussed further in the robustness checks section.

DOI: 10.1002/smj

change in any organization's performance occurs (i.e. when equilibrium is obtained). We report results based on the average of 100 independent simulation runs for each organization structure.

As seen in Figure 2a, performance tends to reach a steady state, and the structural parameter α affects the speed of organizational learning. The bigger the distance penalty, the slower the organization's performance improves. When α is zero, the organization is characterized by a scale-free interpersonal network and learns rapidly. The presence of many well-connected individuals facilitates the exchange of diverse ideas and beliefs across the organization, enabling the organization to learn quickly. However, higher initial learning speed does not equate to greater long-run performance. As shown in Figure 2a, the long-run performance tends to be lower when $\alpha = 0$. Performance appears to be highest when $\alpha = 2$, i.e., when the organization is 'moderately hubby' rather than 'very hubby'. As α increases further, performance deteriorates. Both the learning speed and long-run performance are lowest when $\alpha = 5$ or when the organization is almost free of hubs or long-range connections.

Figure 2b plots the average steady-state performance levels of 100 organizations (when $t = 2{,}000$) across different levels of α. The long-run performance is highest when organizations are moderately hubby (i.e. $\alpha = 2$). Under this archetype, the organization is neither hegemonic nor entirely democratic, with localized clusters as well as visible shortcuts through hubs. Long-run performance is lower when (1) the organizational structure is very hubby (i.e. $\alpha = 0$, 1) and (2) when the organizational structure is only mildly hubby or democratic (i.e. $\alpha = 3$, 4, 5).

To understand why we get this inverted-U shape, it is important to consider why the two extreme cases produce inferior results. When the interpersonal network structure is very hubby or scale-free (i.e. $\alpha = 0$), it is dominated by a few extremely well-connected members. Since these hubs have access to many members of the organizations, they quickly collect and consolidate superior beliefs in the organizations and distribute them across the organizational network. Because hubs are connected to many others, their 'superior peer' set is large, permitting them to compare belief strings across a wide range of individuals in the network and giving them a higher likelihood of adopting beliefs that are, at least initially, advantaged. Because this quickly results in a belief string that is better performing than average and because the hub can disseminate this belief string widely through its contacts, the hub's belief string is diffused throughout the organization rapidly. This drives out diversity of ideas, reducing the combinatorial possibilities and thereby lowering the organization's likelihood of achieving its best possible outcome. The organization prematurely converges on a single solution.

It is important to note that, though both hubs and random connections can be shortcuts in an interpersonal network, hubs have a more extreme effect on diffusion because they have direct access to a large number of people in the network, enabling them to both assimilate and disseminate beliefs faster than a mere shortcut. In online Appendix S2 we conduct a series of analyses that demonstrate how hubs are different from random links and show the differential effects of a hub's ability to *learn from many others* versus *disseminate to many others*. The results show that high levels of "hubbyness" yield significantly worse performance than high levels of randomness in a network. The results also show that it is the hub's ability to aggregate across many others that has the greater effect. When a hub can learn only from the same number of individuals as any other individual learns from, its belief string will not, on average, be any better than the belief string created by the other individuals. Thus it may not be widely adopted even if the hub can disseminate to many others. However, if a hub can learn by comparing across many superior peers, the hub is likely to adopt a solution that incorporates elements of the best solutions that exist at that time, resulting in a belief string that is very likely to dominate the belief strings of many of its peers. The string is thus rapidly and widely adopted, potentially leading to premature convergence.

On the other extreme, when the organizational structure is only mildly hubby or democratic (i.e. $\alpha = 3$, 4, 5), we observe that the speed of learning is slower, as there are few well-connected members to serve as information diffusers. While local clusters of connected nodes may quickly exchange information, the paucity of bridges between them makes it hard for them to learn from other clusters, causing them to become trapped in sets of beliefs that have not yet been substantially improved through learning. Though very heterogeneous beliefs may persist across the

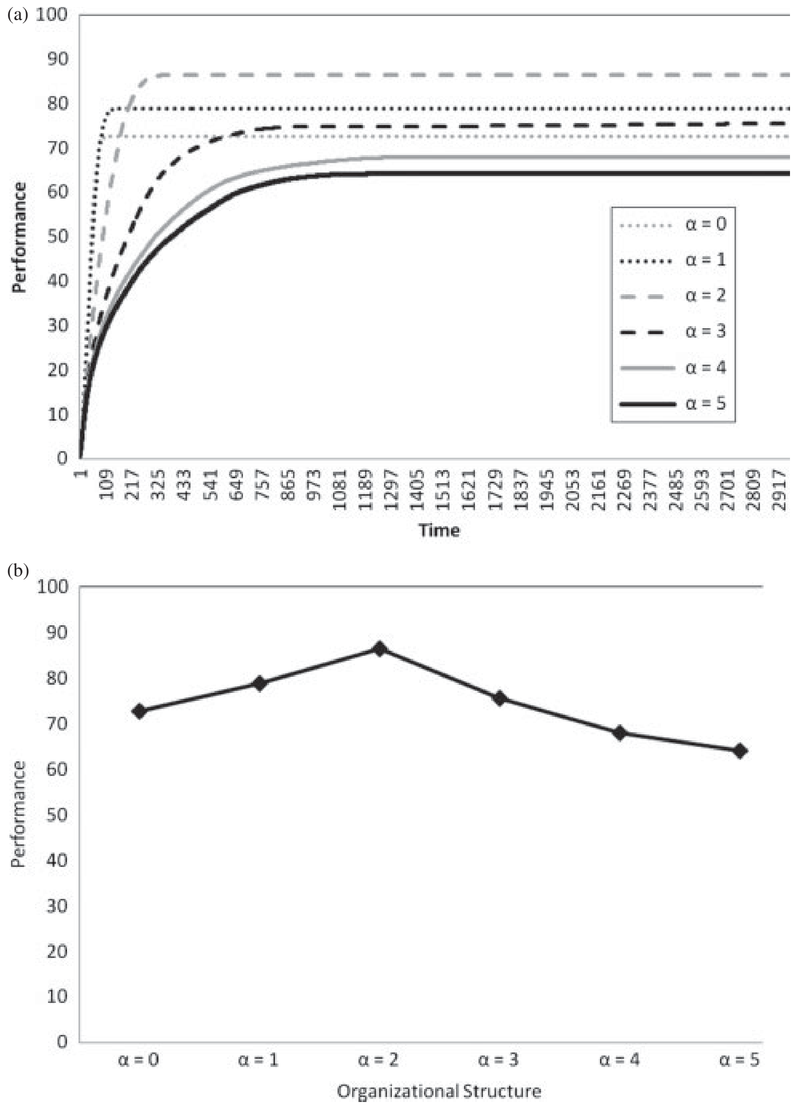

Figure 2. Effect of network structure on learning and performance. (a) Performance over time. (b) Equilibrium performance.

organization, these beliefs are not compared and exchanged throughout the organization, resulting in pockets of convergence on local solutions rather than convergence on a global solution. This is aptly illustrated in Figure 4. In the first panel, we show a single, representative network ($\alpha = 5$) at steady state. The nodes are shaded based on their performance; nodes with the same shade have the same performance. As shown, several subsets of the organization have converged on local solutions resulting in groups of individuals with identical performance, but there is heterogeneity across the organization. Nodes such as number 1 and 34 (highlighted in center of Figure 3a) serve as 'bridges' between clusters, yet the clusters they connect to have not converged in their beliefs.

There are several mechanisms that can cause clusters to become trapped in their beliefs. For instance, suppose a node serves as the only bridge between two clusters and is connected to the same number of nodes in each of those clusters. If the bridging node has lower performance than each of the clusters to which it is connected, it attempts to learn from both and therefore only identifies a 'majority view' about those dimensions upon which the two clusters agree. If the clusters

DOI: 10.1002/smj

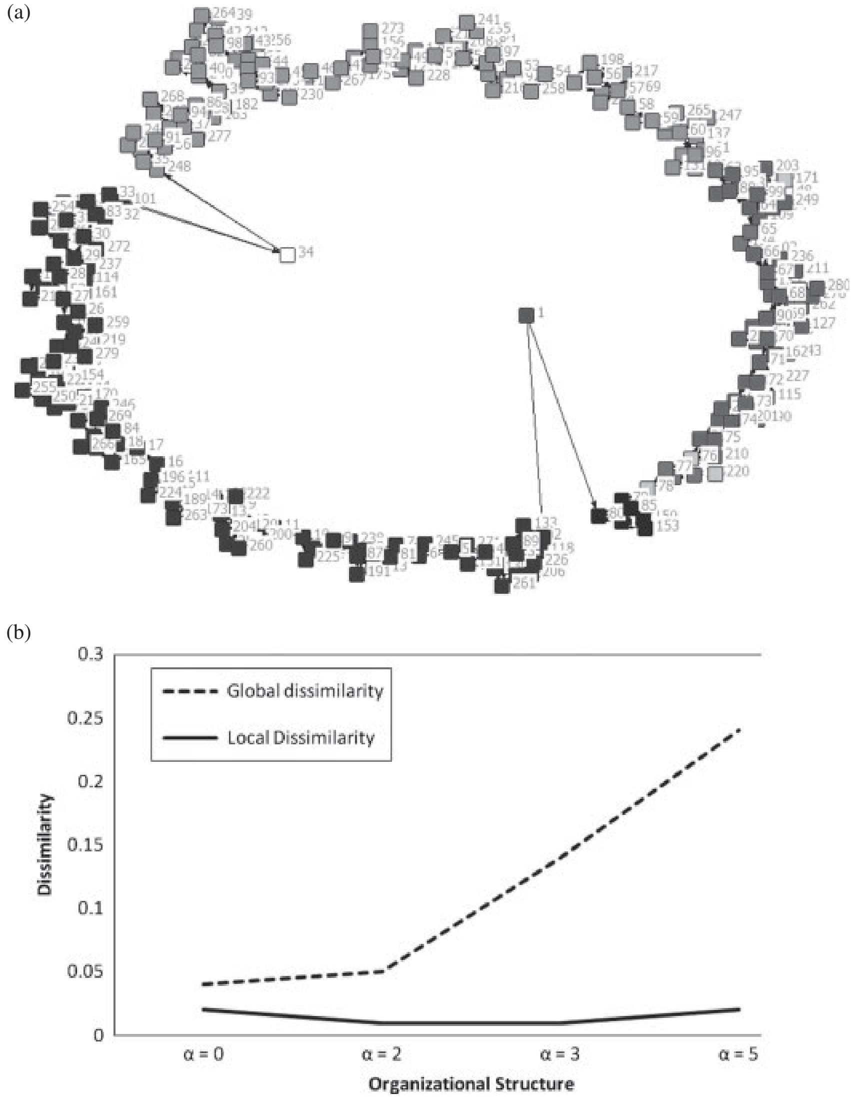

Figure 3. Local convergence versus global convergence. (a) Representative organization at equilibrium when $\alpha = 5$. (b) Local dissimilarity versus global dissimilarity at equilibrium.

disagree about a dimension, it results in a tie, and the learner keeps his original belief. In such a case, the majority view can trap the bridging node in a poor solution, causing it to cease to be an effective bridge since neither cluster will identify it as a superior peer.

Another mechanism is that the performance of the majority view can be inferior to that of the superior peers. Suppose a node is connected to two other nodes that are higher performing than itself, each in a different cluster, but the beliefs of those superior peers match reality correctly in different blocks. In such a case, the 'prevailing' view may be the least common denominator (i.e., those digit blocks that do not match reality). By learning from these nodes, the bridging node sustains a performance lower than each of them. Thus, clusters become trapped even when we resolve ties with a coin flip (i.e., have the node randomly adopt the belief of one of the superior peers in the event of a tie). We present the coin flip results in the robustness test.[7]

[7] In real organizations, such 'bridging nodes' may be unable to resolve the conflict between groups to which they are attached because of the intensity with which the beliefs are held. Klepper

Because the egalitarian networks ($\alpha = 5$) have fewer bridges between clusters, they are more susceptible to these traps. Put more generally, in a sparse, locally clustered and decentralized network, it is easier for information to get 'hung up' somewhere. The lack of shortcuts and redundant paths makes the information transmission process more fragile.

Figure 3b summarizes this outcome by comparing local convergence to global convergence across the different organization structures. To do this, we first compute a global 'dissimilarity index' (Fang *et al.*, 2010) to measure the pair-wise differences in beliefs of all n individuals in an organization. There are $\frac{1}{2}\, n(n-1)$ pairs. For each pair of individuals, there are m beliefs to be compared. Then, we measure dissimilarity in beliefs in an organization, as below:

$$\text{Dissimilarity} = \frac{2}{mn\,(n-1)} \sum_{i=1}^{\frac{1}{2}n(n-1)} \sum_{j=1}^{m} \omega_{ij} \quad (3)$$

where ω_{ij} takes on the value of 1 if two chosen individuals for the ith pair have different beliefs on jth dimension, and 0 otherwise. This index is 'global' in the sense that it summarizes the diversity of beliefs across the entire organization. We next compute a *local* dissimilarity index in two steps. First, for each node, we compare its beliefs only to those of the other nodes to which it is directly connected. Second, we average this local index across all individuals. As shown in Figure 3b, democratic (e.g., $\alpha = 3$, 5) networks have low levels of local dissimilarity just as hubbier networks do, but they have much higher levels of global dissimilarity.

Moderate hubbyness (i.e., $\alpha = 2$) appears to strike a balance between global diffusion and the preservation of diversity, resulting in significantly higher long-run performance. These results echo a fundamental insight on the nature of learning in organizations: in a population of learners within an organization, there exists a fundamental trade-off between the speed of diffusion of superior ideas and the ultimate quality of organizational knowledge (March, 1991). Our model documents how organizational structure may systematically influence this trade-off between speed of learning and the overall organizational performance. We show that organizations with a 'very hubby' interpersonal network learn fast but converge to potentially inferior outcomes. Organizations without hubs may prematurely achieve local convergence and fail to exploit the global diversity of beliefs to improve their solutions. A moderately hubby network enables the organization to attain the highest long-run performance by balancing the dual objectives of (1) preservation of diversity and (2) efficient transmission of superior ideas.

Robustness checks

To see whether the effect of organizational structure changes across a wide range of parameter values, we carry out robustness checks with respect to the (1) problem complexity, (2) nature of learning, and (3) tie resolution, while fixing the parameters that define the various network structures (e.g. distance penalty α). The description of our robustness analyses and their results are available in the online Appendix. In short, we find that our result is remarkably robust to variations in problem complexity assumptions regarding the efficacy of interpersonal learning and methods of tie resolution.

THE EFFECT OF INFORMATION DISTORTION

To study the effect of forgetting, lying, and playing favorites, we simulate organizations in which key individuals (1) inadvertently omit information ('forget'), (2) deliberately misrepresent information ('lie'), or (3) selectively omit or misrepresent information to those who are not part of their inner circles ('playing favorites').

We model inadvertent omission as the following. For each dimension of the hub's belief string, a value of 0 is transmitted to the targets, regardless of what the actual value of the belief is—1 or −1. This effectively causes the hub's belief to be disregarded by the target. In the case of hubs deliberately misrepresenting their beliefs, they transmit beliefs that are opposite to their own true beliefs. This means that, they would transmit a value of 1 when their own belief is actually −1, and vice

and Thompson (2010), for example, argue that many spin-offs occur precisely because groups within the firm cannot come to agreement about the best direction for the firm.

DOI: 10.1002/smj

versa. We assume that hubs in the organizational structure distort information (either inadvertently or deliberately) with probability p, which ranges from 0 to 1.

Apart from these two possible forms of information distortion, hubs may also treat their contacts differentially and choose to misrepresent information to some but not others. We consider here a simple form of such preferential treatment: hubs may vary the percentage of contacts to whom they distort information. We introduce a new parameter *Nonpreferred Rate*, which defines the percentage of a hub's contacts to which the hub distorts information. For any given percentage of distortion, we randomly pick among the existing contacts of a hub. For example, a hub may decide to transmit distorted information to 90 percent of its contacts, while telling the truth to its inner circle—the remaining 10 percent of the contacts.

In short, we explore how various kinds of information distortion may influence the organizational outcomes. Our simulation is based on the following set up. First we choose the top 10 percent of the most connected individual members (we also implemented a version using the top 5 percent and the results are qualitatively similar). Since we have 280 individuals in total, this means the 28 most connected individuals may distort information. We examine the organizational outcomes systematically by varying (1) the type of distortion, (2) the probability of information distortion, and (3) the percentage of contacts that are considered favorites by the hubs.

Figure 4 plots the performance across different levels of distortion for each type of organizational structure. In these results the hubs do not play favorites and distort information nondiscriminately to their contacts. In Figure 4a, we see that modest amounts of deliberate misrepresentation can actually be functional for organizations: across different organizational structures (i.e. $\alpha = 0, 2, 3$), the highest performance is reached when there is some small but positive level of deliberate misrepresentation (i.e. when p is around 0.1 and 0.2). For instance, when $\alpha = 0$, performance is around 73 when p is zero. When hubs deliberately misrepresent information about 20 percent of the time (i.e. $p = 0.2$), performance reaches a peak of 85. At higher levels ($p > 0.2$), performance declines gradually before plunging to a low of 45 when hubs deliberately misrepresent information 100 percent. This inverted-U shaped pattern holds across different structures—some deliberate misrepresentation is significantly performance enhancing.

The pattern is strikingly different for inadvertent distortion (i.e., forgetting), as seen in Figure 4b. On the one hand, inadvertent distortion does not have the strong beneficial impact that modest amounts of deliberate misrepresentation had in Figure 4a. On the other hand, it also does not begin to impact organizational learning outcomes negatively until it reaches very high levels. Put differently, organizational performance appears to be remarkably resistant to information omission by hubs. Only when hubs forget all the time (i.e. $p = 1$), do we notice a decline in organizational performance. This pattern holds for all organizational structures, except the very hubby ones (i.e. $\alpha = 0$), where performance generally increases slightly as p increases to 0.9 before eventually declining.[8] The reason for this robustness to information distortion is that when hubs 'forget' and inadvertently omit information, they transmit beliefs as taking the values of zeroes, even though they may have definitive beliefs such as 1 or -1. Hence, when the recipient of such omitted information computes the majority view, these zero beliefs are simply ignored. Inadvertent omission seems surprisingly 'harmless'.

Why is organizational performance so robust to the introduction of information distortion? Our conjecture is that distortion facilitates the preservation of diverse beliefs. For any given organizational structure, diversity is gradually depleted over time as superior ideas are adopted and diffused across the organizational network. Thus, an improvement in performance is accompanied by a concurrent decrease in diversity. This reduction of diversity, as we discussed before, may prematurely eliminate deviant ideas and reduce the combinatorial possibilities for the overall organizational knowledge. To examine how organizational diversity changes over time with varying levels of distortion, we plot in Figure 5 the average dissimilarity of beliefs among organizational members over time for a specific organizational structure

[8] To test our earlier conjecture that the effect of hubs' distortion is greater than random distortion within the organization, we also ran the model using a random subset of the organization members to distort information rather than the hubs. This attenuates the results significantly: distortion by random members has significantly less beneficial positive impact at modest levels and significantly less deleterious impact at high levels.

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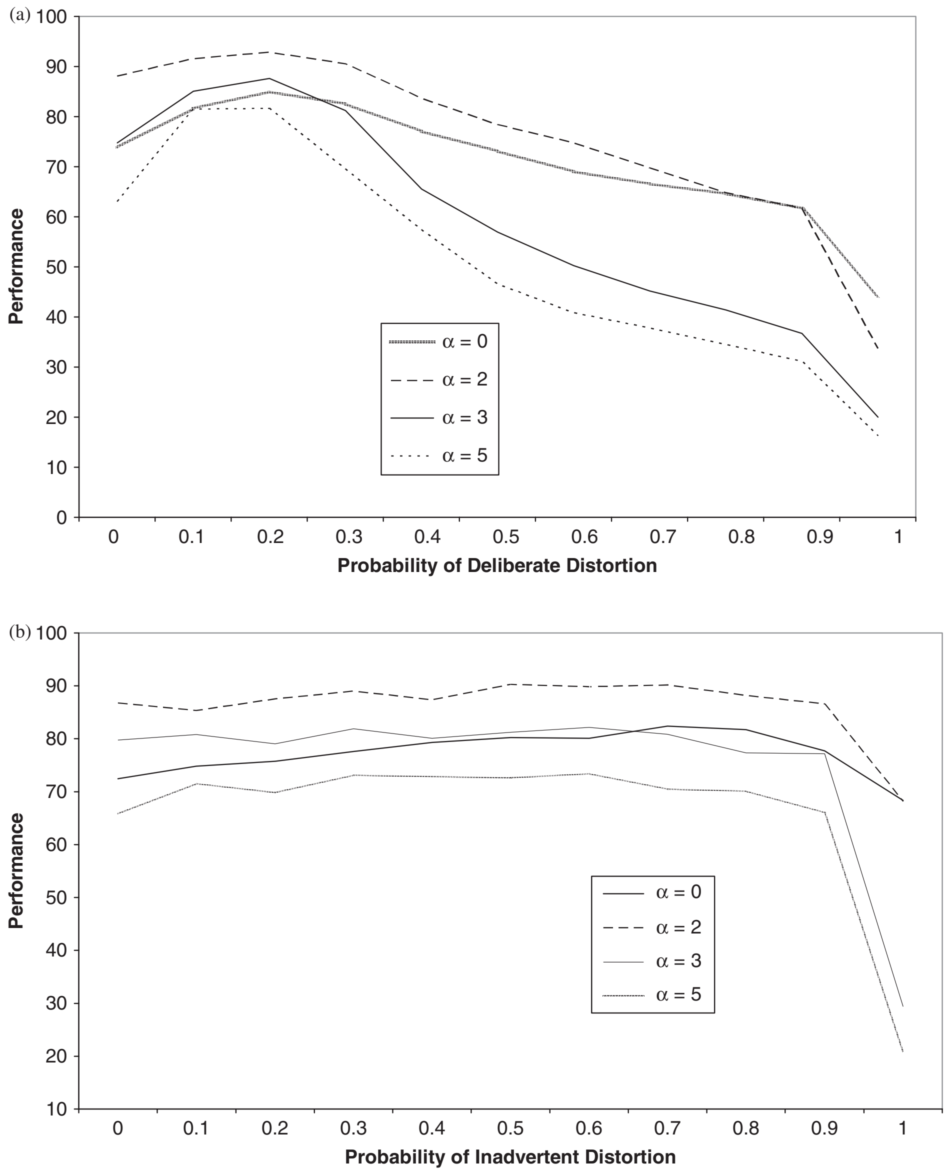

Figure 4. Effect of information distortion. (a) Deliberate misrepresentation by hubs. (b) Inadvertent omission by hubs.

corresponding to $\alpha = 0$, when hubs deliberately misrepresent information at various probabilities.

As shown, an organization tends to lose its diversity of beliefs very fast when there is no or little deliberate information distortion by hubs (e.g., $p = 0$). Since the structure is dominated by a few extremely well-connected individuals (i.e., $\alpha = 0$), dissimilarity among organizational members quickly disappears as these hubs act as bridges in the organizational network. In contrast, when hubs start distorting information, the dissimilarity index curves decline less rapidly, especially for the first 200 periods. This implies that some information distortion helps maintain diversity, essentially thwarting the fast convergence onto a set of fixed ideas.[9]

[9] We also considered the case where *all* members of the organization distort rather than the specific case of hubs distorting which is our focus here. The same qualitative patterns hold, though the results are even stronger: low levels of deliberate distortion have a significant positive effect on performance in every organization structure but then have a strongly negative effect at higher levels of distortion; inadvertent distortion yields a mild increase in performance at all but the very highest levels of distortion.

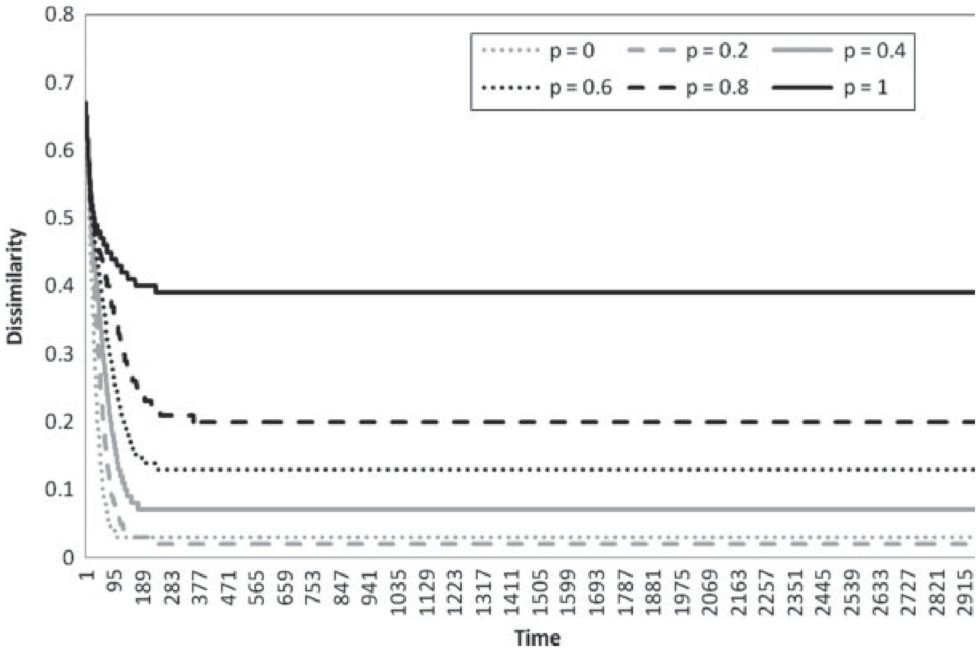

Figure 5. Loss of diversity over time (deliberate distortion). Note: These correspond to the organizational structure *when* $\alpha = 0$.

Next, we vary the percentage of contacts that are considered favorites by hubs (i.e. *Nonpreferred Rate)*. Note that when this percentage equals 100 percent, it means all contacts of a hub are regarded as nonpreferred contacts and thus will receive distorted information. On the other extreme, a *Nonpreferred Rate* of 0 means all contacts of a distortable node are *preferred* contacts, so hubs would actually distort to no one—in this case, it reduces to our baseline model where only truthful information is transmitted by all organizational members.

Figure 6 plots the effect of playing favorites on organizational performance across each of the network archetypes. At low probability levels of distortion (either lying or forgetting), 'playing favorites' (i.e., utilizing a nonpreferred rate of 90 percent so that 10 percent of the hubs' contacts received nondistorted information) does not substantively change the pattern of performance results. At high probability levels of distortion, however, playing favorites appears to attenuate some of the deleterious effects of distortion. For probabilities of lying that exceed 40 percent, for example, playing favorites yields a large performance benefit. The influence on forgetting is more subtle; only when forgetting rates exceed 90 percent do we see large drops in performance, and it is at this high level of forgetting that playing favorites lessens the drop in performance.

These results suggest that when hubs have a high probability of distorting information, providing truthful information to at least some of their contacts helps to increase long-term performance. Intriguingly, providing truthful information to a small set of contacts does not significantly diminish the benefits of lying at low probability levels, suggesting that overall, playing favorites is a relatively benign or even helpful activity, as compared to the baseline, where hubs distort indiscriminately.

DISCUSSION AND CONCLUSIONS

March's seminal 1991 paper highlighted the important trade-off between exploration and exploitation and the role that organizational practices play in that trade-off. Recent work has advanced his ideas and methods by incorporating interpersonal learning and network structure into his models, but these interpersonal network models have tended to be highly 'under socialized'. We have advanced this line of work by introducing two important (and interrelated) features of social learning. First, we 'socialize'

DOI: 10.1002/smj

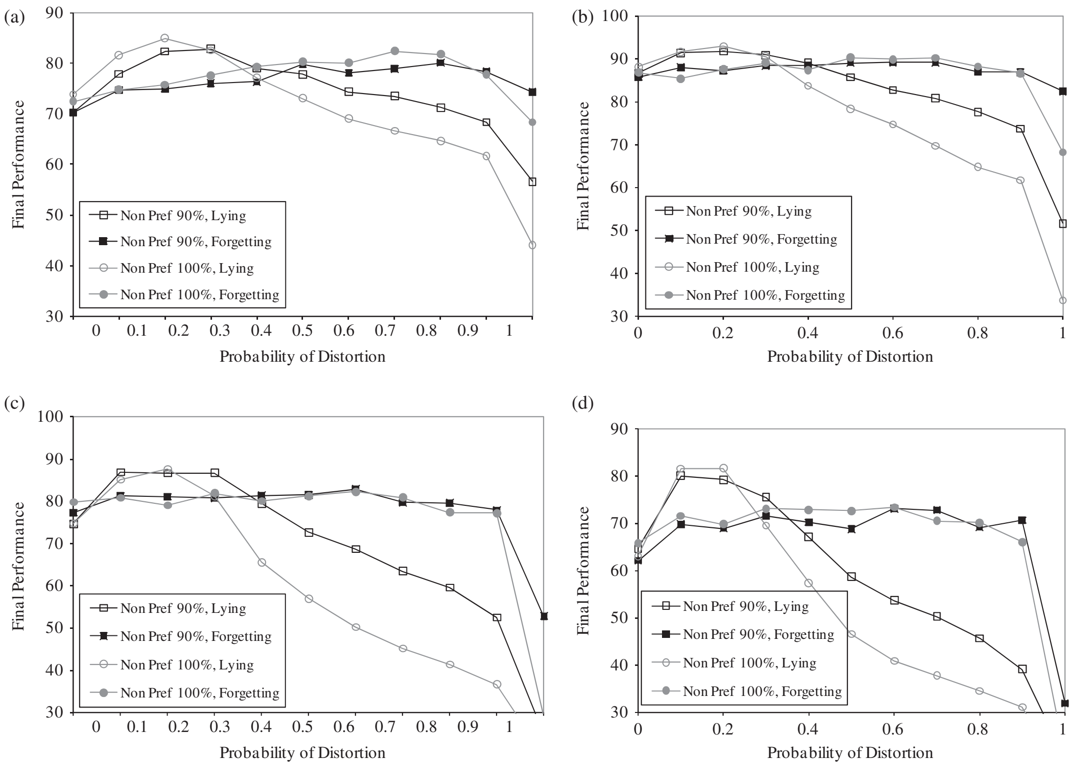

Figure 6. Effect of playing favorites on organizational performance. (a) Very hubby network structure. (b) Moderately hubby network structure. (c) Mildly hubby network structure. (d) Democratic network structure.

how the interpersonal networks are formed in the first place. Though an organizational chart may resemble a purely ordered network, the actual interpersonal relationships and communication pathways between individuals rarely conform to such order. Instead, people often form their connections according to a mix of opportunity (which is highly influenced by physical distance), homophily (which can be thought of as social distance), or based on an attribute of a targeted contact that makes them a desirable connection (visibility, prestige, expertise, etc.). These tendencies lead to interpersonal networks that have clusters based on proximity, and 'hubs' that have many more connections than others. We thus utilized here an algorithm that enables us to *grow* interpersonal networks based on these social dimensions, leading to networks with varying levels of proximity-based clustering and hubs. Second, in real organizations it would be uncommon to assume that everyone communicates all of their information, to all of their contacts, perfectly in every period. We thus further 'socialize' the learning by introducing information distortion: hubs can forget information, lie about information, or play favorites with respect to who receives correct information.

Our baseline model demonstrates that hubs create shortcuts that accelerate the diffusion of superior ideas, which can lead to premature convergence around a homogeneous belief set and poor long-run learning outcomes. This finding is similar to March's original argument that faster diffusion of ideas can lead to loss of diversity in beliefs in the organization, extinguishing the variety necessary for long-run learning. The mechanism, however, is different; March's results were based on individual learning rates (the propensity for an individual to adopt a belief from a superior) whereas our results are based on the access to information provided by the overall structure of the network. Hubs can take into account the information of more contacts; and those contacts, in turn, can benefit from the hubs' learning, leading to faster convergence in beliefs. Hubs' ability to take into account the information of more contacts has a particularly potent effect on organizational learning because it enables the hub to quickly assemble

DOI: 10.1002/smj

a set of beliefs that exhibits the traits of the best solutions that exist *at that time*. This turns out to be somewhat dangerous to organizational learning as this set of beliefs may quickly out-compete other ideas in the organization, extinguishing diversity too quickly. Hubs are thus not mere shortcuts in a network; their ability to aggregate information from many individuals makes them even more powerful agents of knowledge convergence. Interestingly, however, we find that hub behaviors that would typically be interpreted as problems (forgetting, lying, and playing favorites) might improve long-run learning outcomes by helping to preserve diverse beliefs and that these different forms of distortion have significantly different impacts on the long-run learning outcomes. We find that modest amounts of deliberate misrepresentation (lying) by hubs can improve long-run learning outcomes by helping to preserve (or perhaps even create) diversity in organizational beliefs but leads to sharp performance declines at high levels. By contrast, inadvertent omission of information (forgetting) did not yield organizational learning benefits, but it also was relatively harmless—even high levels (up to 90%) of information omission did not deleteriously impact long-run learning outcomes. Finally, if hubs only selectively withhold or misrepresent information to a subset of their contacts (playing favorites), both effects were diminished: both performance benefits and decreases of information distortion were lessened.

These findings have important implications for current research on social networks and organization structure. First, recent advances in graph theory have led to a rapid proliferation of research on the structure of networks. One of the major reasons that networks have garnered such interest by management scholars is that networks are frequently argued to be a conduit for the diffusion of information and other resources. As such, the structure of these networks may play significant roles in learning, innovation, trade, and other important outcomes. Much of the research on network structure has borrowed heavily from math, physics, and biology. The abundance and rigor of the work on networks in these disciplines has advanced the management research on networks very quickly, helping to fuel the excitement about network research in management. There are, however, some dimensions in which results from math, physics, and biology might be too liberally applied, neglecting some of the key differences between, for example, information exchanged between coworkers as compared to a virus that spreads among potential hosts. Our study addresses some of these differences by incorporating more realistic features of social and organizational life. Hubs can become overloaded, causing them to forget. They may also act with agency, deliberately choosing to misrepresent their information or transmit complete and truthful information only to their preferred contacts. While some other studies have incorporated modest amounts of mutation into the learning process, which would be similar to very low levels of our nonselective misrepresentation, we explore here a much broader range of information distortion possibilities, including selective and nonselective information omission, selective and nonselective misrepresentation, and spanning the full spectrum from no distortion to very high levels of each of these types. We find significant and intriguing differences between the effects of information omission and information misrepresentation. While misrepresentation had a strong positive effect at modest levels and then a sharply deleterious effect at higher levels, resulting in a pronounced inverted U-shape, information omission has relatively little effect on performance, with deleterious effects only at extremely high levels.

Though previous work on adaptive systems has suggested the beneficial role of mutation, we do not know of any other study that systematically explored (1) the pattern of the effects of inadvertent omission ('forgetting') and deliberate misrepresentation ('lying') over wide ranges of values, (2) in a system designed to represent the interpersonal learning network of an organization, and (3) with the interacting effects of selective transmission ('playing favorites'). It should be interesting to a social scientist, for example, to note that 'lying' was beneficial only when it occurred at levels less than 40 percent, after which it resulted in a relatively steep decrease in performance. It should also be interesting that both lying and forgetting have an extremely sharp negative impact on performance when they exceed 90 percent. Even selectivity in transmission ('playing favorites') cannot overcome this sharp decline at very high levels of forgetting or lying. Overall, however, the effects of the fallibility or self-interested behaviors of hubs were much more benign than we would have expected. We do not intend our paper to be an endorsement of forgetting, lying, or playing favorites, but it does reveal that there are more nuanced implications of information distortion and diffusion than might first meet the eye.

Second, we also contribute to the literature on organization structure. A fundamental theme in organizational research is that an organization's long-term success depends on its ability to exploit its current capabilities while simultaneously exploring fundamentally new competencies (Gupta, Smith, and Shalley, 2006; Holland, 1975; Levinthal and March, 1993; March, 1991). Tushman and O'Reilly (1996) were first to present a theory of organizational ambidexterity, suggesting that organization structure could help the firm attain superior performance by striking a productive balance between exploration and exploitation. The classic approaches to achieve ambidexterity, as summarized in this literature, include structural separation of groups or the temporal separation of activities (e.g. Bower and Christensen, 1995; Brown and Eisenhardt, 1997; Jacobides, 2007; March, 2004; Puranam *et al.*, 2006; Tushman and O'Reilly, 1996). In line with these recent contributions, our work further elaborates how structural ambidexterity may attain a better balance between exploration and exploitation. In our simulated organizational context, exploitation arises from the *presence of extremely well-connected individuals*, which facilitates the rapid diffusion and assimilation of currently superior knowledge, while reducing heterogeneity of knowledge within the firm. On the other hand, exploration arises from the *learning in local, semi-isolated clusters*, as well as *information distortion by hubs*, which preserve the variety of knowledge in an organization.

Our work also has important implications for practice. Our findings highlight the need for managers to think about how their organizational structure can help to strike a balance between the diffusion of good ideas and the preservation of heterogeneous ideas. Organization structure shapes both the formal and informal interpersonal network. It shapes the formal interpersonal network through obvious means, such as determining who reports to whom, the size of teams, and the explicit liaison roles between teams. The formal structure, in turn, influences the informal interpersonal network. For example, when managers deliberately structure teams to enable cross-functional coordination, they are simultaneously influencing the patterns of social relationships and informal referral networks in the organization. When employees work together, over time they accumulate knowledge about each other's capabilities, habits, and preferences. They also form social attachments and routines that can endure well beyond their current projects. Thus, while the informal interpersonal network might be difficult to identify completely or structure precisely, it is not immune to strategy. The results here suggest that it could be valuable for managers to (1) assess whether their organization's interpersonal networks are too hubby or perhaps not hubby enough, (2) identify individuals who are likely to be playing hub roles in the transmission of information and think carefully about their influence over the spread or preservation of ideas, and (3) consider whether particular activities in the firm would benefit from some temporary isolating mechanisms to prevent idea hegemony. For example, at CERN (the European Organization for Nuclear Research that operates a Large Hadron Collider) teams of physicists and engineers accelerate and collide particles to simulate 'the big bang' in hopes of advancing our understanding of the origins of the universe. Groups of scientists, however, will often disagree about the best solution to a particular problem. To avoid the hegemony of a single solution that could be suboptimal, CERN relies on an extremely nonhierarchical and decentralized decision process and often encourages multiple teams to work on their own solutions. After the teams have had significant time to develop their solution, the groups meet and seek a consensus decision.

Like other models, our study has abstracted away a host of other issues, not because they are unimportant or uninteresting, but because they lie outside of our key dynamic of interest: the role of hubs and information distortion in organizational learning. Future studies may shed light on how these issues may further complicate the punch line highlighted in our work: the dual role of hubs as both lubricant and impediment in organizational learning. First, not all ties in interpersonal networks may be of equal importance. Asymmetry and unequal weighting, though a fact of life, may introduce a set of complex, difficult to interpret dynamics. Second, interpersonal network structure may coevolve with learning and performance. It is, however, nontrivial to simulate and specify the behavioral heuristics of such coevolution and examine how performance outcomes may be different under different assumptions of network evolution. Finally, it is noteworthy that while the majority decision rule is frequently observed in *in-situ* studies of group decision making, it is not the only decision-making rule that can be invoked in a group scenario. It would be interesting to study, for instance, how other plausible behavioral rules of aggregation may impact the dynamical properties we have observed.

To conclude, we have focused on two significant omissions in the study of organizational structure and learning: 'hubs' in the interpersonal network and the effect of hubs omitting or misrepresenting information. Using a simulation model that systematically varies organizational structure, we find that hubs play an intriguing and nuanced 'dual' role in the diffusion and evolution of ideas in an organization. On the one hand, they can accelerate information diffusion, which can both speed up learning, and impair long-run learning outcomes by leading to premature convergence on a sub-optimal equilibrium. On the other hand, to the degree that hubs are prone to forgetting or misrepresenting information to some or all of their contacts (behaviors that have typically been considered undesirable in organizations), they may actually help to preserve requisite variety in the organization's knowledge, enabling higher long-run learning outcomes. Our work highlights the importance of balancing two opposing tensions: the benefits of rapid diffusion of superior ideas versus the benefits of sustaining long-run learning. It also reveals that hubs and information distortion play more complex roles in organizational life than might immediately be assumed.

ACKNOWLEDGMENTS

Authorship is determined randomly and both authors contributed equally. We are grateful to George Huber, Jeho Lee, Sungho Kim as well as participants of the AOM Annual Conference for helpful comments and suggestions. This research is supported by the National Science Foundation under Grant No. SES-0234075.

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SUPPORTING INFORMATION

Additional supporting information may be found in the online version of this article:

Appendix S1. The payoff function.
Appendix S2. Hubs versus random connections.