Network organizations

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It is common to define a network organization as one that is fast and flexible in adapting to changes in the underlying environment. But besides the short-run advantages of adaptability, fast changes in the structure of the organization can also be detrimental in the longer run. This is due to the fact that agents need some stability in the organizational structure in order to channel appropriately (and thus speed up) search. I discuss that trade-off between adaptability and structural stability in a context where not only the environment is continuously changing over time but the organization is also adjusting to those changes. The main conclusion obtained is that, as the environmental volatility increases, the optimal functioning mode of the organization sharply switches from being totally flexible to being completely rigid, i.e. no intermediate configurations are essentially ever optimal. This has stark positive and normative implications on the dichotomy of stability versus change that is at the centre of recent organizational literature.

Keywords: networks; organizations; stability; change; adaptation.

1. Introduction

A ‘network organization’ is usually conceived as an organization that is quick and flexible in adapting to changes in its environment. But changes in the structure of the organization can also be detrimental in the medium run, since it is partly the knowledge of the organization’s structure that mediates (and thus speeds up) search. Here I discuss the tension between these two considerations. That is, I study the trade-off between adaptability and structural stability in a (network) organization that confronts a changing environment.

The model proposed to study this trade-off is particularly simple and stylized. The organization consists of an underlying backbone structure (a one-dimensional lattice network) that remains fixed, combined with a limited number of links that can be ‘rewired’ over time (for simplicity, just one per agent). In the background, there is an environment that changes over time—a phenomenon that we call volatility. More specifically, it is assumed that every node/agent has a target node it has to reach, whose identity independently changes at a rate $p$. The dilemma faced by a node whose target has been reassigned is the following: should I redraw my flexible link to the new target? If this is done, direct access to that node (possibly the target as well in the immediate future) is secured. But, on the other hand, under the assumption that freshly rewired links take some time to become widely available to the organization at large, such an adaptation also imposes a negative externality on others. Namely, it removes from the immediate operational structure of the organization some links that can be particularly valuable for the overall search.

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So, in a nutshell, the problem we pose can be formulated as follows. What is the optimal speed at which the organization should adapt to the changing environment? To cast the question sharply, the adaptability of the organization is assumed to be embodied by a single parameter $q$, the probability with which a node will redraw its flexible link to a new target. In this set-up, the answer delivered by the paper is a radical one: depending on whether the value of $p$ (volatility) is high or low, the optimal $q$ (adaptability) should essentially be, respectively, either 0 or 1. Thus, in this sense, one finds that an optimal organization is typically either totally rigid or totally flexible, and essentially never in between. As we shall explain, this has an interesting bearing on the dichotomy of stability versus change that has been highlighted by recent organization literature.

The rest of the paper is organized as follows. Next, Section 2 provides a brief discussion of the related literature. Then, Section 3 presents the model. The analysis is undertaken in Section 4, while Section 5 concludes.

2. Related literature

There are three distinct branches of literature quite related to our present concerns: (a) the economic theory of organizations, (b) models of search in complex networks and (c) the transactive-memory theory of organizations. I briefly discuss each of them in turn.

(a) The economic theory of organizations has produced a large body of research whose focus has been both on incentive issues and/or the way in which organizations can effectively handle decentralized information. In the latter vein, the work of Radner [1] was a seminal contribution that (abstracting from incentive considerations) first modelled explicitly the organization as a network of informal flows. Other subsequent researchers have followed his lead (see, e.g. [2–4]), all aiming at characterizing the optimal network structure that, under varying conditions and in different senses, best pools the information disseminated throughout the organization. Even more in line with our approach, a recent interesting paper that stresses the issue of organizational adaptability in the face on environmental change is Dessein and Santos [5]. Their focus, however, is on the trade-off between coordination and specialization when individuals have only local information on the environment and their communication is impaired by noise.

(b) In recent years, and partly motivated by the rise to prominence of the Internet, there has been a surge of interest on the problem of how to conduct an effective search in large and complex social networks. Building upon the early experimental work of Milgram [6] on ‘small worlds’ and the subsequent theoretical developments of Watts and Strogatz [7], a key issue in this respect is that of searchability. More specifically, the question is how to find short paths joining the nodes of large networks that (as indeed happens in the real world) involve a significant random component. Kleinberg [8] provided key insights on the problem, formulating it as one of an algorithmic nature. The path opened by this seminal contribution has then been pursued by several authors—see, e.g. Guimerà et al. [9] or Dodds et al. [10]—to address issues of organizational design. Specifically, they pose the problem of how to design the social network underlying the operation of large organizations so as to optimize their search-related performance. In contrast with our approach, however, the underlying network is taken as fixed once and for all, so that the notion of adaptability does not pertain to the organizational structure governing informational flows.

(c) Finally, I discuss the so-called transactive-memory theory of organizations. This theory originates in the work of Wegner [11]. He stressed the importance of the process by which, as new information arrives at an organization, it is first allocated to individuals, then registered in the ‘organizational directory’ and later retrieved in the most efficient manner. This threefold mechanism is what has been
called the organization’s transactive memory system. A large body of theoretical and empirical literature has followed suit (see, e.g. [12] for a survey). In much of it, researchers have emphasized the importance of informal (and thus flexible) links in the successful implementation of an organization’s transactive memory.

A good case in point is provided by the empirical work of Hansen [14]. He studied 120 product development projects in a large electronics company, where each project was separately undertaken by one of the 41 business units of the firm. Hansen started by constructing a knowledge network, on the basis of the informal contacts identified among the members of the different units. Then, much in line with the key assumptions of our model, he found that the overall performance of each unit (specifically, the fraction of projects completed and the speed of their completion) was highly dependent on the existence of short network paths to other units possessing relevant knowledge. Indirect connections, in other words, were crucial for good results, but their value was found to decay significantly with distance. This, indeed, is consistent with the central measure of performance contemplated in our model, which in turn underlies the problem of network design addressed by our theoretical analysis.

3. The model

Consider a large set of nodes \( N = \{1, 2, \ldots, n\} \) arranged along an organizational backbone, which is assumed to be one-dimensional and without boundaries, i.e. a ring. Each node \( i \) is connected to both of its direct neighbours in the backbone, \( i - 1 \) and \( i + 1 \) (where the index here is interpreted as ‘modulo \( n\)’). These links are conceived as formal and rigid ones, possibly reflecting the formal chart of the organization. In addition to such formal links, every \( i \) is also connected to some \( \alpha(i) \) through an informal link, which may well be ‘long-range’ (i.e. far away from \( i \) on the underlying backbone). Such long-range links are flexible and so they can be adjusted over time, as determined by the plasticity/adaptability of the organization (see below for the dynamic formulation). For the moment, we may simply assume that each \( \alpha(i) \) has been randomly selected from \( N \setminus \{i\} \) with uniform probability. The resulting (undirected) network—consisting of the backbone plus the long-range links—will be denoted by \( \Gamma \).

Let us further postulate that each node \( i \in N \) has a target \( \tau(i) \in N \setminus \{i\} \), whom \( i \) has to reach in order to address a specific demand or tackle a particular problem. Again, let us momentarily assume that \( \tau(i) \) has been randomly selected from \( N \setminus \{i\} \) with uniform probability. Then, given the prevailing network \( \Gamma \) and the array of targets \( \tau = [\tau(i)]_{i=1}^{n} \), the performance of the organization is tailored to the average path length (along the network) between every node and its target. More specifically, its aim will be to have this magnitude be as low as possible, so that the objective function that the organization will aim to maximize is given by

\[
\rho = -\langle d(i, \tau(i)) \mid \Gamma \rangle_{i \in N}.
\]

This is motivated by the idea that the network distance separating an agent from a valuable partner (e.g. one that helps undertake current tasks) should have an important bearing on the speed and success

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1 See also Hansen [14] and Schulz [15].

2 These considerations were most decisive for the transfer of knowledge that could be largely codified. Instead, for hardly codifiable knowledge, direct and close contact between the source and the target played a primary role.

3 Conceivably, one could consider other network architectures—e.g. hierarchic or tree-like—to model the backbone of the organization. This, however, would complicate the formal analysis of the set-up, which in our case heavily relies on the theory that has been developed for the so-called small-world networks, i.e. networks defined on a lattice (in terms of the corresponding distance), to which a few lattice-independent links are added to establish some extent of ‘global connectivity’. It seems intuitive, however, that none of the essential features and insights of the model depend on the details posited for the fixed backbone of the organization.
of job completion. As explained above—recall Section 1—this idea is not only intuitive but also enjoys some significant empirical support.

But, as advanced, the focus of the paper is on the tension between adaptability and structure in a dynamic context where the environment changes over time. So, let us introduce time into the model, indexing it by $t = 0, 1, 2, \ldots$ and dating the prevailing states $\omega_t \equiv [\tau_t(i), \Gamma_t]$ accordingly. Suppose that the initial state $\omega_0 \equiv [\tau_0(i), \Gamma_0]$ is constructed randomly, as explained above—i.e. both the target and the long-range neighbour of each node are selected in a stochastically independent and uniform manner among all the other nodes. Then, as time proceeds, the law of motion that governs the change from $\omega_{t-1}$ to $\omega_t$ for every $t \geq 1$ consists of two separate components: target revision and update of the long-range neighbour. For simplicity, we assume that each of these components is implemented sequentially in the following two consecutive stages:

1. **Target revision:** Independently (i.e. ‘simultaneously’) for each node $i$, its previous target $\tau_{t-1}(i)$ is redrawn afresh with probability $p \in [0, 1]$. (Thus, with probability $(1-p)$, we have $\tau_t(i) = \tau_{t-1}(i)$.) When a new target for $i$ is redrawn, each $j \in N \setminus \{i\}$ is selected as the new target with uniform probability. (So, in principle, any given node can act as the target for several other nodes.)

2. **Neighbour update:** Independently for each node $i$, its previous long-range link to agent $\alpha_{t-1}(i)$ is rewired with probability $q \in [0, 1]$ to the current target $\tau_t(i)$. (Thus, with probability no lower than $q$ at every $t$, the long-range link of $i$ connects to its current target, i.e. $\alpha_t(i) = \tau_t(i)$.)

The first component of the law of motion, target revision, embodies the idea of volatility: over time, the environment evolves and the needs/tasks/objectives of individual nodes are affected by it. The parameter $p \in [0, 1]$ modulates the rate at which the environment changes, thus leading to pressure for some adjustment to take place.

On the other hand, the second component, neighbour update, specifies how and when, in response to the aforementioned adjustment pressure, actual changes in the network structure unfold as agents change their long-range neighbours. The parameter $q \in [0, 1]$ is a measure of organizational plasticity. It can be conceived as an attribute of organizations—say, a part their ‘culture’—and will generally differ across them. Sometimes, it may also be regarded as an outcome of design, at least partially. This, for example, is what is implicitly suggested when managers or consultants speak of reshaping the culture of a firm in order to improve its performance.

Finally, we turn to the issue of how to measure performance in the dynamic set-up. As explained and motivated above, organizational performance is associated to the average distance between nodes and their targets. But, in the present dynamic context, we want to add a key twist to it. Specifically, we posit that, in computing node-target distances, only the links in $\Gamma_t \cap \Gamma_{t-1}$ can be used. That is, only the informal links that have remained in place for at least one period are assumed to form part of the operational communication structure of the organization. (At the beginning of the process, we posit that $\Gamma_0 = \Gamma_{-1}$, so that all initial links form part of the organizational structure.)

Several (complementary) justifications can be given to this assumption. One is that some ‘socialization’ time (here, just one period) is required for a fresh link to be formed and become effective. An alternative motivation is that it also takes time for a new link between two individuals to be known (and

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4 This is stressed in the influential work of Schein [16,17], who conceives culture as the background for change in any organization. In fact, somewhat in line with the role of $q$ in our model, he suggests that the ‘shared assumptions and beliefs about the stability of human relationships’ is a key cultural dimension that differentiates organizations.
thus become usable) by the rest of the organization in accessing their targets. Formally, the implication of this assumption is that organizational performance $\rho_t$ at each $t$ is to be measured as follows:

$$\rho_t = -\langle d(i, \tau_t(i)) \mid \Gamma_{t-1} \cap \Gamma_t \rangle_{i \in N},$$

(1)

where the conditioning included in the average $\langle \cdot \rangle$ indicates that, in computing the distances $d(\cdot)$, only links in $\Gamma_{t-1} \cap \Gamma_t$ can be used.

Clearly, it is the delay in the effectiveness of new links contemplated in (1) that introduces the trade-off between adaptability and structure that is at the heart of our model. If no such delay prevailed, instantaneous adaptability to any change in the environment (i.e. a value of $q = 1$) would obviously maximize organizational performance. Instead, when some time must elapse between the establishment of a new link and its effective use by the organization, an interesting tension arises. On the one hand, there is the immediate benefit to the individual adjusting node from having a link (and hence direct access) to its new target. And on the other hand, after any such adjustment by an individual node has taken place, the organization as a whole must face the cost imposed on other nodes by the temporary reduction of their communication structure. In general, as a result of these conflicting considerations, it may be optimal for the organization to limit its adaptability to the recurrent changes in the environment (i.e. display a value of $q < 1$).

4. Analysis

In a nutshell, our main objective will be to shed light on the interplay between the plasticity of the organization (as given by $q$) and the volatility of its environment (as captured by $p$). To fix ideas, a useful way to grasp this relationship is to consider an optimal-design problem in which $p$ is the exogenous parameter and $q$ is the decision/design variable. Naturally, this problem must be formulated in a long intertemporal framework, where volatility and adjustment have a full chance to unfold. Thus, let us take a truly long-run perspective and identify the overall performance of the organization with

$$\rho \equiv \lim_{T \to \infty} \frac{1}{T} \sum_{t=1}^{T} \rho_t.$$

Since the underlying stochastic process is ergodic, $\rho$ is independent of initial conditions and can be conceived as a function of $p$ and $q$ alone. Let us write $\rho(p, q)$ to reflect such dependence. Then, our theoretical concerns are addressed by the following optimization problem: given any $p \in [0, 1]$, find $q^*(p)$ such that

$$q^*(p) \in \arg \max \limits_{q \in [0,1]} \rho(p, q).$$

(2)

In essence, this optimization problem reflects a trade-off between two opposing objectives:

1. **Adaptability**—swiftness in responding to a mismatch between links and targets;

2. **Structure**—preservation of the network connectivity (specifically, the long-range links) required to conduct a search effectively.

5 The same trade-off and qualitative implications would arise if, rather than one period, the (finite) delay involved in a new link becoming part of the communication structure of the organization were longer.
To gain an analytical understanding of the essential implications resulting from this trade-off, we study the problem through an idealization of our framework in which the dynamics of the system is identified with its expected motion. As customary, we call such an idealization the mean-field model (MFM). Given the stochastic independence displayed by the forces impinging on each node (both concerning volatility and link rewiring), it is natural to conjecture that the MFM should capture the essential behaviour displayed by large finite systems. Indeed, this will be confirmed by numerical simulations, whose performance are found to match with great accuracy the theoretical predictions.

The MFM is defined by a dynamical system formulated on a population-wide (anonymous) description of the evolving situation. A sufficient specification (or state) of this system is given by the fraction of nodes that are currently on target—i.e. are connected to their respective target through their long-range links. Let \( \mu(t) \) stand for the fraction of such nodes prevailing at some \( t \). Then, its expected law of motion is given by the following simple difference equation:

\[
\mu(t + 1) = (1 - p)\mu(t) + q[\mu(t)p + (1 - \mu(t))].
\]

It is straightforward to see that the system globally converges to a unique positive fraction of nodes on target given by

\[
\mu^* = \frac{q}{p + q(1 - p)} < 1. \quad (3)
\]

This implies that, in the long run, the MFM predicts that the total number of long-range links that are fully operational (i.e. have been in place for at least one period) is given by

\[
\lambda^* \equiv [(1 - p)\mu^* + (1 - q)(1 - (1 - p)\mu^*)]n = \frac{p(1 - q) + q(1 - p)}{p + q(1 - p)}n. \quad (4)
\]

Our next step is to compute the long-run average distance between a node and its target, when a direct link does not already exist between them. To this end, we note that the ‘operational network’ prevailing at \( t \) (i.e. \( \Gamma_{t-1} \cap \Gamma_t \)) can be conceived as a small-world network of the sort studied by Newman et al. [18], itself a variation of the original set-up proposed by Watts and Strogatz [7]. Very succinctly, such a network is constructed as follows:

(a) One starts with a large set of nodes, arranged linearly along a ring. Each of them is taken to be connected to the two nodes adjacent to it along the ring.\(^6\)

(b) Then, independently across every node, each of them is given an additional ‘short-cut’ with some (small) probability \( \varphi \). This short-cut is a link that connects the node in question to some randomly selected node in the whole set.

Formally, the number of short-cuts in the small-world network can be identified with the number \( \lambda \) of operational long-range links in our set-up. This then allows one to rely directly on the expression derived by Newman et al. [18] to approximate the average network distance in their small-world set-up.

\(^6\) In the general original formulation, the nodes can be directly connected to all those that lie within a certain number of steps away in the ring. This generalization is irrelevant for our purposes.
In terms of our present notation, they found it to be proportional to a function $F(\lambda)$ given by

$$F(\lambda) = \frac{2}{\sqrt{\lambda^2 + 2\lambda}} \tanh^{-1} \left( \frac{\lambda}{\sqrt{\lambda^2 + 2\lambda}} \right).$$

The function above, of course, only applies to the nodes that are not on target. Since the fraction of these in the long run is $[1 - (1 - p)\mu^*]$, the objective function $\psi$ to be maximized in our case is

$$\psi(p, q) = -[1 - (1 - p)\mu^*(p, q)]F(\lambda^*(p, q)), \quad (5)$$

where $\mu^*(p, q)$ and $\lambda^*(p, q)$ stand for the long-run values for $\mu$ and $\lambda$, respectively, given by (3) and (4), the notation highlighting that they both depend on the parameters of the model, $p$ and $q$.

Combining the previous considerations, the optimization problem faced by the organization can be formulated as follows. Given any $p \in [0, 1]$ (the environmental volatility), find the value $q^*(p)$ (optimal plasticity) that solves

$$\max_{q \in [0,1]} \psi(p, q). \quad (6)$$

Once the full dependence on $p$ and $q$ is taken into account, the function $\psi(p, q)$ becomes rather involved, which makes it hard to characterize analytically the solution of the above optimization problem. I choose, therefore, to rely on numerical methods (as implemented, e.g. by standard software packages) to identify the optimal plasticity $q^*$ that solves (6), as a function of the volatility rate $p$.

Figure 1 describes the induced mapping $q^*(p)$ for different values of population size and show that it is qualitatively the same across a wide range in orders of magnitude.

The results depicted in Fig. 1(a–c) provide a stark picture of the way in which the tension between structure and adaptability is resolved in a network organization that is suitably described by our model. It shows that, except for a very narrow transition range, the optimal level of organizational plasticity is either full (i.e. $q^*(p) = 1$) or completely absent (i.e. $q^*(p) = 0$). Thus, if we focus on the rate at which the organization effectively changes its network structure, the conclusions can be described as follows. For low levels of volatility, the rate of change matches that of the environment since the plasticity of the organization is maximal. Thus, as the environment gets more volatile, the organization undergoes a fully parallel (linear) increase in network adjustment. This state of affairs, however, ends abruptly at levels of volatility well below complete target turnover. For, at a value of $p$ sizably below 1, the optimal plasticity of the organization falls steeply to zero. There is, therefore, a wide range for $p$ in which the best performance is achieved by freezing the network of the organization at its original random configuration.

The analytical solutions derived from the MFM closely match the behaviour observed in numerical simulations of the model, even if the population is relatively small. By way of illustration, Fig. 2 shows simulation results for $n = 100$, which can be compared with the theoretical prediction depicted in Fig. 1(a) for the same population size. In both cases we observe that, within a relatively narrow interval for $p$ that lies above $1/2$, there is a sharp transition across extreme degrees of organizational plasticity (i.e. probabilities $q \in \{0, 1\}$). In the simulations the transition is fully completed along the interval $[0.55, 0.62]$, while the theory displays a narrower transition range contained in $[0.54, 0.57]$. 

7 In line with the model proposed by Newman et al. [18], we gain some notational simplicity by normalizing the distance between direct neighbours in the network to zero. This implies that nodes that are directly connected to their targets can be ignored in the performance measure as they lead to no cost or delay in tackling the corresponding problems.
Fig. 1. Optimal plasticity $q^\ast(p)$ as a function of volatility $p$ for various population sizes, $n = 10^2, 10^6, 10^{10}$. The function is shown both for the whole domain $p \in [0, 1]$ as well as for a scaled version that is ‘zoomed in’ on the region where the transition from high to low optimal values takes place. (a) Population size $n = 10^2$, (b) population size $n = 10^6$ and (c) population size $n = 10^{10}$.

Our conclusions shed light on points made, in diverse forms, by the recent organization literature. For example, Schein [16,17] argues that stability and change are ‘two sides of the same coin’, and that both are part of any successful adaptation to an environment in perpetual flux. Moreland and Argote
Fig. 2. The upper surface depicts the average performance $\bar{\rho} \equiv (1/T) \sum_{t=1}^{T} \rho_t$ over $T = 20000$ rounds in a context consisting of $n = 100$ agents where each $\rho_t$ is computed as in (1). The lower line on the $p-q$ plane represents the optimal plasticity $q$ for which $\bar{\rho}$ is maximized at each of the volatility rates $p$ considered (a grid with step value $\Delta = 0.025$). The transition from a situation with full plasticity ($q = 1$) to another with none at all ($q = 0$) occurs as the volatility (the probability $p$) grows from $p = 0.550$ to $p = 0.625$. As explained in the text, this interval is similar to that predicted by the theory (cf. Fig. 1(a)) but somewhat wider.

[12], on the other hand, elaborate on this idea by emphasizing that too much flexibility may deteriorate the so-called ‘intellectual capital’ of the organization (i.e. the knowledge available to an organization through its workers). This capital is accessed by the organization’s transactive-memory system—recall Section 2—whose operation is crucially facilitated by ‘a shared awareness among workers of who knows what (...’).

The model may be regarded as having both descriptive and normative implications. On the descriptive side, one of its predictions is that, to the extent that organizations can be taken to operate efficiently, the most rigid ones should be those operating in the most volatile environments. This, however, raises normative issues as well, bearing on the likely conflict between individual incentives to adjust and the possibly detrimental effects of such an adjustment on the overall performance of the organization.

Our present approach does not take individual payoffs into account, and thus precludes a rigorous study of such normative questions. Any extended model that would do so, however, should probably posit that individual incentives to adjust long-range links are directly related to the current distance between the node and the target. Then, if one were to abstract from any adjustment costs, maximum plasticity would always be optimal from a purely individual perspective. But, as our analysis underscores,
this may be suboptimal for the organization as a whole if the volatility of the environment is relatively high. In essence, the problem at stake is a classical one of externalities—in this case, externalities of individual adjustment on the search effort by others. And, as usual, what the problem may then require is a suitable kind of intervention that, by impinging on individual’s ability or/and payoffs to adjust, leads to a socially optimal outcome. To formulate and analyse this ‘implementation problem’ in any detail is outside the scope of the present paper.

5. Summary and future research

The paper studies a model of a network organization that lives in a volatile environment and must therefore face the trade-off between the adaptability to changing circumstances and the preservation of an operational network structure. Our analysis yielded rather clear-cut conclusions. Specifically, we found that the positive effects of adaptability fully dominate for low levels of volatility but are sharply and completely offset beyond some intermediate threshold. This raises positive and normative issues on the ‘dynamic design’ of organizations, which are left for subsequent research.

Additional issues to be explored in the future concern the sensitivity of these conclusions to some of the simplifying features of the approach. Since the theoretical framework is so stylized, many extensions could be explored. By way of illustration, consider the assumption that the rewiring of a long range link occurs with the same probability, independently of the distance to the target that is closed by the adjustment. In the same spirit of the model, it would be natural to postulate instead that rewiring occurs (say, again with some probability $q$) only if that distance exceeds a certain threshold. Obviously, a suitable choice for this threshold could just improve the overall performance of the organization. But a trade-off akin to that of the original model would still arise and, therefore, it would be interesting to know whether similar conclusions continue to hold, at least qualitatively.

In my view, however, one of the most interesting variations of the model to be considered would affect the postulated backbone of the organization. The present model has assumed that this backbone is a regular boundariless lattice (i.e. a “ring”). Often, however, the formal and stable network of an organization is best conceived as displaying a less symmetric form. A natural alternative is given by a hierarchical tree structure, where each individual—except for the single apex—is connected to one ‘supervisor’. Such a hierarchy is descriptive of many of the real-world structures observed in organizations, and probably this is partly due to the advantages it allows in the routing and processing of information (cf. Radner [1]). Recently, however, it has been argued (see, e.g. [10]) that the addition of long-range links connecting distant parts of an underlying hierarchic structure can greatly improve its overall performance. Indeed, this is supported by a large body of empirical research which finds that ‘(…) much of the real work in any company gets done through an informal organization, with complex networks of relationships that cross functions and divisions’ (cf. [19]).

The models that have been proposed in the theoretical literature to understand the aforementioned considerations, however, have been mostly static. They conceive the organization network as fixed, even if it consists of a complex blend of hierarchic and transversal links. To enrich that approach with a genuinely dynamic model of the organization appears to be an interesting development, which could be carried out along the lines suggested in this paper.

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References
1. Radner, R. (1993) The organization of decentralized information processing. *Econometrica*, 61, 1109–1146.
2. Bolton, P. & Dewatripont, M. (1994) The firm as a communication network. *Q. J. Econ.*, 109, 809–839.
3. van Zandt, T. (1999) Real-time decentralized information processing as a model of organizations with boundedly rational agents. *Rev. Econ. Stud.*, 66, 633–658.
4. Garicano, L. (2000) Hierarchies and the organization of knowledge in production. *J. Pol. Econ.*, 108, 874–904.
5. Dessein, W. & Santos, T. (2006) Adaptive organizations. *J. Pol. Econ.*, 14, 956–995.
6. Milgram, S. (1967) The small-world problem. *Psychol. Today*, 2, 60–67.
7. Watts, D. J. & Strogatz, S. H. (1998) Collective dynamics of ‘small-world’ networks. *Nature*, 393, 440–442.
8. Kleinberg, J. (2000) Navigation in a small world. *Nature*, 406, 845.
9. Guimerà, R., Díaz-Guilera, A., Vega-Redondo, F., Cabrales, A. & Arenas, A. (2002) Optimal network topologies for local search with congestion. *Phys. Rev. Lett.*, 89, 248701.
10. Dodds, P. S., Watts, D. J. & Sabel, C. F. (2003) Information exchange and the robustness of organizational networks. *Proc. Natl Acad. Sci.*, 100, 12516–12521.
11. Wegner, D. M. (1986) Transactive memory: a contemporary analysis of the group mind. *Theories of Group Behavioral Cognition* (B. Mullen & G. R. Goethals eds). New York: Springer, pp. 253–276.
12. Moreland, R. L. & Argote, L. (2003) Transactive memory in dynamic organizations. *Leading and Managing People in the Dynamic Organization* (R. S. Peterson & E. A. Mannix eds). New Jersey: Lawrence Erlbaum Associates, Publishers.
13. Hansen, M. T. (2002) Knowledge networks: explaining effective knowledge sharing in multunit companies. *Organ. Sci.*, 13, 232–248.
14. Hansen, M. T. (1999) The search-transfer problem: the role of weak ties in sharing knowledge across organization subunits. *Admin. Sci. Quart.*, 44, 82–111.
15. Schulz, M. (2003) Pathways of relevance: exploring inflows of knowledge into subunits of multinational corporations. *Organ. Sci.*, 14, 440–459.
16. Schein, E. H. (2002) Models and tools for stability and change in human systems. *Reflections*, 5, 34–45.
17. Schein, E. H. (2004) *Organizational Culture and Leadership*, 3rd edn. New York: Wiley Publishers.
18. Newman, M. E. J., Moore, C. & Watts, D. J. (2000) Mean-field solution of the small-world network model. *Phys. Rev. Lett.*, 84, 3201–3204.
19. Krackhardt, D. & Hanson, J. R. (1993) Informal networks: the company behind the chart. *Harv. Bus. Rev.*, 71, 104–111.