

## A Spinning top model of formal organization and informal behavior: dynamics of advice networks among judges in a commercial court

Emmanuel Lazega, Claire Lemercier, Lise Mounier

#### ▶ To cite this version:

Emmanuel Lazega, Claire Lemercier, Lise Mounier. A Spinning top model of formal organization and informal behavior: dynamics of advice networks among judges in a commercial court. European Management Review, 2006, 3 (2), pp.113-122. 10.1057/palgrave.emr.1500058. hal-01693484

### HAL Id: hal-01693484 https://sciencespo.hal.science/hal-01693484

Submitted on 16 Nov 2022

**HAL** is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers. L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



palgrave-journals.com/emr



# A Spinning top model of formal organization and informal behavior: dynamics of advice networks among judges in a commercial court

Emmanuel Lazega<sup>1</sup>, Claire Lemercier<sup>2</sup>, Lise Mounier<sup>3</sup>

<sup>1</sup>C.E.R.S.O., Université de Paris IX - Dauphine, Place du Maréchal de Lattre de Tassigny, Paris, France;

<sup>2</sup>I.H.M.C.-C.N.R.S., 45 rue d'Ulm, Paris, France;

<sup>3</sup>Centre Maurice Halbwachs-C.N.R.S., 48 boulevard Jourdan, Paris, France

#### Correspondence:

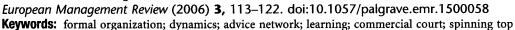
E Lazega, C.E.R.S.O., Université de Paris IX – Dauphine, Place du Maréchal de Lattre de Tassigny, 75775 Paris Cedex 16, France.

Tel: 01 44 05 42 03

E-mail: emmanuel.lazega@dauphine.fr

#### **Abstract**

The longitudinal study of advice networks among 240 judges at the Commercial Court of Paris permits the examination of learning as an interactive process. We argue that a spinning top model is a useful heuristic for intra-organizational learning in dynamic advice networks. This model proposes that a stabilized elite preserves accumulated knowledge in a community that overall experiences high turnover and systematic job rotation, and hence runs the danger of inadequately sharing knowledge among its members. We test the model by analyzing the structure and dynamics of advice networks among judges at the Commercial Court of Paris. This dynamic structure reflects the informal homophilous preferences among judges organized in a strong formal system, a high relational turnover in the selection of advisors, and the emergence of an elite of senior advisors that stabilizes the learning process - much like the behavior of a spinning top. This case study also identifies an endogenous process of increasing and then decreasing centralization of this network over time, raising questions about the maintenance of the stability of the pecking order and about the relationship between learning and seniority. Results illustrate the importance of dynamic over static network analysis and call for a renewed attention to formal structure in organizations.





#### Introduction

ntra-organizational learning has long been considered a central process in organizations.<sup>1</sup> The study of this process is becoming increasingly important as the number of knowledge-intensive organizations – which thrive on innovation – increases, and with it the search for new competitive advantages. Learning as a relational and interactive process can be captured through the study of advice networks. In organized contexts, consulting with someone is usually possible through social exchange in which members obtain advice in exchange for recognition of status and authority of the advisor (Blau, 1955, 1964),

which we call 'cognitive status'. Members with cognitive status usually have hierarchical and/or expert authority (Lazega, 1992).

Intra-organizational learning thus depends on the capacity of the formal organization to channel informal advice seeking. This channelling maintains a good proportion of advice seeking within the boundaries of the organization. It can create a fragile equilibrium between, on the one hand, rapid overall relational turnover in the selection of advisors and, on the other hand, the existence of a stabilized but adaptable elite of advisors with cognitive



status. The formal organization drives the evolution of the advice network itself.

We argue that the image of a spinning top represents this process heuristically. Members of organizations rely on homophilous choices to find advisors. High turnover and systematic job rotation, however, weaken such homophilous ties. We compare the formal organization and the rotation movement that it creates among its members to the body of the spinning top. When this movement destroys homophilous advice ties, members turn to a small and stable elite of authoritative advisors who can thus be compared to the stationary spin axis of the top. The equilibrium reached by the top represents the structural condition for intra-organizational learning. When formality works (Stinchcombe, 2001), knowledge accumulated in the organization is preserved in spite of high turnover and systematic job rotation.

However, this equilibrium is fragile. In effect, when advice networks become too centralized, there is overload for members with cognitive status. Actors at the top of the pecking order of the advice network have to choose between overload of advice seekers and delegation of some of their status - with conflicts of interpretation (with other elite advisors) that come attached to delegation. The mechanism is thus based on the social production of cognitive authorities and the fragile equilibrium that the formal organization must reach in order to keep them useful and productive.

In sum, the dynamics of intra-organizational learning depend on formal organization in three distinct ways. First, the rotation movement created by the formal organization destroys ties based on homophilous choices. Second, this movement also creates an elite of advisors with cognitive authority. Third, turnover and/or conflicts among members of the elite itself require/requires a dynamic process of stabilization of this pecking order over time.

The empirical data on which the study of these processes is based is an organizational and longitudinal network study of advice seeking among judges at the Commercial Court of Paris. In this study, 240 judges (all lay, voluntary, and elected judges coming from the local business community) were interviewed altogether about their advice-seeking relationships within the court. We obtained three measurements of this complete network in 2000, 2002, and 2005. We test parts of our model of the dynamics of intra-organizational learning statistically, using the socalled p2 (Van Duijn, 1995; Van Duijn et al., 2004) and Siena (Snijders, 2001, 2005) models. The models are applied, respectively, to examine the influence of formal structure of the organization on the selection of advisors, and on the characteristics of the relational turnover in the advice networks among the judges. They confirm the heuristic value of the spinning top model. Finally, we speculate about the implication of this heuristic model for future research on the topic and for the evaluation of the capacity of modern organizations to be learning-friendly environments accommodating complex learning dynamics.

#### Advice networks and intra-organizational learning

Knowledge about how advice networks contribute to intraorganizational learning can be useful to the study of the relationship between formal organization and informal behavior. An advice network represents a set of paths through which appropriate information circulates among members of an organized setting. The allocation of this resource through informal ties and interactions reduces the costs of its acquisition during the process of making decisions to solve problems. Members of organizations see expertise and experience as accumulated by the organization, and they rely constantly on advice from others. However, intra-organizational learning through advice seeking does not simply result from the accumulation of individually and informally acquired information. The process is socially organized in a sophisticated way.

The association of the social organization of learning, one the one hand, and social networks, on the other hand, is not in itself a new insight. Different approaches have dominated the recent literature on these topics. One example is the theory of communities of practice (Brown and Duguid, 1991; Lave and Wenger, 1991; Raelin, 1997). This theory assumes that 'collaborative networks', in and across companies, can be managed to generate such communities of practice. These communities should have effects on performance through facilitating learning, mastering a domain of expertise, accelerating innovation. For Wenger et al. (2002), learning in such communities includes at the very least mutual commitment in relationships developed over time and identification of who knows what.

Another example is provided by 'learning network theory' (Van der Krogt, 1998; Poell and Van der Krogt, 1998; Dimovski and Skerlavaj, 2004), which assumes that members learn in every organization and that the learning network merely represents how learning is organized. This leads these authors to identify four kinds of learning networks. A 'liberal' learning network emerges in unstructured, chaotic organizations; a 'vertical' learning network in formalized Tayloristic bureaucracies; a 'horizontal' network of peers in egalitarian organizations (Senge, 1990); and an 'external' learning network in organizations where employees have a strong orientation towards their professional field (Dimovski and Škerlavaj, 2004).

Neither the communities of practice, nor the learning network literatures examine the structure and dynamics of the networks that they assume to be critical to learning. Without systematic and empirical tests, they rely heavily on ideal-types that ignore the complexity of collective learning as a social process. They are also limited in their contribution to our understanding of intra-organizational learning because they do not associate this process with formal structure, authority relationships, social exchange, and specific relational structures.

This paper offers insights about intra-organizational learning based on a micro-sociology of knowledge (Lazega, 1992) and on network analysis. This micro-sociology has also long recognized that learning and knowledge are not purely individual. Learning consists in acquisition and evaluation, by the members of the organization, of appropriate information and knowledge. In our view, learning as a relational and interactive process can be captured through the study of advice networks and social exchange of advice for recognition of cognitive status and authority.

In organizations examined by researchers, advice seeking converges towards senior and recognized members and reflects a process of cognitive alignment on such members who gained the 'authority to know', who provide social approval for specific decisions, and who contribute to the integration of the organization because they link the individual, group, and organizational levels. We think of this alignment as a key ingredient of intra-organizational learning. A status hierarchy provides a social incentive for actors to share their knowledge and experience with others, thus helping in explaining the social organization of the learning process.<sup>2</sup>

Because advice networks are usually shaped by such status games, they are usually highly centralized. They exhibit a pecking order that often closely follows the hierarchical structure of the organization.<sup>3</sup> Members of formal organizations rarely declare that they seek advice from 'people below' in this pecking order. In addition to the existence of a core set of central advisors, the periphery of the network can be complex and characterized by homophilous (Lazega and Van Duijn, 1997; McPherson et al., 2001) horizontal ties (i.e. ties among peers). Members use such ties to mitigate the potentially negative effects of this strong rule for intra-organizational action and learning (negative effects resulting, for example, from not being willing to show that one does not know). Thus, advice networks tend to be both hierarchical and cohesive (at least within subsets of peers), with the hierarchical dimension usually stronger than the cohesive one. In some firms, advice ties are so important that they also play an important role in facilitating the flows of other kinds of resources in co-work and friendship ties (Lazega and Pattison, 1999).

Members with cognitive status usually have hierarchical and/or expert authority. Nevertheless, formal structure is often neglected in recent work on learning. The formal organization drives the evolution of the advice network itself for at least two reasons: firstly because it is the formal organization that allocates different forms of status (hierarchical, expert) to its members and secondly because it has rules for turnover and job rotation that have an effect on selection of advisors. Organizations willing to improve retrieval and protection of their tacit and codified knowledge must be aware of social processes that shape the evolution of such networks. However, the evolution of advice seeking and giving in a complete network has not been studied very closely before. Modeling these dynamics is thus both important substantively and new methodologically. We propose a heuristic model that accounts for the dynamics of advice networks in organizations.

This model, called 'spinning top model', brings together previous knowledge on advice networks and sheds some new light on intra-organizational learning. In particular, we assume that such a process depends on the capacity of the organization to generate an elite of authoritative advisors that manages to remain stable while advice ties among other members of the organization are subjected to rapid turnover (e.g., by a rotation policy, by career movement, by the need to find new knowledge that old advisors cannot provide (Ortega, 2001; Argote et al., 2005)). More generally, the spinning top model illustrates a new approach to the relationship between formal organization and informal social behavior and processes.

#### A spinning top model for a dynamic process

To further explore the link between advice networks and intra-organizational learning, it is important to focus on the temporal and dynamic dimension of this process (Crossan et al., 1999; Easterby-Smith et al., 2000; Bapuji and Crossan, 2004). Learning occurs over time and across levels, if only because members can 'unlearn' and because they must combine what they already know to new knowledge that they build in order to make new decisions. Stable, unchanging advice networks reduce the cost of acquiring timely information, but also increase the risk of acquiring obsolete and inappropriate information. The quality of intra-organizational learning thus depends on changes in these networks. There is a need for a theory of their evolution. It is our intention in this paper to contribute to the description of these dynamics. We use our spinning top model as a guiding metaphor for research on the relationship between formal organization and intra-organizational process in general, and here on intra-organizational learning in particular.

The spinning top heuristic brings together at least three components: a rotating body, a rotation axis, and a fragile equilibrium that depends, in parts, on characteristics of the previous components. Time is taken into account through rotation movement and speed. We think of the rotating block as the learning organization. The rotation axis can represent the pecking order, that is, the emergent hierarchy of members with cognitive status. These members have the 'authority to know' in the organization. Rotation rules across intra-organizational boundaries and through status differences summarize formal structure. The fragile equilibrium created by the rotation movement represents the structural condition for learning collectively in the organization. This equilibrium itself depends on the stability of the rotation axis and the shape of the organization.

This picture is heuristic for several reasons. First, it suggests that time is important in allowing organizations to select members with cognitive status. Cognitive status builds up by reputation for expertise, by the capacity to provide quality control without raising too many controversies or conflicts of definition of the situation, by the trained capacity to speak legitimately on behalf of the collective. Acquiring this status takes efforts and time. The 'authority to know' is produced by long-term individual and collective investments that can be ruined if members with cognitive status leave and behave too opportunistically. The equilibrium reached by the spinning top thus suggests that members with status and cognitive authority in the organization have a strong incentive to keep their status and authority over time, even at some extra expense, to avoid the loss of advantages that come attached to their relative standing.4

Second, this heuristic also suggests that the equilibrium reached by the spinning top is fragile. The number of members with cognitive status varies over time. We can think of several reasons for which this number oscillates, that is, increases and decreases over time. One reason is that members tend to choose advisors that they perceive to



be the most popular (i.e. already chosen by a large number of colleagues). Members sought out by many other members tend to build a reputation; selecting them is perceived to be safe and legitimate. As stressed by a micropolitical perspective, everyone seeks status and believes that they will reach a higher status; access to advisors higher up in the ladder becomes in itself a sign of relative status. This implies that a member highly sought out in time t1 becomes even more intensively sought out in time t2

Another reason is that this behavior creates an overload of requests for advice from a small number of highly central advisors with high cognitive status. Highly sought out advisors often manage this overload by delegating, that is, referring the advice seeker to other advisors.<sup>5</sup> This management of overload threatens the stability of the pecking order in the sense that it brings in new central advisors and requires coordination among the elites in order to avoid destructive status competition and conflicts of definition of the situation between too many chefs. In turn, this strategy triggers either formal efforts of coordination among the elites or a new reduction in the number of advisors with high cognitive status through withdrawal of central advisors who become unavailable (due to retirement or delegitimation). This oscillation threatens the stability of the pecking order, with both positive or negative effects on intra-organizational learning.

These are not simple processes. The spinning top heuristic thus suggests that centralization of advice networks can either remain stable, or increase over time, or decrease over time to reach a balance between elite overload and conflicts of interpretation among them. This metaphor thus leads to the following claims describing the structure and dynamics of advice networks and intraorganizational learning.

#### **Descriptive claims**

Based on the literature mentioned above, we can expect to observe two basic characteristics of advice networks as driven by formal structure. First, advice networks should be characterized by a pecking order reflecting status differences. Second, they should also be characterized by homophilous, horizontal ties. Such characteristics are time invariant.

Based on our spinning top heuristic, we can expect two additional characteristics of advice networks when examined longitudinally. Third, to some extent, the pecking order in advice networks should be stable over time. In effect, the spinning top model suggests that this pecking order exists because it helps members deal with the relational turnover created by rotation movements. Fourth, stability of the pecking order is not automatic; it is fragile and threatened, over time, by expansion, turnover, or conflicts among the elite themselves. Centralization of advice networks should oscillate, that is, increase and decrease over time as members of the elite of advisors either leave (and are 'replaced' by new members) or try to reach a balance between high individual status and overload on the one hand, and consensus on the definition of the situation on the other hand. Periods of centralization of advice networks should be followed by periods of decline

in this centralization, then by periods of recentralization. One of the true challenges facing formal organizations with respect to collective learning is then to maintain the stability of the pecking order.

#### Methods

Although these claims are descriptive, they introduce a temporal dimension providing new insights in an exploratory field of research. In particular, we establish these descriptive claims in one specific organization with statistical models called p2 and Siena. They are applied to examine the influence of structural variables on relational turnover in these networks (Doreian and Stokman, 1997). They can thus confirm the heuristic value of the spinning top model for intra-organizational learning through advice networks.

The p2 model (Van Duijn, 1995; Lazega and Van Duijn, 1997; Van Duijn et al., 2004) provides a flexible way for using explanatory variables to model network structure. We apply it to examine the influence of formal structure of the organization on interactions among its members. The explanatory (independent) variables are actor and dyad characteristics, related to or derived from actors' formal positions in the organization and other relative characteristics. Standard statistical methods, based on loglinear analysis or logistic regression, assume each actor's choices to be independent; such methods do not take into account the fact that the informal interactions between actors are mutually related (Krackhardt, 1988). In p2 models, the unit of analysis, or dependent variable, is the binary relationship from one actor to the other; but it takes into consideration the dependency between the two relationships constituting a dyad as well as the interdependence between relationships from and to one actor.

The assumption of dyad independence is relaxed in the p2 model by incorporating random parameters for each actor with an appropriate covariance structure, representing the interdependence between relationships from and to the same actor. The random actor parameters are viewed as error terms in the regression equation or, equivalently, as unexplained parts of the sender and receiver parameters.6 The models allows researchers to estimate parameters for the propensity of actors to send choices, for the propensity of actors to receive choices, for the propensity of actors reciprocate choices, and for a more general mean tendency (density) to interact with each other. When the density parameter is modeled, as below, a linear relationship between this parameter and dyadic attributes is assumed.

Studying the dynamics of networks raises difficult methodological issues that are addressed by recently developed methods presented in Snijders (2001, 2004, 2005), Snijders and Huisman (2002), Huisman and Snijders (2003) under the name of Siena (for Simulation Investigation for Empirical Network Analysis). It is a program for the analysis of repeated (longitudinal) data on social networks. The statistical analysis is carried out on the basis of computer simulation of a probabilistic model for the evolution of the social network. Siena focuses on differences between two (or more) observations of the same network, that is, on relational changes made over time by members of the network. Dynamics of social networks are

complex due to endogenous feedback effects (e.g., in reciprocity, transitivity, popularity, subgroup formation, in which the existence of ties is highly dependent on the existence of other ties). Siena also comprises a random influence in the simulation model to account for 'unexplained variability' associated with endogenous effects.

Structural endogenous effects are measured in Siena in standard ways. Reciprocity is defined by the number of reciprocated ties. Transitivity is defined by the number of transitive patterns in i's relations (ordered pairs of actors (j, j)) h) to both of whom i is tied, while j is also tied to h). Generalized exchange is measured by the number of three cycles in i's network, that is, cycles in which i seeks advice from j, j from k and k from i. Structural effects can also be presented as attributes, as will be the case here. In Siena, the 'Popularity alter effect' is defined by 1/n times the sum of the indegrees of the others to whom i is tied. It measures the extent to which members tend to select as advisors members who are already sought out for advice by others. The 'Activity of alter' effect is defined by 1/n times the sum of the outdegrees of the others to whom i is tied. It measures the extent to which members who seek out many advisors tend to be sought out themselves as advisors. We introduce these effects in the analyses presented below.

#### Data

Our site is a first-level judicial organization, the Commercial Court of Paris, in which members – who are lay judges – share expertise and consider intra-organizational learning to be efficient. We establish our descriptive claims using observations of advice seeking among the judges in this court. The Commercial Court of Paris is an interesting organization for our purpose because it has a visible and formal rotation rule that reallocates the judges to different Chambers each year. Thus, this organization is particularly useful to explore the spinning top model of formal organization, informal advice seeking, and the dynamics of organizational learning.

The court is composed of twenty specialized and generalist Chambers dealing with very heterogeneous forms of commercial litigation (company law, European community law, international law, unfair competition, multimedia and new technologies, etc.) and bankruptcies. It handles around 12% of all the commercial litigation in France, including large and complex cases (that do not go to arbitration courts). Judges are business people who work as unpaid judges, elected for 2 or 4 years (for a maximum total of 14 years) by the members of the Chamber of Commerce of their local jurisdiction and by sitting judges.<sup>7</sup> They follow a work schedule that rotates them, on a yearly basis, from one Chamber to another. The rotation policy of judges across Chambers is meant to prevent corruption or conflicts of interests (e.g., the occurrence of certain obvious, visible, and damaging homophily effects, such as judges coming from the banking industry concentrating in bankruptcy Chambers).

Tasks are complex and judges have discretion in many areas of business law. Disagreements abound about solutions to provide for many legal problems. Commercial litigation is very heterogeneous and conflict resolution often depends on knowledge of the business and specific

industry in which the conflict takes place. These judges thus seek each other for advice intensively in order to manage these uncertainties intra-organizationally, by tapping into the expertise and experience of their heterogeneous set of colleagues.

We collected data of interest to the argument of this paper at three points in time (fall 2000, fall 2002, and fall 2005). We included the following name generator in the interviews with all the judges about their advice seeking among each other: 'Here is the list of all your colleagues at this Tribunal, including the President and Vice-Presidents of the Tribunal, the Presidents of the Chambers, the judges, and 'wise-men'. Using this list, could you check the names of colleagues from whom you have asked advice during the last two years concerning a complex case, or with whom you have had basic discussions, outside formal deliberations, in order to get a different point of view on this case.' A high response rate allowed us to reconstitute, at each point in time, the complete advice network (outside formal deliberations) among judges at this courthouse. The number of judges at the court varied between 151 and 156 between 2000 and 2005 (with an 87.1% average response rate over the three measurements).

#### Results

Using this data set, we tested the four descriptive claims formulated above.

#### The pecking order among judges

Our first descriptive claim predicted that we should observe a pecking order in these networks. Consistent with Blau (1955) and subsequent studies of advice networks, we did find the familiar pecking order in this data, as confirmed by visual inspection in Figure 1. There is a small 'elite' of advisors, a small fraction of judges who are consulted much more often than others. They are not formally assigned to

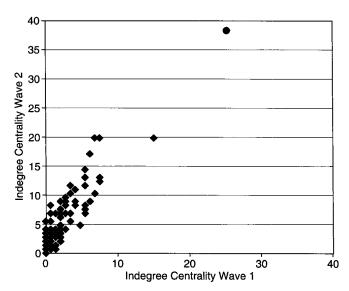


Figure 1 A stable pecking order in the advice network among the judges of the Commercial Court of Paris. This table plots indegree centrality scores of the 91 judges who responded to the name generator in both wave 1 and wave 2. Correlation between scores in the two waves is 0.9.



such a job, but they are often senior judges and presidents of Chamber (Lazega and Mounier, 2003).

A few central members achieve extremely high scores. These highly central judges are among the most senior. Recall that individuals can be judges for a maximum of fourteen years. Within a couple of years, these 'outliers' exit the system and are replaced by upcoming successors.

#### Chamber homophily among judges

Our second descriptive claim predicted the existence of homophilous horizontal ties that mitigate the potentially negative effects of status games related to the pecking order and the tendency not to seek advice from colleagues 'below' in terms of status. To establish this claim, we used a specific dimension of the formal structure of this organization which can be expected to be the most important because it is consistently present in the judges' mind: Chamber membership. Using a p2 model, we test for a Chamber homophily effect because it can matter heavily in the flows of advice. Exchanges are easier with members of one's own Chamber. Table 1 tests for the existence of this homophily effect in the advice network in this organization for the second observation of the network.

The first part of the table (Random effects) displays the variances of the random effects that characterize, as mentioned above, the p2 model. Here the amount of variation in sender and receiver activity is presented. These effects covary negatively; the more judges tend to seek advice, the less likely it is that advice is sought from them. The second part of the table (Fixed effects) displays overall fixed effects and specific fixed effects. First, under overall fixed effects, overall density and reciprocity effects are displayed. The negative value of the density parameter indicates that the probability of a relation is smaller than 0.5 when all other parameters and the random effects are equal to zero. The reciprocity parameter is positive, indicating that advice relations have a tendency to be symmetrical (but not an extremely strong tendency compared to the size of the density effect). Below, under 'Specific density similarity effect', the table displays the specific effect in which we are particularly interested (in bold): Chamber similarity. We find a strong, positive, and significant value for this parameter, indicating that the probability of an advice tie increases when judges are members of the same Chamber. Belonging to the same Chamber, that is, working together often, has a positive effect on establishing an advice relationship. Finally, model fit measures (Deviances) show the difference between the full and empty models. They are 3266.34 for the empty model (i.e. the model without the Chamber similarity effect) and 3121.14 for the full model (i.e. the model with

Table 1 Chamber homophily in judges' choices of advisors

Independent variable	Parameter estimates	
	Full model	Empty model
	Random effects	
Sender variance	3.08 (0.48)	2.63 (0.39)
Receiver variance	2.70 (0.66)	2.22 (0.35)
Sender receiver covariance	$-0.47\ (0.35)$	$-0.10\ (0.24)$
	Fixed effects	
Overall effects		-50
Density	-5.98 (0.20)	-5.55 (0.15)
Reciprocity	1.64 (0.29)	1.73 (0.28)
Specific density similarity effect		
Chamber similarity	1.79 (0.15)	
	Devi	ances
	3121.14	3266.34

This table presents a p2 model of advice seeking among judges in Wave 2. The first part of the table (Random effects) displays the variances of the random effects. Here the amount of variation in sender and receiver activity is presented. These effects covary negatively; the more judges tend to seek advice, the less likely it is that advice is sought from them. The second part of the table (Fixed effects) displays overall fixed effects and specific fixed effects. First, under overall fixed effects, overall density and reciprocity effects are displayed. The negative value of the density parameter indicates that the probability of a relation is smaller than 0.5 when all other parameters and the random effects are equal to zero. This means that the network is relatively sparse. The reciprocity parameter is positive, indicating that advice relations have a tendency to be symmetrical (but not an extremely strong tendency compared to the size of the density effect). Below, under 'Specific density similarity effect', the table displays a specific effect in which we are particularly interested: Chamber similarity. We find a strong, positive, and significant value for this parameter (in bold), indicating that the probability of an advice tie increases when judges are members of the same Chamber. Belonging to the same Chamber, that is, working together often, has a positive effect on establishing an advice relationship. Finally, deviances are model fit measures. They are 3266.34 for the empty model (i.e. the model without the Chamber similarity effect) and 3121.14 for the full model (i.e. the model with the 'Chamber similarity' effect), indicating an improvement in model fit due to the introduction of the 'Chamber similarity' variable into the model. N=156. Standard deviations are in parentheses. Parameter estimation procedure is MCMC (Markov Chain Monte Carlo). Convergence criterion is 0.0001, reached after eight iterations.

the 'Chamber similarity' effect), indicating an improvement in model fit due to the introduction of the 'Chamber similarity' variable into the model. In sum, this analysis shows that our second descriptive claim is established. This model confirms that informal flows of advice in this network are shaped by formal structure: judges tend to select advisors in their own Chamber.

#### A stable pecking order

Based on our spinning top model, our third descriptive claim predicted that the pecking order emerging from the analysis is stable over time. In effect, to some extent, the elite of advisors are stable over time. Correlation between measurements of indegree centrality in 2000 and 2002 is 0.9. However, the same correlation between 2002 and 2005 drops to 0.7. Thus, the first characteristic of the evolution of these networks supporting our spinning top model of intraorganizational learning is confirmed. As we speculated above, however, the drop in the correlation suggests that this stability is weakened by a different social process.

Oscillation: Increasing and decreasing centralization over time Our fourth descriptive claim compares the dynamics of advice networks to oscillation in the centralization of the advice network among judges. In other words, this centralization should increase and then decrease over time as members with cognitive status try to avoid overload at the risk of accepting conflicts of definition of the situation. In order to test for the existence of this oscillation, we turn to a more dynamic analysis of the evolution of this network. This means looking more closely at the structural factors that explain relational turnover in the network, that is, the creation of new ties and the dropping of previously existing ones.

Statistical confirmation for this claim is provided by Snijders' (2001, 2004, 2005) 'actor-oriented' network model, Siena, which is specifically designed to model the evolution of networks through time. The model specification strategy included testing each independent variable on its own and providing a final model that was estimated by including only the significant parameters - with one exception - from the previous models. Table 2 presents the best (most parsimonious) Siena models achieved with this data set.

These tests confirm that judges show a preference for advice seeking from advisors who are already sought out for advice by others: the 'Popularity of alter' effect is strong. During the first period, as shown by a strong 'Activity of alter' effect, they do not seek out advice from other judges who themselves seek out advice frequently. As suggested in our descriptive claims, senior judges - who are already central - become even more central. Increasing centrality of already central judges is the main effect produced by the formal dynamic force behind relational turnover in this organization between 2000 and 2002.

Although smaller by comparison with popularity and activity of alter effects, effects captured by a few structural variables are also significant. If one ignores density (outdegree of the first wave, used as an intercept), reciprocal and transitive relationships also drive relational changes in the advice network in the first period. Judges seek out as advisor members to whom they previously gave advice directly; they also seek out advisors of their advisors. This trend suggests that new ties are established within social sub-groups already identified by actors, reinforcing homophilous evolution. 3-cycles within such groups are associated with a negative parameter, suggesting that generalized exchange is unlikely over time in this fairly hierarchical network. One can also observe that there is a limit to the number of advisors that each judge can seek

Table 2 Collective learning as a cyclical process: increasing, then decreasing, centralization over time

Independent variables	Parameters for period 1 (wave 1-wave 2)	Parameters for period 2 (wave 2-wave 3)
Rate parameter	22.25 (2.03)	30.58 (3.14)
Density	-1.74~(0.09)	-2.23(0.18)
Reciprocity	0.95 (0.16)	0.71 (0.13)
Transitivity	0.50 (0.04)	0.19 (0.01)
Popularity of alter	3.34 (0.40)	3.84 (0.25)
Activity of alter	-14.44 (1.84)	$-1.86\ (1.87)$
Three-cycles of generalized exchange	-0.29 (0.09)	$-0.07\ (0.01)$

This table presents two Siena models analyzing the evolution, over 5 years, of the advice network among judges at the Commercial court of Paris (2000-2005). The rate parameter models the amount of change between two observations of the network, that is, the speed by which the dependent variable changes. The 'density' effect accounts for the observed network density (based on the outdegree of each actor) and can be interpreted as an intercept. The positive reciprocity effect indicates that the tendency to reciprocate an advice relationship drives the evolution of the network. The positive transitivity effect indicates that the tendency to seek advice from one's advisor's advisor also drives the evolution of the network. The negative 'three-cycle of generalized exchange' effect indicates that the tendency to seek advice from an advisee of an advisee does not drive the evolution of the network; this effect shows that status differences do matter in advice seeking among judges, since they do not seek advice from judges 'below' them in the pecking order. The 'Popularity alter effect' measures the extent to which members tend to select as advisors other members who are already sought out for advice, and that this tendency drives changes in the network. The strength and positive value of this parameter indicates that this is the main effect explaining changes in the network: central advisors become even more central over time. The 'Activity of alter' effect measures the extent to which members who seek out many advisors tend to be sought out themselves as advisors. The negative parameter means that this tendency does not drive the evolution of the network. However, this parameter is not significant for the second period, which indicates that during this period network centralization decreases. N=91 for period 1 and N=113 for period 2. Standard errors in parentheses. MCMC (Markov Chain Monte Carlo) estimation procedure.



(a 'ceiling effect' in advice seeking, e.g., for fear of looking incompetent), and that within this limit the concentration of new demands on those who were already important advisors is confirmed. These effects are consistent with Blau's social exchange theory of advice for status.

The second model of Table 2, measuring the evolution of the network for the second period of the study, confirms our fourth claim and captures the oscillation between increasing and decreasing centralization of the advice network. In effect, the relational turnover between wave 1 (in 2000) and wave 2 (in 2002) accounted for a phase of increasing centralization. In turn, the subsequent relational turnover between wave 2 (in 2002) and wave 3 (in 2005) accounts for a decreasing centralization of the network. The 'Popularity of alter' parameter remains strong: central members still attract new demands for advice and the more central they are the more central they tend to become. However, the fact that a judge seeks advice frequently no longer prevents (during the second period) other judges from seeking advice from him/her: the 'Activity of alter' parameter is no longer significant in the second period. This second effect, combined with the first effect and with the drop in the correlation between indegree centrality in wave 2 and indegree centrality in wave 3, indicates a downward tendency in the second period that did not exist during the first period: many central members lose some of their centrality in this downturn and, as a result, new members become more central than they were before, thus joining this elite of judges with cognitive status.

These results establish the spinning top model. They show very clearly that intra-organizational learning, as an informal process, depends on three factors at least. First, the way in which members manage their advice ties in the context of this formal organization. Second, the ways in which central advisors handle overload and conflicts of definition of the situation. Third, the ways in which formal structure can help in dealing with this oscillation of centralization and decentralization of the advice network. In effect, changing levels of centralization over time suggest that this oscillation can weaken collective learning as driven by formal structure.

#### **Discussion and conclusion**

We proposed and established a heuristic model, called 'spinning top model', that helps explore the relationship between formal structure of the organization and endogenous processes such as intra-organizational learning. This exploration is based on the description of the structure and dynamics of advice networks in organizations. The model brings together previous knowledge on advice networks and sheds some new light on intra-organizational learning. In particular, it assumes that such a process depends on the capacity of the organization to generate an elite of advisors that tries to remain stable while homophilous advice ties among other members of the organization are subjected to rapid turnover (e.g., by a job rotation policy, or by the need to find new knowledge that former advisors cannot provide). Intra-organizational learning also depends on the capacity of the organization to manage the oscillation created by increases and decreases in the centrality of these elites.

Our descriptive claims, derived from this heuristic view of the mechanism, receive support from our data set. The dynamics of the advice network examined in this commercial court can indeed be represented intuitively as a spinning top. They are driven by the rotation rule in the formal structure of organization. Since judges seek advice first within their own Chamber, and since they change Chamber every year, the relational turnover in this network is high. Each year, each judge leaves behind several advisors and creates new advice ties within his/her new Chamber. This turnover, however, is compensated by the creation of a set of advisors with cognitive status to whom judges turn for advice regardless of the Chamber in which they work. The centrality scores of members with cognitive status increase, then tend to decrease over time, showing that the issue of stabilization or replacement of this elite of judges adds to the complexity of the dynamics of advice networks.

This social process is thus driven by (formally induced) homophily, relational turnover, centralization of the advice network, and strategies of stabilization of this elite under capacity constraints. This complex process predicts that later observations should find a permanent cyclical pattern of centralization and decentralization of advice networks.

Several questions remain unanswered with this authority-based and oscillatory view of intra-organizational learning, and point to limitations of our work. First, we cannot say that oscillation between centralization and decentralization is the only dynamic process shaping intra-organizational advice networks. The centrality of a few exceptional advisors never decreases (until they exit the system, often with honours). The spinning top model thus shows the importance, in intra-organizational learning, of monitoring and reproducing this cognitive elite.

Second, the nature of this oscillation needs to be examined. Decision making can be quickly centralized to react to a threat; but the pendulum may not swing with the same speed in one direction or in the other: it may take much longer for overloaded members to delegate, reshuffle the system around themselves, and decentralize than it takes to recentralize. Only certain kinds of organizations may then be able to afford the sort of processes requiring far-sighted investments and maintenance.

Third, it is still unclear whether the stabilization of the elite could either be the result of coordination among senior advisors who act jointly to define common solutions to non-standardized problems; or be only the result of independent decisions by individual elites to this oscillating behavior in the delegation of cognitive authority. Fourth, from the perspective of a theory of the evolution of relational structures, this model stresses endogenous intraorganizational learning and leaves out exogenous effects on learning as a social process (such as, in our case, a change in an important area of law, which would suddenly make specific judges specialized in that area more attractive as sources of advice) (Burt, 2004).

In conclusion, we depart from the communities of practice and network learning literatures by stressing the importance of formal structure of the organization and by approaching learning with microsocial processes of homophily in, and centralization of, advice networks. These processes are triggered and shaped by the formal organization (internal differentiations, rotation rules). Intra-orga-

nizational learning thus depends on the capacity of the formal organization to channel informal advice seeking. Examining the dynamics of advice networks shows that this channelling by the formal organization drives the evolution of the advice network itself. This channelling also creates the need to stabilize the fragile structure that it generates through complex social processes. Without such a stabilization, members with cognitive status and authority cannot preserve accumulated knowledge in an organization that overall experiences high turnover and systematic job rotation, and hence runs the danger of inadequately sharing knowledge among its members. Without a dynamic understanding of the relationship between formal organization and informal behavior, organizations cannot evaluate their own capacity to be learning-friendly environments accommodating complex learning dynamics.

#### **Acknowledgements**

This paper was first presented at the Sunbelt Conference in Portoroz, Slovenia, 2004, and at the Intra-Organizational Networks conference at Emory University, 2005. Support from three funding agencies is gratefully acknowledged: the Mission de Recherche 'Droit et Justice' from the French Ministry of Justice, and the 'Cognitique' and 'Systèmes Complexes en Sciences Humaines et Sociales' Programs from the French Ministry of Research. We thank Tom Snijders and Marijtje van Duijn for help and advice with statistical analysis, as well as Prasad Balkundi, Daniel Brass, Noël Jubert, Martin Kilduff, Bruce Kogut, Joe Labianca, David Obstfeld, Michaël Prietula, Olaf Rank, Raymond Sparrowe, and two anonymous reviewers for valuable comments on a first draft.

#### **Notes**

- 1 For general perspectives, see for example March and Simon (1958); Argyris and Schön (1978); Weick (1979); Levitt and March (1988); Huber (1991); Kogut and Zander (1996).
- 2 For example, social exchange and status help to solve a learning dilemma in which it is rational for individuals to pursue the maximum organizational share of joint learning by taking more knowledge than they give; at the same time, the relative withholding of knowledge reduces the total amount of joint learning from which they attempt to appropriate their individual share (Larsson et al., 1998).
- 3 See for example Brass (1984), Krackhardt (1987, 1990), Barley (1990), Ibarra and Andrews (1993), Lazega and Van Duijn (1997), Rulke and Galaskiewicz (2000), Cross et al. (2001); Mizruchi and Stearns (2001), Hansen (2002), Tsaï (2002); Borgatti and Cross (2003); Kilduff and Tsaï (2003), McDonald and Westphal (2003).
- 4 About the costs of acquiring and maintaining status in organizations, see Frank (1985).
- 5 Even when they do not delegate, the equilibrium remains fragile. As concentration of cognitive authority increases with centralization of the advice network, learning becomes dependent upon a decreasing number of sources of authoritative knowledge. As advice provided by this small number of sources starts becoming inaccessible or inappropriate (irrelevant, inaccurate, untimely), members tend to turn to other sources of advice and create new 'stars' in the learning process. This increases the number of central advisors and reduces the centralization of the network until some of the old stars exit the system.
- 6 The p2 model is an extension of the well-known p1 model (Holland and Leinhardt, 1981) with actor and dyad attributes,

- and with random effects. For more precise information about how p2 deals with dependence of observations, see Van Duijn (1995) and Van Duijn et al. (2004). There are several kinds of models for this type of statistical analysis, for example exponential random graph models or quadratic assignment procedures. The most important advantage of p2 over other models is its inclusion of random sender and receiver effects and taking into account their dependence. These effects allow for varying indegrees and outdegrees of actors as often observed in social network data and model them in a parsimonious way.
- 7 For more detailed information about this court, see Lazega and Mounier (2003); Lemercier (2003).

#### References

- Argote, Linda, Aimee Kane and John Levine, 2005, "Knowledge transfer between groups via personnel rotation: Effects of social identity and knowledge quality". Organizational Behavior and Human Decisions Processes, 96: 56-71.
- Argyris, Chris and Donald Schön, 1978, Organizational learning: Theory, Method, and Practice. Reading, Mass: Addison Wesley.
- Bapuji, Hari and Mary M. Crossan, 2004, "From questions to answers: Reviewing organizational learning research". *Management Learning*, 35: 397-417.
- Barley, Stephen R., 1990, "The alignment of technology and structure through roles and networks". Administrative Science Quarterly, 35: 61-103.
- Blau, Peter M., 1955, The dynamics of bureaucracy. Chicago: University of Chicago Press.
- Blau, Peter M., 1964, Exchange and power in social life. New York: John Wiley.Borgatti, Stephen P. and Rob Cross, 2003, "A Relational view of information seeking and learning in social networks". Management Science, 49: 432-445.
- Brass, Daniel J, 1984, "Being in the right place: A structural analysis of individual influence in an organization". Administrative Science Quarterly, 29: 518-539.
- Brown, John S. and Paul Duguid, 1991, "Organizational learning and communities of practice: Toward a unified view of working, learning and innovation". Organization Science, 2: 40-57.
- Burt, Ronald S., 2004, "Structural holes and good ideas". American Journal of Sociology, 110: 349-399.
- Cross, Rob, Stephen P. Borgatti and Andrew Parker, 2001, "Beyond answers: dimensions of the advice network". Social Networks, 23: 215-235.
- Crossan, Mary M., Henry W. Lane and Roderik E. White, 1999, "An organizational learning framework; From intuition to institution". Academy of Management Review, 24: 522-537.
- Dimovski, Vlado and Miha Škerlavaj, 2004, "Organizational learning and its' impact on financial and nonfinancial performance". Proceedings of fifth Organizational Knowledge, Learning and Capabilities conference, Innsbruck.
- Doreian, Patrick and Frans N. Stokman (eds) 1997, Evolution of social networks. Amsterdam: Gordon and Breach.
- Easterby-Smith, Mark, Mary Crossan and Davide Nicolini, 2000, "Organizational learning: Debates past, present and future". Journal of Management Studies, 37: 783-796.
- Frank, Robert H., 1985, Choosing the right pond: Human behavior and the quest for status. Oxford: Oxford University Press.
- Hansen, Morten T., 2002, "Knowledge networks: Explaining effective knowledge sharing in multi-unit companies". Organisation Science, 13: 232-248.
- Holland, Paul W. and Samuel Leinhardt, 1981, "An exponential family of probability distributions for directed graphs". Journal of the American Statistical Association, 76: 33-65.
- Huber, George P., 1991, "Organizational learning: The contributing Process and the literatures". Organization Science, 2: 88-115.
- Huisman, Michael and Tom A.B. Snijders, 2003, "Statistical analysis of longitudinal network data with changing composition". Sociological Methods & Research, 32: 253-287.
- Ibarra, Herminia and Steven B. Andrews, 1993, "Power, social influence and sense making: Effects of network centrality and proximity on employee perceptions". Administrative Science Quarterly, 38: 277-303.



- Kilduff, Martin and Wenpin Tsai, 2003, Social networks and organizations. Thousand Oaks, CA: Sage.
- Kogut, Bruce and Udo Zander, 1996, "What firms do: Coordination, identity, and learning". Organization Science, 7: 502-518.
- Krackhardt, David, 1987, "Cognitive social structures". Social Networks, 9: 109-134.
- Krackhardt, David, 1988, "Predicting with networks: Nonparametric multiple regression Analysis of dyadic data". Social Networks, 10: 359-381.
- Krackhardt, David, 1990, "Assessing the political landscape: Structure, cognition, and power in organizations". Administrative Science Quarterly, 35: 342-369.
- Larsson, Rikard, Lars Bengtsson, Kristina Henriksson and Judith Sparks, 1998, "The interorganizational learning dilemma: Collective knowledge development in strategic alliances". Organization Science, 9: 285-305.
- Lave, Jean and Etienne Wenger, 1991, Situated learning: Legitimate peripheral participation. Cambridge: Cambridge University Press.
- Lazega, Emmanuel, 1992, Micropolitics of knowledge: Communication and indirect control in workgroups. New York: Aldine-de Gruyter.
- Lazega, Emmanuel and Lise Mounier, 2003, "Interlocking judges: On joint external and self-governance of markets". In V. Buskens, W. Raub and C. Snijders (eds) Research in the Sociology of Organizations, Vol. 20. San Francisco: JAI Press, pp 267-296.
- Lazega, Emmanuel and Marijtje Van Duijn, 1997, "Position in formal structure, personal characteristics and choices of advisors in a law firm: A logistic regression model for dyadic network data". Social Networks, 19: 375-397.
- Lazega, Emmanuel and Philippa Pattison, 1999, "Multiplexity, generalized exchange and cooperation in organizations". Social Networks, 21: 67-90.
- Lemercier, Claire, 2003, Un si discret pouvoir. Aux origines de la Chambre de commerce de Paris, 1803-1853. Paris: La Découverte.
- Levitt, Barbara and James G. March, 1988, "Organizational learning". Annual Review of Sociology, 14: 319-340.
- March, James G. and Herbert A. Simon, 1958, Organizations. New York: Wiley. McDonald, Michael L. and James D. Westphal, 2003, "Getting by with the advice of their friends: CEOs' advice networks and firms' strategic responses to poor performance". Administrative Science Quarterly, 48: 1-32.
- McPherson, J.Miller, Lynn Smith-Lovin and James M. Cook, 2001, "Birds of a Feather: Homophily in social networks". Annual Review of Sociology, 27:
- Mizruchi, Mark S. and Linda B. Stearns, 2001, "Gettings deals done: The use of social networks in bank decision making". American Sociological Review, 66:
- Ortega, Jaime, 2001, "Job Rotation as a learning mechanism". Management Science, 47: 1361-1370.

- Poell, Rob F. and Ferd J. Van der Krogt, 1998, "The learning-network theory: A new perspective on organising learning systems". In R.F. Poell and G.E. Chivers (eds) Continuing professional Development in Europe: Theoretical Views, Fields of Application, and National Policies. Sheffield: University of Sheffield Press, pp 1-25.
- Raelin, Joseph A., 1997, "A model of work-based learning". Organization Science, 8: 563-578.
- Rulke, Diane L. and Josephz Galaskiewicz, 2000, "Distribution of knowledge, group network structure, and group performance". Management Science, 46(5): 612-625
- Senge, Peter M., 1990, The fifth discipline the art and practice of the learning organization. New York: Doubleday Currency.
- Snijders, Tom A.B., 2001, "The statistical evaluation of social network dynamics". In M.E. Sobel and M.P. Becker (eds) Sociological Methodology. London: Basil Blackwell, pp 61-395.
- Snijders, Tom A.B., 2004, "Simulation-based statistical inference for evolution of social networks". Paper presented at the Sunbelt conference, Slovenia.
- Snijders, Tom A.B., 2005, "Models for longitudinal network data". In P. Carrington, J. Scott and S. Wasserman (eds) Models and Methods in Social Network Analysis, Chapter 11. New York: Cambridge University Press, pp 215-247.
- Snijders, Tom A.B. and Michael Huisman, 2002, Manual for SIENA, version 1.95.. Groningen: ICS/Department of Statistics & Measurement Theory, University of Groningen.
- Stinchcombe, Arthur L., 2001, When formality works: Authority and abstraction in law and organizations. Chicago: University of Chicago Press.
- Tsaï, Wenpin, 2002, "Social structure of coopetition within a multiunit organization: coordination, competition, and intra-organizational knowledge sharing". Organisation Science, 13: 179-190.
- Van Duijn, Marijtje A.J., 1995, "Estimation of a random effects model for directed graphs". In T.A.B. Snijders, et al. (eds) SSS '95. Symposium Statistische Software, nr. 7. Toeval zit overal: programmatuur voor randomcoefficient modellen. Groningen: iec ProGAMMA, pp 113-131.
- Van der Krogt, Ferd J., 1998, "Learning network theory the tension between learning systems and work systems in organizations". Human Resource Development Quarterly, 9: 157-177.
- Van Duijn, Marijtje A.J., Tom A.B. Snijders and Bonne J.H. Zijlstra, 2004, "p2: a random effects model with covariates for directed graphs". Statistica Neerlandica, 58; 234-254.
- Weick, Karl, 1979, "Cognitive processes in organizations". Research in Organizational Behavior, 1: 41-74.
- Wenger, Etienne, Richard McDermott and William Snyder, 2002, Cultivating Communities of Practice. Boston: Harvard Business School Press.