

COMPARING SOCIAL NETWORKS TO UNDERSTAND A COLLECTIVE MECHANISM

VERTICAL HOMOPHILY AMONG LAWYERS,
PRIESTS, AND SCIENTISTS

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ABSTRACT – This article proposes a sociological approach to comparing networks by searching for interpretable variations in similar social mechanisms across different contexts. It focuses on the mechanism of collective learning examined through advice networks, in particular on how high-status members among lawyers, priests, and scientists seek advice “below” them in the hierarchy. Observations and statistical analysis of these networks using colSBM and ERGM models show that this “downward” advice seeking is based on different types of “vertical homophily,” mitigating the effects of rigid status differences. Understanding such a collective mechanism requires taking into account all the relational processes used by actors to manage cooperation dilemmas, including how those at the top learn (or do not learn) from those at the bottom.

KEYWORDS – Social Network Comparison, Collective Learning, Advice Networks, colSBM, ERGM, Downward Vertical Homophily.

This article proposes a neo-structural sociological method for comparing social networks that are used as indicators for

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the same collective mechanism. The social mechanism, examined here in part, is collective learning understood as the effort to collectively build shared knowledge and experiences as a common good in a form of informal *brainstorming*, and this in the context of controversies that must lead to collective choices.

Advice is an important resource in organizations (see, for example, Blau, 1955; Krackhardt, 1990; Chiffolleau & Touzard, 2014; Compagnone, 2014; Cross et al., 2001; Li et al., 2024; and many others). Without it, members cannot solve generally complex problems together, particularly when it comes to managing normative controversies and making collective decisions. Given the importance of this resource, it would be easy to believe that the flow of advice within an organization is “free,” or at least that no structural barriers are preventing the exchange of information between any two members. However, even in contexts saturated with advice, many factors, including the formal dimensions of social and organizational structures and the attributes that derive from them, create barriers to the exchange of ideas and experiences.

Seeking advice is a complex interaction, infused with the respective social status of the actors involved. Due to a situation of uncertainty, the person seeking advice obtains relevant information in exchange for the deference they show to their advisor and the social recognition they grant them (Blau, 1955). Social exchange is necessary—as opposed, for example, to commercial exchange—and it is not uncommon for the seeker to rephrase the initial question with the advisor. Uncertainty extends to the very nature of the question, which often includes a request for approval or social legitimacy. Social status is therefore an important criterion when selecting an advisor, especially since it is sometimes considered a proxy for quality when the seeker does not know the advisor personally (Lynn et al., 2009; Manzo & Baldassarri, 2015). More generally, “supervised” co-orientation and collective learning very often rely on a concentration of epistemic authority among the central members of the advice network, an authority that can be both recognized and contested.

In all areas of political and social life, there are countless situations where high-status individuals do not listen to those “below them” in the hierarchy. Downward vertical homophily is costly for high-status individuals seeking advice, yet often important and beneficial for the collective. Homophily is well known as a determining factor in the creation and maintenance of ties with people with whom one shares certain attributes

(e.g., Lazarsfeld & Merton, 1954; Coleman, 1961; Kandel, 1978; McFarland et al., 2014; McPherson et al., 2001; Moody, 2001). However, homophily is an abstract and general term. Actors have many ascribed or acquired characteristics on which they can base their homophilous attachments. The analysis, therefore, requires further specification.

People with high status sometimes seek advice from people with lower status who possess valuable expertise or knowledge. They can then acquire this knowledge, while the low-status actor may gain visibility or benefit from sponsorship in return. From the perspective of their subjective social status¹, superiors may view this request as a loss of status, which the use of homophily can mitigate by diverting attention from these status asymmetries and highlighting a common reference group (Hyman, 1960; Wolf, 1990; Lazega & Van Duijn, 1997).

The objective here is to explore this phenomenon of downward vertical homophily in a descriptive manner to compare, in advice networks in different contexts, “who uses what type of homophily to cross downward status boundaries.” For this exploration, we use secondary analysis of data on advice networks among lawyers, among priests, and among scientists, as reconstructed in three separate case studies.

This article is structured as follows. We begin by presenting the methods used to compare networks. Second, we present the advice networks observed in three different organizational and professional contexts but located roughly in the same place on the continuum between bureaucracy and collegiality (Lazega, 2020): a corporate law firm, a Catholic diocese, and a nationwide organized scientific research specialty. Third, we verify the comparability of these networks using the so-called colSBM technique² (Chabert-Liddell, 2022; Chabert-Liddell et al., 2021, 2024). Fourth, homophily variables that affect downward advice-seeking are specified in an ERGM³ model (see, for a general overview: Brailly et al., 2017; Lusher et al., 2013, 2020; Yin et al., 2022) for each context separately. Finally, we interpret the results of this analysis by comparing the attributes that members of each network use for their downward vertical homophily. At this stage, we aim to explore the comparison

1. Subjective social status is, in the literature, the social status assessed by the actors themselves (see, for example: Haught et al., 2015).

2. colSBM is a statistical technique that models a collection of networks (col) using a *Stochastic Block Model* (SBM).

3. ERGM (*Exponential Random Graph Model*) is a statistical technique that models a network as a dependent variable.

method as part of a reflection on social mechanisms rather than to test specific hypotheses.

Comparison of networks

Two successive and complementary methods can be used to make this comparison. The first, known as the colSBM model, is a stochastic block model (SBM) designed to search for and confirm the comparability of networks of different sizes by finding their common structure, where one exists. Each network has its own overall structure or morphology (White, Boorman & Breiger, 1976; Doreian, Batagelj & Ferligoj, 2005). An SBM (Snijders & Nowicki, 1997) allows heterogeneity to be introduced into the relational structures that make up a network. The actors in this network belong to “latent” blocks formed using the actors’ attributes, which shape their relational profile and identify roles. Those belonging to the same block are approximately structurally equivalent and play the same role in the division of labor of the social system represented by the network. SBM helps propose a classification of actors based on these social roles and to summarize the network information using a small number of parameters representing the structure at the “mesoscopic” scale of the network. There are many methods for inferring actors’ block memberships and estimating the model parameters.

Leon Festinger’s classic research (1954) on social comparisons already showed that actors use as reference groups those who resemble them in various ways, including those who share a similar role and occupy a similar position in the division of labor. Structurally similar people tend to recognize and interact with each other. Powerful homophily effects are thus linked to people whom we recognize as occupying similar positions in the organizational universe or social structure, and with whom we compare ourselves. Common characteristics, but also the presence of informal roles identified by structural equivalence in social networks, can induce homophilous behaviors and attitudes (see, for example, Burt, 1982; Galaskiewicz, 1985), particularly in core-periphery structures that can serve as a basis for homophily in advice networks in particular.

With the help of various indicators, this approach 1) identifies actors in different networks playing the same role in their respective networks (the objective of blockmodels in general); then 2) determines the relevance of the common structure in

relation to block structures that are independent of each other; and finally 3) classifies networks into subsets of networks with a common structure, in this case a core-periphery structure (Bienenstock & Bonacich, 1992). We use the approach developed by Jean-Jacques Daudin et al. (2008), as well as a criterion (Biernacki et al., 2000; *Integrated Classification Likelihood*, ICL) for selecting the number of blocks best suited to the data.

In other words, when there is a common structure in networks of different densities, colSBM has the advantage of being able to find it. Overall, the structure identified in all the networks in the collection is sufficiently similar for us to be dealing with the same structure statistically. However, one limitation of using the colSBM method, which analyzes networks of varying densities together, is that, insofar as we try to find blocks with the same connection probabilities in all the networks compared, the densest network has an impact on the structure found in the other networks. In particular, this influence of the densest network on others makes certain effects of latent attributes on relational choices difficult to control with colSBM, and another method is needed in a second step.

This second method is the ERGM model, already used for network comparisons (Faust & Skvoretz, 2002; Lazega, 2004; Krivitsky et al., 2011; Valente et al., 2013; Fischer & Sciarini, 2016; Ingold & Leifeld, 2016). It allows us to focus more precisely on the downward vertical homophily and compare its specific determinants in the three networks. As explained by Julien Brailly et al. (2017) and Dean Lusher et al. (2013, 2020), this method breaks down the network into a set of dyads and triads and reinserts them into their relational neighborhood to identify which of these elementary substructures occur most frequently and are therefore the most structuring in the network under study. This approach makes it possible to test both “endogenous” effects (specific to the relational dynamics themselves, such as reciprocity, transitivity, etc.) and “exogenous” effects (i.e., the attributes of the actors in the network in the form of sociodemographic, behavioral, representational variables). ERGM thus combines, within the same models, social attributes that are classic in sociology (such as gender, age, education, opinions, etc.) and network data. The exogenous effects in the ERGM models used here include the main sources of homophily identified by McPherson et al. (2001), which include social and economic homogeneities such as geography, education, and occupation, work and its organization, including specialization. These social homogeneities offer actors in networks many possible bases for homophily.

Lawyers, priests, and scientists: Three advice networks for the same collective mechanism in different and comparable contexts

In this way, three advice network datasets reconstructed in three different contexts are used to compare the deployment of collective learning and explore the functioning of vertical homophily, particularly top-down homophily. The contexts are a business law firm, a diocese, and a specialized nationwide scientific research community (oncology). These three contexts were chosen for this exploration because organizational sociology positions them broadly in the same way on a bureaucracy-collegiality continuum—namely, professional and collegial contexts where actors can choose their advisors relatively autonomously by framing their requests for advice in personalized social exchanges—and because their networks do have a general core-periphery morphological structure. In-depth organizational and network analyses of each case have been published separately in scientific articles⁴.

In all three contexts, information on advice-seeking was collected using the same standard list-based sociometric name generator in face-to-face interviews. A brief presentation of each case study highlights the importance of downward vertical homophily in each case and clarifies the homophily variables that are retained in the models as exogenous explanatory variables.

The lawyers at the corporate law firm (observed from 1988 to 1991) operate in two large offices/geographical locations (each covering a specific market for their services) and in two different specialties (litigation and corporate). They consult each other extensively on clients, judges, and strategic choices for drafting new contracts or winning court cases against the other side. Together, they build a knowledge base that combines legal practices, business, and reputation. There is a strong hierarchy between lawyers who are partners (co-owners of the firm) and lawyers who are associates (employees), who nevertheless engage in intensive brainstorming together in their daily work (Lazega & Pattison, 2001). In the firm examined here, lawyers reported having an average of twelve colleagues with whom they exchanged work-related ideas and advice. The

4. For the lawyers, see Lazega (1995, 2001); for the priests, see Wattebled (2004), Lazega & Wattebled (2011); for the scientists, see Lazega, Mounier, Stofer & Tripier (2004); Lazega, Jourda, Mounier & Stofer (2008); Lazega, Barben, Barbillon & Donnet (2016).

overall density⁵ of the advice network was 0.17 for 71 actors. The normative tensions, internal controversies, and regulatory issues for which collective learning was taking place here concerned compensation rules, marketing responsibilities, client “ownership,” the clientelistic use of associates, peer review of partners’ work, and the management of conflicts of interest (Lazega, 2001). The status differences used in the analysis of the business lawyers’ advice network are between partners and associates.

The priests of a French Catholic diocese (observed between 1997 and 2003) consult each other on the expectations of their parishioners (to produce a religious “offer” or orientation that suits them and seems consistent), on the bishop’s intentions in terms of changes to be made to the functioning of the diocese, on the management of their local budget (for example, the taxation of their parish tithes), and on several other controversial issues. In this diocese, relations between priests of different religious orientations were very tense, as were those between priests from the two main cities, one very rich and bourgeois, the other a very poor commuter town. In this divided institution (a characteristic that has been omnipresent in the Catholic Church throughout history), the bishop and his vicar, in theory the absolute masters of their diocese, as well as two religious orientations (that of the intellectuals—Dominicans and Jesuits—and that dedicated to serving the “independents”—artisans, small business owners—), occupied a central place and sought to strengthen unity. The bishop’s strategy for managing these long-standing tensions was to co-opt the most vocal “representatives” of these orientations (chosen *intuitu personae*) into an episcopal council, a mechanism of “top-down collegiality” in which the bishop could share some of his power in exchange for specific requests—for example, that priests stop criticizing their colleagues of different religious orientations in public and in the media, a form of structural silence. Each priest cited an average of five colleagues whom he could ask for work-related advice (pastoral, ritual, administrative). The overall density of the advice network is 0.05 per 104 actors (Wattebled, 2004; Lazega & Wattebled, 2011). The status differences used in the analysis of the advice network in this diocese separate priests with administrative responsibilities at the diocesan level from all the others.

5. The density of a network is generally defined as the number of observed relationships between a set of actors divided by the number of possible relationships between those actors.

Scientists were the most visible researchers nationally for three years (1996–1998) before the field survey (1999–2000), i.e., in terms of Impact Factor scores associated with their publications in their field, cancer research. Working in around 100 laboratories collaborating with research centers in the Île-de-France region and major provincial cities, specializing in different types of cancer (leukemia, solid tumors, etc.), combining varying degrees of fundamental research (biology) and clinical research in large specialized hospitals, they sought advice on new avenues of research, on obtaining institutional support for their projects, on access to funds and strategic information concerning calls for proposals, on the recruitment of new postdoctoral fellows, and on their manuscripts before submission to scientific journals. Regulatory debates in their field revolved around which research avenues to invest in collectively, and the chances of thematic and unifying programs in the global competition. The turning point of genetic sequencing had not yet been reached, and the field was still marked by the prestige of French hematology-immunology, whose members had very quickly succeeded in sharing their knowledge and skills in molecular biology through a collective learning mechanism, particularly in the field of leukemia (Bernard & Dausset, 2000). Their field was under pressure to use new techniques to advance understanding the mechanisms of cancer, particularly solid tumors. The overall density of the aggregated advice network is 0.02 for 126 actors. The status differences used in the analysis of the advice network of these cancer research professionals distinguish laboratory directors from others.

In these contexts and their situations of uncertainty, access to advisors is an important social resource for actors. The effect of status on the search for advice is omnipresent, as evidenced by the measures of overall centralization of networks, which are strong for lawyers and priests, although weaker for scientists (for whom social status is less used as a proxy for quality and among whom there is a significant difference between global status and local status).

Table 1. Comparative global characteristics of the three networks

	Advice networks		
	Scientists (n = 126)	Priests (n = 104)	Lawyers (n = 71)
Network centralization ¹	11.87%	32.33%	35.4%
Average degree	7.12	5.01	12.56

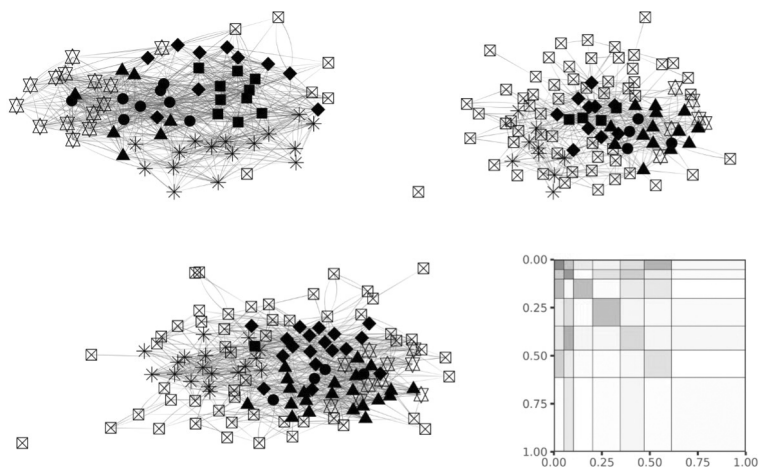
Note: 1. Network centrality (Freeman, 1979) is a measure of how central the most central node in the network is relative to all other nodes. Thus, the network of scientists is approximately three times less centralized than that of priests and lawyers.

Comparison of mesoscopic structures using colSBM

The colSBM approach considers these three networks together (the “collection”) to find a common structure. The best structure found by colSBM comprises seven blocks, which are shown in Figure 1. This structure is complex, both modular and nested, but unevenly asymmetrical. Blocks 1 and 2 form a highly connected core (round and square shapes), with block 2 receiving more incoming connections. Blocks 3 to 6 are blocks with significant internal connections, while also being oriented toward the core. Among these, block 3 (double hollow triangle shape) has low reciprocity, with mainly outgoing links outside its block. Block 7 (envelope shape) is a peripheral block, very weakly connected, except for outgoing links to block 2. The larger the block, the rarer the connections.

The discovery and confirmation of a common core-periphery structure via colSBM suggests that, despite their differences in size and density, these networks are organized according to a similar hierarchical logic, detected solely from the topology of the links. Based on the blocks identified by colSBM, the core-periphery structure of each network can be analyzed separately. The differences between the three networks in terms of downward homophily are also shown in Figure 1 and its colSBM blocks. It should be noted that the density of the networks varies greatly (see Table 1). The lawyers’ network is much denser than the other two. Despite these differences in

Figure 1. Common connectivity structure at the mesoscopic level, and blocks in the networks of lawyers, priests, and researchers



Reading note: Advice networks of lawyers (top left), priests (top right), and researchers (bottom left). The shapes represent the actors' membership in the blocks. Common mesoscale connectivity structure (bottom right): the color gradient represents the probability of interaction (white = 0), and the size of the blocks represents the proportion of actors.

structure, there are enough commonalities between these networks for the common structure to be considered statistically significant (in the sense of BIC-L⁶).

In this structure, the status of the actors plays a somewhat trivial role, because if you have a high status, you are, by definition, more likely to be at the core than on the periphery. However, the specialization of the actors explains part of the modularity of the networks, i.e., it creates groups within the networks, notably the separation of the core into two blocks for the three networks⁷. This two-block core brings together the most central actors, who also cite each other selectively, based on their specialization. This is very clearly visible for the

6. BIC, or *Bayesian Information Criterion*, is a statistical measure used in the selection of statistical models to evaluate the trade-off between model fit and complexity. It is used to compare different models and select the one that best explains the data.

7. Due to space constraints, it would take too long here to provide the connectivity matrix from colSBM and use it to analyze all the contingency tables crossing each attribute variable and the composition of the blocks for each of these networks. These tables are available upon request.

case of lawyers and priests, but less so for scientists, who have a wide range of specializations. For example, to take one of the regulatory issues that is the subject of controversy and ongoing collective learning among lawyers—knowledge of positions and power relations in peer evaluations assessing the quality of partners' work—this issue divides the core along lines of specialization: litigation lawyers do not want this change, while corporate lawyers support it. These positions are thus reflected in the separation of the core into two blocs. In contrast, the elite vs. non-elite institution where actors were trained does not significantly structure the environment, and no particular structure appears to suggest that it facilitates downward homophily. As the structure is complex, being both modular and core-periphery, the structure of the core is influenced by existing internal communities.

Individual analysis of the networks, using the clusters identified by colSBM, also helps to understand certain differences between the three networks. In terms of geographical proximity and for lawyers, the core consists mainly of lawyers from office 1. Cluster 3 mainly includes lawyers from office 2. The connectivity matrix clearly shows that both exhibit downward homophily. For example, we can see how blocks 1 and 2 connect to blocks 4, 5, and 6. There is marked downward homophily between 1 and 6, and between block 2 and block 5, all in office 1. Another example is that for scientists, the variable “laboratory directors” is not linked to the block structure (except for the residual block, which is mainly made up of researchers who are not laboratory directors). For researchers, the core is highly modular. There is no advice seeking from block 2 to block 1. Block 1 even has more outgoing connections than incoming ones. It can be said that block 1 is the part of the core with downward connectivity.

Thus, in this exploratory analysis of the contingency tables of the blocks and available covariates, for lawyers, it is essentially the status and the field of practice (specialty) that divide the core into two, and distance it from the more peripheral blocks. For researchers, it is less status than specialty that explains part of the separation into communities, even though there are blocks that are strongly influenced by status (blocks 3 and 4).

The case of priests is more complex for colSBM because the core is smaller. Analysis with these covariates shows that, for links from the core to the periphery, there are downward homophilous connections from block 1 to blocks 4, 5, and also

6, which are in geographically distinct locations in the diocese, and from block 2 to block 5. However, it should be noted that these links are reciprocal. Blocks 2 and 5 are composed of priests with administrative responsibilities (with a strong reciprocal connection), while the others show no particular preference. One might wonder whether block 5 should not be included in the core, even though it has fewer intra-block connections. In terms of religious orientation (equivalent to specialization), which is closely linked to the block structure, relations from the core to the periphery are mainly within the blocks. This means that differences in religious orientation between priests create too much tension between them (Wattbled, 2004) for them to consider seeking advice from priests belonging to different orientations and different cities. Notice also downward homophilous ties from block 1 to various geographically different blocks in the diocese. For example, block 1 has more outgoing connections (particularly to block 6) than block 2.

Despite these differences in core size, the connectivity structure of each network has many similarities. The core is modular, and downward connections vary from one network to another, mainly through the specialization of the actors. However, since the network of lawyers is denser than the network of researchers and priests, and since we are trying to find blocks with the same connection probabilities in all three fields, the core of the latter two networks (researchers and priests) will be smaller and more difficult to define: in their blocks 1 and 2, there are only actors who have relationships as dense as those in the core blocks of lawyers.

The use of covariates helps us understand how the core-periphery structure of the three networks exposes vertical downward homophily. However, the different ways in which each similarity mitigates the effects of downward homophily in various contexts require analysis at the dyadic and triadic levels and of the effect of status and other covariates on the construction of all these networks. The similarity of several similar core-periphery structures implies verifying the possibility of comparison, but also beginning to test, attribute by attribute, those that have a strong structuring dimension to the point of allowing downward vertical homophily. This is where ERGMs provide statistical parameters that identify effects that are not clearly visible with colSBM. Mesoscopic-level observation motivates a more detailed analysis of the mechanisms underlying downward vertical homophily at the individual and relational levels.

ERGM comparison of the attributes used by actors to create downward vertical homophily

Which actors use which type of homophily to cross formal hierarchical boundaries depending on social contexts? To compare downward advice-seeking strategies, we used the fact that we had social information on similar homophily variables in all three contexts: in particular, variables relating to shared levels of experience and seniority, education, types of specialization, and, finally, geographic location. Given the complexity of comparing mesoscale structures in a collection of networks, we then used ERGMs to make the same comparisons, but at the dyadic and triadic levels. The variables chosen here are, on the one hand, variables reflecting an identity criterion sufficiently shared by members to evoke a common reference group, and on the other hand, variables reported in the three surveys. The case of priests—all men—for example, prevents comparisons based on gender differences.

The approach here, in all three contexts, is firstly to present how we specified the homophily variables for contextualizing the search for advice downward. Second, to present ERGM models exploring the effects of each context on the choice of strategically and culturally acceptable vertical homophily for such downward advice-seeking. Testing the impact of different types of homophily on formal status logic makes sense here because the phenomenon in which we are interested, although less frequent than upward advice-seeking, does exist in varying degrees. For example, in the context of the corporate law firm, a seniority level 1 partner (out of three levels) has a 3% chance of seeking advice from a seniority level 1 associate (out of five levels). The percentages increase as seniority decreases. But we also observed in this firm that most associates approached by partners in the same office and specialty became partners themselves over five years.

Table 2 presents the sociodemographic attributes that the models take into account to construct these exogenous variables in the three contexts: education (level of education), geographic proximity, experience (seniority), and specialization. In each context, actors can use these similarities as a basis for the homophilic choices of advisors.

Table 2. Variable specifications for identifying top-down strategies for crossing status boundaries

Type of network consulting	Lawyers	Priests	Scientists
	Intra-organizational	Interorganizational	Interorganizational
Size	N = 71	N = 104	N = 126
<i>Formal hierarchy (status)</i>	Partners vs. employees	Diocesan hierarchy vs. local responsibilities	Laboratory director vs. other
<i>Experience in the organization</i>	Years of seniority	Years since ordination	Age of researcher
<i>Training/education</i>	Law school (elite, semi-elite, non-elite)	Theology degree vs. non-theology degree	MD-PhD vs. PhD
<i>Specialization</i>	Litigation vs. contracts	Religious orientation	Specialization in a type of cancer
<i>Geographic proximity</i>	Different offices (cities)	Different deaneries (parish groups)	Region

Past analyses have shown that these differences affect advice flows in each context. These dimensions are used to control for status, contextualize the analysis, and test the sources of downward vertical homophily in each of the three networks. To specify the downward search for advice, we construct homophily variables as follows. Based on two formal hierarchical levels (Low/High), we identify four types of cross-cutting links, one per exogenous variable characterizing the actors. Depending on the status of the two actors involved in the advice relationship, we differentiate the effect of each type of homophily on upward (UP), downward (DOWN), core (CORE), or peripheral (PERIPH) advice relationships. For example, concerning the “Education” attribute, we construct four subgroups among the possible links between individuals with the same education based on the hierarchical status of the actors involved in the advice relationship, which gives four dyadic covariates:

1. Within the core (CORE): the box corresponding to the relationship from i to j is equal to 1 if i and j both have high status and have the same education, regardless of what that education is;

2. Within the periphery (PERIPH): the cell corresponding to the relationship between i and j is equal to 1 if i and j both have low status and have completed the same education;

3. Upward advice relationship (UP): the cell corresponding to the relationship between i and j is equal to 1 if i has a high status and j has a low status, but both have the same education;

4. The downward advice relationship (DOWN): the cell corresponding to the relationship from *i* to *j* is equal to 1 if *i* has a low status and *j* has a high status, but both have the same education.

Since we use two status levels in each case, high and low, and divide each homophily effect into four categories: core (both individuals have high status), periphery (both individuals have low status), high (the relationship goes from an actor with low status to an actor with high status), and low (the relationship goes from an actor with high status to an actor with low status), this creates four similarity matrices that we use to estimate the models. These models will test the endogenous effects of structure and the 16 dyadic covariates of homophily, controlling for status. Table 3 presents the final model for each context, revealing the different types of homophily used to create and maintain downward advice links. Table 4 visualizes the results in bold of Table 3, comparing the similarities or homophilies used for downward advice seeking in each of the networks.

Table 3. ERGM models testing vertical homophily in status boundary crossing in each of the three contexts

		Scientists	Lawyers	Priests
	Density	-4.056 (0.329)*	-2.305 (0.430)*	-5.168 (0.550)*
	Reciprocity	3.056 (0.156)*	1.2090 (0.190)*	2.2346 (0.227)*
	Two-path	-0.109 (0.006)*	-0.040 (0.006)*	-
	Alt. In-star 1	0.135 (0.03) *; L=7	-0.139 (0.073); L=5	0.2012 (0.050)*; L=6
	Alt. In-star 2	-	-	-
Centrality effects	Alt. Out-star 1	-0.402 (0.194)*; L=2	-0.117 (0.059) ; L=5	0.1133 (0.223); L=2
	Alt. Out-star 2	0.191 (0.019)* ; L=12	-	-
	Alt. In-Alt. Out-star	-	-	0.4636 (0.232)*; L=2
Triadic effects	Alt. Transitive triad	0.714 (0.036)*; L=3	0.6329 (0.029)*; L=5	0.9801 (0.087)*; L=2
	Alt. Cyclic triad	-	-0.183 (0.021) *; L=5	-0.182 (0.067)*; L=2
	Alt. Down triad	-	0.0521 (0.054); L=2	-
Connectivity effects	Alt. Transitive two-path	-	-	-0.086 (0.014)*; L=4
	Alt. Down and Up two-path	-	-	-

		Scientists	Lawyers	Priests
Organizational affiliation		1.605 (0.238)*	-	-
High status	Homophily	0.016 (0.179)	1.3292 (0.847)	0.1247 (0.355)
	Sender	-0.241 (0.185)	0.3583 (0.782)	0.0797 (0.304)
	Receiver	0.269 (0.271)	-0.147 (0.740)	0.5298 (0.225)*
Seniority	PERIPH	-0.080 (0.107)	0.0485 (0.112)	0.1806 (0.155)
	UP	0.362 (0.139)*	0.0004 (0.280)	0.0834 (0.151)
	DOWN	-0.043 (0.159)	0.0446 (0.219)	0.1699 (0.242)
	CORE	-0.006 (0.118)	1.0330 (0.673)	0.2710 (0.174)
Education	PERIPH	0.033 (0.08)	0.2601 (0.126)*	-0.031 (0.168)
	UP	-0.106 (0.133)	0.0232 (0.282)	0.0246 (0.175)
	DOWN	-0.045 (0.125)	0.6322 (0.192)*	0.5902 (0.265)*
	CORE	-0.022 (0.11)	-0.250 (0.192)	-0.147 (0.203)
Specialty	PERIPH	0.461 (0.072)*	0.2850 (0.093)*	0.7581 (0.152)*
	UP	0.598 (0.161)*	0.8096 (0.297)*	0.0670 (0.324)
	DOWN	0.364 (0.16)*	1.3341 (0.169)*	1.2771 (0.347)*
	CORE	0.194 (0.128)	0.5057 (0.157)*	1.1399 (0.380)*
Geographic proximity	PERIPH	0.007 (0.088)	0.4741 (0.093)*	0.5477 (0.127)*
	UP	0.250 (0.125)*	0.7035 (0.248)*	0.8932 (0.156)*
	DOWN	0.145 (0.122)	1.1122 (0.168)*	0.2439 (0.257)
	CORE	0.350 (0.098)*	0.6110 (0.205)*	0.0572 (0.190)

Note: ERGM models take the observed network as the dependent variable and align two types of explanatory variables: so-called “endogenous” effects, which provide a complex account of how the characteristics of the network itself (density, reciprocity, two-path, different triads, etc.) determine the observed network. These endogenous effects (see Brailly et al., 2017) are incorporated into the model as controls for the so-called “exogenous” effects of attribute variables on the observed network. This article focuses on these exogenous effects, in particular the DOWN effects (in bold) that represent the propensity of actors in each of the three networks to use the attributes listed in Table 2 (status, seniority, specialty, education, and geographic proximity) to build downward homophilous relationships. A * indicates that the parameter estimate is superior to twice the standard error in parenthesis and that the configuration can be considered to be significant (Koskinen & Daraganova, 2013). Tables measuring the goodness of fit of the models are available upon request.

In interpreting these models, we focus here on the exoge-
nous effects of homophily that add the most information about
the mobilization of reference groups in the collective learning
process, particularly the DOWN effects as partial analyzers and
bases for comparison between advice networks. Table 4 visual-
izes these effects, i.e., the main similarities used by members in
each context to cross status boundaries and seek advice from

members of lower status (vertical downward homophily) in each of the three networks.

Table 4. Comparison of bases for downward vertical homophily used by actors to seek advice from subordinates in advice networks in three different contexts

	Lawyers' network	Priests' network	Scientists' network
Downward homophily using:			
...similarity of specialties			
...similarity of education			
...geographical proximity			
...similarity of seniority			

It is in the case of business lawyers, the most centralized and dense environment, that the use of homophily is most diverse. Associates are heavily solicited by partners who play on all similarities to ensure the quality of advice from subordinates. Among priests, the strongest homophily effect is based on religious orientation (“specialty” in this context). Priests with diocesan hierarchical status use this homophily to avoid colleagues with different religious orientations. This selection facilitates a mechanism of “top-down collegiality” (Lazega & Wattebled, 2011) but only within a closed silo (characteristic of Catholic fragmentation) and excluding subordinate priests from other orientations who are perceived as likely not only to attract too many opposing views in regulatory work, but also to break a structural code of silence that would call the institution as a whole into question. It is among scientists, the least centralized milieu, that the formal social status of laboratory directors counts least as a proxy for the quality of advice. Specialization is the only basis for homophily used in the search for advice from below. The absence of geographical homophily for scientists may be surprising given that teams are generally attached to an institution or geographical location and that many studies of co-publication networks reveal geographical effects (same city, same country) (Maisonobe et al., 2016). This absence may be due to institutionalized interregional and international collaborations that decentralize research, which may neutralize references to shared geographical origins.

In all contexts, at least one criterion of homophily is used to cross status boundaries, with consequences for collective

learning: vertical homophily based on specialty is used everywhere. Scientific staff who are directors of their laboratories are the least hierarchical in the comparison, and their network is the least centralized: they consult more often below them, formal status being less of a sign of quality in this environment than in others. Catholic priests have a very hierarchical mindset, but they find ways to seek advice from below, even if it is only from peers with the same religious orientation (an important identity criterion and reference group in the diocese) and the same level of theological education. Education works well for lawyers (for whom an Ivy League law degree is important) and for priests (for whom a doctorate in theology seems to facilitate the creation of the downward link). Geographic proximity works particularly well for lawyers (where it represents a common market for the person seeking advice and the person being consulted), but not in other contexts. It is interesting to note that similarity in seniority as an indicator of experience is nowhere a basis for vertical homophily; it does not help in seeking advice below, probably because seniority is too strongly correlated with formal status from the outset. The models thus show that the structure of advice networks reflects certain dimensions of the expected attenuation of the status rule.

Conclusion

This exploratory analysis shows that the two proposed methods are complementary to comparing social networks that measure the same collective mechanism in different contexts. The two-step analysis first establishes the comparability of networks and finds downward vertical homophily at the level of overall network morphology using colSBM—even though the identification of common structures is strongly influenced by the characteristics of the densest network. This first step requires verification and refinement of trends at the dyadic and triadic levels using ERGMs, which highlight the specific effects of each identity criterion selected by actors to create these downward vertical homophilies. The comparison visualized in Table 4 suggests that this exploration leads to a hypothesis that would need to be verified with more cases and the same type of analysis: the more status is a signal of quality in a given professional environment, the more actors diversify the identity criteria and reference groups for their homophilous and downward advice seeking.

A classic criticism of the approach using complete networks constituted by lists of people selected for their membership in the organization under study is that it ignores the effects of these organizations' embedding in contexts and networks that extend beyond their boundaries. The analyses presented here show that these contexts are, on the contrary, very much present through attributes (exogenous covariates in the models), provided that we reason in terms of collective social mechanisms that facilitate the management of cooperation dilemmas.

This empirical research on the basis of downward vertical homophily is necessarily limited. Among the limitations of the cases studied—with data collected between 1991 and 2003 in environments that were either exclusively male or largely male-dominated—gender does not have the place it would have today in two of these contexts. However, the use of downward vertical homophily based on gender similarities to reinforce or mitigate differences in status between men and women, among men, or among women, remains a mechanism that can be reconstructed using the same method and new data. These inequalities in the attention paid to subordinates, their opinions, and advice, also apply to members of minorities whose contributions are undervalued. Due to its selectivity, downward vertical homophily can also be used strategically to create regimes of opacity and ignorance that remain to be studied.

Another limitation is related to the contributions of a more in-depth knowledge of the professional norms and cultures of the actors. In the mechanism studied, the epistemic authority of the central, or even super-central, actors who supervise collective learning is very well suited to these descents and deviations from the rule of hierarchical status. The variations observed between lawyers, between priests, and between scientists in their propensity to seek advice from below, in the ways they do so, and in their use of homophily for this purpose, may reflect larger differences in professional cultures. Vertical downward homophilies are more or less culturally acceptable depending on the context. Comparing these norms and cultures could add a perspective for understanding the relevance of these downward requests for advice and the ability of homophilies to facilitate them.

Finally, these comparisons teach us that there can be no understanding of a collective mechanism without analysis that takes into account all the relational cogs involved in that mechanism (Lazega & Pattison, 2001). Collective learning as a social mechanism can only be understood by taking into account how individuals learn within the structure in which they operate,

including how those at the top learn (or do not learn) from those at the bottom of the ladder. Understanding a collective mechanism requires a systemic view and a neo-structural method based on complete networks that also allow us to examine all the links that have not been created (White et al., 1976). Considering seemingly unlikely links as important analyzers requires a more complex view of mutually reinforcing social mechanisms, such as in the articulation of learning and regulation in controversies.

In social life, particularly in crises, collective learning may not take place, or may take place only to a very limited extent, under the supervision of a core group of super-central individuals who do not seek to “descend” in terms of social status. It may be useful to remember that people with high social status have many culturally acceptable ways of descending, even if these paths cutting across status boundaries are not always based on the same homophilies in different contexts. Super-central players can thus create the conditions for successful collective learning. Examining these paths is, therefore, also useful for understanding how such super-central individuals assume (or do not assume) their responsibility in collective mechanisms.

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Comparer des réseaux sociaux pour comprendre un mécanisme collectif. L'homophilie verticale parmi les avocats, les prêtres et les scientifiques

RÉSUMÉ – Cet article propose une approche sociologique pour comparer les réseaux, fondée sur la recherche de variations interprétables dans des mécanismes sociaux similaires observés dans des contextes différents. Il se concentre sur le mécanisme d'apprentissage collectif examiné au travers des réseaux de conseil, en particulier sur la manière dont les membres de statut élevé parmi les avocats, prêtres et scientifiques demandent conseil « en dessous » d'eux ou d'elles en termes hiérarchiques. L'observation et l'analyse statistique de ces réseaux par les modèles colSBM et ERGM montrent que cette demande de conseils « vers le bas » s'appuie sur différents types d'« homophilie verticale descendante » atténuant les effets de différences de statut rigides. La compréhension d'un tel mécanisme collectif requiert que tous ses rouages relationnels servant à gérer des dilemmes de coopération soient pris en compte, y compris la manière dont le sommet apprend (ou non) de la base.

MOTS-CLÉS – Comparaison de réseaux sociaux, apprentissage collectif, réseaux de conseil, colSBM, ERGM, homophilie verticale descendante.