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Multilevel Network Analysis

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INTRODUCTION

Contemporary societies are *organisational societies* (Perrow, 1992), promoting combined individual agency and collective agency by organised entities. In order to measure the extent to which they are linked, one solution is to consider them together: action at the level of individuals and collective action at the level of organisations and institutions can be jointly analysed methodologically by statistically combining microscopic and mesoscopic observations as multilevel network analysis. This provides a renewed understanding of the verticality of actors' positions in social life and a new perspective on the social world (Lazega & Snijders, 2015). Both levels are different and interdependent and multilevel network analysis as a research methodology examines these interdependencies systematically. As superposed levels of agency, they can be examined separately as well as jointly since they are linked by the affiliation of members of one level to collective actors at the higher level. Affiliations can be considered as indicators of deeper processes characterising the 'duality' of individuals and groups (Breiger, 1974) in which the co-constitution of levels are the expression of their vertical interdependencies.

In this chapter we focus on a specific kind of multilevel network analysis that Snijders (2016), in his overview of the 'multiple flavours of multilevel network analyses', identifies as *multilevel network analysis* (MNA) – that is, a framework in which different kinds of actors operate at each level and in which both individual and collective agency takes place at each level. Within-level ties exist between individuals who exchange, but also between organisations that collaborate, and each individual is also affiliated to one or more organisations. Since this method of contextualisation considers several interconnected systems of agency, for cross-sectional data this can be expressed by the multilevel *exponential random graph modelling* (ERGM) approach of Wang et al. (2013b). Each 'level' here is a set of actors, or agents, and the levels are interdependent with respect to the conditions for action and/or outcomes. A hierarchical nesting relation between the levels, which is the traditional basis of statistical multilevel analysis, is not required for the data structure of multilevel networks.

Figure 32.1 is a graph representation of a multilevel network of scientists and their laboratories in their field of research. Lines between blue nodes (squares) represent interorganisational collaborations, and lines between red nodes (circles) represent an interpersonal advice network. Lines

Figure 32.1 Example of visualisations of multilevel networks in French cancer research (2000) used to identify multilevel relational infrastructures

between circles and squares represent cross-level membership of researchers in laboratories.

Statistical methodology was developed to use such datasets from a sociological perspective. Indeed, studying contextual effects on individual behaviour can be misleading with methods (such as linear regression) that look only at individual characteristics (Robinson, 1950; Snijders & Bosker, 2012). For example, a scientist's work influences her/his performance or capacity to obtain funding, but this influence varies depending on the laboratories with which this scientist is affiliated. Hierarchical linear models can account for such contextual effects, where within-laboratory effects are obtained first, then between-laboratories variations are represented by meta-analysis across these effects. This approach is also known as *multilevel analysis of networks* (MAN), in which individuals' actions, beliefs and performances within groups are analysed taking into account their nested collective memberships (Snijders & Bosker, 2012). MAN treats the nested structure as a given exogenous structure, and does not aim to take into account and model the dyadic and higher-order interdependencies between individuals based on their relationships or links between groups. It is not plausible that such groups lack an internal structure, nor that they lack links among each other. Network analyses help in introducing more realistic approximations of the internal structure of these groups and of their interdependencies into the modelling of human and social action. This is where MNA becomes useful which aims at modelling the nested structure as part of the endogenous social process. Lazega et al. (2008) show that it is not enough for a researcher to be central at the individual-level network (a *big fish*) to be recognised. His/her achievements vary depending on whether this scientist operates in a big or small, central or marginal laboratory (a *big pond* or a *small pond*). Position in such multilevel networks can thus be construed as combining both networks in four categories: a *big fish in a big pond* (BFBP), a *big fish in a small pond* (BFSP), etc. In the case in point that will be presented below, the BFBP were the most successful and only the *little fish* (LF) in the big ponds could catch up with them over time. In a different context with different constraints, Bellotti et al. (2016) find that BFSP do better than BFBP.

To test such hypotheses, Wang et al. (2013b) pioneered ERGM specifications for multilevel networks, and demonstrated the features of multilevel ERGMs with simulation studies and modelling examples. Combining multilevel network structure and nodal attributes, Wang et al. (2016a, 2016b) proposed *social selection models* (SSMs) where the existence of multilevel network ties is conditionally dependent on not only the existence of other network ties but also on nodal attributes. They demonstrated that nodal attributes may affect network structures both within and across levels.

By treating network ties as outcome variables, on the one hand, ERGMs and SSMs are designed for modelling the interdependencies among the within and meso level, and how various attributes of nodes at different levels affect tie formation in a multilevel context. On the other hand, *autologistic actor attribute models* (ALAAMs), also known as *social influence models* (Robins & Pattison, 2001b; Daraganova, 2013), treat network structures as exogenous, and model nodal outcomes as a combined result of individual's attributes, network positions, as well as the outcomes of their networked neighbours. Instead of treating individual outcomes as independent observations, ALAAMs allow us to test the interdependencies among the outcomes established by network ties as channels of transmission or influence. In multilevel networks, outcomes can be measured at different levels, and multilevel ALAAMs will enable us to test how individuals' positions in a multilevel network and how attributes or outcomes of nodes at a different level may affect individual outcomes.

In the following section, we review ERGMs and SSMs for multilevel networks, and propose some model specifications for ALAAMs for multilevel networks. Using the French cancer research elite dataset, we demonstrate how these models may answer the following key research questions:

- ERGM: How may within-level network structures affect network structures at a different level through meso-level interactions?
- SSM: How may attributes of nodes at one level affect network structures at a different level?
- ALAAM: How may individuals' outcomes be affected by multilevel network structure and outcomes of others?

THE MODELS

Multilevel Network Representation

The simplest multilevel network consists of nodes from two levels as shown in Figure 32.2. Using the French cancer research elite dataset as an example, one of the levels consists of research laboratories and their formal collaboration ties. We label this collaboration network as (A) which is a collection of collaboration ties ($A = \{A_{ij}\}$) where ($A_{ij} = 1$) if there is a collaboration between laboratories i and j, otherwise ($A_{ij} = 0$). The other level consists of researchers and their advice exchange network which is labelled as ($B = \{B_{kl}\}$). Each of the researchers in (B) are members of laboratories in (A). The two-mode affiliation network between researchers and laboratories forms the meso-level network ($X = \{X_{ik}\}$). The overall two-level network (M) consists of the two within-level and one meso-level networks ($M = \{A,B,X\}$). The various nodal attributes (e.g., researcher's gender and age, laboratory's location and size) are labelled by $\left(Y = \{Y_i^A, Y_k^B\}\right)$ where Y_i^A corresponds to attributes of laboratory i, and Y_k^B for researcher k. We use these labels as random variables and their lower cases as instances of the random variables for ERGMs and ALAAMs described below.

ERGM and SSM for Multilevel Networks

Exponential random graph models (ERGMs) model social network tie formation as a result of various social processes arising from the interdependent nature of social ties – that is, the occurrence of one tie may be dependent on the existence of other ties. These social processes are represented by subgraphs, or graph configurations where all ties within each configuration are considered interdependent. Using the various network labels for the multilevel data structure described before, we can express ERGM for multilevel network as

$$\Pr(A = a, B = b, X = x) = \frac{1}{\kappa} \exp \sum_Q \theta_Q z_Q (A, B, X)$$

where

z_Q are graph statistics counting the number of graph configurations of type Q.

θ_Q are model parameters associated with z_Q, where a positive and statistically significant parameter estimate suggests the configuration happens more than one would expect by chance given the rest of the model. Negative parameters mean the opposite.

κ is a normalising constant ensuring a proper probability distribution. κ is intractable even for small networks due to the size of the graph space grows exponentially. The properties and ERGM and estimation of ERGM parameters usually rely on simulations.

From the dyadic independent models to social circuit models (Snijders et al., 2006), Pattison and Snijders (2013) proposed a hierarchy of network tie dependence assumptions guiding the ERGM specification development. These tie dependence assumptions form theoretical bases for constructing ERGM configurations. In single-level networks, such dependencies are usually based on network ties of a single type – for example, the friend of a friend is a friend based on which we can derive a friendship triangle

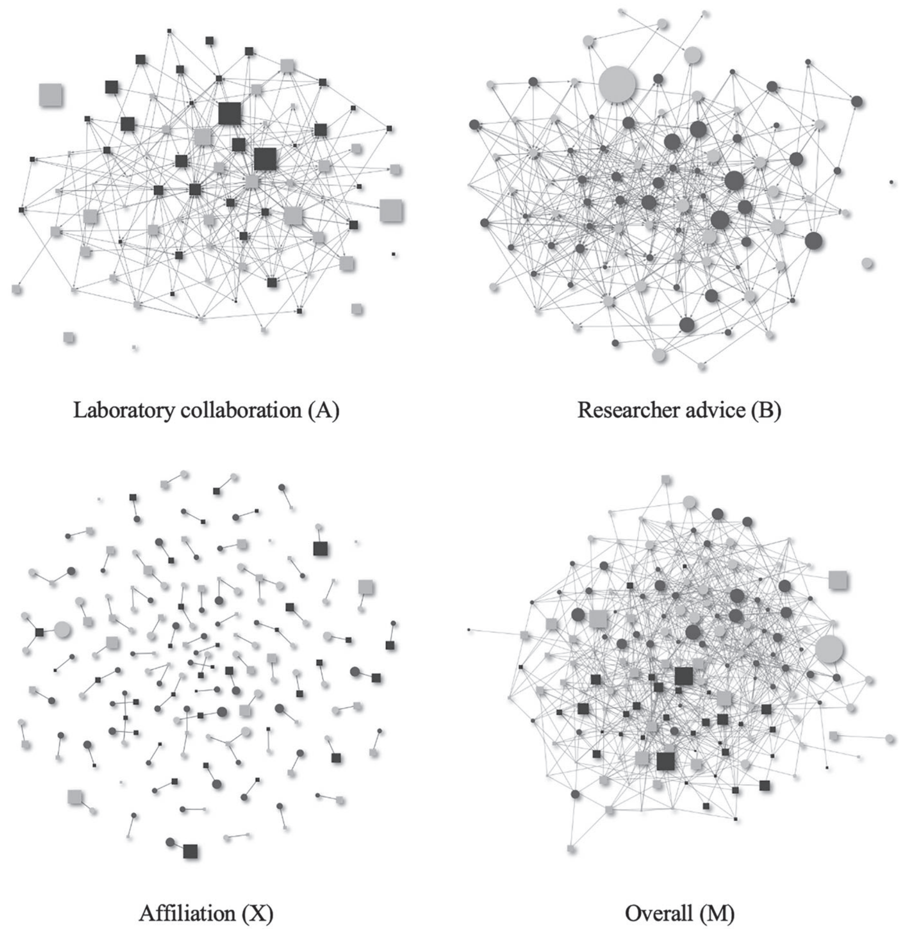

Figure 32.2 A two-level network representation

configuration – or more formally the Markov models (Frank & Strauss, 1986). The most current commonly applied ERGM specifications for one-mode networks are based on social circuit dependence assumption (Snijders et al., 2006). Figure 32.3 presents some ERGM configurations for directed one-mode networks that we use to model within-level network structures.

Extending these tie dependence assumptions to multilevel networks, Wang et al. (2013b) proposed ERGM for multilevel networks with configurations involving both within- and meso-level ties of different types. For example, a cross-level four-cycle follows the social circuit dependent assumption but has two ties from two different levels and two affiliations ties. Figure 32.4 lists a few examples of ERGM configurations for multilevel networks. For the French cancer researcher context, these configurations allow us to test how interlaboratory collaboration and researcher advice exchange may affect each other through cross-level affiliations.

SSMs extend ERGMs by introducing nodal covariates to ERGM graph configurations based on theory and assumptions that social actors with different attributes may have different motivations to form social ties (Robins et al., 2001a); homophily is one such example where people with similar attribute values may be more likely to form ties.

SSMs for multilevel networks can be expressed as

$$\Pr\left(M = m \mid Y^A = y^A, Y^B = y^B\right) = \frac{1}{\kappa} \exp \sum_Q \theta_Q z_Q \left(M, Y^A, Y^B\right)$$

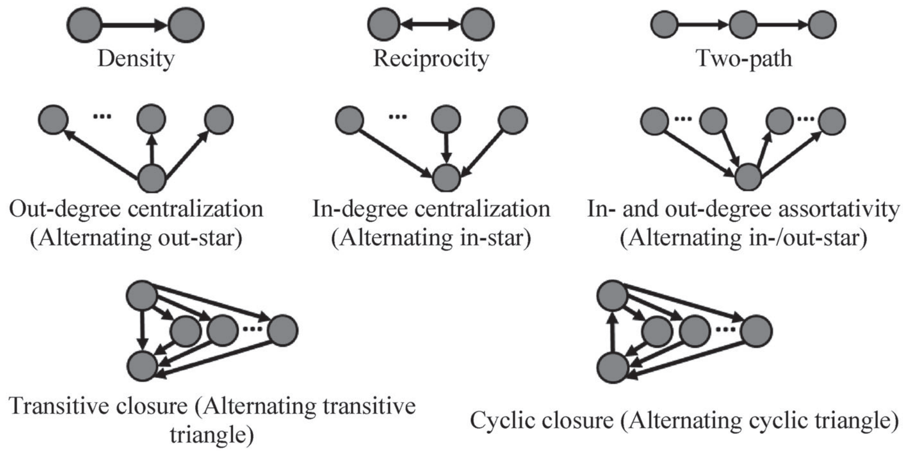

Figure 32.3 ERGM configurations for within-level networks

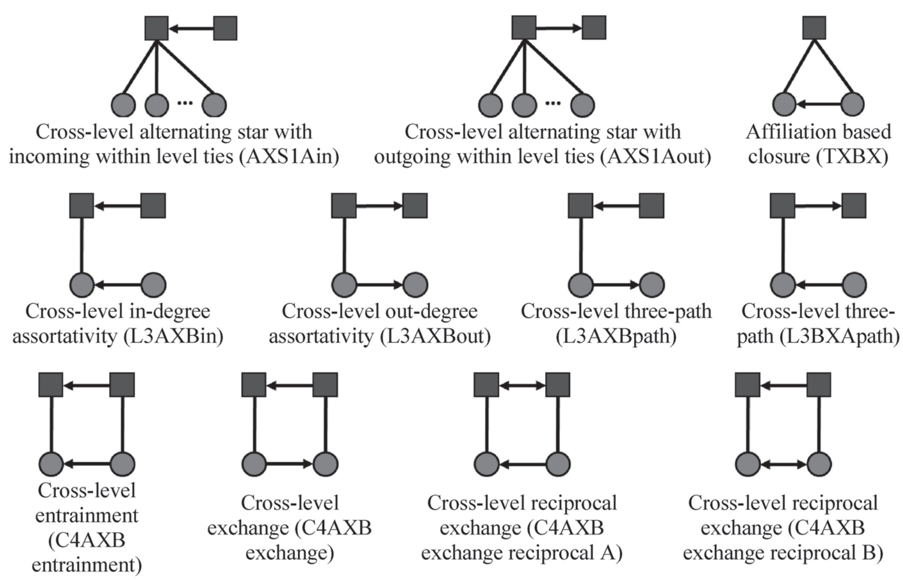

Figure 32.4 ERGM configurations for multilevel networks. Nodes from different levels are represented by different shapes

where attribute values form nodes of different levels serve as covariates, and form part of the graph configurations $z_Q(M, Y^A, Y^B)$. Within each configuration, network tie variables are not only dependent on each other, but also dependent on nodal attribute values. Nodal attributes can have typical forms of binary (e.g., pass or fail of a test), continuous (e.g., age), or categorical (e.g., race). Figure 32.5 lists a few SSM configurations we used in the modelling applications in this chapter. Note that, depending on the types of attribute, these interaction terms can be calculated differently. For example, a positive 'Interaction' effect for binary attribute may suggest homophily – that is, nodes having the attribute are more likely to form network ties – while for continuous attributes, the 'Interaction' statistics are calculated based on the absolute difference between the attribute values of the nodes in the dyad.

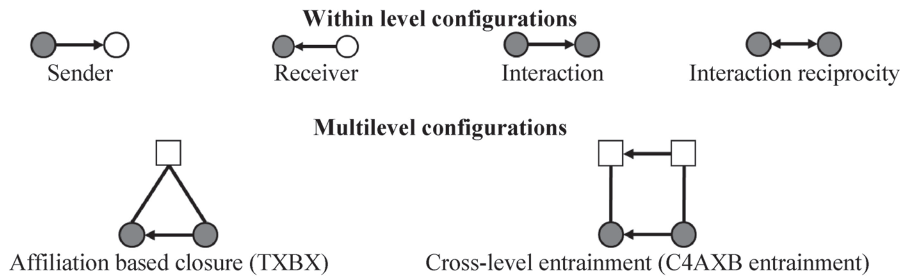

Figure 32.5 Example configurations for social selection models. Attribute values of solid nodes are counted towards the graph statistics

Homophily can then be interpreted from negative parameter estimates for such 'Interaction' effects – that is, the smaller the difference in attribute values, the more likely to form a tie. The same applies to all within- and multilevel configurations. See a more comprehensive list of SSM configurations in Wang et al. (2016a and 2016b).

ALAAM for Multilevel Networks

Auto-logistic actor attribute models share similar model constructs as ERGMs, except that the outcome variables in ALAAMs are binary outcome measures for each individual nodes, and network ties or structures as well as other nodal attributes are treated as predictors for nodal outcomes. Instead of testing how nodal attributes may affect tie formation as in SSMs, ALAAMs are also known as *social influence models* (Robins et al., 2001b) aiming at testing how network structure affects nodal outcomes while taking into consideration the interdependencies among the outcomes established by network ties connections – that is, individual outcomes may be dependent on the outcomes of reachable nodes in the given network.

For a two-level network, let Y^A and Y^B denote the outcome of nodes in level A and B, and Y'^A and Y'^B denote other nodal attributes, ALAAMs for two-level network can be expressed as

$$\Pr\left(Y^A = y^A, Y^B = y^B \mid M = m, Y'^A = y'^A, Y'^B = y'^B\right) = \frac{1}{\kappa}\exp\sum_Q \theta_Q z_Q\left(Y^A, Y^B, M, Y'^A, Y'^B\right)$$

where the variables involved in ALAAM graph configurations $z_Q(Y^A, Y^B, M, Y'^A, Y'^B)$ reflect the possible interdependencies among variables $(Y^A, Y^B, M, Y'^A, Y'^B)$ contributing towards nodal outcomes at both levels. Figure 32.6 presents some example ALAAM configurations.

ALAAMs for multilevel networks allow us to test hypotheses for both within- and across-level influence. Using the French cancer researcher data as an example where big fish (BF) and big pond (BP) represent high-performance researchers and laboratories, example hypotheses may include:

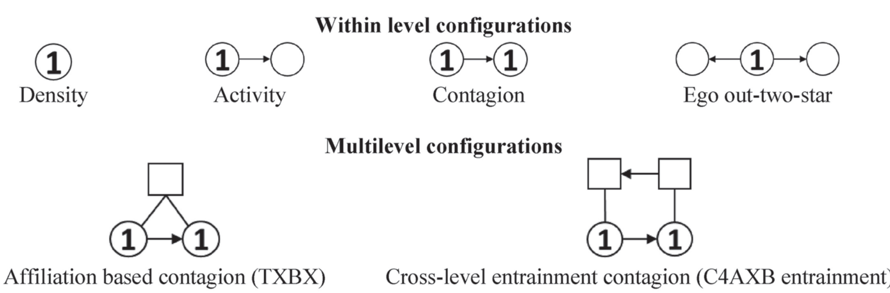

Figure 32.6 Example ALAAM configurations for multilevel networks. Nodes labelled with '1' are nodes having the outcome variable as '1'

- Within the researcher level, seeking advice from BF is more likely to be associated with other BF.
- Within the laboratory level, collaborating with BP is more likely to be associated with other BP.
- Across level, BF are more likely to be members of BP.

For more complex cross-level configuration, using the affiliation-based contagion (TXBX) as an example, we can test whether high research performance is more contagious through advice networks within the same laboratory rather than across different laboratories. We demonstrate some examples of ALAAMs in the application section.

Model Estimation and Selection

Using binary representations of graphs and nodal outcome variables, for a directed network with (n) nodes, the number of possible graphs can be calculated as $2^{n(n-1)}$ while the number of possible nodal level outcomes can be calculated as $2n$ These make the normalising constants (κ) intractable in ERGMs and ALAAMs. The parameter estimations usually rely on simulation-based numerical approximation methods (Snijders, 2002; Handcock et al., 2008; Stivala et al., 2020). These methods typically involve comparisons between the observed graph or outcome attribute statistics and simulated samples from a given set of parameter values. Such comparisons provide directions and scales for updating parameter values with a goal that repeated updates of parameter values will converge and the simulated samples from the converged parameters can reproduce features of the observed data by testing statistics such as *t-ratios*, where (*t-ratio* < 0.1) across all modelled effects suggest a model has converged. For parameter estimation, Snijders (2002) proposed algorithms for Markov chain Monte Carlo (MCMC) maximum likelihood estimations, while Koskinen et al. (2010) and Caimo and Friel (2011) proposed estimation procedures using Bayesian approximations. Stivala et al. (2020) proposed algorithms for estimating large networks with millions of nodes.

Once parameter estimates, hence a converged model, are obtained, the adequacy or model goodness of fit (GOF) of the model can be tested by simulating the converged model, and collecting a greater range of graph statistics beyond the ones included in the model specification, such as the degree distributions, clustering coefficients and geodesic distributions, as representations of the model distribution. Comparing such distributions with the observed statistics using *t-ratios* can serve as the GOF testing statistics, where a t-ratio less than 2.0 suggests the corresponding graph statistic is adequately captured by the model.

These algorithms are implemented in statnet under R (Handcock et al., 2008), or standalone software such as MPNet (Wang et al., 2014) and EstimNetDirected (Stivala et al., 2020). The models presented in this chapter are based on output from MPNet which implements algorithms proposed by Snijders (2002).

For model selection, we use the strategy described in Wang et al., (2016b), where model GOF results serve as guide aiming for the most parsimonious model while providing adequate fit to as many graph statistics as implemented under MPNet.

APPLICATION

This approach to the shaping of the multilevel network across organisational boundaries at the interindividual and interorganisational levels can be illustrated using a case study in the sociology of science, an empirical example of co-constitution without conflation. In this case, the sector of top French cancer researchers – working in an extremely competitive environment – was examined at both the interindividual and the interorganisational levels in 1999–2000. In this context, we identified the systems of superimposed interdependencies, the strategies of the actors who manage these interdependencies, and actors' achievements measured at the individual level. No deterministic order is pre-supposed between multilevel position, strategy and achievements – it is established here by analysis alone. This approach is particularly sensitive to the existence of inequalities between competing actors because these inequalities can render a given strategy more or less 'rewarding' depending on dual positioning as a measurement of opportunity structure.

Data Description

The dataset consists of 97 researchers and their affiliated 82 laboratories. The ties among researchers are defined based on their advice-seeking activities, while the ties defined among laboratories are their collaborations.

Among the 82 laboratories, 36 are in Paris and the rest are in the provinces. The laboratories have between four and 100 staff members, with an average of 28.39 and a standard deviation of 24.05. For social selection models, these two attributes are used as covariates for laboratories.

For ALAAMs, we model what constitute towards BPs. As ALAAMs can only model binary outcomes, we define BPs as laboratories having more than 38 staff or the 75th percentile of the laboratory size distribution.

For researchers, 45 out of the 97 researchers are in Paris, and 50 of them are directors of their laboratories. The researchers' average age is 48.21 with standard deviation of 7.76. Researchers are also categorised by one of seven research areas or specialities. The performance of researchers is calculated based on the average impact factors associated with their publications. Researcher performance is measured based on the impact factors of their publications over five-year periods. Two performance scores are obtained based on the periods 1995–1999 and 2000–2004. We see the former as the past performance with mean at 38.99 and standard deviation of 28.52, and the latter as the current performance with a mean of 39.12 and standard deviation of 28.55. The social selection models presented in this chapter used the current performance as one of the covariates to predict network structure. The ALAAMs, however, used past performance as a covariate to predict the current performance. Again, we use the 75th percentile of the current performance scores, or 51.92 as the cut-off point, where researchers with higher performance scores are seen as BF.

Figure 32.3 presents visualisations of the networks with breakdowns into within-, across- and the overall multilevel structure. The laboratories are represented by blue squares, with darker ones indicating Paris. The size of the laboratory nodes represents laboratory size. The red circles represent researchers with darker-coloured nodes as directors of their laboratories, and size of the researcher nodes represents their current research performance scores.

Modelling Results

We present multilevel ERGM, SSM and ALAAM results for this dataset to demonstrate findings highlighting the cross-level effects.

ERGM: Multilevel structure can explain complicated within-level structure

We extract two models from Wang et al. (2013b) to compare and demonstrate how complicated within-level structure can be explained by multilevel structures. Model 1 in Table 32.1 is an ERGM for the researcher advice network only without considering the multilevel structure, while Model 2 in Table 32.2 presents the multilevel ERGM. The two models have consistent parameter estimates on the negative network density (Arc), the positive tendency for advice ties to be reciprocated (Reciprocity) and the positive tendency for network closure (AT-T). However, in order to obtain a model providing adequate fit to all within-graph statistics, and degree distributions in particular, Model 1 has eight parameters for star-like configurations representing network tie centralisation, while Model 2

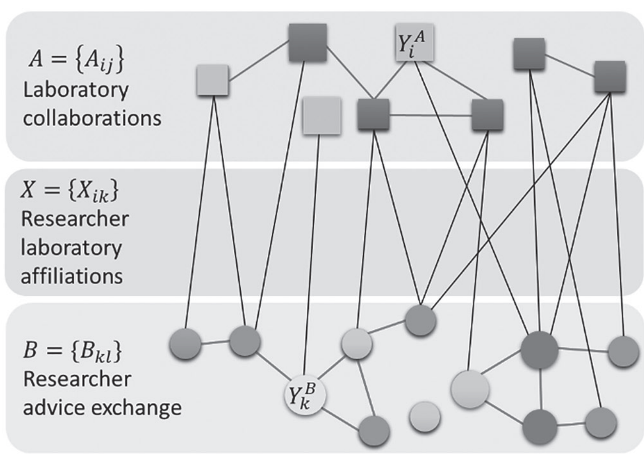

Figure 32.7 Multilevel network among researchers and their affiliated laboratories. Squares represent laboratories, circles represent researchers. For researchers, node size represents performance, darker colour represents directors. For laboratories, node size represents laboratory size, darker colour represents laboratories in Paris

Table 32.1 Within-level ERGM for researcher advice network adapted from Wang et al. (2013b)

	Model (1)		
Effects	*para*	*s.e.*	
Arc	–3.213	1.024	*
Reciprocity	3.534	0.213	*
2-out-star	0.358	0.146	*
3-out-star	–0.018	0.009	
2-path	–0.135	0.010	*
AinS(4.00)	0.596	0.159	*
AoutS(4.00)	–0.722	0.599	
AinS(2.00)	–1.164	0.450	*
AoutS(2.00)	0.384	0.787	
AinAoutS(2.00)	–0.233	0.369	
AT-T(2.00)	0.932	0.067	*

contains none of the tie-centralisation effects, which suggests the complicated degree distribution can be explained by the network structures beyond the within-level advice ties.

Although Model 1 provides adequate fits, the model is almost uninterpretable. Model 2, in contrast, provides rich interpretations on the cross-level network structures. The negative (AXS1Aout) effect suggests laboratories with higher numbers of researchers are less likely to seek collaborations with other laboratories, although this effect diminishes once we bring in nodal attributes as discussed below in SSM. The affiliation-based closure effect (TXBX) suggest advice-seeking and common affiliations are promoting one another. Note that as ERGMs and ALAAMs are models for cross-sectional data, the interpretation is not about casual relationships, but more about association, although the results of the underling dynamic social selection or influence processes are captured by the graph configurations. In this case, we can interpret the positive TXBX effect as researchers are more likely to seek advice within their laboratories, and advice exchange also encourages common affiliations.

The negative L3BXApath cross-level degree assortativity effect suggests the in-degrees of researchers in the advice network is negatively correlated with their affiliated lab's collaboration activity in reaching out to other labs. This may suggest the popular researcher advisors are affiliated with key research labs which do not have the urgency in seeking further collaborations. This effect is also diminished once we include nodal attributes in the SSM.

The cross-level entrainment and exchange effects show interesting dynamics on how 'weak' or non-reciprocal ties may make 'strong' or reciprocal ties at the other level redundant. Both non-reciprocal cross-level entrainment and exchange effects are positive indicators of how the within-level ties are enhancing one another where researchers are more likely to provide or seek advice from others in collaborating laboratories. As ERGMs treat ties as outcomes, the model reflects that advice flow indeed encourages formal collaboration between affiliated laboratories, while formal collaborations may have provided context and resources for the exchange of research advice. However, the cross-level effects become negative as soon as a reciprocal tie is involved. From the laboratories' perspective, mutual collaboration ties may have shared sufficient information or resources that the urge for advice exchange between affiliated researchers is not as immediate. From the researchers' perspective, the reciprocal advice exchange can indicate there is a certain level of interest or lack of knowledge from one another, although the fact that these interests have not yet been translated into formal collaborations suggests collaboration opportunities.

The comparison between Model (1) and (2) shows us how rather complicated within-level network structure can be entirely explained by cross-level effects. The cross-level effects also reveal the dependencies between advice exchange and formal collaborations.

SSM: Within-level network structures can be affected by attributes of nodes at a different level

In SSMs, we bring in nodal attributes as predictors for tie formation. Model (3) in Table 32.2 is extracted from Wang et al. (2016b) as a final SSM for the dataset. The attribute effects in Model (3) suggest that within the advice network, researchers based in Paris are less likely to seek advice (negative Sender effect), but if they do, they tend to seek advice from other researchers in Paris (positive Interaction effect). Researchers tend to seek advice from others of similar age (negative Age Difference effect). Researchers with higher performance are seen as resources of advice (positive Receiver effect), while the negative Performance Difference effect suggests researchers tend to seek advice from others with similar performance. Advice seeking is also more likely to take place within specialities but not exchanged reciprocally (positive Speciality Match effect but negative Speciality Match Reciprocity effects) suggesting a knowledge hierarchy within speciality. The Director attribute does not directly affect advice seeking as

Table 32.2 Multilevel ERGM and social selection model adapted from Wang et al. (2013b; 2016b)

	Model (2) ERGM			*Model (3) SSM*		
Effects	*para*	*s.e.*		*Para*	*s.e.*	
Laboratory collaboration network {A}						
Arc	−3.831	0.556	*	−3.815	0.574	*
Reciprocity	1.679	0.381	*	1.525	0.413	*
2-path	−0.079	0.029	*	−0.090	0.029	*
Isolates	2.017	0.760	*	2.057	0.769	*
AinS (4.00)	0.640	0.268	*	0.737	0.267	*
AoutS (4.00)	0.320	0.086	*	0.334	0.089	*
AinS (2.00)	−0.889	0.614		−1.039	0.618	
AT-T (2.00)	0.446	0.127	*	0.420	0.13	*
Researcher advice network {B}						
Arc	−4.084	0.118	*	−3.975	0.143	*
Reciprocity	3.313	0.212	*	3.361	0.235	*
AT-T (2.00)	1.085	0.072	*	1.046	0.074	*
AT-C (2.00)	−0.384	0.068	*	−0.360	0.073	*
A2P-U (2.00)	−0.071	0.020	*	−0.083	0.021	*
Paris Sender				−0.386	0.101	*
Paris Interaction				0.569	0.094	*
Age Difference				−0.023	0.006	*
Performance Receiver				0.005	0.002	*
Performance Difference				−0.007	0.002	*
Speciality Match				0.786	0.132	*
Speciality Match Reciprocity				−0.795	0.321	*
Collaboration and affiliation {A, X}						
AXS1Ain (2.00)	0.240	0.131				
AXS1Aout (2.00)	−0.324	0.129	*			
Advice and affiliation {B, X}						
TXBX	1.958	0.275	*	1.945	0.265	*
Cross level interactions {A, B, X}						
L3AXBin	−0.006	0.018		0.004	0.017	
L3AXBout	−0.012	0.008		−0.016	0.01	
L3AXBpath	−0.003	0.010		−0.043	0.016	*
L3BXApath	−0.051	0.015	*	−0.013	0.01	
C4AXB entrainment	0.634	0.104	*	0.524	0.114	*
C4AXB exchange	0.639	0.109	*	0.659	0.108	*
C4AXB exchange reciprocal A	−0.293	0.065	*	−0.256	0.096	*
C4AXB exchange reciprocal B	−0.295	0.136	*	−0.328	0.148	*
Director C4AXB Entrainment				0.840	0.180	*

there is no Sender/Receiver or Interaction within-level effect; however, there is a positive Director C4AXB Entrainment effect suggesting laboratory directors' advice-seeking activities are strongly aligned with the formal collaborations between their affiliated laboratories. Without looking into the multilevel models, one may conclude that laboratory directors do not shape the advice network structure, but the multilevel SSM highlights their advice-seeking activities as having strong impact on the collaboration network at the interlaboratory level. This highlights how "unimportant" nodal attributes at one level may play a significant role in shaping the network at a different level.

The SSM also shows that attributes of laboratories are not as important in the multilevel structure compared to researchers' attributes, as none of the laboratory attribute effects are included in the model, while their corresponding graph statistics are adequately fitted. Although the endogenous structural effect part of the SSM Model (3) is remarkably similar to the ERGM Model (2) both in terms of effect signs and significance, it is worth looking into how the attribute effects may explain the few changes between the two models. First, the negative ERGM AXS1Aout is no longer significant and removed from the SSM. AXS1Aout configuration does not involve advice ties, therefore the negative association of affiliation and outgoing collaboration is more likely to be explained by Director cross-level entrainment effect (while the within-advice attribute effects have less impact, as they do not count towards graph statistics involving collaboration ties). It is the directors' advice-seeking activities that drive the negative AXS1Aout effect. Second, we notice the negative L3BXApath becomes non-significant; instead the negative L3AXBpath becomes significant. When the advice network structure is better explained by the researcher attributes, the cross-level degree assortativity dynamics also change. Instead of popular researchers being less likely to be affiliated with laboratories actively collaborating with other laboratories (negative L3BXApath), it is the other way around, such that it is the popular laboratories in the collaboration network that are less likely to be affiliated with researchers who are actively seeking advice.

ALAAM: individual outcomes can be affected by network structures at a different level

We use the proposed ALAAM to model the association among network positions, researcher performance and laboratory sizes, while taking into account various nodal attributes.

As ALAAMs can only model binary outcomes, we need to choose a cut-off point for continuous outcome variables. The cut-off value usually requires justifications depending on the research context. As an illustrative example, we use the 75th percentile of the original continuous outcome values as the cut-off point. Based on such criteria, researchers are considered as having high performance, or being BF, if their current performance scores are greater than 51.92. For laboratories, we use laboratory size as the outcome variable, and consider a laboratory as a BP if it has more than 38 staff members.

Other nodal attributes are used as predictors for these outcomes, like the attribute covariates used in the SSMs, for researchers; we include their Director statues, whether they are based in Paris, Age, research performance scores from the previous year and their areas of specialities as covariates. For laboratories, we use whether they are in Paris as a covariate.

Table 32.3 Within-level and multilevel ALAAM results

	Model (4)			*Model (5)*			*Model (6)*		
Effects	*para*	*s.e.*		*para*	*s.e.*		*para*	*s.e.*	
Laboratory collaboration network {A}									
Density	−2.312	0.481	*				−1.421	0.541	*
Contagion	0.438	0.132	*				0.473	0.154	*
Researcher advice network {B}									
Density				−4.292	0.912	*	−5.034	0.932	*
Contagion				0.295	0.102	*			
Ego out-2-star				−0.026	0.010	*			
Previous performance				0.084	0.022	*	0.102	0.022	*
Advice seeker within Paris							−0.241	0.113	*
Affiliation network {X}									
Director status							−2.034	0.653	*
Cross level interactions {A, B, X}									
C4AXB-exchange contagion on researcher performance							1.242	0.311	*

Table 32.3 presents a set of three ALAAMs for comparison. Ignoring the meso-level structure, Model (4) and (5) only examine how within-level network ties may serve as channels for social influence. Model (6) considers the overall multilevel structure, and allows the test of cross-level contagion – that is, whether high-performance researchers, or BF, and large laboratories, or BPs, are more likely to be associated with one another through cross-level affiliation.

Model (4) is the ALAAM for BPs, and their associated collaboration network positions. The rather simple model provides adequate fit to 35 attribute statistics, including interaction statistics with the Paris location attribute. The positive contagion effect suggests laboratories that are in collaboration with other BPs are also more likely to be BPs themselves. There is no tendency for BPs to be based in Paris – only eight out of the 36 BPs are in Paris.

Model (5) tests the association between BF and their attributes and positions in the advice network only. The model provides adequate fit to 81 attribute statistics, including attribute interaction statistics. The positive 'Previous performance' effect suggests researchers were more likely to be BF if they had higher previous performance. The Contagion effect suggests research performance is influenced by the performance of advice network partners – that is, researchers who seek advice from BF are also likely to be BF. The negative Ego out-2-star indicates active advice seekers are less likely to be BF. There is no evidence that BF are perceived as sources of advice either, as the model fitted the Receiver and Ego in-2-star statistics. The model also provided good fit to all other researcher attributes, hence none of the location, age, directorship and specialities affected researchers' performance given the effects we see in the model.

Model (6) predicts both laboratory sizes and researcher performance while treating the multilevel network structure as part of the predictors. It provides adequate fit to 232 statistics, including attribute interaction statistics with higher-order graph configurations, such as within- and cross-level triangles and four-cycles.

The within-level effects under Model (6) are largely consistent with Model (4) for the BPs, and our interpretation of the BP contagion effect stays. For BF, however, the previous significant within advice level Contagion and Ego out-2-star effects are no longer required, and they are explained now by the cross-level effects. Researchers' previous performance remains a strong predictor for the current performance. Once we include the multilevel effect, the researchers' location attribute becomes a significant predictor for research performance. The negative effect suggests researchers who are based in Paris that are actively seeking advice are less likely to be BF. In other words, advice seekers in Paris may be more likely to be *small fish*.

The positive cross-level exchange-contagion effect suggests researchers who have been seeking advice from, or providing advice to, other BF in collaborating laboratories are more likely to be BF. And the directions of the laboratory collaboration ties are opposite from the directions of researcher advice-seeking ties which form an advice–collaboration exchange loop. This model provides adequate fit to the cross-level entrainment effects; hence it is only the exchange effect affecting the researchers' performance. From a researcher's perspective, on the one hand, seeking advice from BF whose laboratory is collaborating with the researcher's own laboratory may enhance research performance. From the laboratory's perspective, on the other hand, seeking collaboration from laboratories whose BF researchers are actively seeking advice from its own researchers may enhance research performance.

Comparing Model (6) with Model (5), the positive within-level contagion effect as in Model (5) is no longer significant in affecting research performance, instead the collaborations among laboratories provide context, social settings, resources, and opportunities to enhance researcher performance. In other words, advice seeking ties themselves are not channels of influence unless the affiliated laboratories have formal collaborations in place. Researchers who only seek advice with any BF might not necessarily improve their own performance, unless the BF are indeed from a collaborating laboratory. The success of researchers is associated with both their own and their affiliated laboratories' networks.

It is also worth noting that the director status had no effects within levels in either Model (4) or (5) but becomes significant in affecting laboratory sizes through the cross-level affiliation network. This suggests laboratories are more likely to be BP if their affiliated representatives during the data collection were not the laboratory's directors. This may be because not all researchers, hence directors of all laboratories, were interviewed, and larger laboratories had other representatives than the directors providing survey responses.

Given Model (6) has fitted all statistics related to interactions of the outcome and other attribute covariates, therefore neither Age nor specialities of researchers would have affected researcher performance or laboratory sizes. There is also no evidence for association between high-performance researchers and large laboratories. In other words, BF do not necessarily work in BPs, given other significant effects presented in the model.

Such multilevel network analyses as a methodology can be extended to three or more superposed levels. A case of superposed team level, interindividual level in a profession and interorganisational level among institutions of this profession complexifies collective agency but provides models of cumulative advantage mechanisms, what Lazega and Jourda (2016) call the 'structural wings' of Mertonian, meso-level Matthew effects, with their rich-get-richer-through-borrowing effects. Statistical models for such data formats, including cross-level effects to study these mechanisms and their variety, remain to be designed, implemented and used.

MNA RESEARCH POTENTIAL: COMBINING RELATIONAL CAPITAL OF INDIVIDUALS AND SOCIAL CAPITAL OF COLLECTIVES

Two examples of MNA research provide illustration of how these models (especially MERGMs) are used. The first is in the field of economic sociology; the second is in life-course studies.

Analysing the formation of multilevel networks where the unit of analysis is the pair individual–organisation makes it possible to differentiate between superposed levels of agency where links between individuals can influence links between organisations, as when exchanges of information between two competing individuals in a market (for example, two sellers discussing a common buyer's demand and purchasing power) can lead to contracts signed between the companies employing these three individuals (Brailly et al., 2015; Favre et al., 2016). MERGMs thus tease out some of the relational mechanisms making cooperation between competitors possible (Lazega, 2011; Brailly & Lazega, 2012). More generally, taking the meso level of society seriously requires introducing dynamics into the study of different and superposed systems of interdependencies and collective agency.

The first study looks at network formation at each level of specific markets – that is, trade fairs for television programmes in Eastern Europe and Africa. In this trade fair sellers and buyers of TV programmes (distributors and TV channels) meet once a year to discuss contracts, make deals, keep informed about new films, series and game shows, and observe market evolution. The study of the informal exchange of information between sales representatives and formal deal ties between their companies examines network formation at each level. It shows that these networks are heavily interdependent but that each level has its own specific processes. Tie formation between two organisations takes place in a different context than that between two individuals, and it evolves in a different temporality. For each level, specific structural processes emerge and explain the network morphology. This, however, complexifies the co-evolution of networks and behaviour at both levels separately and jointly. Levels are interdependent and influence each other. Supposing that these levels are nested does not imply that they evolve symmetrically and in sync. As emphasised by Lazega (2015, 2016), the co-evolution of the two levels is complex, dynamic and can be partially disconnected if not asynchronous – thus raising the issue of the costs of synchronisation. Structural organisation of each level as well as the attributes and context explaining tie formation at each level can be different. Brailly (2016) identifies at the inter-organisational level a temporality that requires companies to meet regularly at the 'same time next year' in a system that is driven by a core, an 'oligopoly with fringes'. At the interindividual level, sales representatives need to meet 'next time this year' in order to extract more value from their socioeconomic relations in a fragmented and competitive milieu. The long-term deal network between companies influences short-term cooperation ties between individuals, which in return can bring new business opportunities and constraints to their companies.

The potential of this kind of modelling can also be highlighted by combining MNA and life-course research in sociology. The principle of *linked lives* is one of the key tenets of the life-course perspective (Elder et al., 2003; Vacchiano & Spini, 2021), and researchers have long been interested in the influence of these connections on the course of individual lives. What multilevel networks reveal about the life course can be exemplified with research on multilevel networks and status attainment (Vacchiano et al., 2022). MNA thus promises to shed light on how individuals acquire status over time, a question of major interest in life-course research studying cumulative (dis)advantage and social mobility (if any).

Research on social networks and status attainment was already well advanced in the 1990s (Breiger, 1990; Lin, 1999). Networks provide resources, such as information and social support, that facilitate individual action. Accessing and mobilising better resources, conceptualised as relational capital, increases the chances of obtaining, for example, higher paid and more highly skilled jobs. Networks also often mirror ascribed characteristics of individuals (class, gender, ethnicity or human capital), for example through homophily, which exacerbates social inequalities (McPherson et al., 2001). The use of weak ties also increases the chances of networks improving social status (Granovetter, 1973, 1985; Burt, 1992, 2007) by providing individuals with more access to structural opportunities together with fewer constraints. Beyond ascribed and acquired personal characteristics and resources, social resources have also been shown to have an impact on status attainment and social inequalities, namely resources such as information, influence, support, advice or knowledge, to which individuals potentially have access through their contacts. In particular, individuals have access to social resources through mechanisms, such as homophily and transitivity, that link people in similar social positions. These mechanisms make networks a further source of exposure to structural opportunities and constraints (Lin, 1999, 2001).

As seen above in the example of the cancer researchers, individuals embedded in interindividual and interorganisational networks can access, through the latter, resources complementary to their personal resources and their social ties (Breiger, 1974; Lazega et al., 2008; Lazega, 2020; Moliterno & Mahony, 2011). Evidence has emerged from MNA of an additional type of resource that exerts a structural influence on status attainment: resources that derive, under specific conditions, from the organisations to which actors belong and the organisational networks in which they are immersed. Studies by Lazega, Jourda and Mounier (Lazega et al., 2013; Lazega & Jourda, 2016) on cumulative (dis)advantages during academic careers (see Merton, 1968, on this subject) of the researchers whose multilevel networks were examined above show that it is not only personal and social resources that are important for academic success: the centrality and prestige of research laboratories also plays a role. On the one hand, laboratories offer researchers their institutional status, positioning them in the scientific world beyond their individual status (what is called *dual positioning*). This gives researchers complementary access to relational/social capital (through indirect contacts called *dual alters*), which does not depend on their social ties, but on the organisational network of their laboratories – often the networks of their hierarchical or administrative superiors. Dual positioning (whether actors are BFBP, BFSP, LFBP or LFSP) has been shown to matter by providing researchers with a multilevel status, which positions them in the scientific community beyond their personal prestige. This gives them access to complementary resources: infrastructure, reputation and, not least, combined relational/social capital. Indeed, belonging to a BP provides researchers with a wider institutional network, giving them access to resourceful contacts (dual alters), albeit in an indirect way. Access to these indirect contacts is thus a function of affiliation with laboratories of different capacity and power. For example recall that it is researchers with low status in science (LF) who are affiliated with larger labs (BPs) who benefit from the complementary resources of dual alters. Five years after data collection, it is shown that these LFBP are more successful than the LFSP.

Actors navigate their trajectories not only as individuals with their relational capital, but also as members of organisations with their social capital (collective mechanisms) (Lazega, 2020). Based on strong dual positioning, collectively closing multilevel 3-paths provides access to dual alters with complementary resources, which helps some actors (and not others) with an *extended opportunity structure* (Lazega et al., 2013; Lazega & Jourda, 2016) and represent (dis)advantage in competitive social spaces. Lin's social resource theory is developed here with the concept of extended opportunity structure that drives the development of models of status attainment accounting for the structural influence of multilevel networks. In this framework, *vertical linchpins* can give access to dual alters with complementary resources, activating *network lift*. When subordinates are able to borrow the relational capital of their superiors, they can expand their network and reach dual alters who, provided they give access to complementary resources, can create this network lift in terms of performance. Alternatively, when people are weakly active at the next, higher level and others dominate at several levels simultaneously, the latter can exercise power and impose constraint that can end up being taken for granted in the system. In a highly bureaucratised society, it is not rare to see managers exposing subordinates to increasingly open competition, or competing with their subordinates, undermining the latters' activities, networks and projects especially by closing access to dual alters and the extended opportunity structure.

Much remains to be done in understanding the conditions under which this meso-level, extended opportunity structure identified with MERGMs develops social resource theory and provides new avenues of research for combinations of social network analyses and, for example, life-course analyses and understanding of social inequalities.

The challenge here is to understand how social systems at superposed levels co-evolve and how actors at both levels coordinate to generate the socioeconomic structure, with its social processes and (dis)advantages. Other fields of substantive research can benefit from MNA (Glueckler and Doreian, 2016). In political science and sociology, there is something remarkable in the way multilevel relational infrastructures are used in institutional entrepreneurship and institution building processes (Lazega et al., 2016; Lazega, 2018) when they mobilise collegial oligarchies of vertical linchpins simultaneously central and active at different levels of agency. These core cross-level key players concentrate power and punch above their weight in such processes, for example by formulating norms at a higher level and enforcing them at a lower level, thus driving and smoothing adoption processes of regulatory changes. The multilevel character of regulation thus strengthens macro determinants of intrinsically micro- and meso-level processes.

Multilevel models are also used for the study of so-called social-ecological networks (networks comprised of both people-to-people ties and people-to-nature ties) – for example, in supporting resilience to environmental and climate change. Social networks underpin the resilience of human communities to environmental change due to their role in building adaptive capacity (Barnes et al., 2020; Barnes, 2022). Both adaptation and transformation require that social actors and institutions have some level of joint adaptive capacity in order to absorb and shape change. Recent research has begun to disentangle how social networks more specifically relate to adaptation and transformation (Barnes et al., 2020). This work rests on the idea that social-ecological systems can be understood and explicitly modelled as multilevel, social-ecological networks (Bodin et al., 2019). This conceptualisation allows us to consider important relationships in social systems – such as cooperation and communication between key individuals, communities, organisations, or even nations; key linkages in ecological systems – such as trophic food webs, larvae or seed dispersal, or landscape connectivity; and the interactions between these – such as resource extraction, ecosystem service flows, or policy and management actions, including how power manifests in such social-ecological networks and its role in driving adaptation and/or transformation. Multilevel network modelling of this kind is seen as a critical research frontier in this area that can inform the building of more resilient societies and ecosystems to meet the rising tide of dramatic environmental change.

Many policy domains would thus benefit from further applying such an MNA framework. In particular, when each level evolves based on its own dynamics, issues of synchronisation and costs of synchronisation between the temporalities of the levels raise new questions. Some ties at one level remain stable thanks to the fact that other ties at a different level change and create stability from movement at the level of the whole structure (Lazega, 2017). Such dynamic invariants raise, for example, the question of who in society incurs the costs of such synchronisations. Individuals most often incur such costs of synchronisation between levels for the benefit of organisations, an underestimated source of social inequalities for such individuals (Lazega, 2016). To take into account the vertical complexity of a social world in the cohabitation and co-constitution of several levels, it is necessary to further link these levels and their dynamics analytically. An important methodological challenge is to express dynamically the combined and interrelated agency of actors in several actor sets in a multilevel network (Snijders, 2016; Koskinen & Snijders, 2022).

CONCLUSION

Bottom-up and top-down struggles in politics suggest that when a social fact must be observed at analytically different levels of collective action, the analysis of individual agency, relations and skills becomes inseparable from that of organisational agency, structure and culture. To take into account this vertical complexity of a social world in the coordination and co-constitution of several levels, it is necessary to further explore the links between these levels and their dynamics analytically. Analysing superposed levels of collective agency, their synchronisations and unequal costs of such synchronisations (in terms of time and energy spent in complex, collective careers for example) incurred by different levels will lead to new knowledge on social inequalities that are still overlooked in the social sciences. MNA as a method thus helps build a view of how society works that will be useful in the short and long future. With climate change, for example, nationwide policies of management of vital resources will need to synchronise with changes in lifestyles created locally by communities also managing common pool resource institutions (Ostrom, 1990). MNA concepts and methods provide a view of how such interdependent levels of collective agency can co-evolve and coordinate (or not), raising issues of social justice attached to such coordination. These are cutting edge issues that deserve more network analytical research at various levels of society.

More generally, such multilevel actors, forms of agency and processes specify and substantiate dimensions of Breiger's (1974) duality of persons and groups – that is, their co-constitution. Developing MNA dynamics is part of explaining how we all make Breiger's duality happen and how this co-constitution of levels is consequential.

Some of these dynamics evolve beautifully synchronously, others asynchronously. This also extends and relates duality to issues of social justice and inequalities: multilevel networks to somewhere, or to nowhere, are part of duality too.

Social network analysis not only has the conceptual and methodological tools to map these processes, but by its very nature it incorporates in its analyses power asymmetries and structural inequalities in the navigation of social processes in multilevel, nested social contexts. At stake in particular are multilevel solutions to existential problems linked to the transitions that societies face (climate related, ecological, demographic, etc.). How to observe, model and analyse phenomena that are not only characterised by networks of interdependencies between conflicting actors, at one level, but that are also simultaneously dynamic and multilevel raises key issues for the social sciences in endangered societies. Hopefully MNA can help track such phenomena to help manage the dilemmas of collective action that they generate.

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