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Testing Policy Theory with Statistical Models of Networks

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This article presents a conceptual framework for clarifying the network hypotheses embedded in policy theories and how they relate to macrolevel political institutions and microlevel political behavior. We then describe the role of statistical models of networks for testing these hypotheses, including the problem of operationalizing theoretical concepts with the parameters of statistical models. Examples from existing theories of the policy process and empirical research are provided and potential extensions are discussed.

This special issue of *PSJ* provides an overview and examples of how statistical models of policy networks can clarify and test hypotheses from theories of the policy process. Statistical models are a core component of *network science*, a newly evolving research field that integrates developments in network theory, methods, and applications from across many scientific disciplines (Börner, Sanyal, & Vespignani, 2007; Lazer et al., 2009). Political scientists have taken note of the "relational turn" in politics, and have started adopting and developing network science tools to analyze political phenomena (McClurg & Young, 2011) and identify the relationships between network structure, macrolevel outcomes, and microlevel behavior (Fowler, Heaney, Nickerson, Padgett, & Sinclair, 2011).

In public policy, Thatcher (1998) described how the use of network concepts has developed from metaphorical descriptions to a series of overarching frameworks based (at least implicitly) on hypotheses about the dynamics of policy networks. Testing the relevance of these alternative frameworks in specific policy domains requires empirical research on how policy networks form, affect individual and organizational behavior, respond to policy interventions, and influence policy outcomes. The application of network analysis has evolved from the use of relatively simple descriptive methods like centrality metrics to determine the most active and important network members and cluster analysis to find the patterns of association within the network. More recent uses involve statistical tools that allow more detailed understanding of how networks form and change based on both endogenous and exogenous (attribute-driven) processes. The statistical models that we

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discuss in this special issue offer the promise of more precise formulation and more appropriate testing of hypotheses from policy theory frameworks.

Of equal importance, these models provide appropriate estimation techniques for mitigating an important threat to validity in empirical research where the units of analysis are embedded in the same sociopolitical settings (as is the case with most research in public policy): the assumption of independent observations. For instance, most of the commonly used regression approaches by policy scholars rely on model assumptions that do not recognize the interdependence among actors implied by networks. Network models are more in line with modern theoretical perspectives that treat policymaking processes as complex systems that require an analysis of interdependent interactions instead of decomposition into autonomous, independent components.

This introduction to the special issue presents a framework that views policy networks as a "meso-" level concept that mediates causal relationships between macrolevel political institutions (both formal and informal) and microlevel individual behavior of political actors, be they citizens, politicians, organizations, or agencies (Evans, 2001; Rhodes, 1997). This framework can be used to conceptualize how micro and macro variables influence the structure of networks, how the structure of networks in turn influences microlevel behavior and macrolevel variables, and how the constellation of macrolevel variables, microlevel behavior, and network structure implicit in a policy system will influence policy outputs and outcomes.

Statistical models of networks operate in this context by providing useful tools to test hypotheses from policy theories related to specific causal pathways in the framework. However, most of the extant research using statistical models focuses either on *selection* effects—how individual or network variables influence the formation of ties in networks—or on *social influence* effects—how the ties that already exist in networks influence individual behavior and attitudes. Hence, theoretical and methodological advancements are needed to expand the reach of statistical models of networks to explore complex causal processes involving both selection and influence effects in policy systems. For example, recent advances in stochastic actor-oriented (also called actor-based) models permit investigation of joint selection/influence processes in longitudinal data. Potential advances in theory and methods will need to be coupled with empirical research that collects the right kind of data, such as comparative research over many cases and longitudinal research over time.

Policy researchers have focused mostly on three types of statistical models of networks: exponential random graph models (ERGMs; Feiock, Lee, Park, & Lee, 2010; Henry, Lubell, & McCoy, 2011; Thurner & Binder, 2009), actor-oriented models (Andrew, 2009; Berardo & Scholz, 2010), and quadratic assignment procedure (QAP) (Matti & Sandström, 2011; Shrestha & Feiock, 2009). The basic assumptions and uses of these models are discussed in Robins et al.'s article in this issue. The primary challenge for policy theory is to clearly represent key concepts for policy network hypotheses in terms of the parameters in these models. For example, one possible parameter in an ERGM is "reciprocity" where the probability of a relationship from actor A to actor B is higher when the creation of that relationship reciprocates an existing tie from B to A. Ostrom's (1999) Institutional Analysis and Development (IAD) framework hypothesizes that pairs of actors with reciprocal relationships in one domain are more likely to cooperate in other domains as well, and more generally that networks with high levels of reciprocity have a greater capacity for dyadic and multiperson cooperation. Appropriate use of statistical models of networks requires specifying how a particular parameter in the model links to theoretical concepts from policy theory.

Some prominent examples of policy theories and frameworks that are appropriate for application of statistical models of networks include the IAD framework (Ostrom, 1999), the Advocacy Coalition Framework (ACF; Sabatier & Jenkins-Smith, 1993), ecology of games (Long, 1958; Lubell, Henry, & McCoy, 2010), policy diffusion theory (Berry & Berry, 1990), and punctuated equilibrium theory (Axelrod, 1984; Baumgartner & Jones, 1991). For example, scholars in the IAD tradition posit the importance of embedded and reciprocal relationships for helping solve cooperation problems (Brehm & Rahn, 1997; Ostrom, 2009; Ostrom & Ahn, 2003). The ACF assumes that policy outcomes are a product of coalitions of actors with similar policy preferences acting together to influence decisions throughout a policy subsystem, and that the political power of these advocacy coalitions depends on the cohesiveness of the associated networks among actors. The ecology of games can be represented as actors connected to different policy institutions, and allows testing of hypotheses such as collaborative institutions being associated with "closed" network structures. Policy diffusion theory suggests that information and persuasion about innovative policies flows through professional networks of policy decision makers and entrepreneurs (Mintrom & Vergari, 1998; Mooney, 2001; Shipan & Volden, 2008; Volden, 2006). Finally, punctuated equilibrium theory draws attention to the role of multiplex relationships spanning multiple policy, economic, and social arenas as a critical source of policy change (Baumgartner & Jones, 1991; Jones, Sulkin, & Larsen, 2003). We will provide more specific examples of how these theoretical frameworks relate to statistical models of networks later in the article.

The second article in this special issue gives a technical summary of the primary statistical models currently employed in the policy networks literature. Each of the remaining articles presents an application of a statistical model to test theoretical hypotheses in a particular policy area or political system. In addition, each article is positioned within the overall framework presented in this introduction, and concludes with some observations about best practices for using these statistical models to study policy networks. We hope that through richer conceptual and technical discussions (supported by strong empirical contributions), we can trigger further applications of quickly developing network science to the study of policy-relevant phenomena.

Policy Networks as a Meso-Level Concept

Figure 1 clarifies the status of policy network structures as a meso-level variable in a general framework of a policy system that links macrolevel institutional

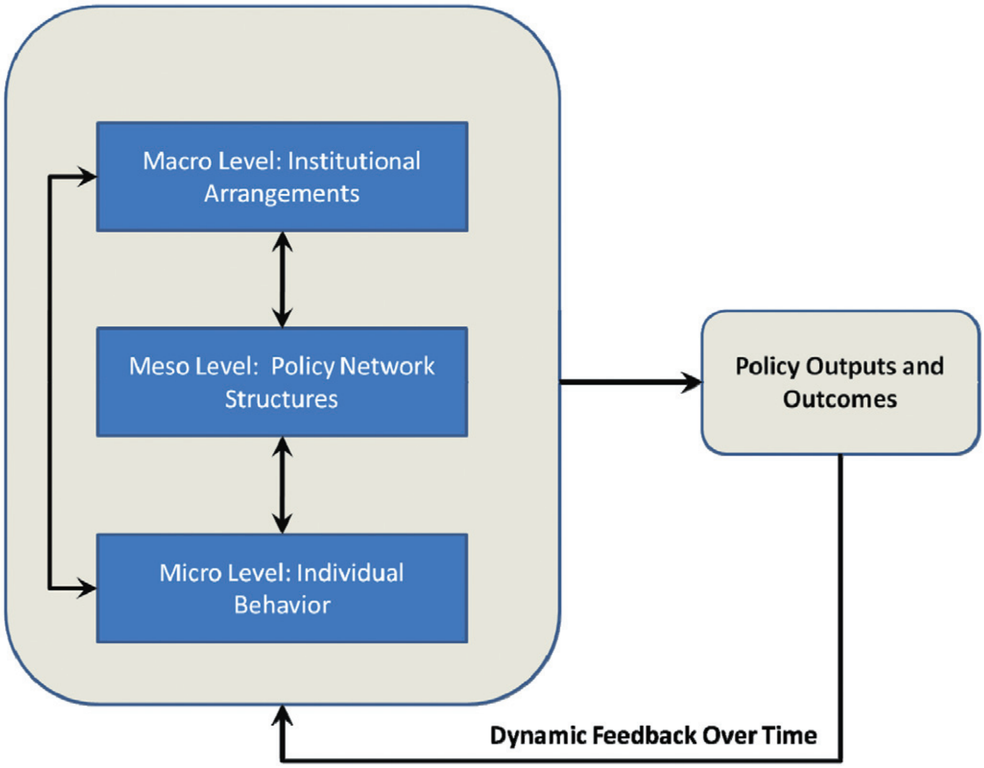

Figure 1. Social Elements of a Policy System.

arrangements to microlevel individual behavior, and overall system properties to policy outputs and outcomes. The traditional social science approach to explain the functioning of a social system is to link macrolevel and microlevel outcomes. For example, economics attempts to understand how individual consumer and producer behavior aggregates to macrolevel outcomes such as inflationary processes, and how macrolevel variables affect individual decisions. However, as Granovetter (1985) famously pointed out, individual actors are embedded in a web of social relationships that affects their economic behavior. Within a market system, for example, buyers and sellers with overlapping long-term relationships are more likely to undertake risky exchanges than less-connected actors.

In traditional policy analysis, macro–micro relationships are analyzed in terms of the feedback between institutional arrangements and individual decisions, the leftmost arrow in Figure 1. Following North (1990), institutional arrangements refers to the set of formal rules and informal norms that both constrain and enable individual behavior. Individuals following rational or other decision-making rules combine with institutional rules to determine policy outputs and outcomes, as indicated by the rightmost arrow in Figure 1. The term "policy" usually refers to intentional changes in these sets of rules, and policy interventions seek to change institutional rules in ways that trickle through the system to eventually affect outputs and outcomes. Policy outputs and outcomes are usually the target of policy evaluation to assess the performance of the system in meeting social goals. Ignoring the mediating role of networks at the very least risks missing an important element linking macro- and microlevel variables in a policy system, and may also lead to incorrect inferences and predictions about policy outcomes.

While cross-sectional studies capture this system at a single point in time, longitudinal studies recognize that the elements of a policy system are connected through dynamic feedbacks over time, indicated by the lowermost arrow. The relationships among these levels of action are also dynamic and reciprocal, as represented by the double-headed arrows connecting networks with both individuals and institutions. A change in institutional rules directly affects network structure by creating new opportunities and incentives for policy interactions. Policy network structures interact with institutional rules to determine the capacity of communities of actors to influence policy decisions, including decisions to change the institutional rules. For example, institutions encourage the formation of coalitions of actors that advocate for their different policy preferences (Sabatier & Jenkins-Smith, 1993).

The lower arrow connecting networks and individuals represents both the *social influence* of networks on individuals and the *selection* by individuals of their network relationships. Policy networks influence individual behavior by structuring the types of resources and opportunities available to individuals, for example, information and trustworthy exchange partners. Networks also provide channels for interpersonal influence, where members of a network shape each other's attitudes and behaviors. Individuals influence policy network structures through choices about network relationships. These choices may reflect a number of different processes driven by different goals, such as the search for similar alters, more access to nonoverlapping resources, bridging between disconnected sections of the network, and so on. Current network studies place the most emphasis on these social influence and network selection effects.

It is crucial to maintain a strong conceptual distinction between institutional rules and network structures. The literature on network governance often uses language that suggests networks are some alternative form of governance to hierarchies or markets. Institutions and networks are not substitutes (Isett, Mergel, LeRoux, Mischen, & Rethemeyer, 2011); they simultaneously and interdependently influence behavior in any policy system and indeed any type of social organization (Feiock & Scholz, 2010). For example, the burgeoning literature on "network management" (Klijn, 2005; Klijn, Steijn, & Edelenbos, 2010; Koppenjan & Klijn, 2004) clearly recognizes the potential symbiotic relationship between institutions and networks in proposals of how to manage the network structure by changing institutional rules.

The conceptual distinction between institutional rules and network structures is also germane to the common conjecture that policy outcomes emerge from informal networks of actors acting "outside" of formal institutions. While it is certainly true that a significant amount of policy interaction occurs outside of a formally written set of legal or administrative rules, these informal interactions are not "rule free." Rather, they are governed by informal norms that are usually not written down, but still shape behavior sometimes in ways contrary to the goals of the formal institutional rules. At the same time, formal rules are not "network free" because they also define a pattern of interaction that influences individual behavior. Even the command-and-control system of the military creates networks of formal interactions, which ironically make even more obvious the importance of informal institutions and networks that exist outside the hierarchical rules; e.g., black markets for military supplies. The assumption of Figure 1 is that both formal rules and informal norms exist simultaneously in a policy system, and both types of institutional arrangements coevolve with the structure of policy networks.

As pointed out by a reviewer, one potential criticism of our conceptual framework is that it is too rigid and does not recognize how networks may operate at multiple levels. To clarify, Figure 1 is a simplified representation of one layer of social action, consisting of a set of institutions, networks, and individuals. For example, Figure 1 could be a set of bureaucratic agency personnel interacting in different ways according to the institutional arrangements of the organization. But there could also be an interorganizational network of agencies, functioning as incorporated actors, operating under a higher-level set of institutions. In other words, individual actors, networks, and institutional arrangements coevolve in layered, complex social systems with dynamic feedbacks over time. It is possible (indeed likely) for an isolated policy system like that represented in Figure 1 to be nested in a broader system of interactions. Regardless of the terminology used to describe these relationships, the key point is that networks mediate the relationship between individual decisions and institutional arrangements, and thus deserve to be studied as a distinct object of social science inquiry. Networks are not equivalent to institutions, or to individual behavior, and the status of networks as a central object of social inquiry is what makes the field of network science exciting, and probably long-enduring.

Statistical models promise to play an important role for quantitatively testing the validity of the primarily qualitative hypotheses developed in the broader literature on network governance and management. Existing qualitative and quantitative empirical work often ignores the complex interdependencies depicted in Figure 1, for instance when network effects are treated as characteristics of an individual in the estimation of general linear models. The statistical models we discuss below, which are applied in the other articles in this issue, directly incorporate assumptions of interdependence, and allow analysts to test propositions about the different causal pathways in Figure 1. However, policy studies to date emphasize application of statistical models to processes of network selection. This not only reflects in part the importance of understanding the emergence of network structure as an important precursor to a broader investigation of the functional role of networks throughout the system, but it also reflects the reality that, at least in the policy sciences, available models (and data) have been primarily directed toward the study of network formation (selection processes). Recent methodological advances have provided some of the tools required to model network influence as well, providing the opportunity for creative advances in understanding the role of networks in policy.

The Evolution of Empirical Analysis of Policy Networks

Policy theory is steeped in the empirical tradition of using descriptive statistics to describe data, and then moving to multivariate models that link dependent to independent variables, and relying on strong assumptions about individual units of analysis and the behavior of error terms. Early approaches to policy network analysis built on this tradition by measuring dependent or independent variables from network data and using them to test expectations about individual-level behavior.

While this approach provided some initial insights, network data often violate the assumptions of traditional multivariate models, and traditional multivariate models are often inadequate for testing hypotheses about more complex network structures. For example, if one actor's performance is affected by its network relationships, then observations of actor performance are not independent, and general linear models that assume independence of observations may produce misleading estimates of the impact of an actor's number of network relationships (for example) on the actor's performance.

Statistical models of networks advance policy research by explicitly incorporating interdependence assumptions among individual observations and by analyzing complex network structures. To date, policy network analysis has mainly employed three types of statistical network methods: quadratic assignment procedures (QAPs), exponential random graph models (ERGMs), and stochastic actor-oriented models (SAOMs). These are summarized in Table 1 and will receive a more in-depth technical introduction in the next article in this volume. The models can make predictions about the formation of relationships between actors, about how relationships affect actor characteristics (including performance), and how network structures interact across different sets of relationships. The parameters of the models represent assumptions about how these various processes operate, and policy theory hypotheses provide expectations about the size and direction of different parameters. Of course, any researcher who wants to actively contribute to the subfield of policy

Table 1. Some Key Analytic Approaches to Networks

Quadratic Assignment Procedure (*QAP*): Tests whether or not two matrices are correlated, either with bivariate or multiple regression measures of association. QAP uses a bootstrapping approach to randomly "relabel" the networks and examine the distribution of network statistics from the resulting population of networks. If the observed correlation or measure of association is outside the 95% confidence interval obtained from the set of bootstrapped networks, the statistic is considered significantly different from zero.
Exponential Random Graph Models (ERGMs): Assumes network ties are formed through a stochastic process, the simplest of which is a Bernoulli process where there is a uniform probability of forming any particular link. More complex models include parameters indicating how the probability of a tie is a function of how that tie will change the frequency of network subgraphs, for example, the number of reciprocal relationships or transitive triads.
Stochastic Actor-Oriented Models (SAOMs): Used for longitudinal network data, and assumes actors are changing network ties in continuous time where the probability of tie formation depends on the state of the network at a particular time. Actors are assumed to choose ties in ways that maximize their utility from the network structure; actors have preferences over their structural position in the network. These models can also assume that actors change their attributes based on network position.

network analysis needs to keep abreast of different types of statistical models that are being developed beyond those presented here.

Early Approaches to Policy Network Analysis

The earliest studies of policy networks focused primarily on descriptions of relationships and their implications for influencing decisions. For example, Blau's (1955) study of government agencies recorded the informal pattern of collaboration within two government agencies, and related such measures as social cohesion to agency performance. Studies describing the structure of policy networks have argued that networks play important roles in national (e.g., Heclo, 1978; Knoke, 1996; Laumann & Knoke, 1987) as well as local policy arenas (Laumann & Pappi, 1976; Scholz & Wang, 2006), and in policy sectors as diverse as health services (Morrissey, Tausig, & Lindsey, 1985; Provan & Milward, 1995), educational performance (Meier & O'Toole, 2002; Mintrom & Vergari, 1998), and environmental issues (Bressers & O'Toole, 1998; Herron, Jenkins-Smith, & Silva, 1999; Jenkins-Smith and St. Clair, 1993; Schneider, Scholz, Lubell, Mindruta, & Edwardsen, 2003).

A second wave of studies utilized regression and other multivariate methods to test specific hypotheses about the influence of network structures on individual behavior. For instance, regression models have found that network measures of degree centrality (Meier & O'Toole, 2002), betweenness centrality, and ego-network density (Scholz, Berardo, & Kile, 2008) influence the performance of schools and of water policy stakeholders, respectively. The focus on individual behavior is derived from the behavioral tradition in social sciences in which explaining variation across individuals is the key intellectual enterprise. These studies demonstrate the relevance of basic network structural concepts for understanding performance in policy networks.

At the same time, the very significance of the network measures in these analyses implies each observed unit is affected by other units of analysis, and such interdependence among observations directly contradicts the regression assumption of independence and uncorrelated errors. For instance, Krackhardt (1988) showed by simulation studies that using standard regression in the presence of even moderate network autocorrelation could result in an increase of effective alpha levels from 20 to 40 percent, and with strong autocorrelation, effective alpha levels could be as high as 60 percent, dramatically above the usual 5 or 10 percent typical in null hypothesis statistical testing. In other words, if the network has anything but a weak effect, statistical inferences about significant regression coefficients are simply not reliable.

This potential problem may not be severe when individual ego networks are sampled and are not interconnected, as in the Meier and O'Toole (2002) study and in national voting studies, but it poses considerable risk of bias in policy studies in which most stakeholders are interconnected with each other. To predict individual-level variables within networks in cross-sectional data, there is a long tradition of social influence models that explicitly take into account aspects of network position and network connections in more principled ways (Daraganova & Robins, forthcoming; Doreian, Teuter, & Wang, 1984; Friedkin, 1998; Leenders, 2002; Robins, Pattison,

& Elliott, 2001; Valente, 1995—for a review of these approaches, see Mason, Conrey, & Smith, 2007). These models explicitly assume that the network is the source of interdependence among individual observations and take the resulting autocorrelations into account. Moreover, different types of associations between network ties and individual variables can be examined, so these methods are more flexible in hypothesis testing than attempting to compensate for autocorrelation effects by constraining regression parameter standard errors.

An additional problem in using network measures for individuals in regression analyses reflects the common problem of multicollinearity when related measures of network position are entered into the model to test alternative hypotheses about expected network effects. For example, measures of network centrality (e.g., degree centrality and betweenness) that are conceptually different (Freeman, 1979) are often highly correlated in practice. Multicollinearity in such cases leads to unstable estimates in which significance levels of related network variables can shift dramatically with the addition or exclusion of a single variable. The problem is exacerbated when theory is not developed enough to determine the appropriate network measure and when regression models are used to explore which measures are most strongly associated with performance. Given the current lack of developed theory about the role of meso-level network concepts in policy studies, regression provides a weak tool for exploring alternative hypotheses about the role of different network measures.

The Advantages and Limitations of Statistical Models

The statistical models listed in Table 1 were developed explicitly to estimate network effects for interdependent observations within a single network, as discussed in the Robins et al. article in this volume. In addition, the models are built on different theoretical assumptions about the relationship between individual behavior and network structure.

QAP (Dekker, Krackhardt, & Snijders, 2007; Krackhardt, 1987) is largely agnostic to any particular relationship between microlevel variables and network structure and any dynamic process that produced the observed networks to be analyzed. Theory is used to guide expectations about what types of associations are expected between different types of network relationships, for example, between a collaboration network and perceptions of trustworthiness and perceived influence. QAP provides a technique for overcoming the assumed independence of observations required for most linear regression models, and can therefore provide unbiased hypothesis tests as described and illustrated in Jasny's article in this volume.

ERGMs (Robins, Snijders, Wang, Handcock, & Pattison, 2007; Snijders, Pattison, Robins, & Handcock, 2006) are models for network structure that assume network relationships emerge from a surrounding neighborhood of other ties. This is a process of endogenous network self-organization where ties come into existence and are maintained or destroyed based on the presence or absence of other ties. In this way, interdependence among ties is explicitly modeled in the form of important network substructure. At the same time, actor attributes may affect the process of tie formation as exogenous predictors of ties, in what can be called a dyadic independent process (Handcock, Hunter, Butts, Goodreau, & Morris, 2008).

ERGM is primarily developed for cross-sectional data (although see Hanneke & Xing [2007] and Desmarais and Cranmer in this issue for discussion of temporal ERGM models), which only captures a snapshot of the network at a particular point in time. However, ERGM does not assume that networks are necessarily static. Rather, the cross-section snapshot represents the accumulation of a dynamic process over time, and theory is used to guide expectations about what types of network structures may have evolved and how they might influence individual behavior. The coefficients estimate the relative frequency in the observed network of each substructure in the model in comparison to a comparable network with randomly assigned ties (or other null model as specified by the researcher). The models analyze which structures in the observed graph are significantly more likely than would occur in the null model, but the position of any given node is subject to stochastic change. For example, networks with a strong tendency toward (degree) centrality will almost certainly have a few very central actors, but which particular actor becomes central at any point in time is a random phenomenon subject to change. When less centrality is observed than expected at random, as in the energy policy networks in Lee, Lee, and Feiock's study (in this volume), the tendency in policy studies to focus on the most central actors without analyzing this base rate information and to explain centrality in terms of the actor's individual attributes is likely to be misleading.

SAOMs, also called stochastic actor-based models (Snijders, 2001; Snijders, van de Bunt, & Steglich, 2010), explicitly consider network structure in the implicit utility function that actors may have, so the individual choices of network partners are assumed to shape network structure. SAOM describes individual or microlevel processes governing network formation, reflecting a tradition shared with network science literature on processes of network formation and networked games in physics (Nowak, 2006) and economics (Jackson, 2008). SAOM is explicitly developed for longitudinal data, and assumes the first observation of the network provides a baseline for analyzing changes in subsequent observations. The baseline network captures the influence of ongoing exogenous forces that structure the network and are not directly analyzed or observed in the model, such as unobserved preexisting legal requirements that structure stakeholder interactions.

SAOM estimates the relative value individuals place on each structure in the model for the periods between observations, when actors are constantly making decisions on how to create, maintain, or destroy connections. SAOMs do not assume that the observed networks represent a stable equilibrium for the estimated motivations but rather model the changes between periods. This feature is particularly important for analyzing networks when motivations and hence the underlying partner selection preferences are not stable, although in such cases, the inferences about processes cannot be generalized beyond the time period of the observations. SAOM can also simultaneously estimate both selection and influence effects. That is, the models can jointly estimate the selection equation to show actor preferences for specific relationship structures and the influence equation to show the impact of network partners and structures on attitudes and performance. For example, an observed correlation between overlapping (transitive) relationships and cooperative behavior can be analyzed into partner selection process in which cooperators only choose other cooperators as partners and the influence process in which actors with overlapping relationships become more cooperative. Each process can generate very different outcomes, so the ability to distinguish between them is critical for testing social capital theory. Similarly, the question of whether more central positions in policy networks enhance performance or whether better-performing agencies become more central requires the capabilities of SAOMs. In short, SAOMs provide the general advantages associated with longitudinal models, at the same time requiring multiple observation periods that can be particularly challenging to obtain in policy studies.

These statistical modeling approaches provide more appropriate tools for understanding the role of networks in policy processes, but there are a number of empirical challenges that require extensions of existing models in order to realize their full potential. Some extensions deserve a higher priority for policy studies than for political science and for other sciences, which is why the field needs to become more directly involved in extending these models. Many of the existing applications focus on selection effects and the dynamics of network structures, while social influence effects and the impact of network position on actor performance will ultimately be more critical for understanding the full role of networks in policy systems. These influence effects are more difficult to estimate in cross-sectional data and are the subject of much current debate (Lyons, 2011). Influence effects can be examined in the SAOM framework as noted above, and there are ERGM versions of influence models for cross-sectional data (autologistic actor attribute models—Daraganova & Robins, forthcoming). The Cranmer and Desmarais contribution in this volume compares the interpretation of SAOM and ERGM-based models of a policy process that include dynamics and influence.

The models also commonly assume that all relevant links and attributes in the network are observed, a standard unlikely to be met by most policy network research, especially those relying on survey data. Systematic methods for handling missing and sampled data using ERGMs have been developed (Handcock & Gile, 2010; Koskinen, Robins, & Pattison, 2010), but more developments are forthcoming. Policy studies require models that can account for both relatively low response rates in surveys and for the ambiguous boundaries of many policy networks. For example, models are needed that can analyze both the relatively stable relationships among central actors and the interaction of more central actors with constantly changing sets of peripheral actors and issues. In addition, alternative observation techniques need to be developed and tested for their effectiveness in correctly observing policy network relationships and their impact on estimation techniques, including techniques for automated collection of policy relationships from archival, media, and Internet texts (e.g., Danowski & Cepela, 2010).

Lastly, more work is needed to build statistical models that explicitly take into account the strength of relationships and the multilevel aspects of networked social systems, including the linking of network processes with institutional variables and ultimately with policy outcomes. To some degree, bipartite network structures can address these issues, but theoretical work in various research domains has called for richer multilevel network conceptualizations (Lazega, Jourda, Mounier, & Stofer, 2008; Moliterno & Mahony, 2011; Pescosolido, 2011). We can look forward to new ERGM- and SAOM-related methods to deal with the strength of relationships and multilevel networks in the future.

Applications of Network Models to Policy Theory

We next describe some examples from several frameworks and theories of the policy process that have used network statistical models to test hypotheses. Each of these theories often develops hypotheses about causal pathways involving networks. Most of the current applications focus on how institutions and individual behavior shapes network formation, and how network structure affects individual behavior, with relatively less attention paid to the interactions between institutional settings and networks. To reiterate, the major ongoing scientific endeavor in the literature is to map the concepts involved in these policy hypotheses into the parameters of specific network models. Each section below first summarizes the key network ideas considered by the relevant theoretical framework, and then describes some of the leading existing applications, or potential applications in cases where research opportunities exist.

Institutional Analysis and Development

The initial endeavor of IAD literature analyzed the impact of alternative institutional structures on the local governance of a common-pool resource (Ostrom, 1990), thus focusing on the macro and micro levels in Figure 1. While the idea of networks and social capital has a long tradition in the IAD framework, more recent studies have applied statistical models of policy networks to a broader range of collection-action settings beyond the simpler systems originally studied by Ostrom. For example, Feiock and Scholz (2010) focus on fragmented policy arenas in which the macroinstitutional structure creates multiple agencies with overlapping authority that could enhance joint outcomes by cooperating and coordinating policies. They argue that networks organized on the basis of informal norms may provide more efficient means of encouraging cooperative, coordinated policy outputs and outcomes than can lead to changes in formal institutions, and they focus in particular on the potential role of voluntary, self-organizing communities.

The IAD assumes that actors are at least boundedly rational and that they seek network relationships in order to improve their individual collective-action outcomes. One critical task is thus to analyze the ability of alternative types of network relationships to enhance outcomes for individuals as well as for the policy arena as a whole. The other is to assess the extent to which actors know about and seek the most effective relationships. To illustrate this task, consider the widely recognized distinction between bridging relationships that span various social boundaries and bonding relationships that increase cohesion within groups. Bonding is associated with social capital and the redundant, overlapping, cohesive, "strong-tie" relationships that can promote the development of trust, common knowledge, credibility of commitments, and maintenance of cooperative norms (Burt, 2005; Coleman, 1988; Putnam, 1993). Bonding relationships support cooperative behavior when the underlying problem imposes considerable risk that one's partner may defect, as when government agencies undertake expensive joint projects that may be represented as prisoner's dilemma games. Bridging relationships or "weak ties" (Granovetter, 1985), on the other hand, support coordination behavior by providing information and other resources more efficiently than bonding relationships when risks are lower. For example, if many local governments are facing the same novel problem and one government finds a solution, other governments can find out about this solution through any set of bridging intermediaries. In such situations, the extra effort required to maintain redundant strong ties would be wasted.

Network analysis provides a tool for translating these general concepts into specific network structures to test hypotheses in statistical models. To test the impact of network structures on performance, for example, Scholz et al. (2008) use a simple measure of how many of an actor's network contacts know each other (egonet density) to represent bonding relationships. They not only find that bonding relationships increase an actor's belief that stakeholders in the policy arena tend to agree with each other, as expected, but also find that bonding relationships do not increase an actor's participation in collaborative policy activities. Collaboration responds instead to bridging relationships as measured by the number of network partners (degree) and the brokerage position of the actor in the network (betweenness centrality), leading the authors to conclude that information available through bridging relationships is more important than credibility from bonding relationships with potential partners in determining participation in collaborative activities.

To test what type of relationships actors seek, Berardo and Scholz (2010) use an SAOM to analyze the evolution of bridging and bonding structures in local water policy arenas. In these models, bonding structures are measured in terms of reciprocity (whether a link from A to B tends to be reciprocated by a link from B to A) and transitivity (whether a link from A to B and B to C tends to create a link from A to C). Bridging structures are measured in terms of the number of actors that your network partners can contact (two-step reach) and a preference for popular partners. The results indicate that actors seek popular partners first and reciprocal relationships second, but do not seek transitive ones or ones with more extensive outreach. They explain how actors create informal policy coordinators by seeking advice from the same source that others seek advice from, and speculate that informal policy coordinators are sought because they provide the most effective means for enhancing policy outcomes.

The two studies taken together suggest that bridging rather than bonding capital may provide both more effective and more sought-after relationships in policy networks than would be expected from the social capital literature. With appropriate data, SAOM analysis could jointly test these interdependent hypotheses, providing a stronger foundation for this extension of the IAD framework. Whether these interpretations of the model will stand the test of time and comparisons across other policy arenas remains to be seen; the results at least illustrate the potential value of statistical analyses of policy networks to provide more detailed testing of bridging and bonding hypotheses.

Advocacy Coalition Framework

The ACF argues that actors with similar social beliefs and policy preferences form political coalitions that compete for influence across multiple policy venues (Sabatier & Jenkins-Smith, 1993). The ACF posits a hierarchical belief system structure, with fundamental core values at the apex and more specific beliefs about attributes of the policy system at the lowest level. How these individual beliefs affect the formation of policy networks and subgroups is one of the key questions for application of statistical models of networks.

Early ACF research empirically analyzed coalitions with qualitative data or descriptive quantitative techniques like cluster analysis of beliefs measured in surveys, but never directly observed relationships between actors (see Jenkins-Smith & Sabatier [1994] for a review). Schlager (1995) criticized these approaches for ignoring the collective-action problems involved with coalition formation, and for assuming rather than testing that similar beliefs produced coordinated action. Statistical models of networks are ideally suited to directly test hypotheses about coalition formation and the evolution of beliefs. Furthermore, network concepts can help extend the basic principles of this framework from the original but empirically limited case of policy arenas with clearly defined competing coalitions to arenas with a wide diversity of relationships ranging from sparse, less structured issue networks to more densely linked policy communities. ACF hypotheses about policy learning and coalition formation may also enrich our understanding of learning and partner selection in networks.

In an early application of network analysis to ACF, Weible and Sabatier (2005) use cluster analysis and multidimensional scaling to identify coalitions based on networks of allies, coordination, and information sharing. They find that ally and coordination networks have a large amount of belief similarity, but information networks have more connections between actors with different beliefs. This suggests that the relationship between beliefs and network formation depends on the type of relationship considered. Descriptive methods of network analysis in this study also provide an important basis for the application of statistical models (see also Weible, 2005).

Henry et al. (2011) contrast similarity of beliefs (homophily) to the role of social capital in knitting together advocacy coalitions, and thus test hypotheses from the ACF and the institutional rational choice perspective. Advocacy coalitions exhibit belief homophily when they are defined by cohesive networks of collaboration among stakeholders with similar belief systems; this is a version of the "birds of a feather flock together" phenomena observed in many types of networks (McPherson, Smith-Lovin, & Cook, 2001). Advocacy coalitions based on social capital are expected to have a high number of reciprocal or transitive relationships (if actor A knows actor B who knows actor C, then actor A knows C). While the social capital hypotheses are anchored in the rational choice paradigm, belief homophily draws on social psychology and considers potentially "irrational" behavior. For example, belief homophily may be strong enough to overcome free-riding problems and effectively drive the formation of collaboration networks. Belief systems may also serve as barriers to policy learning because people discount information that is inconsistent with their policy-core beliefs and overweight consistent information. Hence, subjective beliefs about the causes and consequences of policy problems will be different across advocacy coalitions, and possibly deviate from a more rational and evenhanded analysis of objective data.

These hypotheses are tested with ERGM models that predict the probability of collaborative relationships forming among land-use and transportation policy actors. From Figure 1, these models are about how individual belief systems and preferences for network structure affect the overall process of network formation. Belief homophily was measured using the average distance between two actors' responses to a series of questions about land-use and transportation issues, so that a smaller distance indicated greater similarity in beliefs. A significant negative parameter for this effect was obtained in the model, indicating that collaborative ties are associated with greater similarity in beliefs. Reciprocity and transitivity are directly included in the ERGM model as a structural property of the network. While the parameter for reciprocity was negative, the parameter for transitivity was positive, suggesting that the cohesiveness of coalitions is mainly a function of processes of network closure rather than direct exchange. More in-depth analysis of the data provides evidence that transitivity is supported by policy brokers attempting to strengthen advocacy coalitions. The empirical results suggest that belief homophily and transitivity are complementary social processes that simultaneously influence the cohesiveness of advocacy coalitions. Even when actors with similar belief systems seek to collaborate, network closure driven by policy brokers is needed to reduce free-riding incentives.

Punctuated Equilibrium

The punctuated equilibrium model assumes that incremental policy changes are best explained by the "equilibrium" conditions within a given policy arena, but that major policy changes are best explained by factors exogenous to the arena that dramatically shift the equilibrium (Baumgartner & Jones, 1991, 2009). In particular, actors may participate in multiple policy arenas, expanding conflict and shopping for decisions that shift the status quo in their favor. Thus, to understand the macrolevel changes in institutional arrangements associated with major policy changes, we need to understand how meso-level interrelationships that overlap multiple policy arenas create conditions that cause the collapse of one equilibrium and the emergence of another. In other words, the structure of networks within a policy arena may be sufficient to explain incremental policy changes and implementation results within the arena, but that the "multiplex" structure of networks across multiple arenas may be more important in explaining major policy shifts. Relationships among stakeholders in one policy arena may provide critical pathways for altering stable coalitions in other arenas.

For example, Padgett and Powell (forthcoming) analyze the interactions between social, economic, and political networks that lead to dramatic institutional changes such as the emergence of corporations and partnerships in medieval Tuscany, of joint-stock companies in early Netherlands, and of economic reforms in the communist systems of the former Soviet Union and China. In each case, Padgett and Powell argue that the overlapping roles of prominent individuals across different types of networks provide unique opportunities to forge new institutional relationships that would not have been possible within the existing institutional and relational patterns in each separate network.

Although statistical network models have not been explicitly applied to the punctuated equilibrium framework, ERGMs have been developed for analyzing how actors participate in multiple networks of this type (Pattison & Wasserman, 1999). For instance, Rank, Robins, and Pattison (2010) recently studied the structural logic of intraorganizational collaboration networks of four different types. They determined that the organization's formal structure, while important in dyadic ties, was surprisingly limited compared to friendship ties in influencing the larger scale structures of cooperation.

Ecology of Policy Games

Lubell, Robins, and Wang (2011; see also Lubell et al., 2010) recently revived Norton Long's (1958) "ecology of games" metaphor in a theoretical framework that synthesizes elements of institutional rational choice and punctuated equilibrium. The ecology of games framework emphasizes the critical role of meso-level multiplex relationships for coordinating decision making across multiple macrolevel institutional arrangements that define each policy "game." The ecology of games can be represented as a bipartite network, with different actors linked to different types of institutions. Similar to the idea of venue shopping in the punctuated equilibrium perspective, multiple decision arenas (games) affect the interests of actors in the ecology, so stakeholders have to decide what efforts to put into each potential game and which partners to seek in each of the games. But as with institutional analysis, the ecology of games framework is concerned with how the overall set of institutions and actor decisions combine to solve or not solve underlying collective-action problems.

Lubell et al. (2011) use ERGM models of bipartite networks to show that national and state government actors, along with inclusive collaborative institutions, are central nodes in the ecology of games that serve to coordinate actions. Furthermore, actors are embedded in closed network structures that are analogous to transitive triads in a unipartite network, suggesting that actors tend to participate in similar games to potentially monitor cooperative behavior. A longitudinal study of the ecology of games may be amenable to SAOM analyses of how actors change venues, venue partners, and venue strategies in order to seek desired policy changes. Comparative analysis of the network structure of the ecology of games will provide important insights into how contextual variables like the types of environmental problems and macrolevel political institutions shape the dynamics of the networks among institutions and actors.

The Diffusion of Policy Innovations

The study of the diffusion of policy innovations can benefit from the extensive network diffusion studies of the last few decades (Valente, 1995; see Jackson, 2008, for an outstanding review of models of diffusion in networks). In political science and policy studies, research on policy innovation diffusion dates back to the late 1960s and early 1970s (Gray, 1973; Walker, 1969), but experienced an important resurgence in the 1990s, with Berry and Berry's (1990) explanation of how state governments adopt lotteries. Since then, many scholars have contributed to identifying and describing in detail the functioning of multiple diffusion mechanisms, including but not limited to imitation (Grossback, Nicholson-Crotty, & Peterson, 2004; Shipan & Volden, 2008), learning (Gilardi, 2010; Mooney, 2001; Volden, 2006), geographical proximity (Berry & Berry, 1990), and economic competition (Berry & Baybeck, 2005). Regardless of the political and economic forces driving diffusion, networks play a crucial role because information about the costs and benefits of different policy options flows through them (Berry et al., 2004; Rogers, 1995; Walker, 1969).

In other words, imitation, social learning, economic competition, and other mechanisms that may promote the diffusion of innovative policies require the existence of some sort of networking relationship between the actors that consider adopting that policy (indicated in its simplest form by an obvious flow of information among policymakers). Thus, this type of approach to the study of diffusion of innovations conceives the policy adoption process as one where *social influence* (see Robins et al., this issue) is prevalent, and so the application of some of the statistical models we have presented would be useful in cases where networks were not considered exogenously fixed in the models (a common shortcoming in studies of diffusion of policy innovations).

For instance, SAOMs could be used to study in detail whether certain network configurations are more conducive to the diffusion of innovations than others, and to illustrate the role that certain actors played in those specific configurations. The "connecting" role of policy entrepreneurs in innovation networks, for example (Mintrom, 1997; Mintrom & Vergari, 1998), could be studied in more detail with such an approach.

Additionally, an interesting extension would be to model in detail how links are formed among policymakers and would-be adopters in the network. In addition to *social influence* effects that explain how actors adopt (or do not adopt) policies based on who they know and interact with, there may as well be *selection* effects that lead innovators (or noninnovators) to show a greater tendency to cluster with each other in certain cases. More detailed examinations of the joint occurrence and dynamic relationship of selection and influence effects in policy adoption studies would strengthen current scholarship on policy diffusion, which overall places an important emphasis on the examination of influence effects.

An Overview of Network Analyses in this Volume

The articles in this special issue provide a mixture of instructional advice about how to interpret various network models, applications of innovative network models, and analysis of substantive policy issues. On the instructional front, Robins et al. summarize the assumptions underlying three of the most commonly used network models: quadratic assignment procedure, exponential random graph models, and SAOMs. In order to facilitate the uptake by researchers used to thinking in terms of traditional multivariate models, Desmarais and Cranmer provide a multilevel framework for interpreting ERGM models at the tie, dyad, and node levels. Jasny provides a useful comparison of baseline models for two-mode networks, including permutation tests, conditional uniform random graph tests, and exponential random graphs. Importantly, Jasny provides a more precise definition of what is meant by a "random" graph, which is a term used too loosely throughout applied network literature. Each of these didactic articles also examines a substantive example that illustrates the procedures being discussed.

Several articles use the more standard methods to test hypotheses from policy theories. Lee et al. test hypotheses from institutional analysis about the structure of collaboration networks among local governments in Florida, and estimate ERGM models that show a high level of reciprocity and transitivity in the networks, which is consistent with the creation of bonding ties to solve cooperation problems. Fischer et al. examine the liberalization of the Swiss telecommunication industry between 1997 and 2010, where the sector switch opened up a public monopoly to a wider range of economic competition. Using an SAOM, they show how the collaboration network becomes less dense and fragments into subgroups with similar policy preferences and functional roles in the system.

The remaining articles illustrate the ongoing innovation in statistical models of networks, which is fueled in part not only by the questions being asked by policy sciences, but also by basic methodological advancements. Frank et al. use a statistical model to detect the different groups of actors participating in different climate change planning efforts in the Great Lakes, and show how policy brokers are spanning different periods of time in the evolution of Great Lakes climate policy. Marcum et al. use Bayesian analysis to infer the probable structure of seven different emergency management communication networks, based on potentially error-prone reports from organizational informants. Secondary analysis of the inferred networks demonstrates that several measures of actor centrality are correlated with perceptions of how much command and control is exercised by that particular organization in the context of a specific disaster.

While these articles are good demonstrations of the usefulness of statistical models of networks, they also highlight the fact that most current policy applications of statistical models focus on the structure of the networks, that is, the variables that govern the process of tie formation. Hence, it will be important to continue the collaboration between policy theory and network methods in order to develop statistical models that can illuminate more of the causal pathways in Figure 1.

Conclusion

Network analysis provides an excellent opportunity for refining and testing theories of the policy process. Each of the well-known theoretical frameworks discussed in this article posit some type of network hypothesis about the formation of networks and the effect of networks on individual behavior and policy outcomes. More fundamentally, a network conceptualization provides a framework to understand how the structure of social and policy relationships mediates the causal processes between macrolevel institutions and microlevel behavior. In this sense, the research in policy theory exemplifies the broader trend in all of social sciences where relationships have become a central research topic and network analysis a valuable research tool.

Statistical models of networks explicitly represent core theoretical concepts with specific network metrics. The statistical models are more appropriate than traditional regression approaches because they take into account the necessary interdependence among actors. Instead of viewing this interdependence as an empirical nuisance that needs to be resolved to provide unbiased and efficient estimates, network analysis gives primacy to understanding this interdependence. Without interdependence, there is no reason to study relationships and networks, so to wish away these issues as an empirical nuisance is simply to return to the overly atomistic perspective of individual analysis or the overly aggregated perspective of institutional analysis (Granovetter, 1985).

Statistical models of networks provide a more fundamental basis for inference by specifically taking into account relational dependencies and trying to model the processes that create them. In doing so, statistical models provide a method for examining the relationship between more complex types of network structure and other elements of the policy system. Policy research to date using network analysis has focused primarily on hypotheses of network formation (selection effects), but the models are also capable of analyzing how networks affect individual behavior and policy outcomes (social influence). Future applications of network models need to consider the wider range of causal arrows in Figure 1, as well as more explicitly capture microlevel foundations. Scientific advancement in this field requires further thought about how different network structures relate to theoretical concepts, as well as technical and methodological advancements that improve our ability to accurately estimate key processes. We hope that this special issue will serve as a mile marker and touchstone for future work.

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