2011

# Testing Policy Theory with Statistical Models of Networks

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## Abstract

This paper presents a conceptual framework for clarifying the network hypotheses embedded in policy theories and how they relate to macro-level political outcomes and micro-level 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 policy research are provided and potential extensions are discussed. This paper is forthcoming as the introduction to a special issue of the Policy Studies Journal on statistical models of policy networks.

**Paper Prepared for Political Networks Conference, 2011. Ann Arbor**

**Note to PolNet 2011 Readers: Believe with Caution!**

This paper is in midstream so there are many missing references and sections that need additional work. We would welcome any comments that would help clarify the ideas in the paper, and especially persuade readers about the value of applying statistical models of networks to policy theory. Also, the references to the PSJ special issue might be confusing so feel free to ignore.

This special issue of PSJ provides an overview and examples of how statistical models of policy networks can clarify and test core hypotheses from theories of the policy process. Statistical models of policy networks 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 fields (Lazer cite). 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 and Young 2011) and identify the relationships between network structure, macro-level outcomes, and micro-level behavior (Fowler et al. 2011).

In public policy, Thatcher described how the use of network concepts has developed from rather ambiguous 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 using descriptive methods like centrality metrics, cluster analysis, and regression to statistical models that explicitly include relational variables and model the interdependence among policy actors. The statistical models to analyze policy networks that are discussed and used 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 of empirical research implicit in any study of relationships—the assumed independence among observations. Statistical models like regression, which use individual actors as the unit of analysis, rely on model assumptions that do not recognize the interdependence among actors that is implied by networks. Network models are more in line with modern theoretical perspectives that treat public policy as a complex system that requires 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 macro-level political institutions and outcomes, and micro-level individual behavior (Evans 2001, Rhodes 1997). This framework can be used to conceptualize how micro and macro-level variables influence the structure of networks, how the structure of networks in turn influence micro-level behavior and macro-level outcomes, and how the constellation of macro-level variables, micro-level 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 mechanisms for testing the hypotheses from policy theories. These hypotheses are all related to specific causal pathways in the framework. However, most of the extant research using statistical models focuses on *selection* effects—how individual variables influence network formation—and *social influence* effects—how network variables influence individual behavior and attitudes. Hence, theoretical and methodological advancements are needed to expand the reach of statistical models of networks to more causal processes in policy systems.

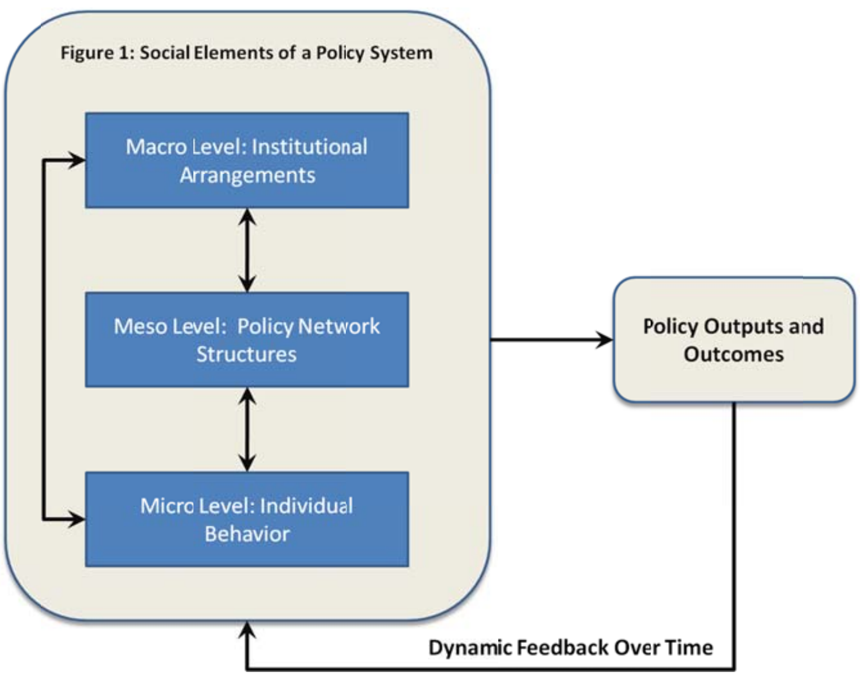
Policy researchers have focused mostly on three types of statistical models of networks: exponential random graph models (ERGM; Feiock et al. 2010, Henry et al. 2010, Thurner and Binder 2008), actor-oriented models (Berardo and Scholz 2010, Andrew 2009, cites), and quadratic assignment procedure (cite). For policy theory, the primary challenge in utilizing these models is to clearly link model parameters to key concepts in policy network hypotheses. 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. The institutional rational choice 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 multi-persom 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 that are appropriate for application of statistical models include institutional rational choice (Ostrom 1999), the Advocacy Coalition Framework (ACF; Sabatier and Jenkins-Smith 1993), policy diffusion (Berry and Berry 1990), and punctuated equilibrium (Baumgartner and Jones 1991). For example, institutional economics posits the importance of embedded and reciprocal relationships for helping solve cooperation problems (Ostrom and Ahn 2003; Brehm and Rahn 1997). 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, that the political power of these advocacy coalitions depends on the cohesiveness of the associated networks among actors. Policy diffusion theory suggests that information and persuasion about innovative polices flows through professional networks of policy decision-makers and entrepreneurs (Mintrom and Vergari 1998; Shipan and Volden 2008, Volden 2006, Mooney 2001). 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 and Jones 1991, Jones, Sulkin, and Larsen 2003). We will provide more specific examples of how these theoretical frameworks relate to statistical models later in the paper.

The first 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 or politics study 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 of policy networks. We hope the combination of conceptual discussion, technical information and practical examples will provide a foundation for further research development.

## Policy Networks as Meso Level Concept

Figure 1 clarifies the status of policy network structures as a meso-level concept in a general framework of a policy system that links macro-level institutional arrangements to micro-level individual behavior, and overall system properties to policy outputs and outcomes. The traditional approach to explain the functioning of a social system is to link macro-level and micro-level outcomes. For example, economics attempts to understand how individual consumer and producer behavior aggregates to macro-level outcomes such as inflationary processes, and how macro-level variables feedback to individual decisions. Similarly, behavioral theories of voting attempt to predict the outcomes of elections based on information processing models of voters.




In policy subsystems, the traditional macro-micro relationships are analyzed in terms of the feedback between institutional arrangements and individual social decisions, the left most arrow in Figure 1. Institutions and individuals then combine to determine policy outputs and outcomes, as indicated by the rightmost arrow from the policy system to outputs and outcomes. Institutional arrangements consist of formal rules and informal norms that both constrain and enable individual behavior (North 1990). 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 determine the performance of the system in meeting social goals, and measures of networks and individual behavior are often used as proxies for policy outcomes when those outcomes are difficult to measure. 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.

Policy network analysis recognizes network structures as a crucial element of the policy system that mediates the relationships between macro-level institutions and micro-level individual behavior, as indicated in Figure 1. As Granovetter noted more generally (1985), individual actors are embedded in a web of relationships that alters their behavior within a given institutional context. 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. Evolutionary game theory has shown that networks structure interactions among actors in a population, which plays a crucial role in determining the dynamics of behavior such as the evolution of cooperation (Nowak 2006). Ignoring the mediating role of networks at the very least risks missing an important element mediating macro and micro-level variables in a policy system, and may also lead to incorrect inferences and predictions about policy outcomes.

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 for policy interactions and new incentives for partner selection. 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. Similarly, the lower arrow connecting networks and individuals represent both the 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. Individuals shape policy network structures through choices about network relationships, which may depend on a number of different processes driven by different goals, such as the search for similar alters, more access to non-overlapping resources, bridging between disconnected sections of the network, etc. Current network studies place the most emphasis on these social influence and network selection effects.

The traditional domain of policy analysis considers the ways in which institutional rules affect individual behavior. For example, institutional arrangements may directly influence individual decisions by punishing or rewarding different behaviors. Network structures can provide similar functions. However, conceptualizing institutions and networks as substitutes (cite problem papers) is too limiting, since institutions and networks simultaneously and interdependently influence behavior in any policy system and indeed any type of social organization. For example, the burgeoning literature on “network management” (Klijn, Steijn and Edelenbos 2010; Klijn 2005; Koppenjan and 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. Statistical models promise to play an important role as the primarily qualitative approaches used to develop these proposals shift to more quantitative methods of testing their validity.

Theories of the policy process analyze the relationships between the elements in the policy system framework as portrayed in Figure 1, but often the role of network structure is not explored in detail or even explicitly. For example, individual behavior is analyzed under different institutional conditions, but only using individual-level variables to explain behavior. Some research does incorporate network effects in regression analyses, but treats them as if they are characteristics of the individual, and effectively ignores the complex interdependencies among individuals that violate the assumptions of most general linear models. The statistical models we discuss below directly incorporate assumptions of interdependence, and allow analysts to test propositions about how network structures affect institutional rules and individual behaviors as well as how institutions and individual attributes affect network structures. Most available studies apply statistical models to processes of network formation, in part because understanding network formation is an important precursor to a broader investigation of the role of networks throughout the system, but also because available models are most developed to study network formation. Recent technological advances have provided some of the tools required to apply network models to other causal pathways in the policy system, providing the opportunity for creative advances in understanding the role of networks in the policy system.

## Testing Policy Theory with Statistical Models of Networks

In this section we briefly introduce the main types of statistical models currently employed in policy network analysis: quadratic assignment procedures (QAP), exponential random graph models (ERGMs), stochastic actor-based models (SABM). These are summarized in Table 1 and will receive a more in-depth technical introduction in the next paper in this volume. These models have in common an effort to account for interdependence. In addition, ERGMs and SABM rely on statistical first principles and assumptions about the probability of observing different configurations of networks. The models can make predictions about the formation of relationships between actors, and how relationships affect actor characteristics, and how network structures are related across different sets of relationships. The parameters of the models define how these various processes operate, and policy theory hypotheses provide expectations about the size and direction of different parameters.

### 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 have described the structure of policy networks and have argued that networks play important roles in central (e.g., Heclo 1978, Knoke et al 1996, Laumann and Knoke 1987) as well as local policy arenas (Laumann and Pappi 1976) for policy arenas as diverse as health services (Morrissey et al 1985, Provan and Milward 1995), educational performance (Meier and O'Toole 2002, Mintrom and Vergari 1998), and environmental issues (Bressers et al. 1995, Schneider et al. 2003, Herron et al. 1999, Jenkins-Smith and Clair 1993, Sabatier et al 1999).

A second wave of studies utilized regression analysis to test specific hypotheses about the influence of network structures on the performance of individuals. For example, a regression model might find that a network measure like degree (Meier and O'toole 2002) or betweenness centrality (Scholz, Berardo and Kile 2008) influences the behavior of an actor. However, the very significance of the network measure suggests that each observed unit is affected by other units of analysis, and such interdependence among observations directly contradicts the regression assumption of uncorrelated errors. This potential problem may not be severe when individual ego networks are sampled that are not interconnected, as in national voting studies, but it poses considerable risk of bias in policy studies in which most stakeholders are interconnected with each other (cite?). There are methods to minimize bias from interdependencies by taking the autocorrelation among observations into account, although their ability to account for the particular types of interdependencies implicitly assumed by the network position measures included in the model are not well known. Statistical models of network explicitly account for this type of interdependency.

A second problem arises due to potential multicollinearity when multiple measures of network position are entered into the model to test alternative hypotheses about expected network effects. For example, while there are several measures of network centrality (e.g;. degree centrality and betweenness) that are conceptually different (Freeman 1979), in practice they are often highly correlated. Multicollinearity in such cases leads to unstable results in which significance levels of other 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 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 poor tool for exploring alternative hypotheses about the role of different network measures.

**The Advantages and Limitations of Statistical Models** All of the statistical models listed in Table 1 explicitly were developed to estimate network effects for interdependent observations within a single network, as discussed in Robins article in this volume.

| **Table 1: Summary of Key Statistical Models of Networks** |
|---|
| *Quadratic Assignment Procedure*: 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 a random network. |
| *Exponential Random Graph Models*: Assume 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 the how that tie will change the frequency of different types of structures within the networks, for example the number of reciprocal relationships or transitive triads. |
| *Stochastic Actor-Based Models*: 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. |

In addition, especially the SABM is built on statistical first principles that elucidate the micro-foundations of individual behavior in relation to network structure. QAP and ERGM are largely descriptive models that fit parameters to data, where policy theory motivates hypotheses about the expected direction, magnitude, and significance of different network parameters. SABM goes further by explicitly considering network structure in the utility function of the actors, and therefore is more transparent about the underlying behavioral assumptions. The broader literature on network science, for example the physics literature on processes of network formation and the networked games literature (Nowak 2006), also have more precise descriptions of the micro-level processes governing network formation. In the tradition of empirical implications of theoretical models, statistical models of networks need further development to more tightly couple the empirical analysis to specific theories of micro-level behavior.

SABM also provide some features not available in ERGMs, which generally reflect the benefits of longitudinal research designs over cross-sectional ones. SABM does not require the assumption of cross-sectional ERGM models that the observed network is in an equilibrium reflecting the desires of the stakeholders, since it only models the changes that occur between observations. SABM controls for exogenously determined links that are not subject to choice by the actor because the first observation of the network provides a baseline for analyzing changes in subsequent observations. Since the first observation will include links reflecting preexisting legal requirements about stakeholder relationships, these requirements will not bias the model of stakeholder choice. Finally, the longitudinal model has the potential to simultaneously estimate the impact of network relationships on performance or other attributes of the actors. 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.

Network models in general still face empirical challenges to realize their full potential. In particular, they commonly assume that all links and attributes in the network are known, a standard unlikely to be met by most network research designs especially those relying on survey data. Systematic methods for handling missing data are being developed for different situations, but more field tests and experiments are required to understand which of these techniques are useful for policy networks as well as how alternative observation techniques affect network data and model estimation based on that data for tests of interest to policy scholars.

## Applications of Network Models to Policy Theory

We next describe some examples from several theories of the policy process that have used network statistical models to test hypotheses. Each of these theories implies something about network structure, and often develops hypotheses about the causal pathways that involve networks. Most of the current applications focus on how institutions and individual behavior influence network formation, and how network structure influences individual behavior (the lower arrow in Figure 1), 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 Rational Choice

The primary endeavor of the institutional rational choice (IRC) literature is analysis of collective-action problems at the level of individuals and government authorities. IRC assumes that actors are at least boundedly rational and that they seek relations with others that may help mitigate collective-action problems. To illustrate the network approach to this issue, consider the widely-recognized distinction between bridging and bonding relationships and the general idea that bridging relationships enhance coordination and information flow while bonding relationships enhance cooperation and trust.

Bonding is associated with redundant, overlapping, cohesive, “strong-tie” relationships that in turn are associated with the development of trust, common norms, credibility of commitments, and maintenance of cooperative relationships (Coleman 1988, Putnam 1993, Burt 2005).

Bonding relationships are sought when the underlying problem imposes considerable risk that the selected partner may defect, for example when government agencies undertake expensive joint projects. Cooperative relationships are supported over time by reciprocal ties (Axelrod), and transitive relationships where a third agency can monitor the behavior of two other partners (Nowak, Coleman 1988). Thus organizational relationships reflect the same principles as individual relationships in which networks of reciprocity and overlapping networks of civic engagement among trusted partners play critical roles in the development of social capital to resolve collective dilemmas (Putnam 1993).

Bridging relationships or “weak ties”, on the other hand, can provide important resources more efficiently than bonding relationships when risks are lower. Bridging relationships are sought when information or resources are available somewhere in the policy arena, and the main problem is to locate them. 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 intermediaries. Similarly, if local governments could take advantage of positive externalities by all adopting similar policies (e.g purchase same equipment to share procurement, maintenance and training costs), then weak ties can serve to coordinate policy choices as long as the policies provide equal payoffs. In such situations, the extra effort required to maintain redundant strong ties would be wasted.

A general policy theory of bridging and bonding relationships would involve hypotheses about both the type of relationships sought by stakeholders and the impact of those relationships on performance and outcomes. For example, when macro-institutions impose prisoners dilemma or public goods games on policy stakeholders, individuals would be expected to seek bonding relationships and bonding relationships in turn will enhance the policy performance of individual actors. On the other hand, bridging relationships may produce better outcomes in some circumstances when information is required, and hence may be sought by stakeholders in those situations. Comparing across systems, networks with different levels of bridging or bonding network structures are expected to perform better under different conditions.

Network analysis provides a tool for translating these general concepts into specific network structures to be included in statistical models. The initial work in this area adopted Burt’s (2005) approach of using regression models to test the impact of network position on individual performance (SBK, B, W, SWB, Shrestha). For example, SBK use a simple measure of bonding social capital in terms of the proportion of the ego’s partners (alters) that are linked to each other, which equals one when all alters are linked and zero when no alters are linked. Using regression analysis where the dependent variable is participation in collaborative policy activities, SBK find no support that bridging ties influence individual behavior. However, there are a wide range of other measures of bridging and bonding social capital that capture different assumption about network processes (Borgatti 2005; Burt) and investigating when these different measures influence behavior is an important empirical task. However, the use of network measures in a traditional regression context is not an effective tool for this task because of the problems of collinearity of measures confounded by the interdependence of observations within a single policy arena.

Statistical models of networks can be used to test specific hypotheses about different measures, although theories about bridging and bonding need to be translated into the slightly different set of concepts and related measures in the ERGM and SABM frameworks. Do stakeholders or policy arenas with higher values of the relevant measure perform better on the relevant outcome measures? Do most stakeholders seek the most productive type of relationships, and are they most prevalent in arenas in which they are expected to be most productive? For example, are agencies that fill structural holes most likely to achieve their policy goals, and do agencies select partners in order to fill structural holes?

Berardo and Scholz (2010) use a SABM to test how different measures of bridging and bonding social capital affect network formation over time in the context of water management. Reciprocity measures the tendency for a directed link from organizations A to B to be reciprocated with a directed link from B to A. In addition, transitivity indicates the tendency for A to have a directed link to C if A is linked to B and B is linked to C. These two measures represent different aspects of bonding relationships. Hypotheses about actor preferences for bonding relationships can be tested by including the specific relationship in the model. Berardo and Scholz found, for example, that the coefficient for reciprocity was significant but the coefficient for transitivity was not. They interpreted this to mean that only reciprocity was sought in the policy arenas they studied, and not transitivity. Thus they inferred that actors were concerned enough about risky exchanges to favor reciprocity, but were not as concerned about risky exchanges for which transitive relationship. Thus the model was sufficiently sensitive to test these slightly different structural representatives of bonding capital.

Perhaps their most important finding was that bridging relationships played the most active role in structuring the network. Actors wanted contacts with popular organizations that already were contacted by other organizations, which is also called preferential attachment. This preference tends to produce highly central actors, which Berardo and Scholz argue represents an emergent central coordination mechanism. Whether these interpretations of the model will stand the test of time and comparisons with other results remains to be seen, but the results at least suggest the promise of utilizing these new families of network models to provide more detailed testing of bridging and bonding hypotheses.

In sum, the longitudinal actor oriented model and related models promise several advantages for testing bridging and bonding hypotheses for posited in the IRC framework. First, they permit and indeed require clear specification of what constitutes a bridging and bonding relationship. Second, they can distinguish which of several possible relationships are critical with less concern about biased estimation that affects regression approaches, although very similar relationships may not be distinguishable in some empirical settings even with these models. Third, they can test for differences in effect for different types of nodes or for different networks within a pooled sample containing networks from multiple independent policy arenas.

**Advocacy Coalition Framework**

The Advocacy Coalition Framework argues that actors with similar social beliefs and policy preferences form political coalitions that compete for influence within multiple policy venues (Sabatier and Jenkins-Smith 1993). 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 and Sabatier 1994 for a review). Schlager (1995) criticized these approaches ignoring the collective-action problems involved with coalition formation, and assuming that similar beliefs always produced coordinated action. Statistical models of networks are ideally suited to directly testing hypotheses about coalition formation. Furthermore, network concepts can help extend the basic principles of this framework from the limiting 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 (cite Heclo, Rhodes?). 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 clustering analysis and multi-dimensional scaling to identify coalitions based on networks of allies, coordination, 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 network relationship considered. The analytical methods also demonstrate the use of more descriptive methods of network analysis, which provide an important basis for the application of statistical models.

Henry et al. (2010) use ERGM models to directly test ACF hypotheses about the formation of policy networks. Using survey data from policy stakeholders in land-use and transportation in California, they hypothesize that advocacy coalitions are defined by cohesive networks of collaboration among stakeholders with similar belief systems. In network terminology, advocacy coalitions will exhibit belief *homophily*, which is a version of the “birds of a feather flock together” phenomena observed in many types of networks (cite).

Henry et al. (2010) contrast belief homophily to the role of social capital in knitting together advocacy coalitions, and thus directly compare hypotheses from institutional rational choice. Advocacy coalitions that are based on social capital are expected to have a high number of reciprocal or transitive relationships (if actor A knows actor B and actor C, then actor B 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 substitute for social capital in 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 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. The parameter for the belief distance variable was negative and statistically greater than zero. 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 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 and the Ecology of Games**

The punctuated equilibrium model assumes that incremental policy changes in a given policy arena are best explained by the “equilibrium” conditions within that arena, but that major policy changes is best explained by factors exogenous to the arena that dramatically shift the equilibrium (Baumgartner and Jones ??). In particular, actors may participate in different policy venues, expanding conflict and shopping for decisions that shift the status quo in their favor. Thus to understand policy change, we need to understand at the systemic level how the interrelationships among policy arenas create conditions that cause the collapse of one equilibrium and the emergence of another.

One implication for policy networks is that 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 arenas may be more important in explaining major policy shifts. That is, the relationships among stakeholders active in multiple policy arenas may provide critical pathways for altering stable coalitions within each arena.

In a similar approach that is more specifically focused on networks, Padgett and Powell (2011?) analyze the interactions between social, economic, and political networks that have lead to dramatic institutional changes including 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 new institutional equilibrium could not be understood if social, economic, and political networks were analyzed separately. It was the overlapping roles of prominent individuals across these networks that 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 yet been applied to the punctuated equilibrium framework, Lubell et al. has revived Norton Long's "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 multiplex relationships spanning multiple policy "games" for coordinating decision-making. 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.

Lubell et al (2011) use ERGM models of bi-partite 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 SABM analysis and show how actors changing venues are attempting to push for policy change.

**The Diffusion of Policy Innovations**

The study of how policy innovations diffuse is also an area of interest for policy scholars that would benefit immensely from a broader use of some of the models that we discuss in this issue. Policy innovation diffusion research dates back to the late 1960s and early 1970s (Walker 1969, Gray 1973), 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 (Shipan and Volden 2008, Grossback, Nicholson-Crotty, and Peterson 2004), learning (Volden 2006, Mooney 2001), geographical proximity (Berry and Berry 1990), and economic competition (Berry and Baybeck 2005). Regardless of the political and economic forces driving diffusion, networks obviously play a crucial role in diffusion because information about the costs and benefits of different policy options flows through them (Berry et al. 2004; Rogers 1995; Walker 1969).

However, despite their importance as conduits for the transmission of resources that enhance the chances of policy diffusion, the networks composed by the policy actors that have a saying in policy adoption and/or consideration have not been analyzed to date with the statistical models we discuss in this issue. This, of course, is not a criticism of the tools used to date by scholars in this tradition, which have provided leverage to sort out the effects that both macro and micro-level variables have on adoption and/or consideration of policies. For instance, Event history analysis (EHA) has been the predominant methodological approach to estimate the probability of policy adoption, where the role of networks as an intervening variable mediating macro and micro-level variables is indicated by the inclusion in models of independent variables such as the decisions of neighboring actors.  Other authors have used methods akin to network models, for example Volden (2006) and Gilardi (2010) use dyadic-based approaches to show how actors "learn" from their peers through the transmission of relevant information.  All this previous work has contributed immensely to our collective knowledge of the conditions that facilitate policy diffusion, and would be certainly enriched by the application of the statistical models we expose in this issue because they would allow for a more comprehensive exploration of how networks interact with macro and micro-level variables that we already know affect policy diffusion.

For this to happen, diffusion networks should be explicitly measured, with the nodes being the (potentially) adopting units, and the links representing the channels of communication between them, through which a variety of resources may flow. For example, many local and state actors gather information about policy options through communication with their colleagues or searching websites of other jurisdictions or government agencies.  Such studies could test core hypotheses from the diffusion literature, for example the idea that policy diffusion is a nation-scale process as opposed to one driven mostly or even solely by geographic proximity at the local or state level (Haider-Markel 2001; Mintrom 2000–see Karch 2007 for a detailed discussion on this subject).

The diffusion of policy innovation is also said to be dependent on the "connecting" role of policy entrepreneurs, who may go beyond geographical proximity to find actors with the knowledge and political resources needed to pursue a particular policy agenda (Mintrom 1997).  While we know some details about the capacity of entrepreneurs to influence policy consideration (Mintrom and Vergari 1998), we still can improve our empirical understanding of how they aid policy diffusion by measuring carefully when and to which potential adopters they relate in networks of diffusion.  For instance, one could measure how potential adopters link to specific entrepreneurs and establish whether sharing access to those entrepreneurs affects the likelihood of adopting common policies. This type of analysis would contribute to dissecting in more detail the real power of entrepreneurs as brokers of information that may create the conditions for the diffusion of policies.

Different types of statistical models could be used to examine these hypotheses. With stochastic actor-oriented or ERGM models, for example, access to given entrepreneurs could be codified as nodal attributes, with the nodes being the potentially adopting units. With cross-sectional QAP procedures one could represent this same type of information with a distance matrix measuring how much potential adopters "share" policy entrepreneurs, which could then be used to explain changes in a different matrix containing data indicating the adoption or not of common policies.

What's important to keep in mind is that the range of questions that could be answered with the statistical models of networks that are discussed and used throughout this issue is substantive and that their answer would surely contribute to a much better developed framework of how policy diffusion works. Some of these questions could be: Does transitivity exist in diffusion? Are races to the bottom triggered by the overlapping nature of information that circulates in tightly-linked clusters or by the ability of governments to gather information through weaker links to more distant parts of the network? Does an innovator only find valuable information in its immediate neighborhood, or does it benefit from a broader search strategy that renders cooperation more likely, even with potential partners who are relatively unknown? We believe policy diffusion scholars stand to gain a great deal from a more extensive use of network analytic techniques to describe the nuanced effects that participation in networks has on the adoption, consideration (and of course, even rejection) of policies.

## Conclusion

Network science and analysis provides an excellent opportunity for refining and testing theories of the policy process. Each of the well-known theoretical frameworks discussed in this paper posit some type of network hypothesis about the formation of networks and the effect of networks on individual behavior and policy outcomes. More fundamentally, network science recognizes that the structure of social and policy relationships mediates the causal processes between macro-level institutions and micro-level behavior. In this sense, the research in policy theory exemplifies the broader trend in all of social sciences where networks have become a central research topic.

Statistical models of networks operationalize the theory by explicitly operationalizing core theoretical concepts with specific network metrics. The statistical models are superior to more traditional regression approaches because they take into account the necessary interdependence among actors. Such interdependence could be considered an empirical nuisance that needs to be handled to provide unbiased and efficient estimates. But statistical models of networks provide a more fundamental basis for inference, including clarifying some of the underlying micro-foundations of network processes. However, much of the policy theory research to date has focused on hypotheses of network formation instead of how networks affect individual behavior and policy outcomes. Future applications of network models must be expanded the wider range of causal arrows in Figure 1, as well as more explicitly capture micro-level foundations.

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