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Ideology, Power, and the Structure of Policy Networks

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This article investigates the role of power and ideology in the endogenous formation of policy networks. According to the Advocacy Coalition Framework (ACF), shared ideology (conceptualized as a system of policy-relevant beliefs and values) is the primary driver of collaboration within policy subsystems. On the other hand, Resource Dependency Theory suggests that power-seeking is an important rationale behind network structure, and that collaborative ties are formed primarily on the basis of perceived influence. Hypotheses are tested using a new method of egocentric network correlation, based on survey data of policy networks in five regional planning subsystems in California (N = 506). Results suggest that ideology is an important force behind network cohesion: Not only do policy elites systematically avoid networking with ideologically dissimilar actors but collaborative ties are also systematically formed among actors with shared beliefs. Power-seeking does not operate on a network-wide scale but may drive network formation among coalitions of ideologically similar agents.

KEY WORDS: policy networks, ideology, belief systems, power, Advocacy Coalition Framework, Resource Dependency Theory, regional planning

Introduction

This article seeks to understand the role of ideology and power-seeking in the formation and persistence of policy networks. Policy networks describe the patterns of interaction among actors working a particular policy system or decision-making process, in reference to a particular type of relationship such as information exchange or political coordination. A growing literature demonstrates the usefulness of networks as an organizing concept to study the policy process (Coleman & Perl, 1999; Klijn, 1996; Koppenjan & Klijn, 2004; Marsh & Smith, 2000; Sikkink, 2009; Tarrow, 2005; Thatcher, 1998). Understanding the structure of networks is also relevant to the praxis of policymaking because policy networks are a key part of the context that shapes the success or failure of governance systems (Dietz & Henry, 2008). For example, network structures that are highly fragmented (characterized by many disconnected groups of actors) or sparse (characterized by few overall relationships) potentially signal entrenched political conflict and noncooperation. Strategies that emphasize "collaborative" approaches to policymaking—such as public participation or stakeholder partnerships—may provide a solution to these dysfunctional structures (Daley, 2007; Leach, Pelkey, & Sabatier, 2002) in part because they

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create networks that incorporate disenfranchised actors in decision making and span traditional cleavages in the policy process.

Despite the promise of collaborative institutions, however, it is still unclear whether these processes actually promote networking and increased levels of collaboration (Leach et al., 2002; Lubell, 2004). The relationships between institutional design and policy networks are muddied by the fact that most networks are shaped by both exogenous constraints as well as endogenous drivers (Podolny & Page, 1998). Policy networks are self-organizing structures that are influenced by formal institutional rules, but are also a central part of the informal institutions that also affect policy outcomes. For example, some agencies are mandated to work together on specific issues, such as when a federal agency must consult with the Fish and Wildlife service when making a decision involving endangered species. However, actors may form network links outside of these mandated relationships in order to better accomplish their policy goals, and even the strength and function of mandated ties may be influenced by endogenous factors that reflect the biases of individual network actors. Thus, understanding how to "create" desirable networks through institutional design also requires an understanding of the endogenous drivers of network structure.

Given the importance of understanding both the formal and informal basis of policymaking, the paucity of research on the endogenous formation of policy networks is surprising. As this literature expands, it is crucial to integrate sound theory into explanations for why policy networks form, grow, and evolve. Without theory to drive inquiry into network structure, the modeling becomes *ad-hoc* and difficult to generalize across different policymaking contexts (Sabatier, 1999; Thatcher, 1998). The work of Weible (2005) and Weible and Sabatier (2005), as well as several articles in this issue (e.g., Ingold, 2011; Matti & Sandström, 2011), are excellent examples of theoretically driven empirical research on the endogenous drivers of policy network structure. These studies test the expectation that networks are ideologically structured—that is, actors with shared belief systems regarding policy issues also tend to share direct collaborative relationships in the network. This suggests that actors' choices of who to network with are driven, at least in part, by ideological similarity.[1]

This article contributes to the growing literature on endogenous network formation by considering the research question, *how do ideological similarity, ideological dissimilarity, and perceptions of power influence policy actors' choices of who to network with?* The dependent variable in this study—collaborative networking choices—is operationalized as the set of trusted collaboration linkages between individual policy actors and specific organizations and stakeholder groups within the policy process. The unit of analysis in this study is the *egocentric network* linking individuals to sets of organizations, measured using a Web-based survey of 506 policy elites across five regional planning efforts in California. These regional planning activities span a wide array of specific professional venues and decision-making activities, including local land use planning as well as more regionally focused transportation planning efforts. In investigating the core research question, this article focuses on clearly stating and testing positive theoretical expectations regarding the endogenous drivers of network structure. However, this research is also problem-oriented in the sense that it contributes to our understanding of how more desirable network structures may be crafted through institutional rules meant to influence endogenous networking choices.

This article builds on prior studies of endogenous network formation in three ways. First, it explicitly looks at asymmetries in the effect of shared versus divergent ideologies on network cohesion. This is important because the theories tested here imply the bases for collaboration may be quite different from the bases of noncollaboration, but previous studies have not emphasized this. This research finds that divergent ideologies are an important predictor of noncollaboration, just as shared ideologies seem to have a positive effect on collaborative ties.

Second, the methods used in this article are more appropriate for policy network data than previously used methods. It develops a new and simple method of egocentric network comparison that allows us to determine, with some confidence, the factors that significantly drive the networking choices of individual policy elites. This method relaxes simplifying assumptions such as independence of network ties or homogenous networking tendencies within organizations.

Third, this article carries on the enterprise of empirically testing theoretically grounded expectations of policy network structure, focusing in particular on the Advocacy Coalition Framework (ACF) and Resource Dependency Theory (RDT). Rather than viewing these strictly as competing perspectives, this article also explores areas of synthesis between the ACF and RDT. RDT is compatible with the theory of coalitions and networking embedded in the ACF, and synthesis can help to strengthen the ACF as a general framework of the policy process. Indeed, the empirical analysis demonstrates that both perspectives explain the cohesion of policy networks—although networking is driven in part by an aversion to ideological rivals (as suggested by the ACF), policy actors tend to form network ties within their ideological groups in a way that maximizes their access to political resources (as suggested by RDT).

Theoretical Explanations of Policy Network Structure

Despite the increased attention to networks in social science research, many theoretical treatments suffer from unclear or ambiguous concepts of what precisely constitutes a network (Marsden, 1990). Without clear conceptualization, it is difficult to judge results and make generalizations regarding the connection between network variables and outcomes of interest. It is useful to note that the general idea of a "network" is just a mathematical abstraction describing the structure of relationships of various types (links) among some set of individual entities (nodes). It is the job of the analyst to attribute theoretically significant meanings to the links and the nodes. Techniques from graph theory and social network analysis (Scott, 2000; Wasserman & Faust, 1994) may then be employed to analyze the structure of these relationships and positions of actors within the network.

What constitutes a policy network? The boundary of a policy network—or the collection of all relevant "nodes"—is the universe of individuals and organizations who actively attempt to influence policy outcomes within a particular policy subsystem. Following Sabatier and Jenkins-Smith (1999), policy subsystems are defined in terms of a policy domain (such as health-care or energy policy) coupled with a specific geographic scope (such as *European* health-care policy or *global* energy policy). These subsystems typically include actors from many different professions, levels of government, and institutional affiliations (Heclo, 1978; Sabatier & Jenkins-Smith, 1999). Once the boundaries of a given policy subsystem are defined, then different types of networks may be defined within the subsystem by focusing on specific types of relationships and in the context of one or more specific programs, decision-making processes, or venues.

This research considers the policy networks that are formed as a result of subsystem actors collaborating with one another in an attempt to translate their goals into policy across the diverse set of processes and venues that exist within U.S. regional planning subsystems. As noted above, the ultimate focus of this article is on the rationales that drive the formation or deletion of collaborative linkages *by the policy actors themselves*, rather than imposed or mandated by external institutions. These voluntary collaborative ties—operationalized here as trusted collaborations—suggest the existence of what the ACF calls "non-trivial degrees of coordination," which are at least one necessary condition for the emergence of advocacy coalitions (Sabatier & Jenkins-Smith, 1999).

Thus, this article is concerned with the endogenous psychological factors behind network formation, which is needed to develop a better understanding of how networks self-organize within policy systems. Regional planning processes are a useful context for studying the endogenous formation of policy networks because, in the U.S. case, there are numerous institutional arrangements that seek to integrate regional planning processes by encouraging the formation of collaborative ties. However, these institutions are often devoid of formal mechanisms of legal enforcement (for example, the federal requirement that U.S. transportation planning be done in consultation with local land use plans) or else participation is explicitly voluntary (such as the participation of local governments within the regional entities known as Councils of Governments, or COGs). Nevertheless, actors must typically coordinate their actions within the regional subsystem to achieve joint benefits or avoid unwanted consequences of uncoordinated planning. Thus, the policy networks that emerge within these regional planning processes should reflect the various endogenous drivers of network structure, and are an illustrative platform for studying the self-organizing tendencies of networks in spite of institutional context.

This research investigates dynamic processes of network formation by positing, first, what certain dynamic processes imply for the structure of policy networks observed at a single point in time. Second, dynamic hypotheses of endogenous network formation are indirectly tested by identifying structural characteristics of cross-sectional networks that are consistent with the hypothesized dynamics. For this reason, the theories to be tested are presented in terms of their implications of network *formation*, whereas the hypotheses to be tested are framed in terms of network *structure*. While many methods are commonly employed to test causal hypotheses of social behavior using cross-sectional data (e.g., linear regression analysis or exponential random graph models), it should be noted that the best these methods can do is identify characteristic signatures of an evolutionary trajectory and (in the case of networks research) cannot necessarily rule out other dynamic pathways to the observed data (Henry, 2007). Indeed, recent networks research shows that the endogenous network formation processes identified by longitudinal models may differ substantially from the processes identified by cross-sectional models in terms of the strength and significance of various drivers (Berardo & Scholz, 2010).

The ACF

The ACF was designed to explain major policy change in policy subsystems dealing with issues that are both ideologically divisive and technically complex (Sabatier & Jenkins-Smith, 1993, 1999; Sabatier & Weible, 2007). A fundamental insight of the ACF is that beliefs relevant to policy are highly resistant to change in the face of contradictory evidence, leading to situations where coalitions of like-minded policy actors entrench themselves in ideological bunkers and talk past one another about policy issues.

The ACF model of the individual explains this resistance to change through a phenomenon known as "biased assimilation," which assumes that policy actors tend to interpret evidence in a way that supports their prior beliefs and values (Innes, 1978; Lord, Ross, & Lepper, 1979; Munro & Ditto, 1997; Munro et al., 2002). According to the ACF, biased assimilation is the most basic engine that drives collaborative networking—and coalition formation—around shared belief systems. This is because policy actors with similar belief systems are likely to have similar interpretations of policy-relevant information, such as the reliability or implications of a particular set of land use forecasts. On the other hand, individuals with dissimilar beliefs are also likely to have dissimilar interpretations of the same piece of information. Divergent interpretations of the same scientific information, or other forms of "objective" evidence that comprise the raw materials of decision making, are assumed to breed distrust among those with competing ideologies (Leach & Sabatier, 2005). As trust is an important prerequisite to political coordination, the result is that collaborative network linkages tend to form primarily among those with similar ideologies because such people are more likely to have shared perceptual filters.

The ACF therefore predicts that the primary determinant of network structure is shared systems of policy-relevant beliefs. This hypothesis is explicitly stated within the ACF (Sabatier & Jenkins-Smith, 1999), and there is some empirical evidence in support of the ACF view of network cohesion (Weible, 2005; Weible & Sabatier, 2005). These studies, however, focus on a single class of beliefs labeled the "policy core." These beliefs are at the heart of the ACF and are defined as basic beliefs and preferred policy strategies concerning a particular, specialized policy area.[2] Policy core beliefs are hypothesized to be especially prone to biased assimilation; however, the biased assimilation phenomenon is not limited to the policy core. Therefore, they are not the only beliefs that matter for network structure. In particular, the ACF suggests two other categories of policy-relevant beliefs, labeled the "deep core" and "secondary aspects," that will also play a role in explaining the formation and persistence of policy networks.[3]

Each type of belief within the hierarchy should have a unique but differential effect on policy network structure. For this reason, a test of the ACF hypothesis that belief systems drive network structure should include all relevant belief types. Some research is beginning to do this—see, for example, Henry, Lubell, and McCoy (2010) and Matti and Sandström (2011). If only subsets of beliefs are considered, scholars are likely to make biased inferences regarding the effect of belief similarity on network structure (the most likely result is that significant effects of beliefs not included in the model will be wrongly attributed to those beliefs that are included in the model). To complicate matters, no comprehensive work has yet been done to reliably and accurately measure the full scope of belief systems in the ACF. This is a particularly difficult measurement challenge because the ACF's definition of a policy-relevant belief is dependent on geographic and substantive context.

One way to deal with this problem is to rely instead on perceived agreement as a metric of overall ideological similarity.[4] Respondent self-reports of agreement not only synthesize the relative effects of different belief types (and interactions between beliefs) into a single measure but do so in a way that does not assume homogeneity across actors in the importance they place on different types of beliefs. Regardless of how internal cognitions are structured, the ACF predicts that perceived agreement is the primary driver of political coordination. Thus, within a policy network, collaborative ties are likely to correspond with perceived agreement relations:

> *ACF Agreement Hypothesis: In policy networks, perceived agreement is positively correlated with collaborative ties.*

In addition to the ACF focus on belief systems as the "glue" of policy networks, the framework also suggests factors that will be negatively associated with collaborative ties. The first is a simple corollary to the view of biased assimilation as the engine of network formation, namely that policy elites will actively avoid networking with those they perceive to be ideologically dissimilar. The common assumption within the ACF literature is that shared and divergent beliefs have continuous and symmetric effect on network structure.[5] However, prior research—most notably the "segregation model" of Thomas Schelling (1969, 1971)—demonstrates that avoidance and attraction are distinct social processes, and that only one (avoidance from dissimilar agents) is needed to explain the emergence of polarized communities (Henry, Pralat, & Zhang, 2011). It is therefore useful to make the flip side of the ACF agreement hypothesis explicit. In particular, the ACF predicts that policy actors will actively avoid forming collaborative ties with those they disagree with. Thus, at a single point in time, disagreement should be a strong predictor of noncollaboration:

> *ACF Disagreement Hypothesis: In policy networks, perceived disagreement is negatively correlated with collaborative ties.*

Resource Dependency Theory and the Role of Perceived Influence

A competing explanation of network structure is provided by RDT. According to this perspective, policy actors are engaged in an ongoing search for the resources they need to carry out their mission and to compete effectively in the policy subsystem (Casciaro & Piskorski, 2005; Pfeffer & Salancik, 1978; Weible, 2005). As no single actor possesses sufficient resources to unilaterally influence policy change, they are dependent upon collaborations with other actors so that resources may be pooled together. Although the application here is to the formation of policy networks, RDT has also been widely applied to the study of strategic interaction between firms (e.g., Boyd, 1990; Das & Teng, 2000).

In a policy context, RDT therefore emphasizes the use of collaborative ties to maximize one's access to political resources. The most efficient way of doing this is to seek out collaborative partners who are influential in the subsystem due to their control over (or access to) critical resources such as information, technology, personnel, or political clout. This yields an RDT hypothesis of endogenous network formation where collaborative ties are formed primarily around perceived influence:

> *RDT Power Hypothesis: In policy networks, perceived influence is positively correlated with collaborative ties.*

This hypothesis of network structure was first formulated and tested by Weible (2005), who found some support for the hypothesis in the case of California Marine Protected Areas. By also testing this hypothesis in the context of regional planning processes, I can determine if the results are robust across different types of policy subsystems. Indeed, it has been noted in the planning literature that networks can be an important mechanism for mobilizing resources and increasing one's political power (Booher & Innes, 2002). Whether collaborative networks are actually used for this purpose, however, they have not been the subject of extensive empirical testing.

A Synthetic Hypothesis: Resource Dependency within Ideologically Similar Groups

It is also possible that ideological similarity and perceived influence interact with each other in a way that causes power-seeking to drive network structure among smaller subgroups of policy actors. For example, suppose that a particular network actor (named "Ego") faces a decision to interact with one of two potential collaborators, *A* or *B*. Ego perceives *A* to be influential and perceives *B* to be ideologically similar. An RDT perspective predicts that Ego will prefer to network with *A*, whereas an ACF perspective predicts that Ego will prefer to network with *B*. In this sense, power-seeking and shared beliefs present competing hypotheses of network structure. On the other hand, supposing that *A* and *B* are both ideologically similar to Ego, will Ego's choice of who to network with be influenced by the perception that *A* is also influential? A final hypothesis of network cohesion synthesizes the ACF and resource-dependency perspectives, and asserts that power-seeking operates under the precondition that agents perceive themselves to be ideologically similar:

> *ACF/RDT Combined Power Hypothesis: Within groups of ideologically similar network actors, perceived influence is positively correlated with collaborative ties.*

Of course, the pattern predicted by this combined hypotheses would also be consistent with a similar dynamic process where the role of the intervening variable is reversed; that is, actors may seek out collaborative ties by searching for ideologically similar actors among groups of actors who are perceived to be influential. For example, D'Souza, Borgs, Chayes, Berger, and Kleinberg (2007) propose a model of network self-organization where actors are subject to a desire to position themselves close to centrally located (powerful) actors, but forming direct ties can be very costly in the sense that one must compete with many other actors in the network who wish to collaborate with the same influential agent. One way to reduce the cost of collaborating with powerful actors is to choose among influential actors who also have shared beliefs, given the additional costs involved in actually maintaining collaborative relationships with ideological competitors.

Still, it is useful to view power-seeking as an effect that is mediated through shared beliefs, rather than the other way around, because this approach helps to address one of the most pointed and lasting criticisms of the ACF. In particular, while ACF literature suggests that shared beliefs are a necessary condition for collaboration, there is still little conclusive evidence that shared beliefs are also a sufficient condition for some groups of actors to overcome collective action problems and emerge as a cohesive advocacy coalition (Schlager, 1995). Other mechanisms must be at work to bind like-minded agents in collaborative relationships, and the ACF/RDT combined power hypothesis provides one candidate explanation.

Research Design: Networks in California Regional Planning

To test these questions, surveys of networking behavior and policy beliefs were conducted among a sample of policy elites in five transportation and land use planning regions of California. "Elites" are defined here as individuals who are both professionally engaged in regional planning processes and who have some degree of specialization in related policy issues. Respondents were sampled from a population including all individuals listed as participants in Environmental Impact Reports according to the California Environmental Quality Act database, as well as all elected and appointed officials from city and county governments within the planning regions. The planning regions studied include the rapidly urbanizing county of Merced; the "ACA" Tri-County region including Alpine, Calaveras, and Amador counties; the Sacramento Area Council of Governments (SACOG) six-county planning region; and the urban southern California regions surrounding Riverside County and San Diego.

The original sample lists included 2,311 individuals across all five regions, with a total of 752 individuals completing the survey (yielding an overall response rate of 33 percent). Potential respondents were initially contacted via email and invited to participate in an online version of the survey, and up to three follow-up emails were sent in case of nonresponse to the initial invitations. At that point, nonrespondents were contacted by telephone and invited to participate in a computer-assisted telephone interview (CATI) version of the survey. These respondents either elected to complete the online survey, participate in the telephone interview, or declined to participate in the study. Of the 752 respondents on whom data were gathered, 506 (67 percent) completed the online survey and 246 (33 percent) completed the telephone interview. However, several of the items used to operationalize the core variables in this article were only measured on the online version of the survey due to the difficulties of measuring many different types of network relations in a telephone interview. Thus, the data used in this article are a subset (approximately two-thirds) of the full sample ($N = 506$; 22 percent of invited respondents).

Network Measurement

The online survey instrument measured several distinct types of network relationships. This was done by first priming respondents to think of a particular type of relationship in the context of regional planning, and then soliciting a list of organizations and stakeholder groups with whom the respondent shares the specified relationship. For example, the network variable *collaboration* was measured by asking respondents, "Please identify organizations/stakeholders that you have collaborated with in the past three years regarding regional land-use issues." A similar method was used to solicit a list of actors that each respondent trusts (network variable *trust*), agrees with (network variable *perceived agreement*), disagrees with (network variable *perceived disagreement*), and believes to be most influential in regional planning (network variable *perceived influence*). In addition, the survey also measured affiliation relationships (i.e., organizations or groups that each respondent represents in the context of regional planning issues) as well as information and advice relationships in three of the five study regions.

These lists were created by providing respondents, after the prompt, with a roster where they indicate organizational actors with which they share the specified relationship. The roster listed a total of 53 organizations and stakeholder categories, including governmental bodies from multiple levels of the federal system, as well as private and nongovernmental groups. Government entities were usually identified by name, and an effort was made on the roster to include all of those organizations that play an important role in regional planning processes. Private and nongovernmental entities were not identified by name, but respondents were asked to identify categories of actors in the private and nongovernmental spheres. For example, these categories included environmental groups, developers/real estate, farming/ranching, media/journalists, and university researchers. Finally, respondents were also given a space to write in organizations or stakeholder groups that were not included in the roster.

Dependent Variable Operationalization: Trusted Collaboration

As stated earlier, the dependent variable in this study is collaborative network relations that are created and maintained by the actors themselves—in other words, network ties that were formed endogenously. While the variable *collaboration* is likely to capture these endogenous network ties, the research design did not explicitly differentiate between voluntary and mandated collaborations. To better distinguish the voluntary aspects of collaboration, a *trusted collaboration* variable is constructed by taking the intersection of the network variables *trust* and *collaboration*. Thus, in order for a respondent to have a trusted collaboration relationship with a particular organization, the respondent must have named the organization as both a collaborator and a trusted partner. This is a more conservative operationalization of the dependent variable than collaboration alone because trust, unlike collaboration, cannot be mandated by institutional rules. In the sections that follow, the term "collaboration" is meant to signify these voluntary, trusted collaboration relationships.

Independent Variable Operationalization: Power and Ideological Similarity

The independent variables *perceived agreement*, *perceived disagreement*, and *perceived influence* were measured directly on the survey, and thus provide at least one operationalization of the independent variables considered in this article. In order to test the ACF/RDT combined power hypothesis, a new variable called *agreement and influence* is constructed by taking the intersection of *perceived agreement* and *perceived influence* variables. As with trusted collaboration, a respondent is assumed to have an agreement and influence relationship with an organization if the organization was named on both the "agreement" and "influence" network lists.

In addition to the use of the *perceived influence* variable as a measure of power, another measure of power is also considered based on the position of organizations within the full network. The variable *betweenness* captures the betweenness centrality—or the number of shortest paths between network actors that pass through a given organization—of the actors within each respondent's neighborhood. Betweenness centrality is offered as a complementary measure of power because it tends to capture the organizations' actual (rather than perceived) access to resources within the network (Freeman, 1979). In particular, high scores on this centrality measure suggest that an organization tends to occupy a position that spans fragmentations (or "structural holes") in the network, and can therefore mediate—and capitalize upon—flows of information or other resources between disconnected actors (Burt, 1992).

In order to measure the betweenness of organizations and groups within each respondent's egocentric network, a unipartite network (linking organizations to other organizations) must be estimated from the survey data. This may be done by invoking the assumption that an organization shares the same network structure as respondents affiliated with the organization. In particular, the "affiliation" survey item is used to attach individual respondents to the organizations they represent, and a directed link from organization *A* to organization *B* is assumed to exist if at least one respondent affiliated with *A* named *B* as a collaborator. The actual betweenness score for an organization, say organization *C*, then becomes the number of all directed geodesic (shortest-length) paths between organizations that pass through *C*.[6]

To construct the variable *betweenness* as an egocentric network variable from these individual centrality scores (to allow for the network correlations described next), a weighted network is constructed linking each respondent to all organizations in their neighborhood. In this network, the strength of each respondent-to-organization tie is equal to the corresponding organizations' betweenness measure. The variable *agreement and betweenness* is constructed by multiplying each of these tie values by zero if the corresponding organization was not named as ideologically similar in the "agreement" survey item; otherwise, the tie strength is multiplied by one. Thus, the *agreement and betweenness* measure assumes that the power (as measured by betweenness centrality) is zero for all organizations not ideologically similar to Ego.

Characteristics of Measured Networks

Table 1 presents a summary of the frequency with which trusted collaboration ties overlap with linkages in the agreement, disagreement, influence, and combined agreement and influence networks. For each of the relationships hypothesized in this article to explain trusted collaboration, entries in the table represent the number of dyads (respondent and organization pairs) where the "explanatory" relationship is observed and a trusted collaboration tie either was or was not observed. For example, the survey measured a total of 1,558 disagreement relationships. Of these 1,558 dyads where a disagreement relationship was measured, 33 of the dyads also contained a trusted collaboration link. Trusted collaboration was not observed in 1,525 of these respondent/organization dyads.

These descriptive measures provide some initial evidence that disagreement has a negative effect on trusted collaboration, and that the intersection of agreement and influence has a positive effect on trusted collaboration. This is, however, a very simple form of network comparison and insufficient to test the above hypotheses. A method is needed to rigorously compare the structures of egocentric networks measured in this study.

Table 1. Overlap between Trusted Collaboration and Explanatory Network Types

	Agreement (2,500 Dyads)	Disagreement (1,558 Dyads)	Influence (3,856 Dyads)	Agreement & Influence (583 Dyads)
Frequency overlap with collaborative tie:	586 (23%)	33 (2%)	355 (9%)	237 (41%)
Frequency no overlap with collaborative tie:	1,914 (77%)	1,525 (98%)	3,501 (91%)	346 (59%)

Hypothesis Testing Approach: Egocentric Network Comparison

Hypotheses of network structure are tested by focusing on egocentric networks, which describe the set of relationships between a particular respondent (named "Ego") and organizations in the respondent's network neighborhood. The basic approach for hypothesis testing is to compare the similarity of a given respondent's various egocentric networks. For example, a high degree of overlap between perceived influence and trusted collaboration networks suggests that the respondent tends to collaborate with those they perceive to be influential. On the other hand, a low degree of overlap between these two networks suggests that perceived influence is either a negative or insignificant predictor of trusted collaboration. For each respondent, the task is to examine the influences on collaborative relationships by comparing the relevant pairs of egocentric networks.

The patterns that emerge across respondents provide evidence used to assess the above hypotheses of network structure. For example, the ACF agreement hypothesis implies that the average respondent will have a strong, positive correlation across agreement and trusted collaboration. In choosing a method for network comparison, it is important to deal with two unique methodological challenges: the nonindependence of network links and the proper identification of each respondent's network boundary. The following sections discuss these challenges and how they are dealt with by the network comparison technique employed in this article.

Methodological Challenge #1: Assessing Significance of Correlations

The formation of ties within a single network is well-known to be an interdependent process; this makes many commonly employed statistical techniques (in particular, techniques that assume independent and individually distributed observations) inappropriate for the analysis of policy networks. Statistical comparisons of network structure must employ methods that are able to assess the strength and significance of correlations without relying on unrealistic assumptions regarding independence or the underlying probability of link formation.

Suppose, for example, that we empirically observe the two egocentric networks depicted in Figure 1. In these networks, Ego is surrounded by 11 organizations that

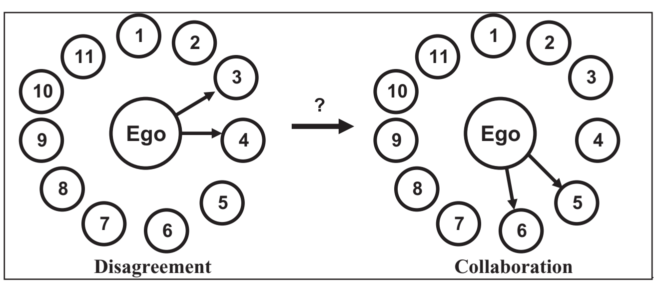

Figure 1. Schematic of the Network Correlation Problem.

may potentially be named as ideologically dissimilar (disagreement, left panel) and as trusted collaborators (collaboration, right panel). It turns out that Ego disagrees with organizations 3 and 4, and collaborates with organizations 5 and 6. One way to quantify the similarity in structure is to attribute a value of one to each dyad in which a link is observed, and a value of zero to each dyad where no link is observed. Then a Pearson product-moment correlation may be performed on the corresponding dyad values across networks. The resultant statistic is known as graph correlation (Butts & Carley, 2001).

These network structures appear to be negatively correlated because Ego does not collaborate with those organizations she disagrees with. This is supported by the observed graph correlation: –0.22 in this example. But does this indicate a *significant* negative correlation between the two networks? Not necessarily. It may be that Ego faces time constraints that do not allow her to collaborate with more than a couple of partners. Thus, the fact that she collaborates with organizations 5 and 6 may make it very difficult for her to also collaborate with 3 and 4. In fact, if Ego were to choose any two collaborators at random then the likelihood that she will not choose 3 or 4 is quite high (also yielding a graph correlation of –0.22).

To test for significance, it is necessary to compare the observed graph correlation with the correlation that would be expected if disagreement (or any other explanatory network variable) has nothing to do with collaboration. Two assumptions are needed. First, the structure of the explanatory network (disagreement in Figure 1) is fixed, and second, that the number of links in the response network (trusted collaboration in Figure 1) are fixed. Next, the links in the response network are randomly permuted. If the random reassignment of links in the response network tends to result in less intense correlations than those observed in the measured networks, then we may conclude that the observed graph correlation is statistically significant.

The convention used here is to determine correlations "significant" when a random permutation of links reveals a stronger correlation no more than 5 percent of the time. This is determined computationally by permuting links 1,000 times and estimating the probability of finding stronger correlations based on the emerging distribution of correlation statistics.[7] Thus, a significant *negative* correlation exists when a random assignment of links leads to a smaller correlation statistic with calculated probability less than or equal to 0.05. Similarly, a significant *positive* correlation exists when a random assignment of links leads to a larger correlation statistic with probability less than 0.05.

Although the statistics relating networks are simple correlations, this method of assessing statistical significance does imply a direction of causality. This is because the method fixes the structure of the explanatory network and randomly permutes links in the response network (trusted collaboration). The null hypothesis is: *Given the structure of the explanatory network, and given the number of linkages in the response network, alters in the response network were chosen at random*. This method is closely related to quadratic assignment procedure (QAP) developed by Krackhardt (1987)—although QAP is normally applied to the analysis of unipartite network structures, the simulation methods and null hypothesis (that alters are chosen at random controlling for underlying structure) are essentially the same.

Not all egocentric network structures may be correlated in this fashion. As this method relies on calculating correlation statistics between the fixed network and permutations of the response network, *the variance of link values must be nonzero in both the explanatory and response networks*. This is because the correlation between two vectors of data is always zero when the variance of either vector is zero; in this case, there would be an unrealistic (zero) probability that a random draw would yield anything other than the observed correlation statistic. The implications of this requirement are that valid correlations may not be calculated in instances where (i) the respondent named no partners in either network item being correlated (due either to the actual lack of relationships or due to missing data); or (ii) in either network, the respondent shares a link of equal weight with all organizations (i.e., the actor agrees with all possible partners, or perceives all other actors to be influential).

Methodological Challenge #2: Identifying the Boundaries of Egocentric Networks

The second challenge is to clearly delineate the boundaries of each respondent's egocentric network. That is, for each respondent, which organizations are to be included within the boundaries of the network and which organizations are to be excluded? Addressing this boundary problem is important because an accurate comparison of network structures requires differentiation between nodes that the respondent has no knowledge of and nodes that the respondent chooses not to name. These are fundamentally different relationships, and the inclusion of "no knowledge" relationships in a network comparison along with "choose not to name" relationships will bias correlation results.

This problem is addressed by including in each respondent's network all of the organizations or groups that were named by the respondent on any network battery. This is a signal that the respondent in question is familiar with all of the nodes to be included in the neighborhood—a reasonable assumption because the survey measured both positive relationships, such as agreement, and negative relationships, such as disagreement.

This method of defining reduced egocentric networks is useful because correlations on full egocentric networks tend to be so large (and consistently positive) that it is difficult to discern any meaningful patterns from the data. Omitting organizations outside of a respondent's network boundary always yields graph correlation statistics that are less than or equal to the graph correlation of "full" networks that include all organizations. We therefore begin to see a substantial number of negative correlations and more modest positive correlations between reduced collaboration and explanatory networks. A corollary is that using reduced networks also tends to be a more conservative method of analysis because many correlations that are statistically significant using full networks are close to zero and insignificant when the reduced networks are considered.

Results

Table 2 summarizes the significant correlation statistics observed between trusted collaboration and the six types of explanatory networks. The percentage of the sample yielding valid correlations is reported in the left-most column, and ranges from 25 (in the case of agreement and influence) to 43 percent (in the case of betweenness). The large number of invalid correlations is likely the result of many respondents naming all of the organizations in their neighborhood as trusted collaborators, which (as noted above) does not allow for valid inferences regarding significance. Of these valid correlations, only significant correlations are reported. The percentages of correlations that are also significant vary widely across explanatory networks and yield some insights as to the strength of the corresponding effects within the population. For example, disagreement is almost always (96 percent of the time) significantly correlated with trusted collaboration, and when these correlations are significant, they are almost always negative (see right-most columns of Table 2). On the other hand, betweenness is less frequently related to trusted collaboration in a significant way, and when it is, the correlation is (on average) close to zero (mean significant correlation = 0.15).

Table 2 also presents the results of two types of hypothesis tests on these significant network correlations. First, a t-test is performed on the sample means of significant correlations to test the null hypothesis that the true mean is zero (one-tailed tests). Sample standard deviations are reported in parentheses. While this is a common analytic approach, one must also be aware that the t-test invokes certain contestable assumptions about the data.[8] For this reason, the t-test is coupled with a

Table 2. Summary of Correlations between Egocentric Explanatory Networks and Trusted Collaboration

Explanatory Network	Valid Correlations (% of Sample)	Significant Correlations (% of Valid)	T-Test	Sign Test	
			Mean Correlation (Std. Deviation)	Number of Negative Correlations	Number of Positive Correlations
Agreement:	199 (39%)	177 (89%)	0.37*** (0.31)	26	151***
Disagreement:	170 (34%)	163 (96%)	–0.18*** (0.22)	154***	9
Influence:	209 (41%)	158 (76%)	–0.02 (0.38)	99**	59
Agreement & influence:	127 (25%)	117 (92%)	0.36*** (0.37)	33	84***
Betweenness:	220 (43%)	43 (20%)	0.15* (0.41)	22	21
Agreement & betweenness:	191 (38%)	119 (62%)	0.38* (0.36)	35	84***

Note: Only statistically significant correlations are included in calculations. T-tests test the null hypothesis that mean correlation is zero (one-tailed tests). Sign tests test the null hypothesis that the median correlation is zero; stars for the sign test indicate p-values for one-tailed tests of the alternate hypotheses that the median correlation is negative (left column) or positive (right column). $*p < 0.05$, $**p < 0.01$, $***p < 0.001$.

nonparametric sign test, which tests the hypothesis that the median correlation is zero in the population (i.e., that the true number of positive correlations is equal to the true number of negative correlations). In Table 2, results of one-tailed tests are presented by indicating significance on the number of negative correlations (if the median is significantly negative), or on the number of positive correlations (if the median is significantly positive). It should be noted that the t-test and the sign test disagree in two instances. Given the assumptions needed to support the t-test, results from the sign test should be given precedence.

The Effect of Ideology on Network Cohesion

These data provide support for the ACF agreement hypothesis. The correlations across agreement and trusted collaboration networks are frequently significant, and tend to be both positive and large in absolute value as indicated by the relatively high mean correlation. There is also strong support for the ACF disagreement hypothesis. Disagreement seems to be an important factor in collaboration network structure, as evidenced by the high proportion of significant correlations, as well as the strongly significant negative valence of these correlations.

Figure 2 provides an alternative visualization of these results using a box-and-whiskers plot to show the distribution of significant correlations between trusted collaboration and perceived agreement and disagreement. While both distributions are well-concentrated in their expected regions (i.e., above zero for agreement and below zero for disagreement), the perceived agreement correlations tend to span a larger range and are more often negative than the perceived disagreement correlations are positive. Thus, there seems to be more variance in the strength of the agreement effect on collaboration (see also Table 2), whereas the effect of disagreement on noncollaboration seems to be highly consistent across individuals. This may

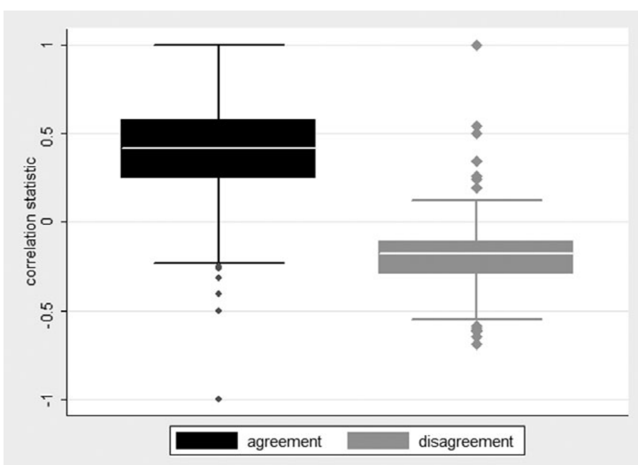

Figure 2. Distribution of Statistically Significant Correlations between Agreement/Disagreement and Trusted Collaboration Networks.

suggest that the factors driving collaboration through agreement are more context-dependent than the factors driving noncollaboration through disagreement. This result is consistent with the notion that mistrust and noncollaboration are driven by biased assimilation, a fundamental social phenomena shared by all actors, whereas the rationale for collaboration is driven by many possible contextual factors.

The Effect of Power on Network Cohesion

Correlations of trusted collaboration networks with perceived influence and betweenness networks lend some weak support for the RDT power hypothesis. Interestingly, the testing of this hypothesis is the only place where the t-test and sign test disagree, and the findings across methods are reversed for the two operationalizations of power. Combined with the observation that betweenness is seldom correlated significantly with collaboration, this suggests that power-seeking explanations of collaboration lend little insight into the structure of policy networks on a network-wide scale. In other words, influence is not likely to drive the formation of ties by itself but is rather likely to be mediated through other factors.

On the other hand, these results lend support for the ACF/RDT combined power hypothesis and suggest that perceived influence provides a strong basis for collaboration among ideologically similar network actors. Figures 3 and 4 visualize the distribution of significant correlations used to test the power hypotheses; of particular note is that the positive effect of power conditional on ideological similarity (i.e., agreement and power) is robust across both the perceptual (perceived influence) and structural (betweenness) definitions of power. These results demonstrate a striking difference between the two concepts of power-seeking: Although it is a weak explanation of network structure on a global scale, it can be a strong predictor of network cohesion locally, among ideological allies.

Figure 3. Distribution of Statistically Significant Correlations between Perceived Influence and Trusted Collaboration Networks.

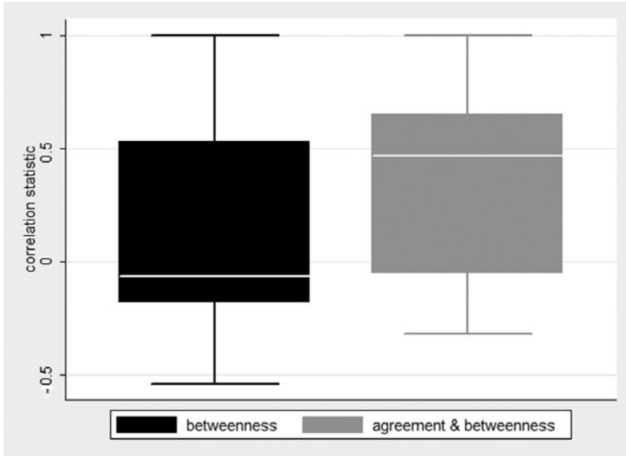

Figure 4. Distribution of Statistically Significant Correlations between Betweenness and Trusted Collaboration Networks.

These results also imply two other possibilities. First, the effect of purely multiplicative interactions could combine to influence collaboration. This is unlikely, however, because perceived influence and betweenness by themselves have very weak positive correlations with collaboration networks. Second, and as noted previously, it may be that these results signal the formation of collaborative ties among like-minded actors conditional on those actors viewing each other as influential. This possibility is a subtle twist on the combined ACF/RDT power hypothesis stated earlier, and would indicate that perceived power is used as a primary filter on network ties while shared beliefs are used as a secondary filter. This research design cannot rule out either possibility although the relative strength of the correlations between influence and collaboration (close to zero) and agreement and collaboration (consistently positive) suggests that actors are seeking powerful collaborators among ideological allies.

Conclusion

Understanding the endogenous drivers of network structure is essential to explaining the emergence of certain policy networks under a given set of institutional constraints. This article investigates two fundamental and complementary explanations: that policy actors form collaborative networks on the basis of ideology, and that policy actors are primarily interested in maximizing their access to political resources.

The data from this study support the ACF view of network formation insofar as systematic cognitive biases seem to play a significant role in driving the structure of policy networks. The positive effects of shared ideology (agreement) and the negative effects of divergent ideologies (disagreement) appear to be closely symmetric. However, theoretically, these should be treated as distinct effects, and the data suggest some slight nuances in how aversion versus attraction processes operate in the self-organization of policy networks. The results of this study are consistent with empirical work on biased assimilation—actors with very different belief systems tend to perceive evidence differently, which breeds distrust and noncollaboration. However, it is also useful to consider the precise mechanisms that drive actors together, which perhaps may be largely dependent on individual proclivities or institutional contexts.

The finding that ideology is a strong polarizing force suggests that shared threats may be an important driver of network structure, while the positive effect of shared ideologies generally supports the ACF view that actors form networks to translate shared beliefs into policy. However, this does not directly address the question of whether shared belief systems are a sufficient condition for network formation. RDT offers one complementary answer; that networks are held together by power-seeking relationships that better enable individual network actors to affect policy change. However, ideological similarity appears to be a necessary condition for power-seeking mechanisms to drive the cohesion of policy networks, thus explaining the emergence of "advocacy coalitions" characterized by shared systems of policy-relevant beliefs.

These results underscore the need to temper expectations of rational networking behavior with the expectation that policy actors are also prone to systematic cognitive bias. The ACF disagreement hypothesis implies that differences in certain types of beliefs will have a major influence on network structure. Understanding which types of beliefs are more or less prone to biased assimilation is an important area for future research because an important design question for collaborative institutions to answer is what to discuss (and what not to discuss) in an open forum.

Another important direction for future work is to integrate the nascent theories of endogenous network formation considered here with data on the exogenous, institutional drivers of collaboration. Future work should focus on careful measurement of the institutional drivers of collaboration, perhaps by applying perspectives such as the Institutional Analysis and Development framework (Ostrom, 1999, 2005) to better understand how rules influence the structure of policy networks. Combined with well-developed theories of endogenous network formation, this will allow us to better understand how individual networking behavior and institutional rules interact to produce observed network structures.

This article applies a new technique of egocentric network correlation to test the core hypotheses. This method represents a step forward in the analysis of policy networks because it does not rely on simplifying assumptions regarding independence of network ties or homogeneity of networking behavior within organizations. However, the trade-off is that the methodology is simple and limited to univariate hypotheses testing. Future applications of this method should consider expanding the analysis to include multiple independent variables to deal with potential confounding effects on network cohesion. This article provides a starting point by considering the effect of overlapping network structures in a test of the ACF/RDT combined power hypothesis.

Finally, it should be noted that this study makes strong theory-based assumptions regarding directions of causality. For example, it is possible that the ideological structure of collaboration networks is a consequence of regional planning institutions providing a forum for disparate groups to interact. Learning and agreement occurs more easily when these opportunities for repeated interaction exist, even in the face of conflicting belief systems (Ostrom, 2005). Thus, if collaboration is causally prior, then over time networked actors will learn and arrive at consensus in their policy-relevant beliefs. The emergent network structures will be consistent with those predicted by the ACF, where network relationships are highly correlated with shared belief systems. Future work should emphasize the collection of longitudinal or time-series network data, coupled with analytic techniques that are appropriate for modeling these dynamic processes, such as the network models described by Snijders (2005).

We need better theories of the policy process (Sabatier, 1999) and the role of policy networks within these processes (Thatcher, 1998). Given the potential of institutions to push networks toward desirable structures, it is crucial to develop a better understanding of how networks self-organize. To do this, we need to employ multiple theoretical frameworks and develop testable models from these frameworks. This also requires dealing with several key methodological challenges in the analysis of network structure. This article takes a further step toward developing a theoretically based model of network cohesion using appropriate methodologies, and provides a basis for further work investigating the role of ideology, power, and other factors in driving the formation of policy networks in various institutional contexts.

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Notes

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1. This article uses the term "ideology" to capture the full range of values, beliefs, perceptions, and other types of cognitions that play an important role in policy debates.
2. In the ACF, beliefs are classified primarily as a function of their substantive and geographic scope. Policy core beliefs are those which have broad application to the issue area under consideration but that are normally not relevant to other issue areas. Examples of policy core beliefs in land use and transportation planning arenas are those beliefs embedded within the Smart Growth movement, such as "building more highways creates urban sprawl" or "light rail investments will increase the density of development" (Handy, 2005).
3. The "deep core" consists of broad normative beliefs that act as a general guide for political behavior (Sabatier & Jenkins-Smith, 1999). Examples include one's position on a classic liberal versus conservative spectrum, or the trade-offs that one is willing to make between environmental protection and economic development. While such beliefs are often relevant to planning issues, they can be applied to a wide range of other policy arenas. "Secondary aspects" include beliefs and policy preferences that have a very narrow geographic and substantive scope. Examples in planning may include beliefs

such as "parking is a serious problem *on my street*" and "stricter parking laws are needed *in my neighborhood*."

4. Focusing on the overall effect of ideological similarity sidesteps the problems that potentially arise from having incomplete measures of beliefs systems, and uncertain causal relationships between specific types of beliefs, biased assimilation, and networking.
5. For example, suppose that two agents within a network have some baseline probability p of forming a collaborative tie with one another. If these two agents experience one "unit" of ideological convergence, then the ACF predicts that the probability of link formation between the two agents will increase by some fixed amount x, to $p + x$. If the effect of ideological similarity and dissimilarity is symmetric, and if the same two agents instead experience one unit of ideological divergence, then the probability they will form a collaborative tie should decrease by x, to $p - x$. If the effect is asymmetric, then the probability may be greater or smaller than $p - x$.
6. The results presented in this article are roughly the same when undirected betweenness scores are used.
7. Analyses were performed in the R statistical package (R Development Core Team, 2008) using code written by the author to simulate random permutations of networks and to estimate the underlying distributions of graph correlation statistics.
8. As the sample sizes here are relatively small, one must assume that network correlations are normally distributed in the population.

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