# Social Networks and the Challenge of Learning for Sustainability: The Case of Regional Planning

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**Abstract:**

Environmental problems usually involve emerging and uncertain information that must be successfully assimilated ("learned") by decision-making communities to have a consequent impact on policy. Despite the importance of successful learning, it tends to be very difficult to alter the beliefs of stakeholders involved in technically complex and ideologically divisive policy arenas. One theory of the policy process, called the Advocacy Coalition Framework (ACF), offers a potential explanation that focuses on the interactions between beliefs, bias, and the emergence of social networks. In particular, the ACF hypothesizes that cognitive biases tend to polarize policy-relevant belief systems. The result is that policy network structures tend to coalesce and self-reinforce around shared ideologies, exacerbating political conflict and making the efficient use of scientific information difficult. Collaborative institutions are hypothesized to attenuate this effect, by providing a forum for meaningful deliberation across competing ideologies and interests. Empirical data used in testing these hypotheses are collected, via online survey, from policy elites in five regional land use and transportation planning processes in California (N = 752). Hypotheses are tested using a variety of network analytic techniques to identify signatures of network growth processes as a result of biased learning. The results lend some support for the ACF view of policy learning, but also suggest that the role of bias is highly context dependent. Future work in the area should pay close attention to the differential role that various types of beliefs play in learning and the formation of policy networks.

**Keywords:** *Social networks, learning, sustainability, regional planning, collaborative institutions*

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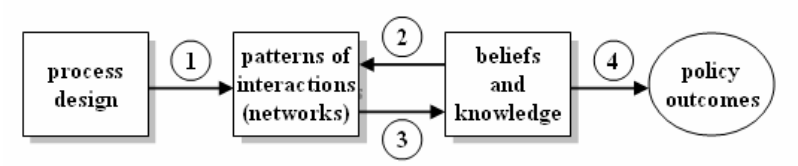
Traditional planning processes are often accused of fragmented and reactionary decision-making. This lowers the economic benefits of infrastructure development, and raises environmental costs. Many regions of the United States recognize the need for better planning processes, and have thus begun to experiment with various types of "collaborative" planning efforts. These processes typically seek to engage a broad array of stakeholders, promote cooperation between local jurisdictions and vertical levels of government, and integrate multiple functional domains such as transportation, land use, and habitat. It is commonly assumed that collaborative processes lead to improved outcomes – primarily because they tend to promote the formation of networks that enable social and policy learning. "Learning" is conceptualized here as the process by which stakeholders and decision-makers hone their ability to deal with complex problems by drawing upon diverse sources of information, developing common understandings of problems to be addressed, and collectively produce innovative policy solutions.

There is much discussion of the importance of successful learning for sustainability (Social Learning Group 2001; Parson and Clark 1995). Although there is a general euphoria surrounding the potential of collaborative policy to promote sustainable outcomes, there is sparse evidence that collaborative institutions and the social networks they produce actually promote learning and improved policy outcomes (Lubell 2004). This underscores a central problem with the literature on the design of planning institutions: The *process* of learning is usually treated as a black box, and we defer instead to strategies that, anecdotally, have appeared to be successful in the past. Understanding how learning occurs by and amongst networked groups of agents will lend more theoretical power to the important question of institutional design to promote learning (Innes and Booher 1999).

I use social networks as the main organizing concept through which to explore policy learning in both traditional and collaborative planning processes. This paper seeks to better understand learning processes by empirically examining the beliefs, values, and surrounding social networks of stakeholders in several planning processes in California. I employ a variety of methods to better understand 1) the relationships between belief systems and social networks, 2) the factors that cause networks (and hence beliefs) to solidify and change over time, and 3) the potential of collaborative institutions to change these tendencies. These results will ultimately shed more light on the important question of how to design governance institutions (collaborative or otherwise) to better deal with complex planning problems. While the focus here is on regional transportation and land use planning, the methods and general approach are also applicable to a wide variety of other policy domains that deal with complex human/environment interactions, placing this research firmly within the emerging field of sustainability science (Clark 2007; Kates *et al.* 2001).

**Learning and social networks**

In the conceptual framework sketched below, the relationships labeled (1) and (4) provide a context for considering networks and learning processes. Turning first to the relationship between process design and patterns of interactions, the environment in which planning occurs is an important determinant of social relationships – both formal and informal – that develop. Transportation planning in the United States, for example, requires that state transportation plans conform to air quality plans; transportation agencies must therefore work closely with air quality agencies in order to fulfill their mission (Johnston 2004). Similarly, the design of decision-making institutions also promotes the formation of informal linkages that lead to the development of new ways of viewing problems and potential solutions. One of the main arguments of the collaborative policy literature, for example, is that collaborative processes create networks that span ideological and institutional boundaries (Schneider *et al.* 2003), therefore increasing the overall level of cooperation and helping stakeholders to overcome collective action problems.




The relationship between knowledge and outcomes (4) is included in this framework to emphasize the policy relevance of learning. There are two man threads of this argument. First, the practice of planning, whether for transportation, land use, or any other human activity, is very much an effort to deal with complex adaptive systems. Human behavior is complex, as are the interactions between human and ecological systems. Dealing effectively with problems of sustainability requires that decision-makers be able to successfully assimilate ("learn") emerging and uncertain information and engage in policy experimentation (Holling 1978). Second, there is an often-realized possibility that decision-makers and other stakeholders do not agree on the basic parameters of the issue to be addressed, and bring conflicting information to bear on policy debates. In such a situation, we may characterize networks as ideologically polarized, with multiple divergent belief systems competing to push policy choices in different directions. Such situations are common in technically complex and value-laden issue areas (such as transportation and land use), leading to environments where the norm is political stalemate rather than constructive discussion and policy improvement (Sabatier and Jenkins-Smith 1999).

Given the relevance of both social networks and knowledge to sustainability and planning, I focus on "learning" as a process that sits primarily at the positions labeled (2) and (3) in the diagram. Turning first to the effect of networks on knowledge and beliefs, social networks are a vital component of learning because they act as a constraint on information exchange and the pooling of knowledge at multiple scales. Multiple perspectives on a problem are useless, for example, if there is no mechanism for synthesizing these

perspectives. Networks are crucial because they are a medium for information sharing, dialogue, persuasion, negotiation, and any other social process that leads to belief change or knowledge production.

On the other hand, social networks are also products of learning due to the inherent co-evolution of individual attributes (such as knowledge and beliefs) and larger network structures (Lazer 2001). Our values and beliefs play a large role in determining who we interact with – thus, as values and beliefs change, individuals may tend to adjust their surrounding networks accordingly. What if actors tend to resist the formation of network ties with others who do not share their values, background, or basic policy preferences? There is convincing evidence that normative beliefs play an important role in determining the structure of policy networks (Weible and Sabatier 2005; Weible 2005). This poses a serious challenge for learning, since a bias for communicating with like-minded individuals only serves to reinforce prior knowledge, and makes it difficult for new ideas to "infect" ideologically homogeneous groups.

When these effects are put together, we see that networks are neither purely endogenous nor exogenous to the problem of learning – while networks act as a constraint on what one agent can learn, what agents have learned influences surrounding networks and their capacity for additional learning. Thus, a better understanding of learning processes depends on considering how beliefs and networks interact and change over time.

A corollary to this is that we can also identify signatures of learning by examining the structural properties of a network. This is the basic strategy used in the current paper. The next section discusses the Advocacy Coalition Framework (ACF; Sabatier and Jenkins-Smith 1999), a theoretical perspective on the policy process that offers testable hypotheses of how learning impacts the structures of policy networks.

## Theory and Hypotheses

### Biased learning and network formation

The main hypotheses of this paper are drawn form the advocacy coalition framework, which includes a very particular view of how learning occurs and the impact of learning on network structure. The ACF views policy-relevant beliefs as being highly resistant to change in the face of contradictory evidence, leading to situations where "coalitions" of like-minded policy elites entrench themselves in ideological bunkers and talk past one another about scientific evidence.

This resistance to ideological change is explained by the ACF model of the individual, which assumes a process of "biased assimilation," whereby policy elites tend to interpret evidence in a way that supports their prior beliefs and values (Innes 1978; Lord, Ross, and Lepper 1979; Munro and Ditto 1997; Munro et al. 2002). This phenomenon is the most basic engine that drives coalition formation around shared beliefs. Since elites with shared beliefs have similar perceptual filters, information exchange, learning, and the development of common views occurs easily among them. Conversely, shared learning is exceedingly difficult between people with conflicting beliefs, since their

perceptual filters will cause them to interpret the same piece of evidence differently. This breeds distrust among people with conflicting beliefs, and causes trust and collaboration networks to form among those with shared perceptual filters.

Thus, biased assimilation impacts learning processes in two ways. The first is that the ease with which two elites are able to learn from each other is directly related to their ideological similarity. To illustrate how this may play out in the real world, consider an environmentalist planner with a radical view on transportation improvements in his local city. He argues that transportation projects reducing travel times from outlying areas to the city center induce urban sprawl, and so the city should not invest in any improvements that increase capacity into the city – including mass transit. This person is closely involved in planning policy, and communicates with both environmental groups and developers. Both of these groups disagree, and present the same argument: the city *should* invest in mass transit, they argue, because growth is inevitable and the region needs to invest in strategies to avoid increased automobile dependence later. Although both groups present identical arguments to refute our hypothetical elite's prior beliefs, the ACF hypothesizes that he is more likely to be convinced by the environmental groups. Their prior similarity in beliefs and values causes learning to occur more easily when the information comes from environmentalists rather than developers.

Second, biased assimilation further constrains learning processes by influencing where policy elites go for information and to discuss policy issues. When individuals with conflicting core beliefs interpret the same piece of evidence differently, distrust tends to breed between them. This result is a belief homophily in the formation of policy networks; that is, elites will demonstrate a bias for forming network relationships with others whom they perceive to be ideologically similar. This effect is compounded by a "devil shift" phenomenon, which further inhibits the formation of ties across actors with competing ideologies (Sabatier *et al.* 1987).

Taken together, the ACF predicts two salient features of policy networks: a high degree of belief homophily (because biased assimilation and the devil shift have influenced endogenous network formation), and small variance in the policy-relevant beliefs held in each networked cluster of actors (because learning occurs easily within these clusters). The hypothesis that belief homophily is at work was demonstrated by Weible and Sabatier (2005) and Weible (2005), who looked at policy networks and belief systems within California Marine Protected Areas. They find that shared beliefs are a better predictor of network cohesion than the alternative, "rational" explanation that elites form networks to maximize their access to political resources (Weible 2005).

A problem with this line of research, however, is that it did not pay enough attention to the different types of policy-relevant beliefs posited by the ACF, and whether those differences matter in terms of network structure. The ACF organizes beliefs into a three-tier hierarchy comprised of deep core beliefs, policy core beliefs, and secondary aspects. These beliefs differ in terms of their

resistance to change are resistance to change (or susceptibility to biased assimilation), and relevance to ongoing debates within the policy subsystem.

The more resistant to change a belief is, the more it acts as a force that drives policy networks. If beliefs are resistant to change, then small ideological differences will be persistent and more influential on individual behavior. Shared deep core beliefs are therefore expected to be the primary beliefs predicting policy networks. Shared policy core beliefs are important, but less so than the deep core. Secondary aspects are relatively unimportant in explaining perceived agreement, although they should still have a positive effect.

The idea that these beliefs vary in the degree of salience to policy debates, however, offers a slightly different picture. The beliefs most important in explaining agreement should be the ones that are discussed frequently; thus, the more relevant a belief is to the subsystem, the more important it should be in determining network cohesion. The argument is simple: if two actors hold wildly different beliefs, but do not discuss these belief differences, then the question of agreement between them is moot. Religious beliefs, for example, can be extremely divisive and resistant to change. In many circumstances, shared religion is a clear rationale driving network relationships. Religion is only infrequently discussed in policy debates. In regional planning, the question of whether or not some person believes in a divine being is unimportant compared to whether or not they believe in smart growth or alternative transportation fuels.

Belief stability and policy relevance thus probably have an interactive effect. We expect for beliefs that are highly resistant to change to have a strong effect on network structure only if they are policy relevant and thus subject to frequent discussion. Thus, although the underlying rationale behind belief homophily in policy networks comes from the resistance to change, this effect is mediated by a salience factor that provides opportunities to either learn or resist learning. This yields a testable ACF hypothesis of network cohesion:

> **ACF Biased Learning Hypothesis:** Shared policy core beliefs are the most important predictor of network cohesion, followed by shared secondary aspects, followed lastly by shared deep core beliefs.

This will be tested using data from five individual types of beliefs relevant to regional land use and transportation planning efforts: environmentalism and economic conservatism (deep core beliefs), inclusiveness and adherence to smart growth principles (policy core beliefs), and perceptions of problem severity (secondary aspects). One of the weaknesses of the ACF is that is difficult to empirically distinguish resistance to change and policy relevance; the classifications are basically an expert judgment by the researcher. It is entirely possible that the classifications are not clean enough to distinguish between different types of beliefs, and thus we might expect overall belief differences to matter regardless of belief types. The empirical analysis will also explore this possibility.

## Methods

### Research design

To test the above hypothesis, survey data on policy networks was collected from policy elites involved in transportation and land use planning in five regions of California. These regions include the rapidly urbanizing county of Merced (*N* = 127), and the "ACA" Tri-County region, including Alpine, Calaveras, and Amador counties (*N* = 111), the Sacramento Area Council of Governments (SACOG) 6-county planning region (*N* = 291), Riverside County (*N* = 116), and the San Diego "SANDAG" planning region (*N* = 107).

Each of these regions contains a collaborative policy process designed to integrate land-use and transportation planning. However, our research was specifically designed to include actors throughout the land-use and transportation policy subsystem in each region, and thus was not limited just to collaborative policy participants. We used multiple archival sources to identify the relevant actors, including a database of environmental impact reports, lists of land-use planners in California, and websites of individual local governments. Thus the networks formed among this universe of policy actors have emerged from a wide diversity of institutional processes, and from which we can isolate participants in a specific collaborative process.

### Network measurement

The survey measured network relationships by soliciting from each respondent as list of organizations or groups with which the respondent shares a specific type of relationship. The most important relationships measured here are collaboration and trust networks. Two methods were employed to generate these lists: checklists via an online survey, and name generators for telephone respondents (who were non-respondents to the online survey).

The checklist included a total of 53 governmental organizations from multiple levels of the federal system as well as private and non-governmental groups. Government entities were usually identified by name, and an effort was made on the checklist to include all of those organizations who play an important role in regional planning processes. At the federal level, for example, this includes the U.S. Department of Transportation, the U.S. Environmental Protection Agency, and public lands agencies such as the Forest Service and the Bureau of Land Management. State-level governmental organizations included bodies such as the California Department of Transportation (CalTrans) and the Governor's Office of Planning and Research. Also included were regional planning authorities and local government actors. For private and non-governmental groups, respondents are asked to identify those *categories* of actors with whom they have a given relationship. These included, for example, environmental groups, developers/real estate, farming/ranching, media/journalists, and university researchers. The checklist also included a frequently used "write-in" category; the write-ins were coded back into the existing checklist as necessary, or the list was expanded.

Respondents who did complete the online survey were surveyed using telephone interviews, and therefore could not be given checklists. In these cases, we used a "name generator" to measure network relationships for these respondents. Using this method, respondents are simply asked to provide the names of several people or organizations they have a relationship with, without any sort of list to guide their answers. The same network relationships were measured for each name generator respondent, however, and we later coded their responses so that they may be compared with our checklist respondents.

**Belief systems and network structure**

The ACF defines an "advocacy coalition" as a group of policy elites who have shared systems of policy-relevant beliefs and coordinate their behavior in an attempt to influence policy. The term "belief coalition" came into use in the ACF literature primarily because of data constraints – ACF scholars typically have very good data on belief systems, but poor data on networking relationships. A belief coalition, therefore, is a way of identifying an "advocacy coalition" without the networking aspect. It is merely a group of individuals with shared belief systems. But these belief systems include many different types of policy-relevant cognitions, including values, policy preferences, problem perceptions, *et cetera*. So belief coalitions must be identified using some sort of scaling technique that pulls out not only the salient beliefs but also the extent to which elites from different coalitions tend to "cluster" at different points on the relevant belief scales.

The approach used here is to consider clustering within four belief scales: environmentalism, inclusiveness, smart growth, and economic conservativism. Problem severity questions are left out for the time being, since these questions do not form a reliable scale. More work is needed to identify the underlying factors within this battery of questions. Clustering (or the identification of "belief coalitions") is performed independently for each scale, so no assumption made here about consistency of respondent answers across scales. That is, person *A* may be a member of the "environmentalism" belief coalition along with persons *B* and *C*, but this does not mean that persons *A*, *B*, and *C* will all be members of the same belief coalition when we look at a different type of belief. For each of these belief scales, k-mean cluster analysis is used to identify <u>two</u> belief coalitions. The assumption that there are only two belief coalitions may be shaky but, in the interim, it simplifies the analysis.

**Scale creation**

Four belief scales are created from individual questions in a section of the survey that solicits general political opinions. Scales are created based on 1) theoretical expectations of which questions measure one of our four types of beliefs, and 2) statistical evidence (Cronbach's alpha reliability scores) of which questions scale well together.

Since these scales are developed based on all respondents, I assume that the same questions will scale together in a roughly similar way across all five

study areas. Of course, these questions were designed to be general measures of policy-relevant beliefs, rather than region-specific beliefs or attitudes.

In the dataset, a new variable was created for each of these four scales. These variable names are noted below.

<u>Environmentalism</u>
*Cronbach's alpha = 0.7784*
*(no variables reversed)*
*Variable name = "enviro"*

q17_1: "Humans are severely abusing the environment."
q17_5: "Plants and animals have as much right as humans to exist."
q17_8: "If things continue on their present course, we will soon experience a major ecological disaster."

<u>Economic conservativism</u>
*Cronbach's alpha = 0.7478*
*(no variables reversed)*
*Variable name = "econ"*

q17_2: "Protecting the private rights of individual citizens is the most important role of government."
q17_6: "In general, government agencies and regulations intrude too much on the daily lives of private citizens."
q17_9: "Government shouldn't put restrictions on property without compensating the landowner at fair market value."
q17_21: "There are too many government regulations on development and growth."

<u>Inclusiveness</u>
*Cronbach's alpha = 0.5275*
*(no variables reversed)*
*Variable name = "inclusive"*

q17_3: "Land-use decision should always consider the interests of multiple stakeholders."
q17_18: "Public policy decisions should consider as many different interests as possible."
q17_20: "Maximizing the scope of public participation in policy decisions improves effectiveness."

<u>Adherence to Smart Growth principles</u>
*Cronbach's alpha = 0.6900*
*(no variables reversed)*
*Variable name = "smart"*

q17_10: “Local regulations that restrict how landowners use their property are good strategies for achieving community goals.”
q17_11: “Land-use policies should always provide affordable housing.”
q17_13: “Land-use policies should emphasize livable communities.”
q17_15: “Land-use policies should promote cultural diversity.”
q17_17: “New development should be located inside existing city boundaries.”
q17_19: “Land-use planning should emphasize alternative modes of transportation.”

**Cluster analysis results**

The next section summarizes results of the belief coalition analyses done using 2-mean cluster analysis in *Stata*.

The basic approach to the identification of belief coalitions is to employ a 2-mean cluster analysis on each scale described in the previous section. This assumes that there are two belief coalitions for each belief, a “low” coalition that tends to score towards the bottom of the scale and a “high” coalition that tends to score towards the top of the scale. Depending on the spread of belief scores, the cluster analysis attempts to identify the most natural cut-off point (somewhere in the middle of the scale) between the high and low belief coalitions.

This cluster analysis was performed in two ways. First, belief coalitions were created based on all respondents from both Stage 1 and Stage 2 ($N = 752$). This presumes that the true distribution of beliefs on each scale is more or less consistent across all study areas. Given the general nature of the questions used to create the scales, there should be a good deal of consistency across regions. Table 1 summarizes the belief coalitions that emerge when all respondents are included in the cluster analysis.

**Table 1:**
**Summary of 2-mean belief coalition analysis across all study areas**

| | **Coalition 1** | | | | | **Coalition 2** | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | **mean** | **std. dev.** | **min score** | **max score** | **size** | **mean** | **std. dev.** | **Min Score** | **max score** | **size** |
| **Environ-Mentalism** | 3.40 | 1.02 | 1 | 4.67 | 415 | 5.94 | 0.68 | 5 | 7 | 333 |
| **Economic conservativism** | 5.03 | 0.82 | 4 | 7 | 390 | 2.77 | 0.73 | 1 | 3.75 | 359 |
| **Inclusiveness** | 6.44 | 0.37 | 6 | 7 | 406 | 4.95 | 0.75 | 1 | 5.67 | 343 |
| **Smart Growth** | 4.15 | 0.67 | 1 | 4.83 | 272 | 5.75 | 0.52 | 5 | 7 | 477 |

These results do indicate that there are fairly clear belief coalitions in the five regional planning subsystems. The presence of a cut-off in roughly the middle of the scale (with the exception of inclusiveness) indicates that our coalitions are forming around the bottom and top of the scales. Non-trivial group sizes at the lower and upper levels of the scale support this – if there are not clear *clusters* at the top and bottom of each scale, the size of our clusters do at least indicate that we are capturing a good deal of variance in all of these belief scales. Finally, the relatively small standard deviation in belief score *within each coalition* indicates that there some degree of bi-modality to the distribution; we are not simply dealing with uniform distributions of beliefs. This would signal randomness in the belief systems, rather than the sort of polarization predicted by the ACF.

We must also address the possibility that these results, based on aggregated respondent data, neglect important differences across our five study areas. To test this possibility, I also performed a cluster analysis on the four belief scales within each individual region. These region-specific coalition results were then compared against the aggregate results presented in Table 1. Table 2 summarizes the results of this comparison. The first column of Table 2 reports the number of respondents that were consistently placed in the same coalition (high or low) in both the aggregated cluster analysis and the region-specific cluster analysis. The second column reports the number of respondents who were placed in different coalitions when the alternative clustering methods were used.

**Table 2: Summary of preceding belief coalition analysis and consistency within individual study areas**

| **Belief scale** | **Region** | **Frequency Coalition matches (percent total)** | **Frequency Coalition Mismatches (percent total)** |
|---|---|---|---|
| Environmentalism | Merced | 95 (75%) | 31 (25%) |
| | Tri-County | 105 (95%) | 6 (5%) |
| | Riverside | 115 (100%) | 0 (0%) |
| | San Diego | 93 (88%) | 13 (12%) |
| | SACOG | 290 (100%) | 0 (0%) |
| Economic conservativism | Merced | 116 (91%) | 11 (9%) |
| | Tri-County | 111 (100%) | 0 (0%) |
| | Riverside | 115 | 0 |

| | | | |
|---|---|---|---|
| | | (100%) | (0%) |
| | San Diego | 95 (90%) | 11 (10%) |
| | SACOG | 273 (94%) | 17 (6%) |
| Inclusiveness | Merced | 112 (88%) | 15 (12%) |
| | Tri-County | 111 (100%) | 0 (0%) |
| | Riverside | 115 (100%) | 0 (0%) |
| | San Diego | 106 (100%) | 0 (0%) |
| | SACOG | 290 (100%) | 0 (0%) |
| Smart Growth | Merced | 127 (100%) | 0 (0%) |
| | Tri-County | 106 (95%) | 5 (5%) |
| | Riverside | 103 (89%) | 13 (11%) |
| | San Diego | 99 (93%) | 7 (7%) |
| | SACOG | 261 (90%) | 28 (10%) |

The aggregated results are fairly close to the region-specific results, although there are some inconsistencies. Overall, Merced seems to the study area that is most sensitive to region-specific clustering. Although these results would not deter me from using the aggregated cluster analysis results in a future study, there are enough inconsistencies to warrant using region-specific coalition data in the following cross- and within-coalition network analysis.

Before turning to the network data, a brief note on the consistency of coalition membership across scales is in order.

**From individual scales to belief systems: Consistency across multiple coalitions**

While the ACF emphasizes the importance of certain types of beliefs in policy relationships, the concept of integrated belief systems is central to the framework's explanation of why interactions occur. This cluster analysis focuses on individual types of beliefs independently of the others – that is, an individual may score high on environmentalism, but this is not necessarily a predictor of how they will score on smart growth or inclusiveness. To go from "beliefs" to "belief systems," it is necessary to show that there is some consistency in belief coalition membership for multiple types of policy-relevant beliefs.

Given these data on membership in individual belief coalitions, one way to measure consistency is to employ Cronbach's alpha to see if coalition membership scales across multiple belief types. This method does shoe some consistency in coalition membership, although the "reliability" of the belief system scale is relatively low (Cronbach's alpha = 0.5088).

We actually get a better scale for belief systems when inclusiveness is dropped. In this case, we have Cronbach's alpha = 0.5516. Furthermore, both smart growth and environmentalism are very important to this belief system scale. When environmentalism is dropped from the four belief types, Cronbach's alpha falls to 0.3567. When Smart Growth is dropped, the Cronbach's alpha drops to 0.2953.

## Results

### Within- and across-belief coalition networking

This section incorporates data on network relationships with belief coalition data to determine the extent to which networking tends to occur within belief coalitions versus across belief coalitions. The general approach used here is to examine, for a given network and a given type of belief, the density of interactions between each pair of coalitions and within each coalition. This exploratory analysis will help us to see whether within-coalition linkages tend to be more frequent than cross-coalition linkages (controlling for the differing sizes of belief coalitions), and allows us to investigate whether the coalitions differ in their tendencies to link inwardly or outwardly.

Density of interactions is defined in the standard way, as the number of linkages of a certain type that could potentially occur divided by the number of linkages that actually do occur. The twist here is that we are looking at multiple density statistics within a single network – for example, within-coalition linkages contribute to within-coalition density, whereas cross-coalition linkages contribute to cross-coalition density.

The following tables report mean network densities, across all study areas. I examine collaboration and information networks, although this analysis can easily be repeated from our companion dataset, <AGGREGATE_coalition_link_summary.dta>, for other network modes. The only beliefs examined here are environmentalism (Table 3) and Smart Growth (Table 4).

**Table 3: Mean density of cross-coalition interactions across all study areas, for environmentalism beliefs**

| | ***Density of linkages to coalition:*** | | | | | |
|---|---|---|---|---|---|---|
| | **COLLABORATION (*N* = 5)** | | | **INFORMATION SHARING (*N* = 3)** | | |
| | Low | High | Moderat | Low | High | Moderat |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | | | | e | | | e |
| ***Linkages from coalition:*** | Low belief coalition | 0.25 | 0.19 | 0.31 | 0.03 | 0.04 | 0.07 |
| | High belief coalition | 0.19 | 0.28 | 0.28 | 0.03 | 0.06 | 0.08 |
| | Moderate belief coalition | 0.35 | 0.35 | 0.50 | 0.05 | 0.06 | 0.16 |

**Table 4: Mean density of cross-coalition interactions across all study areas, for Smart Growth beliefs**

| | | ***Density of linkages to coalition:*** | | | | | |
|---|---|---|---|---|---|---|---|
| | | **COLLABORATION (*N* = 5)** | | | **INFORMATION SHARING (*N* = 3)** | | |
| | | Low | High | Moderate | Low | High | Moderate |
| ***Linkages from coalition:*** | Low belief coalition | 0.20 | 0.17 | 0.21 | 0.04 | 0.04 | 0.05 |
| | High belief coalition | 0.27 | 0.29 | 0.29 | 0.02 | 0.04 | 0.05 |
| | Moderate belief coalition | 0.33 | 0.31 | 0.37 | 0.07 | 0.07 | 0.11 |

This is a useful way of viewing the nuances in our network data when beliefs are put in the picture. For both belief types, agents who are low or high on the scale tend to prefer collaboration with others who are on the same side of the scale. Those with moderate belief scores (whom I am tentatively calling "brokers") generally enjoy high density scores – indicating that these agents are more attractive partners in both collaboration and information sharing networks.

One interesting result is the difference between environmentalism and Smart Growth beliefs in regards to cross- and within-coalition network densities. Generally speaking, it looks like environmentalism (a "value" or "deep core" belief) makes a big difference in cross-coalition ties while Smart Growth (a belief about the utility of a particular policy instrument) has a relatively small effect. This is also a departure from the work of Sabatier *et al.*, who focus on policy core beliefs (in this case, Smart Growth) as the primary driver of network structure. Unfortunately, this analysis does not include problem severity perceptions, and therefore I cannot make any strong inferences about how they will compare. Still, I suspect that environmentalism and economic conservativism (the two "value" scales) correlate strongly with perceptions of problem severity, so I would not be surprised if actors are also collaborating on the basis of *what problems they want to solve* versus *how to solve those problems*.

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