Understanding Advocacy Coalitions: coordination and belief segregation in the United States environmental risk management subsystem

by

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As members of the Dissertation Committee, we certify that we have read the dissertation prepared by Georgia Pfeiffer, titled *Understanding Advocacy Coalitions: Coordination and Belief Segregation in the United States Environmental Risk Management Subsystem* and recommend that it be accepted as fulfilling the dissertation requirement for the Degree of Doctor of Philosophy.

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Final approval and acceptance of this dissertation is contingent upon the candidate's submission of the final copies of the dissertation to the Graduate College.

I hereby certify that I have read this dissertation prepared under my direction and recommend that it be accepted as fulfilling the dissertation requirement.

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Abstract

Policy making, at its core, occurs across networks of policy stakeholders as they communicate, debate, learn, compromise, and fight in an effort to promote their views. The ways in which policy networks form and persist has a tremendous impact on the opportunities available to stakeholders as they undertake policy advocacy activities. In this dissertation, we focus on a key network characteristic, segregation according to beliefs, and study its presence and impacts in the United States environmental risk management subsystem. The Advocacy Coalition Framework provides a theoretical foundation for our expectations surrounding belief segregation and motivates the research questions investigated.

This dissertation presents three distinct studies that contribute to the study of belief segregation in policy networks. The first study is a comparison of the policy networks in the United States environmental risk management subsystem in 1984 and 2014. The second investigates the interaction of advocacy coalition membership, which is partially determined by shared beliefs, and policy activity coordination. The third study explores the Distribution of Egocentric Correlations method for detecting heterogeneous preferences for segregation.

Chapter 1

Introduction

Belief segregation in the political sphere is a fact of American political life. Broadly, belief segregation occurs when there is more contact or cooperation between actors who have similar beliefs than between actors who have dissimilar beliefs. We can observe belief segregation in the political sphere through many mechanisms, perhaps most notably the formation of political parties. Political parties promote policy platforms that summarize their beliefs and values and attract voters who feel similarly. In this way, belief segregation is used constructively to help people find their ideological counterparts to represent their beliefs in the policy process. There is evidence that voters, while not more polarized, are sorting more heavily into party groups according to their ideology (Fiorina, 2017). Framing belief segregation constructively, we can surmise that this leads to a closer ideological match between voters and their representatives.

However, belief segregation can also have negative consequences. Since more polarized voters have sorted into parties by ideology, moderate voters are left without a party that adequately represents their beliefs (Fiorina, 2017). J. Baker et al. (2013) also found increased partisan sorting along religious lines among member of Congress over the time period 1959-2013. J. Baker et al. (2013) assert that while both sides of the aisle retain a religious foundation, this sorting further pushed the party doctrines towards opposing views on the role of the federal government in providing assistance to vulnerable groups. A lack of overlap in policy beliefs can make compromise harder to achieve. In addition to impacts on policy outcomes, growing belief segregation can impact people's attitudes and behaviors. In a 2016 report on partisanship, the Pew Research Center reported substantial growth in the proportions of partisans in each party who held 'very unfavorable' views of the other party. In 1994, less than a quarter of partisans in each party held 'very unfavorable' views of the opposing party, but in 2016, that had grown to over half. Furthermore, through a network simulation of misinformation contagion, Törnberg (2018) found that belief segregated networks and opinion polarization, more so when they are found together, increase the likelihood of misinformation spreading throughout the network.

Belief segregation does not just operate at the level of political parties. Within smaller policy debates, stakeholders align with one another according to their beliefs to amplify their position in the policy space. In a study of policy preferences for water protection, Metz et al. (2018) found network clustering that indicated interdependence across multiple preferences. Not only were stakeholders who collaborated with each other more likely to share preferences while stakeholders in conflict with each other were less likely to share policy preferences, but stakeholders who were in agreement were likely to exhibit similar preferences for multiple policy instruments. This finding emphasizes the extent to which belief segregation on one issue can be related to belief segregation on similar topics.

To handle issues of belief segregation, many policy process scholars turn to the Advocacy Coalition Framework (ACF) to develop a theoretical understanding of the dynamics of belief segregation. The ACF (Sabatier, 1986, 1988; Jenkins-Smith et al., 2014) is particularly useful for analyzing highly contentious policy areas. The models within the ACF describe policy stakeholders, who individually hold complex beliefs about policy issues, building coalitions to promote their beliefs in the policy making process. Coalitions compete to see their beliefs incorporated into policy while compromising as little as possible with the opposing coalition. The ACF fits well with research questions of belief segregation because it provides a systematic and empirically grounded set of definitions, assumptions, and models for behavior in policy areas characterized by diverse and contested beliefs.

Research questions on belief segregation and research questions framed by the ACF both carry an actor-oriented flavor. Belief segregation in a policy area is usually driven by stakeholders in that area choosing to work with partners who hold similar beliefs, or to avoid partners who hold divergent beliefs. Whether through attraction or avoidance, the system-level phenomena of belief segregation is fueled by individual level decisions. The ACF operates in much the same way. Coalitions are only built because actors with similar beliefs come together to coordinate on policy activities. While there may be coalition level competition and interactions, action is fueled by individuals persistence to turning beliefs into policy. This focus on actor level motivations and choices couples nicely with methods from social network analysis (SNA). Networks serve as an abstraction of social interactions where network nodes represent the actors and the ties between them represent many different types of relationships. By representing relationships in mathematical models, we can provide insight into the actors' preferences for relationship formation SNA provides an opportunity for us to focus on the actor-level decisions and network position - particularly through egocentric analysis - while keeping in mind the larger context of the policy subsystem.

In this dissertation, we use use a variety of network methods to examine the actions of stakeholders in a policy subsystem. The stakeholders are represented as nodes in the network and ties between them represent many kinds of actions and relationships that develop within the context of policy development. We conceptualize networks of stakeholders in two different ways. In Chapter 3, we aggregate the individual survey respondents into organization level nodes to create a full network and in Chapter 4, we maintain the respondents as individuals and use egocentric analysis to learn about the activities in the policy subsystem. Since we use SNA to parse the policy subsystem and look for belief segregation, it is worth revisiting our broad conceptualization of belief segregation to develop a SNA approach for identifying the phenomenon. In a policy network, belief segregation occurs when ties representing contact or coordination are more likely to form between actors with similar belief than between actors with dissimilar beliefs.

This dissertation presents three studies on policy networks that are sewn together by a common thread of belief-based network segregation. Two of these studies draw from data on the United States environmental risk management subsystem. These studies incorporate longitudinal and cross-sectional analyses of belief segregation and the impacts it has on activity in the subsystem. The third study is an exploration of the Distribution of Egocentric Correlations (DEC) Method. This study validates the use of DEC to recover information on respondent biases for segregation in egocentric network formation.

In Chapter 2, we introduce the U.S. environmental risk management subsystem. Because environmental risk encompasses many topical subfields, this subsystem spans a complex tapestry of interacting policy issues. In this chapter, we define the subsystem, discuss its emergence and trajectory, and review previous research focused on the professionals working in this subsystem.

In Chapter 3, we take a longitudinal view of the subsystem and evaluate belief segregation and triadic closure at two point in time. First, we study the policy network in 1984, shortly after the subsystem's emergence and compare the results to the ACF expectations for nascent subsystem. Then we study the policy network in 2014, after the subsystem has matured, and compare the results to the ACF expectations for developed subsystems.

In Chapter 4, we take a cross-sectional view of the U.S. environmental management subsystem in its mature form and compare the incidence of coordinated activity within and outside of advocacy coalitions. We add nuance to this study by considering the heterogeneous effects of coalition membership across types of coordination and the variation introduced by stakeholder attributes.

In Chapter 5, we provide a discussion of an innovative method used for studying distributions of egocentric correlations in networks research. We use Monte Carlo simulations to show that the underlying heterogeneous biases that research subjects carry towards segregated tie formation in a secondary network can be recreated by building distributions of correlations. This method provides more nuance in measuring heterogeneous effects than comparable single network statistics.

In Chapter 6, we draw connections between the three substantive studies and lay out recommendations for future research on the U.S. environmental risk management subsystem.

Chapter 2

The United States Environmental Risk Management Subsystem: Background and Previous Research

2.1 Introduction

In this dissertation, Chapters 3 and 4 analyze data collected through two surveys of professionals working in U.S. policy on issues of environmental risk management. The professional networks, career attributes, and policy beliefs of the professionals surveyed provide a window into the ways that belief segregation plays out in a highly contentious policy subsystem in the US context. Before presenting the analysis and theoretical insights gained from the data, we must develop a better understanding of the policy area that we are drawing from. This chapter presents an Advocacy Coalition Framework (ACF) definition of the subsystem, an overview of subsystem activities during the period spanned by the surveys, and a summary of the literature previously published on studies of this subsystem.

2.1.1 Defining the Policy Subsystem

In the ACF, the policy subsystem is the arena where the policy process plays out and it is defined by a topic, geographic scope, and the actors directly and indirectly involved in policy making activities (Jenkins-Smith et al., 2014). In this dissertation, we study professionals from all economic sectors that work in the U.S. federal subsystem on environmental risk management and who use or incorporate the results from formal risk analysis techniques. This is purposefully a very broad subsystem that spans many subfields and incorporates the work of a diverse array of professionals. Working with such a broad subsystem gives a more realistic impression of the policy making process. This inclusive view will allow us to capture coalition ties from multiple smaller, nested subsystems. Large organizations and federal government departments especially will be involved in multiple policy subfields and this wider view can better capture their involvement across issues of environmental risk management. In addition to a broad view on the policy issue, we include stakeholders involved across a range of policy activities. The survey sample in each time step includes professionals producing knowledge - like researchers at universities and think tanks - professionals from purposive groups driven by a cause - like advocates in environmental and public health non-profits - and professionals implementing policy - like state and federal employees. This kind of inclusivity gives us access to a broad range of experiences in the policy subsystem. Overall, we wish to present research that reflects the impressive scope of policy issues and policy actors in environmental risk management.

2.1.2 Overview of the Policy Subsystem

Environmental risk assessment and management informs policy where people and the environment collide, which is to say – everywhere. Broadly speaking, risk assessment is “the process of estimating the likelihood and severity of adverse outcomes of individuals and populations” (Sandia National Lab, 1994, p.6). The outcomes of risk assessments are used to shape regulation that protects citizens from hazards like exposure to carcinogens and to create strategies to mitigate the impacts of natural disasters like floods. Risk analysis can be used on isolated events as they occur to individuals or on system-wide changes and their effect on populations. Perhaps our most expansive environmental risk assessments are those on climate trajectories – assessments of high stakes scenarios where outcomes have far-reaching consequences. Studies of this magnitude take into consideration theoretical considerations from many disciplines, like psychology and decision making, economics, engineering, ecology, and social justice to evaluate possible scenarios for human development (see International Energy Agency, 2003).

In response to increasing public concern about environmental conditions, the U.S. Congress passed a series of bills in the 1970s designed to protect environmental resources, including the Clean Air Act, Clean Water Act, Safe Drinking Water Act, Resource Conservation and Recovery Act, and Toxic Substances Control Act (US Environmental Protection Agency, 2018). This increase in legislation set the stage for formal risk analysis to be introduced into environmental policy. In 1976, the Environmental Protection Agency (EPA) issued its first formal guidelines for cancer risk assessment (Sandia National Lab, 1994), starting the mainstream use of risk assessment in policy making. This is where we place the emergence of the environmental risk management subsystem. Risk management was further ingrained in public agencies when, in a precedent setting 1980 decision, the Supreme Court ruled that the Occupational Safety and Health Administration (OSHA) must provide an estimate of the actual risk associated with exposure to benzene when setting standards (Sandia National Lab, 1994). In addition to policy movements toward formal risk assessment, leadership within the subsystem was signaling a change in priorities that emphasized risk assessment. In 1983, William Ruckelshaus started his second (non-consecutive) term as EPA administrator by giving a speech on formal risk analysis in federal policy making (Ruckelshaus, 1983). The speech signaled the growing importance of formal risk analysis as a path to legitimacy in the policy sphere (Dietz & Rycroft, 1987).

The EPA's growing focus on risk assessment coupled with the quickly expanding environmental regulations, led to a new set of challenges for private corporations as they worked to comply with the new regulations. An environmental auditing handbook published by McGraw-Hill in 1984 opens by recommending a new system of internal environmental regulation that would promote self-regulation and reduce the load on the EPA's resources (see Harrison, 1984). Chapters in the handbook cover the regulations introduced by eight major pieces of legislation including the Clean Air Act, the Clean Water Act, the Resource Conservation and Recovery Act, and the Occupational Safety and Health Act (see Harrison, 1984). Through this book, we see the environmental risk management policy area becoming a critical consideration in the ways corporations do business.

Since that point, the U.S. environmental risk management subsystem has encompassed major debates on topics ranging from nuclear energy to the clean-up of the Chesapeake Bay. These types of specializations constitute smaller policy subsystems nested within our case study. Subsystems, as defined by the ACF, can be both nested and overlapping (Jenkins-Smith et al., 2014), and the U.S. environmental risk management subsystem is no exception to this phenomena. In addition to encompassing many specializations, the environmental risk management subsystem frequently overlaps with other substantive areas. For instance, we see the social justice movement dovetailing with environmental risk management to create policy intended to redress previous unfair practices - like in the instance of federal and state funds directed to clean up the polychlorinated biphenyls (PCB) landfill in Warren County, North Carolina nearly 20 years after protests occurred there (US Environmental Protection Agency, 2017). There is also overlap with the workplace safety subsystem which shares concerns over incidents like the Deepwater Horizon oil rig explosion that killed 11 workers and spilled crude oil in to the Gulf of Mexico (US Environmental Protection Agency, 2018).

Table 2.1 displays a time line of selected developments in environmental risk policy. The timeline starts in 1970 when the federal government was making strides in environmental protection and pollution regulation. The beginning of the timeline shows the rapid policy development of the 1970s and sets the stage of the emergence of formal risk analysis and our policy subsystem of interest. The timeline includes significant policy developments, like the passage of acts through Congress, which would have been opportunities for debate and for coalitions to coalesce. It also includes notable changes in the environment, like the discovery of holes in the ozone layer, and industrial accidents like Three Mile Island and Deepwater Horizon. These events are included because they would provide opportunities for belief realignment and learning. Lastly, the timeline includes some entries that show the overlap of environmental issues with other policy areas like transportation, housing, and social justice. These are included to stress the interconnected nature of policy debates and give a sense of scope in the environmental risk management field. Unless otherwise noted, events on the timeline were selected from the Environmental Protection Agency's *Milestones in U.S. EPA and Environmental History* Timeline (US Environmental Protection Agency, 2018), *Environmental Justice Timeline* (US Environmental Protection Agency, 2017), and Department of Energy's *DOE History Timeline* (US Department of Energy, n.d.).

Year	**Events**
1970	◦ First Earth Day celebrated ◦ Environmental Protection Agency (EPA) established ◦ Clean Air Act passes - EPA can set air quality standards
1971	◦ Lead-Based Paint Poisoning Prevention Act passes - restricts use of lead-based paint in homes ◦ EPA identifies levels of five air pollutants that are linked to "significant harm" ◦ EPA starts testing vehicles' fuel economy
1972	◦ EPA bans DDT ◦ Clean Water Act passes - limits flow of raw sewage into waterways ◦ The Atomic Energy Commission, with industry partners, lay plans to build a nuclear reactor in Tennessee on the Clinch River
1973	◦ Oil embargo by the Organization of Petroleum Exporting Countries (OPEC) prompts research on alternative energy ◦ EPA involved in multiple areas of the transportation sector - introduces transportation controls like exclusive bus lanes in several large cities and starts phasing out lead in gasoline nationwide
1974	◦ Safe Drinking Water Act passes - EPA regulates public drinking water quality
1975	◦ Construction begins on the Alaska Pipeline between the North Slope and Valdez, AK.
1976	◦ Resource Conservation and Recovery Act passes - EPA begins regulating hazardous waste from production to disposal ◦ Toxic Substances Control Act passes - EPA empowered to require reporting, record-keeping, testing, and restrictions on certain substances including polychlorinated biphenyls (PCBs), asbestos, radon, and lead-based paint
1977	◦ The Solar Energy Research Institute is established by the Energy Research and Development Administration in Golden, Colorado The Department of Energy is created replacing several other federal agencies including the Energy Research and Development Administration
1978	◦ Residents of Love Canal, NY discover compounds from an industrial dump leaching up through the soil and the pollution is linked to serious health impacts ◦ Chlorofluorocarbons (CFCs), which cause destruction of ozone layer, banned by the federal government as propellants in aerosol cans
1979	◦ Worldwide oil shortage due to political upheaval in Iran ◦ A reactor at the Three Mile Island nuclear power plant in Pennsylvania partially melts triggering debates on the safety of nuclear power

Year	Events
1980	◦ The Energy Security Act passes - it consists of the US Synthetic Fuels Corporation Act, Biomass Energy and Alcohol Fuels Act, Renewable Energy Resources Act, Solar Energy and Energy Conservation Act and Solar Energy and Energy Conservation Bank Act, Geothermal Energy Act, and Ocean Thermal Energy Conservation Act ◦ Congress creates the Superfund Program to finance the clean up of hazardous waste sites across the United States
1982	◦ The EPA requires elementary and secondary schools to test for asbestos ◦ Protests to halt construction on a PCB landfill in Warren County, North Carolina start the environmental justice movement. Over 500 protesters were arrested and construction moves forward
1983	◦ EPA institutes policy of open communication - key officers' and administrators schedules are publicly posted. ◦ Chesapeake Bay clean up begins as a joint effort between federal, state, and local partners to eliminate pollution from sewage treatment plants, urban runoff and farm waste ◦ General Accounting Office study finds that three out of four hazardous waste landfills are located in communities where African Americans are at least 26% of the population and incomes were below the poverty level ◦ Congress discontinues funding for the reactor on the Clinch River in Tennessee (see 1972)
1985	◦ Hole in ozone layer discovered over Antarctica ◦ Advanced Genetic Sciences, hoping to prevent frost damagae to plants, conducts first tests on gene-altered bacteria
1986	◦ Emergency Planning and Community Right-to-Know Act passes - public has the right to know when toxic chemicals are released into the air, land, and water
1987	◦ Montreal Protocol - designed to phase out production of chlorofluorocarbons (CFCs) - signed by 24 nations, including US ◦ United Church of Christ Commission on Racial Justice study finds that over 15 million African Americans, 8 million Hispanics, and half of all Asian/Pacific Islanders and Native Americans live in communities with at least one abandoned or uncontrolled toxic waste site
1989	◦ 11 million gallons of crude oil spilled in Prince William Sound, Alaska, in Exxon Valdez accident. Exxon Valdez fined $1 billion ◦ EPA bans sales, distribution, and use of daminozide, a pesticide linked to tumors in laboratory animals.
1990	◦ Clean Air Act Amendments pass - institute cap and trade program to reduce sulfur dioxide and tackle the problem of acid rain

Year	**Events**
	○ Indigenous Environmental Network founded to address environmental and economic justice issues
1992	○ United Nations Conference on Environment and Development – 150 nations meet in Rio de Janeiro to coordinate on environmental issues ○ ENERGY STAR Program started by EPA to promote energy efficient products ○ New York City stops dumping sewage into the ocean - it is the last city in the US to do so
1993	○ EPA begins regulating Cryptosporidium, a parasite, in drinking water after an outbreak causes over 100 deaths and 400,000 infections in Milwaukee, WI ○ EPA reports that secondhand smoke is a health risk to nonsmokers
1995	○ EPA introduces first regulations on petroleum refineries - emissions are reduced by a cumulative 53,000 tons at the 192 existing refineries ○ Lead is fully phased out of gasoline, completing a task the EPA started in 1973
1996	○ Food Quality Protection Act passes - institutes higher standards for pesticide use
1999	○ New standards for vehicle emissions introduced ○ DOE launches the Wind Powering America program to encourage the use of wind power
2000	○ DOE returns 90,000 acres to the Northern Ute Tribe and agrees to cleanup and removal of radioactive uranium mill tailings
2001	○ The US joins over 90 nations in signing a treaty on Persistent Organic Pollutants (POPs). ○ Federal and state funds are allocated to remediate the PCB landfill in Warren County, North Carolina and support community-driven economic development, nearly 20 years after the protests there
2003	○ Virginia Electric Power Co faces the largest Clean Air Act Settlement with a utility. They agree to spend $1.2 billion to reduce emissions. ○ The EPA releases the *Framework for Cumulative Risk Assessment* to serve as a guideline for for risk assessments impacting vulnerable subpopulations.
2004	○ Virginia Electric Power Co faces the largest Clean Air Act Settlement with a utility. They agree to spend $1.2 billion to reduce emissions.
2005	○ Explosion at BP refinery in Texas kills 15 people and injures 170 more
2006	○ EPA launches *WaterSense*, a program to help consumers with practical ways to save water ○ EPA is the first federal agency to offset 100% of its energy use with renewable sources

Year	Events
	◦ EPA introduces the Ground Water Rule in response to 1996 data from the Center for Disease Control that showed waterborne disease outbreaks from ground water feed systems. Ground water was previously considered to be safe from contamination ◦ BP spills 200,000 gallons of crude oil onto the Alaskan tundra
2007	◦ BP pays $62 million in the largest criminal fine levied for air violations (due to the 2005 explosion and 2006 spill). They pay an additional $400 million in safety upgrades. ◦ A new study, *Toxic Wastes and Race at Twenty*, show that people of color are more concentrated around hazardous waste facilities than they were at the time of the 1987 UCC study.
2009	◦ EPA finds that greenhouse gases endanger the health and welfare of the American public and can start regulating them under the Clean Air Act
2010	◦ The Deepwater Horizon oil rig, operated by BP, explodes in the Gulf of Mexico. 11 workers are killed and 4.9 million barrels of crude oil are spilled ◦ Gulf Coast Ecosystem Restoration Task Force created by executive order to mitigate impact from Deepwater Horizon spill
2012	◦ EPA finds that greenhouse gases endanger the health and welfare of the American public and can start regulating them under the Clean Air Act
2014	◦ UN Intergovernmental Panel on Climate Change (IPCC) publishes report predicting extreme consequences if GHG emissions are not reduced immediately (IPCC, 2014)

Table 2.1: Timeline of Selected Developments in the Environmental Risk Policy Subsystem

2.2 The Risk Professionals

The risk professionals survey project is an ongoing project currently consisting of three waves of survey collection on samples of professionals working in the subsystem defined earlier in this chapter. These surveys give us a unique opportunity to revisit the same policy subsystem as it develops. While the survey has changed over time to meet the needs of each research context, many elements are recreated in each iteration to enable longitudinal comparisons. This section provides details about the survey instrument used to collect data on the risk professionals and descriptive statistics that compare the population across the samples.

2.2.1 The Survey

1984 Survey

The first wave of the survey, 1984, was collected by Thomas Dietz and Robert Rycroft on a sample of 228 professionals. Dietz & Rycroft (1987) offer an overview of their sampling procedure. They used their experience conducting seminars sponsored by the Environmental Protection Agency to identify a sample seed of 20 individuals. This sample was comprised of active professionals with strong community ties who represented the major institutional groupings active in the environmental policy process, like corporations, environmental non-profits, and universities. All respondents provided 5 nominations for future interviews, creating a snowball sample. New nominations were entered with duplication into a filing system from which names were drawn for interviews. Thus, more prominent individuals were more likely to be selected. The survey collects information on the networks between risk professionals as well as each respondent's beliefs and background.

2000 Survey

In 2000, Robin Sweeney and Thomas Dietz conducted a second wave of the risk professionals survey[1]. They sampled 50 professionals and replicated much of the original risk professionals survey. However, the network questions, where respondents are asked about their professionals contacts, were excluded from this wave. Questions on decision making and stakeholder involvement were added.

2014 Survey

The third wave of data was collected by Thomas Dietz and Adam Douglas Henry in 2014 and includes 281 observations. This dataset was also built using snowball sampling from a seed consisting of 1) participants from a random sample of Congressional hearings on environmental risk, 2) authors on a random sample of National Research Council reports on environmental risk, and 3) attendees of the Society for Risk Analysis (SRA) annual meeting who participated on a topic related to environmental risk. This wave of the survey also recreates many of the questions from the original survey.

[1]This survey is not used in this dissertation because no network data were collected.

2.2.2 Who Are the Risk Professionals?

The risk professionals represent all sectors of the economy and span a wide range of policy topics within risk analysis. Given the broad boundaries of the environmental risk management subsystem, we have an eclectic group of respondents with diverse backgrounds and a variety of current professional positions. We use this section to describe the professionals who responded to the survey. This section includes descriptions of their personal characteristics, both demographic characteristics and their beliefs about select issues in the subsystem, and descriptions of their place within the subsystem, both in terms of the activities that they undertake and their network characteristics.

Demographics

Each survey collects data on respondent demographics that we can use to create a a picture of the risk professionals. First, we have data on respondent gender across all three waves of the survey. The balance between male and female respondents in each wave is shown in Figure 2.1. The proportions shown in the graph are the proportion of the respondents who identified as either male or female out of the total number of respondents who answered the survey question on gender. In terms of gender balance, we see the least equitable distribution in the earliest wave and the most equitable distribution in the middle wave.

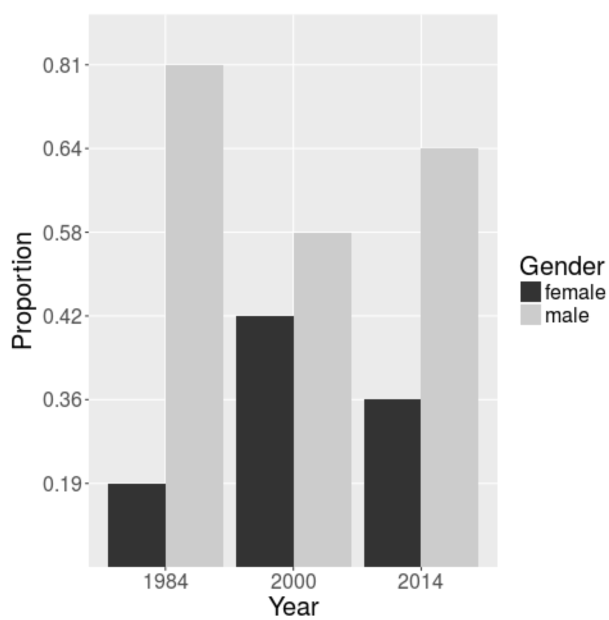

Figure 2.1: Respondent Gender

The first two waves of the survey also ask respondents to report their race. Respondents could identify as 'Asian American'. 'Black', 'White', or 'Other'. Figure 2.2 shows the balance between racial groups in the first two waves. The proportions shown in the graph are the proportion of the respondents who identified in each category out of the total number of respondents who answered the survey question on race. As with gender, we see diversification of the risk professionals moving from the first to second wave.

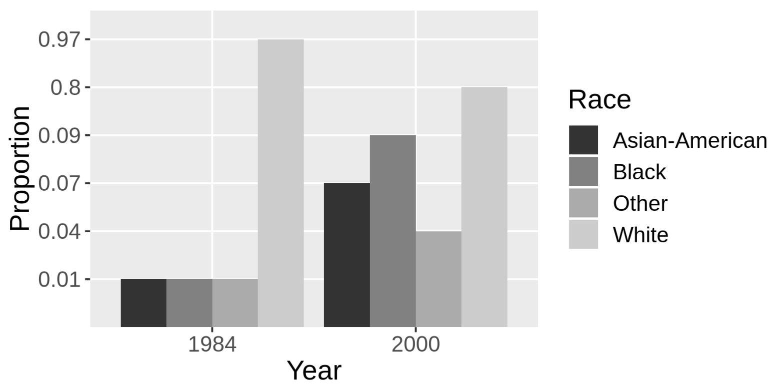

Figure 2.2: Respondent Race

All three waves collect information on the educational background of the risk professionals. Table 2.2 tracks the highest educational attainment by degree across the samples. The percentages shown in the table are the percentages of the respondents who reported their highest degree in each category out of the total number of respondents who reported information on their education. We see a higher concentration of professionals with doctorates develop over time with a sharp increase between the second and third waves.

Table 2.2: Highest Degree

Degree Held	**1984**	**2000**	**2014**
High School	0.5%	-	-
Associate's Degree	2%	-	0.5%
Bachelor's Degree	11%	8%	7%
Master's Degree	20.5%	26%	17%
Law Degree	22%	14%	3.5%
Medical Degree	3.5%	-	2.5%
PhD	40.5%	46%	67.5%
Combination Law/Medical/PhD	-	6%	2%

Beliefs

In addition to personal demographic characteristics, we also have data on the beliefs held by each individual. The survey collects the respondents views on 10 policy issues that we use as a focus in Chapter 3. The question wordings are shown in Table 2.3 which is reproduced as Table 3.3 in Chapter 3. Figures 2.3, 2.4, and 2.5 show the distribution of responses to each of the beliefs. Across the waves of the survey, the belief questions were asked using 4- 5- and 7-point scales to gauge agreement. In this section, all answers were rescaled to a 4-point measure (strongly disagree, disagree, agree, and strongly agree) so they would be comparable across time periods. In the 1984 and 2000 data, we see a higher concentration of responses in the agree and disagree categories, but there are respondents who fall into the strong agree/disagree categories. The data collected in 2014 show a higher proportion of respondents in the extreme categories than the previous two waves of data.

Table 2.3: Policy Core Belief Questions

Variable	Question	Measurement
Adversary	In our democratic society, it is healthy to have an adversary relationship between business and government in areas such as product safety, pollution standards, and safety in the workplace.	1984: 4-scale 2014: 5 scale
	It is healthy to have an adversarial relationship between business and government in areas such as product safety, pollution standards, and safety in the workplace.	2014: 7-scale
Involvement	A high level of public involvement often leads to bad policy decisions.	1984: 4-scale 2014: 5- & 7-scale
Consumer	A consumer should be allowed to choose between a very safe product at a higher price and the same product without safety equipment at a lower price.	1984: 4-scale 2014: 5- & 7-scale
Catastrophic	The risks associated with advanced technology have been greatly exaggerated by events such as Three Mile Island or the Love Canal.	1984: 4-scale 2014: 5 scale
	The risks associated with advanced technology have been greatly exaggerated by high-profile or catastrophic events.	2014: 7-scale
Protecting	On the whole, business does a good job of protecting the public from dangerous products and substances.	1984: 4-scale 2014: 5- & 7-scale
Information	Many environmental policy problems could be resolved with better technical information.	1984: 4-scale 2014: 5- & 7-scale
Planning	The government should engage in more long-range planning.	1984: 4-scale 2014: 5- & 7-scale
Special_ Interest	Most policy decisions reflect the needs of special interest groups rather than the needs of the general public.	1984: 4-scale 2014: 5- & 7-scale
Pollution	The benefits of modern consumer products are more important than the pollution caused by their production and use.	1984: 4-scale 2014: 5- & 7-scale
Development	Development of advanced technology should continue in as uninhibited a regulatory environment as reasonably possible.	1984: 4-scale 2014: 5- & 7-scale

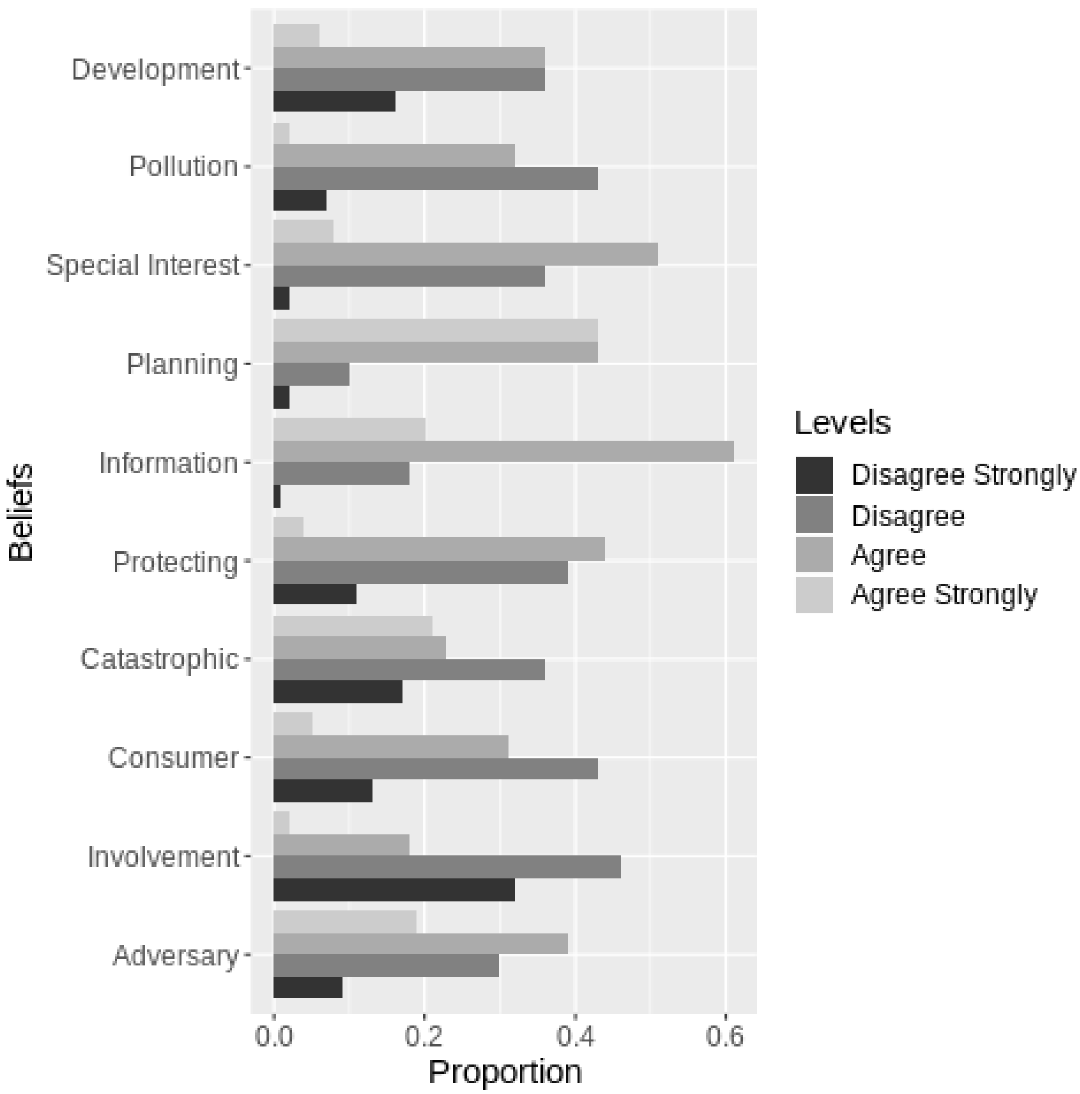

Figure 2.3: Beliefs 1984

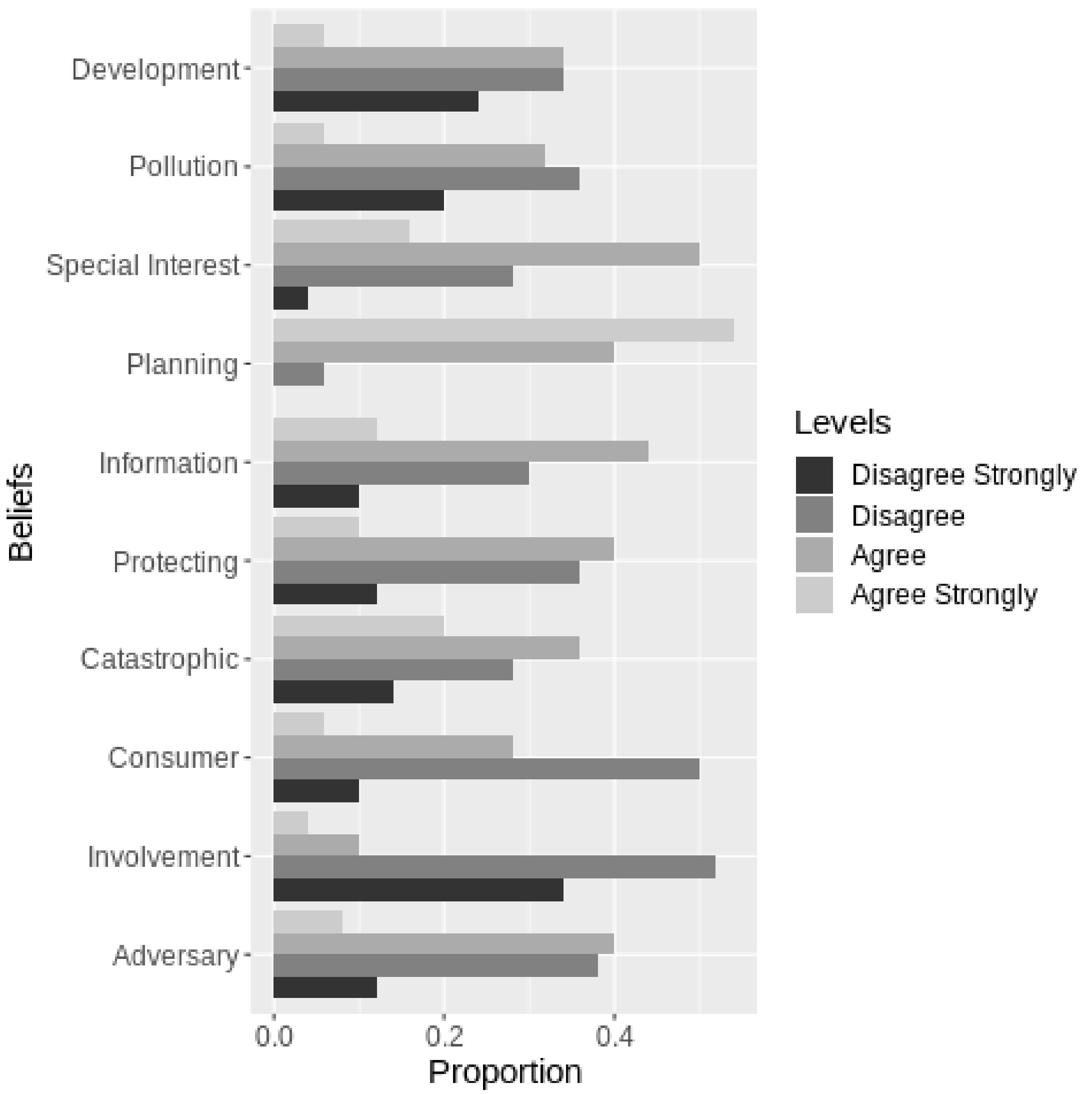

Figure 2.4: Beliefs 2000

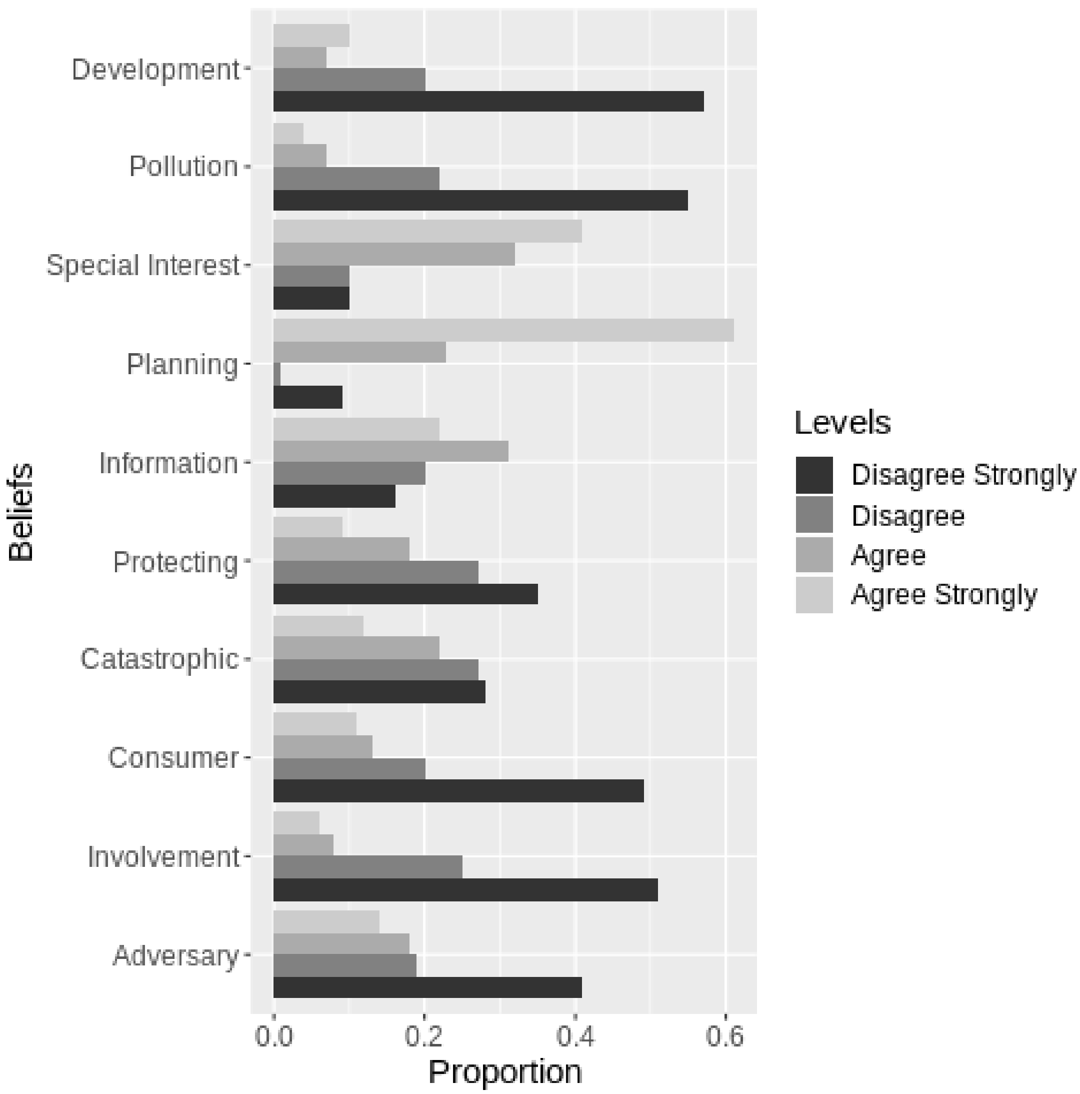

Figure 2.5: Beliefs 2014

Professional Activities

The previous two sections, demographics and beliefs, described the individuals in the samples. This section, professional activities, looks at the individuals' position in the professional arena. We have data from all three survey waves that describe the day to day activities of respondents. In the first two waves of the survey, respondents could select up to two activities. The results from the first two waves are in Figures 2.6 and 2.7. In both time periods, we see considerable reporting on the option 'Working Directly on Policy Issues'. Although the professionals surveyed work in a highly technical field, there is considerable engagement in the policy process. Figure 2.8 shows the results to a similar question asked in the 2014 survey. In the 2014 version, policy activities are not grouped into one category. Instead, we can find the policy activities by combining 'Advocate for Specific Policies' and 'Write/Deliberate Legislation and Rules'. Together, these two categories account for about a quarter of all activities reported.

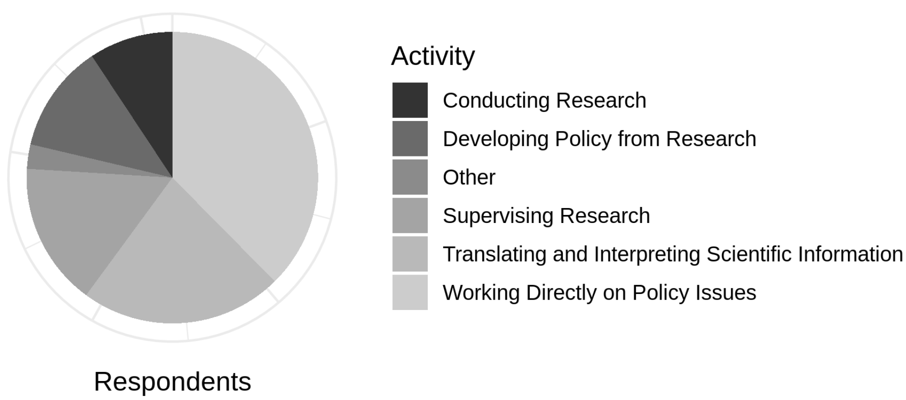

Figure 2.6: Professional Activities 1984

In the 2014 survey, respondents were asked to describe what they thought of as the most pressing environmental or technical risk issue that society faces. In answering this question, many respondents discussed climate change, water availability, and conservation of resources among other issues. Broad topics like these bring in aspects of many respondents work even if they are in separate specializations.

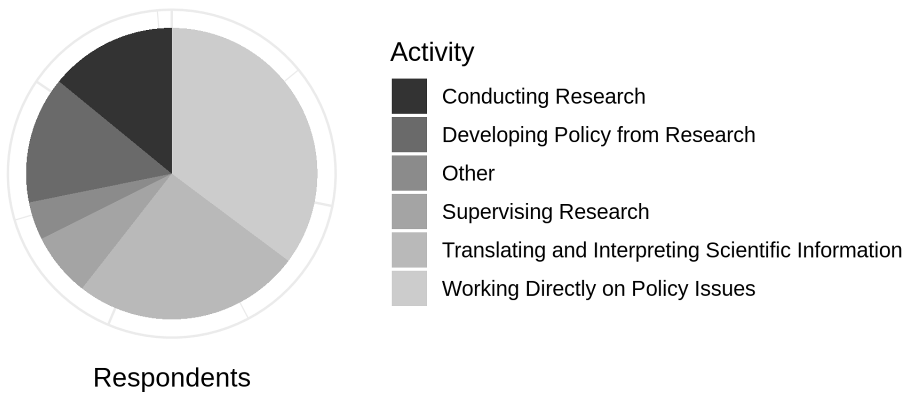

Figure 2.7: Professional Activities 2000

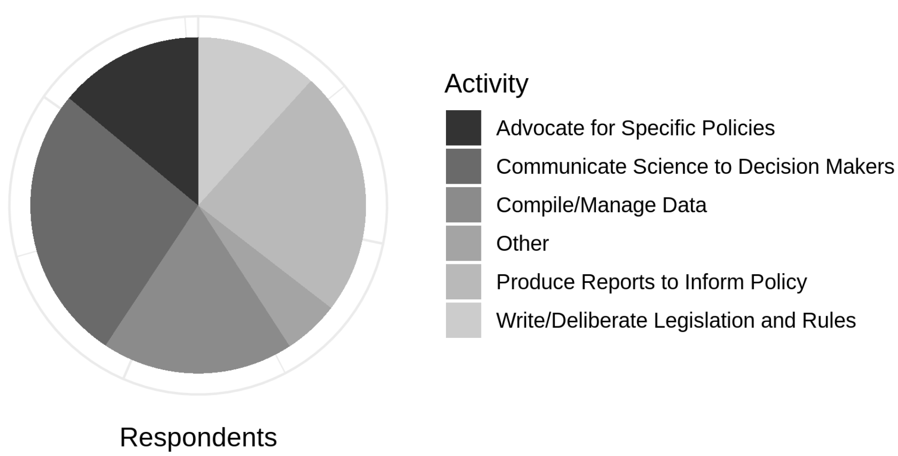

Figure 2.8: Professional Activities 2014

Network Characteristics

Now that we have described the individual risk professionals and their work, we can look at the relationships between professionals. In the first and third waves of the survey, respondents are asked to identify their professional contacts either from a roster, which is the case in the 1984 survey, or by listing organizations that they contacts, which is the case in the 2014 survey. Additionally, respondents in the 1984 survey can choose as many contacts from the roster as they would like while respondents in the 2014 survey were limited to reporting 10 contacts. The box plot in Figure 2.9 shows the resulting distributions of ties in each of the two surveys. We can see that the median number of ties reported in 1984 is roughly equivalent to the maximum number reported in 2014.

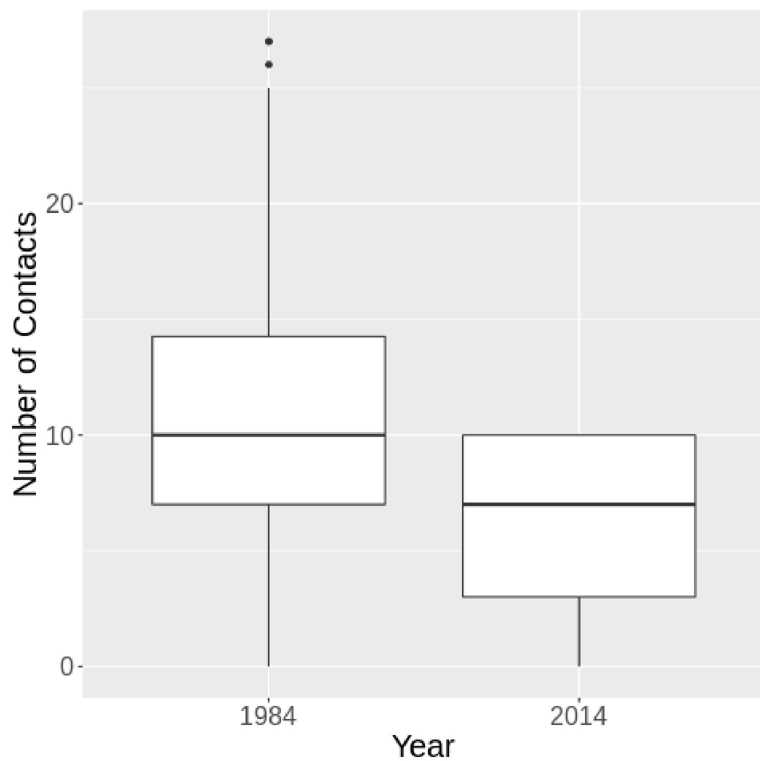

Figure 2.9: Number of Contacts in 1984 and 2014

In addition to reporting their organization contacts, the respondents to the 2014 survey described their interactions with their contacts. Respondents were asked to identify which of type of activities they took part in with each of their contacts. Respondents can select as many of the follow type of interaction as they would like for each of their contacts: jointly advocate for policy, jointly implement programs or policies, write joint publications, seek/provide funding or physical resources, engage in joint research, seek/provide consulting services, seek/provide advice, attend the same meetings, and share information or data. Figure 2.10 shows the number of times each type of interaction was reported across all respondents. Less resource intensive types of interaction, like attending meetings and sharing information are reported more frequently than more resource intensive types of interaction like advocating for policies and implementing programs and policies.

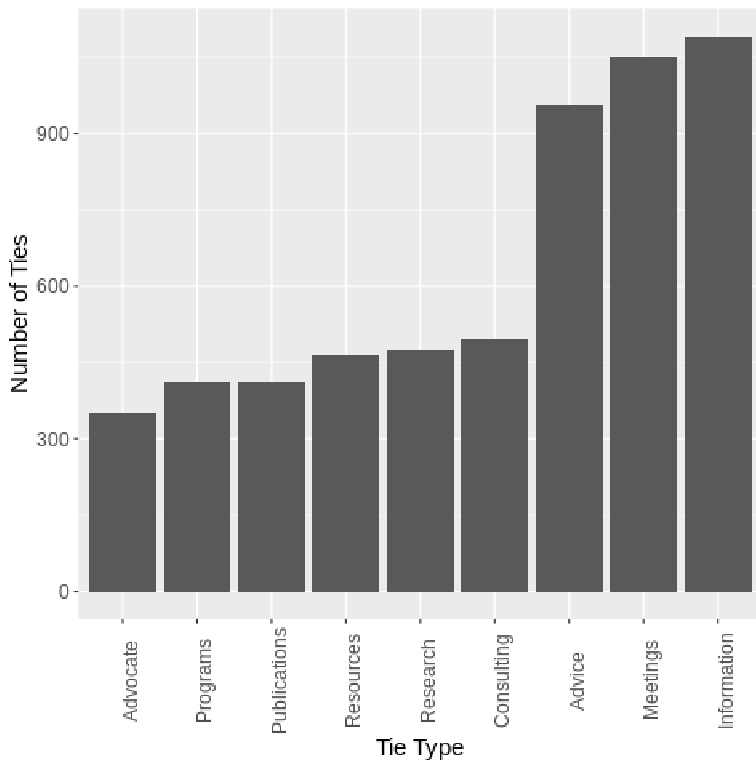

Figure 2.10: Incidence of Interaction 2014

2.3 Previous Work on the Risk Professionals

With three waves of survey data spanning 30 years, the risk professionals research program has brought about a body of literature on the characteristics and behavior of risk professionals over the course of the subsystem. Here, we review the existing literature on each wave of the survey and orient this dissertation in the context of the existing literature.

2.3.1 Pre-Survey Literature

Literature on the research program starts with a publication by Regens et al. (1983) a year before the first survey is deployed. In this paper, Regens et al. (1983) provide their motivation for studying the subsystem and provide context to the environmental risk policy subsystem in the early 1980s. Regens et al. (1983) observed an emerging subsystem where the analysis of risk was just beginning to become a serious consideration in policy debates. The Environmental Protection Agency (EPA) had only recently begun to develop a standard methodology for defining risk starting the 1976 publication of guidelines for cancer risk assessment (Regens et al., 1983). Taking the process a set further, the Office of Health and Environmental Assessment (OHEA) proposed agency-wide guidelines in 1980 that would standardize the process for estimating exposure to toxic substances and mutagenicity risk (Regens et al., 1983). Despite the work towards standardized use of risk assessment, Regens et al. (1983) found that agencies engaged in issues of environmental risk had substantial discretion in the implementation of risk assessments. The EPA and the Food and Drug Administration (FDA), the two lead regulatory agencies on issues of environmental health and safety, cover an astounding breath of economic activities and handle many diverse environmental issues (Regens et al., 1983). This level of technical complexity and the political nature of interpreting risk assessments leads to a subsystem were standardization is extremely difficult and collaboration is necessary.

2.3.2 Literature on the 1984 Survey

After establishing the challenges in the environmental risk policy subsystem, Dietz and Rycroft deployed the first wave of the risk professionals survey in 1984. In a book published on the survey, Dietz & Rycroft (1987) describe the respondents through four different lenses: as an elite, as a new class, as an establishment, and as a policy community.

The risk professionals sample meets some of the expectations on the characteristics generally associated with policy elites. The authors expect to see homogeneity in background on dimensions like gender, ethnicity, and education in a policy elite (Dietz & Rycroft, 1987). The risk professionals are demographically similar, predominately white males, and they overwhelmingly have attended college and frequently hold higher degrees – only 2% do not have a college degree and 87% continued their education past a bachelors degree (Dietz & Rycroft, 1987). However, they are much less homogeneous in terms of fields of study, schools attended, and organizational affiliations than what we would expect to see in most groups of policy elites (Dietz & Rycroft, 1987).

The risk professionals are a better fit for the new class perspective than the elite perspective, but the results in this area are also mixed. The respondents share a world view that "accept[s] the fragility of nature and the threats posed by human activity" (Dietz & Rycroft, 1987, p.48). However, while the risk professionals have consensus on the gravity and cause of the policy problems, they agree less on the solutions – issues like the efficacy and fairness of the political process and the role of science in policy making (Dietz & Rycroft, 1987).

In evaluating the risk professionals as an establishment, we expect to see common view on the processes of implementing risk analysis in policy making (Dietz & Rycroft, 1987). This could include agreement on the causes of problems in the subsystem and on the way that risk analysis is implemented and interpreted. There is a mix of agreement and disagreement among risk professionals on these issues, frequently associated with professional socialization through fields of study and present organizational affiliation (Dietz & Rycroft, 1987). This section, in some ways, foreshadows the study on conflict by Dietz et al. (1989) discussed later in this section.

The last perspective taken in the book is risk professionals as a policy community. Dietz & Rycroft (1987) adopt a definition of policy communities that emphasizes their role as information networks where the actors exchange substantive information, learn from this exchange, and are not locked into a hierarchy or strict organization within the network. This perspective is the best fit for the risk professionals sample. Dietz & Rycroft (1987) find that the risk professionals partake in high levels of communication and are well connected across different types of organizations. Patterns of perception and communication differ by organization type. For instance, corporations and trade organizations are seen as influential and are contacted frequently, while environmental organizations, although regarded more sympathetically, are seen as less influential and contacted less frequently (Dietz & Rycroft, 1987).

Through this book, Dietz & Rycroft (1987) provide a better understanding of the risk professionals sample and justify the framing of the risk professional as a policy community rather than an elite, a new class, or an establishment – a framing that will carry through the literature on the subsystem.

After the initial introduction of the survey data from Dietz & Rycroft (1987), Rycroft, Regens, Dietz, and Stern analyzed the responses from the survey in a series of papers covering the use of scientific and technical information in policy making, the views of EPA officials on incorporating risk analysis and benefit-cost analysis into environmental management, and heterogeneous definitions of conflict across organizations (Rycroft et al., 1987, 1988; Dietz et al., 1989). The risk professionals survey provided a new perspective on these issues because most previous literature had focused on organizational mandates rather than individual perceptions (Rycroft et al., 1988).

The first paper published out of the risk professionals survey, Rycroft et al. (1987), incorporates data from the USATI follow-up survey on the use of scientific and technical information (STI). Respondents were asked to rank a set of attributes of STI on their importance to policy making. This list included the source of the information, the content of the message, the timeliness of the information, and the views of the decision maker. The content of the analysis was most commonly ranked as 'most important', but the authors were surprised at the low rate of importance assigned to the source of the STI (Rycroft et al., 1987). Additional analysis in this paper found that respondents' most commonly kept themselves informed through conversations with colleagues (97%) and secondary literature (91.2%) and that the risk professionals use STI most heavily in the formulation and evaluation stages of policy making but less so in agenda-setting and implementation (Rycroft et al., 1987).

The next study from the risk professionals survey used a subset of the sample to examine the views of EPA officials on the use of risk assessment and benefit-cost analysis (Rycroft et al., 1988). The analysis focuses on the heterogeneity of views on four topics: "(1) whether respondents favor or oppose the use of formal risk analysis in environmental policy; (2) whether they favor or oppose government use of benefit-cost analysis; (3) whether they agree or disagree that society must attempt to place an economic value on human life in order to allocate scarce resources; and (4) which of the three possible methods of valuing life they would choose – allowing people to make their own choices to implicitly accepts risks. Determining that aggregate societal costs do not exceed aggregate societal benefits, or making sure that no one group bears a disproportionate share of the risk burden." (Rycroft et al., 1988, p.416).

The use of formal risk analysis and benefit-cost analysis is favored by a majority of respondents. However, respondents with backgrounds in environmental science oppose both methods (Rycroft et al., 1988). The authors speculate that this could be because these officials lack confidence in researchers ability to fully measure the impact of our actions. Roughly 70% of respondents disagree that with the statement that society must generate an economic valuation of life with this proportion varying by respondent background (Rycroft et al., 1988). On the fourth topic, the distribution of risk, respondents favored the option that ensures that no one group bears a disproportionate risk (Rycroft et al., 1988). However, the option that focused on aggregate societal costs and benefits received the most support from respondents with backgrounds in social science and liberal arts (Rycroft et al., 1988). Across all of the topics studied, educational background had a stronger relation with preference than either the office in which the respondent worked or their job duties.

In the third paper on the original risk professionals survey, Dietz et al. (1989) turn their attention to the respondents' views on conflict. The authors hypothesize that the surveyed professionals will hold views on conflict that increase the legitimacy of their respective organizations and professions. For instance, policy stakeholders affiliated with a corporation that has the resources to cultivate 'in-house' expertise may hold a view on conflict that identified an uninformed populace as the root problem and emphasis the role of experts in making decisions (Dietz et al., 1989). The four philosophies on conflict used in the paper are: 1) *differential knowledge* (from the example above), which focuses on a lack of understanding as the problem and prioritizes the input of experts in policy making; 2) *vested interest*, which emphasizes that risks are usually disproportionately distributed and prioritizes the opinions of stakeholder who will be effected by any proposed action; 3) *value differences*, which argues that value systems are the only way to make decisions, because decisions will ultimately necessitate trade-offs; and 4) *mistrust of expert knowledge*, which holds that conflict arises because people have been conditioned to mistrust expert knowledge because experts often serve the interests of their organizations (Dietz et al., 1989). In support of the authors' hypotheses, they find that survey respondents affiliated with environmental organizations are positively inclined to support the mistrust of expert knowledge framing of conflict while they dismiss the differential knowledge view (Dietz et al., 1989). On the other hand, respondents affiliated with corporations support the knowledge differential perspective with rejecting the vested interest and value differences frames (Dietz et al., 1989). These views lend legitimacy to the organizations where respondents hold affiliations.

2.3.3 Literature on the 2000 Survey

In 2004, Sweeney completed her dissertation project on the 2000 survey of risk professionals (Sweeney, 2004). Her dissertation covered a broad range of topics on the risk professions, notably describing the sociodemographics, ideology, view on the policy process, patterns of communication, and stakeholder involvement found in the subsystem. Her dissertation addresses many of the topics used by Dietz & Rycroft (1987) to describe the 1984 sample. Sweeney (2004) provides a longitudinal comparison of the risk professionals samples and introduces new research topics on the occurrence and perceived efficacy of stakeholder involvement.

The chapter on socio-demographics provides a direct comparison between the professionals who participated in the 1984 survey and the those who Sweeney surveyed along the dimensions of education, gender, race, age, employment and work. In both samples, over 85% percent of the sample have a masters degree or higher (Sweeney, 2004). When examining the respondents by highest educational category – high school diploma; associate's degree; master's degree; law degree; medical degree; doctor of philosophy; more than one of law, medical, or PhD – the only statistically significant difference between survey waves is the higher occurrence of the final category - multiple degree holders - in the 2000 survey (Sweeney, 2004). The educational backgrounds of the respondents in the second wave also shifted away from the physical sciences and towards the biological sciences (Sweeney, 2004). Between the two surveys, women increased from 20% to 42% of the sample and minority representation increased from 3% to almost 20% (Sweeney, 2004). While the mean age shifted from 42.9 to 49.4 years, this change was not statistically significant (Sweeney, 2004). Sweeney also grouped the respondents into several categories of employment to compare across surveys. The biggest, and only statistically significant, difference between samples was the increase in respondents affiliated with the category that included think tanks, the National Research Council and National Academy of Sciences, and universities (Sweeney, 2004). This category expanded from 9.2% of respondents to 28% (Sweeney, 2004). The largest employer in the first wave was the federal executive agencies with 28.2% of respondents; this category dropped to second place with 24% of respondents in second wave (Sweeney, 2004). Finally, Sweeney (2004) compares the type of work done by professionals in both samples, finding that translating research into policy and working directly with policy issues are the most common categories of work reported.

In the ideology chapter, Sweeney (2004) concludes that the 2000 sample of risk professionals shares a world view centered on environmentalism, living in harmony with nature, and participatory decision making and that they eschew a more economic world-view associated with embracing risks from technology and absence of limits on growth. Like the 1984 risk professionals, the respondents in the 2000 sample do not believe that market forces will produce a solution to every problem (Sweeney, 2004). However, the belief that new knowledge could resolve technical problems declined over time between the two sample (Sweeney, 2004). Overall, this chapter continues the discussion that Dietz & Rycroft (1987) started on risk professionals as a new class by addressing their coherence around a belief system.

The policy process chapter covers the themes from Dietz & Rycroft (1987) on risk professionals as an establishment. This chapter focuses on the risk professionals' views on the policy process, the obstacles to policy making, and solutions for creating a better process. Risk professionals in the 2000 survey generally agree that the federal government does not have a cohesive strategy for addressing environmental issues and believe that providing more information and using mediation were possible solutions (Sweeney, 2004). However, the risk professionals in 2000 are less likely to believe that good science will change people's minds than those sampled in 1984 (Sweeney, 2004). This is a particularly interesting observation, because the public availability of high quality scientific data on environmental risks increased dramatically between the two samples (Sweeney, 2004).

To wrap up the longitudinal sections, Sweeney (2004) addresses the communication flows through the policy networks in the 2000 survey. Since the 2000 survey lacks questions on professional contacts, Sweeney has less opportunity for studying this topic than Dietz & Rycroft (1987). However, using the data that were collected, she infers that the communications networks among risk professionals had not changed significantly. The survey respondents continue to report affiliation with a wide range of professional organizations, which give them opportunities to network, and nearly the same proportion of respondents (86% in 1984, 83% in 2000) nominate the maximum number of contacts – 5 – for the snowball sample (Sweeney, 2004). This evidence indicates that communication networks are still broad (Sweeney, 2004). The proportion working in the Washington D.C. area dropped from 78% in the 1984 survey to 64% in the 2000 survey, but Sweeney postulates the growing influence of the internet will mitigate the effect of this change on communication (Sweeney, 2004).

In the last substantive chapter of her dissertation, Sweeney (2004) examines a battery of questions on stakeholder involvement unique to the 2000 survey. She finds that stakeholder processes matter to risk professionals at all levels from local to international (Sweeney, 2004). The survey respondents see the role of stakeholders to be providing information, stating preferences, and providing input (Sweeney, 2004). In contrast, they see the appropriate role for scientists to be communicating data and acting as advisers and the role of policy makers to be listening to the others and making policy decisions (Sweeney, 2004). The risk professionals generally felt that stakeholder inclusion improved the results of the policy making process on principle by being more inclusive and in practice by increasing stakeholder acceptance of the results (Sweeney, 2004).

While Sweeney (2004) made comparisons between the first two waves of the survey, Henry & Dietz (2015) prepared a paper on policy learning that leveraged the two datasets to model change over time. In this study, Henry & Dietz (2015) use networks of organizational contacts, networks of individuals' movement between organizations, and the belief differences between organizations to parse the effects of learning and homophily on policy networks. The belief homophily hypothesis that the authors test states that "policy actors tend to form individual collaborative relationships on the basis of belief similarity" while the learning hypothesis states that "policy actors who maintain collaborative relationships tend to learn beliefs from one another, leading to belief convergence over time" (Henry & Dietz, 2015, p.8). Both mechanisms explain why a network will develop stronger belief segregation over time and both mechanisms can operate at the same time (Henry & Dietz, 2015). Henry & Dietz (2015) find strong support for the homophily hypothesis and weaker support for the learning hypothesis in the risk professionals data.

2.3.4 Literature on the 2014 Survey

To date, there are no published papers on the survey data collected in 2014. This cumulative dataset, spanning thirty years of the U.S. environmental risk policy subsystem, provides an excellent opportunity to explore both the current state of the subsystem and the longitudinal changes. Additionally, the introduction of the ACF into studies of this subsystem by Henry & Dietz (2015) provides scaffolding for developing risk professionals research in a way that contributes to the larger literature on the policy making process. This dissertation serves the dual purpose of expanding the topical risk professionals literature and contributing to the theoretical development of the ACF.

In their foundational work on the risk professionals, Dietz & Rycroft (1987) collected network data and conceptualized the risk professionals as a policy community connected by communication flows across diverse organizations. We take this concept further by constructing and comparing networks of actors that appear in both the 1984 and 2014 data to look for changing belief segregation over the life of the subsystem (see Chapter 3). Chapter 3 complements the previous work on belief segregation in the subsystem by Henry & Dietz (2015). We also use egocentric networks to assess the bounding effect coalitions may have on coordination (see Chapter 4). Chapters 3 and 4 leverage the theoretical development of the ACF to generate research questions and hypotheses and in turn contribute back to the framework's understanding of the policy process.

Chapter 3

Belief Segregation in the Environmental Risk Management Subsystem: An Analysis of Nascent and Mature Subsystems

Abstract

The Advocacy Coalition Framework (ACF) predicts that, in well developed policy subsystems, actors will form ties with partners who share similar beliefs in order to jointly advocate for policy change. This behavior creates belief-based segregation among professional contacts which may inhibit policy outcomes. However, in nascent subsystems where policy stakeholders are still establishing their contacts, the ACF predicts comparatively less belief-based segregation. The process of network segregation that takes place between nascent and mature subsystems can be driven by multiple mechanisms including homophily and social influence and can be reinforced through mechanisms like triadic closure. In this paper, we compare policy networks from 1984 and 2014 in the U.S. environmental risk management subsystem to the ACF expectations for nascent and mature subsystems. This chapter contributes to the understanding of subsystem evolution by providing analysis on the same subsystem at different points in maturity.

3.1 Introduction

At its core, the policy making process depends on stakeholders' relationships with each other. Policy makers are constantly working with and against each other as they promote their respective views and obstruct the success of their opponents. We can study these interactions by conceptualizing stakeholders and their relationships to one another as policy networks. Policy networks evolve over time as participants establish and dissolve relationships. According to the Advocacy Coalition Framework (ACF) (Sabatier, 1986, 1988; Jenkins-Smith et al., 2014), a major factor influencing the formation and dissolution of ties is belief similarity between stakeholders. Stakeholders tend to seek out ties with others who share their beliefs and to use these ties to cooperatively advocate for the representation of those beliefs in policy. This process results in self-selected advocacy coalitions segregated by policy beliefs where stakeholders work with partners with the same policy goals.

Belief-based network segregation can have both positive and negative impacts in the policy process. Cohesion within a subgroup can promote trust and identity (Henry & Vollan, 2014). In the case of advocacy coalitions, a coalition that shares the same core beliefs may be more willing to share information or feel more confident discussing advocacy strategy. However, network segregation around beliefs can also cause problems in policy networks. Network segregation is associated with lowered coordination, resource exchange, and learning (Henry & Vollan, 2014). Studies of knowledge transfer find that information flows most easily through networks when ties connect diverse sets of stakeholders (Crona & Bodin, 2006; Standström & Rova, 2010). Thus, segregation could be substantially detrimental to policy networks as members of the same coalition will lack the diverse contacts needed for gathering holistic information that can better inform policy.

The three mechanisms closely connected with belief segregation are homophily, social influence, and triadic closure. First, segregation itself, which can arise through homophily or social influence. Homophily is a process where actors are more likely to connect with those similar to themselves (McPherson et al., 2001). Second, social influence causes actors to change their beliefs when they are exposed to the beliefs of their contacts (Lazer, 2001). Finally, triadic closure, which can reinforce network segregation. Triadic closure occurs when two actors who are connected by a mutual partner form a tie between themselves. Triadic closure is discussed by Granovetter (1973, p.1362) as a response to "psychological strain" felt by the unconnected nodes when they both share a strong tie with a mutual partner. Indeed, Granovetter (1973, p.1363) refers to the case where two actors share strong ties with a mutual partner but no tie with each other as a "forbidden triad", although he admits that this is an exaggeration.

In this chapter, we explore belief segregation in the environmental risk management subsystem over time. More specifically, we compare belief segregation in 1984, when the subsystem was first emerging, to the ACF expectations for segregation in nascent subsystems. We also compare belief segregation in 2014, when the subsystem was more established, to the ACF expectations for segregation in mature subsystems. In well established policy subsystems, the ACF predicts that policy stakeholders will self-select into coalitions based on their beliefs where they can work together to promote their ideas about policy. Alternatively, new policy subsystems provide more opportunities for ties among actors with different beliefs and may evince less belief homophily and thus less belief segregation.

This chapter consists of nine sections. Section 3.2 introduces the U.S. environmental risk management subsystem. Section 3.3 presents key assumptions from the ACF literature on policy stakeholder behavior and previous research on policy network segregation. Section 3.4 presents the hypotheses tested in this chapter. Section 3.5 introduces the survey data from the environmental risk management subsystem. Sections 3.6 and 3.7 present the analysis on the data from 1984 and 2014 respectively[1]. Sections 3.8 and 3.9 are the discussion of results and the conclusion.

3.2 U.S. Environmental Risk Management Subsystem

In the ACF, the policy subsystem is the arena where the policy process plays out and it is defined by a topic, geographic scope, and actors directly and indirectly involved in policy making activities (Jenkins-Smith et al., 2014). In this paper, we focus on the U.S. environmental risk management subsystem. Environmental risk occurs when factors like pollution, natural disasters, and energy generation impact lives and livelihoods. For instance, production at a chemical plant can impact different groups of stakeholders in different ways - the employees through long-term exposure to the processing inputs, the people living near the plant through byproducts that are discharged into the ground, and the consumers through exposure to the final products. Environmental risks can be managed through multiple means including policy measures to prevent and mitigate impacts. Actors in this subsystem develop policy to address environmental risk at the federal level. They may also work at the international, state, or local levels in conjunction with their work

[1]All analysis was carried out using the R Statistical Package (R Core Team, 2018) and the following associated packages: sna (Butts, 2016), factoextra (Kassambara & Mundt, 2017), clustertend (YiLan & RuTong, 2015), plyr (Wickham, 2011) and ggplot2 (Wickham, 2016).

on the national stage. The environmental risk management subsystem includes policy stakeholders from across all sectors of the economy - government agencies, private businesses, and environmental non-profits are all represented - and across topical specializations - environmental conservation, energy production, infectious disease, and production of consumer products are all included, among other topics. Some actors in the subsystem work directly on forming policy, while others work on generating knowledge through research, communicating research results to policy makers and the public, and implementing policy initiatives.

3.3 Belief Segregation in Policy Networks

The ACF constructs a model of the individual that accounts for judgmental thinking and argumentative behavior. Individuals are conceptualized as policy stakeholders who wish to see their beliefs implemented as public policy and who are subject to psychological phenomena that shape their interactions with their allies and opponents. Individuals are boundedly rational and thus cannot make a full assessment of the information in the subsystem (Simon, 1955, 1985). They are also subject to biased assimilation whereby they interpret and assess new information through their preexisting beliefs, discounting information that conflicts with their views and accepting information that reinforces their views (Lord et al., 1979; Munro & Ditto, 1997; Munro et al., 2002). The ACF also incorporates prospect theory under which individuals are more sensitive to losses than gains (Quattrone & Tversky, 1988). Taken together, these phenomena create a mental environment where stakeholders prefer to gain new information from sources that support their beliefs. They are incapable of perfect knowledge and they are more likely to trust information that aligns with their views. Individuals with these characteristics are likely to prefer contact with partners who reinforce their beliefs. These phenomena are compounded by the “devil shift”, which appears in high conflict situations, where actors question the motivations and reasonableness of their opponents and evaluate them more harshly than a neutral actor would (Sabatier et al., 1987).

Individuals’ beliefs in the ACF are conceptualized according to a three-tiered model where each type of belief plays a different role in the policy process. Policy-core beliefs are beliefs that pertain to the policy topic and scope of the subsystem and can encompass normative or empirical issues (Jenkins-Smith et al., 2014). They are differentiated from deep-core beliefs - which are deeply-held, normative values spanning multiple subsystems - and secondary beliefs - which are specific means for implementing policy (Jenkins-Smith et al., 2014). Policy-core beliefs are the most important in subsystem debates. Stakeholders form coalitions with others who share their policy-core beliefs and advocate for these beliefs to be represented in policy. Since policy-core beliefs are the central topics for debate, this is also where we expect to see stakeholders most strongly express biased assimilation and prospect theory. As a result, we expect them to strengthen their ties with like-minded contacts and move away from contact with their opponents. This will result in growing belief segregation in the subsystem as stakeholders.

Social network analysis (SNA) is a good approach for studying segregation because it focuses on the relationships between actors. These relationships, or the lack thereof, drive patterns of segregation. We can conceptualize stakeholders as nodes in a network and the ties between them can represent any number of relationship types - contact, resource exchange, trust, policy agreement, etc. As the network evolves, stakeholders may form new ties, but they may also break ties. Belief segregation is present in a network when ties are more likely to exist between actors with similar beliefs. In previous studies, we see SNA applied to ACF concepts to assess the presence of belief segregation. In a study of California Marine Protected Area policy development, Weible (2005) finds that pairs of stakeholders coordinate more when they share policy-core beliefs than when they perceive others to have greater political influence. This supports the ACF argument that policy core beliefs hold together coalitions. In a study of land use and transportation planning networks in California, Henry et al. (2010) find that belief dissimilarity negatively influences collaboration, resulting in fewer cross-cluster collaborative links. In both examples, we see the expected belief segregation as stakeholders form coalitions to advocate for policy.

3.3.1 Mechanisms Leading to Network Segregation

Segregation has long been a topic of study in the social sciences, often focusing on the impacts that accompany limited exchange between groups. Researchers have used network studies on segregation to discuss the incidence and impacts of limited inter-racial and inter-ethnic connections in the US and abroad (see Tassier & Menczer, 2008; Allouch, 2013), sex segregation (see McPherson & Smith-Lovin, 1986), and other social cleavages (see McPherson et al., 2001; DiPrete et al., 2011). Early in the literature on segregation, Schelling (1969, 1971) showed how individual preferences for even moderate sorting can result in stark segregation through multiple mechanisms. While Schelling's work highlighted the impacts of individual preference on global dynamics, he did not use an explicitly networked approach in his studies. Freeman (1978) focused on measuring segregation and used a network approach to bring the measurement more in line with the intuitive understanding of segregation. Instead of focusing on spatial separation like previous measures did, he focused on unequal relationships between network nodes (Freeman, 1978). This conceptualization of segregation as an attribute of relationships rather than a restriction on access carries through in current studies of belief segregation in policy networks. Using a network approach on questions of segregation draws attention to the way individuals' constraints and decisions impact population level outcomes.

Network segregation can arise through a preference or aversion to connecting with individuals with similar or dissimilar attributes. Homophily specifically refers to the positive preference for forming ties with partners similar to oneself (McPherson et al., 2001). However, aversion to forming ties with dissimilar partners also results in segregation. In an extension on Schelling's work, Henry et al. (2011) show analytically that when actors in a network are averse to maintaining connections with others who are dissimilar to themselves, network segregation will occur regardless of the level of aversion. That is, actors do not need to strictly prefer a segregated network, small individual aversions will lead to global dynamics of segregation (Henry et al., 2011). In some instances, network segregation can also occur through a process of social influence. Social influence is a type of learning where actors change their characteristics based on their exposure to information and influence from their peers (Lazer, 2001; Henry & Vollan, 2014). This mechanism for segregation will only apply when the segregated attribute is changeable - like beliefs. In the case of social influence, an actor may change their beliefs after being exposed to different beliefs from contacts in their network.

Of course it is also possible to see homophily and social influence in the same network. To demonstrate the mechanisms leading to belief segregation, Henry (2011a) built an agent-based model of social influence and homophily. In this model, the opportunities that each agent in the model had for learning are constrained by their contacts in the network. Agents in the model are assigned static beliefs, similar to the ACF's deep-core beliefs, and a set of changeable beliefs, similar to the ACF's policy-core beliefs. Each agent in the model "learns" from their contacts by updating their changeable beliefs. The update is computed from the beliefs of the contacts and using weights so the agent learns more from contacts who share static beliefs with the agent. This mimics biased assimilation which is central to the ACF model of the individual. After each learning round, agents could break and form ties with various preferences for breaking ties with those that they do not agree with and forming ties with contacts who have similar beliefs - this is where belief homophily and aversion enter the model. Henry (2011a) found that biased assimilation was critical for the emergence of polarization and segregation in the simulated policy networks. The impacts of biased assimilation were more powerful in the model than the effects of homophilic tie formation Henry (2011a).

In a study of the U.S. environmental risk subsystem, Henry & Dietz (2015) prepared a paper on policy learning that leveraged data from 1984 and 2000[2] to model change over time. In this study, Henry & Dietz (2015) use networks of organizational contacts, networks of individuals' movement between organizations, and the belief differences between organizations to parse the effects of learning and homophily on policy networks. The authors found strong support for the homophily hypothesis and weaker support for the learning hypothesis in the risk professionals data.

While homophily and social influence create network segregation, triadic closure can reinforce the phenomena. Triadic closure occurs when two unconnected network actors with a mutual contact form a tie between themselves. Simmel (1950) emphasized the importance of triads as a unit of analysis, noting that the addition of one more actor substantially changes the possible group dynamics. With a closed triad, the relationship between two actors grows much more nuanced as the third actor can serve to strengthen or weaken that connection by interfering with either party (Simmel, 1950). Triads can also reinforce group norms since leaving the group is a higher cost to the actor leaving, who is isolated from the group, than for those who stay, who still have the group for consilation (Simmel, 1950). Through studies that compare Simmel's concept of triadic closure to other theories, Krackhardt (1999) and Krackhardt & Handcock (2007) find support for Simmel, particularly in the case of public facing relations. Closing triads can magnify social influence by providing a mechanism for enforcing norms within the clique. If a stakeholder has two contacts each of which has similar beliefs to itself, we may see the two contacts form a tie because they also have similar beliefs to each other or because they have a mutual contact.

3.3.2 Longitudinal Policy Network Segregation

While the ACF has well-developed expectations about belief segregation in policy networks, it is generally applied to established policy subsystems. In order to capture policy learning and other subsystems dynamics, Sabatier & Jenkins-Smith (1999) consider mature subsystems to be active for a decade or more. When new policy areas emerge, stakeholders face a steep learning curve as they form their initial contacts and solidify working relationships. Studies have begun to emerge with more regularity on the dynamics of emerging subsystems (see Sabatier & Brasher, 1993; Thomas, 1998; Beverwijk et al., 2008; Stevenson, 2009; Bandelow

[2] A survey of risk professionals was collected in 2000 by Robin Sweeney and Thomas Dietz (Sweeney, 2004). However, the 2000 survey did not include network data and is excluded from the present study.

& Kundolf, 2011; Fidelman et al., 2014; Stritch, 2015; Ingold et al., 2017). In this paper, we expand on this literature by offering analysis of the same subsystem at its origin and in maturity. Our first wave of data, collected in 1984, catches the US environmental risk policy subsystem at a time when systematic risk analysis was just becoming a consistent tool in the policy making process. The second wave of data was collected 30 years later in 2014 when stakeholders were well established in the subsystem.

Nascent subsystems can arise through two mechanisms: (1) they can form when stakeholders in an existing subsystem wish to devote more energy to a particular issue and splinter into a differentiated subsystem or (2) they can form through a new conceptualization of an existing issue or the emergence of a new issue altogether (Sabatier & Jenkins-Smith, 1999). In the case of the U.S. environmental risk policy subsystem studied in this paper, we see a new conceptualization of an existing issue. Controversies surrounding the interactions between human society and the natural environment were already a topic of policy debate, but the introduction of risk analysis provided a new conceptualization of the problems at hand. In cases where a subsystem emerges through a new conceptualization or new topic, we expect the initial coalition structure to be fluid while stakeholders learn more about the specific concerns that will drive policy debates (Sabatier & Jenkins-Smith, 1999). However, there is mixed support for this expectation with studies of nascent subsystems finding both that initial coalitions are vague and ill-defined (Sabatier & Brasher, 1993) and finding that stakeholders generally maintained their initial policy view (Beverwijk et al., 2008).

If ties are formed early between stakeholders with similar beliefs, than we will see belief segregation at similar levels in nascent and mature subsystems. In previous studies of nascent subsystems, we see coalition formation occur along three patterns: (1) undifferentiated by coalition, (2) by belief, and (3) carrying over previous contacts.

Undifferentiated stakeholder populations can occur when a subsystem is observed before debates around policy core issues have fully emerged. Fidelman et al. (2014) found that at the introduction of the Coral Triangle Initiative the policy subsystem around coastal and marine issues in the Southeast Asia-Pacific Coral Triangle region was a collaborative subsystem with broad agreement on policy. However, tensions in the subsystem threatened to create delineated coalitions if not carefully managed (Fidelman et al., 2014). Sabatier & Brasher (1993) also find a general consensus during the early years of the land-use and water quality policy subsystem around Lake Tahoe.

However, not all nascent subsystems display the same dynamics. Stritch (2015) provided support for belief segregation in nascent subsystems. Studying the trade union policy subsystem in Canada, Stritch (2015) found coalitions centered around shared beliefs appearing early in the course of the subsystem. Stevenson (2009) found mixed results in the emerging Oregon offshore wave energy policy subsystem where members of one coalition had high policy core belief homogeneity while members of the other coalition did not share beliefs, but considered each other to be allies in a previous policy debate. Bandelow & Kundolf (2011) also found early coalitions shaped by previous ties. The coalitions that they discovered in the policy subsystem around the European global navigation satellite system break into countries with an Anglo-Saxon tradition, who want a closer relationship with the United States, and those from a Roman tradition, who see Europe in competition with other global regions (Bandelow & Kundolf, 2011). In a study of fracking policy in Switzerland and the UK, Ingold et al. (2017) found that stakeholders in all three of the cases examined tended to agree in the fracking subsystem with allies from previous subsystems. This effect was also more commonly seen than policy agreement within groups (Ingold et al., 2017).

3.4 Hypotheses

We have data on the contact networks in the US environmental risk management subsystem in 1984, when formal risk assessment was fairly new to environmental policy making, and 2014, when the subsystem was well established. While the data from each time step cannot be directly compared (this will be discussed in more detail in Section 3.5.2), we can formulate hypotheses on the subsystem behavior at each time.

In the early time period, we have a subsystem created through the new conceptualization of an existing problem. Due to this fundamental change in the way the policy issues are formulated, we do not expect the early snapshot to show mature subsystem dynamics. Reframing an issue can have an undeniable impact on the policy outcomes. For instance, the Environmental Protection Agency's first formal set of guidelines on carcinogen risk assessment, published in 1976, shows a large shift in the treatment of carcinogen regulation due to the introduction of risk analysis (*Interim Procedures & Guidelines for Health Risk and Economic Impact Assessments of Suspected Carcinogens*, 1976). In the preamble to the guidelines, EPA Administrator Russell Train writes on the new perspectives on regulating carcinogens and the balance between eliminating all risks considering the social and economic consequences of such stringent regulation. With these kinds of considerations, we expect the reconceptualization of environmental risk management to create an important shift in the subsystem. Thus, we hypothesize that the contact network in the nascent subsystem will not show belief segregation or strong triadic closure, which we measure through network transitivity.

Belief Segregation in Nascent Subsystem Hypothesis: Belief segregation will not be higher in the nascent U.S. environmental risk management subsystem than in random networks of the same density between the same nodes.

Triadic Closure in Nascent Subsystem Hypothesis: Network transitivity will not be higher in the nascent U.S. environmental risk management subsystem than in random networks of the same density between the same nodes.

In the mature subsystem, the reconceptualization of environmental risk is long past. By 2014, formal risk analysis is well established in the subsystem and the stakeholders involved in the policy process have had time to adapt to the new methods and develop their beliefs and their network connections. At this point, there has been time for the effects of biased assimilation, prospect theory, and devil shift to shape the contact network and fuel belief segregation. Thus, we hypothesize that belief segregation and triadic closure will be significant in the mature subsystem.

Belief Segregation in Mature Subsystem Hypothesis: Belief segregation will be higher in the mature U.S. environmental risk management subsystem than in random networks of the same density between the same nodes.

Triadic Closure in Mature Subsystem Hypothesis: Network transitivity will be higher in the mature U.S. environmental risk management subsystem than in random networks of the same density between the same nodes.

3.5 Data

3.5.1 Data Collection

The data used for this study are from surveys of professionals working in the area of environmental risk management in the United States, referred to here as 'risk professionals'. Samples of risk professionals were surveyed in 1984 and again in 2014 using a similar set of survey prompts. The data from 1984 represent the early stages of the risk policy subsystem in the US and the data from 2014 represent the subsystem after 30 years of maturation. These data give a rare opportunity to study two starkly different periods in subsystem development.

The 1984 data were collected by Thomas Dietz and Robert Rycroft on a sample of 228 professionals. Dietz & Rycroft (1987) offer an overview of their sampling procedure. First, they generated a sample seed of 20 individuals who they identified through their work conducting seminars sponsored by the Environmental Protection Agency (EPA). The sample seed was comprised of active professionals with strong community ties who had participated in the seminars conducted by Dietz and Rycroft, and were identified as representing the major institutional groupings active in the environmental policy process. Each individual surveyed provided 5 nominations for future interviews, creating a snowball sample. New nominations were entered with duplication into a filing system from which names were drawn for interviews, thus more prominent individuals were more likely to be selected.

The 2014 data were collected by Thomas Dietz and Adam Douglas Henry and includes 281 observations. This dataset was also built using snowball sampling from a seed consisting of 1) participants from a random sample of Congressional hearings on environmental risk, 2) authors on a random sample of National Research Council reports on environmental risk, and 3) attendees of the Society for Risk Analysis (SRA) annual meeting who participated on a topic related to environmental risk. Individuals in this sample nominated up to 10 contacts in the policy subsystem who were then added to the sample and contacted for the survey.

3.5.2 Contact Networks

This section details the measurement of the contact networks in 1984 and 2014. Since the professional networks between organizations in the environmental risk management subsystem are sampled in different ways in the 1984 and 2014 surveys, we cannot compare these networks directly to each other. However, we can use the networks in each time step, along with the belief distance networks, to compare the subsystem at each time point to the ACF expectations.

1984

In the 1984 survey, respondents identified the organization where they were currently employed, organizations that they contacted regularly as part of their work, and their affiliations with professional societies. Response options for the current employer represent 77 organizations and types of organizations. When respondents identified their professional contacts, a similar list is available with 82 options. Both lists contain individual EPA offices; the differences in which EPA offices are included accounts for most of the difference between the lists. Once the EPA offices are collapsed into one organizational node, the combined list of ego and alter organizational options contains 23 distinct organizations and 18 categories of organizations. The combined list is presented in Table 3.1. Each respondent could also select up to five professional societies where they had an affiliation. The list of professional organizations is in Table 3.2.

To form a contact network between the organizations, we aggregated the individual respondents into organizational nodes. Nodes could be any organization from Table 3.1 or 3.2. Nodes were included in the network if they had at least one respondent affiliated with the organization who reported their policy-core beliefs. If a respondent included multiple affiliations (one from Table 3.1 and one or more from Table 3.2), they were counted as a part of all organizations that they listed. Contact ties were established between organizations whenever at least one member of an organization listed another organization as a contact. This network has 61 nodes and is shown in Figure 3.1.

A second contact network was created only using distinct organizations as nodes. The categorical nodes – e.g. 'law firms', and 'other federal organizations' – aggregate respondents more broadly than the distinct organizational nodes. This is a concern when we find organizational beliefs as the broader categories may not represent a cohesive group. Thus, the analysis will be completed for networks with and without the categorical nodes. The network of only distinct organizations has 48 nodes and is show in Figure 3.3.

2014

While the 1984 survey used a roster to collect organizational contacts from respondents, the 2014 survey used a free response prompt to allow respondents to list their own organizational affiliations and up to 10 organizational contacts. Since they were not restricted to a predetermined set of options, most respondents listed specific organizations rather than organizational categories. Like in the 1984 case, the respondents were aggregated into organizations and contact networks were constructed for all nodes (distinct and categorical) and again for just distinct organizations.

With fewer categorical options, we see many more nodes in the 2014 networks. The network for distinct and categorical nodes has 227 nodes and the network of only distinct nodes has 222 nodes. However, these networks are also much less dense than the 1984 networks because respondents were limited in the number of contact that they could report. The contact networks for 2014 are shown in Figures 3.2 and 3.4.

Table 3.1: Distinct Organizations and Categories from the 1984 Survey

	Distinct Organizations		**Organizational Categories**
1	Environmental Protection Agency	1	Other Federal Organizations
2	Food and Drug Administration	2	Congressional Committee Staff
3	Nuclear Regulatory Administration	3	Member of Congress
4	National Institute of Environmental Health Sciences	4	Congressional Member Staff
5	Occupational Safety and Health Administration	5	Congressional Support Organizations
6	National Institute of Occupational Safety and Health	6	Consulting Firms
7	Department of Energy	7	Law Firms
8	National Cancer Institute	8	Other Environmental Organizations
9	Department of Labor	9	Regional, State, and Local Governments
10	Department of the Interior	10	Consumer Groups
11	Office of Management and Budget	11	Labor Unions
12	Department of Agriculture	12	Industry and Trade Organizations
13	Department of Transportation	13	Professional Organizations
14	Executive Office of the President	14	Corporations (other than Consulting Firms)
15	Consumer Product Safety Commission	15	Universities
16	Department of Defense	16	Think Tanks
17	Department of Health and Human Services	17	Quasi-Governmental Agencies
18	National Science Foundation	18	Other
19	Audubon Society		
20	National Wildlife Federation		
21	Sierra Club		
22	Natural Resources Defense Council		
23	Environmental Defense Fund		

Table 3.2: Professional Organizations from the 1984 Survey

	Professional Organizations		Professional Organizations - continued
1	Air Pollution Control Association	18	American Society of Preventive Oncology
2	American Association for the Advancement of Science	19	American Statistical Association
3	American Association for Cancer Research	20	Association of Environmental and Resource Economists
4	American Bar Association	21	State Bar of California
5	American Biometrics Association	22	Colorado Bar Association
6	American Chemical Society	23	District of Columbia Bar
7	American College of Toxicology	24	Natural Resources Defense Council
8	American Economics Association	25	New York Academy of Sciences
9	American Industrial Hygiene Association	26	Sigma Xi
10	American Institute of Chemical Engineers	27	Society of Occupational and Environmental Health
11	American Physical Society	28	Society for Risk Analysis
12	American Political Science Association	29	Society of Toxicology
13	American Psychological Association	30	Toxicology Forum
14	American Public Health Association	31	Association for Women in Science
15	American Public Works Association	32	Other Bar Associations
16	American Society of Civil Engineers	33	Other
17	American Society for Pharmacology and Experimental Therapeutics		

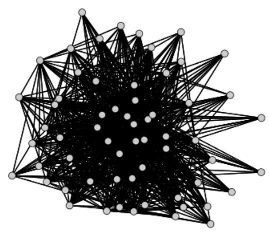

Figure 3.1: Contact Network 1984
Distinct and Categorical Nodes

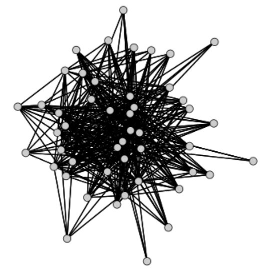

Figure 3.3: Contact Network 1984
Distinct Nodes Only

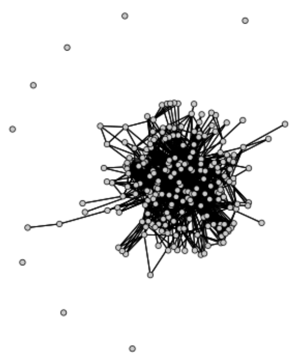

Figure 3.2: Contact Network 2014
Distinct and Categorical Nodes

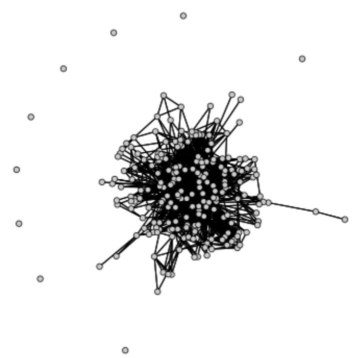

Figure 3.4: Contact Network 2014
Distinct Nodes Only

3.5.3 Belief Distance Networks

Respondents to both waves of the survey reported their views on eleven policy-core beliefs[3]. Respondents to the 1984 survey responded to each question using a four-point scale with options for ‘agree strongly’, ‘agree’, ‘disagree’, and ‘disagree strongly’. Respondents to the 2014 survey responded to the same set of belief questions on either a five-point or seven-point scale, depending on the survey version. The five-point and seven-point scales span options from ‘strongly agree’ to ‘strongly disagree’. To make responses comparable across the 2014 surveys, the seven-point scale was converted to the five-point scale. The question wordings used in all surveys are listed in Table 3.3.

For each policy item in the survey, responses were averaged across all respon-

[3]One of the policy-core beliefs include on the survey is excluded from this analysis because the response choices provided were incompatible across survey versions.

Table 3.3: Policy Core Belief Questions

Variable	Question	Measurement
Adversary	In our democratic society, it is healthy to have an adversary relationship between business and government in areas such as product safety, pollution standards, and safety in the workplace.	1984: 4-scale 2014: 5 scale
	It is healthy to have an adversarial relationship between business and government in areas such as product safety, pollution standards, and safety in the workplace.	2014: 7-scale
Involvement	A high level of public involvement often leads to bad policy decisions.	1984: 4-scale 2014: 5- & 7-scale
Consumer	A consumer should be allowed to choose between a very safe product at a higher price and the same product without safety equipment at a lower price.	1984: 4-scale 2014: 5- & 7-scale
Catastrophic	The risks associated with advanced technology have been greatly exaggerated by events such as Three Mile Island or the Love Canal.	1984: 4-scale 2014: 5 scale
	The risks associated with advanced technology have been greatly exaggerated by high-profile or catastrophic events.	2014: 7-scale
Protecting	On the whole, business does a good job of protecting the public from dangerous products and substances.	1984: 4-scale 2014: 5- & 7-scale
Information	Many environmental policy problems could be resolved with better technical information.	1984: 4-scale 2014: 5- & 7-scale
Planning	The government should engage in more long-range planning.	1984: 4-scale 2014: 5- & 7-scale
Special_ Interest	Most policy decisions reflect the needs of special interest groups rather than the needs of the general public.	1984: 4-scale 2014: 5- & 7-scale
Pollution	The benefits of modern consumer products are more important than the pollution caused by their production and use.	1984: 4-scale 2014: 5- & 7-scale
Development	Development of advanced technology should continue in as uninhibited a regulatory environment as reasonably possible.	1984: 4-scale 2014: 5- & 7-scale

dents who are affiliated with a node in each time period – e.g. the belief score for involvement for the American Association for the Advancement of Science (AAAS) is the average of all involvement scores of those respondents who reported an affiliation with AAAS. Networks of belief distance were created by finding the Euclidean distance between each pair of nodes in the graph[4].

3.6 Belief Segregation and Triadic Closure - 1984

3.6.1 Belief Distance

To test the connection between network contacts and belief distance between organizations, we run quadratic assignment procedure (QAP) correlation on the contact and belief distance networks. In essence, QAP evaluates an observed network statistic by finding its significance based on its position in a distribution of possible values of that statistic controlling for the network structure. In this case, we find the observed level of belief segregation by calculating the correlation between the contact network and the belief distance network.

This gives us a quantifiable value for belief segregation, but we still need to know if this is a comparatively high or low value given the network structure. To create a basis for evaluating the belief segregation statistic, we use QAP. QAP randomly relabels one of the input networks and recalculates the correlation statistic. Repeating this process generates a distribution of correlation statistics for these particular networks, i.e., it controls for the network structure. This distribution is then used as a frame of reference to assess the observed level of segregation. Accordingly, QAP answers the question of whether the observed segregation statistic is significant given the underlying network structure.

With the data from 1984, we run QAP analysis between the contact and belief distance networks for the case with distinct and categorical nodes and again with only the distinct organizational nodes. The test statistics and comparison distributions are shown in Figures 3.5 and 3.6. We can see that in both cases the correlation is close to zero and insignificant. The correlation is -0.03 in the case with distinct and categorical nodes and 0.03 in the case with distinct nodes only. In both cases, these correlation statistics fall well within the most common correlations found when the ties are randomly distributed.

[4]We also explored cluster analysis to group the respondents into belief profiles. However, using Hopkins statistic to assess clustering tendency, we found that the data did not support cluster analysis across policy-core beliefs.

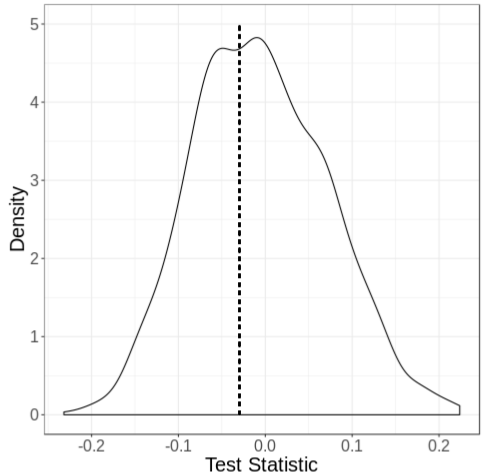

Figure 3.5: QAP Analysis
Test Statistic and Distribution
Distinct and Categorical Nodes

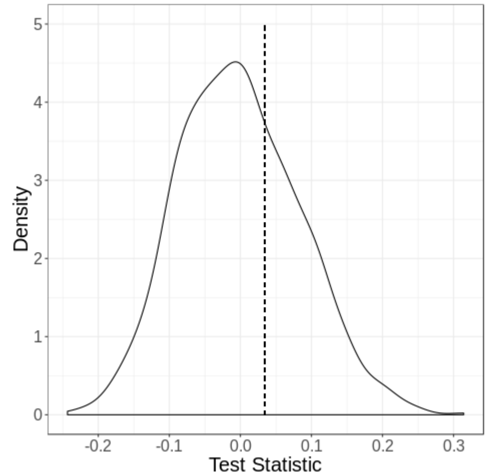

Figure 3.6: QAP Analysis
Test Statistic and Distribution
Distinct Nodes Only

3.6.2 Triadic Closure

To examine the importance of triadic closure we use an algorithm that follows a similar logic to QAP analysis. However, while in QAP analysis we create the comparison distribution by relabeling the nodes, here we create the comparison distribution by rearranging the network ties, i.e., generating random graphs on the same number of nodes with the same density. We want to know if the triadic closure in the contact network is in line with what we would expect to see in random networks of the same size. Like in QAP, we find the observed network statistic from the graph of contact ties in 1984. Then we simulate 2000 graphs with the same density as the contact network and find the transitivity statistic for each of those networks. Network transitivity measures the proportion of potentially intransitive triads in the network that met the transitivity condition - that is the number of triads where if node a is connected to node b and node b is connected to node c, then node a is connected to node c as a proportion of the number of triads where node a is connected to node b and node b is connected to node c, with or without a connection between a and c. The transitivity scores from the simulated networks create the comparison distribution. The results from the 1984 data are shown in Figures 3.7 and 3.8. We can see that triadic closure is well above the usual range for transitivity given a random dispersion of ties matching the same network density.

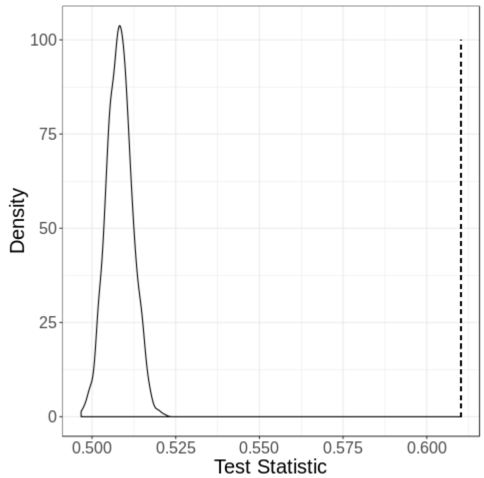

Figure 3.7: Network Transitivity Test Statistic and Distribution Distinct and Categorical Nodes

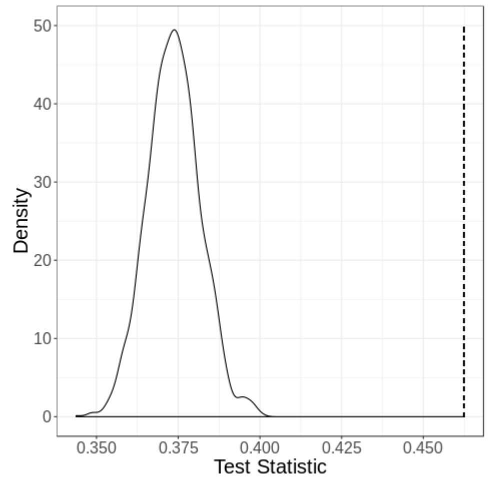

Figure 3.8: Network Transitivity Test Statistic and Distribution Distinct Nodes Only

3.7 Belief Segregation and Triadic Closure - 2014

3.7.1 Belief Distance

We apply the same types of analysis to the 2014 networks. First, we use QAP analysis to examine the belief segregation present in the contact network. The results are displayed in Figures 3.9 and 3.10. We see that there is a significant negative correlation between contact ties and belief distance, meaning that as pairs of organizations have less similar beliefs, we are less likely to observe a contact tie between them.

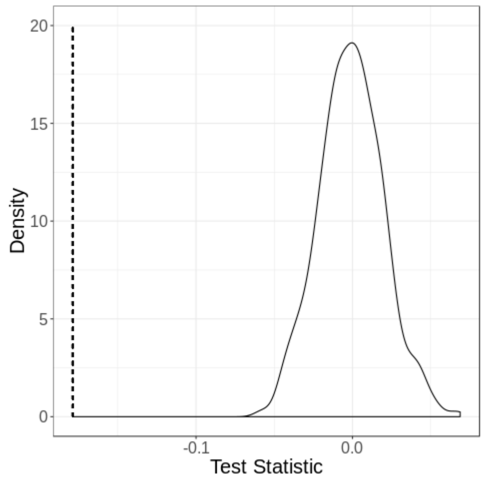

Figure 3.9: QAP Analysis
Test Statistic and Distribution
Distinct and Categorical Nodes

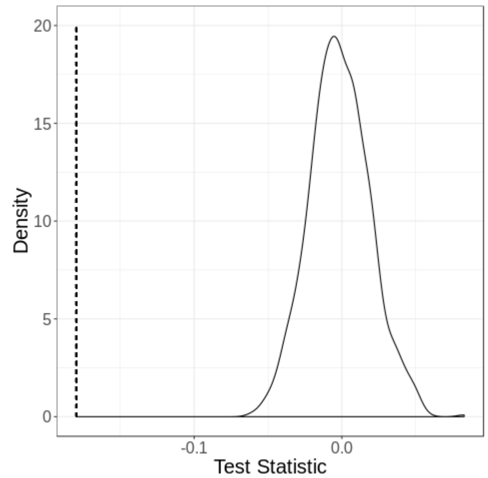

Figure 3.10: QAP Analysis
Test Statistic and Distribution
Distinct Nodes Only

3.7.2 Triadic Closure

The results of the tradic closure analysis are shown in Figures 3.11 and 3.12. In terms of tradic closure, we see network transitivity statistics well outside of the expected range for randomly placed ties.

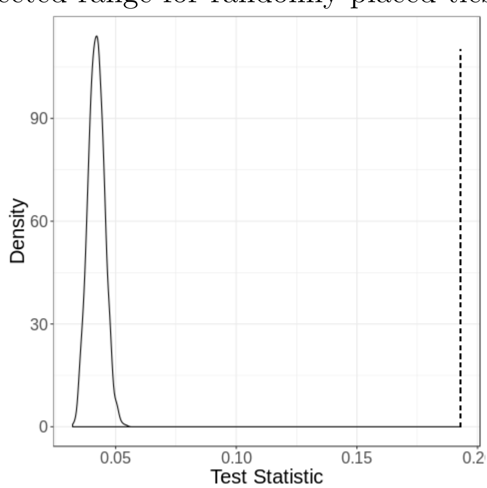

Figure 3.11: Network Transitivity
Test Statistic and Distribution
Distinct and Categorical Nodes

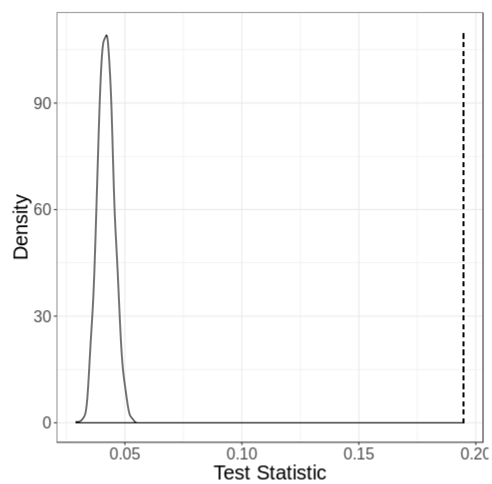

Figure 3.12: Network Transitivity
Test Statistic and Distribution
Distinct Nodes Only

3.8 Discussion

3.8.1 Hypotheses

In this chapter, we set out to test two hypotheses on each set of data. For the nascent subsystem, we had the follow two hypotheses:

Belief Segregation in Nascent Subsystem Hypothesis: Belief segregation will not be higher in the nascent U.S. environmental risk management subsystem than in random networks of the same density between the same nodes.

Triadic Closure in Nascent Subsystem Hypothesis: Network transitivity will not be higher in the nascent U.S. environmental risk management subsystem than in random networks of the same density between the same nodes.

The **Belief Segregation in Nascent Subsystem Hypothesis** was supported by the data collected in 1984. We did not see contacts between organizations in the network significantly related to belief distance. This result held for both the networks with and without categorical nodes. However, the **Triadic Closure in Nascent Subsystem Hypothesis** was not supported by these data. Despite being a new subsystem, the organizations already showed very significant transitivity in their contacts. It is possible that we are seeing some network structures carrying over from previous interactions, like what was found by Stevenson (2009), Bandelow & Kundolf (2011), and Ingold et al. (2017) in previous studies of nascent subsystems.

For the mature subsystem, we had the following two hypotheses:

Belief Segregation in Mature Subsystem Hypothesis: Belief segregation will be higher in the mature U.S. environmental risk management subsystem than in random networks of the same density between the same nodes.

Triadic Closure in Mature Subsystem Hypothesis: Network transitivity will be higher in the mature U.S. environmental risk management subsystem than in random networks of the same density between the same nodes.

The **Belief Segregation in Mature Subsystem Hypothesis** was supported by the analysis with highly significant negative correlation between contacts and belief distance in both the network with and without categorical ties. Additionally, the **Triadic Closure in Mature Subsystem Hypothesis** was supported with highly significant network transitivity statistics indicating more triadic closure in the observed sample than in graphs constructed by randomly assigning their ties.

Overall, this work provides support for the subsystem trajectory hypothesized by the ACF. If changes in policy networks over time create subsystems with more belief segregation, we may see limited opportunities for negotiating and compromise in mature subsystems. The environmental risk management subsystem in particular encompasses vitally important, and hotly contested, policy debates - like those around climate change mitigation and food production - and impediments to policy development could have negative impacts on sustainable development. By better understanding the longitudinal trajectory of subsystems, we can design policy instruments to reshape networks and avoid some of the impacts of belief segregation. In particular, if we can target nascent subsystems with policy interventions, we could take advantage of the period before belief segregation emerges. Developing a policy subsystem that fosters dialogue from the outset may be less resource intensive than intervening in a mature subsystem with ingrained patterns of contact and coordination. The environmental risk management subsystem is an ideal case study for this line of research because this subsystem covers a diverse range of policy debates. The extensive reach of this subsystem provides a more generalizable case study because many of the organizations featured in the subsystem are involved in multiple sub-domains and that activity is captured in our dataset.

3.8.2 Limitations

This study has several limitations. First, while the two surveys used here provide an excellent opportunity to revisit the same subsystem at different times, the difference in network measurement mean that the two time periods cannot be directly compared. Respondents to the 1984 survey may have included more contacts with whom they share less similar beliefs simply because they were able to include as many contacts as they liked from the roster while the respondents in 2014 were limited to 10 contacts. To mitigate this problem, we are careful to compare the analysis of each time period only to the ACF expectations and not to each other. Second, using this data, we cannot test whether the ties in the 1984 are carried over from previous interactions in an earlier subsystem. Testing this would allow us to tie this research more closely to other work on nascent subsystems and would further the discussion on early tie formation, particularly as it relates to the high levels of network transitivity in the nascent subsystem observed here. Third, we cannot differentiate between belief homophily and social influence as mechanisms fueling the belief segregation in the 2014 data. This question was addressed by Henry & Dietz (2015) through a study on risk professionals samples in 1984 and 2000 and could potentially be expanded using the updated data from 2014.

3.9 Conclusion

This work contributes to the research on both nascent and mature subsystems. In the nascent subsystem, our finding of no significant belief segregation, but significant triadic closure raises some new questions about the nature of the early environmental risk management subsystem. It is possible that some of the network structure was brought in from previous contact networks, but that beliefs had not yet developed and solidified in the new areas. However, with such an incredibly diverse group of stakeholders as we have here, there could be something else driving the triadic closure, like sector or membership in nested policy subsystems like energy policy or habitat conservation. In the mature subsystem, we add nuance to the traditional discussion belief segregation by including the compounding impacts of transitivity. This calls for more work to incorporate both effects into the same model, but still serves to highlight the importance of multiple mechanisms for network outcomes.

There are many avenues for future research that could continue out of this paper. First, the surveys measured more dimensions of belief than those used in this paper. The selection of policy-core belief questions used here could be validated and the analysis run using more and less restrictive selections of belief questions to make the results more robust. Second, the current models treat belief segregation and triadic closure independently. There is an opportunity to use exponential random graph modeling to incorporate these network characteristics simultaneously.

Chapter 4

Reconciling Coalitions and Coordination

Abstract

In their efforts to represent their beliefs in the policy process, stakeholders often use their social networks to share information and resources. The Advocacy Coalition Framework predicts that stakeholders will concentrate their efforts on supporting their allies within belief-based coalitions. In this chapter, we examine the degree to which coalitions constrain coordination across the networks of professionals working in the U.S. environmental risk management subsystem. We examine eight types of coordination and find that stakeholders participate in a substantial amount of coordinated activity outside of their coalition. We also find that this participation varies according to the level of risk in the coordination and the stakeholder attributes.

4.1 Introduction

In the policy making process, policy stakeholders undertake many activities to promote their ideas and to find ways to amplify their message. Some of these activities are directly related to policy creation (e.g. lobbying, mobilizing voters, or writing legislation), while other activities increase stakeholder knowledge or help them coordinate with other groups (e.g. networking at events or publishing research findings). However, much of this interaction tends to occur within communities of stakeholders that have shared belief systems, information sources, expertise, and world-views. This process of self-selection into policy communities creates an environment where stakeholders are segregated by ideology - a situation that is widely believed to inhibit problem solving, innovation, and learning.

The Advocacy Coalition Framework (ACF) (Sabatier, 1986, 1988; Jenkins-Smith et al., 2014) is a widely used approach to studying the policy making process. Embedded in the ACF is an emphasis on the relationships between policy stakeholders. In particularly contentious policy areas, stakeholders can fuel belief segregation by focusing their energy on coordinating with like-minded partners. Stakeholders form coalitions around shared policy interest in order to increase their impact. The ACF argues that coordination on policy-oriented activities will overwhelmingly occur within coalitions rather than across coalitions.

While the ACF predicts that coordination outside of coalitions will be more difficult, coordination outside of coalitions is important in the policy making process. Cross-coalition coordination provides channels for communication and learning that can bridge conflicting coalitions. Understanding how and in what contexts coordination occurs outside of coalitions will bring more nuance to the ACF view of the policy process and lead to theoretical developments that more fully capture coordinated activities in the policy process. In this spirit, we focus our analysis on two research questions: first, to what extent is coordination constrained, and not constrained, by coalition boundaries? and second, do differences between stakeholders effect the extent to which coordination occurs outside of coalition boundaries? To answer these questions, we study the professional networks of policy stakeholders who work in the area of environmental risk. Our results compare professional coordination within and across coalitions and examine the association between stakeholders' professional characteristics and coalition constraints on coordination[1].

[1] All analysis was carried out using the R Statistical Package (R Core Team, 2018) and the following associated packages: ggplot2 (Wickham, 2016), VennDiagram (Chen, 2018), igraph (Csardi & Nepusz, 2006), stargazer (Hlavac, 2018), and plyr (Wickham, 2011).

4.2 How Is Coordination Constrained By Coalitions?

The Advocacy Coalition Framework (ACF) gives an understanding of the policy process centered on the actions of individuals through their participation in stakeholder communities. Instead of acting alone, stakeholders form advocacy coalitions with like-minded individuals and use these coalitions to amplify their message. In the ACF, advocacy coalitions are characterized by two conditions. The stakeholders within an advocacy coalition share a common belief system pertaining to their policy topic and they coordinate their efforts to translate those beliefs into policy.

Early in the development of the ACF, Schlager (1995) highlighted the issue of collective action problems - problems where individuals do not have an incentive to act alone, but all individuals will be better off if action is taken - among members of the same coalition. In a review paper of the state of ACF literature, Weible et al. (2009) echo the concerns brought up by Schlager (1995) over coordination saying that the issue was underrepresented in the literature. At the time, only Weible & Sabatier (2005) and Weible (2005) - both discussed below - directly addressed the role of coordination in holding together advocacy coalitions (Weible et al., 2009). Since 2009, additional work has been undertaken addressing coordination in the ACF. We will consider studies on coordination in the ACF in three groups: first, studies that introduce alternatives to the ACF to evaluate the role of beliefs and coordination in holding coalitions together, second, studies that address the measurement of coalition ties, and third, studies that examine coordination outside of coalitions.

Scholars have introduced Resource Dependency Theory (RDT) into studies on coalitions to supplement the ACF's position that beliefs hold coalitions together. Under RDT, stakeholders seek out ties that increase their access to resources (Pfeffer & Salancik, 1978; Casciaro & Piskorski, 2005). In this way, RDT emphasizes the coordination aspect of ACF coalitions. Tie formation for instrumental purposes focuses on the action of coordination rather than the psychological aspect of shared beliefs. Notably, Weible (2005), Henry (2011b), and Matti & Sandström (2011, 2013) all incorporated RDT into ACF studies of environmentally related policy subsystems. Weible (2005) found that beliefs were more important than perceived influence when explaining coordination between stakeholders and their choices of advice and information networks in a study of the California marine protected area policy subsystem. In a study of regional planning networks in California, Henry (2011b) found that perceived influence of partners did not shape system-wide networks but may have impacted networks within coalitions. In two papers covering three case studies of the Swedish carnivore management policy subsystem, Matti & Sandström (2011, 2013) found that perceived belief correspondence was associated with coordination while perceived influence was not, favoring the ACF explanation over RDT. Across all the studies, the ACF proposition that stakeholders come together around common beliefs when forming coalition ties prevailed when compared to RDT. However, while these studies introduce an important perspective on coordination within the ACF, they do not capture the many ways coordination can occur in subsystems. Coordination can take many different forms and the role of each form in relation to coalitions may vary.

In the area of coalition measurement, Weible & Sabatier (2005) and Ingold (2011) have explored alternatives to directly measuring belief agreement and coordination. In their study of the California marine protected area policy subsystem, Weible & Sabatier (2005) suggest that networks where stakeholders identify their allies can be used as a proxy for coordination. Ingold (2011) studied the Swiss CO_2 policy subsystem and found that ally and enemy networks were a close proxy for identifying coalitions, relieving some of the need to measure belief systems. Similarly to the RDT studies, the measurement studies consider coordination as a single concept that can be represented through proxy measurement.

Beyond coalition boundaries, we still expect to see stakeholder coordination. Coalitions exist in policy subsystems, which themselves are nested and overlapping. Stakeholders can work in multiple subsystems as they may have interests in multiple policy domains. Whenever we view a coalition or even a subsystem in isolation, we exclude stakeholder coordination outside of that realm. In her measurement of advocacy coalitions, Ingold (2011) points out that coordination - measured as collaborative relationships - is not sufficient criteria for identifying coalitions for this very reason. In his study of the trade union disclosure policy debate in Canada, Stritch (2015) found that linkages between advocacy communities (ideological groupings of advocates who do not necessarily coordinate on policy issues) were more common when the network focused on lower levels of coordination. In his survey of stakeholders, Stritch (2015) included three forms of "lower level coordination" (providing information, receiving information, and encouraging other organizations to participate) and six forms of "higher level coordination" (cooperating on joint policy research or analysis, jointly funding some advocacy costs, participation in task forces or workshops, joint presentations to government agencies, holding joint strategy meetings, and creating a formally structured coalition). Stritch (2015) found that lower level coordination was more likely to take place between coalitions than higher level coordination. Stritch (2015) incorporated a more nuanced view of coordination allowing types of coordination to vary.

In this paper, we provide an innovative approach to the question of coalition boundaries constraining coordination in two ways. First, we differentiate between eight types of coordination activity and allow each one to interact differently with coalition boundaries. This approach is also used by Stritch (2015), but is not commonly seen in ACF literature. Second, we use a network of policy makers that expands beyond any specific policy debate. This allows us to also to include coordination ties between professionals that may be lost in the sample were focused on specific contentious area.

4.3 How Do Individual Differences Impact Collaboration?

While coalitions drive policy formation in the ACF, individual characteristics drive coalition formation. The ACF assumes that actors are subject to bounded rationality, prospect theory, and biased assimilation. Bounded rationality, a theory developed by Simon (1985), states that actors cannot evaluate every piece of information and often make decisions based on heuristics rather than optimizing outcomes. People do not have the cognitive capacity to evaluate all options before making a decision (Simon, 1985). According to prospect theory, people remember losses more clearly than gains (Quattrone & Tversky, 1988). Lastly, when actors receive new information, they process it in light of their currently held beliefs through a psychological phenomenon called biased assimilation (Lord et al., 1979; Munro & Ditto, 1997; Munro et al., 2002). Actors are more likely to believe information that agrees with their previous beliefs and discount contradictory information. The combination of these phenomena leads to the "devil shift" where actors think that their opponents are harsher than they are in reality (Sabatier et al., 1987).

The profile assigned to actors in the ACF has a profound impact on their expected behavior. Ideas and resources exchanged within coalitions can flow freely since stakeholders are working towards the same ideal and are more likely to accept information from each other due to biased assimilation. Across coalitions, participants are less prone to accept information and advice and may struggle with resource exchange. These biases reinforce ties within a shared belief system and create mistrust between stakeholders in opposing belief systems. This leads to belief homophily, where stakeholders choose to create and keep ties predominately with others within their belief system. Belief homophily and biased assimilation work together to create a network of policy stakeholders segregated by belief and resistant to coordinating across group boundaries.

The ACF hypothesizes that stakeholders in certain types of organizations will behave differently within the subsystem. For instance, the traditional ACF hypotheses - hypotheses that are related to the theoretical development of the framework and are generally applicable across subsystems - include predictions that "within a coalition, administrative agencies will usually advocate more moderate positions than their interest group allies" and "actors within purposive groups are more constrained in their expression of beliefs and policy positions than actors from material groups" (Jenkins-Smith et al., 2014, p.88). This is because purposive groups attract their membership through their commitment to their beliefs and desire to benefit society while material groups are less belief driven, usually focusing instead on profits for motivation (Jenkins-Smith & St. Clair, 1993). These hypotheses convey an expectation that organizational affiliation will shape the behavior or stakeholders regardless of their psychological characteristics. Limited research has been carried out on these hypotheses with support provided by Jenkins-Smith et al. (1991) and Jenkins-Smith & St. Clair (1993) for the difference between purposive and material groups.

We contribute to this area by looking for impacts of stakeholders' professional characteristics on the relationship between coordination and coalition boundaries. While the ACF has a robust model of the individual grounded in well established psychology, there is an understudied expectation that the professional position occupied by the stakeholder will change their role in the policy subsystem.

4.4 Data

To test these hypotheses, we surveyed professionals working in U.S. environmental risk policy. The breadth of this subsystem, which covers many interlocking functional domains including climate change, water quality, nuclear safety, and natural resource management, creates a policy environment where stakeholders have opportunities to work together across specific policy issues. Environmental risk is also a contentious policy arena were we can observe interactions between stakeholders who do not share policy views. The diversity of stakeholders and interactions makes this subsystem ideal for including multiple types of coordination.

The risk professionals targeted in the survey are defined using three criteria: 1) the individual engages in one or more professional activities focused on policy making surrounding risk issues, 2) the individual is engaged in one or more issues of environmental risk, meaning risks to human well-being as a result of environmental changes or risks to ecological systems as a result of human activities or technology and 3) the individual's professional activities have an influence on US federal policy or decision making[2].

Data were gathered from December 2013 to October 2014 through a snowball sample of risk professionals. The initial sample was drawn from the following three sources: 1) published records of Congressional hearings focused on issues of environmental risk, 2) published reports from National Research Council (NRC) committees focused on issues of environmental risk and 3) stakeholders affiliated with events sponsored by the major, Washington D.C. based professional societies focused on issues of environmental risk. All of the stakeholders discovered through the above criteria were included in the sample with the exception of high ranking officials (Presidential appointments and elected officials). During the survey, each respondent was asked who they work with within the subsystem and these nominations were added to the sample.

In the final sample, 281 respondents completed or partially completed the survey. Survey respondents were asked to nominate up to ten organizations they have contact with in the development of science and/or policy surrounding issues of environmental risk. Once these contacts are established, respondents provide information on their interactions with each contact. 52 respondents did not name any organizational contacts and were dropped from the sample. An additional 11 respondents did not receive questions regarding their relationship with each contact and were also dropped from the sample. Analysis was conducted on the remaining 218 respondents[3].

4.5 Coalitions as Networks

4.5.1 Conceptualizing Coalitions

Coalitions are often conceptualized as densely connected groups with implied coordination between all involved stakeholders. However, coalitions are often loosely organized communities rather than well coordinated, well connected groups. Particularly in larger coalitions, stakeholders that are coalition partners may not be directly connected to each other even though they are working towards the same goals and may be coordinating with the same third party.

[2]Since many respondents work on multiple policy issues, the third criteria does not indicate that respondents work exclusively at the federal level. Some respondents also participate on state and local policy issues.

[3]The degree distribution is as follows: 1 contact - 6 respondents; 2 contacts - 11 respondents; 3 contacts - 17 respondents; 4 contacts - 13 respondents; 5 contacts - 21 respondents; 6 contacts - 17 respondents; 7 contacts - 22 respondents; 8 contacts - 16 respondents; 9 contacts - 19 respondents; 10 contacts - 76 respondents.

In this paper, we focus on the stakeholders' decisions to form coalition ties with specific partners instead of focusing on coalitions as groups of stakeholders. Stakeholder decisions are the basis for coalition building and by analyzing ties at this level, we can more directly analyze the ways in which single actors coordinate with select partners. Instead of conceptualizing coalitions as cohesive groups, we conceptualize coalitions as networks. Coalition ties occur when stakeholders share beliefs and coordinate on policy issues with their contacts. This conceptualization is in the same spirit as the ACF's preference for modeling a complex and nuanced individual and allowing coalition dynamics to arise from individual propensities. We look to individuals' networks to find the contacts that are coalition partners.

4.5.2 Measuring Coordination

Coalition ties are measured by combining two responses collected in the survey to reflect the two part definition of advocacy coalitions in the ACF. First, policy stakeholders share policy core beliefs; they have the same goals within the policy subsystem. Second, they demonstrate a non-trivial level of coordination in pursuit of their common goals. The first component of coalition ties, shared beliefs, is fulfilled if a respondent indicates that their contact shares their policy goals. The second component of coalitions ties, coordination, is fulfilled if a respondent indicates that they jointly advocate for policy with a contact. The intersection of policy agreement ties and coordination ties are coalition ties. Cumulatively, the 218 respondents included in this study listed 1551 contacts, for an average of just over 7 contacts per respondents. Of the 1551 contacts listed in the survey, 671 were reported to share policy goals with the respondent and 352 were reported to jointly advocate for policy with the respondent. The Venn diagram in Figure 4.1 shows the overlap between these two types of ties. The area of overlap is where we define coalition ties. In total, there are 265 coalition ties in the dataset, for an average of approximately 1.22 coalition ties per respondent.

4.6 Differentiating Coordination

Respondents identified the types of coordination that they undertake with each of their contacts. Eight types of coordination were indicated in a multiple answer question and respondents could select as many as applied for each contact. These types of coordination ranged from low risk activities like attending the same meetings to high risk activities like jointly implementing programs and policies. The full list of coordinated activities is as follows: attend the same meetings, share informa-

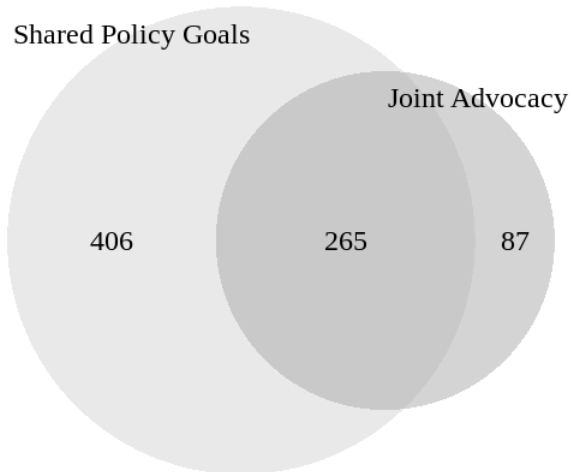

Figure 4.1: Venn Diagram of Shared Policy Goals and Joint Advocacy

tion, seek/provide advice, seek/provide consulting services, seek/provide funding or physical resources, engage in joint research, write joint publications, and jointly implement programs or policies.

When considered through network methodologies, the data are a sample of egocentric networks. In egocentric networks, the central node, called the ego, is the focus of the network. Information is collected on the ego's connections, called alters, and sometimes, although not in our case, information is collected on the alters' ties to each other. In our data, each respondent is an ego and the organizations that they nominate as contacts are the alters. Each respondent in our dataset has a different egocentric network for each kind of coordination that addressed in the survey. For instance, the two network graphs in Figure 4.2 are egocentric networks for the same respondent for different network types. The ego is represented by the node in the center of the graph. The respondent listed 10 organizational contacts, represented by the nodes encircling the ego. The contacts represented by square nodes are coalition partners with the ego, while the contacts represented by circles are not. The graph on the left shows ties where the respondent reported seeking or giving advice and the graph on the right shows ties where the respondent reported jointly implementing programs or policies.

To find the relationship between coordination and coalitions, we examine the proportions of coordination ties that coincide with coalition ties. For example, in Figure 4.2, we see that four contacts are coalition partners (the square nodes in

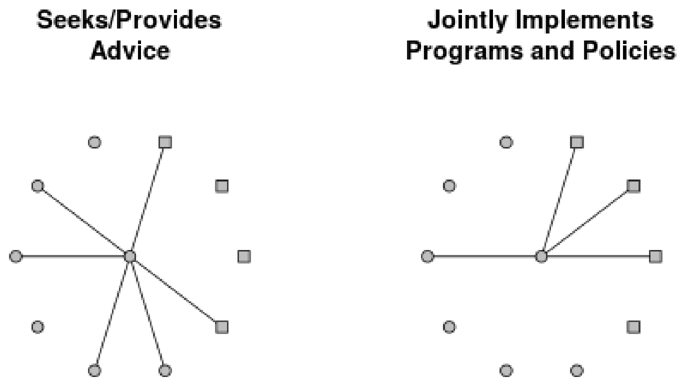

Figure 4.2: Advice and Implementation Egocentric Networks for Survey Respondent

each graph). In the advice graph in Figure 4.2, two out of six advice ties are to coalition partners while four advice ties are not to coalition partners. Thus, the proportion of advice ties that coincide with coalition tie is 4/6 or 0.67. In the implementation graph shown in Figure 4.2, three out of four, or a proportion of 0.75, coordination ties coincide with coalition partners. For each respondent, the egocentric coordination networks are compared the egocentric coalition network to find the proportion of the coordination ties that coincide with coalition ties. For each coordination network, Table 4.1 records the average number of ties for each respondent, the average proportion of those ties that are found in coincidence with coalition ties and the average proportion of ties that do not coincide with coalition ties. The last two columns will always sum to 1.

Table 4.1: Proportions of Coordination In and Out of Coalitions

	Mean Degree (Stand. Dev.)	**Mean Proportion Within Coalition**	**Mean Proportion Outside Coalition**
Information	5.00 (3.55)	0.18	0.82
Consulting	2.30 (2.77)	0.19	0.81
Meetings	4.81 (3.35)	0.19	0.81
Advice	4.38 (3.36)	0.20	0.80
Research	2.17 (2.48)	0.21	0.79
Resources	2.13 (2.58)	0.25	0.75
Publications	1.89 (1.80)	0.26	0.74
Programs	1.88 (2.33)	0.31	0.69

Figure 4.3 shows the mean proportion of each network type that coincides with coalitions. For instance, sharing information has mean proportion overlap of 0.18 - on average, we see almost 20% of information sharing ties go to coalition partners. For comparison, implementing programs and policies has a mean proportion overlap of 0.31 - on average we see just over 30% of joint implementation of programs and policies occur within coalitions. The error bars on proportion are the 95% confidence intervals around the mean.

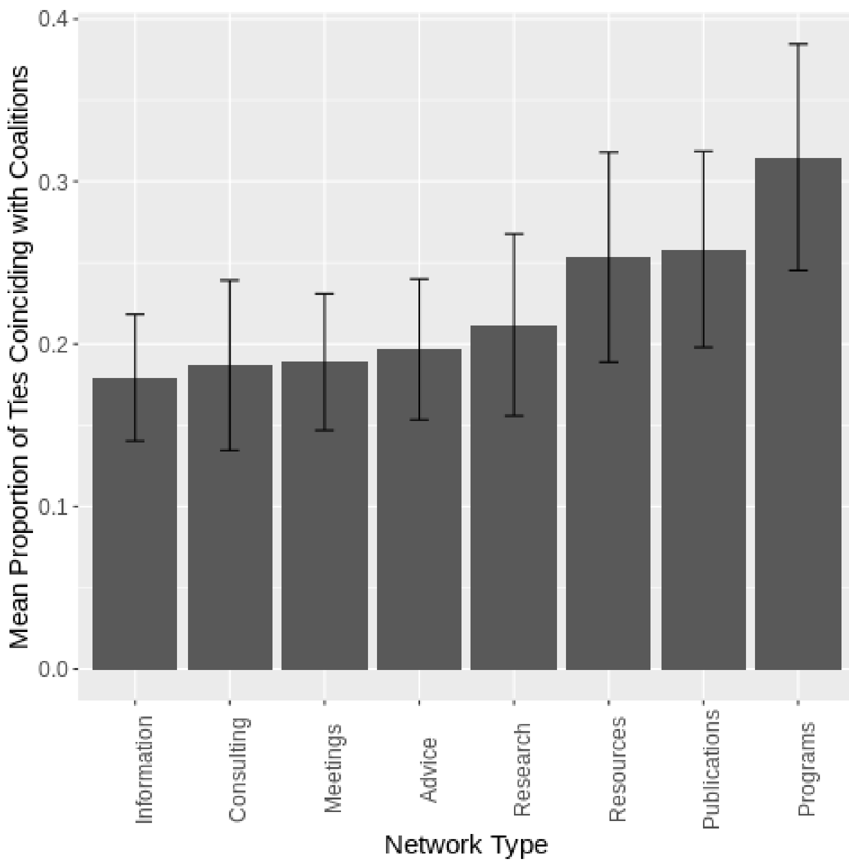

Figure 4.3: Proportions of Coordinated Activities Coinciding with Coalitions

We find two results of particular interest. First, and surprisingly, we find that the clear majority of ties in every coordination type occur without an accompanying coalition tie. This is a marked departure from the hypotheses of the ACF which expect coordination to be concentrated within coalitions. Second, we see that types of coordination are heterogeneous in their relation to coalitions. We explore this further using an analysis of variance (ANOVA) and the Tukey Honestly Significant Differences test to look for significant differences in behavior.

Each type of coordination has a distribution of proportions - one proportion for each survey respondent. First these distributions are compared via an ANOVA to test the null hypothesis that the mean proportion of coordination ties in coincidence with coalition ties is the same across coordination network types. This model is significant with a p-value of 0.005, so we reject the null hypothesis that the means - shown in the column titled *Mean Proportion Within Coalition* - are equal.

Next, we use the Tukey Honestly Significant Difference test (HSD) to find which pairs of networks are significantly different from each other. The Tukey HSD allows us to make multiple pair-wise comparisons of the mean proportions without the risk of inflating the Type I error rate. The Tukey HSD test shows that the incidence of programs co-occurring with coalitions is significantly different at the 0.05 level from the incidence of information, consulting, meetings, and advice co-occurring with coalitions.

In addition to treating each mean separately, we can group them into types of coordination. We see that implementation of programs and policies is different from the four types of coordination with the lowest means. Looking at Table 4.1 or Figure 4.3, we can see that the next largest difference between categories occurs between jointly conducting research and sharing resources. Breaking the types of coordination in to categories here is a post-hoc decision, but this also results in a theoretically interesting set of categories. The types of coordination with lower coincidence with coalitions - information, consulting, meetings, advice, and research - represent activities that carry fairly low risk to an organization. Jointly participating in these activities does not cause organizations to bear a heavy cost to their reputation if their partner fails. The group with higher coincidence with coalitions - resources, publications, and programs - represent activities where organizations have invested more in the success of the joint activity. These activities produce outcomes, like publications and programs, where cooperating organizations will be difficult to distinguish from one another. Sharing resources is in the high risk group because of the potential cost to the organization if this type of relationship fails.

Performing an ANOVA on the proportions of coordination coincidence with coalitions between low risk and high risk activities, we find results that suggest (p-value of 0.06) support the two categories. It seems that stakeholders organize their coordination more within their coalitions when that coordination is high risk and are comparatively more comfortable taking part in low risk activities outside of the coalition.

4.7 Differentiating Stakeholders

To account for stakeholder variation, we look to see if stakeholder characteristics are associated with proportions of coincidence between coordination and coalition ties. This is done with a set of OLS regression models predicting the proportion of coincidence based on the personal factors of the respondents. Proportion of coincidence with coalition ties is modeled on three variables from the survey data: number of years that the respondent has worked in the policy subsystem, whether the respondent is directly engaged in policy related activities, and the number of functional domains where the respondent reported involvement. Survey respondents reported between 0 and 60 years of involvement in the policy subsystem with an average of 22.7 years. Respondents that reported writing or deliberating on legislation and advocating for particular policies were considered policy focused while those who reported compiling and managing data, generating reports and analyses, and communicating technical details to decision makers were considered science focused. Respondents could report both policy and science activities and Figure 4.4 shows the rates of reporting each. 97 respondents only chose science based activities, 106 respondents chose both types of activities, and only 2 respondents chose only policy based activities. Since policy oriented respondents are generally also science oriented, we chose to include an indicator variable for policy related activities. Respondents could also report the functional domains in which they work. These consist of climate change, water quality, natural resource management, natural hazards, toxins in the environment, nuclear safety, air quality, water and food supply, and energy use or production. The number of domains indicated by each respondents is used to proxy the breadth of their work.

A model was estimated for each coordination network type. The results can be found in Tables 4.2 and 4.3. From these regressions, we can see that stakeholder characteristics are associated with differential patterns of behavior. In particular, working on policy related activities significantly increases the proportion of ties that co-occur with coalition ties for all coordination network types. The number of years in the subsystem has a negative, sometimes significant, effect indicating that the longer a risk professional is in the subsystem the less association is seen between their coordination and coalition networks. And finally, the number of domains reported is significant in the model for research coordination where participation in more domains is associated with a higher proportion of coincidence between research and coalition ties.

Table 4.2: OLS - Proportion of Coincidence With Coalition

	Dependent variable:			
	Proportion of Coincidence with Coalition			
	Information	Consulting	Meetings	Advice
	(1)	(2)	(3)	(4)
Years	−0.003	−0.001	−0.004**	−0.002
	(0.002)	(0.002)	(0.002)	(0.002)
Policy	0.232***	0.131**	0.215***	0.228***
	(0.039)	(0.058)	(0.043)	(0.046)
N Domain	0.003	−0.002	0.009	−0.002
	(0.010)	(0.015)	(0.011)	(0.011)
Constant	0.105**	0.148**	0.134**	0.140**
	(0.048)	(0.072)	(0.052)	(0.056)
Observations	181	124	181	174
R^2	0.181	0.045	0.151	0.142
Adjusted R^2	0.167	0.021	0.136	0.127
Residual Std. Error	0.248 (df = 177)	0.298 (df = 120)	0.272 (df = 177)	0.276 (df = 170)
F Statistic	13.051*** (df = 3; 177)	1.865 (df = 3; 120)	10.459*** (df = 3; 177)	9.363*** (df = 3; 170)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 4.3: OLS - Proportion of Coincidence With Coalition

	Dependent variable:			
	Proportion of Coincidence with Coalition			
	Research	Resources	Publications	Programs
	(1)	(2)	(3)	(4)
Years	-0.004^{*}	0.0002	-0.003	-0.003
	(0.002)	(0.003)	(0.003)	(0.003)
Policy	0.214^{***}	0.254^{***}	0.349^{***}	0.187^{**}
	(0.056)	(0.065)	(0.059)	(0.075)
N Domain	0.027^{*}	0.014	0.011	0.010
	(0.015)	(0.016)	(0.016)	(0.019)
Constant	0.093	0.060	0.097	0.242^{**}
	(0.072)	(0.081)	(0.073)	(0.101)
Observations	139	131	152	117
R^2	0.149	0.136	0.218	0.069
Adjusted R^2	0.130	0.116	0.203	0.044
Residual Std. Error	0.315 (df = 135)	0.352 (df = 127)	0.344 (df = 148)	0.380 (df = 113)
F Statistic	7.904^{***} (df = 3; 135)	6.686^{***} (df = 3; 127)	13.783^{***} (df = 3; 148)	2.776^{**} (df = 3; 113)
Note:				$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

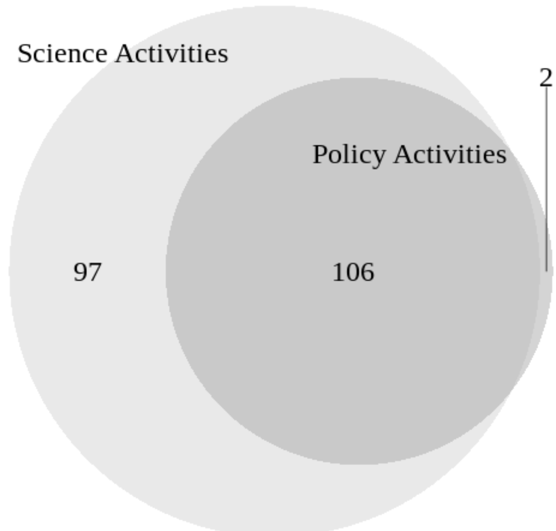

Figure 4.4: Venn Diagram of Science and Policy Focused Professionals

4.8 Discussion and Conclusion

We set out in this paper to explore two research questions: first, to what extent is coordination constrained, and not constrained by coalition boundaries? and second, do differences between stakeholders effect the extent to which coordination occurs outside of coalition boundaries? In response to the first question, we found that the majority of coordinated policy related activities take place outside of coalitions. While this phenomena was ubiquitous across types of coordination, we found variation between types of coordination. The results from the Tukey HSD test show significant differences between the most highly constrained type of coordination - jointly implementing programs and policies - and the four types of coordination with the lowest coincidence with coalitions - share information, seek/provide consulting services, attend the same meetings, and seek/provide advice. Further analysis suggested a difference between low and high risk coordination when it comes to coalition constraints. Taken together, all of this evidence shows that there is far more coordination outside of coalitions than expected by the ACF and that the extent of coordination outside of coalitions is heterogeneous across types of coordination. The ACF does not distinguish between types of coordination or fully address the role of coordination between coalitions. Our data show a robust professional network that exists in addition to policy coalitions and that should be considered for its role in the policy making process. For practitioners wishing to encourage coordinated behavior across a policy subsystem, these results suggest that while low risk activities, like information sharing, may be the easier place to start, high risk activities, like jointly publishing, are not out of reach. However, while coordination may be more accessible than we thought, these results also show us that working together does not mean that stakeholders will necessarily come to agreement on policy issues. In this case study, coordinated activity is found without policy agreement. It would be interesting to ask in future research whether coordination on projects with their opponents leads stakeholders to be more open to compromise on policy issues even when their beliefs do not change.

In response to the second research question, we found that direct involvement in policy related activities is related to a change in the behavior of stakeholders. The amount of time in the policy subsystem and the number of domains where stakeholders report involvement were also occasionally significantly related to stakeholder behavior. The ACF takes a very broad view of stakeholders, opting to include anyone involved in the policy process. While this approach is beneficial for its inclusiveness - stakeholders who work in journalism or research are included in the ACF where they may be excluded in other approaches - the ACF lacks nuance surrounding the heterogeneity of stakeholder behavior. This finding could help practitioners form expectations about where in the policy subsystem intervention is needed to encourage dialogue between opponents. In this study, we see that stakeholders who are engaged in policy oriented activities keep more of their coordinated activities within their coalitions. Practitioners who want to encourage teamwork across groups may try offer more support to the policy oriented stakeholders for building bridges.

By using a dataset that spans stakeholders from multiple organization sectors, functional domains, and types of jobs, we more accurately reflect the networked character of real policy systems. We find that stakeholders frequently reach outside of their coalition to coordinate on policy related activities and that that coordination is related to the types of activities and the substantive focus of the stakeholder. These findings add nuance to the ACF on the topics of coordination and stakeholders and point out directions for future research continuing that conversation.

Chapter 5

Measuring Heterogeneous Segregation in Egocentric Networks

Abstract

Egocentric network analysis fills an important niche in the social network analysis toolkit. Egocentric methods are better suited than full network methods to provide insight into individual level decisions and are often easier to collect and require fewer assumptions. In this chapter, we examine the Distribution of Egocentric Correlations (DEC) method and validate its output through repeated simulations of egocentric samples. The purpose of DEC is to recover information on individual preferences for segregation between multiplex networks. We find that DEC results are sensitive to changes in deterministic preferences, but are not robust to stochastic preferences.

5.1 Introduction

In the previous two chapters of this dissertation, we have examined the presence and impacts of belief-based segregation in policy networks. In this chapter, we take a methodological turn and examine a specific network method for measuring segregation: the Distribution of Egocentric Correlations (DEC). DEC conceptualizes segregation as a relationship between multiplex networks and measures the heterogeneous manifestation of segregation across individuals. For instance, if a sample of office employees were asked to identify which of their coworkers they agreed with politically and which of their coworkers were their friends, we may find that some employees segregate their friendship network based on political agreement while others do not. DEC's use of egocentric networks makes it sensitive to individual differences in preferences.

We can see the type of heterogeneous preferences that DEC measures arise in a case study on friendship formation. Mollica et al. (2003) studied the formation and persistence of same-race friendships when MBA students entered a new program. They found that students of minority racial groups developed friendship networks that demonstrated greater homophily than networks formed among white students. This pattern could lead to decreased access to resources but increased social support for students from minority groups (Mollica et al., 2003). In this example, we see heterogeneous preferences for the relationship between one network (racial similarity) and a second network (friendship). While this research does not require the use of DEC - Mollica et al. (2003) use t-tests and analysis of variance between the respondents' homophily scores - DEC does provide researchers with an additional tool for tackling research questions that center on individual heterogeneity.

Henry (2011b) introduced the DEC method through a study of policy networks engaged in regional transportation and land use planning in California. He examined the role of ideological similarity, ideological dissimilarity, and perceptions of power on actors' choices to form collaborative relationships. This study is another prime example of the conditions that make egocentric networks a valuable tool as the research question focuses on individuals' perceptions and their choices. Henry (2011b) surveyed policy elites who were professionally engaged in five transportation and land use planning regions in California. Survey respondents were provided with a roster of 53 organizations and stakeholder categories and were asked to identify the organizations and groups that they collaborated with, agreed with, disagreed with, and perceived to be influential. Using DEC to analyze these egocentric networks, Henry (2011b) found support for a positive relationship between collaboration and agreement, a negative relationship between collaboration and disagreement, and a positive relationship between collaboration and a combination of agreement and perceived influence. By examining the relationship between respondents perceptions of their contacts and their collaboration with the them, Henry (2011b) used DEC to evaluate competing theories on the prerequisites for collaborative behavior.

DEC is appropriate in situations where we want to study heterogeneous relationship between two networks. DEC is used on egocentric networks; each network consists of a central node, or 'ego', and their direct contacts. Egocentric network analysis is a critical area for methodological development from a practical standpoint. Egocentric data is sometimes more accessible, as it can be collected from an independent sample instead of requiring a full network. Additionally, researchers invoke fewer assumptions when they use egocentric data in its original form rather than transforming it into a full network through aggregation. For an example of this benefit, we can look back to Chapters 3 and 4 in this dissertation. In Chapter 3, we constructed a full network based on individual respondents. To do this, we needed to aggregated individuals into organizations and that required an assumption that organizational beliefs are simply the average of the beliefs of affiliated individuals. However, in Chapter 4, we used egocentric network analysis and were able to drop that assumption. Instead, each respondent represented their own individual views. We were still able to establish trends across the population, but did not need to reshape the data. DEC can provide a way to capture these benefits by leveraging egocentric data.

In this chapter, we seek to validate DEC by showing that it is responsive to changes in individual preferences for segregation. When we program our simulated networks to have different levels of segregation, we wish to test whether the correlations produced by DEC change to reflect the level of segregation. To do this, we simulate populations of network egos and build egocentric networks around them for two types of ties. The structure of the first network is arbitrary. The second network is build based on a preference for segregation. If an ego has a strong, positive preference for segregation, their second network will look like their first network. If an ego has no preference for segregation, the creation of their second network will not be related to their first network. DEC measures the relationship between the two networks and the correlations produced by DEC should reflect the strength of the preference for segregation. To test this, the simulated networks are run through the DEC algorithm and, across repeated simulations, we compare the observed correlation with the assigned preference for segregation[1].

The end goal of this chapter is to encourage appropriate use and interpretation

[1]All analysis was carried out using the R Statistical Package (R Core Team, 2018) and the following associated packages: ggplot2 (Wickham, 2016), ggfortify (Tang et al., 2016; Horikoshi & Tang, 2018), and igraph(Csardi & Nepusz, 2006).

of the DEC method in social science research. By simulating data where the egos have known preferences for segregation, we can compare the results from DEC to the model input. When using DEC on real data, we will not know the underlying preferences for segregation and will rely on the output from DEC to elucidate that hidden trait. Knowing how DEC performs on simulated data, we will better know how to interpret the results from real-world data.

5.2 The Distribution of Egocentric Correlations (DEC) Method

At the core of this method, we wish to know how the ties that individuals have in one network correspond to the ties that they have in another network. If an individual is forming two types of networks, let's say A and B, and they are more likely to form ties in Network B when they already have a tie with the same alter in Network A, they are creating segregation in Network B based on A. In order to determine how segregated the Network B is, we need a way to mathematically compare the ties in each of the two networks. In egocentric networks, we can represent the pattern of ties as a vector with length equal to the number of alters. This provides a mathematical abstraction that we can use for computational work. In the vector, each element represents the ego's tie to an alter. A vector representing an unweighted network will be a series of zeros and ones and a vector representing a weighted network will have decimal values. With vector representations, we can compare two networks through correlation. A correlation score can tell us how well one of the vectors will predict the other one. However, we also want to know if that correlation score is significant. To find this, we follow quadratic assignment procedure (QAP). We create an underlying distribution of possible correlations between the two vectors and compare our observed correlation to the distribution. After the observed correlation - the correlation between the two network vectors - is computed, one of the vectors can be randomly reordered and the correlation recomputed. By repeatedly reordering one vector and recomputing correlations, we can build a distribution of correlations conditioned on the underlying network densities. Significance is then measured by finding the proportion of simulated correlations that are above or below the observed correlation. For instance, if only 3% of simulated correlations are above the observed correlation, than the observed correlation is significant at the 0.03 level. Methods of this type, which use random permutations of matrices to establish expectations, were developed in operations research and explored interdisciplinarily (see Mantel, 1967; Hubert & Schultz, 1976; Sokal, 1979) before being initially written about in the social sciences by F. Baker

& Hubert (1981).

The innovation of DEC comes through its use of the correlations and their significance levels to build a second layer of distributions. Instead of producing one network statistic, like we would see if we performed QAP on a full network, we produce a distribution of egocentric correlations. Recording the correlation for each ego preserves the heterogeneity of the sample instead of diluting the variation into one measure.

From here, researchers can describe the distribution of correlations and their associated significance levels. For instance, Henry (2011b) uses t-tests to determine if the means of the distributions are different from zero as well as using a nonparametric sign test to test that the median correlation is equal to zero. Additionally, if the egos can be separated into groups, researchers could use a two sample t-test or the Tukey Honestly Significant Difference test to look for differences in mean correlations by group. Through these methods, the distributions of correlations provide an opportunity for more nuanced analysis.

5.3 Validating DEC

The goal of DEC is to recover the heterogeneous biases for segregating one type of relationship on the basis of another. In this section, we simulate samples of egos and and their egocentric networks for two types of relationships - referred to as Network A and Network B. Egos are randomly assigned ties in Network A and are assigned a bias score that dictates their preference for forming ties in Network B based on their ties in Network A. We use DEC to deconstruct these networks and we show what information DEC can recover. The following subsections describe this process: in Section 5.3.1 we describe the algorithms used to simulated the networks for each ego, in Section 5.3.2 we use DEC to recover deterministic, discrete bias scores, and in Section 5.3.3 we expand the conversation to include stochastic distributions of bias scores.

5.3.1 Simulating Egocentric Networks

In this subsection, we build a sample of egocentric networks that demonstrate varying levels of homophily between two tie types. The first relationship, referred to here as Network A, represents the characteristic on which egos prefer homophilic tie in the second relationship, referred to here as Network B. Below, we present our methods for constructing Network A and Network B.

Creating Network A

Network A can be thought of as the underlying relationship. Network A exists prior to Network B and is used as a reference point when egos choose ties in Network B. In the example from Mollica et al. (2003), we can think of Network A as the network of racial in-group ties. Network A represents an underlying set of ties that are then used to structure the ties in Network B. Continuing to use the example from Mollica et al. (2003), Network B would be friendship. Since Network A is taken as a preexisting condition to Network B, we create Network A without relation to other ego characteristics. For DEC, Network A can be undirected, or it can be directed, as long as all ties point out. Introducing ties that point towards the ego from other nodes would also require use to introduce the alters' preferences for tie formation, and that is outside of the scope of DEC. Network A can be weighted or unweighted. We will present different methods for network construction in each of these cases even though an unweighted graph can be reduced to a specific case of a weighted graph where the weights are always 0 or 1. Since we are using egocentric networks, we can represent each network as a vector of length m, where m is the number of alters. For instance, Network A for ego ε is denoted as $A_\varepsilon = [a_{\varepsilon 1}, a_{\varepsilon 2}, ..., a_{\varepsilon m}]$ where $a_{\varepsilon j}$ is the value of the tie from ego ε to alter j in Network A. To create either the weighted or unweighted network, we start by choosing a value for d_A, which is our desired density for Network A.

To create an unweighted matrix, we choose every tie with a probably of d_A. Although d_A is our desired density, it may not be the actual density of the final egocentric network.

To create a weighted network, we draw the weights from a beta distribution with a mean of d_A. A beta distribution was chosen because it has support $x \in [0, 1]$, meaning that we will draw values from zero to one and do not need to truncate the values in tails. Truncating the tails of a distribution could change the mean. The shape of the beta distribution is determined by two positive shape parameters, α and β. We set the value of α to 1.5 and set $\beta = (\frac{1-d_A}{d_A}) * a$ in order to achieve a distribution with mean d_A. Multiple beta distributions are shown in Figure 5.1 corresponding to 5 different values of d_A. It is clear that the shape of the beta distribution changes shape substantially across values of d_A. This is not a concern because Network A is taken as a given and a baseline for future ties for the remainder of the sample creation algorithm. The beta distribution provides a reasonable method for stochastically selecting weighted ties.

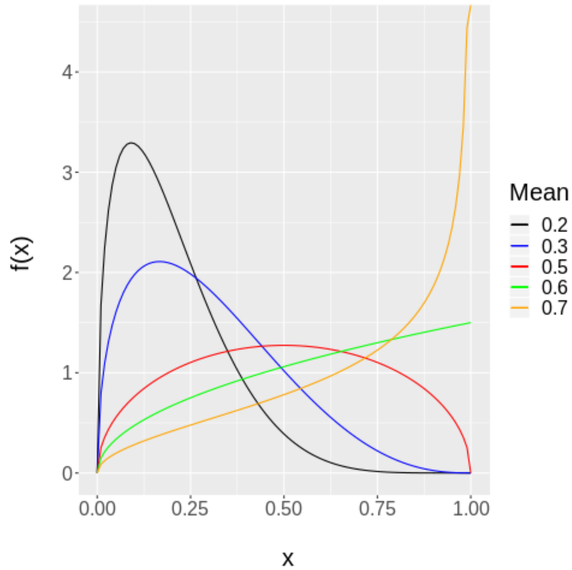

Figure 5.1: Beta Distributions

Creating Network B

Once we have Network A created, we can use it as an influencing factor to create Network B. To form Network B, we need not only Network A but we also need a desired density for Network B, d_B, and a bias factor, ω, that gives the ego's degree of influence from Network A to Network B. The bias factor will be between -1 and 1 and specifies the direction and strength of the preference for forming ties in Network B where there are ties in Network A. When $\omega_\varepsilon = -1$, ego ε has a strong negative preference between the two networks and would strongly prefer to form ties in Network B where there are no ties in Network A. Conversely, when $\omega_\varepsilon = 1$, ego ε has a strong positive preference between the two networks and would prefer to form ties in Network B across the same dyads were they exist in Network A. A bias score of 0 represents no influence from Network A on Network B.

The algorithm for network creation for Network B is more complex than for Network A, so we will illustrate the algorithm with an example. In our example, ego ε's Network A is a weighted graph where $A_\varepsilon = [0, 0.2, 0.5, 0.8, 1]$ and their bias factor, ω_ε, is 1. The example network is shown in Figure 5.2. Generally when using DEC, the number of alters must be considerably larger than 5. Small numbers of alters are not reasonable for finding the significance of the correlations using the method described in Section 5.2

We can visualize the tie weights from Network A in Figure 5.3. The x-axis is the index of each alter and the y-axis is the weight of the tie between ε and that

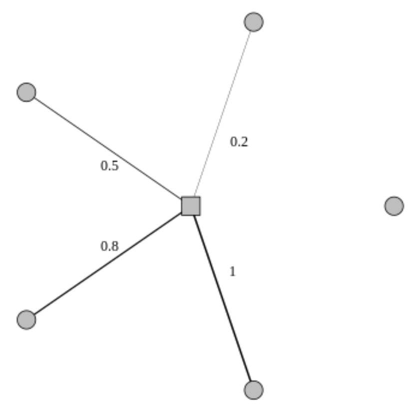

Figure 5.2: Network A - example

alter. The horizontal dotted line at $y = d_{A_\varepsilon}$ is the mean tie weight or the expected value of a randomly assigned tie. Note that d_{A_ε} is not necessary equal to d_A, d_{A_ε} is the actual density of graph A_ε. In our example, $d_{A_\varepsilon} = 0.5$. We can see in the graph that the ties to alters 1 and 2 are weaker than average, the tie to alter 3 is precisely average, and the ties to alters 4 and 5 are stronger than average.

We can think of the weight of each in comparison to the mean as commentary on whether that tie matches expectations. If the weight of the tie is equal to the mean, then we can say that that tie equals its expected value. If a weight is greater that d_{A_ε}, then that tie is stronger than expected and if a weight is less than d_{A_ε} then that tie is weaker than expected. The departure from expectations is quantified by the distance from the actual tie weight to the mean or $a_{\varepsilon i} - d_{A_\varepsilon}$. The difference between the tie strength and the mean show the "pull" that an alter has on the ego in Network A. This pull factor will be moderated by ω_ε, the ego's bias factor, to adjust the probability of forming the same tie in Network B.

To find the probability of forming a tie in each dyad of Network B, we start with a uniform probability of d_B across all dyads and shift that probability based on the influence of Network A. For a tie formed between ego ε and alter j, we adjust the probability of formation, d_B, by $\omega_\varepsilon(a_{\varepsilon j} - d_{A_\varepsilon})$ so that $P(b_{\varepsilon j}) = d_B + \omega_\varepsilon(a_{\varepsilon j} - d_{A_\varepsilon})$. It is possible, depending on the value of d_B and the size of the shift, for $P(b_{\varepsilon j})$ to leave the $[0, 1]$ range. When this happens, we scale the adjustment on Network B, $\omega_\varepsilon(a_{\varepsilon j} - d_{A_\varepsilon})$, so the probabilities $P(b_{\varepsilon j})$ remain within $[0, 1]$.

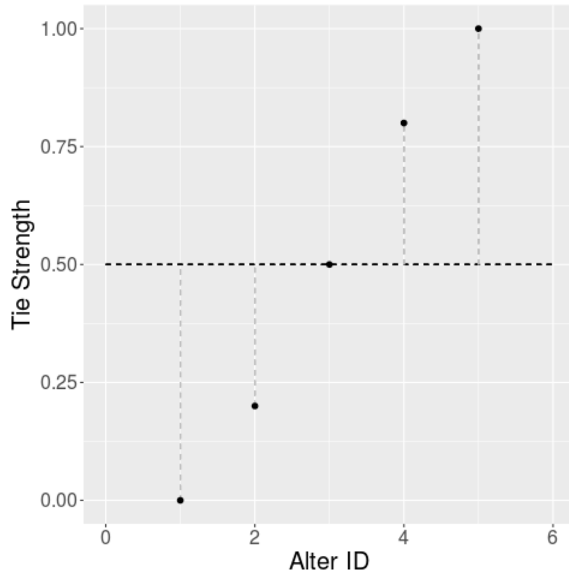

Figure 5.3: Network A Tie Strengths

To illustrate this process and to explore the use of ω, we will work through three examples of finding Network B.

In our first example, $d_B = 0.5$ and $\omega_\varepsilon = 0.5$. Thus, we have $P(b_{\varepsilon j}) = d_B + \omega_\varepsilon(a_{\varepsilon j} - d_{A\varepsilon}) = 0.5 + 0.5(a_{\varepsilon j} - 0.5)$. For instance, ego ε's tie with alter 1 had weight 0 in Network A, which represented a strong negative pull away from the expected value of the tie. The distance between this tie and mean is -0.5, which, when modified by ω_ε exerts an influence of -0.25 on the corresponding tie in Network B. Thus, after starting $P(b_{\varepsilon 1})$ at $d_B = 0.5$, we shift it to -0.25 due to the influence from Network A. Otherwise stated, $P(b_{\varepsilon i}) = d_B + \omega_\varepsilon(a_{\varepsilon i} - d_{A_\varepsilon}) = 0.5 + 0.5(0 - 0.5) = -0.25$. Figure 5.4 shows the results of this process. The horizontal dashed line represents both d_{A_ε} and d_B since they are both 0.5. The grey point show the value of the tie in Network A and the red points represent the probability of the tie forming in Network B. We can see how the probability of tie formation in Network B is pulled away from d_B by the value in Network A. The bias factor, ω_ε, indicates how far along the vertical dashed grey lines the red points will travel. For instance, if we changed ω_ε to 0.75 the red points would move as shown in Figure 5.5. The point from alter 3 does not move because it is not pulled away from d_{A_ε} in Network A, so the term $\omega_\varepsilon(a_{\varepsilon i} - d_{A_\varepsilon})$ always equals 0.

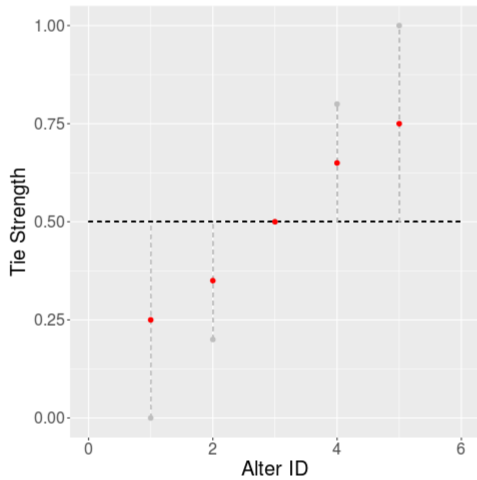

Figure 5.4: Probability of Tie Formation in Network B: $\omega_\varepsilon = 0.5$

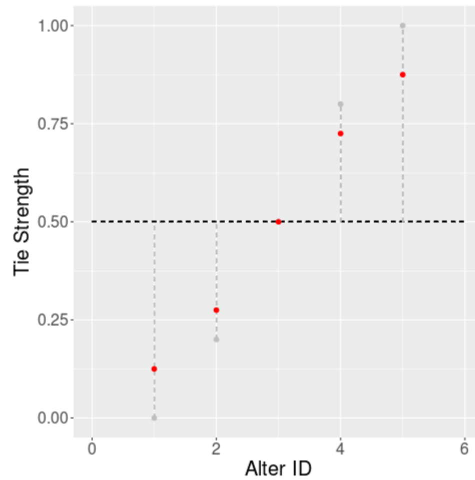

Figure 5.5: Probability of Tie Formation in Network B: $\omega_\varepsilon = 0.75$

In our second example, $d_B = 0.5$ and $\omega_\varepsilon = -0.5$. Changing the bias factor to a negative value means that the probability of forming a tie in Network B is inversely related to the strength of a Network A. In this scenario, Figure 5.6 shows the probability of tie formation in Network B as influenced by Network A.

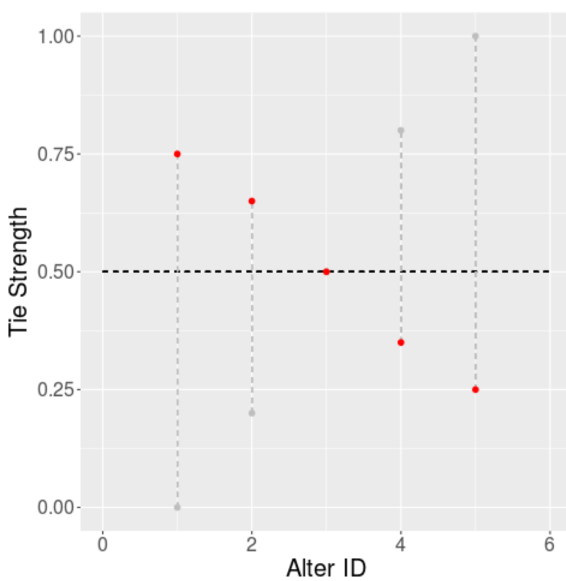

Figure 5.6: Probability of Tie Formation in Network B: $\omega_\varepsilon = -0.5$

In our third example, $d_B = 0.6$ and $\omega_\varepsilon = 1$. This is our first example where

$d_B \neq d_{A_\varepsilon}$; now ego ε is, on average, more likely to form ties in Network B than in Network A. Additionally, ego ε now has a very strong propensity to choose ties in Network B that coincide with ties in Network A. We'll still use $P(b_{\varepsilon j}) = d_B + \omega_\varepsilon(a_{\varepsilon j} - d_{A_\varepsilon})$, but the baseline density for Network B has changed. Since we can no longer use the same line for d_{A_ε} and d_B on the graph, d_{A_ε} and the tie strengths from Network A are dropped from our visualization. Figure 5.7 shows a horizontal, black, dashed line for d_B and red points for the probabilities of tie formation for each alter in Network B using $P(b_{\varepsilon j}) = d_B + \omega_\varepsilon(a_{\varepsilon j} - d_{A_\varepsilon})$. The horizontal grey lines mark $P(b_{\varepsilon j}) = 0$ and $P(b_{\varepsilon j}) = 1$, the logical boundaries of this axis.

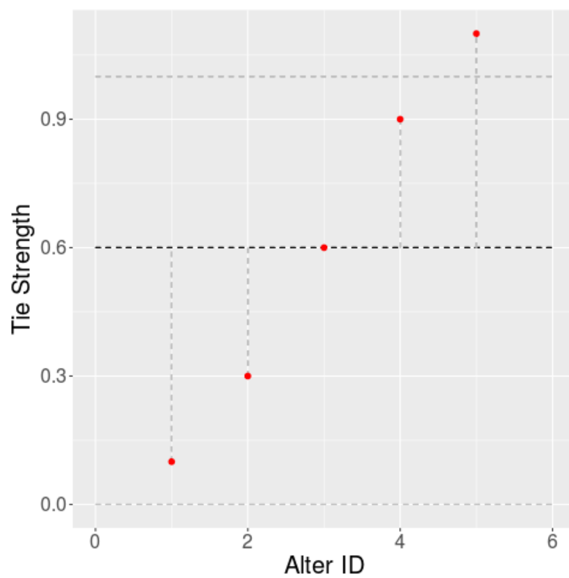

Figure 5.7: Probability of Tie Formation in Network B: $\omega_\varepsilon = 1$

The third variation clearly introduces a problem as we see the probability of tie formation exceed 1 for alter 5. To solve this problem, we scale the adjustment to d_B, $\omega_\varepsilon(a_{\varepsilon j} - d_{A_\varepsilon})$. This preserves the relative impact of the tie strengths in Network A, but keeps the probabilities of tie formation within the range $[0, 1]$.

To start, we need to know when to scale the adjustment term on $P(b)$. To test the need for scaling, we check whether the maximum movement away from d_B will fit in the space available. When $\omega_\varepsilon \geq 0$ we check the following two conditions:

$$\omega_\varepsilon * \max_{1 \leq j \leq m} (a_{\varepsilon j} - d_{A_\varepsilon}) \leq 1 - d_B$$

and

$$\omega_\varepsilon * \left| \min_{1\le j\le m} (a_{\varepsilon j} - d_{A_\varepsilon}) \right| \le d_B$$

When $\omega_\varepsilon < 0$ we check the following two conditions:

$$|\omega_\varepsilon| * \max_{1\le j\le m} (a_{\varepsilon j} - d_{A_\varepsilon}) \le d_B$$

and

$$\omega_\varepsilon * \min_{1\le j\le m} (a_{\varepsilon j} - d_{A_\varepsilon}) \le 1 - d_B$$

If these conditions are broken, then we proceed to scale the adjustment term. To do this, we start from the condition that was violated and scale the influence from Network A down to the space available. In our example, we test the first set of conditions where $\omega_\varepsilon \ge 0$ and find that $\omega_\varepsilon * \max_{1\le j\le m} (a_{\varepsilon j} - d_{A_\varepsilon}) \le 1 - d_B$ gives us $0.5 \le 0.4$, which is clearly not true. The amount of movement away from d_B does not fit in the space available. We see this on the graph where one of the red points is above the grey dashed line. To avoid this problem, we need to shorten $\omega_\varepsilon(a_{\varepsilon j} - d_{A_\varepsilon})$ so that

$$\omega_\varepsilon * \max_{1\le j\le m} (a_{\varepsilon j} - d_{A_\varepsilon}) \le 1 - d_B$$

In our example, we need to scale $\omega_\varepsilon * \max_{1\le j\le m} (a_{\varepsilon j} - d_{A_\varepsilon})$, which is 0.5, down to $1 - d_B$, which is 0.4. To do this, we scale each adjustment to Network B down by 20%. All adjustments must move in tandem by the same percent in order to preserve d_{A_ε}. We take $P(b_{\varepsilon j}) = d_B + \omega_\varepsilon(a_{\varepsilon j} - d_{A_\varepsilon})$ and change it to $P(b_{\varepsilon j}) = d_B + s * \omega_\varepsilon(a_{\varepsilon j} - d_{A_\varepsilon})$ where s is a scaling factor, in this case, 0.8.

Effectively, this scaling is equivalent to constructing a new version of Network A where the tie weights are shifted closer to the mean. In our example, this can be represented as $\hat{A}_\varepsilon = [0.1, 0.26, 0.5, 0.74, 0.9]$. When we make these shifts, our original graph of tie weights in Network A, Figure 5.3, becomes Figure 5.8. The grey points in Figure 5.8 represent the original tie weights and the black point are the scaled values.

Now if we move forward with the third variation where $d_B = 0.6$, $\omega_\varepsilon = 1$, and Network A is scaled to $\hat{A}_\varepsilon$, we find that the conditions hold. Using our new, scaled network, $\hat{A}_\varepsilon$, we can find $P(b_{\varepsilon i}) = d_B + \omega_\varepsilon(\hat{a_{\varepsilon i}} - d_{A_\varepsilon})$ for each $b_{\varepsilon i}$. This results in the probabilities of tie formation shown in Figure 5.9. In this version, all of the probabilities are back in the range $[0, 1]$ and we have preserved d_B at its original value.

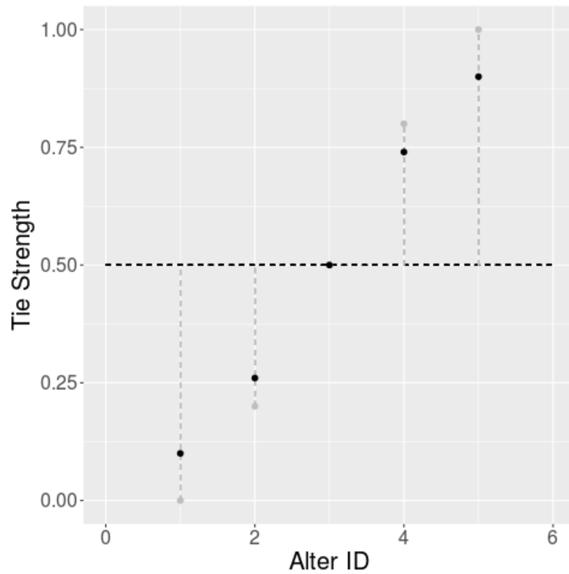

Figure 5.8: Scaled Network A

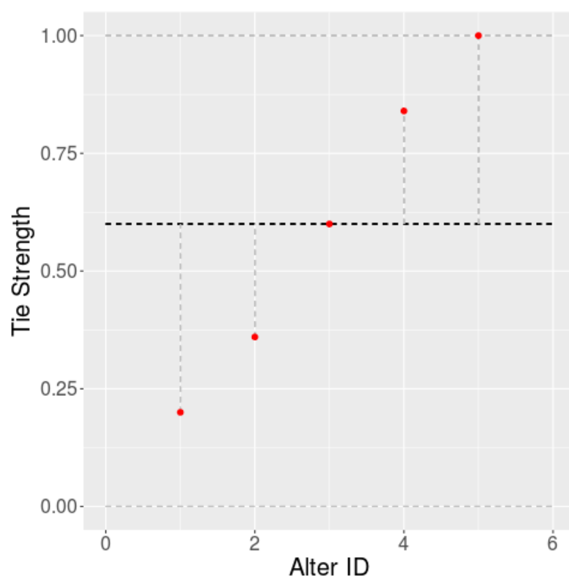

Figure 5.9: Probability of Tie Formation in Network B: $\omega_{\varepsilon} = 1$ Network A Scaled

5.3.2 Recovering Deterministic Bias Factors Through DEC

The DEC method should detect changes in the correlations between the networks as the value of ω changes. In this subsection, we explore the outcomes of the DEC method through examples and repeated simulations of cases with one, two, and three distinct values of ω. We expect to see the correlations found through DEC change magnitude in response to changes in ω and we expect DEC to produce correlations that can be differentiated from each other based on their underlying value of ω.

Unimodal ω

First, we'll look at the case where ω can only take one value. For our example simulation, we create a sample of 100 egos, each with 50 alters. The target densities for Network A and Network B are both set to 0.3. In this example, Network A is an unweighted graph. Since this is the unimodal case, each ego has the same bias factor, ω, of -0.3.

After we created the networks, we ran a DEC analysis to produce a distribution of correlations - one correlation for each ego. The distribution of correlations is shown in Figure 5.10. The distribution has a mean correlation of -0.298, which is very close to the original value of ω. A t-test on the null hypothesis that the mean correlation equals ω returned a p-value of 0.87, supporting an equivalence between the two values. We used a Kolmogorov-Smirnov (K-S) test to determine if this distribution of correlations could have been drawn from a normal distribution. When compared to a normal distribution with same mean and variance of the sample of correlations, the K-S test returned a p-value of 0.67, supporting the claim that the correlations resemble a normal distribution. While we started with a deterministic ω, the network creation algorithm introduced stochasticity and diffused the correlations.

To add robustness to this example, we conducted repeated simulations with a unimodal, deterministic ω. Each simulation proceeded similarly to the example above, creating a sample of 100 egos with 50 alters each. We run 100 simulations of 100 egos each using the unweighted version of Network A and another 100 simulations on 100 egos each with the weighted version of Network A. In each simulation, we vary the target densities of each network and the value of ω. The target densities, d_A and d_B, are drawn from a uniform distribution over $[0.2, 0.8]$. One value of ω is drawn for each simulation from a uniform distribution over $[-1, 1]$. Table 5.1 summarizes the results from these simulations using the same statistical tests that we presented for the example above. The table shows two results for each type

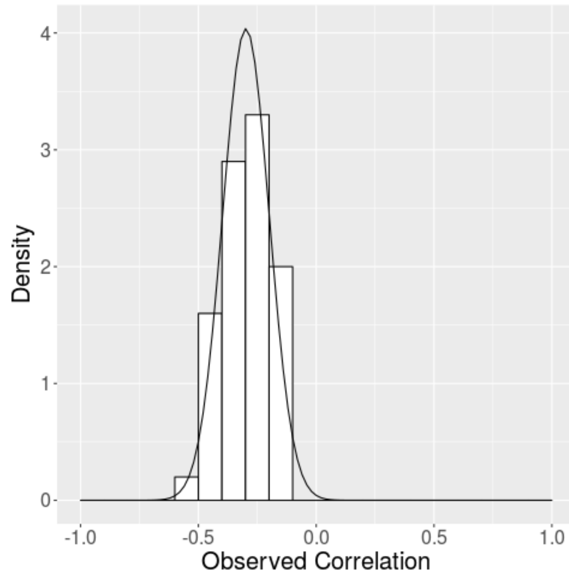

Figure 5.10: Distribution of Correlations from Deterministic Unimodal ω

of simulation (unweighted and weighted Network A). First, we report the percent of simulations where the K-S test supported a normal distribution of correlations. Second, we report the percent of simulations where the t-test supported equivalence between the mean correlation, labeled $\hat{c}$ in the table, and ω. Significance is determined at the 0.05 level for all results in the table.

Table 5.1: Repeated Simuations of Deterministic Unimodal ω

	Unweighted A	Weighted A
% Normal	99%	100%
% $\hat{c} = \omega$	49%	7%

The row summarizing the percent of normally distributed correlations meets our expectations. While each ego is assigned the same value of ω, our network creation algorithm introduces stochasticity to the process, which adds variance to the correlations. In the second row, our naive expectation, extrapolating from the example, may have been to see a higher percent of cases where the mean correlation is significantly close to ω. There are multiple mechanisms that may be causing the mean correlation to differ from ω.

For the unweighted version of Network A, the need to scale down the influence from Network A onto Network B can cause this phenomena. When we need to scale down the influence from Network A, we take $P(b_{\varepsilon j}) = d_B + \omega_\varepsilon(a_{\varepsilon j} - d_{A_\varepsilon})$ and change it to $P(b_{\varepsilon j}) = d_B + s * \omega_\varepsilon(a_{\varepsilon j} - d_{A_\varepsilon})$ where s is a scaling factor. If we think of it like this: $P(b_{\varepsilon j}) = d_B + (s * \omega_\varepsilon)(a_{\varepsilon j} - d_{A_\varepsilon})$, then we can imagine that ω is being scaled down. Since scaling effectively moves ω closer to zero, we do not expect the original value of ω to be the mean correlation when scaling plays a large role. If we divide the simulations that use an unweighted Network A into two groups, one where $\hat{c} = \omega$ and one where $\hat{c} \neq \omega$, we can find the mean number of scaled networks in each simulation by group. Of the 100 egos per simulation, we see on average 3.7 with scaled Network A when $\hat{c} = \omega$, and on average 52.6 with scaled Network A when $\hat{c} \neq \omega$. The need for scaling is driven by a combination of increased distance between d_A and d_B and a large absolute value of ω. A large distance between d_A and d_B creates a situation where the pull from Network A above (or below) the mean is likely to be greater than the space available above (or below) the mean in Network B. A large absolute value of ω means that most of the pull from Network A will transfer into Network B, increasing the chances that $P(b_{\varepsilon j})$ will leave the range $[0, 1]$.

For the weighted version of Network A, the correlations are generally smaller in absolute value than ω. In the weighted version of Network A, ties can take on many more distinct values than in an unweighted graph. Since correlation measures the way the two vectors move together, the variation present in Network A ties while Network B ties can only be one of two values will cause the vectors representing those graphs to have lower absolute correlation. This pulls the correlation away from the ω value.

Taking this a step further, we want to investigate whether the mean correlation from DEC tracks with the movements of ω. Since we know that the correlations are distributed normally, we can take the mean as a reasonable representation of the correlations emerging from each value of ω. In the cases where the mean correlation is statistically equal to ω we can clearly see that changes in the underlying bias of each ego change the outcome of DEC in a predictable way, but we need to verify that the changes in ω still carry through to the mean correlation for the cases where the mean is not statistically equal to ω. We'll first examine the results from the unweighted simulations. As a baseline, Figure 5.11 shows a scatter plot of ω and mean correlations when the two are statistically equivalent. Overlaid on the scatter plot is a reference line with slope 1. The mean correlations and ω increase at a one-to-one rate and stay almost exactly on the reference line. A Pearson's product-moment correlation test returns a statistic of 0.999 with a p-value of approximately zero.

When we look at the same information for the 51 simulations using an unweighted Network A that did not result in a statistical equivalence between ω and the mean correlation, we find a correlation of 0.97 with a p-value approaching zero, but we learn more from an examination of the scatter plot in Figure 5.12. In the scatter plot, we can see a few important aspects. First, this situation is mostly found when ω is very large or very small. These extreme values of ω contribute to a situation where Network A needs to be scaled. As discussed earlier, a prevalence of scaled network will move the mean correlation closer to zero. This can also be exacerbated when target densities d_A and d_B are far apart, which is not controlled for in this graph. In these situations where the mean correlation and ω are not statistically equivalent, we still see the mean correlation moving as ω moves, but there is a weaker impact.

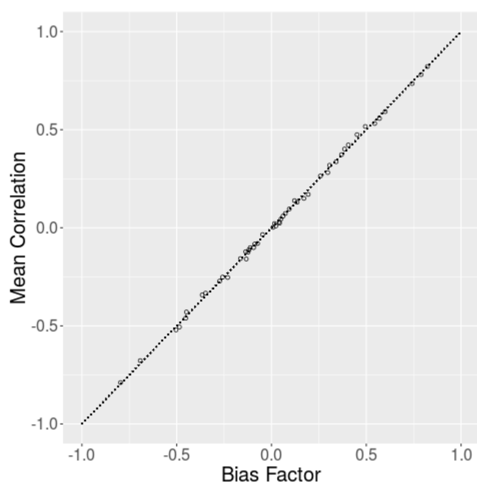

Figure 5.11: ω and Mean Correlation When Statistically Equal Unweighted Network A

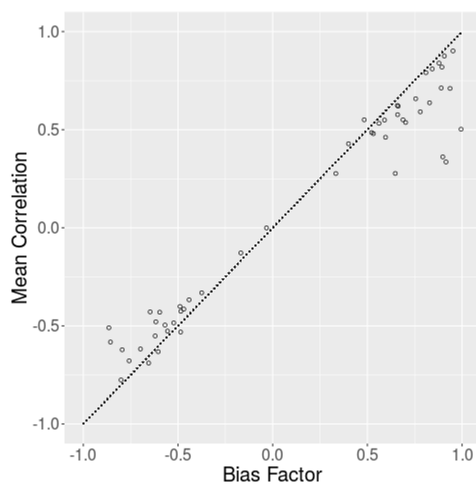

Figure 5.12: ω and Mean Correlation When Statistically Unequal Unweighted Network A

Since a much higher proportion of simulations have unequal mean correlation and ω when Network A is weighted, we also look at the scatter plots for these simulations. There are only 7 simulations where the mean correlation and the value of ω are statistically equivalent, so we refrain from running a correlation on that sample. We can see in the scatter plot in Figure 5.13, that these 7 simulations all have ω and mean correlation values near zero, but they do follow the pattern that we expect. As ω moves, the mean correlation moves with it. For the simulations where the mean correlation and ω are statistically unequal, we see a strong correlation, but the points no longer align well with the reference line of slope 1. A correlation test on this sample yields a statistic of 0.97 and a p-value approaching zero. We see the mean correlation change as ω changes, but effect is weaker for the weighted version of Network A than it was for the unweighted versions Network A.

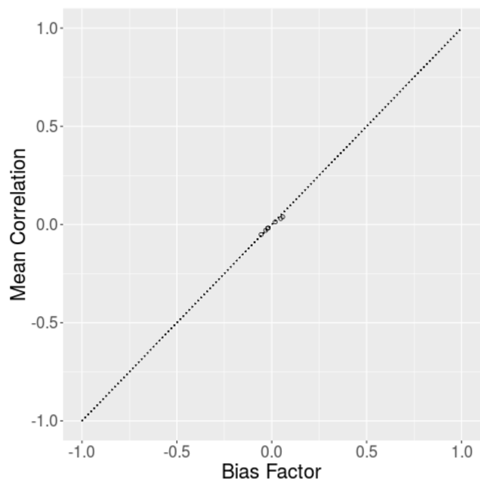

Figure 5.13: ω and Mean Correlation When Statistically Equal Weighted Network A

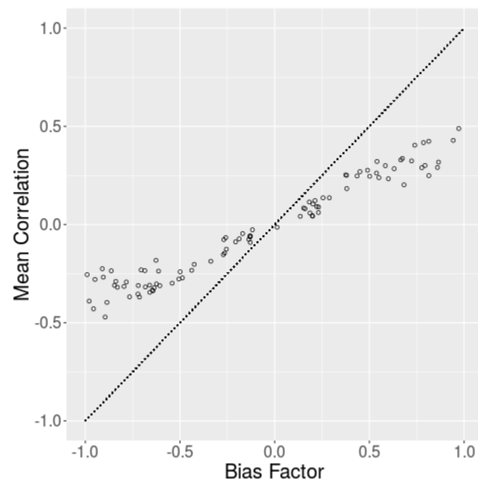

Figure 5.14: ω and Mean Correlation When Statistically Unequal Weighted Network A

Bimodal ω

We also want to consider cases with multiple values of ω. This brings us to the bimodal, deterministic ω simulations. In the bimodal simulations, ω can take on two distinct values. In our example, we use a sample of 100 egos with 50 alters each. Half of the ego have an ω value of -0.3 and the other half have a value of 0.7. The target densities of both networks are set to 0.3. Network A is an unweighted graph.

In this example, we find that the mean correlation for the first 50 egos is -0.258 and the mean for the second 50 egos is 0.7. The distributions of correlations are show in Figure 5.15. We run t-tests comparing the means to the assigned values of ω and find a significant difference between the first value of ω and the first mean and no significant difference between the second value of ω and the second mean (p-values of 0.008 and 0.79). A two sample t-test found that the means were significantly different from each other (p-value of 0.00). K-S tests confirmed that the correlations were in line with two normal distributions (p-values of 0.85 and 0.99).

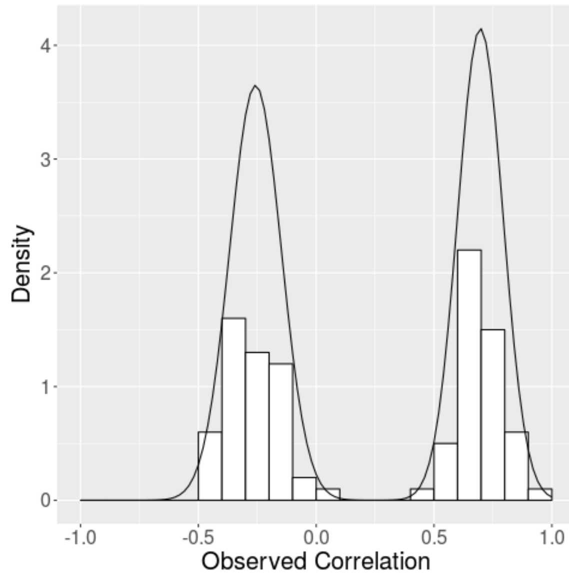

Figure 5.15: Distribution of Correlations from Deterministic Bimodal ω

For the repeated simulations, we use same parameters as the unimodal case, but we drawn two values of ω from a uniform distribution over $[-1, 1]$ and assign the first value to 50 egos and the second value to 50 egos. In the results table from these simulations, Table 5.2, we add an additional row for the percent of simulations where the two means are significantly different from each other. The percents in the first two rows, % normal and % $\hat{c} = \omega$, are calculated from samples of 200 values of ω since there are 2 values of per ego. The third row is calculated from a sample of 100 pairs of ω values. Significance is determined at the 0.05 level for all results in the table.

Table 5.2: Repeated Simuations of Deterministic Bimodal ω

	Unweighted A	Weighted A
% Normal	100%	100%
% $\hat{c} = \omega$	57%	9.5%
% $\hat{c_1} \neq \hat{c_2}$	92%	84%

In this set of simulations, we see all of the ω values returning normally distributed correlations. We also see similar results to the unimodal example in the second row when we compare the mean correlations to ω. This is not surprising because the network creation algorithm is consistent across cases. In the third row, the percent of simulations with a significant difference between the correlation means is consistently high across weighted and unweighted versions of Network A. This is encouraging since the goal of DEC is to pick up on the heterogeneity in implicit bias factors. The situations where the means are not distinguishable have much smaller differences between means. In the simulations with an unweighted Network A, the mean difference between means when the difference is significant is 0.76. When the difference is insignificant, the mean difference is 0.05. For simulations with weighted Network A, the mean differences are 0.83 and 0.11 for significant and non-significant differences respectively. In both cases, weighted and unweighted, the t-tests between the mean differences when significant and non-significant returns a p-value that is approximately 0.

Trimodal ω

For our final deterministic simulation, we consider the case with three possible values for ω. For this simulation, we increase the number of egos to 150, but maintain the 50 alters for each ego. The target densities are both set to 0.3. The values of ω are -1, 0, and 1. Network A is unweighted.

In this simulation, the mean correlations for each groups of egos are -0.45, 0.02, and 0.88. We can see that the first group, the group where $\omega = -1$ has the largest difference that we have seen between the mean correlation and ω for a sample with unweighted Network A. The third group, where $\omega = 1$, also has a larger difference than what we have observed in previous examples. When we run t-tests to compare the means to the values of ω, we find that the means of the first and third groups are significantly different from ω, while the mean of the second group, where $\omega = 0$, cannot be differentiated from 0. Using such strong values for ω in the first and third groups, we created simulations where the adjustments from Network A onto Network B where more likely to push the probabilities of tie formation in Network B outside of $[0, 1]$. All 50 egos with $\omega = -1$ required a scaling factor with an average scaling factor of 0.57. Of the 50 egos with $\omega = 1$, 44 required a scaling factor with an average scaling factor of 0.1. None of the egos with $\omega = 0$ required scaling on Network A. Scaling down Network A decreases the strength of its influence and thus dilutes the correlations between Network A and Network B.

Following the t-tests comparing the mean correlations to ω, we wish to see if the mean correlations are statistically different from each other. Since this involves multiple comparisons, we use Tukey's Honestly Significant Difference (HSD) test to control for the increased risks of Type I errors. The p-values for all comparisons are approximately 0, so the three means are all significantly different from each other.

Finally, we come to the K-S test to determine if the three groups of egos have normally distributed correlations. The p-values for the three groups, $\omega = -1$, $\omega = 0$, and $\omega = 1$, were 0.58, 0.86, and 0.37. We expect the third group of egos to have the lowest p-value, because these correlations are truncated at 1 and cannot fill out the upper tail of the distribution. The correlations and the normal distributions are shown in Figure 5.16.

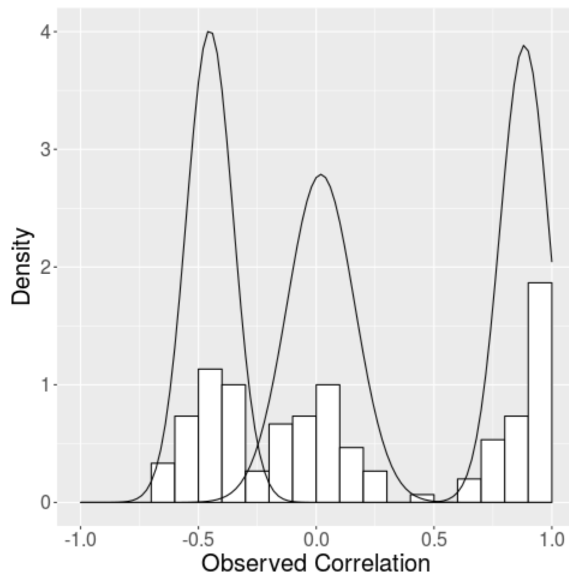

Figure 5.16: Distribution of Correlations from Deterministic Trimodal ω

For the trimodal repeated simulations, we increase the number of egos to 150 so that each value of ω is assigned to 50 egos. Otherwise we use the same model parameters as previous repeated simulations. The results of the repeated simulations are summarized in Table 5.3. Significance is determined at the 0.05 level for all results in the table.

Table 5.3: Repeated Simuations of Deterministic Trimodal ω

	Unweighted A	Weighted A
% Normal	100%	100%
% $\hat{c} = \omega$	48.3%	6.3%
% $\hat{c}_i \neq \hat{c}_j$	88%	88%

The results from the trimodal repeated simulations continue to confirm the patterns that we saw in the previous unimodal and bimodal cases. While the mean correlation only coincides with the value of ω in specific situations, the DEC method does a typically pick up on differences between different ω values across egos.

5.3.3 Recovering Stochastic Bias Factors Through DEC

With the deterministic assignment of ω, we were able to consider situations where egos fall into distinct categories with heterogeneous preferences across groups. However, we also want to consider the situation where we find heterogeneous preferences with a single group or when we cannot easily split the egos into distinct categories. To test DEC under these conditions, we assign ω based on probability distributions instead of deterministic values. In this chapter, we use normal and uniform distributions. Our goal in this subsection is to see if the distributions of correlations produced by DEC mirror the distributions of ω values.

Normally Distributed ω

For our first simulation with a stochastic ω, we use a normal distribution to assign ω to egos. Our example has 100 egos with 50 alters each and $d_A = d_B = 0.3$. Each ego is assigned a value of ω that is drawn from a normal distribution with mean 0.2 and standard deviation 0.08. Once we run DEC, the resulting distribution of correlations is shown in Figure 5.17.

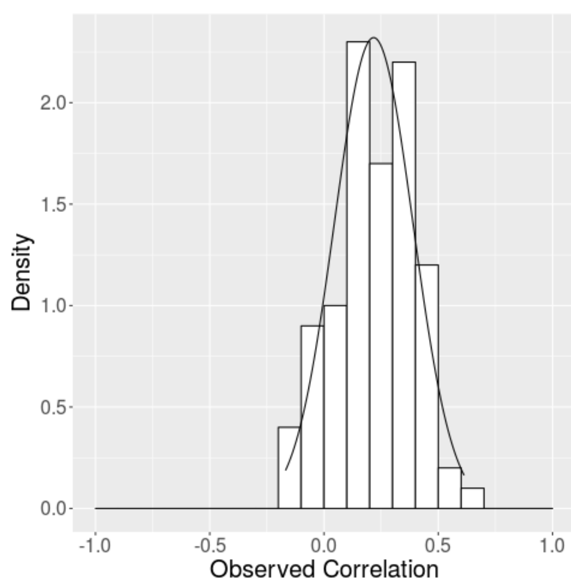

Figure 5.17: Distribution of Correlations from Normally Distributed ω

To find out if the distribution of ω is impacting the distribution of correlations, we use the K-S test to determine if the distribution of correlations could have been drawn from the same type of distribution as the ω values. Since we will later use uniform distributions for ω, we use the K-S test to test both normal and uniform distributions against the observed correlations. In our example of the normally distributed ω, the p-value of the K-S test against a normal distribution with the same mean and standard deviation as the sample is 0.85. The p-value when comparing the sample to a uniform distribution with the same minimum and maximum is 0.03. We can comfortably say that the distribution of correlations is significantly different from a uniform distribution and strongly resembles a normal distribution.

As with the deterministic cases, we run 100 simulations similar to the stochastic normal shown example above and summarize the results in Table 5.4. For the stochastic assignments of ω, we wish to see if the distribution of the correlations that are returned by DEC match the distribution of ω. For each simulation in this set, we draw a mean and standard deviation to create a normal distribution for ω. The mean is drawn from a uniform distribution over $[-0.8, 0.8]$ and the standard deviation is drawn from a uniform distribution over $[0.01, 0.08]$. Each simulation has 100 egos and each ego is assigned a value of ω from the normal distribution defined from the selected parameters. As with the simulations on the deterministic assignments of ω, each ego has 50 alters and d_A and d_B are drawn from uniform distributions over $[0.2, 0.8]$. For each simulation, we take the 100 network correlations, one from each ego, and compare that sample to a normal distribution using the K-S test. The mean and standard deviation of the comparison distribution are set to the mean and standard deviation of the sample. Since we will use a uniform distribution of ω in the next case, we run a second K-S test comparing the sample of correlations to a uniform comparison distribution to see if the sample could have been drawn from a uniform distribution as well. The results of the K-S tests are summarized for simulations on both unweighted and weighted versions of Network A in Table 5.4. Significance is determined at the 0.05 level for all results in the table.

Table 5.4: Repeated Simuations of Normally Distributed ω

	Unweighted A	Weighted A
% Normal	100%	100%
% Uniform	13%	5%

We can see that in this case, each simulation returns a distribution of correlations that could have been drawn from a normal distribution. In some cases, 13%

when Network A is unweighted and 5% of cases when Network A is weighted, the sample of correlations could have also been drawn from a uniform distribution.

Uniformly Distributed ω

Next, we assign uniformly distributed values of ω to the egos. We start with the same example parameters - 100 egos, 50 alters each, target densities of 0.3, unweighted version of Network A - and draw an ω value for each ego from a uniform distribution over $[-1, 1]$. Figure 5.18 shows the distribution of correlations with both a normal and uniform distribution overlaid.

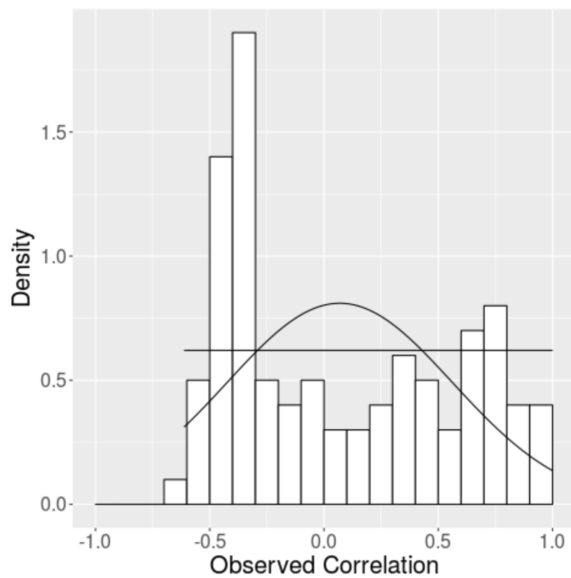

Figure 5.18: Distribution of Correlations from Uniformly Distributed ω

When we run the K-S tests on this sample, the K-S test for the uniform distribution with a minimum equal to the smallest correlation and the maximum set to the largest correlation returns a p-value of 0.03, so we can reject the null hypothesis that the sample of correlations was drawn from a uniform distribution. The K-S test for the normal distribution returns a p-value of 0.14. While we fail to reject the null hypothesis that the correlations are from a normal distribution, this p-value (and the graph in Figure 5.18) is not enough to inspire confidence that the correlations follow a normal distribution. In Figure 5.18, we see a distinct spike in correlations around -0.4. In the deterministic trimodal example, we saw egos with $\omega = -1$ move their correlations into this range due to the scaling required in the network creation algorithm. The spike in Figure 5.18 and the absence of extremely low correlations is most likely due to this phenomenon.

Since the extreme values of ω can cause complications, we run a second example of a uniformly distributed ω where we bound the distribution over $[-0.3, 0.5]$, keeping the rest of the simulation parameters the same as before. In this case, the distribution of correlations are shown in Figure 5.19. In this case, we see a clearer fit to the normal distribution. The p-value for the K-S test on a normal distribution is 0.66 and the p-value for the K-S test on a uniform distribution is 0.1. We cannot reject the uniform distribution as strongly as we could when ω was normally distributed, but we can make a better case for the normal fit than a uniform fit once the uniform distribution endpoints for ω are removed from the extremes.

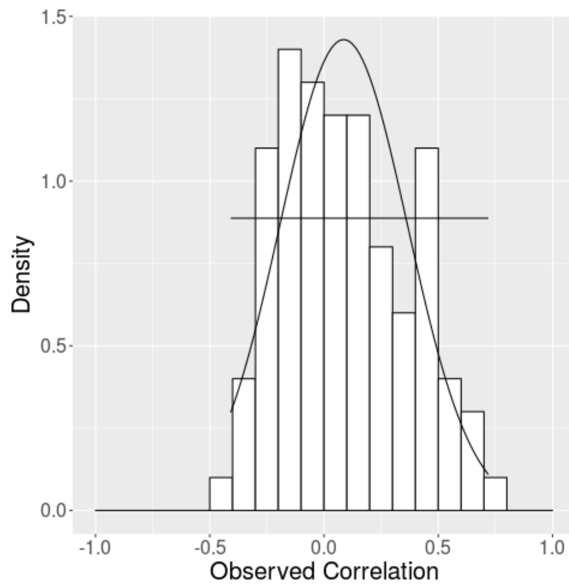

Figure 5.19: Distribution of Correlations from Bounded, Uniformly Distributed ω

Again, we run 100 simulations to add some robustness to our analysis. Since we want a uniform distribution of ω, we draw two endpoints from a uniform distribution over $[-1, 1]$. The smaller endpoint is assigned to the minimum of the uniform distribution and the larger endpoint is assigned to the maximum. The other simulation parameters remain the same: 100 egos, 50 alters each, d_A and d_B drawn from a uniform distribution over $[0.2, 0.8]$. The correlations produced by DEC were compared to both normal and uniform distributions with the K-S test and the results are summarized in Table 5.5. Significance is determined at the 0.05 level for all results in the table.

Here, we see more of the samples of correlations could have been drawn from uniform distributions than when ω was normally distributed, but overwhelmingly,

Table 5.5: Repeated Simulations of Normally Distributed ω

	Unweighted A	Weighted A
% Normal	100%	100%
% Uniform	27%	27%

the samples of correlations could have been drawn from normal distributions. The uniformly distributed ω did not carry through into the distribution of correlations in such a way that would easily distinguish it from a normally distributed ω

5.4 Conclusions

Through examples and repeated simulations, we have a better understanding of the strengths and limitations of DEC. In the unimodal, deterministic assignment of ω, we learned that the results from DEC reflect the values of ω most closely when both Network A and Network B are unweighted, but there is still a strong correlation between the mean correlation and ω when Network A is weighted. In the bimodal, deterministic assignment of ω, we learned that DEC can differentiate between mean correlations across groups as long as the mean correlations are sufficiently different from each other. The trimodal, deterministic assignment of ω reinforced the lessons from the bimodal example and also started a discussion on the impact of extreme values of ω. The stochastic assignments of ω challenged the DEC algorithm and showed the limitations of DEC in distinguishing between distributions of ω. The normal distribution of correlations that forms around deterministic values of ω shaped the overall distribution in such a way as to overpower the uniform distribution of ω.

The generalizability of the findings in this paper rests on the validity of the network creation algorithm. This algorithm was developed to reflect a link between the two types of networks, but maintain the stochastic nature of tie formation. However, to increase the generalizability of the paper, we would consider approaching the analysis with other network creation algorithms for comparison.

Overall, DEC achieved its stated goals of providing a method that measures the segregation of one network on the ties of another and preserving the heterogeneity across egos. Methods like this one play an important role in network analysis as they bring a nuanced look to the differences between individuals and effectively leverage data by maintaining its internal variability.

Having DEC in our suite of tools, we can find areas well suited for its use. In Chapter 4 we see a likely candidate for the use of DEC. We could consider using the correlation between coalition network and coordination networks in place of proportion overlap. In this case, we used the proportion overlap because the egocentric networks were small. Small numbers of alters make it harder to calculate the significance of the correlation which would have been an important component of the analysis. However, data limitations notwithstanding, this research question is an example of a possible application of DEC. In this application, the coalition network would have been the underlying Network A and the coordination networks would have been Network B. Instead of comparing the mean overlap with coalitions across types of coordination (see Figure 4.3), we would have compared the mean correlation. Moving forward in studies of belief segregation in policy networks, the DEC method will be useful in cases where we expect subjects to carry different preferences for network segregation.

Chapter 6

Conclusion

This dissertation presented three studies on segregation in policy networks. The first two studies use the Advocacy Coalition Framework (ACF) to build arguments and structure expectations around belief-based segregation in the US environmental risk management policy subsystem. The third study focused on a specific methodology available for recovering heterogeneous preferences for segregation. These studies contribute both to theoretical and methodological aspects of social science research. However, there are limitations to the work presented here and questions that are left open. This chapter provides a brief discussion of the contributions, limitations, and future work brought up by this dissertation.

6.1 Contributions

6.1.1 Theoretical

Chapter 3 examines network structure in the nascent and mature policy networks in the same system. It is very rare to have data on the same subsystem 30 years apart and this chapter provides a unique look at the networks created by the stakeholders engaged in issues of environmental risk. Studies like this one on longitudinal segregation are important because a better understanding of subsystem trajectories could help us to design better policy subsystems where excessive belief-based segregation does not limit the flow of information and the opportunities for truly collaborative work. While the time steps in this chapter were not directly comparable, we did find evidence that suggests that segregation plays a role in mature subsystems potentially more than it does in nascent subsystems.

In Chapter 4, we move to the impacts of belief-based segregation as stakeholders form advocacy coalitions. We study the comparative occurrence of coordination within and outside of coalition boundaries. The ACF centers its focus on the actions of advocacy coalitions, but individuals' actions are not necessarily constrained to their policy advocacy efforts. By explicitly looking at coordination outside of coalitions, we create a broader conceptualization of what it means to be an active policy stakeholder. This chapter makes several distinct contributions. First, we conceptualize coalitions as networks of loosely organized stakeholders instead of tightly connected groups. Second, we find and discuss considerable coordination outside of coalitions - particularly coordination on low-risk activities. Third, we introduce stakeholder heterogeneity based on type of work and other characteristics.

Chapters 3 and 4 together present a more complete picture of the nuanced role of belief segregation in policy networks. Chapter 3 shows support, albeit dampened by the measurement issues, for a trajectory of increased belief segregation in the environmental risk management subsystem. This increased segregation is generally seen as a negative force, limiting dialogue and policy innovation. However, Chapter 4 shows substantial coordination happening between stakeholders across coalitions. Putting these chapters together, we see a possible opportunity to low risk coordination to bridge the increasing belief segregation in policy subsystems.

6.1.2 Methodological

The biggest methodological contributions from the dissertation occur in Chapter 5. Network methods fill an important niche in statistical analysis because they allow us to look at collections of individuals as a whole system rather than independent pieces. However, by taking a system level view, we can miss the heterogeneity within samples. The DEC method, presented in Chapter 5, responds to this shortcoming in network analysis by pushing the use of egocentric networks as a path for incorporating the social aspects of behavior, but maintaining the independence of each unit of analysis. Full network analysis, like the analysis we undertake in Chapter 3 is useful for taking a system-level view, but washes out heterogeneity. The analysis in Chapter 4 also takes an egocentric approach and, as a result, we can look for differences among different types of stakeholders. This methodological emphasis on egocentric networks is what enabled our theoretical contributions on stakeholder heterogeneity in Chapter 4.

6.2 Limitations

While each study presented here contributes to the larger body of research on the policy making process and the use of network methods in social science research, there are clear limitations to the work. Chapter 3 provides a unique opportunity to revisit the same subsystem over time, but there are challenges to longitudinal research programs. In this case, the change in context over 30 years is difficult to control for. In the first time step, it is likely that the survey captured a high proportion of the key organizations because the subsystem was smaller. The later time step samples organizations from a much larger group of active participants and may have lost of the tight focus that was more achievable at an earlier point. Additionally, that adjustments to the sampling methodologies lessened the comparability over time. These types of challenges are inherent in longitudinal studies, but still impose a limitation on the interpretability of the results. Chapter 4 introduces a view of advocacy coalitions as networks as opposed to groups. This perspective works well for studying coalition ties is a broad subsystem, like environmental risk management, where we see many opportunities for smaller, more focused working groups. However, this network perspective on coalitions would benefit from more development as an independent piece of research. Chapter 5 demonstrates the usefulness of the DEC method, but we see that the method reaches a limitation on determining underlying preferences when they are drawn from distributions rather than assigned in clearly differentiated values.

All of these limitations are opportunities for future work and motivate a more refined look at the existing research questions in the field. The studies presented here move the Risk Professionals research program forward and, in the process, open new questions and lines of inquiry.

6.3 Future Research

In addition to addressing the limitations discussed above, there are some broad areas of research that this dissertation makes note of, but does not directly address. On the theoretical side, we address the presence and some of the constraining impacts of belief segregation in policy networks. However, we do not directly study mechanisms leading to segregation. In Chapter 3, we discuss the role of homophily versus social influence in causing measurable segregation. Henry & Dietz (2015) have undertaken research on this topic using Risk Professionals data that could be extended using the most recent wave of data.

From a practical standpoint, this research could be extended to investigate interventions that can promote better flows of information and resources. In Chapter 4, we found that stakeholders were more likely to take part in low risk rather than high risk coordinated activities across coalition boundaries. Given that belief segregation in policy networks can limit the flow of information and opportunities for compromise and other collaborations, future research could investigate way to leverage low risk interactions into opportunities for more meaningful work. This avenue for future work would be relevant to practitioner needs and, if successful, could provide post hoc intervention to improve communication and resource sharing in segregated networks.

Methodologically, the question of survey respondent aggregation is a critical area for future research. In Chapter 3, we aggregated individual survey respondents into the organizations where they were affiliated. This is a useful, and often necessary, approach for building full network models, but it introduces assumptions that should be pursued in independent research.

6.4 Conclusion

Policy making is a messy and complicated process. Research programs, like the one on the Risk Professionals, give us an opportunity to take snapshots of dynamic processes and piece together a better understanding of the motivations and behaviors of the people engaged in policy making. This dissertation strives towards an understanding of advocacy coalitions and the role that belief segregation plays in their maturation and in the strategies pursued by the stakeholders within them. We contribute to the theoretical development of the Advocacy Coalition Framework by bringing attention to the heterogeneity of stakeholders and the impact that that has on their behaviors. We also contribute methodologically by demonstrating the value of egocentric approaches to studies of diverse populations. We close this dissertation in the hope that future researchers can take inspiration from this work and continue to develop theoretical, practical, and methodological insights into the policy making process.

References

Allouch, N. (2013, September). *The cost of segregation in social networks* (Tech. Rep.). Fondazione Eni Enrico Mattei. Retrieved from `https://www.jstor.org/stable/resrep00954`

Baker, F., & Hubert, L. (1981). The analysis of social interaction data: a non-parametric technique. *Sociological Methods & Research*, *9*, 339-361.

Baker, J., Tuch, S., & D'Antonio, W. (2013). Religion, politics, and issue polarization in the United States Congress, 1959-2013. *Studia Religiologica*, *46*, 235-250.

Bandelow, N., & Kundolf, S. (2011). Belief systems and the emergence of advocacy coalitions in nascent subsystems: a case study of the European GNSS program Galileo. *German Policy Studies*, *7*, 113-139.

Beverwijk, J., Goedegebuure, L., & Huisman, J. (2008). Policy change in nascent subsystems: Mozambican higher education policy 1993-2003. *Policy Science*, *41*, 357-377.

Butts, C. T. (2016). sna: Tools for social network analysis [Computer software manual]. Retrieved from `https://CRAN.R-project.org/package=sna` (R package version 2.4)

Casciaro, T., & Piskorski, M. J. (2005). Power imbalance, mutual dependence, and constraint absorption: a closer look at Resource Dependency Theory. *Administrative Science Quarterly*, *50*, 167-199.

Chen, H. (2018). Venndiagram: Generate high-resolution venn and euler plots [Computer software manual]. Retrieved from `https://CRAN.R-project.org/package=VennDiagram` (R package version 1.6.20)

Crona, B., & Bodin, Ö. (2006). What you know is who you know? communication patterns among resource users as a prerequisite for co-management. *Ecology and Society*, *11*.

Csardi, G., & Nepusz, T. (2006). The igraph software package for complex network research. *InterJournal*, *Complex Systems*, 1695. Retrieved from `http://igraph.org`

Dietz, T., & Rycroft, R. (1987). *The risk professionals.* New York, NY: Russell Sage Foundation.

Dietz, T., Stern, P., & Rycroft, R. (1989, March). Definitions of conflict and the legitimation of resources: the case of environmental risk. *Sociological Forum*, *4*, 47-70.

DiPrete, T., Gelman, A., McCormick, T., Teitler, J., & Zheng, T. (2011). Segregation in social networks based on acquaintanceship and trust. *American Journal of Sociology*, *116*, 1234-1283.

Fidelman, P., Evans, L., Foale, S., Weible, C., von Heland, F., & Elgin, D. (2014). Coalition cohesion for regional marine governance: a stakeholder analysis of the Coral Triangle initiative. *Ocean and Coastal Management*, *95*, 117-128.

Fiorina, M. (2017). *Unstable majorities: Polarization, party sorting, and political stalemate.* Stanford, CA: Hoover Institution Press.

Freeman, L. (1978). Segregation in social networks. *Sociological Methods and Research*, *6*, 441- 429.

Granovetter, M. (1973). The strength of weak ties. *The American Journal of Sociology*, *78*, 1360-1380.

Harrison, L. (Ed.). (1984). *The McGraw-Hill environmental auditing handbook.* New York, NY: McGraw-Hill Book Company.

Henry, A. (2011a). Belief-oriented segregation in policy networks. *Procedia – Social and Behavioral Sciences*, *22*, 14-25.

Henry, A. (2011b). Ideology, power, and the structure of policy networks. *Policy Studies Journal*, *39*, 361-383.

Henry, A., & Dietz, T. (2015, April). Policy learning in an evolving environmental risk policy network. In *Midwest political science association 2015 conference.*

Henry, A., Lubell, M., & McCoy, M. (2010). Belief systems and social capital as drivers of policy network structure: the case of California regional planning. *Journal of Public Administration Research and Theory*, *21*, 419-444.

Henry, A., Prałat, P., & Zhang, C.-Q. (2011). Emergence of segregation in evolving social networks. *Proceedings of the National Academy of Sciences of the United States of America*, *108*, 8605-8610.

Henry, A., & Vollan, B. (2014). Networks and the challenge of sustainable development. *Annual Review of Environment and Resources*, *39*, 583-610.

Hlavac, M. (2018). stargazer: Well-formatted regression and summary statistics tables [Computer software manual]. Bratislava, Slovakia. Retrieved from `https://CRAN.R-project.org/package=stargazer` (R package version 5.2.2)

Horikoshi, M., & Tang, Y. (2018). ggfortify: Data visualization tools for statistical analysis results [Computer software manual]. Retrieved from `https://CRAN.R-project.org/package=ggfortify`

Hubert, L., & Schultz, J. (1976). Quadratic assignment as a general data analysis strategy. *British Journal of Mathematical and Statistical Psychology*, *29*, 190-241.

Ingold, K. (2011). Network structures within policy processes: coalitions, power, and brokerage in Swiss climate policy. *Policy Studies Journal*, *39*, 435-459.

Ingold, K., Fischer, M., & Cairney, P. (2017). Drivers for policy agreement in nascent subsystems: an application of the advocacy coalition framework to fracking policy in Switzerland and the UK. *Policy Studies Journal*, *45*, 442-463.

Interim procedures & guidelines for health risk and economic impact assessments of suspected carcinogens (Tech. Rep.). (1976). Environmental Protection Agency.

International Energy Agency. (2003). *Energy to 2050: Scenarios for a sustainable future.* Paris, France: Organisation for Economic Co-operation and Development.

IPCC. (2014). Summary for policymakers [Book Section]. In C. Field et al. (Eds.), *Climate change 2014: Impacts, adaptation, and vulnerabiltiy. contribution of working group ii to the fifth assessment report of the intergovernmental panel on climate change.* Cambridge, United Kingdom and New York, NY, USA: Cambridge University Press.

Jenkins-Smith, H., Nohrstedt, D., Weible, C., & Sabatier, P. (2014). The Advocacy Coalition Framework: Foundations, evolution, and ongoing research. In P. Sabatier & C. Weible (Eds.), *Theories of the policy process* (p. 83-101). Boulder, CO: Westview Press.

Jenkins-Smith, H., & St. Clair, G. (1993). The politics of offshore energy: empirically testing the Advocacy Coalition Framework. In P. Sabatier & H. Jenkins-Smith (Eds.), *Policy change and learning: An Advocacy Coalition approach* (p. 149-175). Boulder, CO: Westview Press.

Jenkins-Smith, H., St. Clair, G., & Woods, B. (1991). Explaining change in policy subsystems: analysis of coalition stability and defecation over time. *American Journal of Political Science*, *35*, 851-880.

Kassambara, A., & Mundt, F. (2017). factoextra: Extract and visualize the results of multivariate data analyses [Computer software manual]. Retrieved from `https://CRAN.R-project.org/package=factoextra` (R package version 1.0.5)

Krackhardt, D. (1999). The ties that torture: Simmelian tie analysis in organizations. *Research in the Sociology of Organizations*, *16*, 183-210.

Krackhardt, D., & Handcock, M. (2007). Heider vs Simmel: emergent features in dynamic structures [Conference Proceeding]. In E. Airoldi, D. M. Blei, S. E. Fienberg, A. Goldenberg, E. P. Xing, & A. X. Zheng (Eds.), *Lecture notes in computer science* (p. 14-27). Pittsburgh, PA: ICML 2006 Workshop on Statistical Network Analysis.

Lazer, D. (2001). The co-evolution of individual and network. *Journal of Mathematical Sociology*, *25*, 69-108.

Lord, C., Ross, L., & Lepper, M. (1979). Biased assimilation and attitude polarization: the effects of prior theories on subsequently considered evidence. *Journal of Personality and Social Psychology*, *37*, 2098-2109.

Mantel, N. (1967). The detection of disease clustering and a generalized regression approach. *Cancer Research*, *27*, 209-220.

Matti, S., & Sandström, A. (2011). The rationale determining advocacy coalitions: examining coordination networks and corresponding beliefs. *Policy Studies Journal*, *39*, 385-410.

Matti, S., & Sandström, A. (2013). The defining elements of advocacy coalitions: continuing the search for explanations for coordination and coalition structures. *Review of Policy Research*, *30*, 240-257.

McPherson, M., & Smith-Lovin, L. (1986). Sex segregation in voluntary associations. *American Sociological Review*, *51*, 61-79.

McPherson, M., Smith-Lovin, L., & Cook, J. (2001). Birds of a feather: homophily in social networks. *Annual Review of Sociology*, *27*, 415-444.

Metz, F., Leifeld, P., & Ingold, K. (2018). Interdependent policy instrument preferences: a two-mode network approach. *Journal of Public Policy*. doi: 10.1017/S0143814X18000181

Mollica, K. A., Gray, B., & Treviño, L. K. (2003, March). Racial homophily and its persistence in newcomers' social networks. *Organizational Science*, *14*, 123-136.

Munro, G., & Ditto, P. (1997). Biased assimilation, attitude polarization, and affect in reactions to stereotype-relevant scientific information. *Personality and Social Psychology Bulletin*, *23*, 636–653.

Munro, G., Ditto, P., Lockhart, L., Fagerlin, A., Gready, M., & Peterson, E. (2002). Biased assimilation of sociopolitical arguments: evaluating the 1996 U.S. Presidential debate. *Basic and Applied Social Psychology*, *24*, 15-26.

Pfeffer, J., & Salancik, G. (1978). *The external control of organizations: A resource dependence perspective*. New York, NY: Harper and Row, Publishers.

Quattrone, G., & Tversky, A. (1988). Contrasting rational and psychological analysis of political choice. *American Political Science Review*, *82*, 719–736.

R Core Team. (2018). R: A language and environment for statistical computing [Computer software manual]. Vienna, Austria. Retrieved from `https://www.R-project.org/`

Regens, J., Dietz, T., & Rycroft, R. (1983). Risk assessment in the policy-making process: environmental health and safety. *Public Administration Review*, *43*, 137-145.

Ruckelshaus, W. (1983). Science, risk, and public policy. *Science*, *221*, 1026-1028.

Rycroft, R., Regens, J., & Dietz, T. (1987). Acquiring and utilizing scientific and technical information to identify environmental risks. *Science, Technology, & Human Values*, *12*, 125-130.

Rycroft, R., Regens, J., & Dietz, T. (1988). Incorporating risk assessment and benefit-cost analysis in environmental management. *Risk Analysis*, *8*, 415-420.

Sabatier, P. (1986). Top-down and bottom-up approaches to implementation research: a critical analysis and suggested synthesis. *Journal of Public Policy*, *6*, 21-48.

Sabatier, P. (1988). An advocacy coalition framework of policy change and the role of policy-oriented learning therein. *Policy Sciences*, *21*, 129-168.

Sabatier, P., & Brasher, A. (1993). From vague consensus to clearly-differentiated coalitions: environmental policy at Lake Tahoe, 1964-85. In P. Sabatier & H. Jenkins-Smith (Eds.), *Policy change and learning: An advocacy coalition approach* (p. 149-176). Boulder, CO: Westview Press.

Sabatier, P., Hunter, S., & McLaughlin, S. (1987). The devil shift: perceptions and misperceptions of opponents. *The Western Political Quarterly*, *40*, 449-476.

Sabatier, P., & Jenkins-Smith, H. (1999). The Advocacy Coalition Framework: an assessment. In P. Sabatier (Ed.), *Theories of the policy process* (p. 117-166). Boulder, CO: Westview Press.

Sandia National Lab. (1994). *Choices in risk assessment: The role of science policy in the environmental risk management process.* Washington D.C.: Regulatory Impact Analysis Project, Inc.

Schelling, T. (1969). Models of segregation. *The American Economic Review*, *59*, 488-493.

Schelling, T. (1971). Dynamic models of segregation. *Journal of Mathematical Sociology*, *1*, 143-186.

Schlager, E. (1995). Policy making and collective action: defining coalitions within the Advocacy Coalition Framework. *Policy Sciences*, *28*, 243-270.

Simmel, G. (1950). Quantitative aspects of the group. In K. H. Wolff (Ed.), *The sociology of georg simmel.* Glencoe, Illinois: The Free Press.

Simon, H. (1955). A behavioral model of rational choice. *The Quarterly Journal of Economics*, *69*, 99-118.

Simon, H. (1985). Human nature in politics: The dialogue of psychology with political science. *American Political Science Review*, *79*, 293–304.

Sokal, R. (1979). Testing statistical significance of geographic variation patterns. *Systematic Zoology*, *28*, 227–232.

Standström, A., & Rova, C. (2010). The network structure of adaptive governance: a single case study of a fish management area. *International Journal of the Commons*, *4*, 528-551.

Stevenson, J. (2009). *Mapping the political landscape of wave energy development off the Oregon coast* (Unpublished master's thesis). Oregon State University.

Stritch, A. (2015). The Advocacy Coalition Framework and nascent subsystems: trade union disclosure policy in Canada. *Policy Studies Journal*, *43*, 437-455.

Sweeney, R. (2004). *Environmental risk decision-making: risk professionals and their use of analytic-deliberative processes* (Unpublished doctoral dissertation). George Mason University.

Tang, Y., Horikoshi, M., & Li, W. (2016). ggfortify: Unified interface to visualize statistical result of popular r packages. *The R Journal*, *8*. Retrieved from https://journal.r-project.org/

Tassier, T., & Menczer, F. (2008). Social network structure, segregation, and equality in a labor market with referral hiring. *Journal of Economic Behavior and Organization*, *66*, 514-528.

Thomas, G. (1998). *Analyzing environmental policy change: U.S. landsat policy, 1964-1998* (Unpublished doctoral dissertation). Colorado State University.

Törnberg, P. (2018). Echo chambers and viral misinformation: Modeling fake news as complex contagion. *PLoS ONE*, *13*.

US Department of Energy. (n.d.). *DOE history timeline.* https://www.energy.gov/management/office-management/operational-management/history/doe-history-timeline. (Accessed: 2019-01-17)

US Environmental Protection Agency. (2017, June). *EPA environmental justice timeline.* https://www.epa.gov/environmentaljustice/environmental-justice-timeline. (Accessed: 2019-01-16)

US Environmental Protection Agency. (2018, May). *EPA history.* https://www.epa.gov/history. (Accessed: 2019-01-16)

Weible, C. (2005). Beliefs and perceived influence in a natural resource conflict: an advocacy coalition approach to policy networks. *Policy Research Quarterly*, *58*, 461-475.

Weible, C., & Sabatier, P. (2005). Comparing policy networks: Marine protected areas in California. *Policy Studies Journal*, *33*, 181-201.

Weible, C., Sabatier, P., & McQueen, K. (2009). Themes and variations: taking stock of the Advocacy Coaltion Framework. *Policy Studies Journal*, *37*, 121-140.

Wickham, H. (2011). The split-apply-combine strategy for data analysis. *Journal of Statistical Software*, *40*(1), 1–29. Retrieved from http://www.jstatsoft.org/v40/i01/

Wickham, H. (2016). *ggplot2: Elegant graphics for data analysis.* Springer-Verlag New York. Retrieved from http://ggplot2.org

YiLan, L., & RuTong, Z. (2015). clustertend: Check the clustering tendency [Computer software manual]. Retrieved from https://CRAN.R-project.org/package=clustertend (R package version 1.4)