The Relational Nature of Legislating

by
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Abstract

JUSTIN H. KIRKLAND: The Relational Nature of Legislating.
(Under the direction of Thomas Carsey.)

Since the economic revolution of the 1970's legislative scholars have produced important works examining the relationships between policy preferences and individual choices in a legislature. This focus on understanding individual preferences versus outcomes has led scholars to ignore potential inter-legislator influences on choices. In other words, in the study of relationships between a bill and a legislator scholarship has overlooked the importance of the relationship between one legislator and another legislator. These studies represent an effort to push our theoretical understanding of inter-legislator dynamics forward and build a more comprehensive understanding of how legislators influence, collaborate with, and cooperate with one another. Taken together they provide a unified picture of influence diffusion across a chamber by examining both how relationships between legislators affect outcomes and how institutions affect the formation of legislative relationships. Building on seminal sociological work on the importance of tie strength towards achieving an exogenous goal, I generate a novel theory of influence in a legislature. It will turn out that only the weakest ties between legislators actually produce changes in the probability a legislator will experience success. This is because weak ties between legislators are attempts to generate novel cooperation and support. Strongly tied legislators are strongly tied because of implicit support, thus the observation of the relational tie tells us nothing about their behaviors we could not have learned before a legislative session ever began. Strong ties do not indicate cooperation, they indicate similarity. Weak ties, however, occur between legislators fundamentally different most of

the time, but who cooperate on some legislation in order to improve its odds of survival. It will also turn out that the formation of these cooperative ties is fundamentally effected by the behavioral constraints of a chamber. In particular, the nature of an electoral district and the size of a legislative chamber will play key roles in the development of cooperative relationships between legislators.

For my wife, Laura, whose support and love never falters.

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Chapter 1

Introduction

At Senator Edward Kennedy's memorial service, a number of his fellow senators spoke in his honor. They all noted a lifetime of legislative accomplishments that resulted in many regarding Kennedy as the most successful senator of his generation. Interestingly, the majority of those praising Kennedy's life of public service attributed his success to his ability to collaborate with his fellow legislators. Many observed that Kennedy was never reluctant to seek out bipartisan support for legislation about which he cared strongly, and looked for allies wherever he could find them. While Kennedy remained a staunch liberal and cornerstone of the Democratic Party, his partnerships on landmark legislation included Republicans Judd Gregg on student loan forgiveness, John McCain on immigration reform, and Orrin Hatch on healthcare insurance reforms for children. These are hardly the partners we would expect a progressive liberal like Kennedy to have.

Kennedy's penchant for seeking out unorthodox allies, the legislative successes that produced, and his colleagues' respect for him that resulted from these efforts serve to remind legislative scholars that legislating is an inherently relational enterprise. Scholars have frequently overlooked the complex interdependencies in legislative activities in their analyses of legislative behaviors. This oversight is both a theoretical and analytical problem. While Kenendy's choices of partners might seem odd from a proximity model view, his (and most other successful senators) legislative careers are marked by a consistent attempt to engage with those across the aisle during the most important votes. A view of a legislature as a set of interdependent actors building coalitions, taking cues from one another, seeking advice, and collaborating on lawmaking while also pursuing individual legislative goals has the potential to incorporate these type of relationships into what we already know about legislative behavior.

Scholars should envision this complex web of collaboration, cue taking, and advice seeking that exists between legislators as an interdependent network of activities. Legislators are actors in a bounded network with a fixed number of possible partners. They connect to one another through their common efforts, common interests, and time spent together. The choices of the other members in the chamber condition their choices about with whom they work. The rules and institutions of the legislature also influence those choices. For example, the powers granted to committee chairs and speakers almost certainly influence which other legislators seek out their favor. The development of expertise in committee will structure the network of advice and cue taking. Thus, legislators influence one another, and that influence is conditioned by their institutional environment.[1]

In my dissertation, I adopt this relational perspective as a useful way to think about legislative behavior. Some of the earliest work on legislative behavior recognized legislators as "specialists in human relationships" (Routt 1938). I intend to demonstrate a) why relationships are important elements in determining legislative outcomes, and b) how several types of institutions influence those relationships. To accomplish these examinations, I require data on legislative interactions across institutional contexts. To measure legislative interactions, I have constructed social networks of legislative cosponsorships across the 99 state legislative chambers of the United States.

A social network is a system of interactions comprised of V actors and E connections between those actors. An "edge" $e \in E$ exists between two actors if the two actors are

[1]This is not an overly controversial claim. Game theorists have long recognized that strategic interdependence between actors is a function of the rules of their particular game.

connected on the relationship of interest. Alternatively, a social network can be thought of as a square, or adjacency, matrix where rows and columns represent the actors under study and element ij of the matrix represents the connection between actors i and j. The cosponsorship networks I have gathered represent connections between legislators i and j as the number of times legislator i has cosponsored bills introduced by legislator j. Thus, the cosponsorship network is *directional* in that a connection points towards j from i, but not in the reverse direction. The cosponsorship network provides me with a measure of legislative collaboration (or co-support). Developing cosponsorship networks across the U.S. state legislatures provides me with institutional variance useful in demonstrating that the development of legislative relationships is conditional on the institutional context of the actors.

In chapter 2, I develop and test a general model of the impact of legislative relationships on legislative outcomes. Building on sociological work by Mark Granovetter (1973), I construct a model that predicts that the legislative relationships with the greatest impact on legislative outcomes are the relationships between actors with observable differences between them. In other words, it is the weak ties between legislators who harbor fundamental differences from one another that change the legislative process. A collaborative relationship between Edward Kennedy and John Kerry does little to alter either's level of legislative success. A collaborative relationship between Edward Kennedy and Orrin Hatch can fundamentally alter each actor's level of support in the chamber. Pairing cosponsorship networks from eight state legislatures and 15 years of U.S. House activity with data on bill outcomes in committee and on the floor, empirical analysis largely corroborates my expectations. Weak ties between legislators both increase legislative success and occur between legislators who are different from one another. Strong ties exist between legislators who are similar to each other and have no effect on measurable legislative outcomes.

Having demonstrated that legislative relationships are important, chapter 3 begins my investigation into the institutional influence of legislative relationships. In 2002, the Supreme Court of North Carolina mandated that legislators change the 17 state legislative districts that currently elected multiple members to the state's lower chamber from multi-member districts to single member districts. This exogenously imposed change in electoral context provides an ideal natural experiment in which the behavior of the treatment group (legislators from multi-member districts) can be compared to a control group prior to receiving treatment (the legislators from single member districts prior to 2002) and to themselves before and after treatment. Existing literature on free-rider problems among legislators whose constituencies overlap indicates that legislators from shared districts ought to be unlikely to work together on legislation. Contrary to this expectation, I find that legislators from multi-member districts are much more likely to collaborate (even controlling for political party) than their single member colleagues are, and that once these legislators no longer share a district their collaboration ceases. Thus, the empirical evidence strongly implies that multi-member districts were generating, not inhibiting, collaboration.

In chapter 4, I discuss the nature of group interactions in legislatures and how frequent interactions might alter the network of legislative collaboration. I construct a mathematical model in which legislators build connections to those most similar to them ideologically, but, through their interactions with one another, they can learn about unexpected similarities to other legislators. The most frequent and useful interactions for this kind of learning occur in committees where legislators develop expertise and discuss legislation amongst a small group of fellow experts. As a result, the model predicts that a) as the size of legislatures grow, the chambers will exhibit more partisan relational networks, and b) controlling for chamber size, larger committees will limit the degree of partisanship in the collaborative network. I then introduce the network summary statistic modularity to measure the degree of partisanship in a cosponsorship network. My results bear out the expectations of my model, indicating that large chambers are more partisan than smaller chambers and large committees limit that partisanship.

In my final empirical chapter, I focus on a methodological problem in social network analysis. Summary statistics are useful ways for scholars of social networks to examine and compare networks of interest. Unfortunately, due to the complexity of social network data and a lack of understanding regarding the distribution of network phenomenon, reference distributions for summary network statistics are poorly understood.[2] In this chapter, I use nonparametric permutation tests to generate reference distributions for the network summary statistic modularity. Modularity is a popular tool for assessing the degree of separation in a network along a trait of interest (i.e. party-based clustering in cosponsorship), and permutation tests can tell us when a modularity score of interest is greater than a random separation of the network would generate. This chapter also provides an analysis of the properties of the reference distribution, which are a function of the attributes of the networks themselves.[3]

Together these examinations demonstrate that a relational approach to the study of legislatures can provide important insights for legislative scholarship. Legislative relationships are critical determinants of legislative outcomes, and the institutional environment in which they occur influences legislative relationships. While this work does not mean to imply that the more individual actor-oriented approach of micro-economic studies of legislative behavior is without merit, it does demonstrate that more system-level or

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[2]For example, it is well understood that difference-in-means follow a T-distribution with n degrees of freedom, making the T-distribution the appropriate reference against which one would compare a difference-in-mean statistic. No such reference exists for network density or the network clustering coefficient or any other network summary.

[3]The network density, size of groups in the network, and "true" level of modularity in the network all influence the size and location of the reference distribution.

relationship-level studies of U.S. legislatures are productive avenues for novel theoretical and empirical insights. In particular, proximity models of legislative politics imply that a legislator's position within the ideological distribution is the critical component in his or her legislative success, while my relational approach indicates that a legislator's position within a relational environment is also a key element in accomplishing legislative goals. Bridging large distances in that relational environment is key to passing legislative proposals, while bridging ideological distance is of no real importance in a proximity model.

Chapter 2

The Relational Determinants of Legislative Outcomes

Legislators are strategic, goal-oriented actors motivated by three main goals: 1) increased institutional prestige, 2) re-election, and 3) good public policy (Fenno 1973). Legislators are also social beings pursuing those goals in a social construction (a legislature) comprised of interdependent relationships (Patterson 1959, Clark, Caldeira and Patterson 1993, Peoples 2008, Fowler 2006a, Fowler 2006b). These two empirical facts beg the question how might a strategic, goal-oriented legislator make use of the relational environment he or she operates within to pursue his or her goals? What good are collaborative relationships to actors motivated by Fenno's trinity of legislative goals, and, by extension how do relationships influence legislative outcomes? Research on relationships in legislatures has uncovered that a link exists between legislative relationships and legislative outcomes (Peoples 2008, Arnold, Deen and Patterson 2000, Tam Cho and Fowler 2010), but the path from relationship to outcome remains hazy at best. My research provides a theoretical framework, based on seminal sociological research (Granovetter 1973, 1983) for understanding how relationships and positions within a relational network influence legislators' goals and thus, legislative outcomes.

I develop a theory of influence diffusion across a legislative network that predicts that weak ties between legislators increase the probability of legislative success while strong ties between them do not. I test the theory using cosponsorship data from the U.S. House of Representatives as well as the lower chambers in eight state legislatures. Using cosponsorship of legislation to measure relationships between legislators has some precedent (Fowler 2006a, Fowler 2006b), and, while cosponsorship may be a noisy indicator of legislative relationships, there is ample evidence that legislators expend a great deal of effort seeking cosponsors for their bills, and that they carefully weight their own decisions regarding whether to cosponsor the bills introduced by others (Kessler and Krehbiel 1996). Multilevel logit models provide strong support for my theory, indicating that weak ties between legislators are the ones that yield increases in legislative success.

Most early work on relationships between legislators has focused on studying one legislature at a time. In a series of articles taking advantage of a unique elite level survey of the Iowa legislature from 1965, Patterson and Caldeira (1987), Caldeira and Patterson (1988), and Clark, Caldeira, and Patterson (1993) note that friendships between Iowa legislators are driven by party, geographic proximity, convergent attitudes, and campaign activism. Conversely, education and legislative experience predict respect between legislators (with no apparent conditioning effects from attitude divergence). Using 1993 elite level interviews with the Ohio State House of Representatives, Arnold, Deen, and Patterson (2000) find that friendship between two legislators strongly predicts the likelihood of a similar vote at roll call, even when controlling for ideological and partisan similarities. Using the same Ohio data, but with several methodological improvements, Peoples (2008) continues to find that the social relationships between legislators have strong influences on their subsequent behavior at roll call.

A noticeable limitation with all of these studies is their lack of generalizability. Studying elite level surveys in one state prevents researchers from testing a general theory of relational legislating. In order to increase generalizability, some scholars have moved to studying cosponsorship in a legislature as an observable indicator of legislative relationships. Fowler (2006a, 2006b) provides one of the earliest examinations of cosponsorship in a legislature as a social network. By using cosponsorship, Fowler is able to examine several years of the U.S. House. His work on the U.S. House of Representatives indicates that a legislator's centrality to the social network measured via cosponsorship positively impacts the success of both bills the legislator sponsored and amendments to bills the legislator offered. Gross and Shalizi (2009) also examine the cosponsorship network in the U.S. Senate and find that social predictors like being from the same state, same region, shared religious denomination and gender predict senators' decisions to cosponsor one another. In other recent work, Bratton and Rouse (2009) study cosponsorship in nine state legislatures and find that gender and ethnicity predict state legislators' decisions about cosponsorship.

While generalizability remains problematic, the more important limitation in the studies of relationships between legislators has been their weak theoretical basis. None of these studies have developed general theoretical accounts of how and why strategic, goal-oriented political actors form relationships and how those same strategic actors might make use of relationships to achieve their own ends. I address this shortcoming by offering a theory of influence diffusion animated by goal-oriented actors who make use of relationships to achieve legislative success and influence. Additionally, I will overcome problems of generalizability by studying several state legislatures and the US Congress simultaneously.

2.1 Ties Between Legislators and the Diffusion of Influence

To focus on paths through a legislative social network for increasing legislative success, I draw heavily on social networking theory developed by Granovetter (1973, 1983). Granovetter argues that when observing information transmission across a social network, the strength of relational ties is an important consideration. Consider, first the individuals strongly tied in a social network. These actors are generally strongly tied[1] in the network because of their similarities. In a friendship network for example, strong ties are a result of common interests, activities, and outlooks on life. Those who are weakly tied in the network are tied together as a result of some interactions that lead to an association but they retain important differences on the dimensions that generate strong ties. Thus, weak ties typically occur between individuals with important fundamental differences.

Granovetter's initial work focused on job change, uncovering that amongst those individuals who changed jobs, the information about new employment opportunities came from acquaintances rather than close friends. The close friends of job changers (strong ties) share important similarities that prevent them from having novel information to exchange. They provide no information to the potential job changer that is not already easily accessible. Acquaintances however, interact rarely and retain differences that grant them access to information the potential job changer does not already possess. Thus, those weakly tied to the job changer provide novel information that strong ties simply cannot provide because of the nature of strong tie development. Subsequent work on the "weak ties" hypothesis has focused both on the value of these bridging or weak ties

[1]For Granovetter tie strength is a function of the frequency of interactions. Strong ties are then defined as people who see each other often. Weak ties are acquaintances who rarely interact.

to information transmission across the entire network and the value of non-redudant information provided by weak ties to individual performance. Levin and Cross (2004), Cross and Cummings (2004), Morrison (2002), and Constant et al. (1996) all demonstrate the value of bridging ties in individual learning. By building weak ties, individuals in a network accrue information they could not gather through their network of strong ties.[2]

Now consider a similar argument within a legislature. Legislators develop their working relationships in an effort to effect certain goals, one of which is legislative success (Anderson et al. 2003). A legislator's desire for success (defined as bills sponsored by the legislator surviving veto points in a chamber) is a natural extension of the trinity of legislative goals originally developed by Fenno (1973): re-election, good public policy, and influence within the chamber. Bills a legislator sponsors are more often than not bills the legislator believes to be good public policy and by passing more legislation an individual legislator has a greater influence on what a chamber produces. So, understanding how a legislator's relational network influences his/her legislative success provides insight into how a strategic legislator makes use of relationships to achieve the most basic goals of legislators.

Within this relational network, strong ties (meaning frequent collaboration) form as a result of similarities between legislators on factors like ideology, party, and demographics. Because of these similarities, strongly tied legislators have the same preferences for good public policy (one of the three major legislative goals) and commonly support the same pieces of legislation as a result *even if they did not a have strong tie between them.*[3] Weak ties (meaning infrequent collaboration) alternatively, form between legislators who choose

[2]Other studies (Burt 2004, Perry-Smith and Shalley 2003, Tiegland and Wasko 2000) have found that as the number of weak ties an individual has increases, creativity and performance in the work place increase. Bridging ties provide access to alternative points of view that, in turn, increase creativity and help in the diffusion of good ideas once they have been developed.

[3]Bratton and Rouse (2009), who only examine strong ties, demonstrate that ideology, party, gender and race all play important roles in strong tie formation.

to work together on occasion, but because of some critical difference do not support one another all the time. These ties are critical for legislative success precisely because they form between legislators who do not share many other similarities. Weak ties represent cooperation that is non-redundant to similarity. Establishing relationships with those less similar to themselves allows legislators to expand their potential sphere of influence beyond those who are already predisposed to support them because of some set of shared characteristics. By building weak ties, legislators expand their influence beyond their similarity-based network of support.

To further elucidate this argument, consider Figure 1. In the first panel of Figure 1, legislator "d" operates within a clique of strong connections to three other legislators. These strong ties indicate the base of support the legislator would have received on the first day of session simply because of similarities to other legislators. Had legislator "d" never formed these ties, the support of legislators "a", "b", and "c" would have still existed because of similar traits like policy preferences, gender, party, etc. Thus, if legislator "d" wishes to expand his or her influence beyond similarity based support, he or she must consider forming a new (or weaker) tie to one of the legislators in the opposing triangle. By building this bridging tie, seen in the second panel of Figure 1, "d" has gained access to legislators whose support was not pre-existent.

As a more concrete example, we might think of legislator "d" as former Senator Edward Kennedy and "d"s strong ties as the other Democrats in the Senate. These other Democrats would have supported Kennedy's legislation whether he had ever built relational connections to them or not because of their shared policy preferences. Instead, we can consider legislator "e" as Orrin Hatch. Kennedy's relationship with Hatch has generated something novel in the network by expanding Kennedy's potential support beyond those most similar to him.[4]

[4]Sulkin and Bernhard (2010) have provided evidence that cosponsorship decisions are highly reciprocal

(a) No Weak Ties between Legislators

(b) Legislator “d” forms a Weak Tie

Figure 2.1: Legislator “d” builds a Bridging Tie to a new cluster of Legislators

While not explicitly discussed in Granovetter's original work, this weak ties argument implies that not all weak ties are equal. The value of weak ties is a result of their novelty of information or influence. By providing access to new resources, weak ties provide something strong ties cannot. The better the resources that weak tie provides the more useful the weak tie becomes. For example, gaining the support of a legislator who has little influence on other legislators adds only one legislator's support. However, generating a weak tie to a colleague who is him or herself strongly tied to several other legislators[5] can provide a large increase in the likelihood of legislative success. By creating a tie to one legislator who is connected to many others, a legislator can probabilistically increase the chances of entire cliques[6] of legislators becoming new support clusters.

Returning to the real world example, when Kennedy elects to form a weak tie in the legislature he can choose his cooperative partner. For example, he might choose between building a connection to Orrin Hatch (the second most well-connected Senator across the 108th Congress) or Elizabeth Dole (the second least-connected Republican in the 108th Senate (Fowler 2006b)). By choosing to work along side Hatch rather than Dole, Kennedy can convince many of Hatch's colleagues to consider his legislation as potentially useful. This is of course a probabilistic influence. Many Republicans are more likely to carefully consider legislation if Hatch and Kennedy are working together than if legislation has been supported by Kennedy alone, or if legislation has been supported by Kennedy and

(though not perfectly) indicating that collaborative choices between legislators carry weight in decision-making even after the immediately cosponsored bill has completed the legislative process. They also present evidence that violations of the norm of reciprocity are often punished. This means that the immediate cosponsorship relationship continues to affect legislative behavior in the future.

[5]That secondary connection must also be of the strong type. Gaining the support of a legislator who is strongly connected to many others, implicitly gathers the support of these others. Gaining the support of a legislator who is weakly connected to many others means the new legislative base provides limited implicit support through the new weak connection.

[6]Bratton and Rouse (2009) also find a high degree of clique like behavior amongst legislators in several chambers that is even more fine grained than party. Legislators seem to separate themselves into small groups of people working together regularly.

an unpopular Republican like Dole, but are not deterministically certain to support the Hatch-Kennedy legislation. Thus, Kennedy's choice of partners is influenced by how well-connected his potential partner is within a network of new supporters, or the number of *secondary connections* the connection to Hatch provides.

From this basic argument about the paths of influence across a legislative network, I generate four hypotheses. *First, the effects of weak ties and secondary ties that stem from them will provide increases in the probability of legislative success.* While the coefficients on each variable are important in and of themselves, the argument specifies that success is a result of building bridging ties to novel support clusters. Accordingly, I am more interested in the combined effects of both weak and secondary ties, than either variable alone. *Second, the combined effects of strong ties and secondary ties that stem from them will provide no statistically distinguishable increase in the probability of legislative success.* This would indicate that strong ties play little role in shaping legislative influence because those to whom a legislator is strongly tied already support that legislator regularly. *Third, legislators who build weak ties to a legislator with many strong connections are the most successful in passing legislation.* Thus, a conditional relationship emerges in which weak ties to highly central legislators are the most important paths to legislative success. *Finally, pre-existing similarities like race, gender, and party will contribute to the formation of strong ties more than the formation of weak ties.* Weak ties create success through the expansion of influence beyond the support for a legislator generated through similarities. These similarities, then, should *not* drive weak tie formation. If weak ties occur between very similar legislators, it is not their novelty that produces their influence.

In order to fully test these predictions, empirical models of legislative success will need to control for potential alternative explanations of bill survival and passage in a chamber. Bill sponsors may have a host of advantages that improve their likelihood of success when proposing legislation. Particularly, committee chairmanship is likely to play a critical role in legislative success (Evans 1991). In many chambers, committee chairs hold power over the sequence of proposals within their committees, are important party fundraising and policy players, and direct the activities of their committees through conference committee activities and subcommittee appointments. Thus, they wield significant advantages in determining which pieces of legislation survive veto points. Additionally, the majority party status of the sponsor is likely to play a critical role in bill success (Cox and McCubbins 1993, Rohde 1991). Membership in the majority party affords a legislator enough partisan support to pass legislation on the floor, as well as ensuring that the chair of potential committees of deliberation will share the party identification of the sponsor. Finally, seniority affords bill sponsors strategic experience in knowing when to propose legislation in order to improve its likelihood of success. Spending time as a legislator brings with it knowledge and experiences (as demonstrated by the term limits literature, see Kousser (2005)), that improve an individual's understanding of when it is best to propose legislation in order to improve the odds of success.

Finally, most of these alternative explanations for bill passage are legislator-specific constructs. The weak ties theory of influence diffusion is itself centered on the legislator as the important unit of change in the network. This is in contrast to previous treatments of cosponsorship (the measurement of tie strength I will use), which focus on bill-specific reasons for cosponsorship without a real consideration of the intedependence in these choices (Wilson and Young 1997, Kessler and Krehbiel 1996). In order to control for bill-specific reasons for veto point survival, I include a measure of the number of cosponsors on each piece of legislation. Accounting for this bill-specific alternative hypothesis means the relational variables in my models will capture only legislator-specific traits, controlling for bill-specific popularity. Previous work on legislative success (Anderson et al. 2003, Volden and Wiseman 2009, Ellickson 1992, Frantzich 1979, Moore and Thomas 1991, Bratton and Haynie 1999) has measured success as the number of bills or proportion of bills a legislator successfully shepherds through the legislative process. By keeping the dependent variable in these analyses at the legislator level, this work has risked confounding legislator- and bill-specific reasons for bills to be successful. By keeping my unit of analysis at the bill and including legislator specific covariates, I can avoid this potential problem.

2.2 Design and Data

I make use of cosponsorships between state legislators in order to measure tie strength. I have measured cosponsorship networks for eight state legislatures in 2007[7]: North Carolina, Alabama, Minnesota, Mississippi, Alaska, Hawaii, Indiana, and Delaware.[8] While there are certainly limitations to the use of cosponsorship as an indicator of the strength of a relationship between two legislators, this approach has some precedent (Fowler 2006a, Fowler 2006b, Bratton and Rouse 2010, Gross and Shalizi 2009). Cosponsorship behavior has been demonstrated to be interdependent (Desmarais et al. 2009), thus justifying its treatment as a network, and a number of studies (Koger 2003, Campbell 1982) have demonstrated that decisions about who and what to cosponsor represent decisions about cooperation and collaboration. Whether one regards cosponsorship as position taking (Mayhew 1974) or as intra-legislative signaling (Kessler and Krehbiel 1996), theoretical treatments of cosponsorship all recognize that the behavior is driven by similarity to

[7] In order to gather cosponsorship data across many states in a timely fashion, I have developed a web-scraping routine that allows for the extraction of the instances of cosponsorship from legislative websites. This web-scraper is based on the package RCurl (Lang 2007) in the statistical package R. Example code for this routine can be made available upon request.

[8] These eight states were selected for reasons of data availability. They were the only states in which I could gather all the requisite parts of my model in a reasonable time frame. Though these states represent a convenience sample, they also represent a reasonable distribution of chamber party polarization, professionalism and geographic region.

other actors and the strategic calculation of the costs of cooperation.

In order to account for this between-legislator variance in the rate of sponsorship, I have divided the network observations of the instances of cosponsorship by the number of bills each legislator has sponsored. Thus, the observation of tie strength is a proportion of cosponsorship between legislator i and legislator j in the cosponsorship matrix. In order to differentiate between strong and weak ties, the networks of proportions must be subset into weak tie and strong tie networks. To subset the network I classify any connection between two legislators stronger than the mean plus one standard deviation connection strength for that particular state as a strong tie. Any connection below this threshold but greater than zero is a weak tie. A connection of zero is considered no tie. In North Carolina, if the average tie strength is 0.2 and the standard deviation of tie strength is 0.1, any connection between legislators that is greater than or equal to 0.3 is considered strong. Any connection between 0 and 0.3 is considered weak. This threshold is to some degree arbitrary, but the appendix to this article provides an alternative operationalization of these concepts in an effort to overcome concerns about the designated threshold I choose. Censoring the networks in this way yields two network matrices, a strong and weak ties matrix, in which strong ties are particularly frequent interactions and weak ties are less frequent interactions. The out-degree of legislator i in any social network A is the number of ties directed away from legislator i in that network. Thus, the out-degree of legislator i in the strong ties network is the number of strong connections legislator i has created to other legislators.[9] I use out-degree measures for each legislator in both the strong and weak ties networks to develop the legislator-specific measures of strong and weak relationships.

To measure secondary connections I make use of a network statistic called "alter degree". Alter degree for legislator i measures the number of connections of every other

[9]Recall that the strong and weak ties networks are made up of only ones and zeros, so counting the degree of actor i is equivalent to counting the number of strong ties of actor i

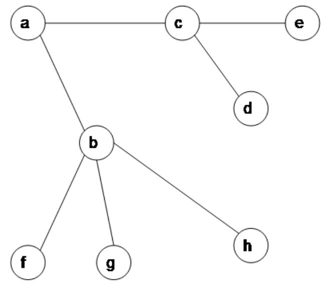
legislator to whom i is connected. Alter degree then, adds up the "friends of a friend" or "friends of an acquaintance" in the cosponsorship network depending on whether the initial tie is strong or weak. Figure 2 illustrates this relationship more clearly.

In Figure 2, Panel (a), legislator A has an out-degree of 2, meaning legislator A has two connections. Legislator A also has an alter degree of 5, meaning those two legislators A is connected to have 5 connections themselves. In Panel B, legislator A has increased his or her connections to other legislators but has not increased secondary connections, meaning legislator A's alter degree will not change. In panel 3, we see legislator A increase secondary connections without increasing his or her own connections. By choosing different connection sets, legislator A can increase support for legislation.[10]

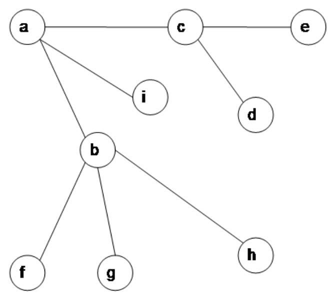
Using out-degree and alter degree statistics, I can measure strong, weak, and secondary connections in order to test my assertions about the nature of tie strength and legislative success. This produces four measures, strong ties, weak ties, secondary connections from weak ties, and secondary connections from strong ties. These sets of statistics will be highly collinear (one can only have secondary connections by having direct connections first), but I will provide several model specifications to demonstrate the robustness of my results to this collinearity.

I measure legislative success as whether or not a bill sponsored by a legislator has survived potential veto points in the chamber. Thus, a bill surviving committee deliberation has some success over a bill that does not. A bill that passes from the chamber has more success than a bill that survives committee deliberation but does not pass. I make use of two dichotomous variables, committee survival (coded 1 if a bill survives committee deliberation, 0 if not) and bill passage (coded 1 if a bill passes from a chamber, 0 if

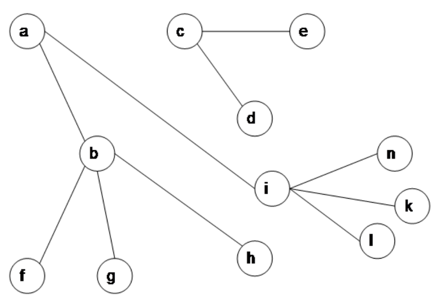
[10]When measuring alter degree, I make use of only secondary connections of the strong type. If legislator i is weakly connected to legislator j, then legislator i has built a bridging connection to all those legislators who inherently agree with and support legislator j, those to whom j is strongly connected. Legislator j's weak ties are those who regularly do not support j and, thus, will not support i simply because j does.



(a) Legislator "a" with alter degree 5



(b) Legislator "a" with alter degree 5, but increasing direct ties



(c) Legislator "a" with alter degree 6, without increasing direct ties

Figure 2.2: Legislator A changes direct and indirect connections

not). Using these two veto points provides identifiable opportunities for legislation to die across all eight chambers that I study. This data gathering results in 12,900 bills across 668 legislators, with 4,301 surviving committee deliberation and 2,644 passing out of the chamber.[11]

To control for potential alternative explanations, I also measure the seniority of the sponsor of a bill, the majority party status of the sponsor of a bill, the institutional advantages of the sponsor of a bill (dummy variable coded 1 if the sponsor is a committee chair or speaker of the chamber, 0 if not) and the number of cosponsors on an individual bill. Recall that the network statistics I use are summaries of the entire legislative session, thus any incidental covariance in the network measures I use that results from the number of cosponsors on a specific piece of legislation should be controlled for by accounting for the number of cosponsors on a specific bill as a control. I make use of a multi-level logit model (Gelman and Hill 2005) with varying state-level intercepts to test whether network connections have unique impacts on the probability of a bill surviving important veto points. The form of the committee stage model is:

$$Pr(Y = 1|X) = \alpha_j + X_i\beta \tag{2.1}$$

$$\alpha_j \sim N(\mu_{state}, \sigma^2) \tag{2.2}$$

where $X_i\beta$ includes the covariates of the model. By varying the intercept at the state-level, I can account for the fact the there is variance by state in the probability that bills will survive veto points. The covariates in the model include: Weak Ties, Strong Ties,

[11]Because I use every bill in each lower chamber in my analysis, there may be some concerns that the weak ties I observe are all on inconsequential bills or all from a particular policy realm. As such, I calculate the average number of weak ties per bill for each committee in each state. The distribution of means in each state was a peaked distribution. This indicates that the average number of weak ties per bill was similar across each committee in a state. Taken further, this means for example that bills sent to local government committees had the same number of weak ties connected to their sponsors as bills sent to the appropriation committees in each state.

Secondary Ties from Weak Ties, Secondary Ties from Strong Ties, an interaction of Ties and Secondary Ties for both Weak and Strong classifications, Institutional Advantages of the Sponsor, Tenure of the Sponsor, Majority Party Status of the Sponsor, and the number of cosponsors on a specific bill. Thus, this model accounts for variance in the dependent variable at the state-, sponsor-, and bill-specific levels[12].

2.3 Results

I begin my analysis by creating a multi-level logit model in which the dependent variable is coded 1 if a bill survives committee deliberation and 0 otherwise across eight state legislative lower chambers in 2007.[13] Expectations are that in each model, the effects of weak ties (either direct or secondary ties stemming from weak ties) will produce positive effects on success. The fully specified interactive models should also have a positive interaction term for the interaction between weak ties and secondary ties stemming from weak ties. Because the interpretation of conditional or interactive arguments is best presented graphically, I focus on using plots to demonstrate the results of my modeling efforts. The tables containing the results of these models are present in Appendix A. In all of the multi-level models I present, the network connection variables are normalized by subtracting out the state mean and dividing by the state standard deviation.

Figure 2.3 presents the (a) varying marginal effect of strong ties, (b) varying marginal effect of weak ties, and (c) the difference in the marginal effect of strong and weak ties

[12]A common concern in the social networking literature is serial correlation or interdependence in models. This is only a concern in empirical models if the dependent variable is interdependent. Interdependence in the measurement of independent variables poses no real issues for estimation.

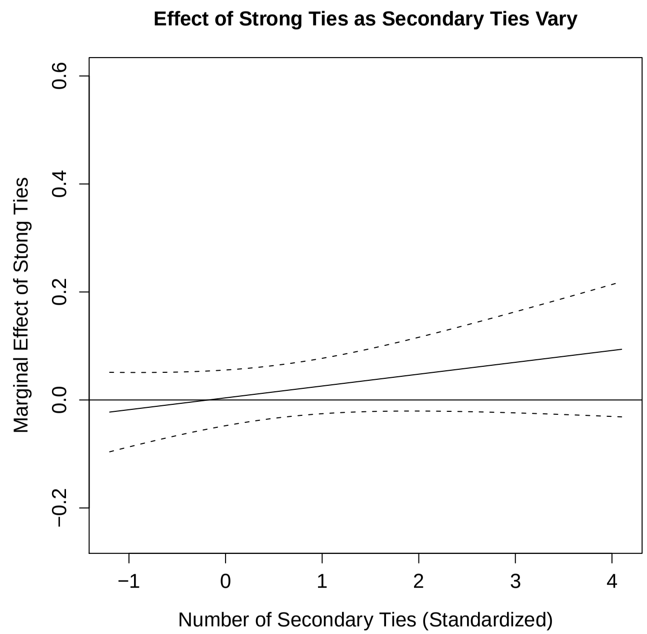
[13]In the appendices, I provide several alternative specifications to this full model in an effort to deal with the collinearity present in the network independent variables. Weak ties has a variance inflation factor of 12.9 and secondary weak ties has a variance inflation factor of 6.4 in the full model indicating that concerns about multicollinearity are warranted (Gujarati 2003 p. 363).

across the range of secondary ties along with 95% confidence intervals around these estimates. The plots show that the effect of strong ties is never statistically distinguishable from zero regardless of the number of secondary ties those strong ties produce. Alternatively, as the number of secondary ties increases the marginal effect of weak ties move from statistical insignificance to a positive and significant relationship demonstrating the hypothesized conditional relationship. Additionally, rather than just comparing the marginal effects to zero the third plot indicates that the marginal effects of weak ties are also greater than the marginal effect of strong ties at a statistically distinguishable level.[14]

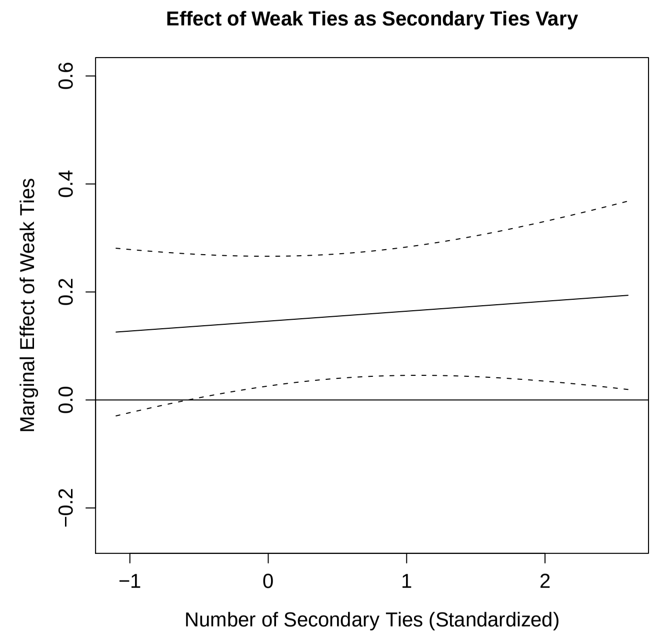
Figure 2.4 plots the predicted probability of bill survival at the committee stage as a function of both strong and weak ties and their interaction terms as reported in Table A1, model 4. In the surface plots, strong ties appear in the darker gray with grid lines and weak ties appear as the light gray with grid lines. The plots are three dimensional, allowing both direct and indirect ties to vary across their respective ranges simultaneously and allowing the marginal effects to also vary as the opposing variable changes values as required by the conditional interactive model. The plots demonstrate that increases in weak ties lead to increases in legislative success. While the coefficient on secondary ties stemming from weak ties is negative, the positive interaction term actually generates a positive change in bill success as secondary ties increase.

The plane created by the marginal effects of strong ties from a fully-specified, interactive model is much flatter, indicating that strong ties (and the secondary ties from them) produce little net effect on bill survival. In fact, moving from the minimum on both weak ties and secondary ties from weak ties to the maximum on both of these variables

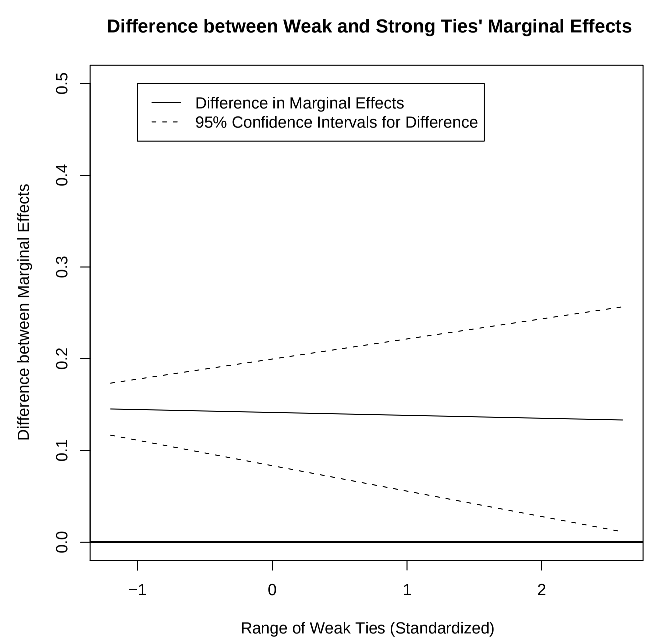
[14] This difference is created by generating a random multivariate distribution of the coefficients using the variance-covariance matrix from the model. This multivariate approach takes advantage of the variance *and* covariance between strong, weak, and secondary ties, rather than just the variance in one parameter as reported by standard errors.



(a) Marginal Effect of Strong Ties



(b) Marginal Effect of Weak Ties



(c) Difference in Effect of Weak Ties and Strong Ties

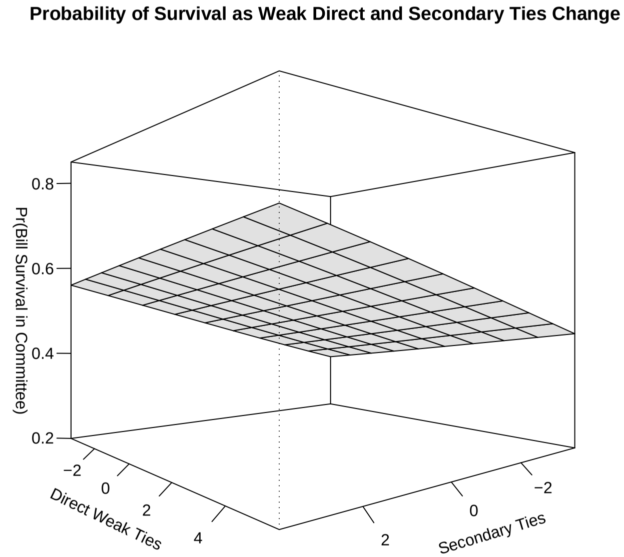
Figure 2.3: Marginal Effect Plots for Varying Effects of Strong and Weak Ties

produces a change in the probability of bill survival from 0.35 to 0.66 (a statistically significant shift). The same jump from minimum to maximum on strong ties and secondary ties produces a decrease in the probability of bill survival from 0.51 to 0.49.

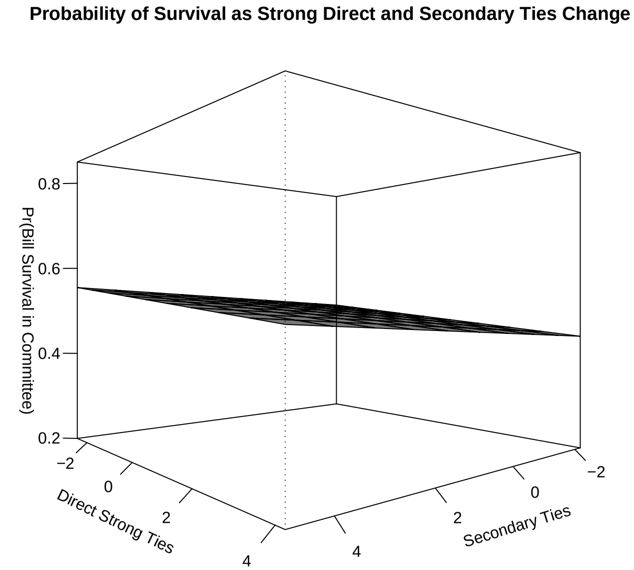
This result is reinforced by the contour plots which allow weak ties, strong ties, and secondary ties to vary. The third dimension (the probability of bill survival) is captured using color with darker colors representing higher predicted probabilities. The contour plot for strong ties and their resultant secondary connections is uniform in color indicating there is very little change in the probability of bill survival as strong ties and secondary connections vary. The contour plot for weak ties shows more dramatic shifts in color with the darkest shades appearing in the upper right corner. This indicates that the highest probability of bill survival occurs when both weak ties and their secondary connections from weak ties are maximized.

Next, I move to an analysis of the effects of strong and weak ties on bill passage from state lower chambers. Unfortunately, there is a significant sample selection problem that must be confronted. Bills that pass on the floor face a selection bias from survival at the committee stage. No bills across all eight legislatures that I study manage to pass from the chamber without being reported out by a committee (the U.S. House has procedural shortcuts that allow for passage from the chamber without a committee report). I control for this potential sample selection bias using the one-stage extension of Heckman (1979).

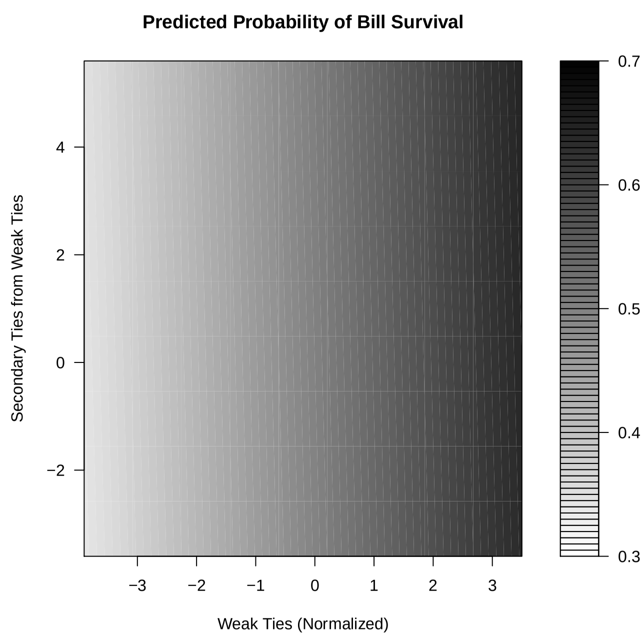
Table 2.1 reports the results of a single-stage sample selection model in which the selection equation predicts bill survival at the committee stage and the outcome equation predicts bill passage from state legislatures. Column 1 reports the selection results while column 2 reports the outcome results of purely additive models. The single-stage Maximum Likelihood approach to sample selection is more efficient than the two stage approach initially devised by Heckman (1979). Thus, rather than calculating the inverse Mill's ratio and executing a two-stage multi-level sample selection model, I simply use



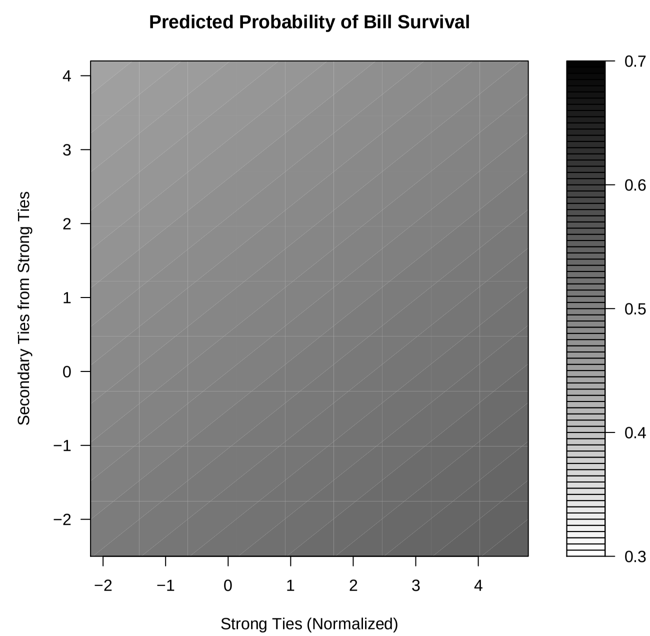
(a) Weak Ties Surface Plot



(b) StrongTies Surface Plot



(c) Weak Ties Contour Plot



(d) Strong Ties Contour Plot

Figure 2.4: Probability of Bill Survival in State Legislatures as Weak and Strong Ties Vary.

Table 2.1: Heckman Probit Model Predicting Bill Passage in State Legislatures

Variable	Column 1	Column 2
Sponsor Institutionally Advantaged	0.175 *	-0.087
	(0.029)	(0.048)
Sponsor Tenure	0.001	0.010 *
	(0.002)	(0.003)
Sponsor Majority Party	0.234 *	0.078
	(0.029)	(0.069)
Number of Cosponsors on Specific Bill	0.018 *	-0.009 *
	(0.002)	(0.002)
Weak Ties	0.090 *	-0.022
	(0.041)	(0.064)
Strong Ties	0.007	0.001
	(0.018)	(0.028)
Secondary Connections from Weak Ties	0.001	-0.039
	(0.028)	(0.044)
Secondary Connections from Strong Ties	-0.029	-0.046
	(0.019)	(0.031)
Intercept	-1.034 *	1.503 *
	(0.070)	(0.194)
N		12900
LogLik		-9799.72
ρ		-0.819

Note: Columns (1) and (2) report the results of a Heckman sample selection model. Column (1) reports the selection equation and column (2) reports the outcome equation. The dependent variable of the outcome equation is a dichotomous measure of bill passage from lower state legislative chambers. Models have standard errors in parentheses. Maximum Likelihood is the method used to estimate the model. State level dummy variables are estimated but not reported for space considerations. * $p < 0.05$.

the single-stage sample selection model with state dummy variables. The selection model results appear to be in keeping with the models produce in Table A1. The outcome model has far fewer significant results indicating that the independent variables do most of their work at the committee stage rather than on the floor of legislatures. Differences include the coefficient on the number of cosponsors on a particular bill changing signs and tenure becoming statistically significant.

Despite the fact that analysis of bill passage presents less support for the theory of weak ties, the expectation that weak ties and their subsequent secondary connections produce increased legislative success receives support at the committee stage and strong ties provide no increase in success at the committee stage or at the passage stage. This is strong support for the weak ties theory as I have outlined it. State legislators wishing to increase their own influence over the legislation their chamber produces receive considerable increases in success by building bridging connections to legislators that they do not regularly work along side. Legislators who attempt to increase their own legislative success by reinforcing the clusters they have always operated within do themselves little good.

2.3.1 Weak Ties and the US House of Representatives

As an alternative test, both to ensure generality and to cross-check my results with independently gathered data, I test the weak ties theory over time on the U.S. House of Representatives. Cosponsorship network data has been gathered and maintained by James Fowler (2006a, 2006b). I merged this with data from the Congressional Bills Project (Adler and Wilkinson 1991-2008). These two independently collected data sources provide all of the requisite variables needed to test the theory of weak ties in the U.S. House. Additionally, analysis of the U.S. House also allows me to include estimates of legislator ideology through the inclusion of DW NOMINATE scores, an option not readily available at the state legislative level.[15]

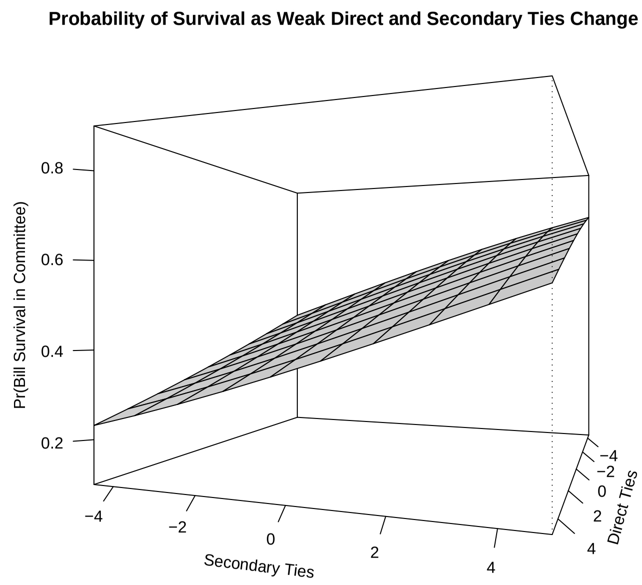
The construction of network measures for the U.S. House works exactly as it did for state legislatures. I examine the 102nd through 108th U.S. Houses (1991-2004), providing me with two sessions of the House before the Republican take over of the mid 1990's.

[15]There is considerable danger in equating NOMINATE scores to ideology or preferences. My own analysis has shown that examining floor voting alone overlooks much of the strategic interplay within a legislature. Nevertheless, NOMINATE provides a reasonable estimate, widely used across the field with high face validity.

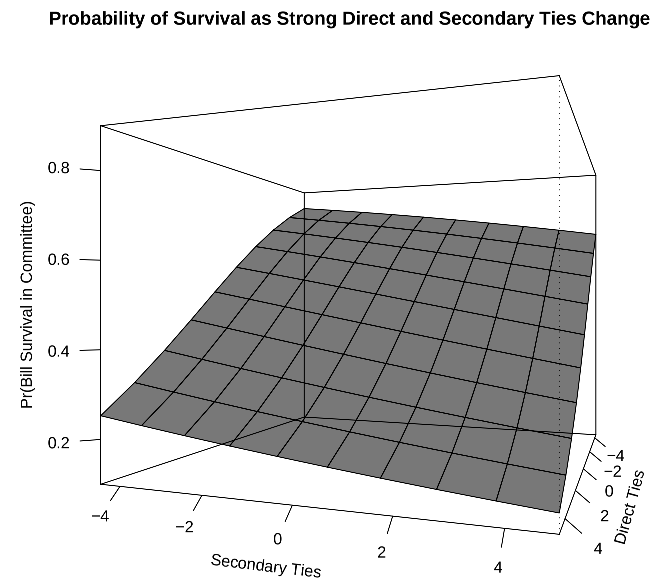
This includes a sample of 37,056 bills, of which 3,925 eventually passed and 3,650 were reported out by a committee. The unique procedures of the U.S. House do allow for some bills to pass from the chamber without ever having been reported out by committee, thus sample selection at the bill passage stage is less of a concern. The results from a logit model predicting bill survival at the committee stage in the U.S. House are presented in the Appendix, in Table A2. The analysis in this table mirrors the analysis of bill survival in state legislatures, except in this model I am able to include NOMINATE scores for legislators.

Once again, because the interpretation of conditional models is best done graphically I focus the presentation of the model's results in plots. Figure 2.5 plots the estimated probability of bill survival in the U.S. House as both direct and secondary ties increase simultaneously from the coefficients in Table A2, Column 2 (located in the Appendix). The marginal impact of the variables is also allowed to vary according to the coefficients on the interaction terms in the model.[16] We see a similar pattern in Congress to what we saw in the states. There is a positive change in probability of survival over the increasing values of weak ties and secondary ties from them. The plane representing increases in strong ties actually indicates a significant decrease in the probability of survival as strong ties and secondary ties from them increase. This indicates that weak ties produce success at the committee stage in both state legislatures and in the U.S. House. A move from the minimum number of weak ties and the minimum number of secondary ties stemming from them to the maximum on both values changes the probability of bill survival from 0.46 to 0.54. The corresponding shift in number of strong ties produces a decrease in the probability of bill survival from 0.84 to 0.14. The interactive effect is once again positive indicating that weak ties become increasingly important as they lead to more and more secondary ties.

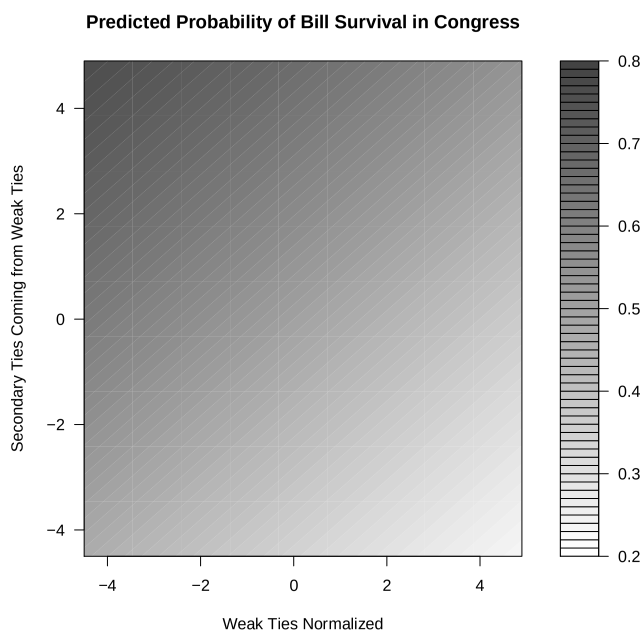
[16]Because the interaction term is itself statistically significant, we do not require a marginal effects



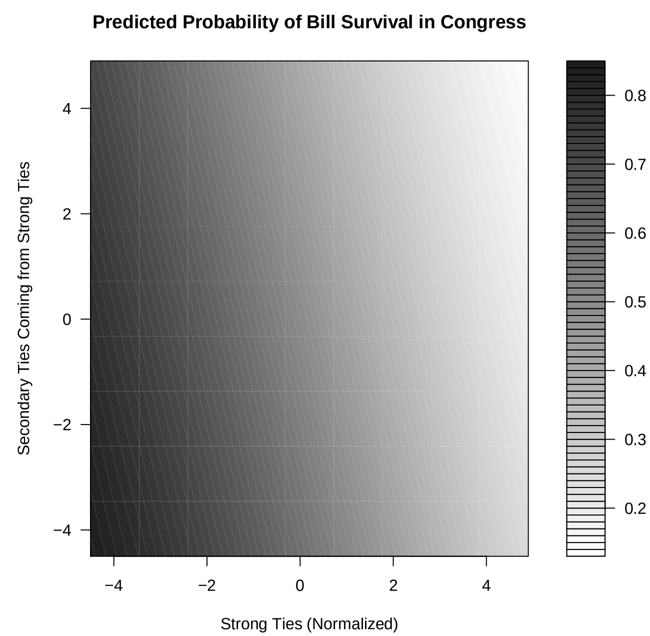
(a) Weak Ties Surface Plot



(b) Strong Ties Surface Plot



(c) Weak Ties Contour Plot



(d) Strong Ties Contour Plot

Figure 2.5: Predicted Probability of Bill Survival in the US House as Strong and Weak Ties Increase.

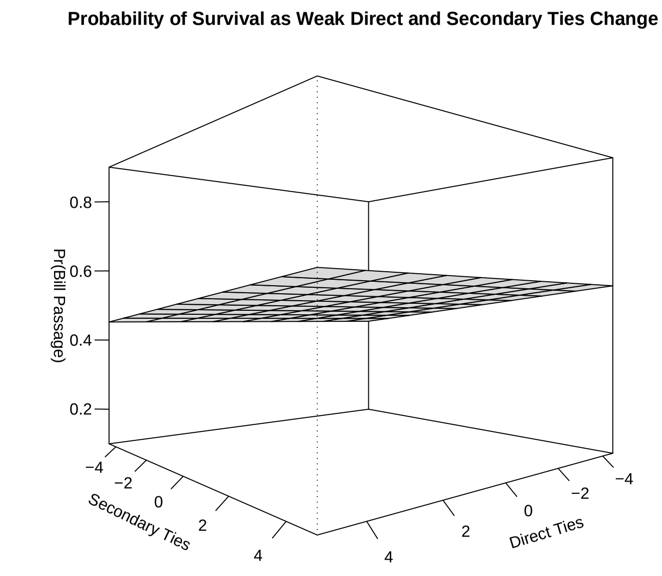
Because bills in the US House can pass from the chamber without having been reported out by committee, sample selection is less of a concern here. Of the 37,056 bills in the data set 1,163 passed without ever having been reported out by committee (out of the 3,925 bills that passed in total). Sample selection estimators are not designed to capture selection effects from imperfectly censored data. Thus, I report two multi-level models with varying intercepts by Congress, but without a control for sample selection bias in Appendix A, Table A3. These models are identical to the models presented in Table A2, except the dependent variable is a dichotomous variable coded 1 if a bill passes from the US House and 0 otherwise[17]. Figure 2.6 presents the predicted probability of bill passage as strong and weak ties vary, and their marginal effects vary, as reported in Table A3. The continued consistent pattern emerges. The predicted probability of bill passage increases dramatically as the combination of weak ties and secondary ties from them increases. The reverse is true for strong ties. Utilizing the same jump from the minimum on both ties and secondary ties stemming from them, weak ties produce a positive change in the predicted probability of bill passage from 0.44 to 0.57. Strong ties, alternatively produce a decrease in the probability of bill passage from 0.68 to 0.30.

2.3.2 Predicting the Formation of Ties

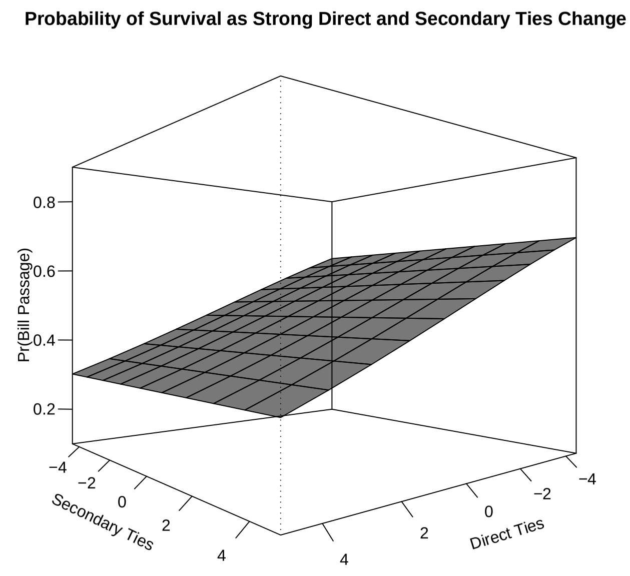
The analysis of legislative success in these eight state legislatures and the U.S. House provides clear empirical support for the notion that weak ties generate increases in legislative success and, thus, are the most useful paths to achieving legislative goals. However, this argument about the best paths of influence rests on expectations about the nature of tie

plot to observe that the relationships are conditional

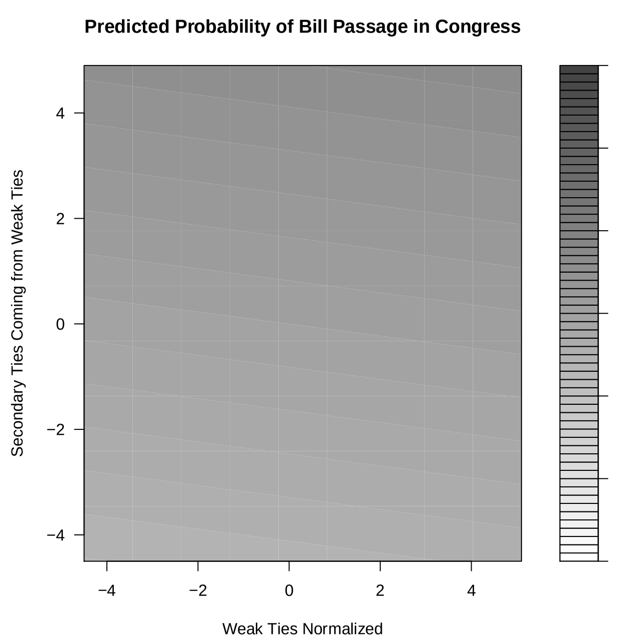
[17]Because sample selection remains a concern on some level, I have also specified a model for bill passage that includes bill survival at the committee decision stage as an independent variable. The results from this specification indicate that bill survival in committee is a significant positive predictor of bill passage, but its inclusion does not alter the substantive results of my models. All the significant variables remain significant and in the same direction and the interpretation of the three dimensional plots remains the same.



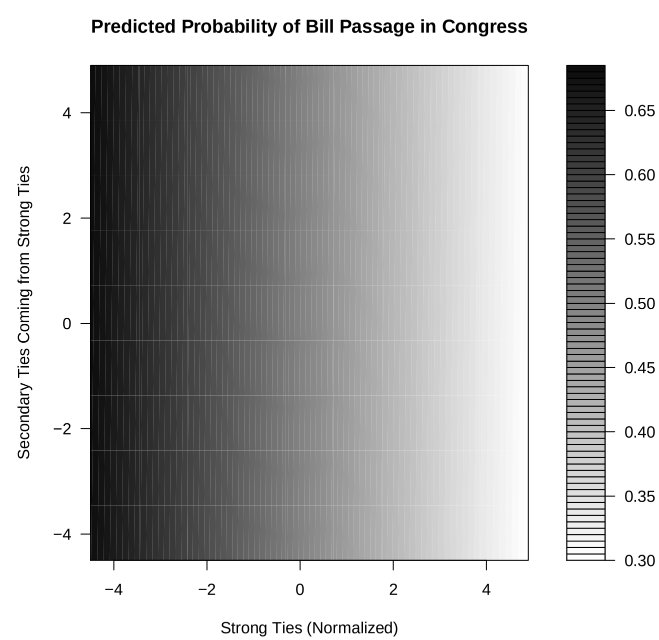
(a) Weak Ties Surface Plot



(b) Strong Ties Surface Plot



(c) Weak Ties Contour Plot



(d) Strong Ties Contour Plot

Figure 2.6: Predicted Probability of Bill Passage in the US House as Direct and Indirect Ties Increase.

formation and tie strength itself. Weak ties are the best paths for increasing influence across a social network because weak ties occur between individuals who are dissimilar on important dimensions. Strong ties are very nearly incidental, resulting from similarity between actors that existed before the actors ever met one another.

To test the notion that strong ties form between similar legislators and weak ties do not, I make use of the social network summary statistic modularity (Newman 2006, Waugh et al. 2010). Modularity measures how well a division separates a network by creating a measure of the number of ties within a division versus the number of ties across a division. For example, if a researcher believed a legislature was extremely polarized along party lines then the expectation would be that a network had a high modularity score for partisan divisions. This would indicate that there are many connections within a party and very few connections across party lines. Thus, modularity can measure the degree to which connections in a network are based on or correlated with similarities between actors in the network.

Table 2.2 provides a comparison of modularity statistics between the strong and weak networks in my eight state legislatures along three dimensions: party, race, and gender. All three of these dimensions have been the subject of social network analysis for legislatures (Desmarais, Cranmer and Fowler 2010, Bratton and Rouse 2010) and are also similarities which should drive the creation of collaborative relationships. I expect that modularity statistics for the strong ties network will be higher in each state than along the weak ties network for each dimension. This would indicate that strong ties commonly form amongst legislators of the same race, gender, and party while weak ties do not commonly form along these dimensions. I operationalize race as a partition between African American and non-African American legislators. Because Alaska and Hawaii have no African American state representatives and Minnesota had only one African American state representative (2008 Directory of African American State Legislators), no modularity estimates exist for these three states along this dimension.

Along each similarity dimension in every state lower chamber, similarities divide the strong ties network better than the weak ties network.[18] This means that in each state similarities are driving the creation of strong ties more than the creation of weak ties. Taken together with the empirical results predicting legislative success, this implies that weak ties are important because they represent the generation of non-redundant support for legislators.

2.4 Discussion

Network studies of legislative behavior have taken the important step of acknowledging and accounting for interdependence in behavior amongst legislators. This research has taken the next step in this enterprise by developing a theory for how and why that interdependence is used by strategic legislators and influences legislative outcomes. The strong connections we observe between legislators are a result of their latent similarities on dimensions that drive their preferences for policy. Legislators of the same party, the same gender and the same race will often form strong relationships that are essentially incidental. The support these legislators have for one another would have existed whether the tie between the two was ever actually formed, because their latent similarities generate similar policy goals. The weak ties we observe between legislators are strategic attempts by legislators to alter their base level of support and increase their legislative success.

Empirical evidence from a wide range of legislative networks provides support for this perspective. My results demonstrate that consistent with theory, weak ties occur between legislators quite different on important pre-existing dimensions, where strong

[18]Because modularity is essentially a complex proportion, the measure itself provides no sense of uncertainty. To deal with this, I have taken a bootstrap style approach to assessing unceratinty which is presented in the Appendix.

Table 2.2: Modularity on Three Pre-Existing Dimensions in State Legislatures

	Party		Race		Gender	
Variable	Strong Ties	Weak Ties	Strong Ties	Weak Ties	Strong Ties	Weak Ties
North Carolina	0.28	-0.028	0.058	-0.0062	0.051	-0.015
Minnesota	0.18	0.016	—	—	0.045	0.011
Mississippi	0.12	0.023	0.11	0.011	0.039	-0.029
Indiana	-0.043	-0.15	0.013	0.001	0.012	-0.0078
Hawaii	0.022	-0.035	—	—	0.023	-0.026
Delaware	0.012	-0.018	0.020	-0.0029	-0.0052	-0.012
Alabama	0.14	0.09	0.14	0.013	0.034	0.011
Alaska	0.14	0.010	—	—	-0.0030	-0.012

Note: Columns (1)-(6) report modularity statistics across eight state legislatures along three sociological dimensions for both the strong and weak ties network. Columns (1) and (2) measure modularity along party lines. Columns (3) and (4) measure modularity along racial lines. Columns (5) and (6) measure modularity along gender lines. Modularity estimates along the Race dimension for Alaska and Hawaii are absent because there were no African American state representatives in these two states in 2007.

ties are defined by these similarities. Additionally, the strong ties between these similar legislators contribute nothing to a legislator's level of success when controlling for partisanship, seniority and institutional position. Instead it is the weak ties (which are intentional attempts to generate support) that increase the likelihood of legislative success. By generating ties to legislators with dissimilar qualities, new avenues of influence and support can be created. This suggests that legislative scholars taking a social networks based approach carefully consider which types of ties they wish to study. If scholarship is interested in what causes certain kinds of connections then pre-existing similarities like race, party, and gender are important elements, but if scholarship is interested in how individual connections influence legislative outcomes then understanding that legislators form different kinds of connections as a result of different circumstances is particularly important.

This research paints an interesting normative picture also. Legislators interested in increasing their chances of achieving their own agendas best accomplish this through cooperation with legislators unlike themselves. Highly clustered or polarized chambers provide little opportunity for the bridging ties necessary for legislative success. Thus, there seems to be a genuine empirical reason for legislators to seek increased cooperation and decreased polarization within their own chamber. Cooperation across similarities (which would drive up the number of weak ties a legislator has) would seem to be a reliable way to reduce uncertainty about policy outcomes in ways similar to those described by Krehbiel (1991) in the information theory of legislative organization. By demonstrating diverse support for his or her bills, a legislator may be able to assuage chamber-level concerns about the anticipated outcomes of legislative decisions. Additionally, while scholars have rightly bemoaned the increasing polarization in legislative chambers it is possible that a broad, polarized distribution of ideal policy points can be overcome and legislation can move forward if legislators are willing to cooperate with those dissimilar from themselves. A legislature with more bridging ties should be able to be more responsive to changes in the political world than a more balkanized chamber, even in the face of polarized ideal points.

Chapter 3

Multi-Member Districts' Effect on Legislative Collaboration

American legislatures are more than a collection of individual agents calculating the costs and benefits of legislation once implemented. They are social constructions inhabited by social beings that have complicated influences on one another. In other words, a legislature is a social network of rational actors making decisions in an interdependent system of relationships. Legislators influence and are influenced by their relationships with one another. Party (Sarbaugh-Thompson, et al. 2006), geographic distance (Caldeira and Patterson 1987, Caldeira and Patterson 1988, Clark, Caldeira, and Patterson 1993), and gender (Bratton and Rouse 2009, Desmarais et al. 2009) all influence these relationships, and these relationships in turn influence legislative outcomes (Fowler 2006a, Peoples 2008, Arnold, et al. 2000, Kirkland 2011). Qualitative interview evidence provides strong support for the notion that legislators take cues and signals from one another about which legislation to support (Kingdon 1973, 1989, Ray 1982, Songer, et al. 1986, Sullivan, et al. 1996).

The evidence that relationships play an important role in legislating is strong. What is missing from this literature is an understanding of how the institutions of a legislature influence the formation and maintenance of legislative relationships. The structure induced equilibrium school of thought (Shepsle 1979, Shepsle and Weingast 1994) tells us that institutional arrangements help a chamber avoid sub-optimal outcomes by constraining behaviors. However, most of the work in this tradition has focused on how institutions influence choices over bill outcomes and committee behavior. If institutions in a legislature can influence choices by legislators, then these institutions can also affect choices over collaborative relationships. For example, multi-member districts force legislators to share geographic constituencies, which should alter their incentives for collaboration and provide natural allies for use in the securing of policy benefits.

In this research, I take advantage of a unique opportunity to study institutional change in a legislature. Using cosponsorship data as an indicator of a collaborative relationship between two legislators, I study the transition in the North Carolina legislature from a multi-member district system to a single-member system in 2002. I couple this with cross-sectional analyses of cosponsorship networks in the four states that use some combination of single-member and multi-member districts (Maryland, New Hampshire, Vermont, and West Virginia). Results support my theory indicating that multi-member systems generate or strengthen relationships between actors with shared constituencies.

3.1 Institutional Incentives for Collaborative Relationships

To understand how multi-member districts might shape legislative behaviors, I begin by assuming that legislative policy preferences are multidimensional and are driven by a desire to satisfy constituents' preferences for government action (Crespin and Rohde 2010, Talbert and Potoski 2002, Hixon and Marshall 2006). That is, legislators prefer to sponsor, promote, and pass legislation that assists them in maintaining their positions as elected representatives. I also assume that some issues have clear partisan definitions, while other issues are less easy to define along a partisan continuum.[1] For example, some legislative issues like abortion fall cleanly along partisan lines. However, legislators from multi-member districts or similar geographic regions may have very similar preferences over distributive legislation even if they are of different parties. In single-member districts that use partisan primaries, this implies that legislators must balance their legislative behaviors (and thus, revealed legislative preferences) between the preferences of their partisan constituency and the preferences of their general election constituency.

In multi-member districts, the connection between constituency preferences and legislative preferences/behaviors is less clear. Legislators can obtain elected positions even when they finish in second (or even third) place in an election, meaning the threshold for a successful election is no longer 50% of the district plus one. This provides legislative candidates with more freedom to position themselves away from median voters in ideological space. So long as a legislator can obtain a plurality of voters large enough to ensure a second place vote, the ideological location of that plurality is no longer critical (Cox 1984). This also means that incumbent legislators have some freedom of movement in their own legislative behavior. The ability to create a winning coalition that does not include the median voter, and may not have to include a majority of their own party provides legislators with increased freedom in their legislative and electoral positions.

Nonetheless, even though the need for a pure majority is no longer present, incumbent legislators in multi-member districts would still like to maximize their incumbency advantages.[2] That is to say, while legislators from multi-member district no longer require

[1]Cox and McCubbins (2005) suggest that parties use the political process to kill legislation that divides the party. The very fact that the party is divided on some issues suggests that some dimensions are not defined by party preferences.

[2]Legislators from multi-member districts are confronted with weaker incumbency advantages. Thus, the need to maximize the ones they possess is extremely strong (Berry, Berkman, and Schneiderman 2000, Carey, Niemi, and Powell 2000).

a district majority to retain office, they would still like to avoid challenges from credible candidates. Maximizing an incumbency advantage means taking advantage of the opportunities incumbents have that challengers do not, one of which is actually passing legislation that benefits a district. However, given the lack of awareness about legislative behavior that most voters possess, it is unlikely that voters will be able to distinguish which of their legislators to reward for policy that benefits a multi-member district. This is the source of the free-riding problem often associated with multi-member district legislators (Snyder and Ueda 2007). As such, a legislator from a multi-member district may have an incentive to capitalize on his or her district-alter's legislative accomplishments and claim credit without providing any effort (Mayhew 1974).

Alternatively, a legislator from multi-member districts who seeks to *maximize* his or her advantages should recognize that maximizing advantages means maximizing policy benefits returned to his or her district. That same legislator should also recognize that the natural partnership formed by membership in a multi-member district provides unique coalitional advantages.[3] Through collaboration with his or her district-alter, a legislator can increase the odds that both individual's legislation passes.[4] Thus, each member of a multi-member district has an incentive to assist the other legislators from the district in passing legislation. This will provide all the incumbents from the district with more opportunities for credit claiming, and thus, help ward off electoral competition. Because partisan pressures still exist for these legislators, the collaborative patterns from legislators in multi-member districts should still exhibit a strong partisan component. However,

[3]Squire and Moncrief (2010 p. 27) summarize the results of research on the differences between multi-member district and single-member district legislators, which includes the fact that legislators from multi-member districts obtain more funding for their home districts. Thus, the natural coalition of the multi-member district wields larger influence than single-member districts.

[4]Kessler and Krehbiel (1996) and Kirkland (2011) demonstrate that patterns of cosponsorship have important influences on the odds that a bill will survive certain veto points in a legislature.

the multi-dimensional nature of legislating means that legislators from multi-member districts can work together even across party lines on bills that do not have a clear partisan definition.

The desire to maximize policy benefits to a district and to collaborate with a district-alter I describe would create the increased levels of dimensionality in the legislative behavior of legislators from multi-member districts observed by Bertelli and Richardson (2004). Legislators from these districts are under pressures from both their legislative party and their re-election constituency (which may not be strongly partisan) that can be competing, which in turn generate solutions to voting patterns that scaling procedures cannot simplify to a single partisan dimension. These competing pressures also would create the increased party diversity and factionalism in legislatures using multi-member districts observed by Adams (1999). Natural partnerships besides the political party exist in legislators using multi-member districts. Thus, partisans have coalitions besides the political party they wish to respect.[5]

This geographically based inducement of collaboration is somewhat at odds with early comparative work on the effects of mixed member and multi-member systems. Loewenberg and Patterson (1975) hypothesize that legislators from multi-member districts are more likely to toe the party line than their single-member colleagues. Because the single-member district legislators have clear geographic constituencies, they will occasionally have incentives to deviate from party preferences. Multi-member district representatives lack a clear signal about which geographic constituencies they represent, thus these legislators have less incentive to deviate from party positions. Stratman and Baur (2002) provide evidence supporting this notion when they uncover that single-member district

[5]Because U.S. senators also share constituents, there is reason to believe that this same pattern of collaboration should exist in the Senate. Gross and Shalizi (2009) observe the expected patterns amongst senators. The authors observe strong state effects on cosponsorship between senators after controlling partisanship. This result is in keeping with constituency overlap as a reason for collaboration between legislators.

representatives tend to serve on committees where they can serve their constituents while multi-member district representatives tend to serve on committees that serve the party. However, Haspel et al. (1998) and Herron (2002) find no difference in the party cohesion of multi-member versus single-member elected representatives. While multi-member district legislators may not know precisely who in their district has elected them relative to single-member district representatives, the notion that multi-member legislators do not wish to enhance their electoral chances through service and funding for their district seems untenable. While in most international mixed member systems candidates are a part of a party list submitted for an election, in U.S. elections candidates arrive on the ballot via primary voting share providing them with a clearer image of their geographic constituencies.

This notion of constituency induced collaboration particularly across party lines, is also at odds with some of the existing literature on the influences of shared constituency in American legislatures. In particular, Richardson, Russell, and Cooper (2004) note that the Arizona House, which uses multi-member districts is more ideologically polarized than the Arizona Senate, which uses single-member districts. Additionally, Schiller (2000) notes that U.S. Senators from the same state generally act as rivals rather than partners. In an effort to differentiate themselves, Senators from the same state craft very different agendas focusing on different issues and different constituencies in their legislative behavior. Snyder and Ueda (2007) note that legislators from multi-member districts have incentives to free ride on the effort of the other legislators from their districts, and thus, are less likely to collaborate to pursue legislation. Given that constituents rarely know precisely who to credit for outcomes, legislators from the same district have limited incentives to work together to achieve goals.

Snyder and Ueda also point out, however, that several forces at work within multi-member districts may discourage free riding. One of these forces is the potential for increased effectiveness through coordinated behavior. By acting as a team, legislators from a multi-member district can wield larger power within the chamber than they could by acting as rivals. Coupled with the result that legislators from multi-member districts face decreased incumbency advantages (Carey, Niemi, and Powell 2000) and an increased need to maximize the advantages they do possess, this would indicate that multi-member district legislators have an incentive to be productive and work together in the legislature to ward off challengers. This need for productivity, however, must be balanced with the need to satisfy partisan constituencies and party leadership.

Thus, multi-member districts generate collaboration between legislators from multi-member districts particularly on issue dimensions not clearly defined by party. The natural partnership created by multi-member districts provide coalitional advantages that grant legislators from these districts increased opportunities for credit-claiming and make better use of their incumbency advantages. From this characterization of the impact of multi-member districts on legislative behaviors, I generate several hypotheses. First, shared party identification will drive tie formation. Even legislators from multi-member districts feel partisan pressures because of the procedural advantages controlled by parties. Second, a shared constituency encourages the formation of ties between legislators as legislators try to maximize the benefits provided to them by shared district coalitions. Third, the influence of a shared constituency is not conditional on party. Both cross party and co-partisan legislators from the same district have opportunities to collaborate on legislation not well defined by party. Finally, legislators from multi-member districts will be closer on second and third dimensions of behavior than their single-member counterparts. This implies that once an analysis controls for party, these legislators behaviors will appear more similar to one another than their single-member counterparts' behaviors.

3.2 Design and Data

In order to test my hypotheses about multi-member districts and their influence on collaborative tie formation between legislators, I require an observable indicator of a legislative collaboration. I make use of the instances of cosponsorship of bills between legislators in order to measure tie formation and strength.[6] This approach has a large precedent (Fowler 2006a, Fowler 2006b, Bratton and Rouse 2009, Gross and Shalizi 2009). Additionally, there is ample anecdotal evidence that cosponsorship matters to legislators (Tam Cho and Fowler 2010) and is a useful indicator of a collaborative relationship between representatives (Koger 2003). Regardless of whether cosponsorship represents a signal to constituents (Mayhew 1974) or a signal to other members (Kessler and Krehbiel 1996), legislators take the act of cosponsorship as a serious signal of support for other legislators and their legislation (Campbell 1982).

Additionally, my expectations about similarity between legislators are based on a multidimensional conception of behavior. The social network of cosponsorships between legislators is a multidimensional phenomenon (Talbert and Potoski 2002, Zhang et al., 2008, but see Aleman et al., 2009), making it an ideal legislative behavior for examination.[7] Aggregate roll call voting patterns (a potential alternative operationalization) have been noted on many occasions to be one-dimensional (Poole and Rosenthal 1997,

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[6]One might imagine an alternative measurement of collaboration as co-voting on roll calls. I believe cosponsorship to be the better measure because cosponsorship requires a decision to send a signal by both the potential cosponsor and potential sponsor. Sponsors can turn down cosponsors and cosponsors can refuse to sign onto bills. It is much less likely that a bill's sponsor will turn down a vote than it is that a bill's sponsor will turn down a cosponsor. Thus, cosponsorship represents a type of coordinated behavior that co-voting is unlikely to tap.

[7]Each of the studies cited here observe higher dimensionality in cosponsorship than in roll call voting. Disagreement between the studies about the appropriate number of dimensions largely stems from disagreements about how to treat decisions not to cosponsor a bill. Talbert and Potoski use NOMINATE, which treats decisions not to cosponsor as "Nays." Aleman et al. use a principal components analysis that focuses on the agreement matrix, and thus, has many fewer zeros about which to worry. The debate about which method is appropriate is largely irrelevent to the point I make, which is that cosponsorship has higher dimensionality than roll call voting. Both papers agree on this point.

Shor, McCarty, and Berry 2010, Wright and Schaffner 2002, but see Crespin and Rohde 2010). This single dimensional may emerge from a variety of sources (Crespin and Rohde 2010, Koford 1989, Heckman and Snyder 1997), but regardless of cause makes roll calls an inappropriate test for my theory.

Using a web-scraping routine, I have developed cosponsorship networks [8] based on the instances of cosponsorship on every lower chamber bill for the North Carolina House of Representatives in 1997, 1999, 2001, 2003, 2005 and 2007.[9] During the 2000-2002 redistricting cycle, North Carolina's lower legislative chamber switched from a system that had 17 multi-member districts electing 30 of the 120 legislators to a system that exclusively used single-member districts in legislative elections. This institutional change provides the opportunity to isolate the influence of multi-member districts and accurately test my hypotheses concerning the influence of multi-member districts on individual legislators.[10] Because legislative turnover is low, I can examine the legislators who were members of multi-member districts and study their behavior relative to single-member legislators contemporaneously and relative to their own behavior after the institutional change. Any change in their behavior is then directly attributable to the change in the nature of their electoral district. North Carolina also makes an ideal test case for this theory because the change from multi-member districts to single-member districts was mandated by the State Supreme Court (Stephenson vs. Bartlett 2002), meaning the treatment effect I examine is exogenous to the actors I study. I also reproduce my

[8]A social network is an adjacency/square matrix where A_{ij} represents the number of time legislator i has cosponsored legislator j.

[9]Supplemental Appendix A to this article contain descriptive statistics for the data used in the analysis.

[10]It is possible that these 17 multi-member districts represent a non-random sample of the districts in North Carolina, meaning the treatment of institutional change is not being applied at random. However, whatever non-random characteristics might have been the impetus for the creation of the multi-member districts did not *change* in 2002. This means that any observed change in behavior at this time point cannot be a function of the static characterstics that generated the non-random selection of multi-member district creation.

models of the North Carolina cosponsorship network in four other states that use some combination of single-member and multi-member districts (NH, VT, MD, WV).[11]

Testing hypotheses about relational, interdependent outcomes like cosponsorship poses some unique methodological problems (Cranmer and Desmarais 2011, Erikson, et al. 2009). Primarily, standard regression techniques will produce biased and inefficient coefficients because of the violation of the standard regression assumption of *conditionally independent outcome variables.* Social network scholars have developed a number of techniques for analyzing relational data. I employ the latent space approach to social networks[12] (Hoff et al. 2002) which models the probability of some Y_{ij} given some X, Z, θ, where X is a matrix of observed characteristics, θ is a vector of parameter values, and Z is a vector of positions in latent Euclidean social space of the actors in the model.[13] The latent social space refers to a space of unobserved latent characteristics that represent

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[11] In the 2001-2002 session, the Democrats controlled a majority of the lower chamber seats with a 62-58 advantage. Following the 2002 election, the Republicans retained a slight 61-59 advantage. This change in majority party control could potentially threaten inferences regarding the contemporaneous institutional change. One could imagine that the incentives for collaboration may be quite different in the Republican and Democratic controlled chambers. However, this is not quite as dire a threat to inference as it may seem. In fact, just before the opening of the 2003-2004 session Michael P. Decker (a generally conservative legislator) switched allegiance from Republican to Democrat. This abrupt change means that the Democrats and Republicans were tied for chamber control at 60-60. This also means that the Democrats retained substantial procedural power over almost the entire sample I observe (the exception being 1997), electing co-Speakers of the House in the 2003-2004 session and splitting committee chair positions with the Republicans. Investigations would later reveal that Decker accepted a $50,000 bribe from Democrat Jim Black in order to switch parties. There is no reason to expect that a tied chamber would prove less collaborative and thus be collinear with the change I predict in 2003. In fact, Fenno (1973) might lead us to expect *more* collaboration in a tied chamber.

[12] An alternative to the latent space approach is the Exponential Random Graph Model (ERGM). The ERGM has not been extended to cases with non-binary edges making it an inappropriate modeling choice for this data. Thus, to use an ERGM I would have to censor a great deal of information out of the dataset and collapse counts of cosponsorship between two actors to dichotomous observations. Additionally, cosponsorship networks are commonly dense graphs (meaning they have many connections) and ERGMs are commonly nonconvergent in dense social networks.

[13] Accordingly, the unit of analysis in my models will be the dyadic observation of tie strength between two legislators. Y_{ij} in these models will represent the number of times legislator i cosponsored legislator j

patterns of connections in network relations. In other words, the latent social space represents unmodeled similarities between actors that are implied by their relationships with one another. A probability measure over these unmeasured but distinguishable characteristics fits a model in which the presence of a tie between two individuals is dependent on the presence of other ties. For example, a tie between i and j and i and k suggests that j and k are not very far apart in the latent space. The distance between j and k is dependent on the observations of both the connection between i and k and i and j. Thus, based on their patterns of connections between other actors in the network, the latent space model allows for the assessment of distance between two unconnected actors while simultaneously controlling for the interdependence inherent in network data. This interdependence in latent space positions allows the model to control for common network effects like reciprocity or transitivity that would ordinarily bias results. Given these estimated positions, the ties in the network can be assumed conditionally independent and can be modeled as some function of positions and actor or pair specific characteristics using standard glm models like a Poisson. Scholars have successfully used the latent space model to study the impact of race and gender on cosponsorship in Congress (Desmarais et al. 2009), conflict between Asian states (Hoff and Ward 2004a), and affinity between monks (Hoff et al. 2002).

While latent space models of social networks allow for traditional hypothesis testing on relational variables, they are also useful as dimensional placement tools. Because these models place actors in a multi-dimensional social space based on their connections with one another across many bills, they provide me with the opportunity to observe whether multi-member legislators are closer on nonpartisan dimensions of behavior to one another than their single-member colleagues are. Using the 2002 change in North Carolina can provide a clear examination of whether multi-member legislators are closer than their colleagues on these dimensions when they share a constituency, and whether that similarity on alternative dimensions diminishes once shared constituencies are eliminated.

3.3 Individual Behavior and Multi-Member Districts

In testing my hypotheses about the formation of ties between individuals who share a constituency in North Carolina before and after the elimination of multi-member districts, I estimate a Poisson latent space model.[14] The latent space generated by this approach accounts for the interdependence between actors allowing for the estimation of exogenous pair-specific characteristics like shared party identification and shared constituency. Thus, the coefficient values reported are standard Poisson coefficients controlling for interdependence between actors. In these models, the dependent variable is the dyadic observation of the number of cosponsorship between two legislators in the network of cosponsorship counts. As independent variables, I include a dummy variable if two actors are in the same party, if two actors share a constituency,[15] an interaction of these two variables, and two latent space dimensions. The coefficient on same party is expected to be positive and significant, the coefficient on shared constituency is expected to be positive and significant, and the interaction is expected to be insignificantly different from zero.[16]

Rather than present a series of six tables of coefficients, I place the tables in an

[14]Recall that the network of cosponsorships I model is a count network of the instances of cosponsorship between two people across all the bills of a legislative session.

[15]I define shared constituency as any pair of legislators who at one point in time shared a district together. Two legislators in 2003 from single-member districts who had been from multi-member districts are coded one for shared constituency. For example, Cary Allred (R) and E. Nelson Cole (D) were elected from the multi-member 25th district in 2001. They were elected from separate districts in 2003, but are coded as having a shared constituency because in the past they came from a multi-member district. This allows me to observe whether collaboration between members from these kinds of districts persists into the future in spite of the change in the nature of their district.

[16]While including a term expected to take on an insignificant coefficient is unusual, this allows me to demonstrate that the effects of multi-member districts are the same within and across parties. An additive term alone would fail to make such a distinction.

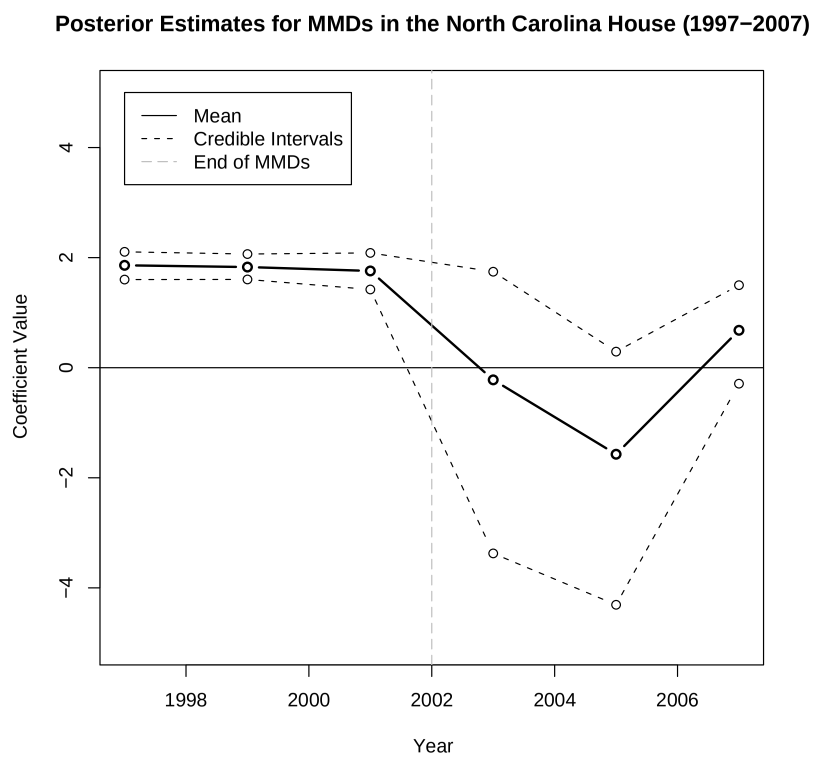
appendix and present the results graphically. In Figure 3.1, I present the coefficient estimates for the shared constituency variable from the Poisson regressions from 1997-2007 along with their 95% credible intervals.[17] The right hand panel of Figure 3.1 also plots the coefficients for the interaction of same party and shared constituency. Before the elimination of multi-member districts, shared constituency was a strong predictor of tie formation between actors. This indicates that legislators from multi-member districts cosponsored one another at a higher rate than legislators from single-member districts. However, after the elimination of multi-member districts, those same individuals who once shared a multi-member district (and who once had connections with one another in a cosponsorship network) no longer work together at a rate higher than other members do.[18] The interaction term in the right hand panel is only significantly different from zero in 2005 and 2007 well after the change in electoral systems. This indicates that multi-member districts' effect on cosponsorship is not significantly different for same party versus cross-party pairs of multi-member legislators. Because I draw this inference only from legislators who at one point shared a constituency and this inference is based on individuals who are present throughout the time series, I can be reasonably certain that the only change occurring is their loss of a shared district. It is unlikely that their policy preferences are changing, given the stability in ideology of political elites (Poole and Rosenthal 1997) and their party identifications have not changed.[19]

There is the potential, however, that the change in collaboration is a result of a

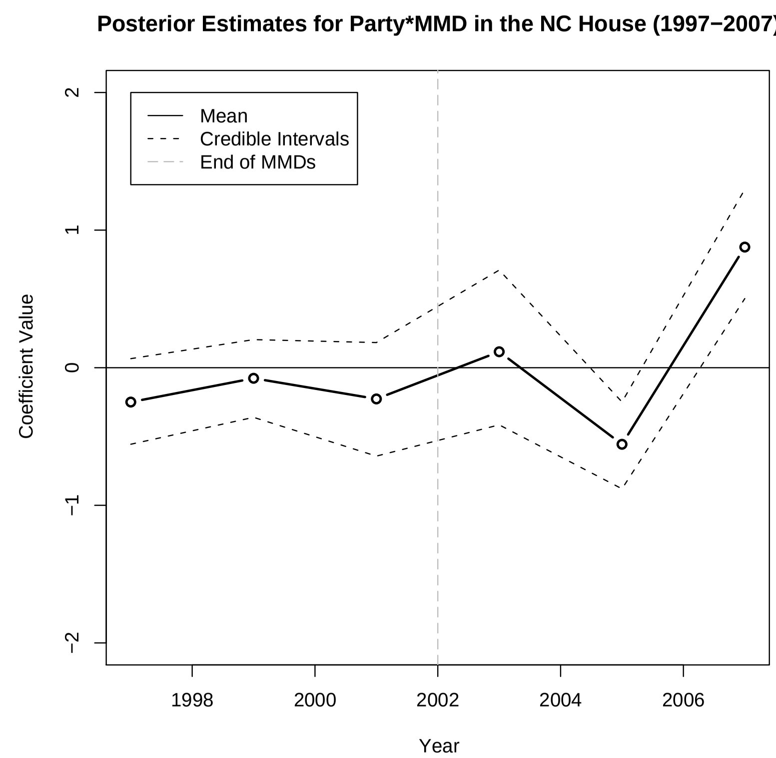
[17] The table that produces this plot is located in Appendix C as Table 7.8.

[18] In Supplemental Appendices D and E to this article, I present several other operationalizations of this test. I include an analysis of specific kinds of legislation rather than the universe of bills and an analysis of roll call voting rather than cosponsorships.

[19] While the models I present are simple specifications, Appendix C presents a series of graphs indicating the quality of predictions from each model. The models accurately predict 89% of ties across all six North Carolina models. This suggests that even though the model specification contains only three variables there is vary little variance left to explain.



(a) Shared Constituency Coefficients



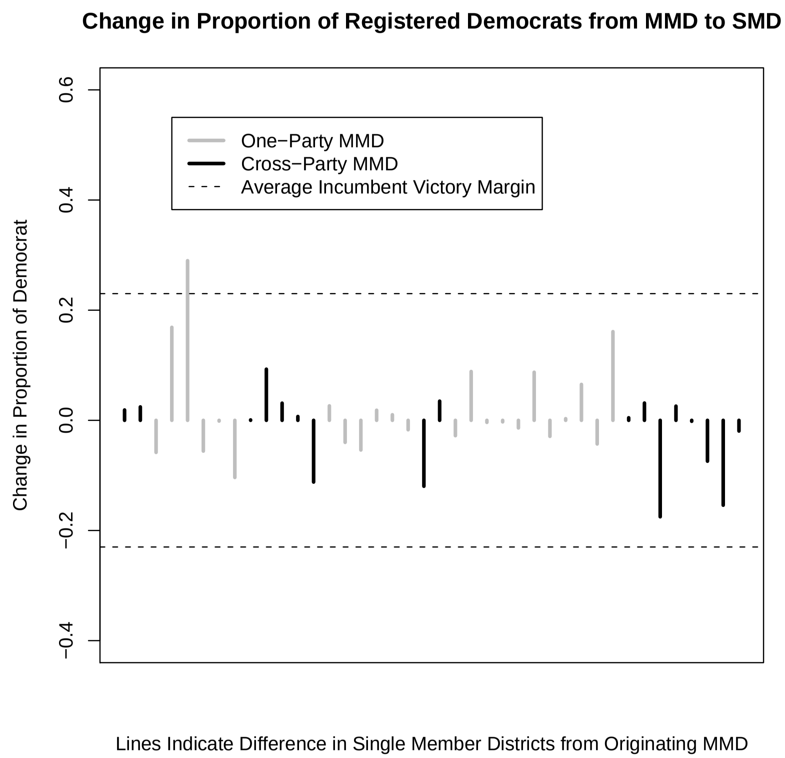
(b) Interaction Coefficients

Figure 3.1: Multi-Member District Coefficient Estimates and Credible Intervals for Legislators Who Shared a District (1997-2007)

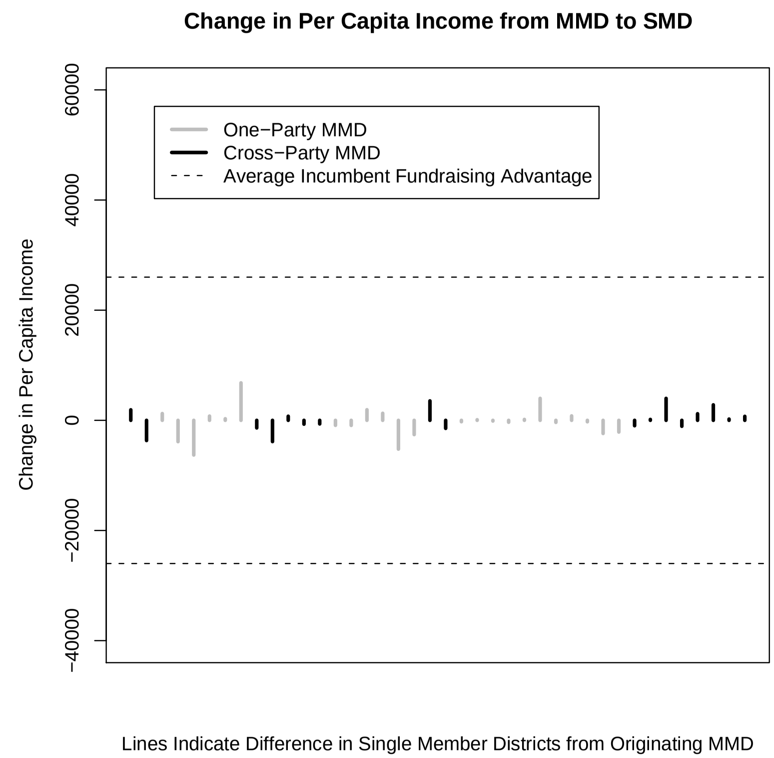
dramatic change in constituency from the multi-member district system to the single-member district system. For example, a Republican and a Democrat from a multi-member district may cooperate because they have an overall moderate constituency. During redistricting this moderate multi-member constituency may be broken up into more extreme single-member districts, which in turn may cause the drop in collaboration. In this scenario, similarity in constituency causes collaboration not the institution of multi-member districts. If, however, the constituencies in the single-member district are very much like the original multi-member district, then the same representatives work together when they share a district and stop after the division of their district, even though their districts remain similar. This would strongly imply that it is the institution of shared constituency and not similarity in constituency that is causing collaboration.

Figure 3.2 shows the change in the proportion of registered Democrats and the change in per capita income in the resulting single-member district from the originating multi-member districts. For example, if a single-member district's proportion of Democrats is very different from its original multi-member district's proportion of Democrats, then the lines from zero in the left panel will be quite long.[20] Additionally, the dotted lines in the figure provide a sense of the magnitude of these changes by plotting the average incumbent advantages held in both vote totals and fundraising. Only one of the multi-member districts has a shift in partisanship such that it might affect an average electoral outcome. None of the districts have a shift in income that would influence the fundraising advantage held by incumbents. The figure indicates that in terms of both partisan make-up and income distribution, the resultant single-member districts look very much like their originating multi-member districts. This provides evidence that what is driving multi-member based collaboration is the institution of a shared constituency,

[20]As an example, the multi-member district 4 for North Carolina's House was 53% Democrat before redistricting. The redistricting effort created the single-member districts 13 and 14 from the 4th district. These two districts were both roughly 55% Democrats, creating a change of roughly +2%.



(a) Partisan Change



(b) Income Change

Figure 3.2: Change in Partisan Makeup and Income as Districts Transition from Multi-Member to single-member Districts

not a similar constituency. Once this active sharing of constituents vanishes, members who once worked together cease working together even though their districts look quite similar. There are large, observable changes in legislative behavior when there are only small changes in the make up of legislators constituencies. Thus, it seems unlikely that the election of ideologically similar legislators for the 2001 session created the collaboration between legislators observed under multi-member districts. If these legislators were ideologically similar in 2001, they would have no reason to cease collaborating in 2003.[21]

Because legislative turnover is low, a reasonable number of the former members of multi-member districts from 2001 remain in the dataset in 2003. However, over time elections eliminate these members from the data set. This means that by the end of the series of regressions I present, there are very few members left in the dataset who were once members of a multi-member district. As an alternative specification for shared constituency after the elimination of multi-member districts, I create a variable coded one if two legislators represent a district that was ever part of a multi-member district and zero otherwise. In this measure, legislators who never themselves shared a constituency may be coded as joint members of a formerly multi-member district because these legislators replaced individuals who did share a constituency.[22] While the inference from these individuals is less precise in determining the effects of multi-member districts on collaboration between individuals, specifying shared constituency in this way increases the sample of legislators from formerly joined districts. Additionally, it is unlikely that the

[21]Rather than simply graphing the data, I have also included the ideological makeup of a legislator's district as a covariate in latent space models of the cosponsorship networks for 2001 and 2003. This covariate adds a term to the network model that measures the absolute difference in the North Carolina House Democractic vote share in two legislators districts. When this difference is high then legislators have very different proportions of Democrats voting for them. This covariate takes on the expected negative and statistically significant sign, but does not effect the sign or significance of the other covariates.

[22]To create this variable, I generate a centroid (a point in the geographic center) in each of the 2003 legislative districts. I then overlay the 2001 district maps on top of these centroids. If two centroids from 2003 districts are in the same 2001 district then these 2003 districts are coded to have once been a part of the same constituency.

individuals who have taken over what was once a multi-member district came to politics in a vacuum. They were likely active in politics or attentive to politics when the district was multi-member, thus they may have some awareness of the norm of collaboration with representatives of other constituents.

Once again, I present the results of this alternative specification graphically in Figure 3.3.[23] The same consistent image emerges. Before the elimination of multi-member districts, legislators from the same multi-member district collaborate regularly. Following the elimination of multi-member districts, legislators from formerly multi-member districts no longer work together at a noticeably higher rate.

Figure 3.4 presents coefficient densities on same party from the models in Table 7.8. Being members of the same party strongly predicts tie formation between two legislators both before and after the elimination of multi-member districts. Because the party coefficients from both the models analyzing legislators who were once members of a multi-member district and legislators who represent what was once a multi-member district are virtually indistinguishable, I present only the coefficient densities from the model associated with Figure 3.1.

Finally, the latent space model produces estimates of positions for actors in a latent social space (Hoff et al. 2002). These positions are defined by the patterns of connections observed in the dependent variable while controlling for the specified covariates.[24] Therefore, these positions represent actor positions in a social space on unmeasured dimensions. Figure 3.5 plots these network positions for North Carolina legislators in 2001 and 2003. My theory specifies that multi-member legislators will be closer to one another on non-partisan dimensions than single-member legislators will. Accordingly, I construct a simple latent space model with a covariate for same party and two latent dimensions.

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[23]The table of results appears in Appendix C as Table 7.9

[24]For example, transitivity or reciprocity in network connections provide information about the distance between actors in the social space.

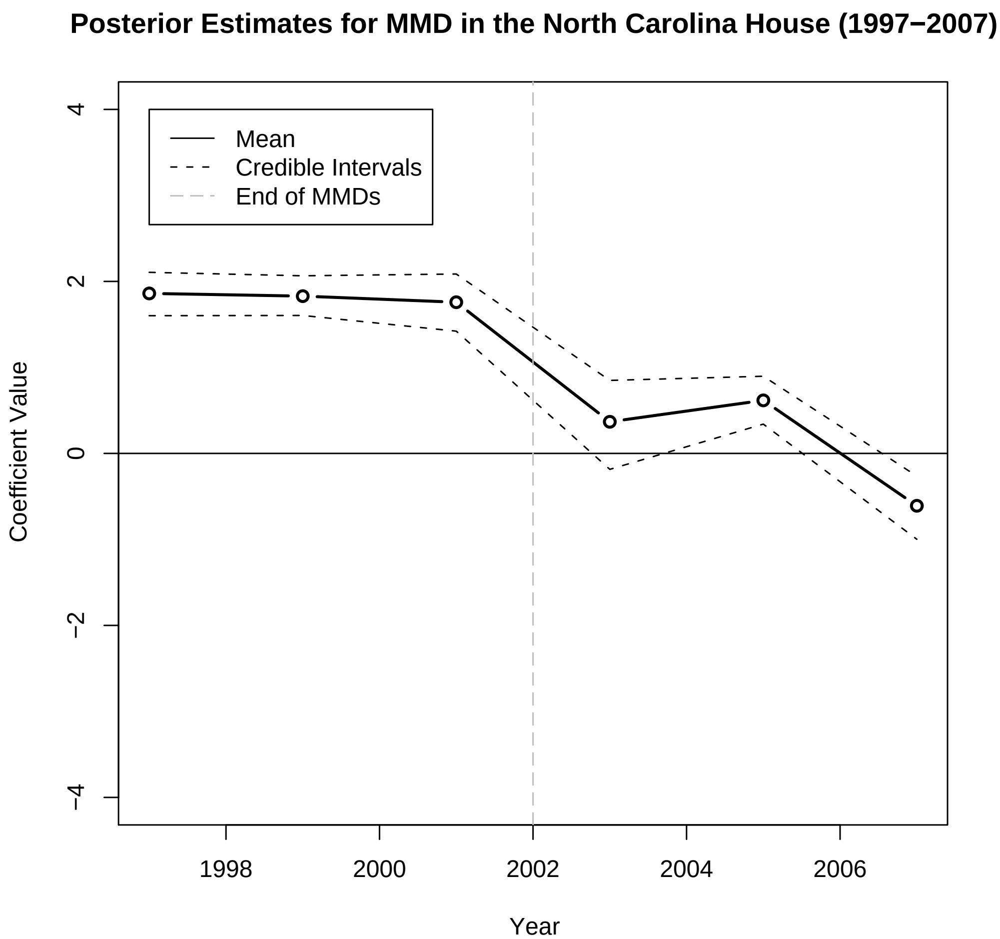


Figure 3.3: Multi-Member District Coefficient Estimates and Credible Intervals for Legislators from Formerly Overlapping Districts(1997-2007)

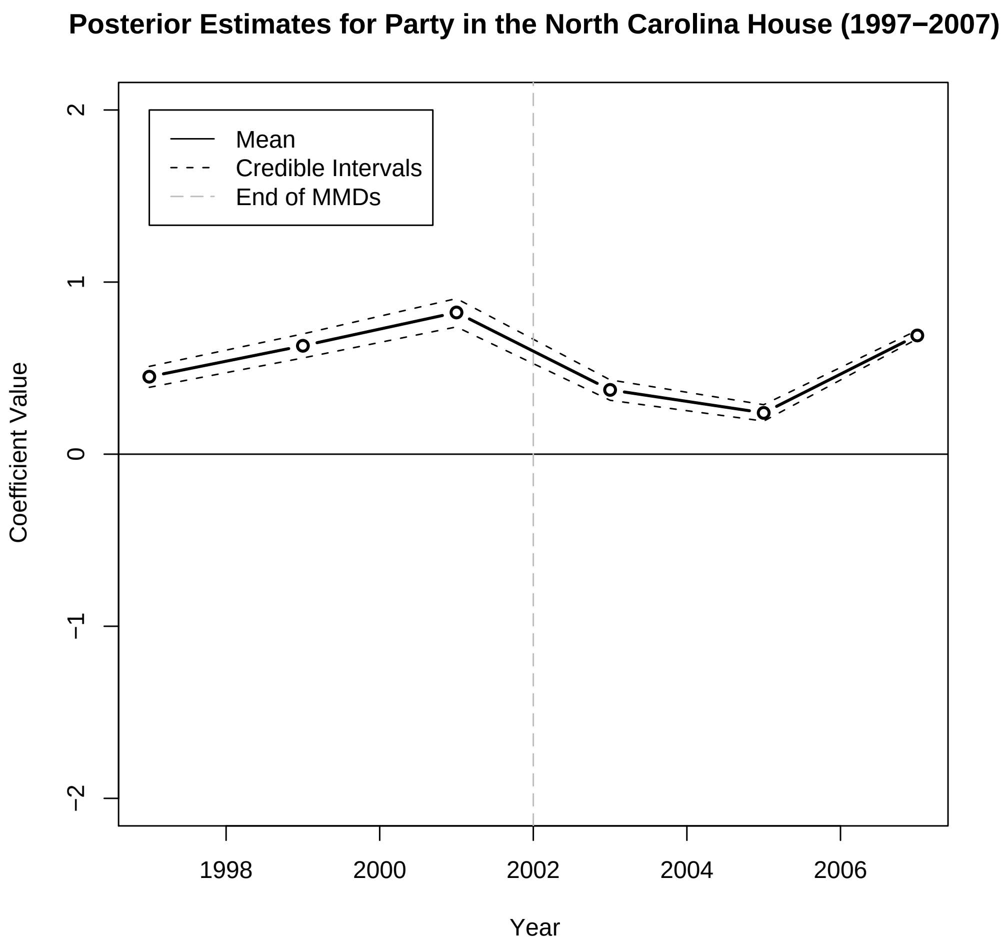
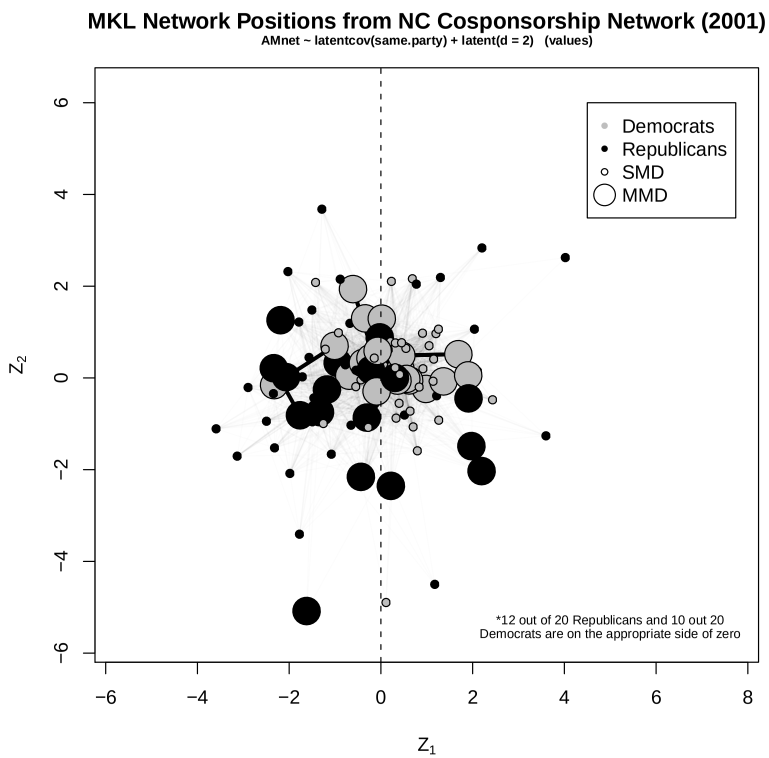


Figure 3.4: Party Coefficient Estimates and Credible Intervals (1997-2007)

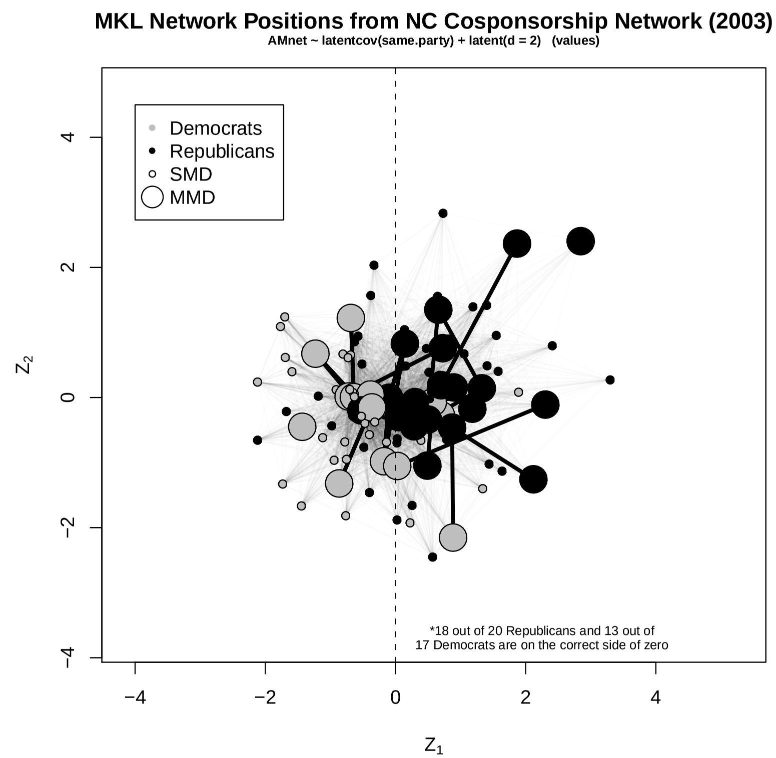
These latent dimensions are the first and second observable dimensions of legislative behavior after party.

When looking at actual differences in positions between legislators, I make use of rank order comparisons and the Wilcoxon rank sum test. The Wilcoxon test is a location shift test that will determine the probability of a location shift in the distribution of ranks for two different samples. It provides a useful way to differentiate whether the distribution of position differences in the legislative network systematically ranks legislators from multi-member districts lower than other pairs of colleagues. The Wilcoxon test is useful here because it does not require any assumptions about the distribution of differences. Multi-member district legislators are closer to one another on the first dimension controlling for party than the average two legislators not sharing a district in both 2001 (p-value of 0.001) and 2003 (p-value 0.007). On the second dimension however, multi-member legislators are closer than the average pair of legislators not sharing a district in 2001 (p-value of 0.003) but no longer closer than expected in 2003 (p-value of 0.36), precisely as predicted.

Comparing the distances on dimensions of behavior between legislators who share a district and all other legislators is a relatively weak null comparison. A more strenuous comparison of multi-member similarities relative to other legislators is to compare legislators who share a district to pairs of single-member legislators who are of the same party (rather than all single-member legislators). The differences on the first dimension of cosponsorship behavior controlling for party between legislators who share a district are also significantly smaller than differences between pairs of single-member legislators who are in the same party in 2001 (p-value of 0.044). Yet, this difference is no longer statistically significant in 2003 (p-value of 0.15). The difference between legislators who share a district and pairs of same party single-member legislators is insignificant on the second extra-party dimension in both 2001 and 2003. Once again, empirical evidence



(a) NC Network Positions in 2001



(b) NC Network Positions in 2001

Figure 3.5: North Carolina Legislators' Positions in Two Dimensional Social Space in 2001 and 2003

indicates that in 2001, multi-member legislators were more similar to one another than their single-member colleagues were, but following the exogenously imposed change in electoral districts in 2003, these same multi-member legislators are no longer statistically significantly different from their single-member colleagues. If the common cosponsorship between legislators I observe were just a function of multi-member districts electing two similar legislators, then there would be no reason for movement following the elimination of multi-member districts, particularly given the fact that their districts changed very little before and after the switch.[25]

3.3.1 Mixed Member Systems in Other States

While the inferences drawn from my analysis of North Carolina are clean thanks to the observable change in institutions, a more general examination can be crafted using states that use combinations of multi-member and single-member districts in legislative elections. There are four such states in the country: New Hampshire, Vermont, West Virginia, and Maryland.[26] Within these states, I can make the similar comparisons as in North Carolina to determine whether shared constituency encourages collaboration across other state legislatures.

Figure 3.6 replicates the analysis from Figure 3.1 in each of the 4 states I mention, but only in 2007. The plot presents point estimates from a Poisson Latent Space model with two latent dimensions. The points in the plot represent the actual point estimates and the lines coming off the points represent 95% credible intervals. Grey points represent model

[25]Analysis of roll call votes also indicates that legislators from multi-member districts change their voting behavior following the change to single-member districts. Because these analyses involve the exact same individuals, this means that the voting behavior and cosponsorship behavior of individual legislators is changing following their change to single-member districts. The roll call analysis is presented in Appendix E to this article.

[26]New Hampshire elects 96% of its 400 legislators from multi-member districts. Vermont elects 57% of its 151 legislators from multi-member districts. West Virginia elects 63% of its 100 legislators from multi-member districts, and Maryland elects 79% of its 141 legislators from multi-member districts.

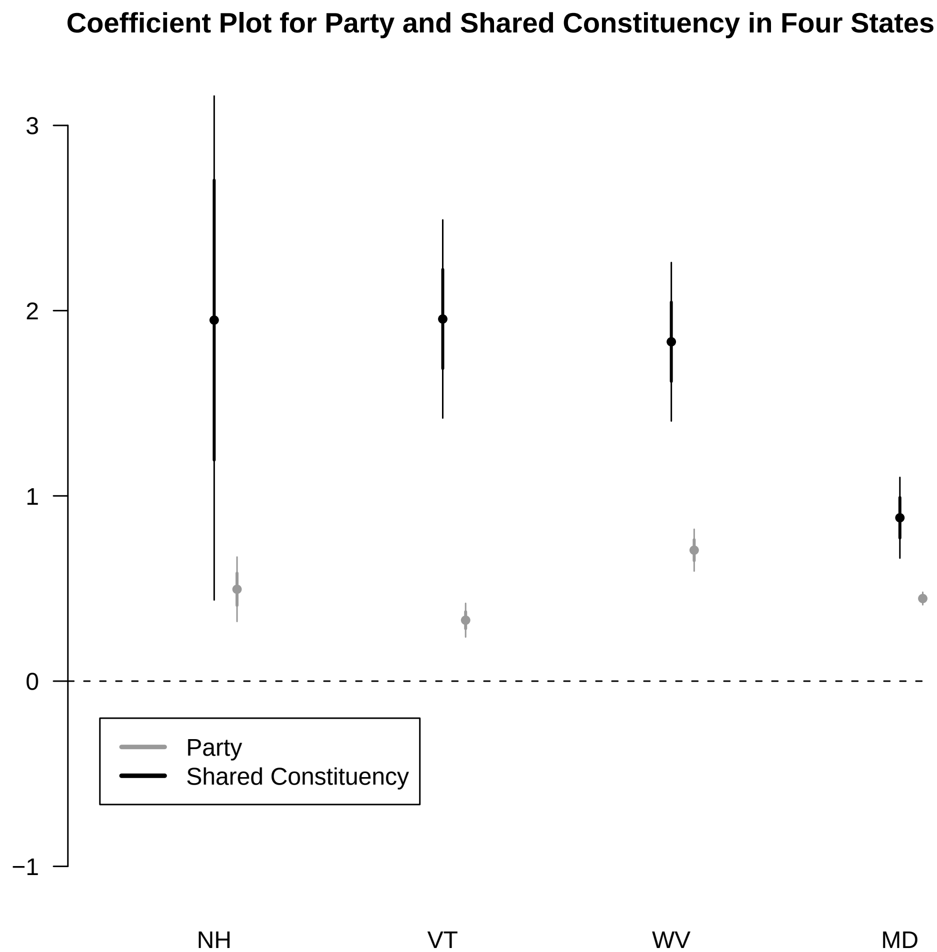


Figure 3.6: Multi-Member District Coefficient Estimates and Credible Intervals in NH, WV, VT, MD

estimates for party's effect on cosponsorship behavior and black points represent the effect of shared constituency on cosponsorship behavior for members of opposite parties. The interaction term demonstrating the effect of shared constituency for members of the same party is not presented in the plot, but is reported in Table 7.10 in the appendix. This interaction is never statistically different from zero. The consistently positive effect in each of these states mirrors the results in North Carolina, indicating that shared constituency is a driver of cooperative behavior in these states as well.

Once again, I make use of the Wilcoxon rank test in order to examine whether differences on first and second dimensions after controlling for party are smaller for multi-member legislators than pairs of single-member legislators. The hypothesis here is that the distribution of differences between legislators will systematically rank pairs of legislators who share a district lower than pairs of single-member legislators. This indicates that their differences are on average smaller than differences between single-member district legislators. There is a statistically significant shift downward in the rankings of difference between legislators who share a district in Maryland (p-value of 0.0001) and West Virginia (p-value of 0.000). Vermont misses the 0.05 cut off, but there is a significant shift downward at the 0.10 level (p-value of 0.061). There is no statistically significant difference between legislators who share a district and their single-member colleagues in New Hampshire (p-value on downward shift of 0.489). The same pattern appears when comparing legislators who share a district to pairs of single-member legislators of the same party. Maryland and West Virginia have significant shifts downward (p-values of 0.001 and 0.000, respectively), and Vermont has a significant shift downward at the 0.10 level of significance (0.080). New Hampshire has no significant shift. New Hampshire's insignificant findings are likely a result of the limited number of single-member legislators elected in that state (only 4% of 400).

While these comparisons are taking advantage of only within legislature variance and not temporal or between legislatures variance, these results do indicate that cosponsorship is more common among legislators from a shared constituency in each of these four states. Furthermore, in three of the four states, legislators from multi-member districts are more cohesive than single-member legislators from the same party. Thus, in both a natural experiment and a cross-sectional comparison of legislatures, the hypotheses about the influences of multi-member districts on cosponsorship behavior receive support.

3.4 Discussion

This research has demonstrated how the electoral institution of a shared constituency influences the subsequent collaborative behavior of state legislators. By granting legislators freedom to position themselves away from median voters in ideological space and granting them a natural coalitional partner, multi-member districts increase the probability that two legislators will collaborate over the course of a bill's life. When those two legislators are from the same party, multi-member districts increase their rate of collaboration. When those two legislators are of different parties, multi-member districts actually create collaboration. Using a natural experiment from North Carolina's state legislature, empirical evidence indicates that multi-member district legislators are more likely to cosponsor together and that multi-member legislators are closer together on unobserved dimensions driving behavior when controlling for party. In the absence of multi-member districts, these characteristics fade away, and legislators formerly from multi-member districts begin to look exactly like their single-member counterparts. Cross-sectional evidence from Vermont, Maryland, and West Virginia provide additional evidence supporting these hypotheses.

Most early work on multi-member districts in state legislatures focuses on understanding the effects of these institutions on questions of representation, like how these institutions influenced the minority, gender and partisan makeup of a chamber (Gerber et al. 1998, Niemi et al. 1985, Niemi et al. 1991, Grofman et al. 1986, Welch and Studlar 1990). Prior work on the post-electoral behavior of legislators from multi-member districts indicated that these districts amplified polarization, created rivals rather than partners, and created incentives to free-ride on the efforts of other legislators from the shared district. I find that multi-member districts actually generate collaboration when controlling for partisanship. This collaboration stems from efforts by legislators in multi-member districts to maxmize their limited incumbency advantages and ward off potential challengers. Additionally, this work provides clear evidence that institutional arrangements in a legislature can and do influence the collaborative behavior of legislators. By altering the incentives for shared credit claiming, rules and constraints can engender or eliminate cooperation between members. It is possible then that other legislative institutions beyond multi-member districts can condition the collaborative behavior between representatives.

As Snyder and Ueda (2007) point out, this coordinated behavior by legislators from multi-member districts should alter their legislative productivity and their district's share of legislative benefits. Kirkland (2011) has noted that both a large and diverse coalition of support helps legislators pass bills. Thus, multi-member districts provide legislators with natural allies that should help them swing legislative outcomes in favor of their home district. Legislators from single-member districts lack allies expressly interested in helping them benefit their home districts. Additionally, by creating an electoral environment where legislators are free to position themselves away from the party or district median, multi-member districts should limit the party cohesion within a legislature (a result supported by Adams 1996) and create more ideologically diverse political parties.

Finally, this work points to the importance of studying cosponsorship if scholars are interested in the multi-dimensionality of legislative behaviors. Roll call analysis consistently produces one-dimensional solutions of ideal point placements for legislators. Cosponsorship can allow scholars to examine the multi-dimensional elements of legislative choice by providing a window into decision-making earlier in the legislative process.

Chapter 4

Chamber Size Effects on the Cooperative Structure of Legislatures

In order to achieve some of their legislative goals, legislators are often forced to collaborate with one another and build reliable relationships in a complex network of interactions. These collaborative choices and the resultant network of relationships are subject to many of the typical factors generating social networks (Newman and Park 2003, McPherson et al. 2001, Desmarais et al. 2009, Bratton and Rouse 2009, Louch 2000). For example, legislators are more likely to cosponsor other legislators to whom they are similar, a network phenomenon called homophily. However, unlike most social networks built around instances of friendship or affect, collaborative choices between legislators occur in a strategic environment among actors pursuing goals like re-election, influence, and different incarnations of public policy (Fenno 1973). Legislators must balance their choices about whom to trust and with whom to collaborate with the potential costs of those relational decisions. Because of these potential costs from association, the development of legislative relationships in this strategic context will be subject to the constraints imposed by the institutional environment that shape legislative choices.

Research noting the complexity of legislative decisions or collective decision-making more generally extends back as far as Arrow (1963). Legislatures, however, provide structures that help limit the complexity of these choices in a multi-dimensional space.[1] These structures or institutions induce equilibria by eliminating choices or providing information about key players in the legislative process that allow legislators to focus their selections on a constrained set (Shepsle 1979, 1994). While the majority of the work on structure induced equilibrium has focused on voting behavior, relational choices are subject to similar complexities and can be similarly affected by institutions that increase or decrease the costs associated with navigating that complexity.

Two of the most basic, yet most fundamental, institutional characteristics of a legislative body are the size of the chamber and the size of the committees in the chamber. Legislators must learn about one another to develop collaborative and cooperative partnerships. While a large chamber provides more potential partners, it also provides more individuals about whom a legislator must learn. Larger chambers also produce many more combinations of potential collaborative networks an individual might develop making the choice of an optimal collaborative network more difficult. Committees, alternatively, provide an opportunity for legislators to interact with one another in a setting of fewer actors. Committees afford legislators time to learn specific information about one another and the chance to gain insights about potentially valuable partnerships. Larger committees help legislators develop a more optimal collaborative network by providing them chances to learn about a greater number of potential partners.

In this research, I develop a theory of informational costs associated with relational choices in a legislature. Specifically, I argue that chamber size and committee size alter the ease/difficulty of selecting collaborative partners in a legislature by providing or obscuring information about legislative preferences on multiple dimensions. Large chambers make it relatively more difficult to learn about the preferences of all the potential

[1] While a great deal of work has pointed to the endogeneity of internal institutions in the U.S. Congress (Gilligan and Krehbiel 1989), almost all U.S. state legislatures have exogenously structured institutions through their state constitutions. Even the U.S. Congress is subject to some exogenous institutions like elections and term lengths.

relational partners in a chamber. When there are many partners to learn about, legislators will rely on simple cues to determine their relational selections. Committees, alternatively, reveal individual preferences on substantive dimensions through committee interactions. Similar to the floor's use of committees to learn about bill outcomes (Gilligan and Krehbiel 1989), individuals use committees to learn about one another. By revealing otherwise hard to learn information, committees facilitate the formation of connections between legislators that would not exist in a purely partisan legislature. Thus, these institutions shape the organization of the aggregate collaborative network of a legislature in systematic ways. I use a computational model to more rigorously evaluate my theory and generate some testable hypotheses.

I test the predictions from my computational model using data on legislative cosponsorship networks from 96 state legislative chambers in 2007. I use summary statistics for these social networks to assess how the size of a legislative chamber shapes the collaborative network of legislatures. Results indicate that as chambers grow in size, networks become more partisan and the distance across a collaborative network grows. Alternatively, as committee sizes grow, distance across the collaborative network shrinks.

4.1 Relationships and Legislative Choices

The majority of the work on legislative relationships has focused either on how individual factors influence relational formation (Bratton and Rouse 2010, Gross and Shalizi 2009, Desmarais et al. 2009) or on how the patterns and positions of relationships in the legislative network influence outcomes (Fowler 2006, Tam Cho and Fowler 2010). These works have consistently shown that 1) relationships between legislators form in structured, predictable ways and 2) that the network of relationships between legislators has important implications for legislating. For example, Tam Cho and Fowler (2010) have shown that the "small world" properties (Watts and Strogatz 1998) of the cosponsorship network, intended to capture the balance of clustering and distance in the cosponsorship network for the U.S. House, is a powerful predictor of the number of important pieces of legislation that the House produces.

We know from institutional literature, however, that legislative choices are subject to constraints imposed by legislative structures (Shepsle 1979, 1981). These structures induce equilibria by constraining choices and eliminating potential outcomes from the choice space of legislators (Shepsle and Weingast 1987). Relational choices are also likely to be subject to institutional constraints. Political party affiliations, for example, are useful heuristics for individual legislators in determing whom to trust. Given a large number of potential informants, party provides legislators with a simple cue about who is and is not similar to one another and thus likely to provide valuable information (Kingdon 1981). Rules that influence the familiarity of legislators with one another are also likely to influence collaboration. Without sufficient time to explore the relational environment, legislators are likely to develop relationships along obvious lines. Sarbaugh-Thompson, et al. (2006) provide support for this notion by demonstrating that there are fewer bipartisan relationships in the Michigan House following the implementation of term limits.

One of the institutions commonly found to play a pivotal role in structuring legislative choices is the committee system for a chamber. Committees help reduce a complex environment of legislative choices down to a more manageable set of alternatives by providing information from policy experts (Gilligan and Krehbiel 1989) and a focused set of critical veto players (Shepsle and Weingast 1987, Cox and McCubbins 2005). Francis (1982), in some of the early work comparing committee systems across state legislatures, shows that the optimal committee system for efficient deliberation is a function of the size of the legislative chamber. Francis and Riddlesperger (1982) also show that committees in state legislatures have become the focal point of agenda control, meaning that legislators view committee memberships as useful pieces of information regarding which actors in the chamber hold critical veto power.

In addition to the committee system of a legislature designating key veto players in the deliberation process, it is also a tool for developing and disseminating expertise. Aldrich and Rohde (2004) point out that much of the work done in committees is not nearly as divisive as we might believe and that much committee activity is extremely accordant. Indeed, Hamm, Hedlund, and Post (2011) point out that most state legislative committee systems are formed to fill the knowledge and expertise needs of the floor, while Battista (2009) observes that larger, less polarized legislatures tend to focus their committee systems on building informative committees and Richman (2008) indicates that committees are more likely to be populated by ideological outliers when the floor is increasingly uncertain.

The size of a legislative chamber and of the committees within that chamber have important influences over the complexity of choices faced by the membership. Analysis on the "yoke" of a deliberative body (the set of alternatives which cannot be beaten by other legislative proposals) indicates that as the size of a deliberative body increases the size of the yoke decreases. Thus, as chambers get larger the set of optimal proposals decreases and choices become much more unstable. (Karotkin and Paroush 2003, Koehler 1989, Feld, Grofman, and Miller 1988, Miller, Grofman, and Feld 1989). Several comparative studies at both national and sub-national levels support this idea, indicating that as legislative chambers increase in size government spending also increases (Bradbury and Crain 2001, Bradbury and Stephenson 2003, Chen and Malhotra 2007, Gilligan and Matsusaka 1995, Gilligan and Matsusaka 2001, Weingast et al. 1981). As the number of legislators in a chamber increases, the demands placed on the chamber for pork projects increase even if the population the legislature represents does not. This indicates that the decision space over distributive outcomes becomes more complex as the number of legislators in the chamber increases.

4.2 Informational Problems and Collaborative Decisions

I begin with an assumption that the decision to cosponsor a piece of legislation is a decision on two dimensions. Legislators either a) cosponsor a bill in support of the legislation itself or b) cosponsor a bill in support of the legislator who sponsors the bill. Thus, the decision to cosponsor a piece of legislation either is an expression of a policy preference for some bill over the status quo or is an expression of support for an individual. This second dimension of support would stipulate that if a legislator faced two bills that produced the same policy outcomes he or she would be more likely to cosponsor legislation from the bill sponsored by the individual he or she prefers to support.[2] These choices along a personal/legislator-specific dimension give rise to the interdependence observed in a cosponsorship network, creating a legislative choice that cannot be modeled exclusively as a function of policy preferences (Cranmer and Desmarais 2011).

I also assume that cosponsorship represents a credible commitment to support legislation (Bernhard and Sulkin 2010). That is, when a legislator elects to cosponsor a bill, that confirms to both the sponsor and the chamber at large that the bill will proceed with the support of that cosponsor. Prior work adopting this perspective has indicated that cosponsorship commitments that are violated are met with punishment both from the sponsor of the bill, *and* from the chamber at large (Bernhard and Sulkin 2010). Individual legislators who cosponsor a bill and then renege on that cosponsorship, themselves

[2]Kirkland (2011) shows that both legislator and legislation specific characteristics are important determinants of bill outcomes. Additionally, Koger (2003) shows that legislators often make cosponsorship choices without carefully considering the content of the bill. Instead, they make their choices based on who has made the cosponsorship request.

experience less legislative successes (defined as bills passing in the chamber) and smaller cosponsorship coalitions in the future. The other legislators in a chamber notice this violation of commitment and take this violation seriously. This immediately implies that the decision to cosponsor a bill is costly for legislators. Choosing the wrong partners/bills can lead to reprecussions into the future of a legislative session.[3]

Thus, legislators deciding whether to cosponsor legislation are confronted with informational problems. A decision to cosponsor a bill brings with it a commitment to support legislation that may turn out to be less than desirable, at which point a legislator needs to either provide sustained support for a bill he or she does not like or suffer the consequences of a violated commitment. A decision to never cosponsor bills, however, means that many preferable pieces of legislation may not develop sufficient support to emerge from the chamber. This means that the potential costs of a cosponsorship choice are a function of the uncertainty surrounding bill outcomes, whether that uncertainty arises through uncertainty about implementation (Gilligan and Krehbiel 1989) or uncertainty about a sponsor's preferences.[4] Institutional structures that alter the level of information in a chamber regarding bill outcomes or alter the cost of gathering that information about bill outcomes will affect cosponsorship choices. Specifically, legislative institutions can shape the patterns of interdependence in the cosponsorship network of a chamber by generating greater or lesser knowledge about individuals' preferences, which in turn alters the observed relationships between legislators. Said more simply, individual legislators can be more confident in their commitments to support legislation if they have greater

[3]The fact that violations of the cosponsorship commitment are punished implies that successful executions of the commitment may be rewarded. Consistently fulfilling cosponsorship commitments by both cosponsoring and voting for bills should lead to increased levels of trust between the partners.

[4]Knowledge of the sponsor's/introducer's preferences for a bill outcome are a necessary beginning point for any model of legislative outcomes. Whether the sponsor is acting strategically or sincerely, a legislator must know the preferences of a bill's sponsor in order to gauge the outcome associated with that bill. They may have assistance from outside sources in learning a sponsor's preferences, but the case remains that there remain informational costs associated with committing to support someone else's proposals.

knowledge about potential relational partner's preferences.

The difficulty in choosing whom to support in a legislature then is a function of the potential variance in each legislator's preferences across dimensions. To select a relational partner (in other words, to select whom to support), a legislator requires information about the preferred outcomes of a potential partner on many dimensions. The more potential partners there are in a chamber, the more difficult gathering this information becomes. Thus, faced with an increasing need for collaborative partners and a more complex environment from which to choose them, legislators from very large chambers will rely heavily on simple cues in the choice of whom in the chamber to support. In an environment where decisions are potentially costly and increasingly uncertain, risk-aversion should prevent legislators from engaging in commitments to cross-partisan legislation.

Additionally, because information on multiple dimensions is harder to gather in a large chamber, the cosponsorship/commitment network becomes less efficient than might otherwise be the case. An inefficiently organized network is one in which information introduced at any single point in the network must make many transfers between actors to reach all other actors in the network (Latora and Marchiori 2001). Thus, a network with n actors in it is considered inefficient as the maximum distance across the network approaches $n - 1$. As bridging ties form, shortcuts across the network develop and the maximum distance across the network shortens, meaning information introduced at one point in the network takes less effort to disperse across the entire network.[5] Because individual legislators rely on overly simply cues, they overlook opportunities to form bridging relationships across divisions like party. This lack of bridging ties in a large

[5]This definition of efficiency is based on the optimal distribution of relationships in an organization. A more efficient distribution of relationships in an organization provides a number of benefits including improved communication and diffusion of information, faster accomplishment of group tasks, and increased individual learning and creativity (Levin and Cross 2004, Burt 2004, Perry-Smith and Shalley 2003, Tiegland and Wasko 2000). Other definitions of efficiency for a legislature might include faster decision making on bills or less time spent passing the budget. These measures, however, generally involve activity by actors outside the organization (governors and legislators from the alternative chamber), which might effect the measure even if the organization is internally efficient.

chamber produces an inefficient network in which information or influence is difficult to move from one point on the network to other points in the network (Granovetter 1973, 1983). Without bridging ties that result from interactions across pre-existing differences (Kirkland 2011), social networks become inefficient distributors of information or influence. As result of this failure to bridge, both the aggregate adaptability of a network and individual performances in a network suffer (Burt 2004, Levin and Cross 2004, Morrison 2002, Perry-Smith and Shalley 2003).

While large legislative chambers make it difficult to gather information on many dimensions about other legislators, the committee system in a chamber can provide information to individual legislators both about potential bill outcomes (Gilligan and Krehbiel 1989, Krehbiel 1993) and about the preferences of individual legislators on certain issue dimensions. When a committee approves, amends, or kills legislation in a chamber, it provides a signal about the preferences of the actors on that committee on their substantive dimension of expertise. In other words, through committee decisions legislators get to view additional voting behavior on bills that may never reach the floor. Additionally, through common committee assignments, two legislators who might not otherwise engage with one another are given the opportunity to interact, bargain, and learn about one another.[6] Committee deliberation provides each with an opportunity to learn about one another for issue dimensions on which they both have expertise. Thus, by generating more information about legislative preferences across dimensions, committees can help reveal opportunities for bridging ties across divisions that will improve the organization and efficiency of the cosponsorship network.

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[6]Indeed, the lifelong frienship of Ted Kennedy and Orrin Hatch (the most famous bipartisan relationship of the modern Senate) began through their participation on the Labor and Human Resources Committee in 1981. Hatch's need for Kennedy's cooperation in the small group was much more pronounced than it would have been in a larger environment. Through their committee work, the two were able to learn more about one another and opportunities for cross-party ties were quickly formed. Hatch and Kennedy developed a better understanding of one another's preferences that facilitated commitment to support one another on some dimensions.

4.3 A Spatial Simulation of Revealed Similarities

In this section, I analyze a computational model of the process of network formation outlined earlier. I develop the model as an effort to add precision and consistency to the process described in the previous section. In other words, the model adds rigor to the transition between the speculated learning process and the tested hypotheses. At the heart of this model is the simple notion that committee interactions provide legislators with chances to learn about their colleagues.[7] This knowledge will affect their choices about network connections, which in turn influence network topology and structure. The model I propose begins with some fixed set of actors representing legislators with preferences or attributes arrayed in a multidimensional Euclidean social space. The decision by any two actors to form a connection in the network is a function of their distances in this social Euclidean space. The closer two actors are (or the more similar two actors are) the more likely a connection is to form between them.[8]

The results I present here begin with a chamber of 80 actors. I provide each actor with a random party assignment (Democrat or Republican with probability of 0.5). Each actor is then assigned an attribute or preference from a bimodal distribution in which the two modes are centered on 0.5 and -0.5, respectively based on the actor's party assignment. Each mode has a standard deviation of 0.25.[9] This first bimodal dimension of choice represents the dominant liberal/conservative dimension of American politics. Next, I randomly assign each actor preferences/attributes on nine additional "committee"

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[7]Computational models have been commonly used in the simulation of networks, where equilibrium analysis is often intractable. See for example Guimera et al. (2005) and Macy and Skvoretz (1998)

[8]This spatial approach to network formation is at the heart of the data generating process hypothesized in the distance-based latent space approach to social network analysis (Hoff, Raferty, and Handcock 2002).

[9]The bimodal distribution is actually a mixture of two normals with the same variance, but different means. Actors are assigned their "preferences" by receiving a position on one of these two normals. Thus, it is possible to get conservative Democrats and liberal Republicans, but unlikely.

dimensions of preference. I draw these preferences from a normal distribution centered on zero with a standard deviation of 0.5. Because each actor's "committee" preferences are drawn from a new distribution, these extra dimensions of preference are uncorrelated with the primary dimension of preference.[10] Thus, to tie new dimensions of behavior to the dominant partisan dimension, I replace the new dimensional position with a weighted average of the new position and the dominant first dimension. An actors first "committee" preference, then, is some combination of their party preferences and an alternative preference.

This weighted average designed to generate correlated preferences across dimensions has an added bonus. The weight of the partisan dimension in the new "committee" preference for an actor is similar to the power of party to structure committee assignments to the party's benefit (Rundquist and Carsey 2002). When the weight on the partisan dimension in the calculation of an individual's committee preferences is high, then this is akin to political parties being capable of populating committees with people more similar to the party median than the chamber median. Figure 4.1 provides a plot of the simulated actors' preferences on the first "partisan" dimension, the second uncorrelated "committee" dimension, and the averaged "committee" dimension when the weight on the partisan dimension is 0.75.[11] The averaged dimension pulls the two parties closer together and provides some places of overlap, but is not nearly as random of the unaveraged dimension. As the weight on the partisan dimension increases in the creation of committee preferences, committees become increasingly similar to the initial partisan distribution of preferences in the chamber.

[10] The notion that committee preferences ought to come from a normal distribution centered around zero is based in Gilligan and Krehbiel (1989) who assert that committees preferences should mirror the floor median.

[11] The 0.75 weight implies that an actor's preferences on the committee dimension are 75% partisan preferences and 25% committee preferences. I vary this combination in the simulation allowing partisanship to determine committee preferences more or less.

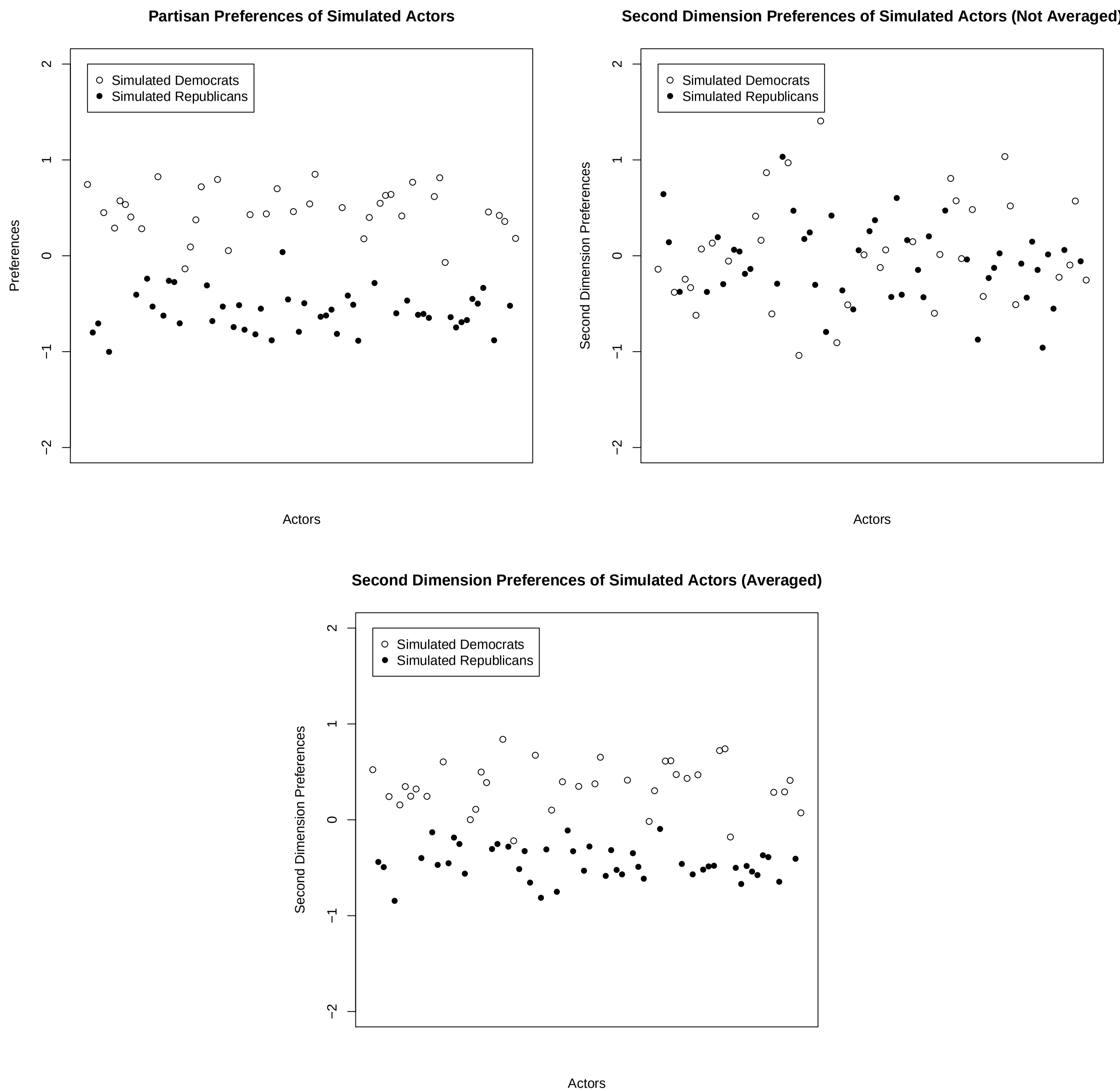

Figure 4.1: First and Second Simulated Dimensions of Behavior for a Network of Legislators

At this point every actor has 10 dimensions of preferences, one for his or her party preference and nine others representing committee preferences. I then randomly assign actors into committees until each of the nine committees in the chamber reaches some pre-determined size. After I assign the actors to their committees, they generate their connections to one another. Each actor perceives the other actors' preferences on the first partisan dimension. If two actors do not overlap in a committee assignment, then these two actors perceive their alter's preferences on the second through ninth dimensions to be equal to their alter's preference the first dominant dimension. If two actors share a committee assignment, then they "learn" each other's committee preferences and update their perception of distance using these revealed preferences rather than their party preferences.

Figure 4.2 presents an illustrative version of this process for three legislators in two committees. Legislators A, B, and C all possess three dimensions of preference indicated by the numbers in parantheses. The second and third dimensions of preference are related to each's first dimension of preference. Each assumes the other's preferences are consistent across all dimensions with the first dimension of preference. Through co-assignment to the same committee, Legislators A and B learn one another's second dimension of preference (a legislator can only learn one additional dimension of preference for each common committee assignment). Because Legislators A and C are not co-assigned they assume the distance between them on all dimensions is consistent with the distance between them on the first dimension. Had the two been co-assigned and learned an additional dimension of preference, they would have perceived that a shorter ideological distance separates them (5 instead of 6). In the model, this process is repeated until committees reach some pre-determined size then legislators evaluate the perceived differences between themselves and other actors across all 10 dimensions of preference.

These ten distances between any dyad of legislators i and j are summed together. This

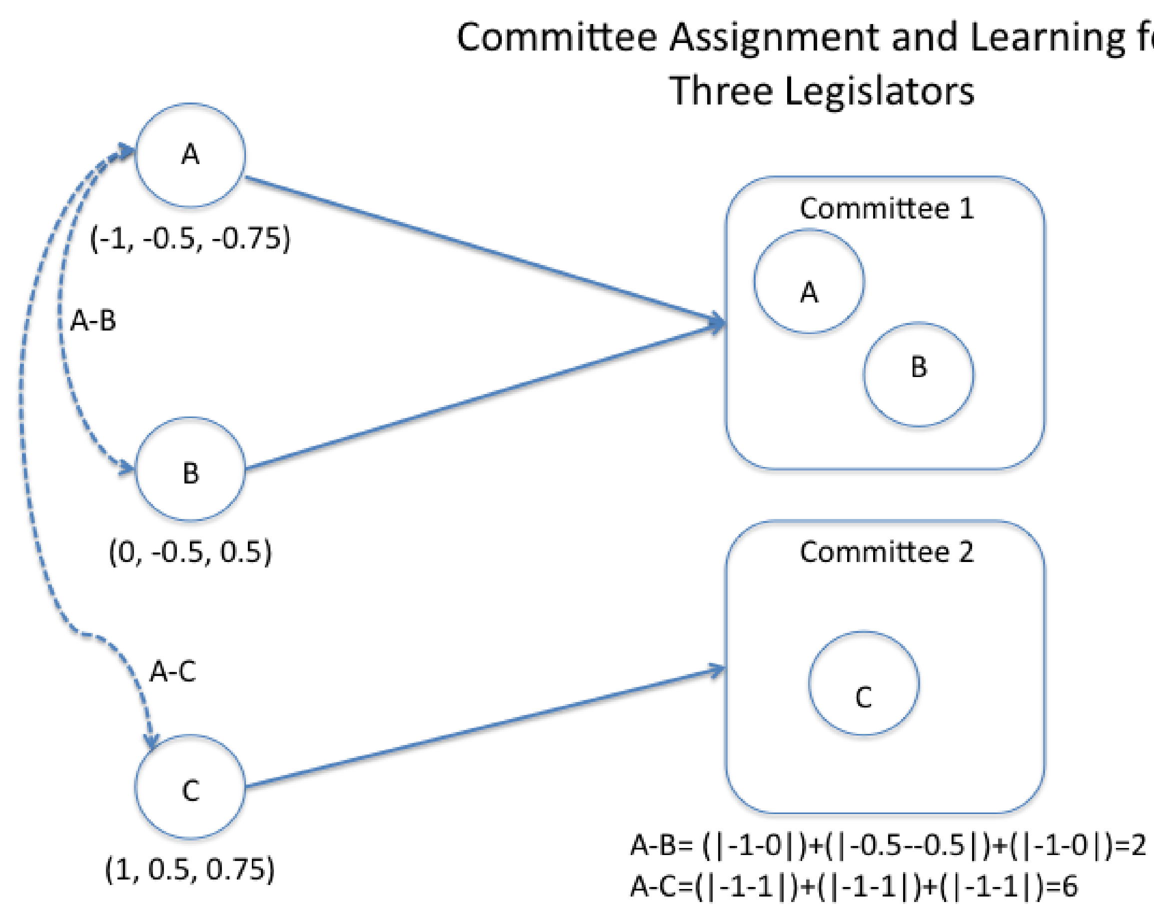

Figure 4.2: An example of committee assignment and learning. Through co-assignment, Legislators A and B learn one another's second dimension preferences. If Legislators A and C have been co-assigned to the same committee, their perceived distance would have been 5 rather than 6.

sum is subtracted from a baseline rate of connection to form a rate parameter, λ, for a Poisson distribution.[12] Thus, every actor in the network has some rate of connection to every other actor in the network. As the perceived distance between two actors grows, the rate parameter between the two actors decreases. When the perceived distance between two actors is small, the rate parameter is larger. I then draw a single observation from a Poisson distribution for the dyad using the rate parameter based on the distance between actors in the dyad. This draw from a Poisson distribution makes the realization of the network probabilitstic rather than deterministic. Thus, two actors who are similar to each other are more likely, but not guarenteed to have stronger connections to one another.[13] I do this for every dyad in the chamber to generate a network of counts. Finally, I assess the average path length across this simulated network and the partisan modularity[14] for this simulated network using the random party assignments. The entire process from preference generation to network formation represents one iteration of the model.

I run the model and record the path length and modularity for the simulated network 250 times for one fixed committee size. I then increase the size of committees by one, run the simulation for another 250 iterations, and continue this process over a sequence of potential committee sizes. I consider committee sizes from two members up to 50

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[12]I utilize a Poisson distribution because cosponsorship networks used for my empirical analysis are aggregated count networks. Draws from the Poisson will provide a count of interactions between the hypothetical actors in the network.

[13]Said slightly more formally, $Y_{i\to j} = Poisson(\exp^{(\theta_{ij})})$, where $\theta_{ij} = \alpha - (\sum_{g=1}^{k} |i_g - j_g|)$ for all k dimensions of choice. α reflects the baseline density of connections between all the actors in the network. $|i_g - j_g|$ represents the perceived distance between actors i and j on dimension g. In the case where two actors share no committee assignments, $g = 1$ for all k dimensions. In the case where actors do share a committee assignment, $g = 1$ for all the committees they do not have in common, and $|i_g - j_g|$ for the common committee dimension is updated to contain the actors "true" differences on this dimension. The more committee assignments actors have in common, the more often $g \neq 1$ and the more often actors perceive the "true" distances between themselves.

[14]Party modularity is a measure of how partisan a legislative network is. Higher values represent increased partisanship. I discuss the details on modularity scores in the next section.

members. Because I have fixed the chamber size in this simulation at 80 actors, changing committee size is functionally equivalent to changing the ratio of committee size to chamber size. Because the only moving value in the model is the size of committees, I can isolate the theoretical impact of changing committee sizes controlling for chamber size on the formation and topology of legislative networks.

To summarize, each actor in a network has 10 correlated dimensions of preference. Actors in the model form connections with other actors based on their perceptions of the distance between themselves on these dimensions of preference. An actor assumes that a potential partner's ten dimensions of preference are the same as that potential partner's first dimension of preference. If the two actors share a committee assignment, they learn new information about one another's committee preferences and this committee preference replaces their beliefs on one of the dimensions of preference. The more committee assignments two actors have in common, the more actors update their beliefs about one another's preferences to include new information. This new information has the potential to shorten (or lengthen) the distance between two actors in the social space and make connections more (or less) likely, capturing the intuition that legislators learn about opportunities for collaboration through common committee assignments. Finally, I measure common topological statistics for the networks that result from increasingly larger committees.

Figure 4.3 presents the change in simulated path length as committee size increases for simulations with weight on the partisan dimensions of 0.65, 0.75, 0.8, and 0.9. The grey dots in the plot represent the path length of simulated networks and the bold line represents the line of best fit from a model in which the committee size is regressed against the average path length of the simulated network. For each of the partisan dimension weights a statistically significant negative relationship is present. Consistently across the simulations even when the attributes of the actors do not change in meaningful ways, increases in committee size decrease the path length of a legislative network. Thus, even if the characteristics of legislators do not change, the level of interaction between legislators on a committee can alter the pattern of collaboration within the chamber.

The learning process that takes place through committee interactions is unlikely to influence bipartisanship as measured through network modularity. Modularity measures the number of ties between actors of the same party versus the number of ties between actors of different parties. Given that committees provide legislators with an opportunity to learn about both members of the other party and their copartisans, they should have little effect on the balance of within versus across party ties regardless of how large committees become. However, the total chamber size should still have an influence on the balance of copartisan versus bipartisan ties. Given some fixed size of committees, increasing chamber size gives legislators more other individuals about which they have to learn. This larger pool of potential partners weakens the learning effect of committees and makes partisanship a more powerful component in tie development.

Using the same spatial model that generates the results from Figure 4.3, I fix the size of committees in the simulated legislature at 15 members and the number of committees at 9. I then calculate the party modularity score for legislatures of 50, 60, 70 80, 90, and 100 members. I also run the simulations for each value of party weighting in the calculation of committee preferences. Thus, chamber size varies independently of committee size in four simulations. I present these results in Figure 4.4. Once again, the grey dots represent the party modularity scores for each simulated network and the bold line represents the regression line from a model predicting party modularity as a function of chamber size. The legend of the plot reports the coefficient estimate from the regression.

Regardless of the weights placed on partisan preferences in the development of committee preferences, increases in chamber size increase the party modularity for simulated networks. As chambers grow larger, their networks become increasingly partisan. Each

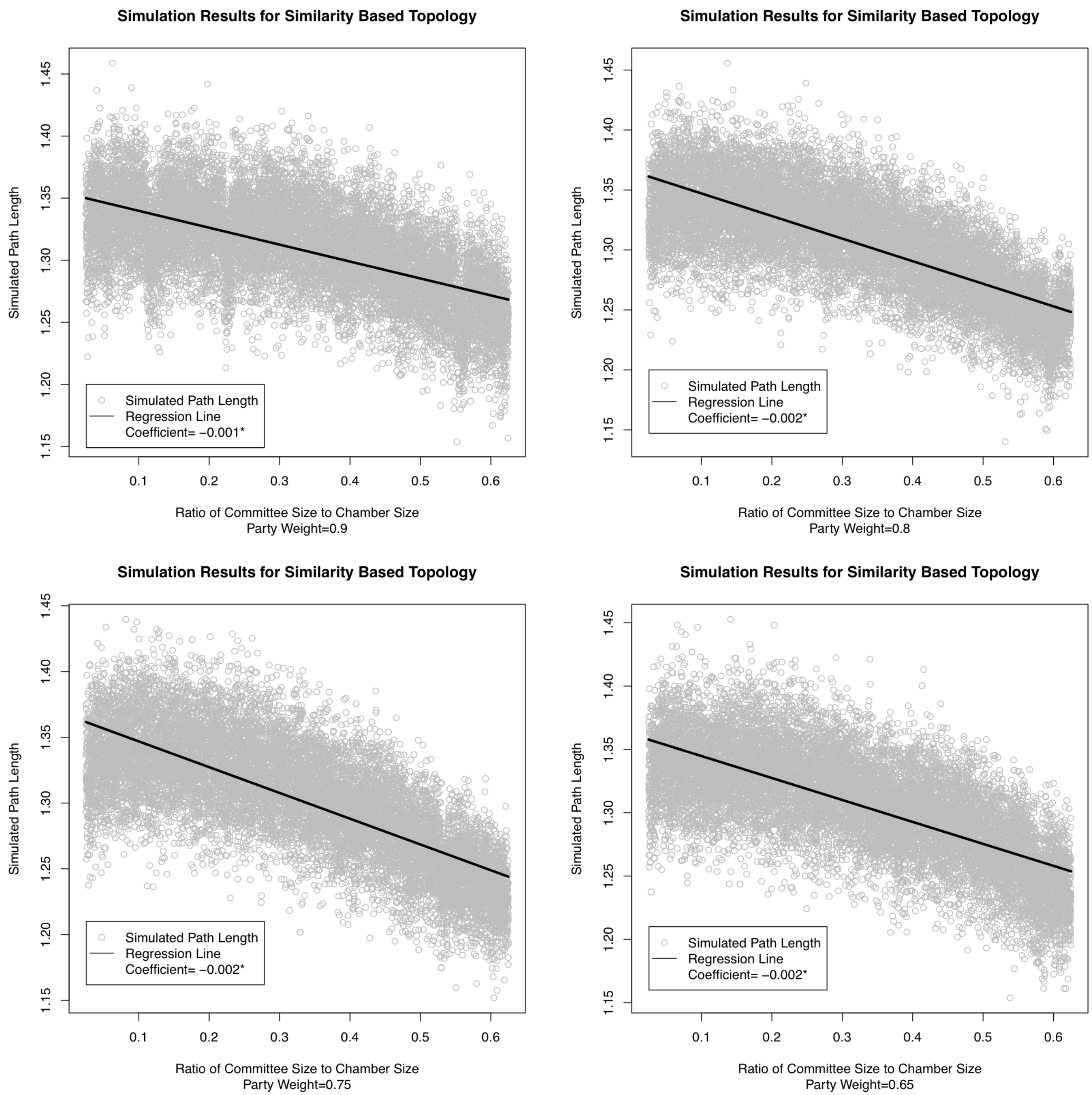


Figure 4.3: Simulated Relationship between Committee Size and Average Path Length in a Legislature

simulation demonstrates positive and statistically significant coefficients for the bivariate relationship, and because nothing else in the model is allowed to vary in systematic ways I can be confident that the results of the simulations are a function of only chamber size and not some other unanticipated influence. As chambers get larger and larger, actors are relying more and more on their first dimension preferences in determining their network connections which in turn increases the level of partisan division in the collaborative network.

From this spatial model of network formation, a few hypotheses emerge. First, as legislative chambers increase in size partisan modularity scores for legislative chambers' collaborative network will increase controlling for committee size. Second, as committees within a legislature grow in size the average path length in the collaborative network will decrease controlling for chamber size.

4.4 Data and Methods

In order to test my theory regarding the size of legislative chambers and its influence on the collaborative network amongst legislators, I use cosponsorship networks from 49 states in 2007 resulting in 96 legislative chambers.[15] To gather these networks, I made use of the RCurl package (Lang 2007) in the R statistical program (R Core Development Team 2008) to scrape bill status/history data from state legislative websites. A few states record cosponsorship information in unorthodox ways, making scraping of the websites difficult. In these states, cosponsorship networks were hand-coded from bill histories. In gathering these data, I focused only on chamber bills. There are no cosponsorships included from chamber or joint resolutions. In states that allow cross-chamber cosponsorship, I recorded

[15] The Idaho House and Senate and Washington State Senate cosponsorship networks are not included. Idaho did not record legislative cosponsorships in 2007 and the Washington State Senate is a fully connected network, meaning every potential connection in the network is realized.

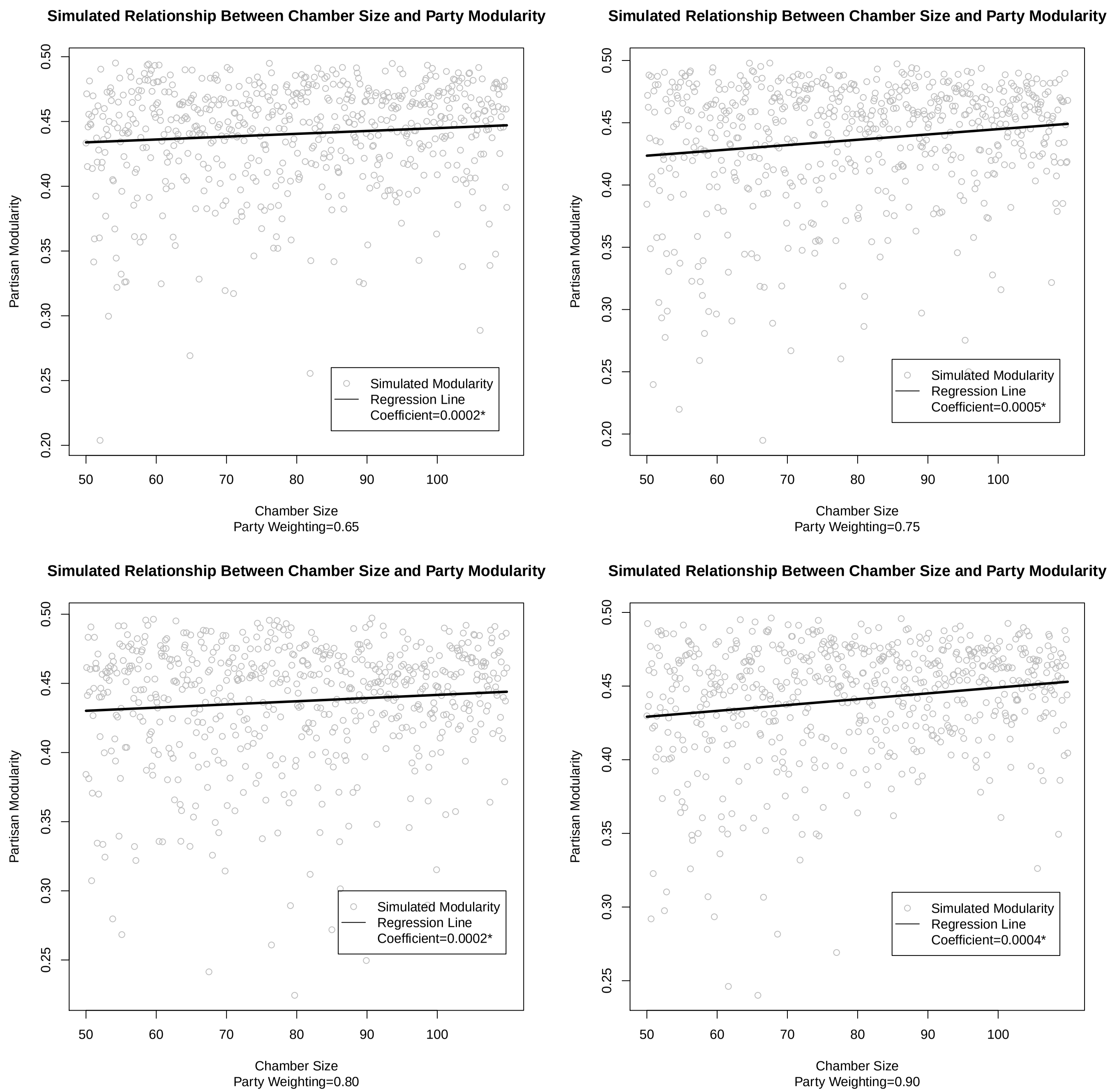


Figure 4.4: Simulated Relationship between Chamber Size and Party Modularity in a Legislature

only lower chamber member-to-member cosponsorships for bills originating in the lower chamber and only upper chamber member-to-member cosponsorships for bills originating in the upper house.

The instances of cosponsorship in a chamber are recorded in an adjacency matrix where element ij represents the number of times actor i has cosponsored actor j. The diagonal elements of this matrix are always zero (meaning no legislator can cosponsor him or herself). To test my theory, I use two key summary measures from these cosponsorship networks: the average path length of the cosponsorship networks (Watts and Strogatz 1998, Albert and Barabasi 2002) and the party modularity of the cosponsorship networks (Waugh et al. 2010, Zhang et al. 2008, Girvan and Newman 2002). These measures will represent the dependent variables in my state-to-state comparisons.

The average path length of a network measures the amount of ties or links it takes the average actor in the network to reach any other actor in a network. As the number of bridging ties in a network increases, the distance from any point in the network to any other point in the network decreases. A lower average path length reflects this decrease in distance, thus average path length can summarize the degree to which a network is shortened by bridging connections (Watts and Strogatz 1998). It is also a useful summary of how easily negotiable travel across a network is. Low path length indicates a network that is traversed easily and, thus, is efficiently organized, while high path length indicates that a network is inefficient and difficult to travel across (Latora 2002, Jackson 2008 p. 57).

The average path length of the cosponsorship network is an effective way to capture how efficiently legislators have organized their collaborative efforts and whether collaboration can move information or influence across the chamber quickly or disjointedly. The New Hampshire lower chamber has the largest average path length (332), not altogether surprising given that the New Hampshire lower chamber is the largest state legislative chamber in the country. Louisiana's upper chamber has the second largest path length (111). Iowa's Senate, alternatively, has the lowest path length (1.03) indicating that it is very nearly a fully connected network. Figure 4.5 presents a plot of lower state legislative chambers and their average path length scores. There is substantial variation in the measure of network organization, but the distribution is skewed towards one (a well-connected network).

The second summary measure of interest is the partisan modularity of a legislative network. Modularity is a network summary statistic that quantifies the effectiveness of a partition for a particular network. In other words, modularity measures how many ties in a network cross over a division versus how many ties remain within a division. For example, if there were many ties in the cosponsorship network within the same political party and very few ties across or between political parties, then the partisan modularity for that network would be high. If there were many ties across party lines and few within a party, then partisan modularity would be low. Thus, modularity provides an important measure of bipartisanship in state legislatures. In states where party modularity is low, collaborative ties across party lines are common. In Figure 4.6, the modularity score based on the shape of the nodes in the hypothetical social network on the left would be extremely high, where as the modularity score based on shape for the social network on the right would be extremely low.

The most bipartisan state legislative chamber in the country is the Indiana upper chamber with a party modularity score of -0.051. The New York Senate is the most partisan chamber in the nation with a party modularity score of 0.4.[16] Figure 4.7 plots the party modularity scores across all legislative chambers in the dataset. Virtually all

[16] To give these figures some context, the cosponsorship network for the 102nd-108th U.S. House of Representatives had an average party modularity score of 0.17. This figure is different from the calculation provided by Waugh et al. (2009), because in their article, the authors focus on uncovering the maximum modularity in the congressional cosponsorship network as a measure of polarization for the chamber rather than measuring the partisan modularity.

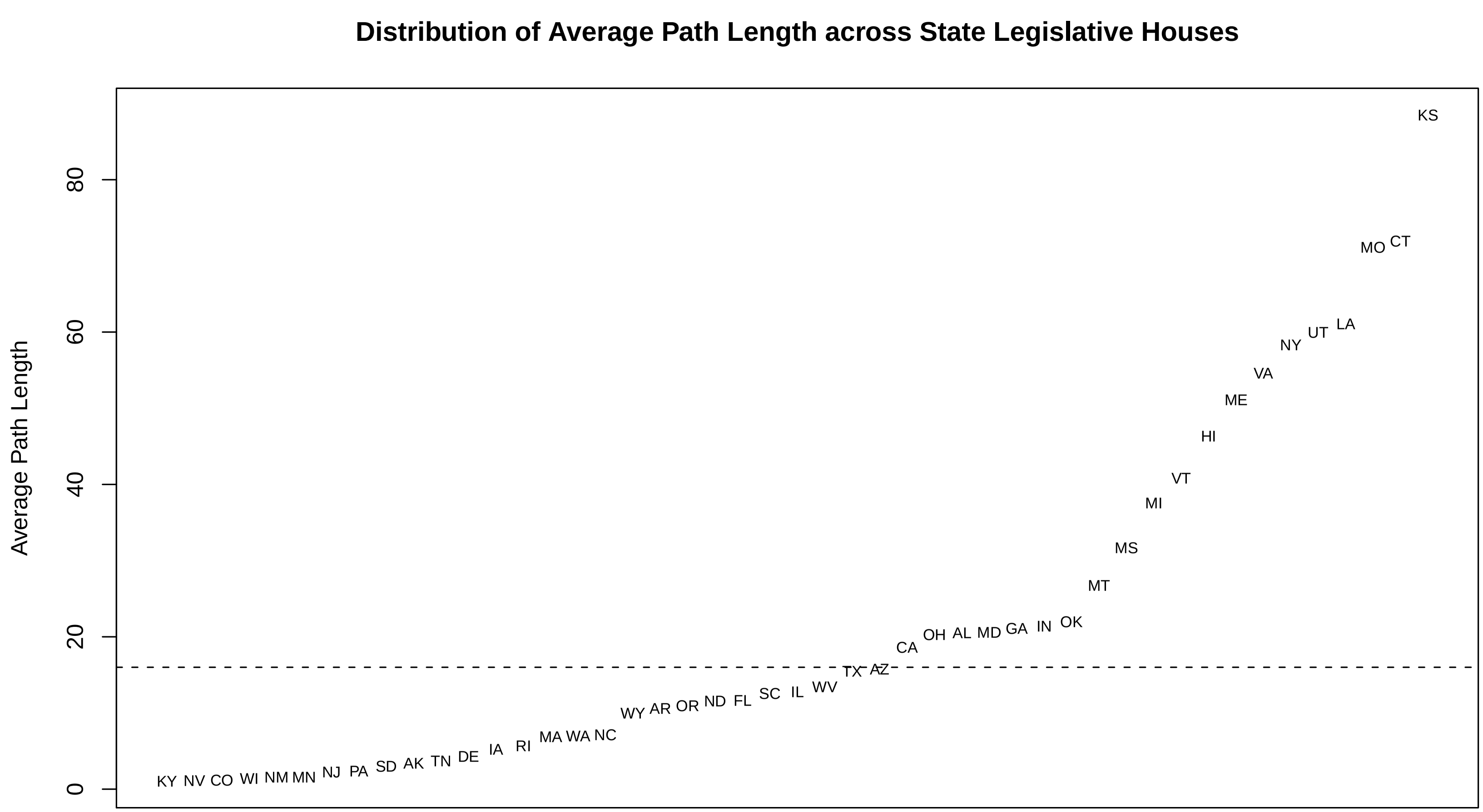
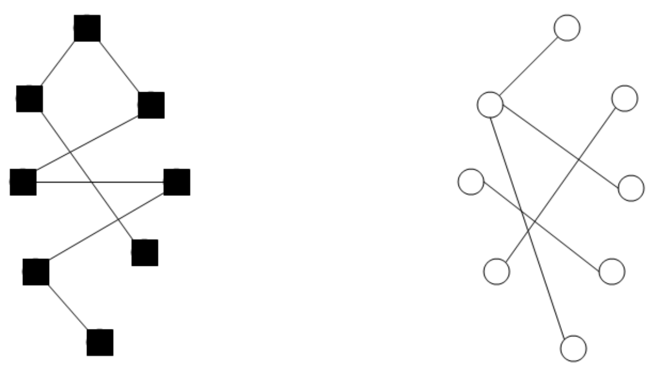
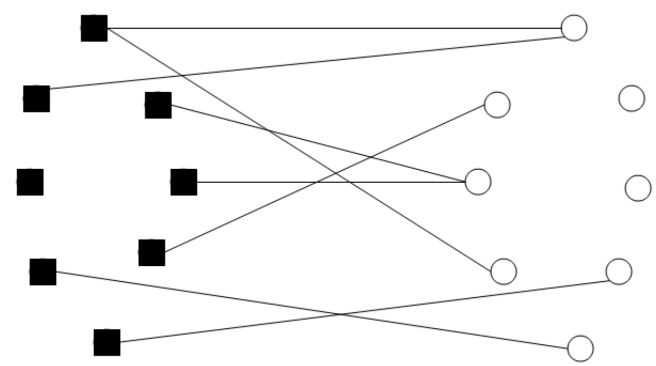


Figure 4.5: Distribution of Average Path Length Across State House Cosponsorship Networks in 2007



(a) High Modularity Based on Shape



(b) Low Modularity Based on Shape

Figure 4.6: High and Low Shape Modularity Networks

of the observations have positive party modularity indicating that in nearly every state, party structures collaboration to some degree.[17] The median modularity score is 0.12, slightly below the average for the 102nd-108th U.S. House of 0.17.

Taken together, these summary statistics characterize the organization of collaboration in a legislature and the degree to which that collaboration is segregated. To analyze the influence of legislative chamber size on the organization of collaboration in a chamber, I measure the number of legislators in a chamber, the number of committees in a chamber, and the average size of committees in a chamber. Legislatures often assign legislators to more than one committee, meaning simply measuring the number of legislators and the number of committees is insufficient for capturing the amount of interactions legislators might have in committees. Through differing levels of multiple assignments, two chambers with 50 legislators and 5 committees might have very different levels of interaction. One chamber may have five committees of 10 legislators and the other may have five committees of 20 legislators with every legislator serving on two committees.[18]

4.4.1 Alternative Explanations and Control Variables

My computational model and the theory on which it is based focus on chamber size and committee size as key elements in legislators learning about one another. Other institutional or environmental conditions might generate the patterns realized in the legislative network. For example, the amount of turnover in a state legislature should

[17]No party modularity score is calculated for the Nebraska unicameral because it is a non-partisan chamber. Also, note that the extremes of the state legislative lower chamber modularity scores are not Vermont and New York. The most partisan lower chamber is the Iowa House and the least partisan lower chamber is the North Carolina House.

[18]These measurements are not scale free network summaries when measured on dichotomous networks. The cosponsorship networks I use here are counts of cosponsorships. This means that any theoretical connection between the number of actors in the network and average path length or modularity of a network should not pose a problem for inference. In a binary network, path length should obviously go up as the number of actors in the network increases, but in a count network this is no longer the case. I provide more discussion of this in Supplemental Appendix B.

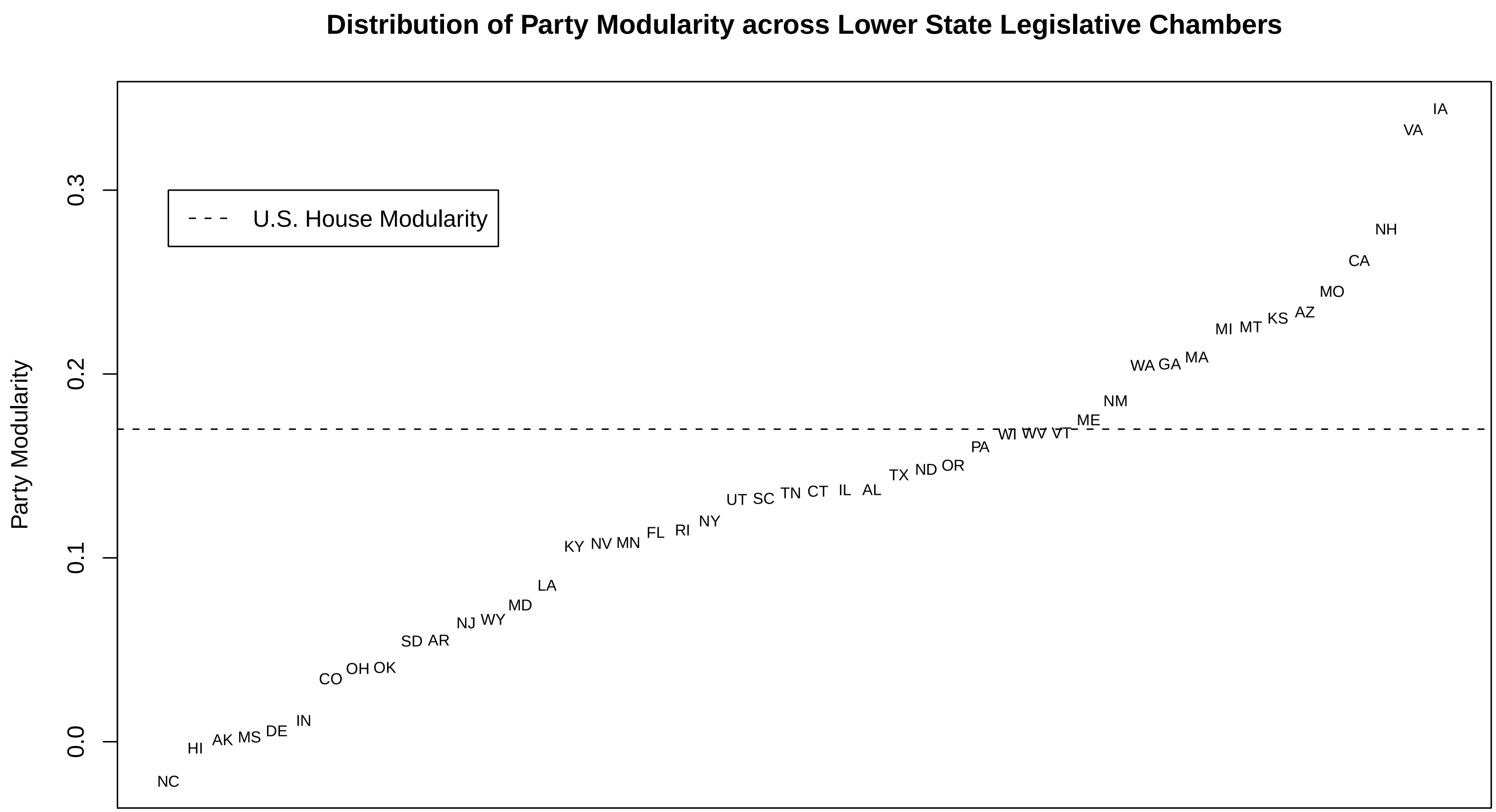


Figure 4.7: Distribution of Partisan Modularity across Legislative Lower Chambers

also have an influence on the ability of legislators to learn about one another. As new members arrive with more frequency, legislators are forced to re-learn information about freshmen legislators who replaced colleagues with whom a legislator may already have been familiar. In order to control for this possibility, my statistical models include a dummy variable coded 1 if a state legislature has term limits for its members along with a variable indicating the percentage of turnover in the chamber during the previous legislative election. Additionally, the pattern of cross-party ties in a chamber (which affect both partisan modularity and path length in a network) may be a result of the importance of the party label in elections. In elections where the parties are evenly matched and thus are more likely to be moderate, it should be easier for legislators to maintain cross-party relationships without damaging their electoral opportunities. I include the Holbrook and Van Dunk measure of legislative competition (Holbrook and Van Dunk 1993) to account for this possibility with the expectation that higher levels of the index predict higher path length and more modularity.

The size of the majority party may also play a role in determining the pattern of ties in a chamber. Fenno (1973) speculated that bi-partisanship would be more valuable in a chamber that was evenly divided and, thus, might be more common. To account for this possibility, I also include a measure of the partisan balance in the chamber in my statistical results. Finally, the level of professionalism in a state seems likely to influence the level of efficiency and cross-party cooperation in a legislature. Legislatures that are more professional provide both more opportunity for cross-party collaboration (due to longer periods of interaction from longer sessions) and more information about potential partners (due to better resources). I include the Squire Legislative Professionalism Index (Squire 2007) with the expectation that increased professionalism is correlated with decreased partisanship in the cosponsorship network and decrease path length.

4.5 Results

Table 4.1 presents OLS results predicting the partisan modularity and average path length of cosponsorship networks for 96 legislative chambers. I begin with OLS results for party modularity scores across the states reported in Model (1) of Table 4.1. The computational model from the previous section allowed chamber size to vary while holding constant committee size, network density, party balance, and the number of committees in a chamber.[19][20] Also, it is possible that it will be easier to detect partisan behavior in legislatures where more cosponsorship opportunities exist. The number of bills introduced in a legislative session is included to account for this possibility, but never reaches statistical significance. Model (2) presents the same analysis, but with the average path length of a legislative cosponsorship network as the dependent variable.

The models in Table 4.1 indicate that party modularity increases as chamber size grows just as predicted, even when controlling for party electoral competition and party balance in the chamber.[21][22] Recall that modularity is bound between -1 and 1 and that

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[19]I have also included a dummy variable coded 1 if the chamber is a lower legislative chamber and zero otherwise to capture whether or not there are significant differences between Houses and Senates. The dummy variable is statistically indistinguishable from zero in predicting party modularity. Upper chambers have no more or less statistically distinguishable partisan cosponsorship networks than lower chambers.

[20]Modularity is continuous and bounded between -1 and 1. While OLS may be acceptable for such a model, I have also transformed modularity into a variable that is continuous and bounded between zero and one by adding one to the modularity score and dividing by two. Using this transformed variable, I have run a generalized linear model with a beta link function (appropriate for dependent variables that are continuous over the 0 to 1 space). This alternative specification presents the same signs and significances as the OLS model.

[21]Both of these variables are statistically insignificant on their own. Additionally, F-tests reveal a p-value of 0.145 indicating that the joint explanatory power of both variables is also statistically insignificant.

[22]The observed modularity value of a count network is not fundamentally tied to the size of the network (Kirkland 2011). Existing simulation work reveals that large networks with no real community structure are no more likely to produce high modularity values than smaller networks are. Thus, the modularity measurement itself is not creating the observed relationship in the data.

Table 4.1: OLS Models of Network Structure in State Legislatures

	Partisan Modularity	**Average Path Length**
Variable	Model 1	Model 2
Chamber Size	0.0006 *	0.615 *
	(0.0003)	(0.083)
Average Committee Size	0.003	-2.105 *
	(0.002)	(0.777)
Number of Committees	-0.000	-0.520
	(0.001)	(0.379)
Network Density	-0.009	-29.62 *
	(0.034)	(10.52)
Number of Bills Introduced	0.000	0.001
	(0.000)	(0.001)
Holbrook and Van Dunk Index	0.001	0.249
	(0.0008)	(0.266)
Squire Professionalism Index	0.225 *	-13.18
	(0.090)	(27.81)
Term Limits Dummy	-0.008	7.312
	(0.022)	(6.821)
% of Membership Turnover	-0.0008	-0.560
	(0.001)	(0.351)
Margin of Party Balance	-0.0006	-0.036
	(0.0006)	(0.189)
Intercept	-0.013	22.78
	(0.053)	(16.42)
N	95	96
Adjusted R-Squared	0.1571	0.5664

Note: Models (1) and (2) report the results of Ordinary Least Squares regression models. The dependent variable in Model (1) is the party modularity score for a state legislative cosponsorship network which are continuous and bounded between -1 and 1. The dependent variable in Model (2) is the average path length of a state legislative cosponsorship network. Standard errors are reported in parentheses below coefficient estimates. There are only 95 observations in Model (1) because Nebraska is a nonpartisan chamber making it impossible to calculate party modularity scores. * $p < 0.05$ in a one-tailed test.

chamber size ranges from 20 to 400. Thus, holding the other variables at their means and using the coefficients from Model 1, a change from the minimum chamber size to the maximum chamber size produces a jump in party modularity from 0.10 to 0.203. This is equivalent to a jump from the 63rd most partisan chamber in the nation to the 20th most partisan chamber in the country. Figure 4.8 plots the predicted partisan modularity of a state legislature as chamber size increases from the model reported in Table 4.1.[23] As chamber size increases, the modularity of state legislatures passes the typical level of partisanship observed in the U.S. House. This is strong support for the hypothesis that increasing complexity in the choices of collaborative partners increases the reliance of legislators on party as a collaborative heuristic. Of the remaining independent variables, only the Squire professionalism index has a significant effect on the bipartisanship in the chamber. The coefficient indicates that, contrary to predictions, increases in professionalism predict increases in partisan modularity.

While the coefficient on the average size of committees is positive, it is statistically indistinguishable from zero. Surprisingly, the Holbrook and Van Dunk competition index is also statistically indistinguishable from zero, indicating that the level of electoral competition between parties has little observable effect on the bi-partisanship of the parties in government. Shorter-term measures of electoral competition like membership turnover also fail to reach traditional levels of significance. Thus, it would seem there is little connection between the aggregate nature of state legislative elections and the structure of bipartisanship in a legislature. There may still be individual electoral influences on collaboration (for example, very marginal legislators may avoid cross-party collaboration), but aggregate levels of competition do not seem to be influencing the cross-party collaboration of the parties themselves.

[23]The plot excludes the New Hampshire lower chamber since its size is so drastically different from other state legislative chambers. Models removing the New Hampshire lower chamber actually show a stronger relationship between chamber size and modularity indicating that it is a leverage point moving coefficients estimates closer to 0.

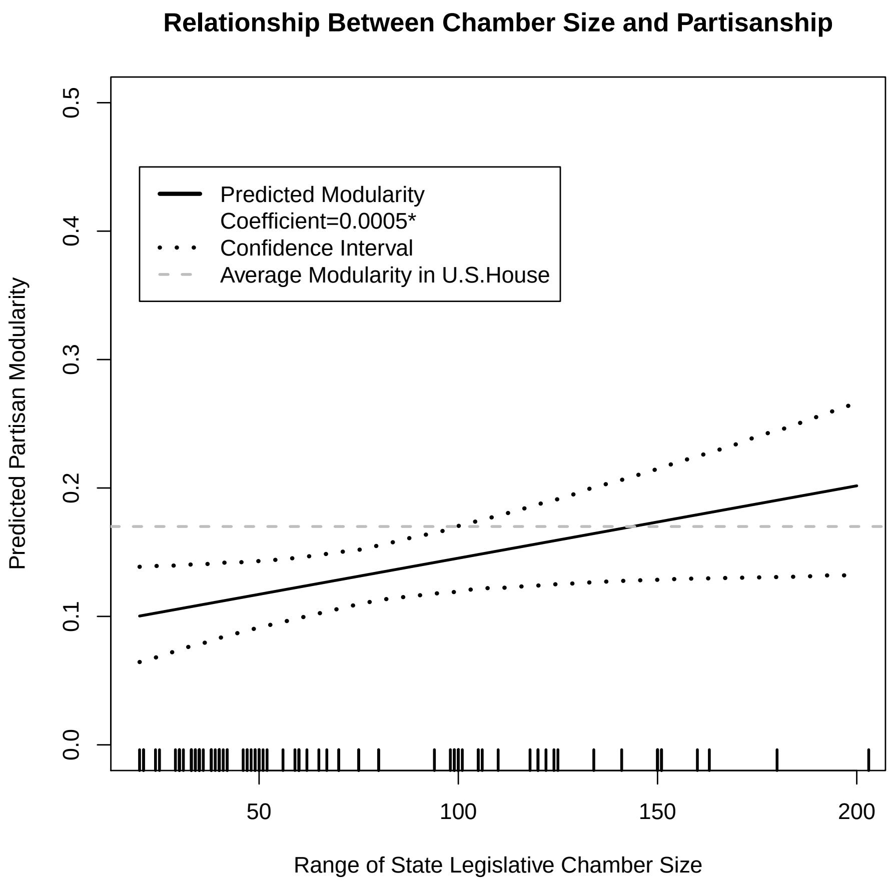

Figure 4.8: Bipartisanship and Chamber Size in State Legislatures

Moving from the model of partisan modularity to the model using average path length as the dependent variable, a similar story continues to emerge. In Model (2), the coefficient on chamber size is positive and statistically significant indicating that as chamber size increases, the average path length across a legislative cosponsorship network also increases.[24] This is expected given that as chambers become larger there are more actors across which information must travel. In addition to chamber size, the coefficient on the average size of committees in a state legislature is negative and statistically significant. This indicates that controlling for the other covariates in the model as committees get larger the average path length of the cosponsorship network shrinks.[25] In other words, as committees grow in size the distribution of relationships in the cosponsorship network becomes more efficient and information and influence require fewer links to travel across the entire network. The only other statistically significant covariate in the model is network density. The coefficient on network density has a negative sign indicating that as cosponsorship becomes more frequent and the network becomes denser, the path length across the network shrinks.[26]

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[24]Model (2) presents OLS coefficients with the average path length of a cosponsorship network as the dependent variable. Average path length is a continuous variable bound between 1 and inf. Figure 4.5 also indicates a skewed distribution of this variable across states. Given the skewed and bounded nature of the variable, OLS may be a less than ideal modeling choice. Thus, I have also run a generalized linear model with a gamma link function and an OLS model with the logged average path length as the dependent variable. Both of these models present the same signs and significances as the OLS model I present.

[25]As noted, it should be no surprise that larger networks have longer path lengths. The key result from these analyses is that path length is connected to *committee size*. Nevertheless, the fact that average path length is not a scale free measure of network topology may be of some concern. Thus, I have also run regressions of chamber size and committee size in which the dependent variable is the average path length of the network divided by the average path length of a randomly generated network with the same number of actors and the same number of nodes. This dependent variable measures how much *more* organized the observed network is than might be expected at random. These regressions again indicate that committee size increases efficiency by decreasing path length.

[26]The correlation coefficient for cosponsorship network density and cosponsorship network path length is -0.443, so while the two concepts are clearly strongly related both retain independent variance. Results from an OLS regression indicate that chamber size, professionalism, electoral competition, and term limits are statistically significant predictors of network density. Thus, the results indicating that committee size predicts path length are not a function of committee size influencing density. The fact

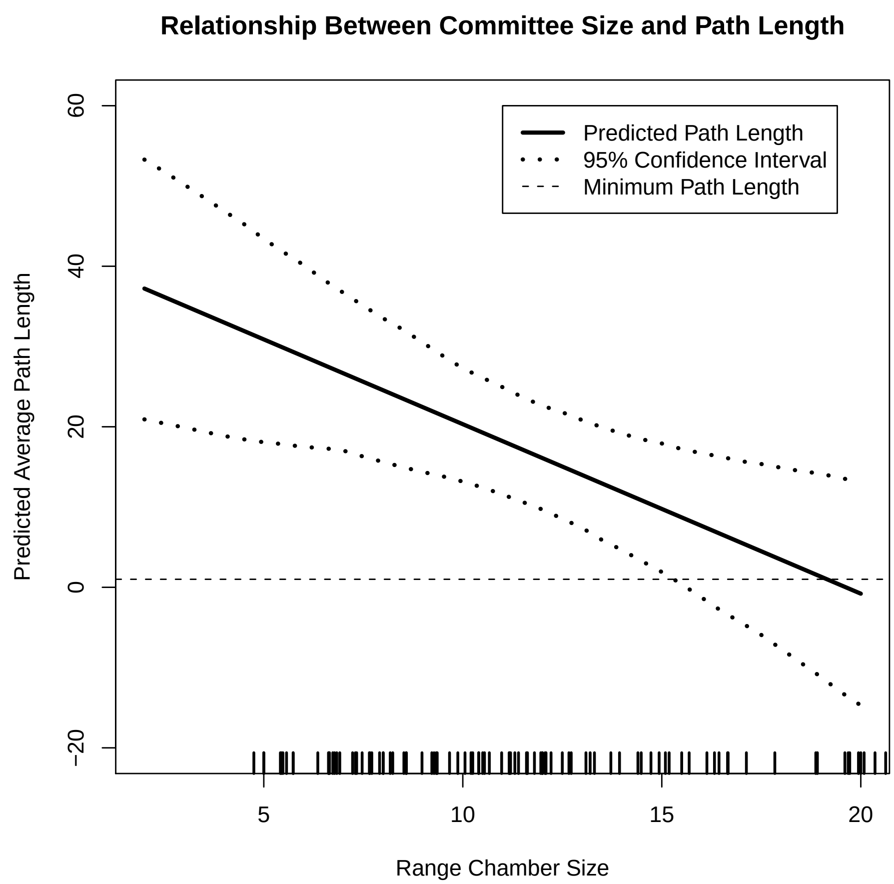

Figure 4.9: Network Path Length and Committee Size in State Legislatures

Figure 4.9 plots the predicted average path length of a state legislative cosponsorship network as the average committee size increases. Controlling for the other variables in the model, increasing committee size from a 12 member committee to a 15 member committee is associated with a decrease in the average path length from 25.686 to 22.527 for a 75 person legislature. Thus, the change in committee size has decreased the number of transmissions a piece of information must pass through to reach the entire chamber by three ties. Information or influence at any point in the legislative network can now move to the rest of that network more efficiently.

Taken together these results indicate that as legislative chambers get larger, parties become more powerful predictors of network formation and legislative networks become less efficiently organized as indicated by the increase in path length for large chambers.[27] Alternatively, the average path length model indicates that when committees grow in size legislative networks become more efficient. Committees, however, have no effect on the overall partisanship of the network. All of these results are in keeping with a model of network formation where legislators learn new information about their colleagues through specialized committee interactions.

4.6 Discussion

This study is the first to consider that the collaborative network of a legislature is a function of the institutions of the chamber. I have argued that the difficulties in partner

that network density is negatively related to chamber size could be taken as further confirmation of the theory. Commitments to support legislation simply become less common when chambers become larger because the uncertainty surrounding commitments becomes weaker. I elaborate on these results in the appendices to this article.

[27] I have also calculated these models as seemingly unrelated regressions to allow for correlation in errors of the models that may results from extracting data for each model from the same cosponsorship network. These seemingly unrelated regression results mirror those from the ordinary OLS models I present. The correlation of the residuals is a relatively low 0.128.

selection exert a strong influence over collaboration between legislators and that legislative institutions can exacerbate or mitigate these difficulties. Changing chamber size and committee assignments can alter the ways in which legislators interact and work together. Committee interactions and committee outputs provide legislators with information about other legislators' preferences on multiple dimensions and reveal similarities that allow for more confidence in commitments to collaboration and support, thus facilitating bridging ties that create more efficient networks. Large legislative chambers, alternatively, obscure these preferences and create a reliance on party to structure partner selection, in turn creating less efficient networks.

Regression results from 96 cosponsorship networks across state legislative chambers indicate that aggregate patterns of cosponsorship are responsive to legislative institutions in predictable ways. As expected, large chambers encourage collaborative relationships defined by political party. Large chambers also lack the bridging relationships necessary to generate the most efficient distribution of the network. Increasing committee sizes can mitigate this effect and generate a more efficiently distributed network with shorter distances between legislators. However, the organizational power of committee interactions is limited. These results seem to indicate that committees are useful ways of revealing information about potential collaborative partners that legislators might not otherwise learn. By forcing interactions with other legislators, committees encourage ties that might not otherwise exist.

These results have important implications for the study of legislative interactions and the study of polarization in legislatures. Research has consistently demonstrated that legislative interactions play a critical role in determining when and what legislation passes the veto points of a chamber (Kirkland 2011, Fowler 2006, Peoples 2008). Also, if we take the notion of cosponsorship as evidence of a commitment to support legislation that can reap both punishment and reward, then the notion of more bipartisanship in this network seems key. Producing bipartisan commitments to support legislation may smooth legislative deliberation and help limit the possibilities of gridlock. The results I have presented indicate that the environment in which they occur conditions these relational interactions and commitments. Even when none of the attributes of individual legislators or powers of the political parties change, the simple size of the groups legislators interact within plays a key role in determining their subsequent legislative behaviors. Thus, taken with other efforts, this research suggests that there are relational determinants of legislative outcomes, institutional determinants of legislative outcomes, and institutional determinants of legislative relationships.

Additionally, scholars of legislative polarization have failed to appreciate that the size of a chamber can increase or decrease partisan divisions in observed behaviors. Large chambers create an informational environment that is difficult for individuals to navigate. This difficulty increases the reliance of individuals on simple heuristics for decision-making the most prominent of which is likely to be party. Additionally, inherent in most of the work on polarization is the notion that parties are not just far apart in ideological space, but that they are also uncollaborative across this divide. This research and the cosponsorship networks generated for it provide a measure of that collaboration which includes independent variance from floor voting behavior and can allow researchers to assess both distance between parties in floor voting and collaboration between parties at earlier stages.

Finally, the spatial model I have developed is general to many human social networks. The basic elements of the model dictate that people form connections with others based on similarities and that specialized group interactions can facilitate learning about others and the development of social connections that might not otherwise exist. When any network becomes overly large, the actors in the network will begin to rely on the clearest cues available regarding similarity. Networks become more segregated even when the characteristics of the actors themselves have not changed. Specialized group interactions can generate connections based on less obvious and more difficult to learn similarities. Though there are several extensions to my model that can be developed, these size-based effects are likely to extend to many types of social networks.

Chapter 5

Hypothesis Testing with Network Partition Quality Statistics

The quantitative analysis of social networks has experienced a large increase in popularity over the last 10 to 15 years. As the tools for such analysis have become easier to access and more efficient to use, more social scientists have adopted a social networks perspective as a potentially useful lens through which to examine human behavior. With this advance in a networks perspective have come a number of new tools for analyzing and measuring constructs of interest in networks. Unfortunately, many of these new measures lack clear ways to assess the uncertainty inherent in any single sample of a network. This lack of clear measurements for uncertainty in network summary statistics is due at least in part to a lack of understanding regarding the distributional properties of networks and their summaries.

Fortunately, as computational power increases and nonparametric techniques like bootstrapping and permutation testing become more popular, the need for researchers to rely on established probability distributions as references for their statistics is diminishing. This holds particular promise for scholars of social networks who wish to engage in hypothesis testing on their network summaries. In this article, I demonstrate how a researcher might use permutation testing to assert whether or not a particularly popular network summary statistic, network modularity, is different than might be expected at random. The permutation test proves to be a useful way to assert when modularity is unusually large given the variance in a single measurement of a social network and when an observed modularity score might be due to random chance.

After introducing and providing a simulation-based analysis of the permutation test, I provide a demonstration of that test using real world data on the network of cosponsorships in U.S. state legislatures. This practical demonstration provides a quick and understandable measure of how the major political parties of the United States structure the collaborative activities of state legislators, and when that structuring is unusually powerful. I also offer a second demonstration using international trade networks. This analysis indicates that there is only a very brief window in which international trade is unusually well defined by regime type. While regime type modularity in the international trade network varies quite a bit, it is only in the period just prior to World War II where regime type partitions the trade network better than expected due to random chance.

5.1 Measuring Partition Quality with Network Modularity

Community detection is the act of partitioning or dividing a social network into distinct subgroups. Community detection algorithms attempt to partition networks so that there are dense connections between all the actors in a subgroup (or *community*) and sparse connections between actors of different subgroups. A community is then the set of actors within a single group in an optimal partition of the network with the implied assumption that something unique about that group of actors caused their within group cohesion and has set them apart from the other groups. Scholars have developed a variety of approaches to discover communities in an observed network (Newman 2003, Newman 2004, Newman and Girvan 2004, Pons and Latapy 2005, Newman 2006, Reichardt et al. 2006, Raghaven, Albert and Kumara 2007).[1] Most, if not all, community detection routines rely on quality statistics to assert which potential network partition is the best, and thus, represents the "true" community structure.

To measure the quality of network partitions, scholars of social networks typically use the popular quality statistic modularity (Newman and Girvan 2004, Newman 2006).[2] Modularity is usually defined as the number of ties within a group compared to the number of ties that might be expected at random.[3] With the most common definition of "at random" in place, this simplifies to a measure of the number of ties within a group relative to the number of ties between any two other actors in the network. The mathematical formula for network modularity using the industry standard definition is:

$$Mod = \frac{1}{2m} \sum_{ij} [A_{ij} - \frac{k_i k_j}{2m}] * \delta(c_i, c_j) \tag{5.1}$$

where m is the total number of connections in the network, A_{ij} is the connection between actors i and j, k_i is the total number of connections actor i has, and $\delta(c_i, c_j)$ is the Kroneker delta for communities of actors i and j.[4] Thus, modularity examines all the actors in the same community ($\delta(c_i, c_j)$), adds up their connections with one another (A_{ij}), and subtracts the connections we might expect those actors to have in the network generally ($\frac{k_i k_j}{2m}$). Finally, the sum of all these components is normalized by the total number of connections in the network ($\frac{1}{2m}$). In networks with edge weights, where

[1]The *igraph* package for social network analysis has six different algorithms for community detection (Csardi and Nepusz 2006).

[2]The initial article debuting modularity by Newman and Girvan (2004) has more than 2100 citations as of 2011.

[3]The precise definition of what "at random" means can vary a bit depending on the questions in which an analyst is interested. It is generally considered to be the number of connections (called edges) within groups if a network with the same communities had the same number edges placed between dyads randomly.

[4]Kroneker's delta is a mathematical operation which returns a value of 1 if the two numbers within the operation are equal to one another and zero otherwise.

connections between actors take on more than a zero or a one, the calculation is very similar. In these weighted networks, A_{ij} becomes the connection strength between i and j, m becomes the sum of all the edge weights in the network, and k_i becomes the total weighted connections of actor i.

Modularity values range between -1 and 1. A value of 1 occurs when no ties cross community lines and all the ties within a community are realized. A value of -1 occurs when no ties within a community are realized and all the possible ties across communties occur. It is possible for modularity to take on a value of precisely zero, which occurs when all the ties in a network are realized.[5] However, as I will demonstrate in the next section, finite samples and stochastic social behaviors can generate non-zero modularity values even in networks where no real community structure exists.

5.2 Simulating a Reference Distribution for Comparison

While the point estimate of modularity is derived relative to some null model, the modularity score itself communicates nothing about the distribution of modularity under that null model. In order to provide a sense of the degree to which an observed modularity score reflects something unusual for a given network, analysts require some sense of the baseline level of modularity that might be observed at random in that network. By generating a reference distribution for modularity in a given network, scholars can develop a better sense of the degree to which a division partitions the network unusually well. A

[5] Thus, all the ties within communities and across communities occur. This means that modularity is *not* a true probabilty distribution. Technically, it is a discrete measure, that can only take on a finite number of values because there are only a finite number of possible community structures in any particular network.

useful avenue for generating reference distributions for modularity is permutation (Erikson, Rader, and Pinto 2010, O'Gorman 2005, Edgington and Onghena 2007). Using permutations of actors' attributes that could potentially divide a network, an analyst can simulate a random distribution of modularity for a particular social network and a particular attribute.

The permutation test works as follows. First, an analyst measures a network and either through theoretical insight or community discovery develops a partition of interest for the network. That partition of interest provides a modularity score, but the analyst would like to know whether that modularity score is better than one might expect at random (implying that the partition is better than one might expect at random). The analyst then takes the community memberships defined by the partition and rearranges them amongst the actors, maintaining the size of groups, but randomly assigning each actor to a new community. This new partition with randomly assigned community memberships also produces a modularity score. This random assignment to communities is done hundreds (or perhaps thousands) of times and a distribution of modularity scores emerges.[6] Table 5.1 provides an example of a partition and its implied membership permutations.

The permutation approach to generating reference distributions scrambles the co-memberships while maintaining hypothesized group sizes and all the measured connections in the networks.[7] Thus, the permutation approach is operating on the $\delta(c_i, c_j)$ of the initial modularity equation. This means the summation is including randomly chosen actors, but maintaining the size of the groups the summation adds up. None of the other

[6]Technically, the permutation approach does not develop a continuous reference distribution. Because there are only a fixed number of permutations for any vector, there are also only a fixed number of possible modularity reference values. However, for any network of at least 40 actors there are more than 100,000,000 possible permutations of two different communities with 20 actors in each.

[7]In my discussions, I work with a community structure of two groups, but community structures can contain many more than two groups. Permutations scramble the co-memberships by relabeling the memberships of the actors.

Initial Memberships	Permutation 1		Permutation T
1	1	...	0
1	0	...	0
1	1	...	0
0	0	...	1
0	1	...	1
0	0	...	1

Table 5.1: Permutations of Known Network Partition

elements in the modularity equation are disturbed. The range of modularity values generated by the permuted membership vectors allows an analyst to observe the non-zero modularity values that a random membership vector might generate and compare the observed modularity to this range.

5.2.1 A Simulation for the Permutation Reference Distribution

A simple test of the approach I outline might ask 1) does modularity increase as connections within groups strengthens and 2) can the permutation reference distribution identify when non-zero modularity is due to chance?[8] To answer these questions, I simulate networks with varying in-group connection strengths and assess modularity and its reference distribution. First, some n set of actors are randomly assigned to g groups. Then I generate a network of connections between the actors. Actors not in the same group have some baseline rate of connection, α, and actors in the same group have some increased rate of connection α plus a bonus value, β. I then draw a single observation from a Poisson distribution using the rate of connection between two actors as the λ parameter for the dyad. This generates a network of count connections between actors

[8]The question of whether modularity does the task its designed for has been answered before, but is a useful verification step and helpful for introducing modularity to those unfamiliar with the statistic.

where actors in the same group are likely to have higher connection levels, but not guaranteed. Actors not in the same group are also likely to have some level of connection between them, but because their connections come from a probability distribution, they may have very large connections or no connection at all. This mimics the probabilistic nature of network formation in networks with some true community structure and some random noise.[9] Figure 5.1 provides a graphical representation of this process in a network of six actors in two groups of three.

Once I have simulated a network based on group membership, I measure the group modularity of the count network for the initial group assignments and the reference distribution of group modularity using 1000 permutations of the group assignments. This represents one iteration of the simulation. I perform 500 iterations of this procedure for some fixed bonus value. Next, I increase the bonus value providing actors in the same groups with a higher rate parameter, and thus, an increased likelihood of a large connection. I have two expectations for these simulations. First, as the bonus value for within group connection strength increases, the group modularity score should also increase. This would indicate that modularity is doing its job well measuring higher quality partitions when group membership is a stronger determinant of network behavior. Second, when the bonus value of within group membership is zero, the observed modularity score will be contained within the reference distribution of modularity generated through the permutation of group membership. When the within group bonus value is zero, the probabilistic translation of group membership into network behavior may produce nonzero modularity scores. The reference distribution of modularity I generate will indicate when the observed modularity score is a result of effective network divisions and when the modularity score is a result of the stochastic nature of social behaviors.

Figure 5.2 presents results from a simulation using 50 actors randomly assigned to

[9]This is the same process used to test the "fastgreedy" algorithm by Newman and Girvan (2004), but with count edges instead of binary edges.

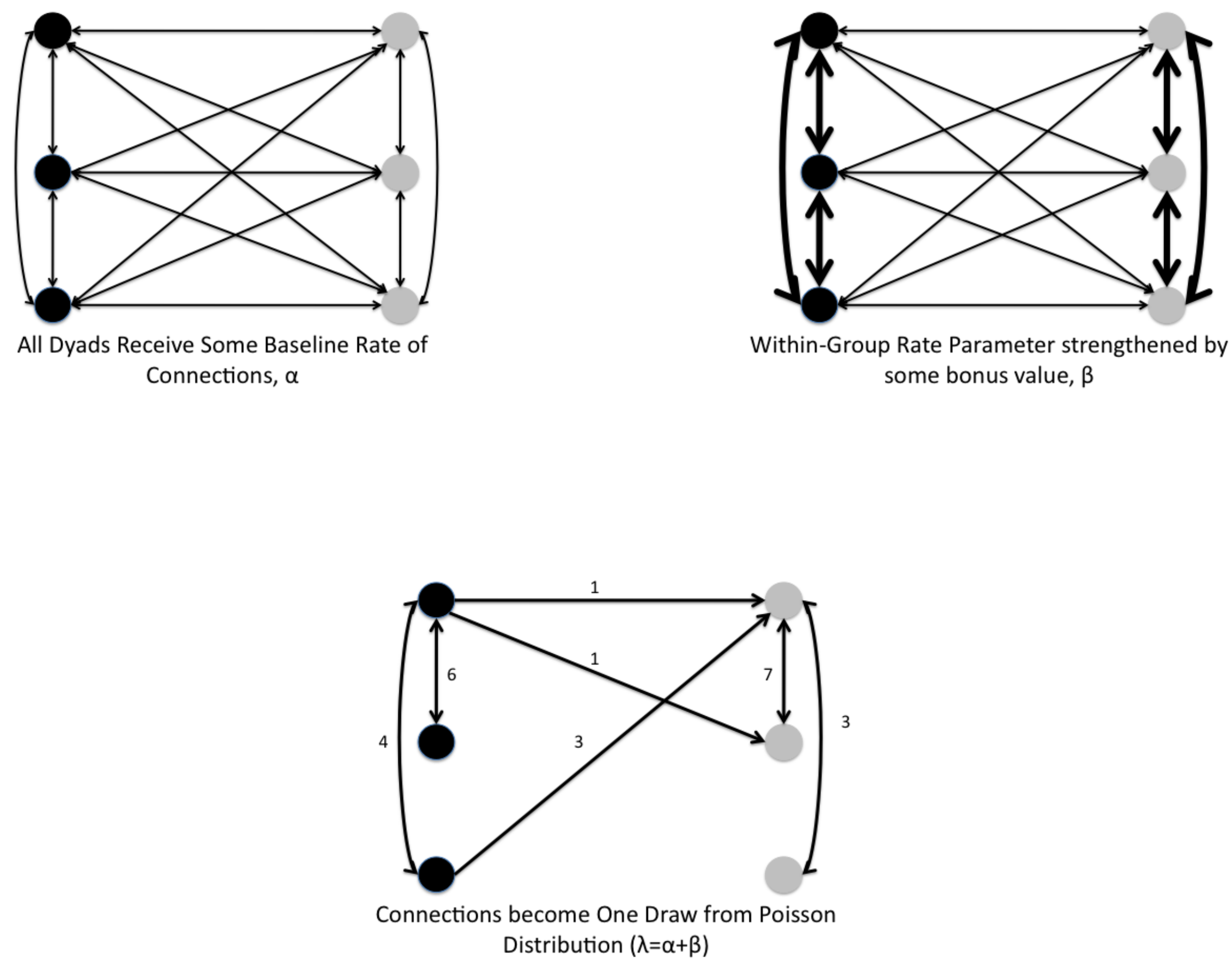

Figure 5.1: Simulating Networks with Community Structure

three groups. The baseline rate of connection α is one, and the bonus value for two actors being in the same group varies from 0.5 to 3.0. Thus, the λ parameter passed to the Poisson distribution varies between 1 and 4. To give these numbers some magnitude, the average connection strength between actors not of the same group across all the simulations is 0.98. The average strength of connection for actors in the same group when the bonus value is 0.5 is 1.475. The average connection strength for members of the same group when the bonus value is 3.0 is 4.005. An α of one was selected to minimize the odds of the simulated networks containing actors completely unconnected from the remainder of the network. These isolated actors present unique challenges in community detection since there is no way to evaluate whether they belong to *any* potential community. Figure 5.2 nicely reflects the expectation that as within group connections become more distinct from out-of-group connections, modularity indicates a higher quality partition of the network. Thus, modularity is performing its designated task well. Additionally, Figure 5.2 also indicates that for all the positive bonus values of within group connections, modularity never overlaps with the reference distributions I generate. This indicates that Type I error (accepting the null hypothesis when the alternative of group structure is true) is unlikely to occur using the permutation approach. When an attribute is a true division of a network, modularity will reveal its quality and the reference distribution will not cause scholars to question it.

Figure 5.3 presents the same results at a much closer level and includes the results for modularity scores and the reference distribution of modularity when the within group bonus value equals zero. When this value equals zero, the rate of connection within groups is the same as the rate of connection between groups. In this circumstance, I expect that modularity will generate non-zero values due to the stochastic generation of the network (though they should remain close to zero). These non-zero modularity scores should frequently overlap with the reference distribution of modularity, indicating that

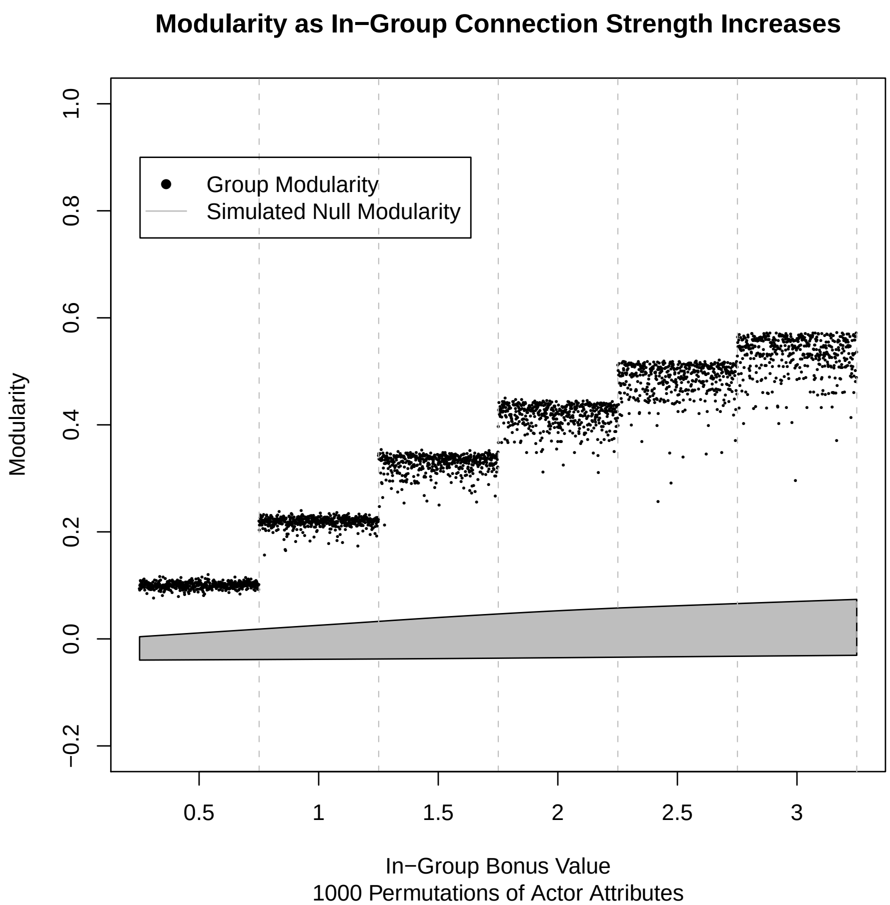

Figure 5.2: Observed Modularity Score and Null Modularity Region as In-group Connection Increases

while modularity may be non-zero it is no different from a modularity score expected at random.

This is precisely what I observe in Figure 5.3. When the within group bonus value is zero, the reference distribution of modularity covers the entire range of the non-zero modularity scores that the probabilistic networks generated. The size of the reference distribution would grow as the number of permutations increased. As the in-group bonus value increases from zero, the distance between the reference distribution of modularity and the observed modularity score increases. Modularity will appear less like a draw from a random distribution the more an attribute divides the relevant network well. Thus, this permutation approach to assessing uncertainty in modularity scores is valuable in discovering when modularity might not just be large or small, but when modularity might be larger or smaller than expected at random.

5.3 An Example from State Legislatures

To provide a practical example from applied research, I utilize modularity and its reference distribution to determine the degree to which party structures the collaborative activities between legislators in U.S. lower state legislative chambers. Political parties have long been noted to structure the individual behavior of legislators in office, and research on the patterns of legislative interaction has also demonstrated that the relationships between legislators can largely be predicted by political party affiliation (Caldeira and Patterson 1987, 1988, Clark, Caldeira, and Patterson 1993, Sarbaugh-Thompson, et al. 2006).

To determine the power of party in structuring collaborative activity, I utilize a unique data set of cosponsorship networks between state legislators in lower chambers for the year 2007. An edge exists between two legislators ij if legislator i has cosponsored a bill sponsored by legislator j. I measure cosponsor-sponsor connections for every bill

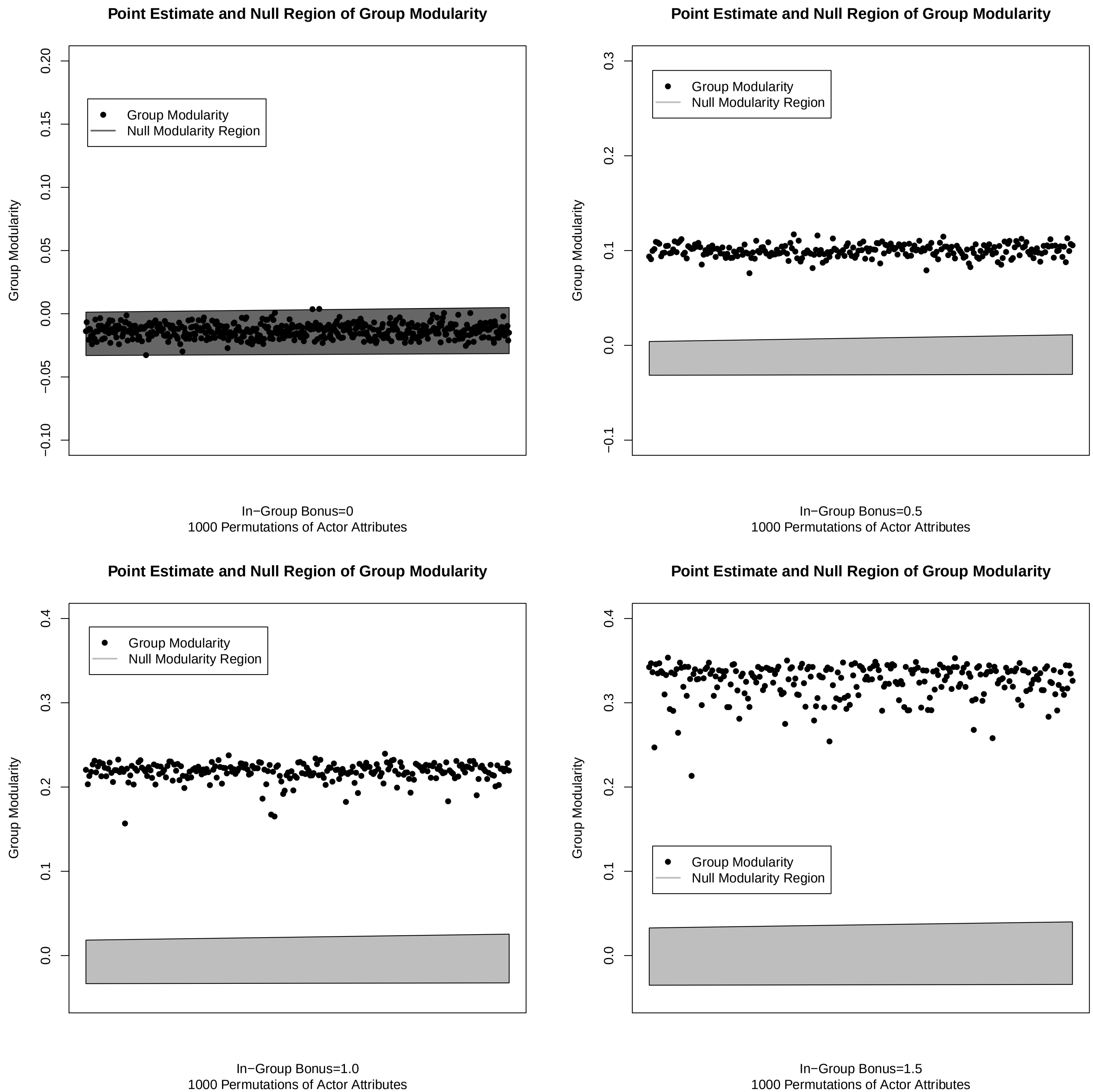

Figure 5.3: Group Modularity Scores and Null Modularity Region Created by 1000 Permutations for Simulated Networks

introduced in the calendar year of 2007 (Kirkland 2011, Fowler 2006a, Fowler 2006b). No resolutions are considered. This results in 48 social networks comprised of counts of cosponsorship between legislators.[10] I then record the political party affiliation of each legislator in the chamber. Using the modularity function from the *igraph* package in the R statistical language (R Core Development Team 2008, Csardi and Nepusz 2006), I assess the quality of political party as a division of the cosponsorship network along with the null distribution of modularity that results from permutations of the party affiliation vector.

Figure 5.4 presents the results of measuring party modularity for the lower state legislative chambers. Each point represents the actual modularity measurement for party in a particular state's lower legislative chamber cosponsorship network. The grey bar represents the reference distribution of modularity for the state's cosponsorship network generated by 1000 permutations of the party membership vector. Notice the two states indicated by the arrows in the plot. The point furthest to the left is the measurement of party modularity for the Hawaii lower legislative chamber and the indicated point further to the right is the measurement of party modularity for the North Dakota lower legislative chamber. Ignoring the null distributions momentarily, an analyst encountering these two results would be reasonable in assuming two things: 1) North Dakota's legislative network appears to have a larger party modularity score, therefore 2) North Dakota's legislative network is *more* structured by party than the Hawaii's legislative network is.

The empirical evidence warrants the first of those two statements. The party modularity score for the North Dakota legislative network is larger than the party modularity score for the Hawaii legislative network. However, the second of those two statements represents an incorrect inference. Using the reference distributions of modularity for each

[10]Nebraska is unicameral. Scholars typically treat its lone chamber as a Senate (Wright and Schaffner 2002). It is also non-partisan, meaning it can have no party modularity score. Additionally, the Idaho legislature did not actually record cosponsorships until 2009. While I have obtained that data to complete the data set, for comparability reasons I do not present it here.

state's cosponsorship network, this analysis indicates that party structures the Hawaii cosponsorship network. The party modularity score for the Hawaii legislative network falls just outside the range of modularity scores for randomly drawn divisions of the network of the same size. The North Dakota cosponsorship network is no more structured by party than it would be by a random division of the social network.

Figure 5.4 uses the entire range of the simulated reference distribution for modularity. This means that outliers from the distribution may cause a rejection of a particular partition as effective. Some analysts may prefer to use 95% of the density or 99% of the density of the reference distribution in an effort to mimic a traditional cutpoint for a hypothesis test. Figure 5.5 presents the same data as Figure 5.4, but now includes indicators for both 99% and 95% of the density of the simulated reference distribution. These regions represent the bulk of the density of the simulated reference distribution rather than the entire simulated distribution. Notably, in several places (Oklahoma and North Dakota), use of the entire reference distribution would cause an analyst to accept the hypothesis of no partisan structure, while the 99% region would allow an analyst to comfortably reject the hypothesis of no partisan structure. Ultimately, the choice of using the entire simulated reference distribution or some subset is analogous to the somewhat arbitrary choice of p-values in a hypothesis test and is best left in the hands of the applied researcher.[11]

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[11]Figures 5.4 and 5.5 demonstrate that the size and location of the permutation reference distribution change from network to network. In the supplemental appendices to this article, I provide an analysis of the properties that influence the size and location of the distribution. In summary, the density of the network, the size of the subgroups in the network, and the true level of modularity in the network all exert influence over the properties of the reference distribution.

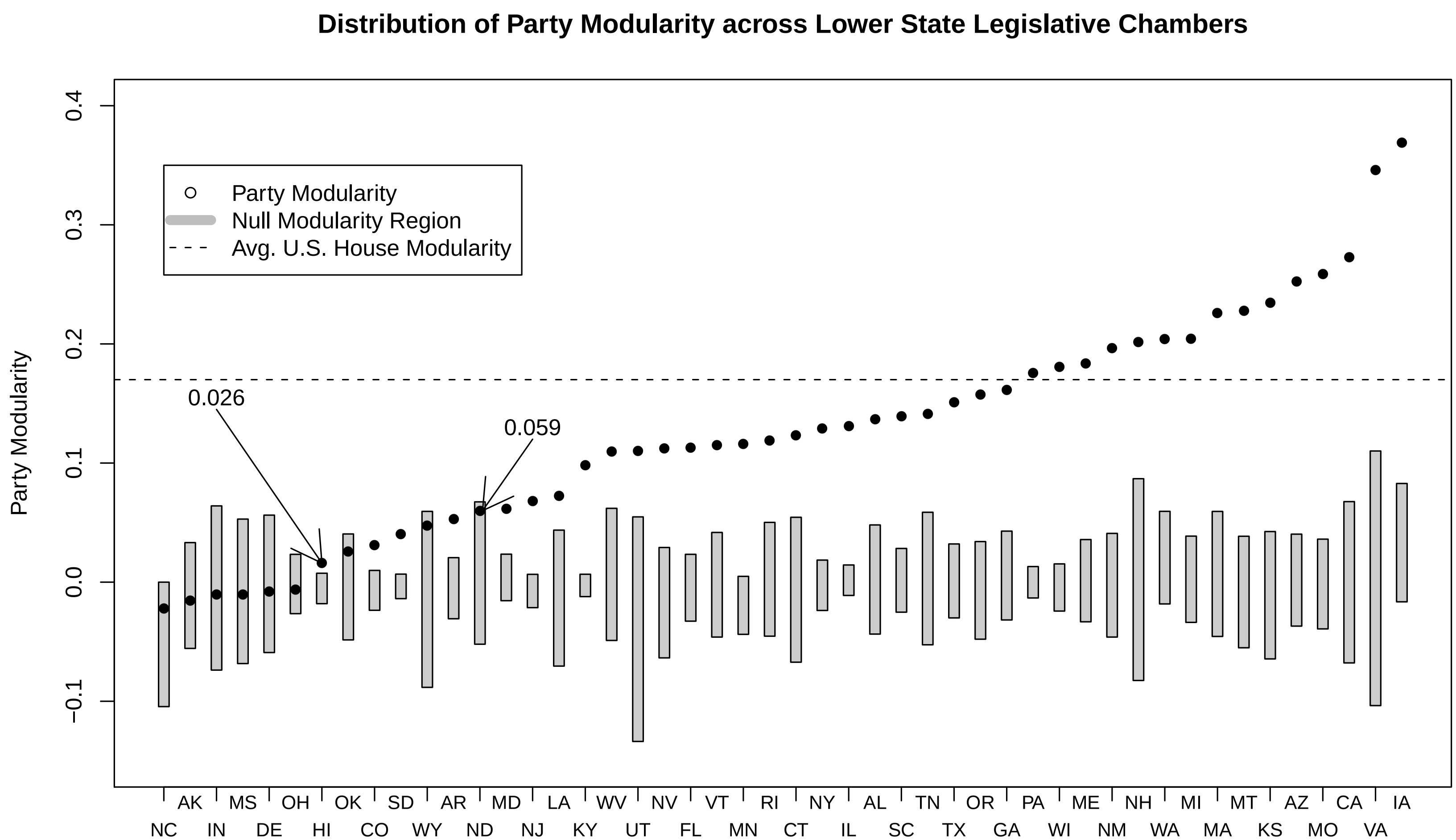

Figure 5.4: Reference Distribution for Party Modularity for State Cosponsorship Networks

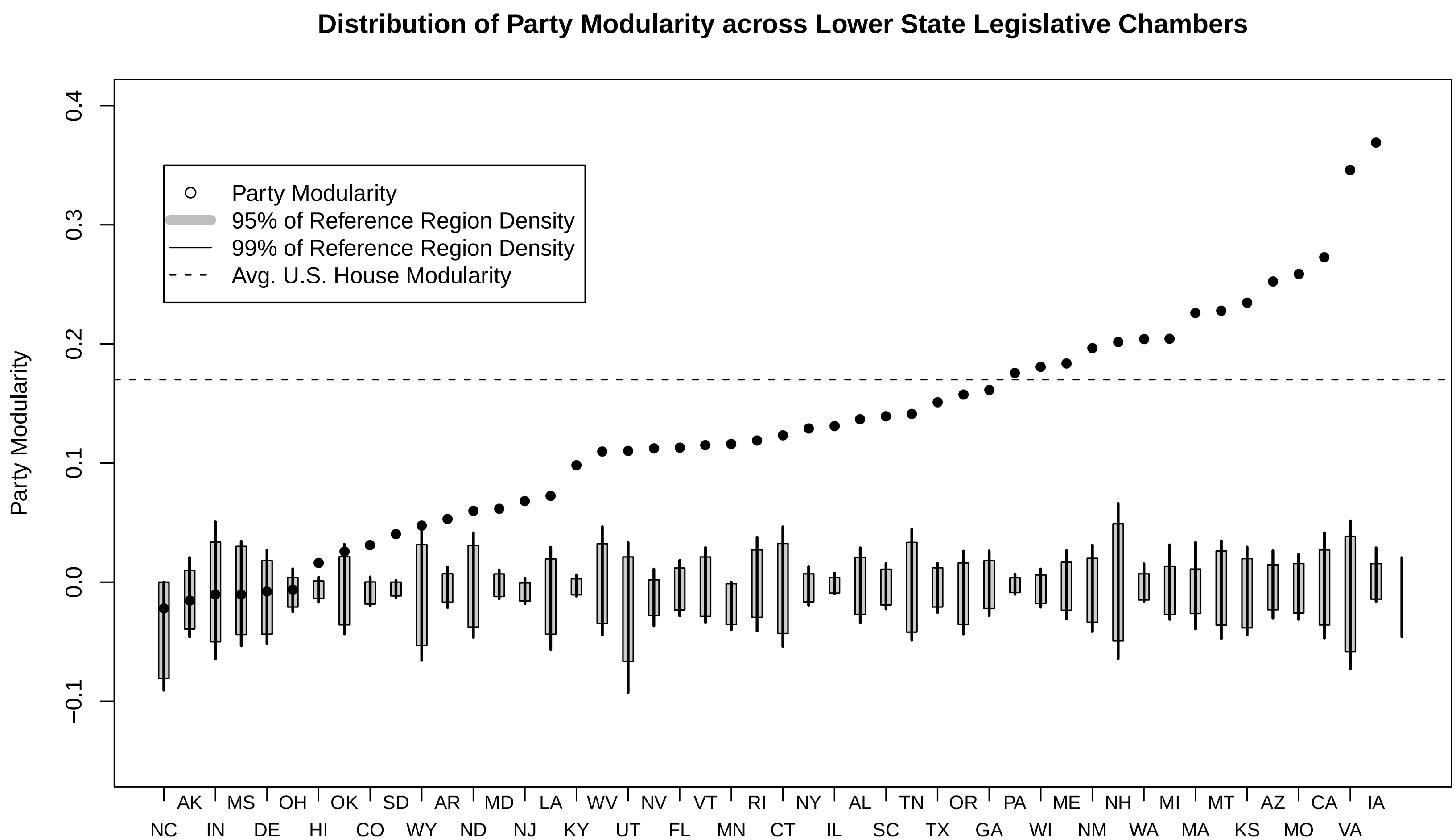

Figure 5.5: 95% Reference Distribution for Party Modularity for State Cosponsorship Networks

5.4 An Example Using International Trade

A common hypothesis in the analysis of international trade is that democracies will trade with other countries more often, and that they will more commonly trade with one another (Aidt and Gassebner 2010, Mansfield, Milner, and Rosendorff 2000, Mansfield, Milner, and Rosendorff 2002, Morrow, Siverson, and Tabares 1998, Yu 2010). This immediately implies that the international trade network should have high modularity along the political regime dimension. Democracies having unusually strong trade connections with one another would lead to clustering in the trade network amongst democracies with autocracies either being isolated from all other countries or being highly clustered themselves.

To test this hypothesis, I utilize the Correlates of War dyadic trade data set to construct international trade networks from 1870 to 2006 (Barbieri, Keshk, and Pollins 2009). I then categorize country-year observations using Polity IV measures of regime type (Marshall and Jaggers 2007). While it is possible to use the raw Polity IV scores as the categories themselves, this may be an overly specific category scheme. Instead, I collapse Polity IV scores into three categories, one if a country-year Polity IV score if greater than zero, a second if a country-year Polity IV score equals zero, and a third for country-year Polity IV scores less than zero.[12] I then use this category scheme to test whether countries with similar Polity IV scores are more likely to have strong connections with one another than not. The results of this analysis are presented in Figure 5.6. As the figure indicates, while the actual polity-based modularity scores of the international trade network vary quite a bit, they are virtually never distinct from the modularity reference distribution generated through permutations. This means that the polity categorization scheme I employ rarely divides the international trade network better (or worse) than a

[12]While it is possible to use the raw Polity IV scores as a set of categories, R's modularity formula struggles with negatively valued category assignments.

random division of the international trade network would.

While across the majority of the series regime type fails to separate the trade network better than random chance, there is a brief period prior to World War II where polity scores do seem to be effective partitions. In 1935, 1936, 1937, and 1938 the permutation test indicates that countries with similar Polity IV scores are more likely to have strong connections with one another (and weak connections with countries of dissimilar Polity IV scores) than would be expected due to random chance. This may be a result of the simplification of categories I employed. Thus, to guard against a faulty inference based on a categorization choice, Figure 5.7 presents results of permutation tests using three different categorization schemes based on Polity IV scores for the period of 1935-1945. The first panel of Figure 5.7 uses the same scheme as Figure 5.6. The second panel uses two categories, pooling Polity IV scores of 0 with the positive polity scores category. The third panel uses a four category scheme where Polity IV scores greater than 5 are a group, scores between 0 and 5 are a group, scores between -5 and -1 are a group, and scores less than -5 are a group. In each of these schemes, similar polity scores seem to divide the network effectively. Thus, from 1935-1938, the international trade network seems to be partitioned effectively by regime type, while in all other time periods regime type does not seem to drive trade partner choices.

Figure 5.7 also helps emphasize the important point that an increase in the magnitude of a modularity score does not necessarily imply a more effective partition than random chance would generate. The absolute value of the modularity scores from 1939 to 1945 is greater than the absolute value of modularity scores from 1935 to 1938, but the size of the region of modularity scores expected due to random divisions of the network is much larger in this later period.[13] Thus, it is the period of 1935-1938 that seems to have

[13]The supplemental appendix to this article contains a discussion of network attributes that cause this wider gap. The 1939-1945 period has much larger modularity reference regions because the trade networks in this period are extremely sparse networks.

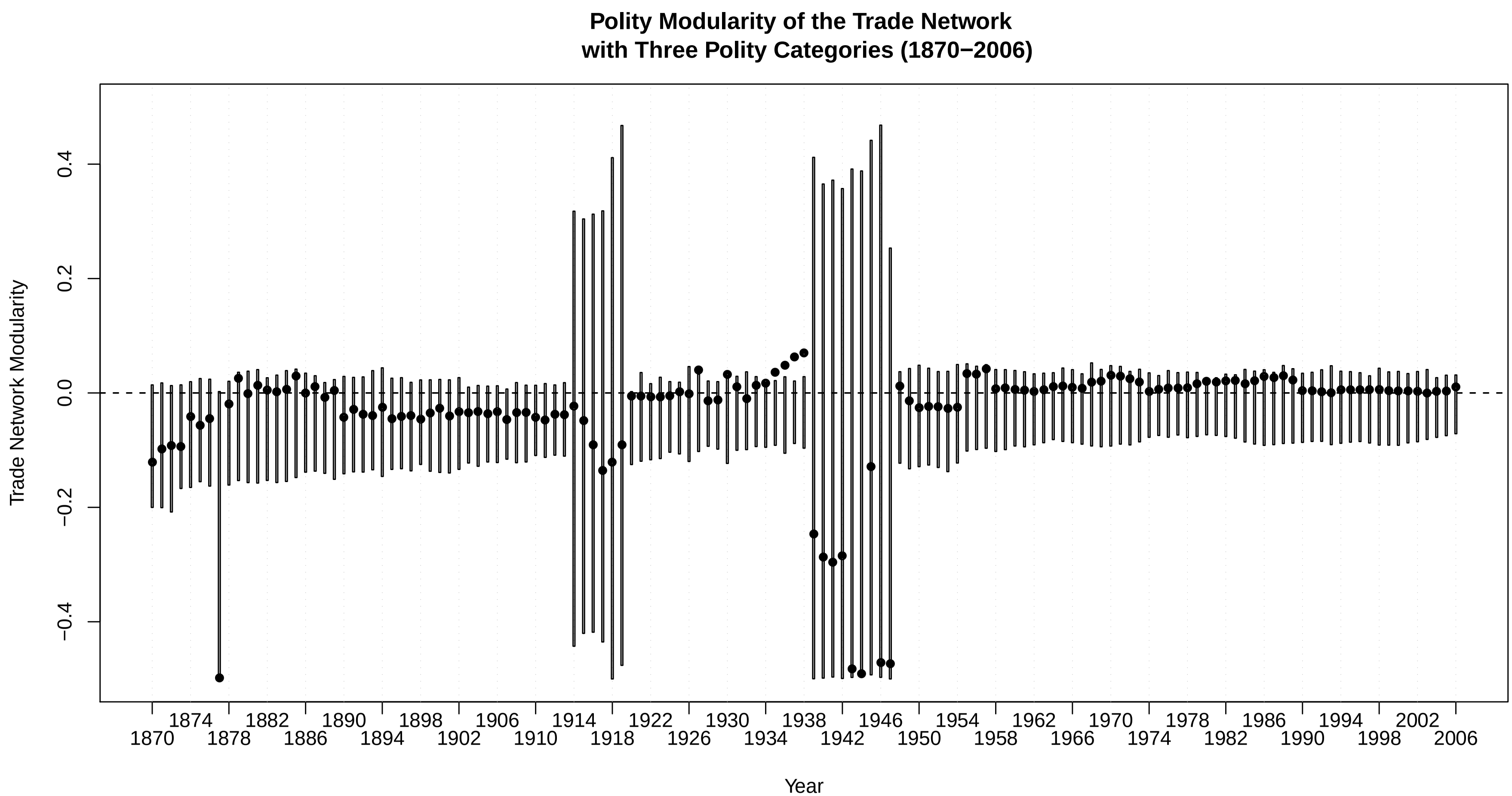

Figure 5.6: Polity Modularity and Reference Distributions for the International Trade Network with Three Categories (1870-2006).

a modular international trade network well-partitioned by regime type.

5.5 Properties of the Simulated Random Distribution

Several interesting things emerge from Figure 5.5 that warrant further explanation. The reference distributions across the state cosponsorship networks are of different sizes, as are the 95% densities of the reference distributions. Additionally, the reference distributions are centered close to zero, but vary in their actual locations. In order to understand why these elements of the reference distribution change, I will work through each piece of the modularity equation and demonstrate its impact on the subsequent reference distribution.

As indicated earlier, the mathematical formula for network modularity is:

$$Mod = \frac{1}{2m}\sum_{ij}[A_{ij} - \frac{k_i k_j}{2m}] * \delta(c_i, c_j) \tag{5.2}$$

The first term of the equation is $\frac{1}{2m}$, where m represents the number of connections (or "density") of the social network of interest. As m approaches its maximum, this normalizing fraction becomes an increasingly smaller number. Regardless of what is added together by the summation, it will be multiplied by an increasingly small quantity as the network becomes more dense. Thus, as network density increases, the resultant modularity reference distribution should collapse towards zero.

Figure 5.8 provides the results from a simulation testing this hypothesis. In the simulations, there are 50 actors assigned to two groups with equal probability. The connections between the actors are governed by a Poisson distribution with a baseline rate of connection, α, and some group bonus value, β. In these simulations β=0, but α varies from -0.5 to 1.0 in increments of 0.5 with 500 simulations for each value of α. When α is low, the network is extremely sparse. When α is higher, the network has greater

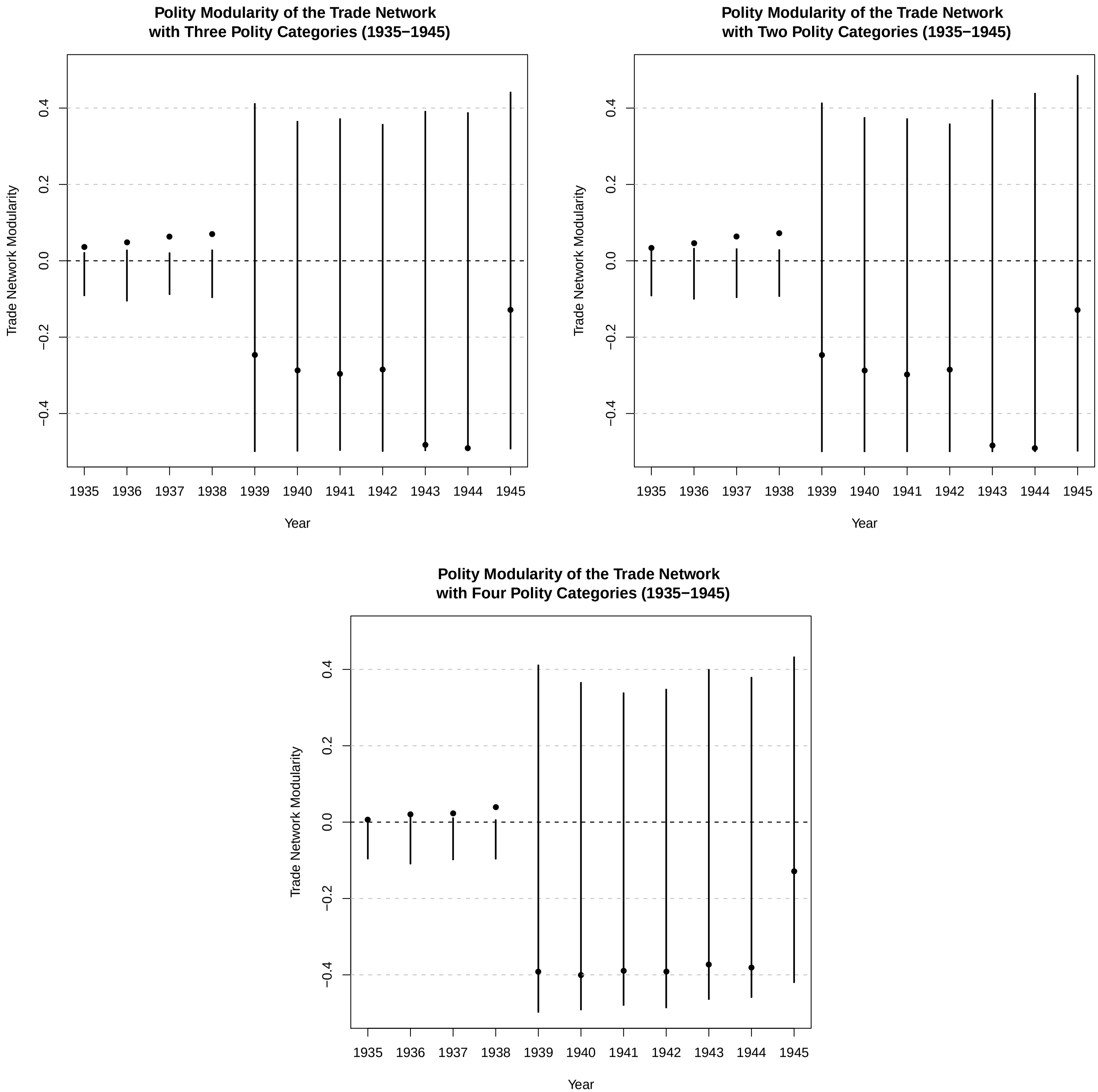

Figure 5.7: Polity Modularity and Reference Distributions for the International Trade Network with with Different Category Schemes (1935-1945).

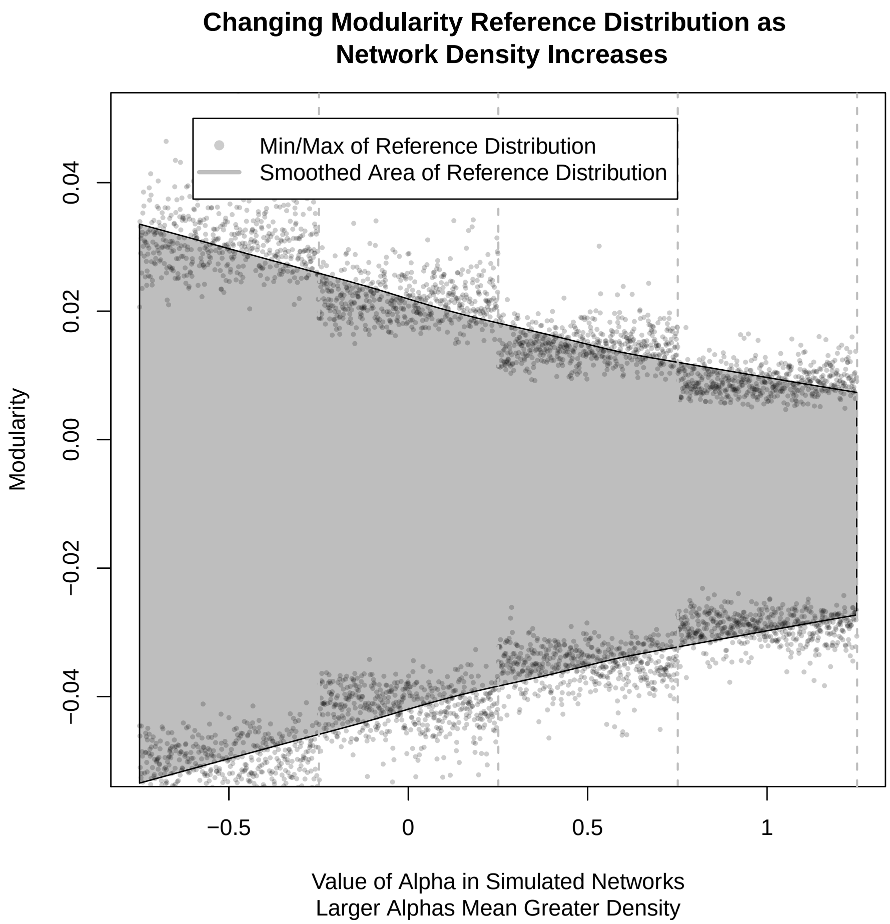

Figure 5.8: Range of the Reference Distribution as Network Density Increases

density. Therefore, in these simulations, there is no real community structure, and I fix the probability of co-membership at 0.5. The density of the network is all that is changing. The grey dots in the figure represent the upper and lower 95% reference distribution limits from each simulation. The grey area represents a smoothed polygon amongst these dots. The figure confirms the expectation that as the density of the network increases, the modularity reference distribution shrinks. Thus, modularity values in sparse networks face a more difficult test in order to be distinguished from randomly drawn partitions of the network than do modularity values in dense networks.

Next, consider $\sum_{ij} \delta(c_i, c_j)$, the third term of the equation. Summed across all potential ij combinations, this value is equivalent to the probability that any two actors from the network chosen at random will be in the same category or community.[14] This value can vary from a minimum of $\frac{1}{NumberofHypothesizedGroups}$ to 1. As this value increases and the probability of two actors being in the same community increases, the possible permutations of the membership vector contain less new information being added to the reference distribution. In other words, there is less possible variance in the permutations of the membership vector as the probability of co-membership goes up. Because there is less variance in the possible permutations of the membership vector there should also be less variance in the resultant reference distribution.

To test this hypothesized relationship, I have again constructed simulated networks of 50 actors in two groups. There is no in-group bonus in the network so connections between actors in the same community are equally as strong as relationships between actors in different communities. However, rather than leaving the probability of assignment to group 1 and group 2 equal, I vary that probability. I change the probability of actor assignment to group 1 from 0.5 up to 0.8 in increments of 0.1 with 500 simulations for each probability value. Thus, the size of group 1 relative to group 2 is increasing across the simulations and the probability of co-membership in the same community is also increasing.[15]

Figure 5.9 plots the results of this simulation. The simulation reveals that as the probability of group 1 assignment increases (increasing the size of group 1 relative to

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[14]For example, the probability that two legislators are of the same party is equivalent to asking what is the probability that $i = Democrat$ and $j = Democrat$ OR $i = Republican$ and $j = Republican$. The probability that any actor selected at random is a Democrat or Republican is simply the size of these groups divided by the network's size. The joint probability that both i and j are Democrats is the product of the individual probabilities, or $(\frac{NumberofDemocrats}{NetworkSize})^2$. Thus, the probability of any two actors randomly chosen from the cosponsorship network being of the same party is given by: $(\frac{NumberofDemocrats}{NetworkSize})^2 + (\frac{NumberofRepublicans}{NetworkSize})^2$.

[15]The probability of two randomly chosen actors being in the same group when the probability of being assigned to group 1 is 0.5 is also 0.5. The probability of co-membership when the probability group 1 assignment is 0.6 is 0.52. When the probability of assignment to group 1 is 0.7, co-membership has a probability of 0.58, and finally, when the probability of assignment to group 1 is 0.8, co-membership has a probability of 0.68.

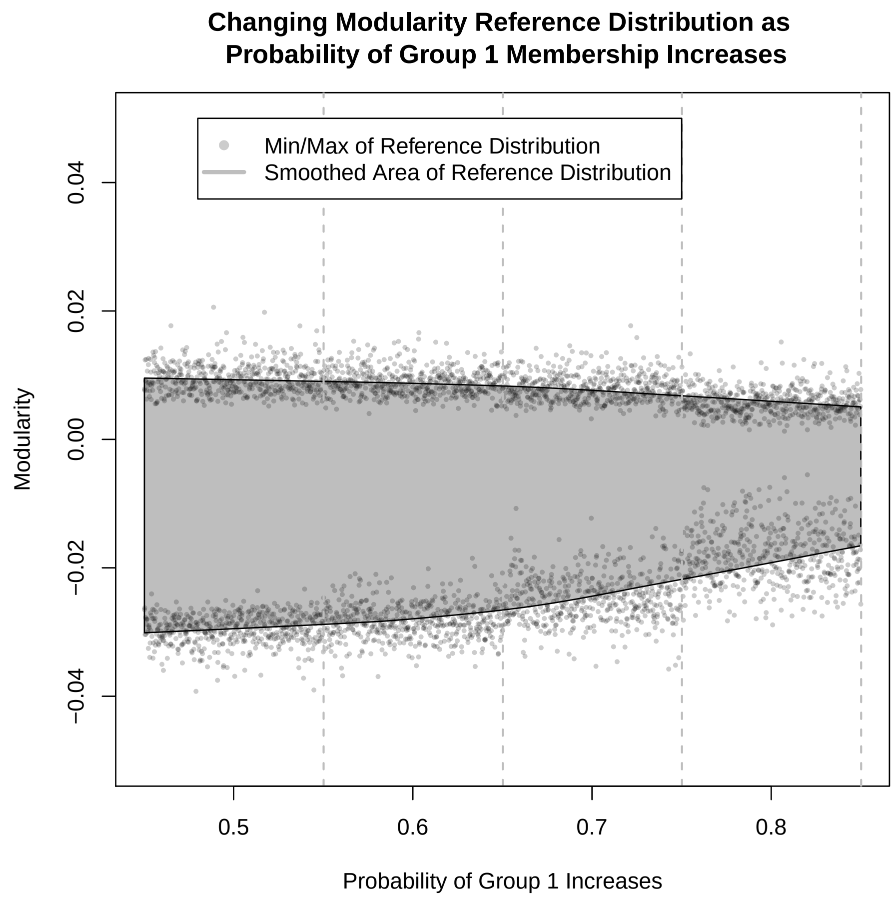


Figure 5.9: Range of the Reference Distribution as the Probability of Being in Group 1 over Group 2 Increases

group 2), the reference distribution for modularity shrinks. This is in spite of the fact that there is no difference in the strength of relationship within groups versus across groups. I also hold network density constant across the simulations. Thus, the relative sizes of the hypothesized communities in the community structure of a network influence the variance of the reference distribution for network modularity. A highly modular network with one large community and other smaller communities is more unexpected than a highly modular network in which the community sizes are relatively equal.

The final piece of the modularity equation is $\sum_{ij}[A_{ij} - \frac{k_i k_j}{2m}]$. Recall that this term is measuring the strength of connections between two actors, A_{ij}, and substracting the strength between those actors that might be expected to randomly occur in the network, $\frac{k_i k_j}{2m}$. To work through the impact of this term on the resultant reference distribution, consider a network with some "true" group structure. If a network has some real group structure (even if it is not the structure currently being tested), then when two actors of *different* groups are added together this value will come to zero. The observed strength of connection between two randomly chosen actors of different communities, and the expected connection strength those actors should cancel out. If two actors are truly members of the same community, and have stronger connections as a result, those two actors will consistently have stronger connections then they are expected to have at random, resulting in a positive value. Thus, when there is a stronger community structure in the network, the summation using random partitions will consistently add together values increasingly greater than zero to values that average out to zero resulting in a distribution centered above zero. This implies that the permutation-based reference distribution will shift upwards as the network being considered becomes more modular.

To test this assertion, I have constructed simulated networks with 50 actors in two groups. Each actor is assigned to group 1 or group 2 with equal probability. As before, the connections between the actors are governed by a Poisson distribution with a baseline rate of connection, α, and some group bonus value, β. The baseline rate of connection α is fixed at 1, but I vary β from 0 to 5 in increments of 1 with 500 simulations for each value. Thus, the network is becoming increasingly modular as β increases, while all the other potential components of modularity are being held constant. Figure 5.10 plots the results of this simulation. The light grey dots represent the minimum and maximum values of 95% of the density of the simulated reference distribution. The dark grey dots represent the midpoint in a single simulation of the permutation reference distribution. The black line is a lowess smooth over these midpoints. The figure demonstrates that as the true modularity of a network increases, the midpoint of the reference distribution increases.

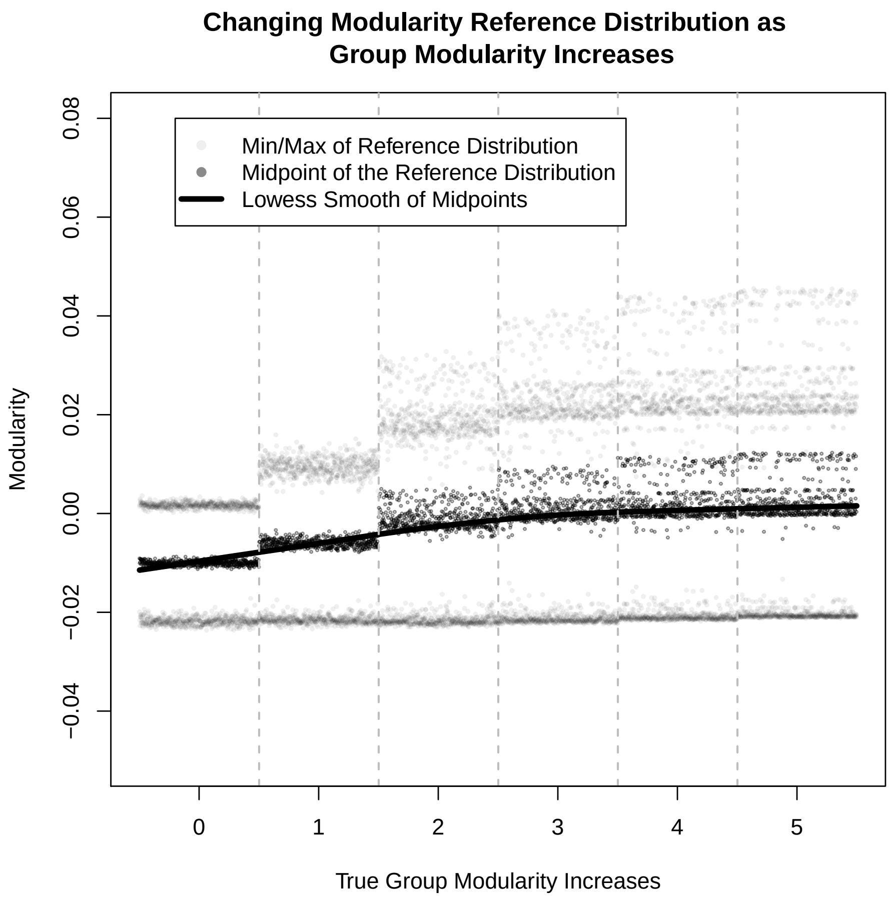


Figure 5.10: Midpoint of the Reference Distribution as True Network Modularity Increases

Thus, the true community structure of a network drags the reference distribution in its direction.

Each piece of the modularity equation influences the subsequent permutation reference distribution, either in location or in scale. A network's density and the probability of co-membership of the hypothesized groups affect the variance in the permutation reference distribution. The degree to which a network is actually modular drives the location of the reference distribution. More modular networks pull the reference distribution upwards.[16]

5.6 Discussion

Summary statistics are critical ways for researchers to measure and express the structure of a social network, but the complexities of network analysis make hypothesis tests for such statistics difficult. Computational, nonparametric approaches provide a powerful way to measure the uncertainty surrounding any given summary statistic from a social network and to test that statistic against a reference distribution generated directly from the data. I have demonstrated one such test for a popular network summary statistic – network modularity. Permutation testing for network modularity provides an easily interpretable test for the hypothesis that a particular group structure partitions a network better than might be expected at random with the added benefit of a freedom from many statistical assumptions that come with using known probability distributions as references for comparison. Thus, the permutation test I advocate, and nonparametric approaches more generally, represent important tools for network scholars seeking to explore and compare social networks.

I have also provided an example of network modularity and its attendant reference distribution from cosponsorship networks in the lower chambers of U.S. legislatures and for the international trade network from 1870-2006. Network modularity provides an intuitive way to capture how partisan the collaborative networks of legislatures are and the degree to which international trade is clustered by regime type. The least partisan legislature seems to be North Carolina, though many other chambers are no more structured by party then they would be by random chance. The most partisan chamber seems to be Iowa's lower chamber. Iowa and Virginia's lower chambers appear to be quite a

[16] The next appendix to this article includes a regression analysis of these relationships in the state legislative data.

bit more partisan than the other legislative chambers. Finally, only international trade in the period just before the second World War seems to be partitioned by regime type. Moving forward, it would be valuable to develop confidence intervals around the point estimates of modularity. This would facilitate inter-network comparisons in ways that the permutation reference distribution does not.

Chapter 6

Conclusion

The preceding chapters have demonstrated that: a) legislative relationships play a critical role in the production of bills by a legislature, and b) those same legislative relationships are influenced by the design and rules of a legislature. There are electoral motivations for legislative collaboration that can be influenced by electoral institutions, and there are internal chamber and committee structures that also influence legislative collaboration. The scholarly implications here are large. Much of the existing work on legislatures examines legislative behavior through a micro-economic lens with a focus on individual actors and their preferences for bill outcomes. My work suggests that alternative levels of analysis are fruitful avenues for the continued development of legislative studies. The study of legislatures as organizations with emergent properties (rather than as a collection of individuals who are simply the sum of the individual parts) can facilitate greater focus on organizational efficiency, optimal design, and adaptation to external changes. One of the primary goals of research into complex systems is the unification of micro-level motivations for human behavior and macro-level organizational outcomes that seem to be more than/different than the sum of individual agents. This sort of a perspective, focused on legislatures as complex, adaptive organizations, has the potential to provide novel and important insights into how representative democracies aggregate the policy preferences of mass public into policy outcomes.

Additionally, this work points to the importance of continued research on relationships between legislators and how they alter outcomes above and beyond the accumulation of legislative preferences. Indeed, some of the earliest work on legislative behavior (Routt 1938) asserted that legislators are “experts in human relationships” rather than experts in any policy arena, and that this ability to negotiate, cooperate, and manipulate others is what sets legislators apart from the mass public. The coalitions developed within a legislature can cut lines of obvious division in a legislature (i.e. political party), and surprising coalitions are key to legislative outcomes even in the two party systems of most U.S. legislatures.

This research also points out the utility of testing legislative theories in multiple legislative venues. As Squire and Hamm (2005) point out, legislative studies, and particularly the study of legislative institutions, is *necessarily* a comparative endeavor. General theories of legislative behavior can and should be tested across legislative settings, and the U.S. state legislatures provide excellent comparative units for the U.S. Congress. There is a tremendous volume of legislative theory specifically developed to provide scholars with a better understanding of the U.S. House and Senate. As data from state legislatures becomes easier to gather, our opportunities to generalize these theories and better adjudicate between rivals will only expand. Additionally, understanding the state legislatures is a useful exercise beyond their utility as a counterfactual for Congress. State legislatures are more likely to engage in institutional reforms, have wide cross-sectional variance in their institutional structures, electoral mechanisms, and constituency makeups, and in many cases pre-date the U.S. Congress by decades. A general understanding of state legislatures would provide scholars with a more comprehensive understanding of the connections between all of these components and facilitate the development of more comprehensive legislative theories. For example, scholars are more likely to develop explanations for why some legislative institutions are chosen over others by studying state legislatures than any single chamber individually.

While there are many scholarly implications of this research, the broader normative implications are simpler to outline. Congressional politics in the early 21^{st} century has been marked by gridlock, polarization, and a failure to compromise between critical veto players in the legislative system. My research tells us that this need not be the case, and indeed was likely not the case in other legislatures. Even in an environment of polarized political parties and political preferences, citizens can design legislative institutions that encourage collaboration. Polarization need not automatically imply a dysfunctional organization. This is encouraging news, for while the attitudes of legislators may be very difficult to change,[1] the institutions of a legislature are much simpler to alter. Indeed, in the past decade, two state legislatures have altered the institutions at the hearts of Chapters 3 and 4 in this dissertation. North Carolina's lower chamber removed multi-member districts as electoral institutions in 2002, thus decreasing the number of cross-party collaborations that existed in the chamber. Alternatively, in that same year, Rhode Island decreased the size of its lower chamber, decreasing the power of party to structure legislative collaboration.

My examination of the weak ties theory also reveals that the legislators who are most successful in passing legislation are those who are most willing to cross obvious lines of division between legislators. Thus, while the narrative of the early 21^{st} century U.S. legislature is one marked by bitter partisan divides and little in the way of collegiality, it remains those legislators open to compromise who produce the largest share of legislative outcomes. So long as legislators develop clusters of support smaller than the chamber itself, bridging ties across those clusters will help individuals succeed in achieving their legislative goals.

Future research on the nature of legislative relationships should focus on developing

[1] Polarization has also reached the mass public's attitudes, thus creating a legislature from the mass public that is not polarized would be difficult.

more conservative tests of the weak ties theory of legislative outcomes. The empirical test I develop utilizes a large n sample across many states, providing a very general examination of the hypotheses generated. Further research on the topic should consider both developing tests of the hypotheses in a smaller n setting and pitting the weak ties hypotheses against alternative models more directly. For example, legislative scholars have long relied on the proximity model of behavior as a means to determine which legislation would pass or fail in a legislature with the implication that legislation targeted at the median voter on the relevant dimension would be most likely to be successful. Unfortunately, each legislative dimension may have a unique median voter meaning that testing the weak ties theory of influence and the proximity model of legislative outcomes across many issue dimensions may be very difficult. Thus, an attempt to examine the added explanatory power of weak ties to a proximity model might examine a subset of legislation where the ideological distribution of legislators is well understood and then see what novel coalitions created by legislators on that dimension add in terms of predictive power.

Further research might also consider a qualitative approach to both the influence of legislative relationships on outcomes and the influences of institutions on legislative relationships. My work has relied on cosponsorship networks as reasonable proxies for legislative collaborations. Qualitative investigations would allow scholars to examine the validity of this approach while also gathering data on other legislative networks of interest. In particular, my hypotheses regarding chamber and committee size and its influences on partner selection would seem like ideal candidates for more in depth qualitative examination. If committees do indeed provide opportunities for collaborative relationships, interviews would be helpful in uncovering those relationships.

Outside of stronger tests of my own theories, new research on bipartisanship and legislative relationships might also consider the electoral impacts of these sorts of choices.

Harbridge and Malhotra (2011) have shown that while all partisans espouse a preference for bipartisanship, strong partisans evaluate legislators more poorly when they actually behave in a bipartisan manner. Thus, bipartisanship may lead to greater legislative success, but may also have serious electoral implications, particularly in primary elections where strong partisans are the critical constituency.

Finally, future scholarship would benefit from the development of a unified agent-based model of coalition politics in U.S. legislatures based on the weak ties theory of legislative outcomes. Such a model would approach a legislature as an organization of individual agents competing and cooperating in the production of legislation, and requiring the assistance of others to do so. Precisely when and why coalitions arise, who are likely to form those coalitions, when they run counter to political party structures, how long coalitions can persist, and how the actors in those coalitions are benefited by the coalition's existence would all be questions of interest in such an effort. A more formalized model of the process outlined in Chapter 2 would provide a clearer understanding of the implications of legislative relationships across all types of legislatures.

Chapter 7

Appendices

7.1 Appendix 2A- Model Results for the Analysis of Legislative Success

In Table 7.1, I present four models in which the dependent variable is a dichotomous outcome coded 1 if a bill survives committee deliberation in a state and 0 otherwise. The graphical analysis presented earlier provides easier interpretation of these highly conditional results and demonstrates strong support for the weak ties theory of influence diffusion. Within the table itself, the results indicate that strong ties produce negative insignificant effects on the probability a bill will survive at the committee stage in both models 1 (direct connections) and 2 (secondary connections). The results also show a consistent positive effect for direct weak ties. Additionally, models 3 and 4 show a positive interaction term indicating that the marginal effect of direct weak ties increases as the weak ties lead to larger and larger secondary connections. Recall, however that the individual coefficients on ties are less important than their combined effects. The path to individual success should be through a combination of weak ties to secondary connections. Model 3 shows a positive effect for both direct and secondary weak ties and a positive interaction term and Model 4 shows a positive effect for direct weak ties and a positive interaction term. Thus, it would seem that the combined effects of these variables produce increased legislative success for individuals.

Table 7.2 mirrors the analysis from Column 3 and 4 performed in Table 7.1, this time using data from the US House. The dependent variable is dichotomous, coded 1 if a bill was reported out by a committee and 0 otherwise. Rather than allowing for varying state intercepts, I allow for intercepts to vary by Congress. I have included the absolute value of the bill author's DW Nominate score in order to control for the possibility that members closer to the median ideologically experience more legislative success because they generate more palatable legislation to both sides of the ideological spectrum. Interestingly, the replicated analysis in Table 7.2 from Columns 1 and 2, do not demonstrate the same relationship as we see in Table 7.1. Instead of having positive effects felt through direct connections, the models demonstrate that legislative success through weak ties plays out through a positive coefficient on secondary connections and a positive interaction term between direct connections and secondary connections. Both models in Table 7.2 present negative and significant coefficients on direct weak ties, but as with the state analysis the more important test of the weak ties theory lies in the combined effects of direct and secondary connections which is presented in the graphical analyses in Figures 5 and 6 in the main body of the paper.

In the next table in this appendix, I present two interactive models of bill passage on the floor of the US House. The dependent variable is dichotomous, coded 1 if a bill passes on the floor and 0 otherwise. While sample selection may be a small concern here, many more bills pass without being reported out by a committee in the US House than in the states, alleviating the need for a selection model to some degree. Once again, the models in Table 7.3, Columns 1 and 2 report negative coefficients on direct weak ties, but positive coefficients on secondary ties and on the interaction term between direct

Table 7.1: Logistic Regression Models Predicting Bill Survival at Committee Stages in State Legislatures

Variable	Model 1	Model 2	Model 3	Model 4
Sponsor Institutionally Advantaged	0.289 *	0.294 *	0.294 *	0.302 *
	(0.048)	(0.048)	(0.048)	(0.049)
Sponsor Tenure	0.001	0.001	0.001	0.001
	(0.002)	(0.002)	(0.003)	(0.002)
Sponsor Majority Party	0.386 *	0.391 *	0.384 *	0.398 *
	(0.052)	(0.051)	(0.051)	(0.052)
Number of Cosponsors on Specific Bill	0.032 *	0.031 *	0.031 *	0.032 *
	(0.003)	(0.003)	(0.003)	(0.002)
Weak Ties	—	0.111	0.081	0.146 *
	(—)	(0.061)	(0.058)	(0.073)
Strong Ties	—	-0.004	—	0.004
	(—)	(0.026)	(—)	(0.031)
Secondary Connections from Weak Ties	0.028	—	0.011	-0.014
	(0.044)	(—)	(0.045)	(0.051)
Secondary Connections from Strong Ties	-0.039	—	—	-0.060
	(0.031)	(—)	(—)	(0.034)
*Weak * Secondary Connections from Weak*	—	—	0.036	0.018
	(—)	(—)	(0.034)	(0.038)
*Strong * Secondary Connections from Strong*	—	—	—	0.022
	(—)	(—)	(—)	(0.019)
Intercept	-0.942*	-0.900*	-0.934 *	-0.944 *
	(0.243)	(0.257)	(0.261)	(0.260)
$\widehat{\sigma}_{state}$	0.443	0.502	0.501	0.493
N	12900	12900	12900	12900
LogLik	-7663	-7663	-7661	-7659

Note: Columns (1), (2), (3), and (4) report multi-level logistic regression coefficients with varying intercepts by state. The dependent variable is a dichotomous measure of bill passage from committee. Models have standard errors in parentheses. Varying intercepts are not reported, but anova tests indicate that state level intercepts significantly improve model fit. Higher Log Likelihood indicates better model fit. * $p < 0.05$.

Table 7.2: Logistic Regression Models Predicting Bill Survival at Committee Stages in the US House (1991-2005)

Variable	Model 1	Model 2
Sponsor Institutionally Advantaged	1.052 *	1.048 *
	(0.052)	(0.053)
Sponsor Tenure	0.020 *	0.023 *
	(0.004)	(0.004)
Sponsor Majority Party	-0.004 *	-0.0041
	(0.002)	(0.0022)
Number of Cosponsors on Specific Bill	0.003 *	0.003 *
	(0.0004)	(0.0004)
Absolute Value of DW Nominate Score	-0.595 *	-0.275 *
	(0.118)	(0.125)
Weak Ties	-0.338 *	-0.160 *
	(0.018)	(0.027)
Strong Ties	—	-0.261 *
	(—)	(0.032)
Secondary Connections from Weak Ties	0.115 *	0.096 *
	(0.019)	(0.019)
Secondary Connections from Strong Ties	—	-0.046 *
	(—)	(0.022)
*Weak * Secondary Connections from Weak*	0.043 *	0.048 *
	(0.015)	(0.015)
*Strong * Secondary Connections from Strong*	—	-0.034
	(—)	(0.019)
Intercept	-2.387 *	-2.551 *
	(0.063)	(0.071)
$\widehat{\sigma}_{Congress}$	0.007	0.012
N	37056	37056
LogLik	-11285	-11233

Note: Columns (1) and (2) report multi-level logistic regression coefficients with varying intercepts by Congress. The dependent variable is a dichotomous measure of bill passage from committee. Models have standard errors in parentheses. Varying intercepts are not reported, but anova tests indicate that Congress level intercepts significantly improve model fit. Higher Log Likelihood indicates better model fit. * $p < 0.05$.

and secondary weak ties. This positive interactive effect is responsible for the increases in bill passage as direct and secondary weak ties increase observed in Figure 2.6, in spite of the negative coefficient on direct weak ties presented in the model.

7.2 Appendix 2B- An Alternative Approach to the Measurement of Weak Ties

In my analysis of the impact of relational determinants of legislative success, I differentiate between the impact of strong and weak relational ties arguing that strong ties provide little opportunity for influence. The empirical analysis I employ to test the hypotheses that result from my weak ties theory are based on the admittedly arbitrary (though not without precedent) distinction between strong and weak ties occurring at the mean level of connectivity in a social network, plus one standard deviation. While to my mind standard deviations exist for just this purpose (to identify unusually high or low positions in a distribution) I understand that some readers may be skeptical of analysis confirming my theory based on an arbitrary censoring rule. Accordingly, I offer a sensitivity analysis in Table 7.4. This sensitivity analysis re-examines the analysis presented in Table 7.1, this time using alternative cutpoints to distinguish between strong and weak ties. The first two results in Table 7.4 make use of the mean plus 0.75 standard deviations as a cutpoint between strong and weak ties. The second two models present an analysis using the mean plus 1.25 standard deviations. I only present the fully specified additive and analogous interactive models from Table 7.1.

While the interactive effects in these models have become negative and very near to zero, the general finding that weak ties lead to increases in bill survival and thus legislative success remains consistent across disturbances to the cutpoint distinguishing

Table 7.3: Logistic Regression Models Predicting Bill Passage in the US House (1991-2005)

Variable	Model 1	Model 2
Sponsor Institutionally Advantaged	1.127 *	1.117 *
	(0.052)	(0.052)
Sponsor Tenure	0.011 *	0.015 *
	(0.004)	(0.004)
Sponsor Majority Party	-0.005 *	-0.004 *
	(0.002)	(0.002)
Number of Cosponsors on Specific Bill	0.004 *	0.004 *
	(0.0003)	(0.0003)
Absolute Value of DW Nominate Score	-0.784 *	-0.436 *
	(0.117)	(0.122)
Weak Ties	-0.310 *	-0.122 *
	(0.018)	(0.026)
Strong Ties	—	-0.274 *
	(—)	(0.031)
Secondary Connections from Weak Ties	0.080 *	0.064 *
	(0.019)	(0.019)
Secondary Connections from Strong Ties	—	-0.041
	(—)	(0.021)
*Weak * Secondary Connections from Weak*	0.042 *	0.046 *
	(0.015)	(0.015)
*Strong * Secondary Connections from Strong*	—	0.014 *
	(—)	(0.019)
Intercept	-2.209 *	-2.379 *
	(0.077)	(0.079)
$\widehat{\sigma}_{Congress}$	0.0221	0.0216
N	37056	37056
LogLik	-11881	-11825

Note: Columns (1) and (2) report multi-level logistic regression coefficients with varying intercepts by Congress. The dependent variable is a dichotomous measure of bill passage from committee. Models have standard errors in parentheses. Varying intercepts are not reported, but anova tests indicate that Congress level intercepts significantly improve model fit. Higher Log Likelihood indicates better model fit. * $p < 0.05$.

Table 7.4: Logistic Regression Models Predicting Bill Survival at Committee Stages in State Legislatures

	.75 Standard Deviations		1.25 Standard Deviations	
Variable	Model 1	Model 2	Model 1	Model 2
Sponsor Institutionally Advantaged	0.311 *	0.312 *	0.307 *	0.305 *
	(0.048)	(0.049)	(0.049)	(0.049)
Sponsor Tenure	0.001	0.001	0.001	0.001
	(0.003)	(0.002)	(0.002)	(0.003)
Sponsor Majority Party	0.419 *	0.417 *	0.404 *	0.404 *
	(0.052)	(0.052)	(0.051)	(0.052)
Number of Cosponsors on Specific Bill	0.030 *	0.030 *	0.030 *	0.030 *
	(0.002)	(0.002)	(0.003)	(0.002)
Weak Ties	0.141 *	0.149 *	0.151 *	0.166 *
	(0.057)	(0.068)	(0.066)	(0.068)
Strong Ties	—	0.002	-0.006	-0.018
	(—)	(0.034)	(0.026)	(0.029)
Secondary Connections from Weak Ties	-0.091	-0.088	-0.069	-0.048
	(0.049)	(0.054)	(0.050)	(0.055)
Secondary Connections from Strong Ties	—	0.018	0.004	-0.0003
	(—)	(0.028)	(0.026)	(0.027)
*Weak * Secondary Connections from Weak*	-0.008	-0.004	—	-0.038
	(0.034)	(0.039)	(—)	(0.042)
*Strong * Secondary Connections from Strong*	—	0.014	—	0.014
	(—)	(0.023)	(—)	(0.021)
Intercept	-0.841 *	-0.942 *	-0.926 *	-0.883 *
	(0.252)	(0.257)	(0.252)	(0.259)
$\widehat{\sigma}_{state}$	0.468	0.483	0.494	0.490
N	12900	12900	12900	12900
LogLik	-7659	-7569	-7659	-7659

Note: Columns (1)-(4) report multi-level logistic regression coefficients with varying intercepts. The dependent variable is a dichotomous measure of bill passage from committee. Models have standard errors in parentheses. Varying intercepts are not reported, but anova tests indicate that state level intercepts significantly improve model fit. Higher Log Likelihood indicates better model fit. * $p < 0.05$.

strong and weak ties. In all four models presented above, increasing direct weak ties leads to increases in bill survival controlling for the other variables in the model. The interaction terms are so small that their negative conditioning effects never bring the marginal effect of direct ties back down to zero/statistically insignificant. This analysis provides more robust support for for the overall conclusion that the most efficient paths to legislative success remain weak ties rather than strong ties.

7.3 Appendix 2C- Matching to Reduce Model Dependence

To test my hypotheses about weak ties leading to legislative success, I have made heavy use of hierarchical or multi-level logit models. While hierarchical models were designed with this sort of multi-level data in mind, they come with two limitations. First, they are most useful in datasets with many small clusters whereas this state level data is the reverse, a few very large clusters. Secondly they are rather sensitive to multicollinearity, requiring collinear variables to be centered or normalized in order to reach convergence. This creates some concerns about the level of model dependence in my results. In other words, I am imposing a number of parametric assumptions on data and violations of these parametric assumptions may be driving results. Ho et al. (2007) suggest making use of matching techniques to limit model dependence and more clearly estimate robust results.

In Table 7.5 I present four logit models, in which the dependent variable is bill survival at the committee stage in state legislatures. Unlike the analysis in Table 7.1, these data have been matched using the “MatchIt” package in R, treating direct weak ties, direct strong ties, secondary weak ties, and secondary strong ties as treatments, respectively. Because matching software has yet to successfully implement continuous treatments (though the statistics for such an algorithm have been developed, see Hirano and Imbens (2004)), matching requires a dichotomous treatment variable. In order create this dichotomous treatment, I take each of the four continuous treatments I wish to study and code them one if the variable is above its own median and zero otherwise. This forced choice is less preferable than matching on a continuous treatment would otherwise be, but matching in this way does limit the impact of model dependence on the outcomes observed even if it obscures information about the important treatment variables. I use nearest neighbor matching to produce the matched data and summary statistics indicate that balance is always improved in the matched sample over the unmatched samples. Because these data have been matched and standard logit models are used, the data have not been normalized explaining the differences in the magnitudes of the coefficients from Table 7.1.

Table 7.5 is presented using all of the matched data set, thus the treatment variable coefficients represent the average treatment effect (ATE) for the entire sample of moving from below the median on the treatment variable to above the median on the treatment variable. In all four models presented direct weak ties have a positive coefficient and in three of the four models presented the interaction between direct and secondary ties is positive. Additionally, in all four models direct strong ties and secondary strong ties have a negative effect on bill passage and in two of the four models the interaction between direct and secondary strong ties is negative. This is strong evidence that even when the data are matched on several different potential treatment variables and model dependence is reduced using a matching approach, the most efficient path to increased bill success remains through weak ties.

While the matching approach presented above forces different choices on a researcher interested in a continuous treatment, it can represent a nice robustness check by ensuring that the influence of the parametric assumptions in a model are wreaking as little damage

Table 7.5: Matched Logistic Regression Models Predicting Bill Survival at Committee Stages in State Legislatures

Variable	Model 1	Model 2	Model 3	Model 4
Sponsor Institutionally Advantaged	0.300 *	0.329 *	0.289 *	0.293 *
	(0.049)	(0.049)	(0.049)	(0.049)
Sponsor Tenure	-0.001	0.005	0.001	0.001
	(0.003)	(0.003)	(0.002)	(0.002)
Sponsor Majority Party	0.368 *	0.396 *	0.395 *	0.366 *
	(0.052)	(0.052)	(0.053)	(0.052)
Number of Cosponsors on Specific Bill	0.031 *	0.031 *	0.031 *	0.031 *
	(0.003)	(0.003)	(0.003)	(0.003)
Weak Ties	0.145	0.008 *	0.000	0.004
	(0.139)	(0.003)	(0.004)	(0.003)
Strong Ties	-0.002	-0.119	-0.001	-0.004
	(0.003)	(0.085)	(0.003)	(0.003)
Secondary Connections from Weak Ties	-0.000	-0.000	-0.236	0.000
	(0.000)	(0.000)	(0.136)	(0.0001)
Secondary Connections from Strong Ties	-0.0002	-0.0005 *	-0.0002 *	-0.131
	(0.0001)	(0.0001)	(0.0001)	(0.081)
*Weak * Secondary Connections from Weak*	0.0001	-0.000	0.009 *	0.000
	(0.0001)	(0.000)	(0.003)	(0.000)
*Strong * Secondary Connections from Strong*	-0.000	0.0004 *	-0.000	0.006
	(0.000)	(0.0001)	(0.000)	(0.003)
Intercept	-0.711 *	-0.840 *	-0.730 *	-0.785 *
	(0.120)	(0.129)	(0.133)	(0.130)
N	12790	12776	12782	12760
LogLik	-7553	-7551	-7560	-7568

Note: Columns (1), (2), (3), and (4) report logistic regression coefficients with unreported dummy variables by state. The dependent variable is a dichotomous measure of bill passage from committee. Models have standard errors in parentheses. State level dummy variables are not reported but anova testing indicates that they significantly improve model fit. In Column (1) direct weak ties are considered the treatment (and are thus matched on in the matching stage). In Column (2) direct strong ties are considered the treatment. In Column (3) secondary weak ties are considered the treatment. In Column (4) secondary strong ties are considered the treatment. Higher Log Likelihood indicates better model fit. * $p < 0.05$.

as is possible. By reducing model dependence through matching and pairing this with highly parametrized multi-level models, the case for the weak ties theory is made even stronger.

7.4 Appendix 2D- Creating an Assessment of Uncertainty in Modularity

Modularity as a statistic is bounded between negative one and one, and because the distribution of modularity has yet to be explored I have a limited ability to draw inferences about the magnitude of the differences between the strong and weak ties networks. In order to provide some intuition about the statistical magnitude of the observed differences in modularity, I have simulated a null distribution of modularity for a given state's strong ties network. To do this, I take a particular state's strong ties network, randomly draw 25,000 partitions of that network and record the modularity of that randomly drawn partition on the strong ties network.[1] This creates a distribution of modularity for potential random partitions, and 95% of the density of this distribution centered around the mean can inform us of the degree to which the observed modularity score is likely at random. While this is not a perfect approach to drawing inferences about the magnitude of differences of these statistics, it does provide some empirical ground for asserting that these similarity partitions are more effective at separating actors in the strong ties network than in the weak ties network.

These random partitions can take on any type of division, even dividing the network into sets of 1 and $n-1$ groups. Allowing the partitions to take on any shape generates

[1]Because the strong ties network has some effective partitions in it, the standard deviation of modularity from randomly drawn partitions in the strong ties network is higher than the standard deviation of modularity from randomly drawn partitions in the weak ties network. Thus, the standard deviation of the strong ties network represents the more conservative estimate.

the widest possible distribution for random modularity scores. Restricting the type of divisions that could be considered (for example, only allowing divisions that divide the network into groups the same size as the observed political party memberships) shrinks the null distribution of modularity by limiting divisions that might actually divide the network well because of their size. Thus, while restricting the random divisions to match the size of the real world divisions might create different null distributions for different attributes (meaning there would be a different null distribution of party modularity and gender modularity), this is actually a less conservative test than the nearly fully random exploration I use here.

These empirically derived distributions of modularity for each state indicate that party is a better than expected partition of the strong ties network in North Carolina, Minnesota, Mississippi, Hawaii, Alabama and Alaska, while party is only a better than expected partition of the weak ties in Minnesota and Alabama. Gender is a better than expected partition of the strong ties network in North Carolina, Minnesota, Mississippi, Hawaii, and Alabama, while it is never a better than expected partition of the weak ties network. Race is a better partition of the strong ties network than expected at random in North Carolina, Mississippi, and Alabama and is also never a better than random partition of the weak ties network. Using the range of 95% of the density of the simulated distribution as a mark of statistical difference between the modularity of the strong and weak ties networks, party always creates statistically larger modularity scores in the strong ties network than in the weak ties network. Gender creates larger modularity scores in North Carolina, Minnesota, Mississippi, and Hawaii, while gender fails to partition the strong ties network better than the weak ties network in Indiana, Delaware, Alabama, and Alaska. Race creates larger modularity scores in North Carolina, Mississippi and Alabama. These results demonstrate that strong ties are in large part driven by the pre-existing similarities between legislators while weak ties are not driven by these similarities. Coupled with the empirically supported notion that weak ties are also the ties which lead to increased legislative success, this would seem to be strong evidence in support of the weak ties theory of influence diffusion in a legislative network.

This reinforces the evidence from the main body of the paper. Even when accounting for the uncertainty in the measure of modularity, strong ties are largely driven by similarities while weak ties are not.

7.5 Appendix 3A- Descriptive Statistics

To test my expectations regarding the effect of shared constituency on collaboration between legislators, I make use of cosponsorship data and district overlap data from the North Carolina General Assembly from 1997-2007. Table 7.7 presents descriptive statistics for this data. The density of the cosponsorship network refers to the proportion of potential network connections that are realized. In other words, it is the proportion of legislators connected to one another. The number of dyads sharing a constituency refers to the number of pairs of legislators being coded as having formerly shared a district (the definition of shared constituency used in Figure 3.1). Both the number of bills sponsored and the density of the network increase sharply in 2005, meaning the change in the coefficients reported in the paper that occurs in 2003 cannot be caused by changes in the opportunities for or frequency of cosponsorship.

There is a large drop in the number of dyads being coded as sharing a constituency, which may be responsible for the change in the precision of estimates reported in Figure 3.1. This makes the second analysis using the number of legislators coming from districts that were once multi-member more important. Both analyses show a large change in covariate values at the 2002 cutpoint. Because this is a Bayesian model (with flat priors), I can directly interpret the posterior coefficient distributions as probabilities. While

Table 7.6: Modularity on Three Pre-Existing Dimensions in State Legislatures

	Party		Race		Gender		
Variable	Strong Ties	Weak Ties	Strong Ties	Weak Ties	Strong Ties	Weak Ties	95% Uncertainty Region
North Carolina	0.28	-0.028	0.058	-0.0062	0.051	-0.015	-0.017, 0.011
Minnesota	0.18	0.016	—	—	0.045	0.011	-0.022, 0.015
Mississippi	0.12	0.023	0.11	0.011	0.039	-0.029	-0.033, 0.026
Indiana	-0.043	-0.15	0.013	0.001	0.012	-0.0078	-0.037, 0.026
Hawaii	0.022	-0.035	—	—	0.023	-0.026	-0.025, 0.0049
Delaware	0.012	-0.018	0.020	-0.0029	-0.0052	-0.012	-0.052, 0.036
Alabama	0.14	0.09	0.14	0.013	0.034	0.011	-0.023, 0.014
Alaska	0.14	0.010	—	—	-0.0030	-0.012	-0.046, 0.020

Note: Columns (1)-(6) report modularity statistics across eight state legislatures along three sociological dimensions for both the strong and weak ties network. Columns (1) and (2) measure modularity along party lines. Columns (3) and (4) measure modularity along racial lines. Columns (5) and (6) measure modularity along gender lines. Modularity estimates along the Race dimension for Alaska and Hawaii are absent because there were no African American state representatives in these two states in 2007. Column (7) reports the 95% density region of a simulated distribution of modularity using randomly drawn partitions for a given state.

Table 7.7: Descriptive Statistics for the Analysis of the North Carolina House (1997-2007)

Variable	1997	1999	2001	2003	2005	2007
Number of Bills Introduced	1765	1866	1809	1807	2895	2808
Density of the Cosponsorship Network	0.37	0.27	0.23	0.41	0.60	0.71
Number of Dyads Sharing Constituency	30	30	30	10	8	6
Democrats/Republicans	59/61	66/54	62/58	60/60	63/57	68/52

the precision of the estimates reported in Figure 3.1 does decrease following the 2002 institutional change, 88.9% of the posterior density of the coefficient estimate on shared constituency in 2003 is below the minimum of the 2001 estimate. If I instead use the lower 95% confidence interval for the 2001 estimate, 93.8% of the posterior density for the 2003 estimate is below this threshold. Even in the face of much smaller numbers of observations on shared constituency, there is reasonable certainty that the coefficients are different than one another.

7.6 Appendix 3B- Latent Position Methods for Social Network Analysis

In order to model the effects of a shared district and to model the latent dimensions driving collaborative choices, I use the latent space model for social network data (Hoff et al. 2002). The latent space model accounts for interdependence in network data by placing actors closer to one another in a latent social space if they are more strongly connected. The model then estimates actors' positions within this space simultaneously with pair- and individual-level covariates via standard MLE or MCMC processes. The latent space model has two ways in which it can calculate these positions, either through a standard distance model or a projection model. In my estimations, I focus on the distance model because of its strong connections to spatial decision models commonly used in legislative analysis. In the distance model, two actors i and j are considered more likely to be tied if their positions in the latent space are closer to one another. Thus, the simple logistic model predicting the existence of a tie takes on the form:

$$logodd(y_{i,j} = 1|z_i, z_j, x_{i,j}, \alpha, \beta) = \alpha + \beta * x_{i,j} - |z_j - z_i| \tag{7.1}$$

Without any observed covariates, this model simplifies to a baseline probability of connection (α) and the distance between two actors on an unobserved dimension. The location parameters z_i are placed within a user specified dimensional space $\Re^k$, which can be as simple as two-dimensional and where k is specified before estimation. Likelihood ratio tests allow researchers to determine whether additional dimensions provide worthwhile increases in model fit. As k approaches ∞, the error term of the model vanishes and the LSM fits data arbitrarily well. A particular benefit of the latent space model is its foundations in generalized linear model theory. Because the latent space model is a standard glm that controls for interdependence through the latent space, it is easily extendable to non-binary social networks.

The estimation of the latent space model proceeds as follows, where Z is the matrix of positions in the latent social space:

1. Identify an MLE $\hat{Z}$ of Z, centered at the origin, by the direct maximization of the likelihood.

2. Using $Z_0 = \hat{Z}$ as a starting value, construct a Markov chain over the parameters as follows:

   (a) Sample a proposal $\check{Z}$ from $J(Z|Z_k)$, a symmetric proposal distribution.

(b) Accept $\check{Z}$ as Z_{k+1} with probability $\frac{p(Y|\check{Z},\alpha_k,\beta_k,X)}{p(Y|Z_k,\alpha_k,\beta_k,X)}\frac{\pi(\hat{Z})}{\pi(Z_k)}$

(c) Store $\tilde{Z}_{k+1} = argmin_{TZ_{k+1}} tr(\hat{Z} - TZ_{k+1})'(\hat{Z} - TZ_{k+1})$, where T is the procrustean transformation of Z

3. Update α and β with a Metropolis-Hastings algorithm.

I utilize the statnet package in R (Handcock et al. 2008) to estimate the models, using the default (and diffuse) priors over Z. I utilize a burn-in period of 25,000 runs and store a sample space of 5,000 posterior simulations. The Markov chains from each state mix well and subsequent checks indicate that the models reach convergence in each chamber.

While the distance model has some theoretical and intuitive appeal, the latent space model has an alternative parameterization based on projection. This projection-based approach assumes that actors have unique characteristics/positions on a k-dimensional sphere. In this case, the likelihood of a connection between two actors is a function of the angle on the sphere imposed by their positions. In other words, if the angle formed between two actors and the origin is less than 90 degrees, a tie between the two is likely and if it is more than 90 degrees, a tie between the two is unlikely. Said yet another way, the projection model specifies that if two actors unobserved characteristics are "pointed" in the same "direction" they are likely to form a tie and if they are in different directions, the tie is unlikely. This allows for asymmetries in the connections implied by the latent space. While the work I present here relies on the distance method, future work might take advantage of this parameterization for a number of problems. For example, there seems to be a nice parallel in these model choices to the spatial versus directional debate in voting behavior.

7.7 Appendix 3C- Model Results from Latent Space Models of Cosponsorship

In the main body of this paper, I present graphical analysis of a model of cosponsorship behavior in the North Carolina House from 1997-2007. While this graphical analysis facilitates comparisons well, interpretation of graphics is somewhat less precise than results presented in a table. Below I present two tables of results from Poisson latent space models over time. In the first table, shared constituency in 2003, 2005, and 2007 is a dummy variable coded 1 if two legislators were ever representatives of a multi-member district together. In the second table, shared constituency in 2003, 2005, and 2007 is coded one if two legislators represent districts that were ever a part of a multi-member district. Thus, in the second analysis I code two legislators as having shared a constituency although they were themselves never a representative of a multi-member district. The variable "edges" represents the intercept of the latent space model and indicates the Poisson parameter on the number of edges or connections expected by the model controlling for all the other covariates. These representatives inherited districts that were at one point multi-member, but no longer are.

While model fit statistics can be reported for these types of models, the likelihood based BIC may be a less than intuitive way to understand how well the latent space models predict outcomes. As an alternative, Figure 7.1 presents the density of prediction errors for each of the models in Table 7.8. A prediction error is defined as the difference between the actual Y_{ij} and the predicted Y_{ij} from the latent space model. The figures show that in each of the models the distribution of errors is highly peaked around zero, indicating that the models accurately predict the weight of tie formation more often than not. The average value is actually 89% of ties accurately predicted within one bill

Table 7.8: Poisson Latent Space Models of Cosponsorship in the North Carolina House (1997-2007)

Variable	1997	1999	2001	2003	2005	2007
Party	0.45	0.630	0.82	0.37	0.24	0.69
	(0.39, 0.51)	(0.56, 0.70)	(0.74, 0.90)	(0.31, 0.43)	(0.19, 0.29)	(0.66, 0.71)
Shared Constituency	1.86	1.829	1.76	-0.22	-1.57	0.67
	(1.60, 2.10)	(1.60, 2.07)	(1.42, 2.09)	(-3.37, 1.74)	(-4.31, 0.29)	(-0.29, 1.54)
Party * Shared Constituency	-0.25	-0.077	-0.23	1.36	2.08	-0.28
	(-0.56,0.066)	(-0.36, 0.20)	(-0.64, 0.18)	(-0.64, 4.51)	(0.16, 4.82)	(-1.29, 0.75)
Edges	0.93	0.559	0.35	0.98	2.14	2.13
	(0.87,0.996)	(0.49, 0.63)	(0.27, 0.43)	(0.92, 1.05)	(2.09, 2.19)	(2.11, 2.16)
Likelihood BIC	34339	30343	22753	36949	64212	83078
Number of Dyads	15129	15876	15129	15129	15129	15876
Number of Legislators	123	126	123	123	123	126

Note: Reported coefficients are from a Poisson Latent Space Model for 1997-2007 with two latent dimensions. 95% credible intervals are reported in parentheses. In this model shared constituency is coded (1) if two legislators ever represented the same constituency simultaneously. Likelihood based Bayesian Information Criterion is reported as a measure of model fit.

Table 7.9: Poisson Latent Space Models of Cosponsorship in the North Carolina House (1997-2007)

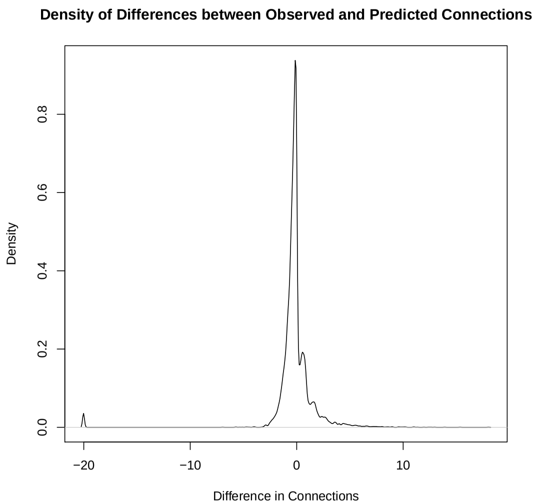
Variable	1997	1999	2001	2003	2005	2007
Party	0.45	0.630	0.82	0.38	0.20	0.68
	(0.39, 0.51)	(0.56, 0.70)	(0.74, 0.90)	(0.31, 0.43)	(0.15, 0.25)	(0.56, 0.70)
Shared Constituency	1.86	1.829	1.76	0.36	0.61	-0.61
	(1.60, 2.10)	(1.60, 2.07)	(1.42, 2.09)	(-0.18, 0.84)	(0.34, 0.89)	(-0.99, -0.26)
Party * Shared Constituency	-0.25	-0.077	-0.23	0.11	-0.55	0.87
	(-0.56,0.066)	(-0.36, 0.20)	(-0.64, 0.18)	(-0.41, 0.71)	(-0.88, -0.24)	(0.50, 1.29)
Edges	0.93	0.559	0.35	0.97	2.171	2.14
	(0.87,0.996)	(0.49, 0.63)	(0.27, 0.43)	(0.92, 1.03)	(2.11, 2.21)	(2.11, 2.17)
Likelihood BIC	34339	30343	22753	36981	64139	83084
Number of Dyads	15129	15876	15129	15129	15129	15876
Number of Legislators	123	126	123	123	123	126

Note: Reported coefficients are from a Poisson Latent Space Model for 1997-2007 with two latent dimensions. 95% credible intervals are reported in parentheses. In this model shared constituency is coded (1) if two legislators represent a district that was ever a part of a multi-member district. Likelihood based Bayesian Information Criterion is reported as a measure of model fit.

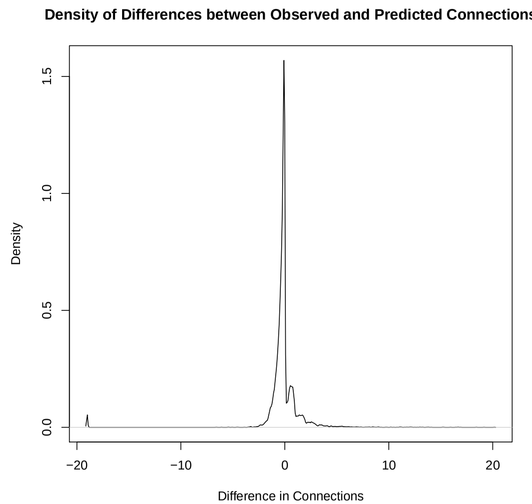
cosponsorship. In addition to providing a clearer interpretation of model fit, this error analysis indicates that concerns about under-specification are unwarranted. There is very little variance in the network not already predicted by the two dimensional latent space model I utilize, thus there is very little information for omitted variables to explain.

As additional analysis in the main body, I present graphical results from states other than North Carolina that use combinations of multi-member and single-member districts. I report the results that generate these graphical results below in Table 7.10. Once again, the model results indicate that sharing a constituency increases cosponsorship behavior both within and across parties. Party still strongly structures the cosponsorship network.

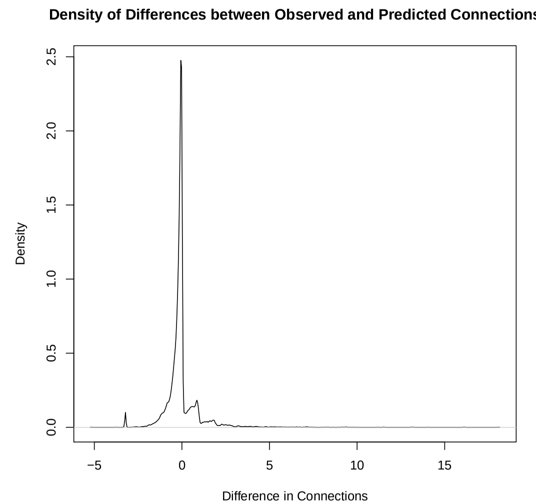
Once again in order to provide a more interpretable indication of model fit, Figure 7.2 reports the density of the differences in the predicted and observed connections strength in the cosponsorship networks. In each of these states, the bulk of the errors in the model are centered on zero, indicating that there are few predictive errors and the model fits quite well. These strong levels of model fit are a function in large part of the latent dimensions' ability as predictors. It would be surprising if the latent space, derived directly from the dependent variable, did not provide large improvements to predictive ability. This is similar to the increases in predictive accuracy a model receives for including random effects for cluster variables. The cluster random effects in a hierarchical model improve predictive accuracy by modeling cluster means in addition to covariates not unlike the latent space placing actors in space as a function of each actors transitive and reciprocal relationships.



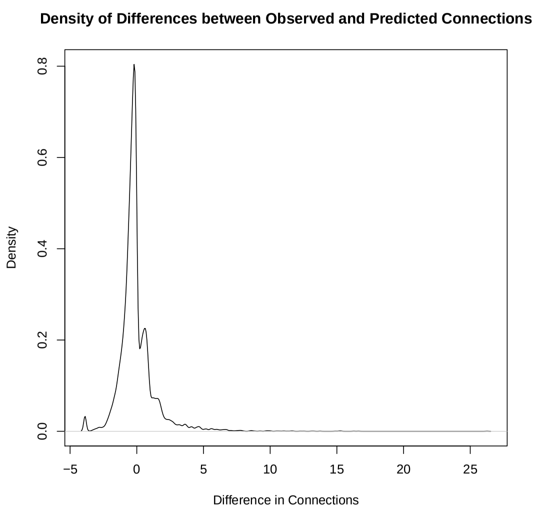
(a) 1997



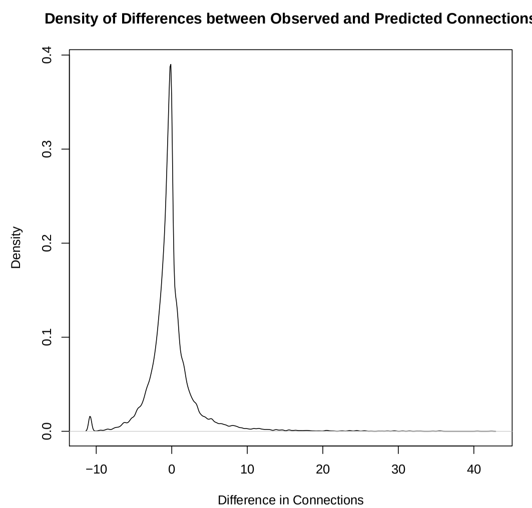
(b) 1999



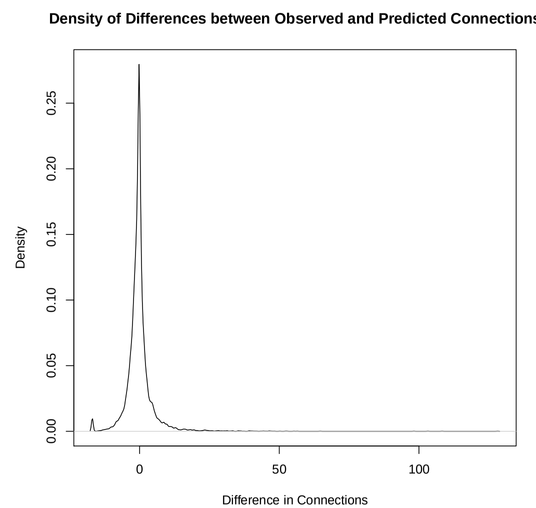
(c) 2001



(d) 2003



(e) 2005



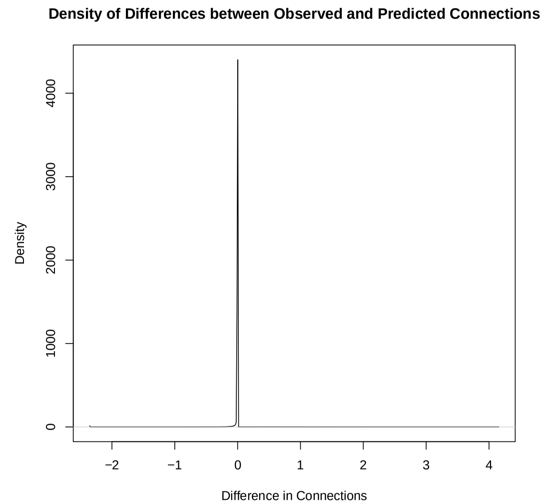
(f) 2007

Figure 7.1: Density of Prediction Errors from Poisson Latent Space Models

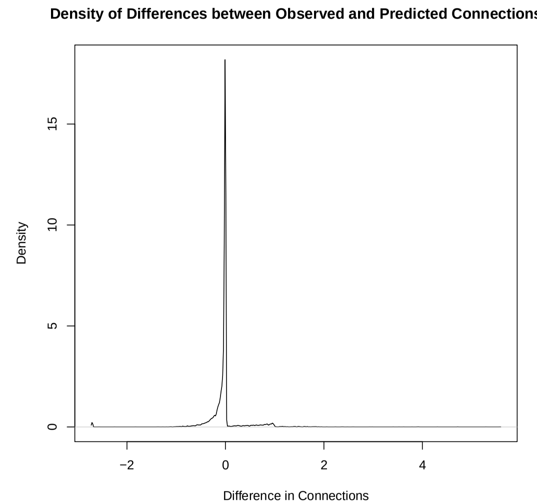
Table 7.10: Poisson Latent Space Models of Cosponsorship in State Legislatures (2007)

Variable	New Hampshire	Vermont	West Virginia	Maryland
Party	0.496	0.329	0.707	0.446
	(0.31, 0.67)	(0.24, 0.42)	(0.59, 0.82)	(0.40, 0.48)
Shared Constituency	1.949	1.955	1.832	0.882
	(0.80, 3.46)	(1.42, 2.49)	(1.40, 2.26)	(0.66, 1.10)
Party * Shared Constituency	-0.701	-0.596	-0.115	-0.036
	(-2.17, 0.45)	(-1.23, 0.04)	(-0.59, 0.35)	(-0.26, 0.19)
Edges	0.356	0.666	0.262	2.015
	(0.18, 0.54)	(0.58, 0.76)	(0.15, 0.37)	(1.96, 2.04)
Likelihood BIC	9840.739	12500.84	10189.17	51583.23
Number of Dyads	158404	22801	10404	19881
Number of Legislators	398	151	102	141

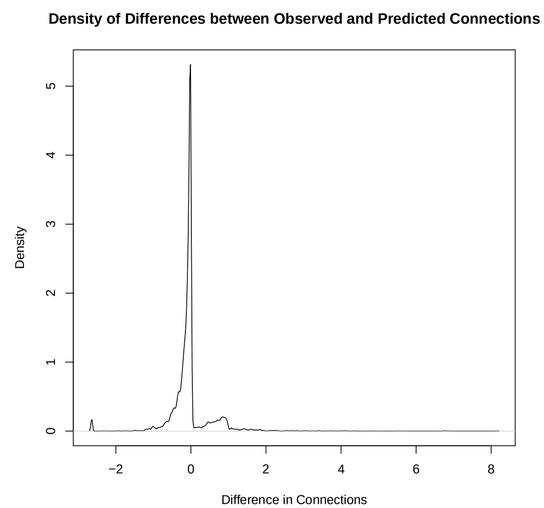
Note: Reported coefficients are from a Poisson Latent Space Model for New Hampshire, Vermont, West Virginia and Maryland's lower chambers in 2007 with two latent dimensions. 95% credible intervals are reported in parentheses. In this model shared constituency is coded (1) if two legislators represent the same constituency simultaneously. Likelihood based Bayesian Information Criterion is reported as a measure of model fit.



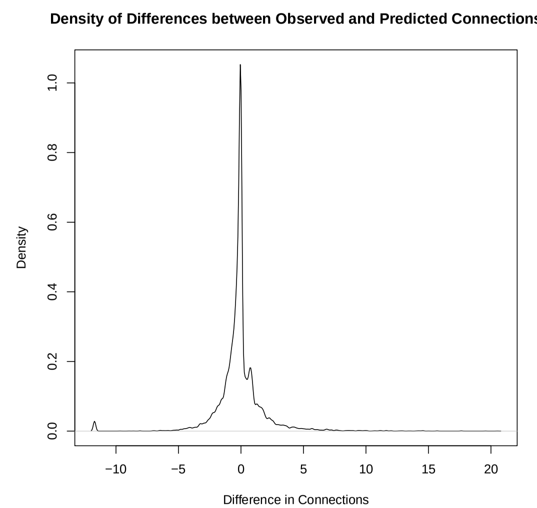
(a) New Hampshire



(b) Vermont



(c) West Virginia



(d) Maryland

Figure 7.2: Density of Prediction Errors from Poisson Latent Space Models in Four States (2007)

7.8 Appendix 3D- Committee Specific Results from Latent Space Models

The results presented in the main body this article suggest that legislators from shared districts collaborate on legislation more often than their colleagues from single-member districts. This result exists controlling for party and alternative, unmeasured dimensions of behavior. However, the possibility exists that the collaboration that occurs between legislators in a multi-member district is not a general phenomenon, but instead is a result of collaboration on a specific type of legislation. For example, legislators from multi-member districts might collaborate on bills that bring projects back to their home districts, but oppose one another on all other legislation. In order to evaluate whether the observed collaboration created by shared constituency is content specific, I have re-constructed the cosponsorship networks in North Carolina's legislature in 2001 and 2003. Instead of including all legislation, I construct three different cosponsorship networks for each year, a network for bills referred to the Appropriations Committee, a network for bills referred to the Finance Committee, and a network for bills referred to the Rules Committee. In the network for the Appropriations Committee bills, a tie between i and j exists if legislator i cosponsors a bill sponsored by legislator j and the bill's first referral was to the Appropriations Committee. In North Carolina, the Appropriations Committee deals with expenditures by the legislature, the Finance Committee deals with revenue/taxes created by the legislature, and the Rules Committee receives the bulk of the substantive legislation before it is re-referred to expert committees. Thus, examining only bills referred to each of these committees allows me to discover whether collaboration generated by shared constituency is specific to pork projects, substantive legislation, or occurs in all three areas.

Figure 7.3 plots the coefficients and their 95% credible intervals from a model predicting the number of cosponsorships between actors for each of the three committee types in 2001 and 2003. The models are run precisely as in the main body of the paper, with covariates for co-partisanship, shared district, an interaction of co-partisanship and shared district, and two latent unobserved dimensions. I place the coefficients for each variable from all three models side-by-side to facilitate comparisons across committee models. The black points represent the coefficients in 2001 and the grey points represent coefficients in 2003. In each of the models, co-partisanship is a statistically significant predictor of collaboration in 2001 and 2003. Just as in the general models, the coefficient on shared constituency is signficant in 2001 but not 2003 for each committee type. Finally, the interaction term for co-partisan and shared constituency is negative and significant for the Appropriations Committee in 2001, but is insignificant for the other five models.[2] Even on taxation issues, shared constituency generates collaboration. Additionally, there is no significant difference in collaboration for cross-partisan and co-partisan legislators from the same district.[3] Thus, it would seem that the results I report in the main body of the paper are not specific to pork-barrel legislation or substantive legislation, but occur in many types of bills. That the model uncovers significant cross-party, shared constituency effects on bills focusing on taxation seems to be strong evidence that the observed collaboration crosses across many bill types.

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[2]The marginal effect of shared constituency and same party remains positive even with the interaction term's negative influence.

[3]The interaction term between the two is insignificant implying that the marginal effect of same party, shared constituency on cosponsorship is no different than the marginal effect of cross party, shared constituency. Because the covariates are all dummy variables, a full marginal effects plot is unnecessary.

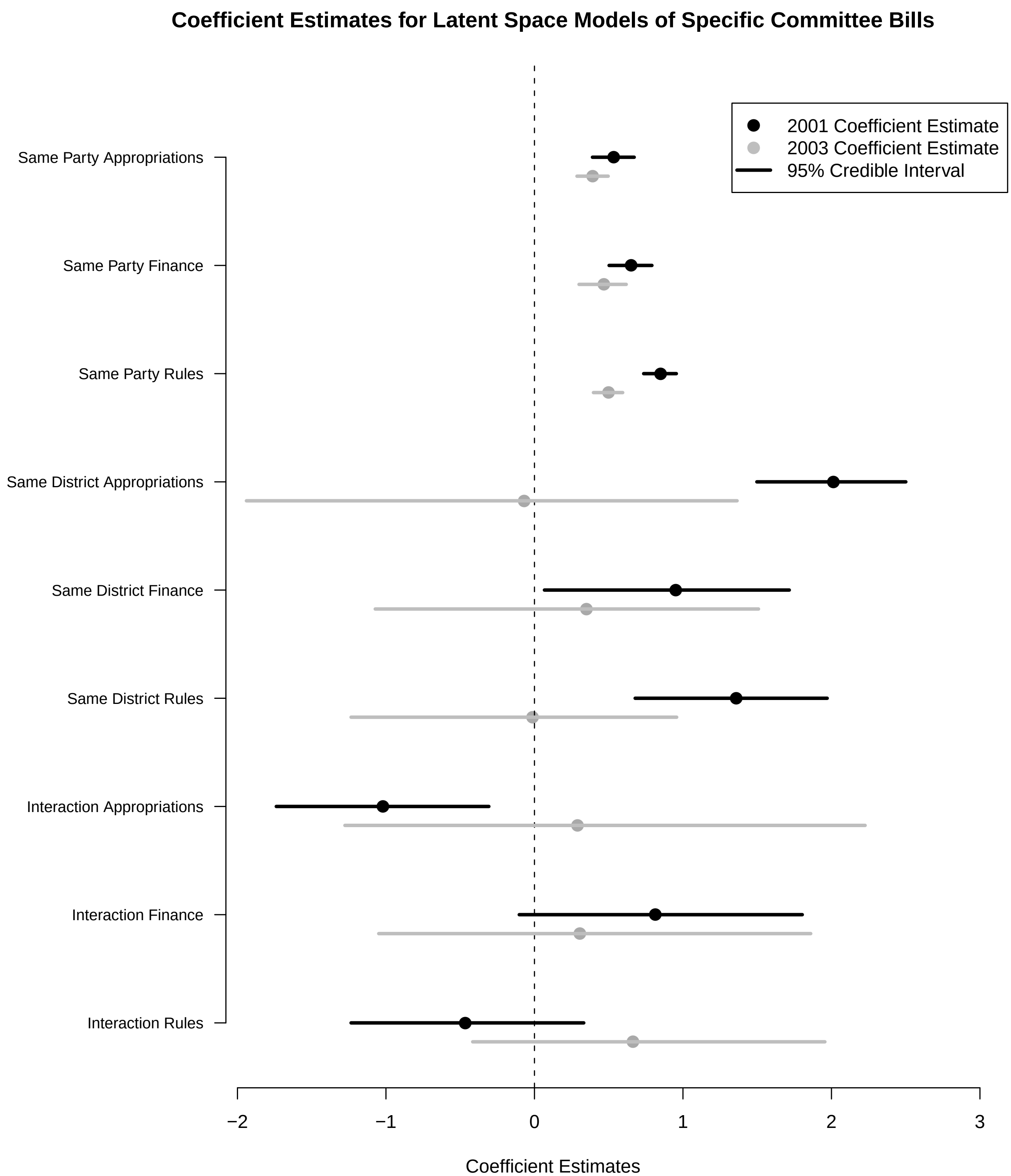

Figure 7.3: Coefficient Estimates and Credible Intervals for Appropriations, Finance, and Rules Committee Networks in 2001 and 2003

7.9 Appendix 3E -But What About Roll Call Votes

Throughout the paper, I have used cosponsorship networks as a test of induced legislative collaboration through shared consituency. I believe cosponsorship to be the most appropriate test for this hypothesis because cosponsorship requires an active decision by both a sponsor and a potential cosponsor. Decisions by a bill's sponsors about whom to solicit as cosponsors sends a signal to the floor about the legislation being sponsored (Kessler and Krehbiel 1996). Decisions about what to cosponsor send certain kinds of signals about individual legislators to their colleagues (Kirkland 2011). Thus, both actors must wish to send a signal and must agree to send that signal collaboratively. Sponsors can reject cosponsors, and cosponsors can turn down requests from sponsors. Additionally, cosponsorship can occur on *any* bill sponsored in the chamber. Alternatively, roll call voting is much less a sort of dyadic behavior and is subject to selection mechanisms in ways that make it a less ideal indicator for my analysis. Legislators are expected to take vote on nearly all legislation that comes to roll call, meaning they can be less selective about the type of signal they wish to send with their votes. Additionally, there is much less concern from the sponsor of a bill about who votes for a bill. He or she simply wishes for a majority of legislators to vote in favor of his or her legislation. Crafting the appropriate coalition is much less important at this stage of legislative deliberation. Finally, roll calls are subject to selection at the committee stage meaning patterns of co-voting at the roll call stage would represent coordinated behavior on only a small subset of the possible opportunities for collaboration.

Nevertheless, there is a lengthy tradition of roll call analysis in legislative studies and if my theory is correct I should be able to detect changes in roll call voting behavior after the change in the North Carolina legislature to single-member districts. Additionally, it is possible that legislators place little weight on cosponsorship making common cosponsorship an unimportant political activity. Roll call votes are clearly an important veto point in the chamber and carry a great deal of weight in determining policy outcomes. As such, I have gathered the roll call votes for legislators in the North Carolina House for the 2001-2002 session and the 2003-2004 session. Using Optimal Classification (Poole 2000, 2005), I fit a two-dimensional solution to the roll call votes by North Carolina House members for each session.[4] Figure 7.4 plots the coordinates of legislators on the first dimension for the 2001 and 2003 legislative sessions. Republicans are colored grey and Democrats are colored black. As expected, the first dimension of the solution has a strong partisan structure with very little overlap between the two parties.

As before, I create a vector of differences between actors on the first dimension of the solution. I can then compare the differences between legislators in the same district to differences between their colleagues from single-member districts. Because the distribution of differences is unknown, I again use the Wilcoxon Rank Test, which assesses whether there is a systematic difference in the ranking of differences between shared district and single-member district legislators. In 2001, the differences between members of the same district but different parties were ranked as statistically smaller than differences between members of different parties and different districts (p-value of 0.021). There was no measureable difference between members of the same party and same district versus members of the same party but different districts. In 2003, the differences in first dimension preferences between same districts, cross partisans and different district, cross partisans is no longer statistically significant. Cross-partisans from formerly multi-member districts no longer have distinct behaviors from the cross-partisan single-member colleagues. There were still no measureable difference between members of the same party and same district versus members of the same party but different districts.

Thus, even using the less appropriate but perhaps more politically important roll

[4]The one-dimensional solution explains over 90% of voting behavior by legislators in both sessions. The addition of a second dimension adds virtually no explanatory power to the solution.

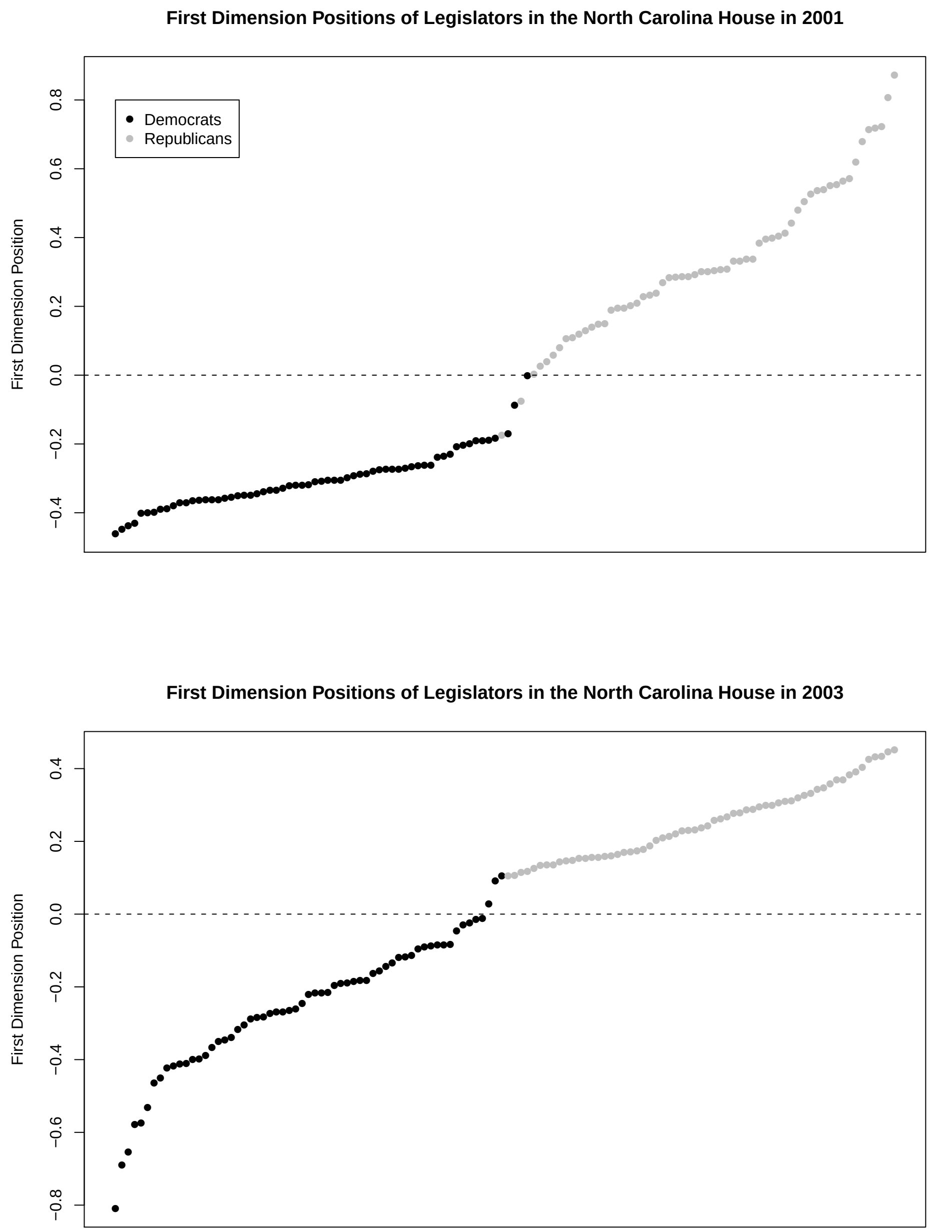

Figure 7.4: Optimal Classification in One Dimension of Roll Call Voting by NC House Legislators in 2001 and 2003

call voting measures, multi-member districts created increased levels of similarity in voting patterns amongst cross-partisans. These similarities vanished once multi-member districts were eliminated. Recall that these inferences are drawn on the same set of multi-member district legislators before and after their district change, and that their new districts are not particularly different from their prior districts. What has changed is the nature of their elections and the fact that they no longer *share* a district.

7.10 Appendix 4A - Adding Unbalanced Parties to the Model

The spatial model I use holds constant or randomly varies several elements of the data generating process in order to isolate the influences of group size on network formation. One of these elements is the distribution of party affiliations in the chamber. I randomly assign actors in the model to one of the two parties with probability of 0.5. While I allow the importance of party preferences for an individual to vary, I hold the balance of partisans in the chamber at 50/50. In order to demonstrate that the results of the computational model are robust to this choice, in this section I will present results from the computational model where one of the two parties holds an advantage. In this model, I assign actors to the political party coded 1 with probability 0.6 and the other party with probability 0.4. This is akin to saying one of the two parties performed unusually well in the preceding election and now holds a large majority in the chamber.

Otherwise, the simulation of the data proceeds precisely as before. Actors have their preferences generated from distributions. They are assigned committees and they learn about one another's preferences through overlapping committee assignments. The connections between the actors are a function of their perceived distances across all the dimensions of the preference distribution. I then calculate the distance across the subsequent network using the average path length and calculate the partisanship of the network using party modularity. Once again, while chamber size and committee size are allowed to vary systematically, the attributes of the actors themselves are only allowed to vary randomly. This assures that any systematic patterns observed in the network topology are a function of group size only.

Figure 7.5 plots the average path length as a function of varying the size of committees for a legislature of 80 actors. Committees are allowed to take on sizes ranging from 2 members to 50 members. As with the results presented in the main body of the paper, when committees become larger distance across the network shrinks. Even in a more partisan environment, actors learn about one another through common committee assignments and their updated knowledge provides opportunities for connections that otherwise would not exist. These novel connections shrink the distance across the legislative network, resulting in a more efficient distribution of relationships amongst the actors.

Figure 7.6 plots the partisan modularity for a network split along a 60-40 party divide with committee size fixed at 15 members. The network takes on chamber sizes of 50, 60, 70, 80, 90, and 100 actors. For each of the four party weightings in committee preferences, the relationship between chamber size and party modularity is positive and statistically significant. Thus, it would seem that the sensitivity of partisan modularity to network size is not a function of the number of actors associated with each party in the chamber. Their relative propensity to work within parties versus across parties remains sensitive to the size of the chamber, but not to the distribution of party affiliates.

A number of other extensions to the model may be worth pursuing, including introducing strategic connections by individual actors. In the computational model I present, actors build connections to one another based on some set of similar characteristics, but

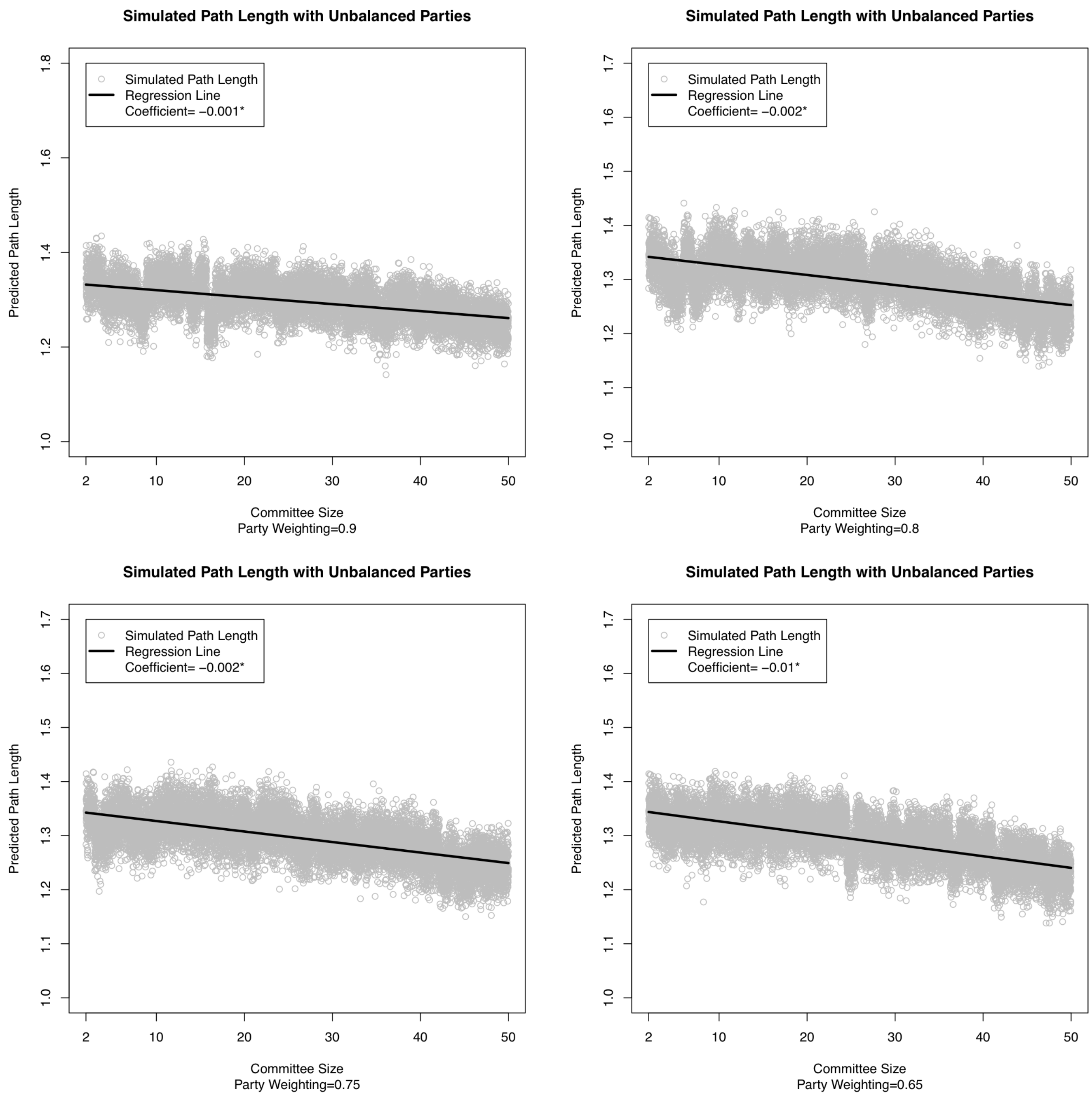

Figure 7.5: Simulated Relationship between Committee Size and Average Path Length in a Legislature for a 60-40 Party Split

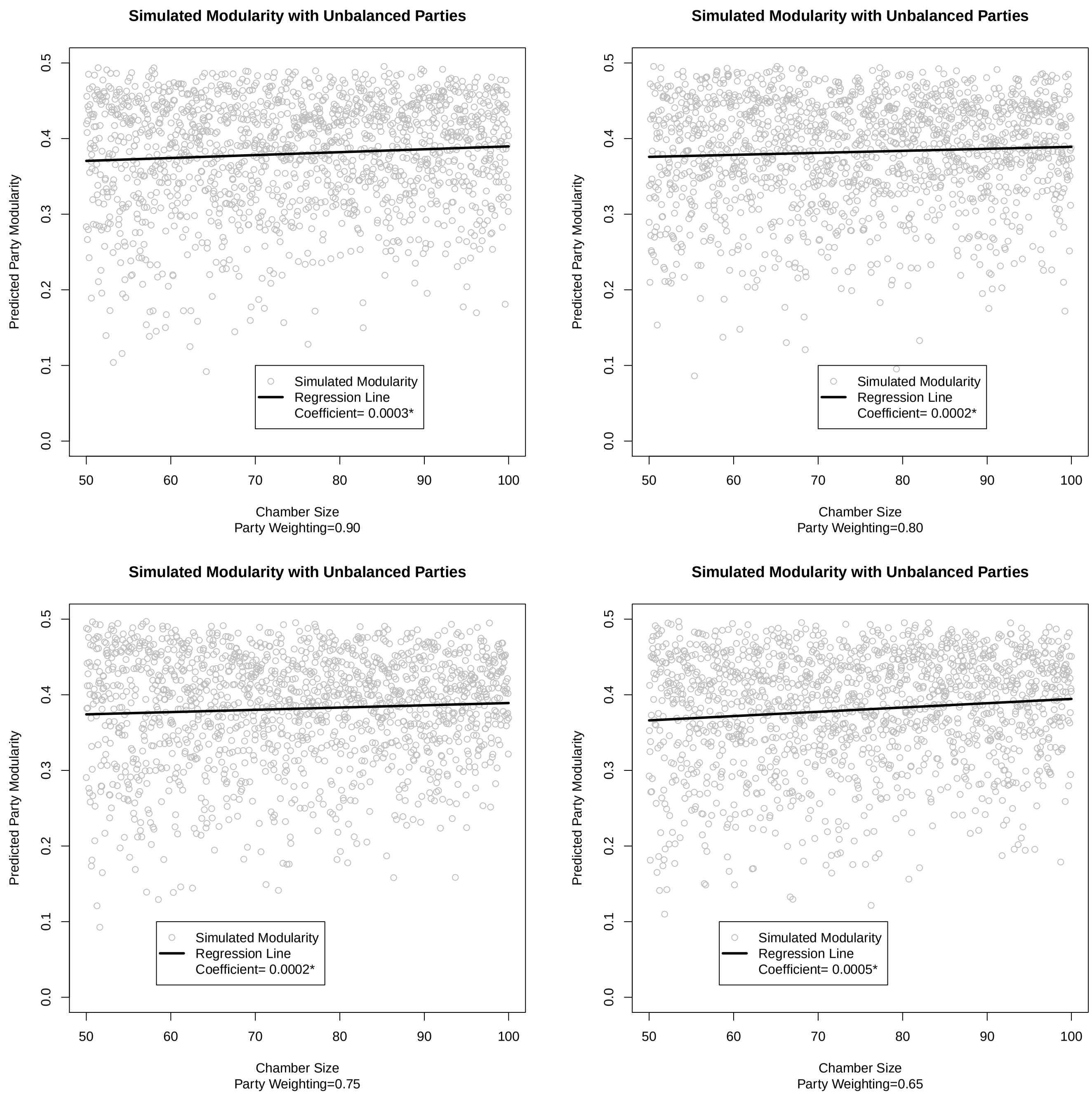

Figure 7.6: Simulated Relationship between Chamber Size and Partisan Modularity for Legislaturse with a 60-40 Party Split

in the real world, connections between actors are likely a function of both similarity and strategy. It may also be possible to incorporate sender and receiver effects into the model that reflect varying levels of prestige actors might have in a legislature. For example, committee chairs or speakers may be more desirable relational partners. While these extensions are certainly worth pursuing, it is unlikely that they will affect the results I present here. My simulations control for individual level attributes rather thoroughly. These individual-level extensions are likely to affect the intercepts of my simulations, but not the slopes of the actual regression lines.

7.11 Appendix 4B - Exploring Measures of Network Topology

Throughout my analysis, I focus on two measures of network topology: party modularity and the average path length of a cosponsorship network. Network topology refers to the global shape and structure of a network, which I assert is responsive to some of the fundamental instutitions of a legislature. The global structure of a network is necessarily hard to summarize in a single statistic, but path length and clustering are common measures associated with the long line of research on small world networks (Tam Cho and Fowler 2010, Watts and Strogatz 1998). Modularity allows me to examine clustering along a relevent dimension rather than measuring the general tendencies toward any type of clustering in the network. Other measures of bridging ties such as Burt's structural holes measure are calculations at the individual level, rather than measures of global network properties.

In particular, I focus on the size of a legislature and the size of committees within that legislature. These institutions covary with the measures of network topology in predictable ways, which I take as support for my theory. Alternatively, however, it is possible that the regression relationships I observe in my networks are not a function of a theoretical relationship of interest, but are instead a characteristic of the measures I chose. For example, if modularity along any dimension increased whenever the size of a network increased because of how modularity is calculated, then the relationship I observe would not be support for the partner selection model I advocate. To alleviate this concern, this section provides a detailed introduction to the measures I chose and demonstrates why the relationships observed in the data are not generically expected given my measures.

Modularity is a quality statistic developed primarily in statistical physics as a tool for engaging in community detection. In community detection exercises, an analyst attempts to partition a network of interactions into distinct groups, or communities, where all the actors within a community have strong connections to one another and relatively weak connections to actors in other communities. This partitioning exercise necessarily requires some way to evaluate the quality of a particular partition. Modularity is one such evaluation (and the most popular way). Modularity can actually be measured using a variety of calcuations, but the general aim is to take the observed strength of connections between members of a community and substract from it the number of connections that would be expected between two randomly chosen actors in the network. The most common formulation of modularity, and the calculation I use is:

$$Mod = \frac{1}{2m}\sum_{ij}[A_{ij} - \frac{k_i k_j}{2m}] * \delta(c_i, c_j) \tag{7.2}$$

where m is the total number of connections in the network, A_{ij} is the connection between actors i and j, k_i is the total number of connections actor i has, and $\delta(c_i, c_j)$ is the Kroneker delta for communities of actors i and j.[5] Thus, modularity examines all

[5]Kroneker's delta is a mathematical operation which returns a value of 1 if the two numbers within the operation are equal to one another, and zero otherwise.

the actors in the same community ($\delta(c_i, c_j)$), adds up their connections with one another (A_{ij}), and subtracts the connections we might expect those actors to have in the network generally ($\frac{k_i k_j}{2m}$). Finally, the sum of all these components is normalized by the total number of connections in the network ($\frac{1}{2m}$). In networks with edge weights, where connections between actors take on more than a zero or a one, the calculation is very similar. In these weighted networks, A_{ij} becomes the connection strength between i and j, m becomes the sum of all the edge weights in the network, and k_i becomes the total weighted connections of actor i.

The results of my analysis indicate that modularity based on party affiliations in legislative networks is tied to the size of the networks. If cosponsorship networks were binary, then both the total number of connections in the network ($2m$) and the number of connections each actor has (k_i) would be tied to the number of actors in the networks. However, because the cosponsorship networks are counts, m and k can be much larger than N, where N is the total number of actors in the network. As such, these is no fundamental connection between network size and modularity scores in count networks. This result is also supported by Kirkland (2011).

The other measure I make heavy use of throughout the paper is the average path length in a network. Average path length calculates the average shortest distance from any node in the network to any other node in the network as if the connections between them were paths that could be traveled. Path length is a global property of a network that reflects how much more efficiently a set of relationships is distributed than a random graph. Average path length is weakly connected to the size of a given network (Watts and Strogatz 1998), thus it is no surprise that there is a strong positive connection between chamber size and average path length. However, these is no *a priori* measurement-based reason to expect that path length would be connected to committee size.

As with most network statistics, there are a variety of ways that average path length could be calculated. An analyst must account for the distance between connected nodes and isolates in a network (actors with no connections), and in weighted networks, how to properly reflect the distance between nodes. To deal with isolates, I utilized a measure of path length that takes the distance between isolates and the rest of the network to be the maximal distance conceivable across the network. So in a 100-actor network, the distance between an isolate and any other actor in the network is 99. The isolate *must* travel across all the other actors to reach any particular actor. This amplifies the connection between path length and network/chamber size, but once again introduces no reasons for path length to be connected to committee size.

The more pressing problem for the path length calculations is how best to deal with weighted edges. Asserting that the distance between two actors who have cosponsored with one another once is equal to the distance between two actors who have cosponsored one another 10 times is problematic. My measure of path length uses the Djikstra algorithm to calculate the shortest paths across the network for each actor and averages across them (Csardi and Nepusz 2006). Djikstra's algorithm (Djikstra 1959) is asymptotically the fastest known single-source shortest-path algorithm for arbitrary directed graphs with unbounded nonnegative weights and in this case measures distance between nodes as being proportional to the edge weight between them. Thus, a cosponsorship of 1 produces a distance of 1 and a cosponsorship of 10 produces a distance of 1/10. No connection between actors is treated the same as for isolates, the distance is the maximum possible distance across the network.

7.12 Appendix 4C - A Model of Network Density

My empirical analysis uses the network statistics average path length and party modularity as dependent variables with network density as an independent variable. This is a control variable intended to account for the possibility that the patterns described by my model may be easier to detect in legislatures where cosponsorship is more common. However, density itself maybe a quantity of theoretical interest. The learning model that I advocate essentially asserts that legislators will become more risk averse in partner selection as the size of the legislature grows. If this is true, then it is reasonable to expect that as legislatures grow in size cosponsorship will generally become less common and network density will decrease.

Table 7.11 provides a regression analysis with the network density from the 96 legislative cosponsorship networks as the dependent variable. Network density is calculated by dividing the total number of connections in the network by the total number of connections that could exist in the network. It is bounded between 0 and 1, and is a scale free measure of the frequency of connection. Thus, it is perfectly comparable between networks and has no measurement based reason to correlated with chamber size. I include the same variables as the analyses reported in Table 4.1 as predictors of network density. As the table indicates, the coefficient on chamber size is negative and statistically significant meaning that as legislative chambers grow in size, cosponsorship becomes less common.[6] This reflects the increasing risk aversion in large chambers that my theory expects.

Interestingly, though it never proved a significant predictor of party modularity of average path length, the term limits dummy variable also has a significant and negative effect on network density. This implies that legislatures with term limits also have less frequency of cosponsorship.

[6] Because network density is bound between 0 and 1, OLS is not an ideal estimation technique. Thus, I have also run a beta regression with the same independent variable, which is more suited to a dependent variable distributed between 0 and 1. The beta regression coefficients are in the same direction and significance for each of the variables as those reported by OLS.

Table 7.11: OLS Models of Network Density in State Legislatures

Variable	Coefficients
Chamber Size	-0.002 *
	(0.001)
Average Committee Size	0.010
	(0.008)
Number of Committees	-0.002
	(0.004)
Number of Bills Introduced	-0.000
	(0.000)
Holbrook and Van Dunk Index	0.005 *
	(0.002)
Squire Professionalism Index	0.542 *
	(0.284)
Term Limits Dummy	-0.131 *
	(0.069)
% of Membership Turnover	-0.001
	(0.003)
Margin of Party Balance	-0.003
	(0.002)
Intercept	0.249
	(0.168)
N	96
Adjusted R-Squared	0.1489

Note: Model reports the results of Ordinary Least Squares regression model. The dependent variable is the density of the cosponsorship network for a state legislature which is continuous and bounded between 0 and 1. * $p < 0.05$ in a one-tailed test.

7.13 Appendix 5A - Bayesian Models of Reference Distribution Properties

The simulations presented above demonstrate the relationship between the various pieces of the modularity formula and the subsequent modularity reference distribution I propose. These results indicate that the variance of the reference distribution is driven by the density of the network and the probability of co-membership in the hypothesized group structure. The midpoint of the reference distribution is influenced by the degree of "true" modularity in the network. Tables 7.12 and 7.13 provide an additional examination of these hypotheses using the data from the state legislatures example in Figure 5.5. In Table 7.12, I present results from a Bayesian OLS model predicting the range of the 95% reference distribution from these empirical examples.[7] The independent variables in the model are the legislative network's density, size (measured as the number of actors in the network), party-based modularity, and probability of party co-membership. Table 7.13 uses the midpoint of the legislative network's reference distribution as the dependent variable with the same independent variables.

As expected from the simulations, the probability of co-membership and the density of a network are negatively related to the range of the reference distribution in the empirical examples. The actual party-based modularity score is positively associated with the midpoints of the legislative network's reference distribution. Thus, the relationships observed in the simulations are supported in the empirical data. Table 7.14 reports the results from the Raftery diagnostic used to assess model convergence from the regression models. As the table reports, convergence is suggested by the model diagnostics. The

[7]The Bayesian model has a burn-in period of 1000 iterations and a posterior sample of 10,000. I use diffuse priors. Both the Raftery and Geweke tests indicate model convergence.

Table 7.12: Bayesian OLS Model Predicting the Size of 95% of the Random Modularity Region

Variable	Mean	Standard Deviation	90% Posterior Density
Density	-0.062	0.011	(-0.081, -0.042)
Network Size	-0.000	0.000	(-0.000, 0.000)
Probability of Co-Membership	-0.077	0.046	(-0.154, -0.002)
Party Modularity	-0.024	0.032	(-0.078, 0.028)
Intercept	0.116	0.028	(0.070, 0.163)

Note: Cell entries report the mean, standard deviations, 2.5%, and 97.5% quantiles of the posterior distribution from a model predicting the range of the simulated reference distribution. The dependent variable in the model is the range of 95% of the simulated modularity reference distribution. The Bayesian model contains flat priors with a burn-in period of 1000 iterations and a sample size of 10000. Both the Geweke and Raftery diagnostics indicate that the model has reached convergence.

Table 7.13: Predicting the Location of the Null Modularity Region

Variable	Mean	Standard Deviation	90% Posterior Density
Density	0.006	0.007	(-0.006, 0.018)
Network Size	0.000	0.000	(-0.000, 0.000)
Probability of Co-Membership	0.016	0.030	(-0.033, 0.065)
Party Modularity	0.064	0.021	(0.029, 0.097)
Intercept	-0.024	0.018	(-0.054, 0.006)

Note: Cell entries report the mean, standard deviations, 2.5%, and 97.5% quantiles of the posterior distribution from a model predicting the location of the simulated reference distribution. The dependent variable in the model is the midpoint of the entire simulated modularity reference distribution. The Bayesian model contains flat priors with a burn-in period of 1000 iterations and a sample size of 10000. Both the Geweke and Raftery diagnostics indicate that the model has reached convergence.

suggested burn-in periods are low, and the total iterations is well below the 10,000 iterations I estimate. Additionally, the dependence in the Markov Chain is also very low. While convergence in an MCMC can never be guaranteed, the suggestion of convergence is re-iterated by the Geweke convergence diagnostics.

More traditional regression diagnostics also reveal no problems with the model specification. Using a standard OLS model, rather than a Bayesian model (though the two are identical save some small rounding error thanks to my use of diffuse priors) allows me to make use of traditional tests of violated OLS assumptions. The Brusch Pagan test

Table 7.14: Raftery Diagnostics for Regression Models

Variables	Burn-In	Total Iterations	Dependence Factor
Intercept	2	3867	1.03
Network Density	2	3929	1.05
Network Size	2	3710	0.99
Probability of Co-Membership	2	3834	1.02
Party Modularity	2	3834	1.02
σ^2	2	3757	1.00

Note: The Raftery diagnostic reveals 1) the appropriate number of burn-in iterations to suggest MCMC convergence, 2) the appropriate number of total iterations for the MCMC algorithm, and 3) the dependence factor or autocorrelation between MCMC samples. High levels of dependence in the Markov Chain indicate a variety of problems which suggest non-convergence. The dependence factor in a chain that has likely converged is 1.0

for non-constant variance confirms that heteroskedasticity is not a concern, the Durbin Watson test for autocorrelation in the errors reveals that serial correlation is not a concern, and the Bonferroni adjustment reveals that there are no leverage points or outliers influencing the results. Variance inflation factors are all very close to one, indicating that multicollinearity is not inflating the standard errors. The R^2 from the OLS version of the model reported in Table 7.12 was 0.4626, and finally the R^2 from the OLS version of the model reported in Table 7.13 is 0.2382.

7.14 Appendix 5B - R Code for Simulations

```
# 3-22-11 #

#  MCMC Modularity #

#############################




#########################

#Clear Memory and Set the Seed
```

```
rm(list=ls())
set.seed(11)
library(igraph)

#########################
#Set the Parameters
num<-50 #actors in the network
groups<-3 #number of groups
rec.cor<-500 #record the correlations
alpha<-1 #baseline rate of connection
bonus<-0 # bonus for shared team

###################
#Create Matrices for data
max.vec2<-matrix(0, rec.cor, length(bonus))
mod.min<-matrix(0, rec.cor, length(bonus))
mod.max<-matrix(0, rec.cor, length(bonus))
mod.min2<-matrix(0, rec.cor, length(bonus))
mod.max2<-matrix(0, rec.cor, length(bonus))

###################
#Loop over parameter space

#########################
#Loop repeatedly within one set of parameter values
for(jj in 1:rec.cor){
```

```
mat<-matrix(0, num, num)
actors<-sample(seq(1,groups,by=1), num, replace=T)

#########################
#Create Actor connections based on group assignment
for(i in 1:length(actors)){
zz<-which(actors==actors[i])
qq<-which(actors!=actors[i])
mat[i, zz]<-rpois(length(zz), exp(alpha+bonus))
mat[i, qq]<-rpois(length(qq), exp(alpha))
}
diag(mat)<-0


#######################################
#Permute Vector for distribution of Modularity
AMz<-graph.adjacency(mat, mode="directed")
library(gregmisc) #Load Permutation Library
mod2<-numeric(length=1000)
for(mm in 1:length(mod2)){
actors2<-sample(actors) #Permute Group Assignments
mod2[mm]<-modularity(AMz, actors2) #Modularity with Random assignment
}


#########################
```

```
#Record Modularity Scores
max.vec2[jj]<-modularity(AMz, actors) #Group Mod
mod.min[jj]<-min(mod2) #Minimum Random Assignment
mod.max[jj]<-max(mod2) #Maximum Random Assignment
mod.min2[jj]<-quantile(mod2, 0.025) #Minimum Random Assignment
mod.max2[jj]<-quantile(mod2, 0.975) #Maximum Random Assignment
print(jj)
}


dput(max.vec2, file="NoBTeamModActors50.txt")
dput(mod.min, file="NoBMinModDist.txt")
dput(mod.max, file="NoBMaxModDist.txt")
dput(mod.min2, file="MinMod952.txt")
dput(mod.max2, file="MaxMod952.txt")
```

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