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Cosponsorship Networks in the U.S. Congress:
Measuring the Success of Female Legislators

By
Brian Jewett

Claremont Graduate University
2022

Approval of the Dissertation Committee

This dissertation has been duly read, reviewed, and critiqued by the Committee listed below, which hereby approves the manuscript of Brian Jewett as fulfilling the scope and quality requirements for meriting the degree of Doctor of Philosophy in Political Science.

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Abstract

Cosponsorship Networks in the U.S. Congress:
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By

Brian Jewett

Claremont Graduate University: 2022

Previous scholarship has demonstrated that minority group members in the United States Congress generally are more supportive and collaborative within and beyond their respective groups compared to their majority group counterparts (Craig et al., 2015; Rouse, Swers and Parrott, 2013). In some cases, increased levels of collaboration positively influence legislative success and in others they do not, the results often depending on the characteristic of the group itself and the institutional setting within which the group operates. Additionally, prior studies within the domains of social network analysis and legislative behavior have shown that certain social network measures within a legislative context are associated with higher levels of legislative activity and success. Combining these elements, along with traditional variables found in many studies of legislative behavior, in a longitudinal analysis of gendered effects within both chambers of Congress has to my knowledge never been explored. This research examines chamber- and gender-specific sponsorship and cosponsorship data using the methods of social network analysis and logistic regression models during the 102nd through 114th Congresses. The methods used in this analysis test the hypotheses that female legislators in both chambers 1) exhibit greater sponsorship and co-sponsorship activity rates than their male counterparts, 2) form better social networks metrics than their male counterparts, and 3) despite these characteristics, are less successful than men in passing their sponsored binding, force-of-law

measures through each chamber compared to male members in each chamber. I expect that women in Congress are not as successful, despite demonstrating success-based characteristics, because of prejudicial attitudes perpetuated by each chamber's dominant gender group, males. The results of my analyses confirm that female representatives and senators are more active cosponsors than men and form better networks in the House of Representatives than men as measured by some but not all network measures used in the analyses. However, when comparing the legislative success of women to their male counterparts, the results were different for each chamber; females in the House were less successful than males in achieving success for their sponsored legislation, but in the Senate there were no statistically significant findings to support the same conclusion. I suggest that the differences in membership size, length of terms of service, and other institutional characteristics between the two chambers are factors contributing to the different results.

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unwavering faith that I would be successful; you were right, as always. You have been my head cheerleader, therapist, and editor-in-chief, and you have succeeded at all of them, marvelously. I know these past six years have been tough on you as I was either at work or constantly away working on my studies after work; when I was home, I was often ‘away’ mentally thinking about those studies. This Ph.D. is as much yours as it is mine. I am grateful for you and will always appreciate you. To Montana, Maddie, and Molly, you probably thought it was strange that dad was going for a doctorate at his age and when he already had a family, a career, a mortgage, several dogs, and a cat. Well, it’s certainly not the usual trajectory, but what is ‘usual’ anyway? One of my main hopes of enrolling in and completing my studies was for you to see that no matter where you are at in life or how old you are, you can always follow your passion and achieve your goals. Have faith, be committed, and persevere.

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Chapter 1: Introduction

I think in some regards the gender biases are more profound and more central to our culture than even the racial ones, and that to me was the surprise.

– *Former Senator Carol Moseley Braun, Hidden Brain Podcast, Too Sweet, Or Too Shrill? The Double Bind For Women, October 18, 2016*

Relationships are direct means for achieving goals within an organization, whether those goals are for an individual, a group, or for the entire organization. It is difficult for an individual within an organization to accomplish anything in isolation, void of interaction or ties with other members within or outside the organization. The relationships that individuals have with other organization members are the means to an end and nowhere is this more evident than in legislatures. Legislators are involved in a variety of relationships and connections including, but not limited to, legislator to legislator, legislator to interest group, and legislator to constituent relationships. Each relationship is based on something of value to each actor within the relationship. The legislator-to-legislator relationship develops in one of two ways, either during the course of legislative service, or it existed prior to the legislators commencing their service. During terms of service, the legislator-to-legislator relationship can develop, and can lead to, legislative collaboration, legislation support, information sharing, access to power, influence, mentoring, and a variety of other things.

The connection itself, regardless of how it formed or what it is based upon or what it signals, is a building block of social networks. A social network is a way of thinking about social systems that focuses attention on the relationships among the individuals that make up the social system itself (Borgatti, et al., 2013). The study of networks is called social network analysis, a method used to describe the structure of a network or capture aspects of an individual's position in the network (Scott, 2013). Network analysis can be applied to the study of these legislative

relationships, behavior, and activity to better understand the consequences of the relational ties between legislators.

One way to operationalize relational ties in legislatures is through cosponsorship acts on legislative proposals. Cosponsorship activity is a useful way to study both relationships and connections between members of a legislative body and the emergent outcomes from these connections. Studies of cosponsorship activity, using social network analysis or more traditional social science methods, have yielded robust results related to legislative behavior and legislative success. Cosponsoring is a signaling mechanism for support and collaboration; it can demonstrate a legislator's policy area of interest and expertise, and can be considered as a predictor of a measure's future legislative success (Fowler, 2006; Wilson and Young, 1997; Browne, 1985).

Most legislative behavior and social network studies have aggregated cosponsorship data based on all members of legislative bodies or all types of legislative proposals (binding, force-of-law proposals, rules-based proposals, or ceremonial proposals). There are some studies in the field that disaggregate the types of legislation (by legislative proposal type) or examine different groups (e.g. gender or racial) in legislatures rather than the entire membership. This analysis is unique in that it examines only legislative proposals that carry the force of law (binding) within both chambers of the United States Congress. The types of US Congressional legislation that are binding include public bills, private bills, and joint resolutions.¹ I chose to focus on binding legislative proposals because these are the types of legislation that have the greatest magnitudes of policy implication for large numbers of people in the country (or for the entire country in many cases).

¹ Legislative proposals that are focused on the rules and procedures of each chamber or express sentiment include concurrent and simple resolutions and are not included in this analysis.

This analysis also disaggregates by group within each chamber by studying the differences in legislative activity, network formations, and legislative success by gender group. By disaggregating by gender, a primary aim of this analysis is to better understand if women are more disadvantaged than men when it comes to legislative success. As discussed earlier, prior scholarship has found that high levels of cosponsoring activity can lead to legislative success for the legislative proposal's sponsor. However, some studies have shown that proposals sponsored by minority groups in Congress, that is racial, ethnic, and gender groups, fail more often than those sponsored by dominant groups despite increased levels of support and collaboration (measured through cosponsorship activity) on these minority-group-sponsored proposals (Craig et al., 2015; Rouse, Swers and Parrott, 2013). I extend on these prior findings using the relational lens of social network analysis.

In addition to analyzing cosponsorship data through a relational lens by gender group and by force-of-law legislative proposals only, this research encompasses thirteen terms (26 years) of Congress, providing a rich database of sponsorship and cosponsorship acts by each gender group. Research in the domains referred to in this analysis often use qualitative approaches such as surveys, interviews, and case studies. These approaches provide unique and rich accounts of legislative behavior and processes, however they do have limitations. One primary limitation of a qualitative approach is gaining access to enough US Congress members to generate a significant sample size of relational and personal account data. Thus, this approach would likely not lead to a confident generalization of results. By analyzing secondary data over 26 years of Congress, there is a very large sample size of data that provides rich descriptions of network formations and of legislative activity and success patterns by each gender group. Furthermore, another interesting event occurred during the study period: female membership in both chambers doubled

from 10 percent of membership at the beginning of the study period (102nd Congress) and to 20 percent of membership by the end of the study period (114th Congress). This study captures the effect of this doubling in size of female members of Congress. In addition to the data related to sponsorship, cosponsorship, network measures, and gender, this study also controls for traditional variables of legislative behavior that have been shown in prior research to be influential to legislative activity and success (Talbert and Potoski, 2002; Burkett, 1997; Kessler and Krehbiel, 1996; Campbell, 1982). These legislator attributes are seniority, party affiliation, majority party status, party leadership positions, and committee chair and ranking member positions.

I hope to illuminate some of the dynamics of policymaking in one of the oldest democratic legislative institutions in the world; one that has been and continues to be predominantly male. Despite females comprising slightly over 50 percent of the US population, only 313 women have ever served in Congress through the last full legislative term ending 2016 (Manning and Brudnick, 2015). This gross underrepresentation of a large segment of our nation in the national legislature has significant policy implications, particularly for female-sponsored, and arguably female-oriented, agendas and policy issues.

This introductory chapter has set the stage for the direction of the research and analysis described in this paper. The second chapter reviews prior relevant scholarship and theory including those on cosponsorship activity, legislative behavior and gender, and social network analysis. The third chapter presents the research design and methods framework and three formal hypotheses. This chapter also presents the data and variables employed in the analysis. The fourth chapter presents the analysis and results of the tests of the three study hypotheses. The fifth chapter is a discussion section that provides a summary of results and their interpretation,

the implications of this study and the policy implications of the study results, study limitations, and suggestions for future extension of this work. The final chapter provides short concluding remarks situating this study in the greater context of the domains of legislative activity, behavior, and outcomes for gender-based groups as well as other segments of Congress and society.

Chapter 2: Review of Literature

It has been a standard rule in both the Senate and House that bills and resolutions (hereinafter referred to as bills or measures) are introduced by only one legislator, called the sponsor. While other Senators and Representatives (hereinafter referred to as legislators) can submit or introduce a bill along with the original legislator, the submitting legislator whose name appears first on the bill is officially labeled as the bill sponsor.² The other legislators who help introduce or submit the bill are then labeled as cosponsors. Under House rules, only public bills can have cosponsors; private bills cannot include cosponsors (Davis, 2019; Oleszek, 2019). In the Senate, there are no rules prohibiting the inclusion of cosponsors on a private bill. A small minority of Senate private bills include cosponsors, and in those rare cases the number of cosponsors is usually very small (GovTrack, 2020).

After initial bill submission, other legislators may sign on as supporters of the bill. These legislators are also known as cosponsors of the submitted bill. Since the 1930s, members of the U.S. Senate have been able to cosponsor legislative measures without limit; that is, a bill may be cosponsored by the maximum number of senators and each Senator may cosponsor as many measures in a legislative term as they choose (Fowler, 2006b; Campbell, 1982). Before 1967, House rules prohibited Representatives from cosponsoring bills. This restriction was lifted in 1967; however, limitations were placed on the number of cosponsors a bill could secure (a maximum of 25 cosponsors per bill). In 1978, House rules were amended to allow unlimited cosponsorship, thus mirroring the cosponsorship rules of the Senate (Campbell, 1982; Deschler, 1979).

² Congressional Research Service Report RS22477, *Sponsorship and Cosponsorship of House Bills*, October 7, 2019; Congressional Research Service Report 7-5700, *Sponsorship and Cosponsorship of Senate Bills*, March 27, 2018.

Bill cosponsorship is an integral activity within the policy stages framework, with initial considerations in the formal agenda-setting stage and reaching its peak trajectory during the policy formulation process (Anderson, 2015). During these stages, bill supporters will seek cosponsors through various mechanisms, such as “Dear Colleague” letters delivered to legislator offices in an initial effort to emphasize the highlights of a bill and why it is important to support it through the legislative process (Campbell, 1982).

Bill supporters, including the sponsor, recruit cosponsors for a variety of reasons, ranging from a simple show of support for another member to a demonstration of expertise in a specific public policy area. At the initial stages of the policy cycle, legislators reveal their true policy and personal preferences through their cosponsorship activity. Before floor voting takes place, bill cosponsors can take a formal position on an issue with fewer constraints from party and committee leaders (Talbert and Potoski, 2002). They can show their support for a measure that they believe is good public policy, whether for their constituents or for the greater good (Talbert and Potoski, 2002; Campbell, 1982).

In addition to support for a measure for policy reasons, cosponsorship can be a means of showing support for another member or exhibiting legislative influence. According to theories of intra-legislative signaling, cosponsorship is meant to influence other legislators (Kessler and Krehbiel, 1996). A member’s cosponsorship act may be a means to gain influence with the sponsoring member for future reward or to thank the member for previous support on their bill; commonly referred to as “logrolling”. In the case of an influential member who cosponsors another’s measure, the purpose of the act may be to signal to other members that they should also support the measure (Campbell, 1982).

Length of tenure can also influence the rate of frequency of cosponsorship activity. In the House, junior members cosponsor at greater rates than do more senior members (Krehbiel, 1995; Campbell, 1982). However, in the Senate, according to Campbell (1982), seniority is not a prominent factor for cosponsorship frequency because junior senators have greater access to senior senators due to the smaller size of the Senate and longer election cycle compared to the House. Regardless of chamber, as junior members increase their tenure, they begin to establish their enterprises and may start to cosponsor at greater rates to build their reputations in specific policy areas and advertise their policy positions to their constituents and fellow legislators (Swers, 2005; Burkett, 1997).

When deciding to cosponsor a bill, legislators consider party affiliation, their constituency demands, interests, and ideologies, the sponsoring legislator's ideology, and their own electoral vulnerabilities within their respective states or districts (Koger, 2003; Talbert and Potoski, 2002; Campbell, 1982; Mayhew, 1974). These considerations generally support electoral connections theories that posit that legislators who share similar ideologies tend to cosponsor each other more frequently than they do with those who are ideologically dissimilar (Kessler and Krehbiel, 1996; Mayhew, 1974). However, results are mixed on the impact that electoral vulnerability has on a member's decision to cosponsor. Mayhew (1974) found that those legislators that experienced a slight electoral margin in their last election or who believe they are electorally vulnerable in the next election cycle tend to cosponsor more frequently than legislators who enjoyed a large electoral margin or face limited competition in their upcoming election. Campbell's (1982) analysis showed that electoral margin influences cosponsor productivity, but only in the Senate. The larger the electoral victory for a Senator, the fewer times a Senator will cosponsor; this finding was not present in the House analysis (Campbell,

1982). Prior studies of the House found no evidence that suggests electoral margin and cosponsorship productivity are related (Garand and Burke, 2006; Koger, 2003; Kessler and Krehbiel, 1996; Krehbiel, 1995). In the Senate, from the years 1975 through 2000, Harward and Moffett (2010) found a statistically significant positive relationship between electoral margin and cosponsorship activity, however the coefficient was too close to zero to deem it of substantive significance.

If a member's constituency is well informed of her/his cosponsorship activity and the content of the bills cosponsored comport with the primary ideological leaning of the constituency, cosponsorship activity can yield tremendous benefit for the legislator, particularly if the goal is re-election (Campbell, 1982; Mayhew, 1974). However, when disaggregating Congress by chamber, the findings are robust for the House but less so in the Senate. In one of the early empirical treatments of legislator motivations to cosponsor, Campbell (1982) found a statistically significant relationship between a legislator's ideology and the number of times the legislator cosponsored bills. This finding was present in both chambers; however, the magnitude of the effect for the House was almost twice that of the Senate (Campbell, 1982).

Prior research yields mixed conclusions about the effect that party affiliation has on the cosponsorship activity of a member of Congress. Talbert and Potoski (2002), in their analysis of the 103rd and 104th Congresses, contend that party affiliation dominates bill cosponsorship activity in both chambers. Campbell (1982) finds a significant negative relationship between the two variables, but in the Senate only (Senators from one party are less likely to cosponsor a bill sponsored by a member from another party). Krehbiel's (1995) House analysis suggests that cosponsorship is only slightly explained by partisanship while Garand and Burke (2006) found

no significant relationship between party affiliation and House members' level of cosponsorship activity in the 102nd through 105th Congresses.

Legislative Impact of Cosponsorship Activity

Clearly, there are many reasons that influence the calculus underpinning legislator cosponsorship activity. Not only have the reasons been well-examined over the past few decades, but there has also been considerable scholarly research focusing on the *impacts* that the act of cosponsoring has on the legislative process, particularly on legislative outcomes. Some legislative behavior researchers suggest cosponsorships are relegated to a form of “cheap talk” and at best provide a measure of legislative signaling void of much influence on legislative effectiveness (Wilson and Young, 1997; Kessler and Krehbiel, 1996).³ Others have demonstrated that cosponsorship activity is not without substantive meaning, in particular, that it provides useful information regarding legislator policy preferences and can influence policy outputs. If legislators considered the act of cosponsoring to be a meaningless exercise, they would cosponsor any bill that is remotely of interest to them or simply not cosponsor any bills. However, this unfettered approach is not the norm. Fowler (2006a), in his analyses of cosponsorship activities in Congresses from 1973 to 2004, explained that the number of introduced measures in each legislative term often exceeded 20,000 for both chambers of Congress. However, during these terms, the average House member cosigned a paltry 3.4 percent of the introduced measures, and the average Senate member cosigned a smaller amount at 2.4 percent of introduced measures (Fowler, 2006a). The opportunities to cosponsor are abundant, yet Legislators are highly selective when officially signing on as supporters. This selectivity suggests that Legislators take the act of cosponsoring seriously.

³ The term “cheap talk” implies that the act of cosponsorship is not detrimental to a legislator’s electoral security and has little to no influence in the policymaking process.

They also take quite seriously the act of reneging on their official support of a bill. As bills mature through the legislative process, changes in bill language may alter a member's support for a bill. When this happens, a member may decide that the revisions are not aligned with the original intent and the legislator may choose to withdraw their support. When this withdrawal happens, it can be costly to the member. Bernhard and Sulkin (2013) found that legislators who reneged on their support for a bill damaged their relationships with other members who sponsored and cosponsored the bill and jeopardized their ability to form future legislative support coalitions.

Given that legislators take the act of cosponsoring seriously, what impact does the act have on the advancement of bills through the legislative process and ultimately to legislative success? In an analysis of four state legislatures, Browne (1985) found that the *number* of cosponsors is, when taken alone, more important for a bill's passage than the attributes of the supporting cosponsors, such as majority party membership, committee membership, and a member's prior legislative success. While this research design lacked a rigorous statistical analysis (only simple descriptive statistics were presented), it provides an early tracing of the debate on the impact of cosponsoring on legislative outputs.

Subsequent scholarship on the effects of legislative cosponsorship activity employed more substantive methodologies aimed at the US Congress and yield similar findings: The act of cosponsoring signals how well legislators work together, but, more importantly, the level and characteristics of cosponsorship activity may be general predictors of which bill will move successfully through the legislative process. In general, this research has emphasized legislators' interests in cosponsoring to influence the policy process and subsequent policy outcomes (Kessler and Krehbiel, 1996). As discussed earlier, electoral motives and other legislator

attributes influence a legislator's decision to cosponsor. This position-taking acts as a mechanism for chamber leaders to select bills for the formal governmental agenda that may provide political benefit to members (Koger, 2003). As Koger (2003) notes, chamber leaders assess the nature of a bill's cosponsorship support often in terms of number of cosponsors as well as the diversity of cosponsors to determine if the bill will incur more benefit than its costs to support it through the process. In Koger's (2003) analysis of House cosponsorship activity, his research found that bills enjoy more success in committee and floor votes if the cosponsorship support is bipartisan and ideologically diverse.

Wilson and Young (1997) found that bills with cosponsors received more consideration in committee and had a better chance of getting through the committee stage than non-cosponsored bills. Yet, when it comes to the all-important floor vote, the difference in passage rates between cosponsored (approximately 11 percent) and non-cosponsored bills (approximately 8 percent) is less dramatic (Wilson and Young, 1997). Based on these findings, the researchers contend that cosponsorship activity has minimal impact on a bill passing a floor vote in either chamber (Wilson and Young, 1997); this study is one of the few that yields this finding. Caution should be exercised in interpreting the results of this analysis because the authors considered the entire population of bills in only one legislative term, the 99th Congress. Applying the same methodologies to multiple Congressional terms and a disaggregation of the introduced bills might yield more robust results and interpretations.

Implications of Cosponsorship Activity at the Group Level

Much of the prior research on cosponsorship activity in the U.S. Congress has largely been aggregated to the whole chamber level or entire Congress level. However, there have been several research efforts that examine cosponsorship activity at group levels within Congress,

particularly with respect to racial minorities and gender. These treatments are important in assessing both descriptive and substantive representation in Congress. The membership of the U.S. Congress is disproportionately white and male, and it is this characteristic that has important implications at the intersection of female representation and legislative effectiveness (Craig et al., 2015). To be a successful legislator, relationship ties, collaboration, and coalition-building are paramount. By collaborating with other legislators – both within their own parties and across party lines – legislators can increase their influence over group decisions, shape the outcome of legislation, and develop more efficient and effective policy (Barnes, 2016). Through collaboration, legislators can increase the probability that a bill is passed into law (Barnes, 2016).

Analyzing cosponsorship activities is ideal for examining these processes of coalition formation and the integration of women into the institution of Congress (Rouse et al., 2013). Craig et al. (2015) contend that cosponsoring legislation is an effective means for minority groups (racial and gender) in Congress to build coalitions, establish long-term influential relationships, and enjoy legislative success. To achieve this success, members of Congress must rely on others in their group as well as the entire legislative body. However, prior research indicates that minority groups, despite high cosponsor activity levels, are at a significant disadvantage compared to majority groups in building support for their agendas and advancing their measures to becoming law (Craig et al., 2015). If minority members draw support predominantly from colleagues of the same race, ethnicity, or gender, their small group size might not be able to counteract majority group preferences. Past studies have demonstrated this effect and the resulting obstruction of minority group legislation, policy interests, and advancement to leadership and other influential positions in the legislative body (Bratton, 2006; Kathlene, 1995; Thomas, 1994; Dodson and Carroll, 1991). These barriers are imposed by a

dominant group. In the U.S. Congress, that group is the established white male legislators in both chambers. The result for female legislators is that they are marginalized and are less influential in the policymaking process. To overcome their marginalized status, female legislators are motivated to collaborate, both with other female legislators and with male legislators (Barnes, 2016). Collaboration manifests itself through women developing professional networks and working relationships with other female legislators (Barnes, 2016). Often, these relationships are based on sponsorship and cosponsorship activities.

To mitigate the effects of barriers placed by the dominant group, some researchers argue that increasing the number of female legislators in Congress to achieve critical mass will not only achieve descriptive representation but substantive representation as well. Critical mass theorists such as Kanter (1977) contend that individuals are not able to express their true preferences until a critical mass of their group is achieved. Since this early research, there have been mixed findings of the effects of increasing numbers of women in legislative settings in the United States and throughout the world (Mendelberg, et al., 2015; Paxton, et al., 2007). Researchers and activists contend that a membership range of 15 percent to 30 percent is the threshold required for women to make substantive policy impacts in legislative bodies (Paxton, et al., 2007). However, Bratton (2005) found that in U.S. state legislatures women were more successful in floor votes when they constituted a *smaller* percentage of the legislative body. Not only have female legislators struggled to influence policy decisions as their numbers increase, but they also face increasing backlash from their male counterparts who represent the majority groups in their respective settings (Barnes, 2016; Mendelberg, et al., 2015).

When female legislators can express their policy preferences, they often do so through the sponsorship and cosponsorship mechanisms. Cosponsorship allows members to support bills

that more accurately reflect their true policy preferences, in contrast to the circumscribed choices that are offered in a floor vote (Swers, 2005). Not only does cosponsorship act as a means for women to collaborate and build coalitions to overcome dominant group obstacles and marginalization, but it is also becoming a more effective mechanism for women to increase substantive representation of females in the United States, particularly with respect to female-oriented public policy issues (Swers, 2005). In her analysis of the 103rd and 104th Congresses, Swers (2005, 2002) found that female legislators support and advocate for legislation whose content is primarily focused on issues largely specific to women (e.g., reproductive rights, wage equality, domestic violence prevention) at far greater rates than do male legislators. This finding has been supported by other scholars as well (see Barnello and Bratton, 2007; Reingold, 2000).

Standing in institutional positions is influential in the policymaking process and a necessary ingredient for legislative success. The usual positions of power in the U.S. Congress are committee chair seats and party leadership posts, with committee position yielding the most influence with respect to passing legislation (Cox and Terry, 2008; Swers, 2002). Cosponsorship activity among women tends to increase when female legislators are members of the majority party and achieve seats on powerful committees within their respective chambers. For example, in the Republican-controlled 104th Congress, moderate Republican women used their majority status to pursue legislation regarding children, family, and general health care (Swers, 2005). The relationship between members' committee positions and their cosponsorship agendas suggests that the inclusion of more women on relevant committees could expand the openness of the congressional agenda to proposals concerning various social welfare issues (Swers, 2005). However, the barriers to accessing power positions are still present (Barnes, 2016). Prior research suggests that expanding the representation of women in strategic positions of power

should then enable women to provide influence over policy decisions and increase substantive representation within the formal governmental agenda (Barnes, 2016; Swers, 2005).

Principles of Social Network Analysis

Social network analysis emerged as a methodological technique in the 1930s to help explain the concept of social structure within the social anthropology field (Scott, 2013). Since that time, an increasing number of researchers in a variety of fields, most notably sociology, have employed network analysis to formally study the complexities of social relationships and their antecedents and consequences. According to Prell (2012), social network analysis “involves theoretical concepts, methods, and analytical techniques to uncover...social relations [of] individuals and groups, the structure of those relations, and how relations and their structures influence (or are influenced by) social behavior, attitudes, beliefs and knowledge” (p. 1). As network analysis became more prominent, network theories and methodologies have been formalized, its underpinnings becoming more technical, and its perspective has become transdisciplinary as it is being applied in a wide range of social science research. Despite its prevalence in the social sciences, the domain of political science has only recently embraced network analysis as a method of inquiry, with it gaining prominence in the early 2000’s. The original resistance in political science may stem from initial concerns to combine relational data and non-relational data in the same model because relational data contain observations that are usually not independent of each other and the data typically are scale-free.⁴ Ward, et al. (2011) contend that the combination of the emergence of networking technologies and the rapid growth in the availability of relational data “has shattered the myth upon which a lot of empirical

⁴ For purposes of this discussion, non-relational data are characterized as observations or cases that have fixed characteristics or attributes, such as gender and race, or observations measured by structured scales such as income and age.

investigations in political science were predicated; namely, that individuals don't affect other individuals who are being studied” (p. 247). Political scientists realized how powerful network analysis can be when fortified with empirical data that demonstrates the presence (or absence) of connections between actors or nodes *and* that these connections have measurable and significant effects (Ward, et al., 2011).

Network theory conceptualizes the mechanisms and processes that interact with network structures to yield certain outcomes for individuals and groups (Borgatti and Halgin, 2011). Network analysis is a comprehensive, paradigmatic way of taking social structure seriously by studying directly how patterns of ties allocate resources in a social system (Wellman, 1998). Within a network paradigm, structural relations are more important for explaining and predicting observed behavior than are non-relational data. These structural relation explanations contrast sharply with more traditional approaches such as those in political science that emphasize static concepts (attributes) such as gender, race, or political party affiliation (Knoke and Yang, 2008). As network analysis, as theory and as a methodological technique, becomes more prominent across social science fields, researchers are discovering that its dynamic perspective complements, rather than conflicts with, traditional approaches that emphasize non-relational attributes and independence among observations to explain complex phenomena.

The basic portrayal of a network is a set of nodes linked by a set of ties. Nodes represent an entity of study, usually actors or agents, representing individuals or collectivities, such as organizations (Borgatti, et al., 2013). Ties are the links between pairs of nodes and can represent many types of things including, but not limited to, resource flows, information flows, or simply a friendship connection. Ties are directed or undirected and operationalized as a social connection or relationship. The entire representation of the nodes and interconnecting ties is referred to as a

network. The pattern of ties within a network generates a structure with nodes occupying positions within the structure; explaining the connection between the structure and network consequences lies at the heart of network theory (Borgatti and Halgin, 2011). These ties represent bonds that can align and coordinate action among nodes or groups of nodes, often with greater capability than a single node or group of nodes within the entire network (Borgatti and Halgin, 2011). Besides direct access, these ties can give nodes indirect access to others in the network. Thus, both direct and indirect ties are used by members within the network (social system) to search and find resources (Wellman, 1988). Because of these characteristics, ties can yield rich information about social structure antecedents and consequences.

Social Network Analysis and Legislative Behavior

According to Bonacich (1987), status can be a function of the status of those to whom one is connected. In network terms, this characteristic is described by “centrality” measures indicating which situations yield an increase in power through association with powerful others within the network, and conversely, which situations yield an increase in power through association with *less* powerful others within the network. In a legislative network, where bargaining is omnipresent, it can be advantageous for powerful legislators to be connected to those who are less powerful because bargaining costs are minimal; that is, the less powerful are reliant on the powerful and thus are more likely to agree with the interests and requests of the powerful. For minority groups in Congress, including females, connections to more central (powerful) actors allow for greater access to resources, such as influence and information, that these less powerful actors would otherwise not be able to achieve on their own or within their own-group ties.

There are numerous ways to measure the connections between legislators, but not all of them are practical. Direct observation, legislator interviews, and legislator surveys could yield robust data on legislator relationship patterns and consequences; yet these measurement techniques would be very time-consuming and costly to implement and are not without their research design challenges (e.g., response bias, survey responses could vary over time, etc.). Furthermore, it is unrealistic to expect to gain access to many legislators to conduct such activities and ensure sufficient data for the analysis. Due to these obstacles, researchers use cosponsorship activity as a proxy measure for legislator connections and relationships given that the activity has elements of both strategic and interpersonal influences (Kirkland and Gross, 2014). Members are tied or connected to each other in social network terms if they cosponsor a bill sponsored by another member, or if two or more members cosponsor the same bill. Examining cosponsor ties provides rich information about patterns of communication (particularly intra-legislative signaling), coalition-building, and the processes by which legislators attain leadership positions (Burkett, 1997; Kessler and Krehbiel, 1996). In addition, cosponsorship activity as manifestations of relational bonds between legislators offers interesting insights into the access to, and use of, power within legislative networks. Another benefit of using cosponsorship activity to study relational patterns in Congress is that there is unprecedented access to legislative archives containing this information. These resources provide scholars with the opportunity to compile a wealth of cosponsorship data and construct a wide variety of network measures at both the macro and micro levels and across many points in time (Kirkland and Gross, 2014).

Over the past twenty years, there has been active research applying social network analysis to legislative behavior and sponsorship/cosponsorship activity within legislative

networks. The cumulative findings from these research efforts are that cosponsorship ties demonstrate communication, support, and collaboration links between legislators. Furthermore, social relations matter in legislative networks; that is, they directly affect cosponsorship activity levels and, more importantly, influence roll-call voting in legislative chambers, even after controlling for legislator attributes (Peoples, 2008). By examining dyadic pairs of legislators, Peoples (2008) found that the social relation aspects of tenure similarity (seniority) and committee overlap among legislators were strong and significant attributes to how they voted in chamber floor votes. Seniority in the Senate is also believed to be strongly associated with the level of cosponsorship activity levels but has an inverse effect; cosponsorship activity by longer-tenured legislators decreases compared to more junior members (Burkett, 1997). In network terminology, Burkett's (1997) hypothesis that years of Senate service would be positively correlated with centrality and prestige in the cosponsorship network was not supported in any of the legislative terms she analyzed. This finding is unsurprising given that long-serving senators likely exert their influence through other means (e.g., party leadership positions or high-ranking committee assignments) and have established reputations, i.e., they do not rely as much on cosponsoring acts to establish their reputations as much as junior senators do.

Within a social network framework, the presence of weak relational ties between legislators, operationalized through cosponsorship connections, actually increases the likelihood of legislative success, whereas strong ties do not correlate with success after controlling for partisanship, seniority, and institutional position (Kirkland, 2011). In this context, weak legislative ties are defined as intentional attempts to generate support for a measure between dissimilar legislators; these ties yield new avenues of influence and thus support can be created (Kirkland, 2011). Thus, diversity within the cosponsorship network, as in most networks,

appears to promote success (here, legislative success). Kirkland's analysis examines eight different state legislatures from one year (2007) and applies a second analysis to seven U.S. Congressional terms (limited to the House of Representatives only), thereby providing more generalizable results than most of the prior research at the time.

Fowler (2006a, 2006b), and Tam Cho and Fowler (2010) embarked on the most comprehensive analyses of the relationships between legislators measured by cosponsorship activity to determine the impacts of these relational ties on legislative accomplishments. These studies showed that the cosponsorship stage of the legislative process, viewed through the lens of social network analysis, has considerable implications for legislative success. Fowler (2006b), in an analysis of all pieces of legislation of both chambers of Congress from 1973 through 2004, showed that, when a bill approaches a majority number of cosponsors in each respective chamber, the marginal effect of adding the next cosponsor on the probability of passage increases exponentially. However, once a bill achieves majority cosponsorship support, the marginal effect of additional cosponsorship support on bill passage diminishes rapidly (Fowler, 2006b).

Using a novel centrality-based network metric measuring how connected legislators are to each other through the frequency of their cosponsorship acts ("connectedness"), Fowler (2006a, 2006b) demonstrated that more highly connected legislators experience higher success rates when it comes to passing their own amendments on a chamber floor, after controlling for legislator party and ideology. Fowler (2006a, 2006b) found that the connectedness measure outperformed other measures of network centrality in predicting the number of successful amendments proposed by each legislator. Continuing with the same approach and dataset, Tam Cho and Fowler (2010) demonstrated that 'small-world' legislative networks in the House of

Representatives consisting of densely connected legislators via cosponsorships are more likely to produce landmark legislation than less-dense networks of legislators.⁵ While denser, stronger ties were typically found within the majority party of the Senate, regardless of party affiliation, highly-clustered small world networks were not influential in the Senate, likely due to the inherent small size of the Senate and its different institutional structure as compared to the House (Tam Cho and Fowler, 2010; Burkett, 1997).

Legislators are strategic, goal-oriented actors motivated by three main goals: (1) increased institutional prestige, (2) reelection, and (3) good public policy (Fenno, 1973). Legislators are also social beings pursuing these goals within a social construction (a legislature) comprised of interdependent relationships (Peoples, 2008; Fowler, 2006a; Fowler, 2006b; Caldeira, Clark, and Patterson, 1993). These characteristics lead to the question of how might strategic, goal-oriented legislators make use of the relational environment (that is, the network) they operate within to pursue these goals? Prior research on relationships in legislatures demonstrates that a link exists between legislative relationships and legislative outcomes (Kirkland, 2011; Tam Cho and Fowler 2010; Peoples, 2008). Craig et al. (2015) contend that cosponsoring legislation is, in many cases, an effective means for minority groups (here, female legislators) in Congress to achieve their goals, form coalitions, establish long-term influential relationships, and enhance their rates of legislative success. The existing scholarship on legislative cosponsorship suggests that the act of cosponsoring a bill is a key factor leading to the success of a bill. Measured as a relational act, cosponsoring a bill shows support and collaboration between legislators.

⁵ According to Tam Cho and Fowler (2010), small-world networks are characterized by average path lengths that are smaller than what would be found in a random graph of the same size of network. The average path lengths in a small-world network are so short that most nodes in the network can be reached in a relatively small amount of steps, resulting in highly clustered groups of nodes (Tam Cho and Fowler, 2010).

Gender, Network Analysis, and Legislative Behavior

Despite the interest and efficacy of studying cosponsorship activity in a social network framework, there is sparse research at the intersection of cosponsorship activity and gender-based network attributes of the U.S. Congress. Much of the previously cited research relies on full Congress or chamber network representations. Only a handful of researchers have disaggregated congressional or chamber-based data into group-level networks such as female and male legislative networks measured through cosponsorship ties. Clark and Caro (2013) performed an analysis of gendered cosponsorship networks within the Arizona state legislature that found that gender is the primary influence that shapes legislative collaboration on female-oriented public policies.

Demographic minority groups tend to be more active cosponsors as they try to support intra-group interests and overcome marginalization by the dominant group—in this case, white males (Craig, et al., 2015). As a minority group in Congress, female legislators collaborate with their colleagues on a more frequent basis (with males as well as with other minority groups), particularly through cosponsorship activity, whether cosponsoring another female member's bill or a male legislator's bill (Barnes, 2016; Craig, et al., 2015; Swers, 2005). In social network terms, the active cosponsoring by females indicates that female legislators give and receive more relational ties with the inference being that they have more connected networks than their male counterparts.

The scholarship in this domain suggests that better-connected legislators achieve more legislative success than less-connected legislators. Yet despite these measures indicating successful networks, female legislators still do not enjoy the same levels of legislative accomplishment as male legislators. This outcome could partly be explained by the findings that female legislators sponsor more female-oriented legislative acts, which have generally been less

viable for passage. However, females cosponsor more bills than their male counterparts do and they out-produce them in the number of sponsored bills that span a broad spectrum of policy issues, not just those focused on women's issues (Atkinson and Windett, 2019; Volden, et al., 2016; Anzia and Berry, 2011; Swers, 2002).

Another consideration to help explain the lack of comparative legislative success is the party affiliation of female legislators. Are congresswomen less successful when they are not in the majority party? It is common knowledge that the party in power in Congress is usually more influential in the policy process, through the control of what bills will be considered in committee and by the active coordination of floor votes. However, for female-sponsored legislation, prior research suggests it is not a minority party issue that determines its fate. Volden, et al. (2016; 2013) find that women in the minority party *are more effective* lawmakers than their male minority-party counterparts while female members *of the majority party* fare no better than their majority-party male counterparts in terms of legislative effectiveness. However, when the proposed legislation focuses on women's issues, only two percent of those bills become law and those that are sponsored by women themselves have a paltry one-percent passage rate (Volden, et al., 2016).

I contend that a major reason that female legislators in the U.S. Congress are less successful at achieving legislative success is because of the prejudicial attitudes perpetuated by the institution's dominant group: its male members. This prejudice is not only evident in Congress, but in most institutional and organizational settings throughout the United States. In a network-based management analysis, Brass (1985) found that women are not well-integrated into male-dominant coalitions particularly when men are in the strong majority, a membership profile like that of Congress. Another analysis of gender-based networks demonstrated that men develop

more, and stronger, homophilous ties across multitudes of networks than women, an environment that leads women to form more heterophilous ties to secure access and influence within organizations (Ibarra, 1992).⁶ Phelan and Rudman (2010) assert that women in organizational settings are caught in a double bind between their gender and leadership that poses a significant barrier to gender equality in all workplace settings. When attempting to overcome this dilemma, women must convey their ambition and ability to lead by demonstrating agency; however, when doing so they face prejudicial backlash, a cause and effect that men do not experience (Phelan and Rudman, 2010).

Volden et al. (2016) found that bias against female legislators in the U.S. House of Representatives manifests itself in the committee process. The authors find that, of the bills sponsored by women from 1973 through 2014, only 7.7 percent receive attention in committee compared to 11.5 percent for male legislative sponsors, and women's issue proposals suffer even greater reduction (Volden et al., 2016). Similarly, studies of women elected officials find that they tend to experience discrimination in the legislature, especially when it comes to seeking leadership positions (Craig, et al., 2015). These findings have important implications for female legislative success in the House because committee action is more influential than floor action on final bill decisions (O'Connor, et al., 2004). In the Senate, the influence of floor action on legislative success is commensurate with the influence of committee action (O'Connor, et al., 2004). Given these institutional differences, female senators may enjoy more success than female representatives.

⁶ The terms 'homophilous' and 'heterophilous' are frequently used in the social network literature. In the context of this research, homophily refers to the tendency of legislators to more frequently associate with other legislators who share similar characteristics, such as gender, ethnicity, or party affiliation. A heterophilous tie, in this context, would be a demonstrated relationship between non-similar legislators, such as a male legislator frequently cosponsoring a female legislator's bills.

Huckfeldt and Sprague (1995) find that there is considerable homophily in political discussion networks, with men demonstrating much higher levels of segregation than women. This segregation manifests itself in many ways in legislative institutions and networks, thus affecting gender-based voice and authority. Karpowitz and Mendelberg (2014) claim that in majority-rule legislative institutions where women are in the small minority, female legislators experience a negative balance of interruptions when speaking. This experience leads to women losing their influence, both in their own eyes and in others, particularly in majority-rule legislative environments where majorities have no short-term need to consider minority opinions (Karpowitz and Mendelberg, 2014). At the state level, Kathlene (1994) found that female state legislators encounter more hostile speech patterns than do men. These prejudicial responses have a significant deleterious effect in that they obstruct the ability of females to access power positions in Congress, regardless of past legislative productivity (as noted above, these positions exert influence in legislative accomplishment). The relationship between committee positions and cosponsorship agendas suggests that the inclusion of more women on influential committees (influential to policy passage) could expand the openness of the congressional agenda on women-sponsored bills and policy outcomes (Swers, 2005). As noted earlier, this feature may be particularly relevant to female House members given the strong control of the Speaker of the House to affect committee assignments, agenda setting, and bill action (O'Connor, et al., 2004). The resulting policy outcomes are of critical importance to affecting female substantive representation in the United States.

Literature Review Summary

Prior scholarship has shown that the act of cosponsoring has significance within the policy process. Not only does the act supply low-cost opportunities for legislators to signal their

support for policy positions to their constituents and to their legislative colleagues, but the act can also influence the progress of legislation from agenda setting through policy adoption.

In addition, prior scholarship has shown that female legislators cosponsor more often than their male counterparts. They are more active because they are more collaborative in the legislative process than are men. They use the act to elevate their status in Congress, overcome their marginalization as a minority group, and advance their interests, whether those interests are broad across all groups or focused on women's issues. Viewing a cosponsorship tie as a relational act, female legislators, by being more active cosponsors, form more clustered, collaborative networks and these characteristics supply rich perspectives of legislative behavior. Prior scholarship in this area has demonstrated that denser networks with high centrality measures, such as Fowler's (2006a,b) connectedness measure, portend positive outcomes, in this case, successful legislative floor votes.

Yet, there is a curious lack of sub-congressional chamber analysis focusing on gender-based cosponsorship networks, their network attributes, and implications for successful outcomes across many legislative terms, particularly current legislative terms as female membership of Congress has currently surpassed the twenty-five (25) percent mark. Could it be that this percentage is not meaningful enough; in other words, have we not reached the necessary critical-mass threshold? Regardless of the reasons for the paucity of research in this area, it is worth examining, particularly within the past thirty years where female membership in Congress has risen dramatically compared to the prior thirty years (roughly ten percent membership in 1992 to the twenty-five percent in the current 117th Congress). Given this rise, are there trends that would suggest that female legislative effectiveness is on the rise? This analysis will help to answer these questions and fill a current gap in the scholarship in this domain.

Chapter 3: Research Design and Methodologies

The basic premise of the prior scholarship on legislative behavior and social network analysis is that legislative productivity and effectiveness are related not only to the institutional rules and norms of Congress and the attributes of its legislators but also to the social dynamics of those legislators within congressional chambers (Kirkland and Gross, 2014; Tam Cho and Fowler, 2010). In hopes of contributing knowledge to this scholarship, my contention is that female legislators in the U.S. Congress, despite better congressional network dynamics than their male counterparts (e.g., higher centrality metrics, greater network clustering, and active collaboration with the male dominant group), are less successful with their sponsored legislation passing chamber floor votes compared to male legislators. This outcome implies that the prejudicial attitudes perpetuated by the institution's male legislators mute the effects of these strong female legislator network dynamics. A complementary purpose of this analysis is to expose any trends in female legislative behavior and effectiveness rates that may have occurred from 1991 through 2016 as more females joined the ranks of Congress during this period.

Research Hypotheses

To study these issues, this analysis examines the relationship between gender-specific sponsorship and cosponsorship acts, social network metrics, legislator attributes, and legislative success for female- and male-sponsored legislation across multiple terms of each chamber of Congress. Because this research is aimed at legislative cosponsorship activity and legislators' consequential networks, and the success rate of legislation sponsored by female legislators, the following hypotheses are formulated:

Hypothesis 1: Female legislators within both chambers of the United States Congress exhibit greater rates of sponsorship and cosponsorship activity (on average) on binding, force-of-law congressional measures than their male counterparts.

Hypothesis 2: Female legislators within both chambers of the United States Congress exhibit greater network centrality, cohesion, and “connectedness”⁷ values (on average) on binding, force-of-law congressional measures than their male counterparts.

Hypothesis 3: Despite sponsoring and cosponsoring at greater rates and forming better networks as measured, female legislators are less successful in passing their binding, force-of-law measures in both chambers of the United States Congress than their male counterparts, controlling for other variables.

Based on prior scholarship and my initial analyses in this area, I expect to find that Hypothesis 1 and Hypothesis 2 will be validated in both chambers of Congress. Yet, despite the implications for success attributed to greater legislative activity and more collaborative, connected legislative networks, I expect that the results of the analysis will support my inference (through the validation of Hypothesis 3) that women are less successful, in both chambers, at getting their bills passed during floor action due to sexist norms and actions perpetuated by the male dominant groups in both chambers of Congress. There are three prongs of prior scholarship that are referenced in this paper from which I base this claim: one, past empirical findings demonstrate that legislators who are more active in sponsoring and cosponsoring are generally more successful in achieving sufficient floor votes to pass their bills; two, past empirical findings demonstrate that legislators who form better networks (as previously defined) are generally more successful in achieving sufficient floor votes to pass their bills; and three, past empirical findings demonstrate that females in organizational settings typically face obstacles presented by male dominant groups designed to suppress female voice and authority within those organizations.

One caveat to be considered in this analysis is the different institutional characteristics between the House and Senate and the influence this difference may have on the results. While I

⁷ See Fowler (2006a,b)

hypothesize that females in both chambers enjoyed less legislative success than men during the study period, I anticipate that the magnitude of the differences between gender groups may be greater in the House than in the Senate. There are numerous differences between the two chambers that form the basis of my proposition. One, unlike the House, the Senate has a long tradition of strong bonds formed among all members largely due to the chamber's intimate size and greater term lengths than those enjoyed by House members (Barnes, 2016; Uslander and Zittel, 2011). These characteristics encourage senators to have a good relationship with each other and work together across party lines rather than constantly considering re-election opportunities every two years (Uslander and Zittel, 2011). Second, the House and Senate have different procedural rules and ways of conducting business (O'Connor, et al., 2004). The House, with over four times the membership body of the Senate, has strict rules on how much time a member has for floor debate; and furthermore, not every representative has the opportunity to influence legislation whereas senators enjoy more floor debate time and can influence legislation when they want (O'Connor, et al., 2004). Related to this point, the House elects a Speaker who exerts a tremendous amount of control over the chamber's operations, including agenda setting, committee assignments, and the legislative adoption process (O'Connor, et al., 2004). The Senate has no such position, with majority and minority party leaders often working across party lines to influence legislative productivity. Finally, according to O'Connor, et al. (2004), it has become more difficult to adopt legislation in the Senate due to a substantial increase in the chamber's workload during the 1990s and 2000s. Based on the prior scholarship that states that members of the Senate are more collegial and have stronger working relationships than those found in the House, I anticipate that the difficulties in passing legislation in the Senate may

affect both gender groups. Whether this effect equally impacts women and men is something that could be considered in future studies.

Research Design

Theories and scholarship in the fields of legislative behavior and cosponsorship activity, gender and legislative behavior, and legislative networks and social network analysis inform the formation for the hypotheses proposed here and the research design and methods to be utilized. The proposed research method approach for this study is explanatory and solely quantitative; that is, using archival data and employing empirical analyses through deductive reasoning. The study will be an observational comparative one where the results of the analysis will be used to compare the characteristics and performance measures of female and male legislators and their cosponsorship networks. The scholarship in this domain has utilized similar methods for collecting and analyzing data.

Quantitative, Qualitative, or Mixed Methods Approach?

Does a study of relational data implore the use of qualitative methods? Such methods do help to explain phenomena through perceptions of personal experience and are frequently utilized in studies of structural and network analysis (Stake, 2010). These perceptions and experiences typically yield rich information about the relationships formed in Congress and their influence on sponsorship and cosponsorship activity as well as on the policy process itself. Given the benefits of qualitative methods and the complementary benefits of quantitative approaches, it seems to be a logical conclusion to incorporate both methods in a mixed approach. Where qualitative studies of legislative social networks would illuminate the relationships between cases (legislators), quantitative studies of networks would simultaneously help researchers understand the relationships between variables, *including* relational data such as social network measures. In addition, a mixed methods approach may help mitigate potential

omitted variable bias, particularly information related to 1) legislator personal experiences and perspectives on the value of cosponsoring legislation thus informing the question of how influential is the activity during the policy cycle, 2) the experiences of female legislators in seeking successful floor votes for their legislation, and 3) the obstacles that female legislators face as a minority group in Congress and the effect of those obstacles in legislative activity, relationship-building, and personal advancement within their respective chambers.

Given the listed benefits of using both approaches, why is a qualitative analysis not included in this study? As for all studies at the intersection of legislative network analysis and cosponsorship activity, qualitative analyses suffer from three limitations: time, access, and bias. In general, qualitative studies take more time to conduct than those that employ secondary data, particularly during their data collection and management phases. Finding and collecting relational information and data from legislators, when they are spread across the country or in session in Washington, D.C., would be a monumental undertaking. There simply would not be enough time to gather relevant data from a sufficient sample of legislators for purposes of this study. Despite time being an obstacle, the biggest obstacle to the data-gathering process for this type of study is gaining access to the legislators themselves. Given the stature and responsibility of a member of Congress and the enormous demands placed on their time, it would be impossible to interview enough legislators personally or by phone. In addition, given their demands and responsibilities, a survey approach would likely yield little to no result. Finally, biases are not limited solely to quantitative methods; qualitative studies also can suffer from biases that can degrade a study's external and internal validity. Assessing social contact among legislators through qualitative mechanisms may enhance measurement validity, yet may suffer biases due to potential misreporting, cognitive constraints, and politically motivated strategic

considerations (Kirkland and Gross, 2014). Furthermore, for reasons listed in this section, lack of sufficient time and access to interview or survey legislators would not yield a sufficient sample size thus jeopardizing the generalization of findings to Congress in its entirety.

For this study, like many in the social sciences, internal validity is of great concern when testing theory (Campbell and Stanley, 1963). However, external validity is of equal concern and importance in applied social science research. To reduce threats to external validity, the design of this study will incorporate a large sampling of the cosponsorship activity of all legislators in the U.S. Congress with respect to binding, force-of-law legislation over multiple terms of Congress. Working with large sample data enhances generalizability and helps to diminish the distinction between internal and external validity (Gerring, 2012). Furthermore, larger samples reduce the variance of model estimators thus promoting more confident inferences. To help mitigate internal validity threats in this study, the research design and methods utilized include the examination of the same variables of interest across multiple time periods (102nd through 114th Congresses), incorporation of a “control” group (in this case, male members of Congress are the control group, or comparison group), and model diagnostic testing. The following chapter describes these techniques in greater detail.

Network Constructions

The three primary elements of network research design are social settings, relational form and content, and level of data analysis (Knoke and Yang, 2008). To ensure proper data measurement and analysis, this study’s network research design assesses these elements to answer the research question, test the stated hypotheses, and guide the accompanying analyses. The social setting for this research effort is straightforward: legislators of both chambers of the United States Congress over multiple legislative terms. While the entire legislative body of Congress during this time-period will be studied in this analysis, it is a relatively small setting in

comparison to many network analysis designs. The setting characteristics of this design are advantageous to the study because the boundaries are well-defined, the population scope is identifiable and relatively static during the study period (generally, 100 U.S. Senators and 435 U.S. Representatives per legislative term), and cosponsorship data from each legislative term are easily accessible and relatively error-free.⁸

For this analysis, relational form and content are also relatively straightforward and stable. Cosponsorship acts are well-established proxies for relational ties in network literature examining legislative influence, productivity, and outcomes (e.g., Kirkland and Gross, 2014; Tam Cho and Fowler, 2010; Fowler, 2006a,b). For measuring valued ties in this study, cosponsorship acts are enumerated to demonstrate frequency of relations between two pairs of legislators and in some case intensity of relations if the number of ties in a particular dyadic relationship is remarkable compared to others within a legislative term. Relational content attempts to capture the meanings of a relational tie from a researcher's perspective (Knoke and Yang, 2008). This is a construct validity assessment to ensure that what we are measuring as network analysts is appropriately represented by the tie.

According to Knoke and Yang (2008), there are seven primary relational elements in network analysis. Of these seven, instrumental relations involve actors who contact one another to obtain a resource for the benefit of one or both actors. In this case, cosponsorship ties represent instrumental relations between legislators who contact each other to obtain support for a measure and possibly to trade support at some later time. Presumably, and based on prior

⁸ The author notes that some errors in legislator characteristics were found in the archival data used for this analysis. This is expected when managing large datasets. Every attempt has been made to correct those errors; however, it is likely that some errors remain. These remaining errors, if any, are likely few in number and can be attributed to random noise in the data.

literature, this support often manifests itself in binding vote actions. This relational tie is the only one studied. Consequently, this research design considers a single-layer network.⁹

In network studies, there are typically four levels of analysis: node, dyad, small group (triads and cliques, for example) and whole network (Borgatti et al., 2013; Knoke and Yang, 2008). The first three levels can be characterized as micro-level units of analysis while the whole network approach is generally considered to be a macro-level one. Network studies often focus on one level but can describe two or more levels independently of each other if the research questions warrant this approach. Network studies do not try to deduce knowledge from one level to another because the structural relationships and related emergent phenomena between levels of analysis are separate and distinct (Knoke and Yang, 2008). In this research effort, the level of analysis is conducted at the node level (the legislator). Each node's network outcome will be aggregated to generalize findings about female legislators (not the group or whole network) in comparison to male legislators. This approach is like that of Tam Cho and Fowler (2010), who aggregate individual-level data to each chamber of Congress. Their aggregation approach likely loses some rich information about the influence of social components on legislative accomplishment whereas my analysis further disaggregates to the gender-based group level to elicit information related to the effect of a legislator's gender on legislative success, within a social network context.

Furthermore, this analysis not only examines differences in female and male members of Congress but also conducts the node-level analyses longitudinally (1991-2016) *and* at discrete time intervals vis-à-vis two-year legislative terms. Per Kirkland and Gross (2014), disaggregation into time intervals can yield additional information regarding legislative

⁹ If multiple ties or relational layers were considered in the analysis, it would involve the design of multiplex networks.

chambers and individual and group-level response to exogenous stimuli that higher-level aggregation may otherwise obscure. Another benefit of this approach is that measurement of multiple time intervals helps address threats to interval validity. By examining all legislative terms in one interval *and* specific legislative terms as separate intervals, structural and other changes in cosponsorship relations and their impact on legislative success over the course of the twenty-six-year study period can be detected.

Variables

There are two types of variables in this study: network-based and attribute-based. The variables are constructed and reported at the individual (also called the enterprise) level; that is, the level of the legislator.¹⁰ Network-related variables are dynamic measurements of the characteristics of legislator relationships measured on a continuous scale. Network variables are based on relational data operationalized through each cosponsorship tie. This study will treat and report these variables as raw values rather than in normalized form for the following reasons: one, I believe that the use of raw values, compared to the use of normalized values, more effectively demonstrates the strength or intensity of relationships between actors in a network; and two, network analysis often reports normalized measures on scales outside the boundaries of -1 and 1 due to the multi-relational nature of network data. This characteristic makes it more difficult to interpret the coefficients of network variables in traditional statistical models.

Network variables are mutable and can change from one legislative term to another depending on the frequency of sponsorship and cosponsorship activity by each legislator, while the included legislator attribute variables are less dynamic. Legislator attribute variables relate to

¹⁰ In some legislative network studies, such as Burkett (1999), individual legislators are identified as ‘enterprises’. The term refers to a legislator’s office, including staff, but for network analysis purposes, the enterprise is considered at the individual or node level of analysis.

the individual characteristics of each legislator, such as gender, party affiliation, and legislative committee membership. Some of these variables, such as majority party status, can change over time but these changes occur less frequently across legislative terms than do network-based measures. These network and legislator attribute variables have been identified and analyzed in the scholarship of the field to some degree; yet this study uniquely combines most of them in various time intervals and based on gender differences.

The dependent variable in this analysis is a binary response one; that is, for each legislative proposal (binding proposals only), either the proposal passed a chamber floor vote, or it failed on the floor. Legislative accomplishment in Congress can mean different things to different scholars of congressional legislative behavior. For example, Volden and Wiseman (2014) maintained comprehensive datasets that measure each legislator's effectiveness in terms of legislative productivity and accomplishment. According to the researchers, these datasets incorporate fifteen indicators that collectively capture the proven ability of a legislator to advance their agenda items through the legislative process and into law (Volden and Wiseman, 2014). The indicators represent different stages of the bill consideration process, not just floor votes, as well as certain attributes of each legislator. Fowler (2006a,b) considered any piece of legislation that passed a chamber floor vote as a legislative accomplishment, if the legislation contained at least one cosponsor signature. Like Fowler (2006a,b), my analysis solely considers whether a measure passed a chamber floor vote and disregards prior stages of the bill consideration process or policy cycle because of my fundamental concern for the policy implications of each bill on some segment or all segments of American society. Passing committee or sub-committee hurdles, for example, has few if any policy implications for the American public.

The leading question after considering this approach to the dependent variable is what constitutes a significant piece of legislation? A precise definition is likely impossible, but several scholars have attempted to categorize and operationalize legislative accomplishment. Mayhew (1991) defines important legislation as that which is “both innovative and consequential—or if viewed from the time of passage, thought likely to be consequential” (p 37). According to Mayhew (1991), the arbiters to make these judgments are contemporary journalists who specialize in end-of-session congressional reviews and policy specialists who craft related historical analyses of prior congressional policy. In their analysis of cosponsorship and legislative success, Tam Cho and Fowler (2010) utilized the Mayhew definition to derive their dependent variable. Volden and Wiseman (2014) categorize bills as being either commemorative, substantive, or substantive and significant. In their coding system, a bill is deemed substantive or substantive and significant if it was the subject of write-up in the Congressional Quarterly Almanac. Like Mayhew, Clinton and Lapinski (2006) define significant legislation as a statute or constitutional amendment that has been identified as noteworthy by a reputable chronicler-rater of the congressional session.

This study’s definition of legislative success is situated between those of Mayhew (1991) and Fowler (2006a,b). The focal points of this study are the hypothesized differences in legislative success between male and female legislators and the policy implications of the hypothesized gender disparity in legislative effectiveness consequently affecting female substantive representation in the United States. Therefore, this analysis solely considers two types of legislative proposals within each chamber of Congress, bills and joint resolutions, because these forms of legislative business are the only ones that are binding and carry the force of law within U.S. public policy development (Govinfo, 2021; Dove, 1997). The other types of

legislative proposals are concurrent resolutions and simple resolutions. These types of congressional bills are largely operations-based, in that they make or amend rules for both chambers (concurrent resolution) or to one chamber only (simple resolution) or are used to express the sentiments of a chamber; in both cases, these legislative proposals are not binding (Govinfo, 2021).

Bills are either public or private. Public bills have elements that affect the general public and private bills contain elements that affect individuals and organizations (Govinfo, 2021). While private bills may affect a certain individual (most deal with immigration and residency requests), congressional rules prohibit private bills from including cosponsors, a main operational element of the relational network and legislative behavior framework of this study (Govinfo, 2021). Therefore, only public bills, rather than private bills, are considered in this analysis. The data sources described later in this paper clearly identify each type of legislative proposal, including information on public and private bills, so that I could select only those legislative proposals that are binding. Table 1 provides a listing of each type of legislative proposal as presented in the data sources, the formal coding for each type used by both chambers, and an example proposal name. This type of coding system was an invaluable resource for properly identifying which legislative proposals would be included in this analysis. For descriptive efficiency, I refer to public bills and joint resolutions as ‘bills’ or as ‘legislative proposals’ and as ‘significant’ throughout the rest of this paper.

Table 1. Legislative Proposal Coding System

<i>Proposal Type</i>	<i>Congressional Coding</i>	<i>Purpose</i>
Bills	H.R. - House Bill S. - Senate Bill	A binding legislative proposal. Public bills affect the general public. Private bills affect individuals or organizations.
Joint Resolutions	H.J. Res. - House Joint Resolution S.J. Res. - Senate Joint Resolution	A binding legislative proposal that requires approval of both chambers. Joint resolutions are typically used for limited matters, such as single appropriations for a specific purpose or for a constitutional amendment.
Concurrent Resolutions	H. Con. Res. - House Concurrent Resolution S. Con. Res. - Senate Concurrent Resolution	A non-binding legislative proposal that requires approval of both chambers but does not require the signature of the President. Concurrent resolutions are typically used to make or amend rules that apply to both chambers or to express a sentiment of both chambers, such as congratulating a country, an organization, or an individual.
Simple Resolutions	H. Res. - House Simple Resolution S. Res. - Senate Simple Resolution	A non-binding legislative proposal that requires approval solely from the chamber the proposal was introduced in and does not require the signature of the President. Simple resolutions are typically used to make or amend rules that apply to the chamber the proposal was introduced in or to express a sentiment of the chamber.

Source: Govinfo website; <http://govinfo.gov>.

Independent Variables (Network-based)

The sponsorship and cosponsorship activities of each legislator provide information regarding levels of legislator support, collaboration, agenda setting, influence, and prominence in a legislative body. In social network terms, each cosponsorship act is a directed tie from a

cosponsoring legislator to a sponsoring legislator. In this study, two legislators are linked, or have formed a relational tie (also known as an edge), if one has cosponsored another's bill, even if the cosponsorship act happened only once during the legislative term between these two legislators. While the aggregation of these ties forms a cosponsorship network, the individual ties are useful to study the relationships between legislators and their potential effect on legislative productivity and success. At a minimum, the cosponsorship act itself demonstrates the cosponsoring legislator's explicit support for the sponsor, the bill, or both (Kirkland and Gross, 2014).

From these relational ties, many social network metrics can be calculated and have been utilized in causal inference studies. The most common of these measures are degree centrality, eigenvector centrality, average path length, and clustering coefficient.¹¹ In addition, Fowler (2006a,b) developed a unique centrality measure called 'connectedness' which provides information as to the frequency and numbers of cosponsorships between legislators. Fowler (2006a,b) found that the measure helps explain legislative influence and legislator roll call votes. Harward and Moffett (2010) utilized this connectedness measure in their study of major bills in the Senate from 1975 through 2000 and also found the measure helped to explain legislative effectiveness within their research design.

Of these previously employed measures, this study includes degree centrality, clustering coefficient, and connectedness, while omitting average path length and eigenvector centrality. Average path length has been applied in legislative network studies that focus on network size and related implications, which are not the focus of this study. Several legislative network studies such as Kirkland and Gross (2014) and Fowler (2006a) use eigenvector centrality;

¹¹ In addition to the explanations in this section, brief definitions of these measures and those used in this study can be found in the Glossary section.

however, its use is inappropriate for this study as explained later in this section. Two network measures unique to this field of study that are employed in this analysis are Bonacich power centrality (“beta centrality”), a special form of eigenvector centrality, and E-I index, which measures group embedding based on the number of ties within and between groups (Hanneman and Riddle, 2004). A final general note on these selected variables is that several of the measures can be analyzed and displayed in their raw form or can be normalized for comparative purposes. Later sections of this paper will describe where this process occurs in the analysis.

Degree Centrality

Various positions in a structural network can be advantageous or disadvantageous to nodes or actors within the network (Hanneman and Riddle, 2005). An advantageous position in a network translates to more opportunities and fewer constraints for an actor within the network (Hanneman and Riddle, 2005). This favorable position for the actor can yield greater network influence, power, and prestige (Borgatti, et al., 2013; Hanneman and Riddle, 2005). One way to measure the advantage or disadvantage of an actor’s network location is to consider the number of degrees, or direct ties, the focal actor has to other actors in the network. Figure 1 illustrates that Actor 1 has five direct ties in the network; in network terminology, Actor 1 has degree five, whereas Actor 2 has degree two because it has two direct ties in the network, those to Actors 1 and 3. In a cosponsorship network focusing on one bill, the sponsor will be the focal actor and if there are cosponsors, the only ties present in the network are from each cosponsor to the sponsor. Therefore, as demonstrated in Figure 2, Sponsor has degree five, and the Cosponsors each have degree one.

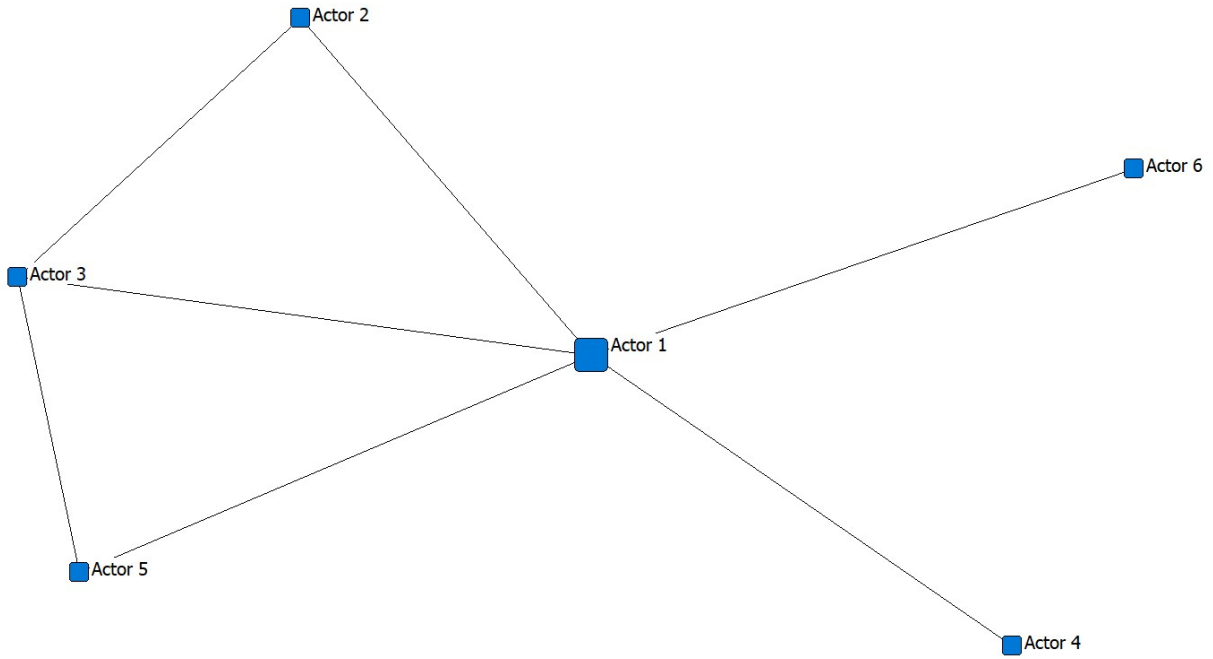


Figure 1. Network Illustration of Actor Degrees

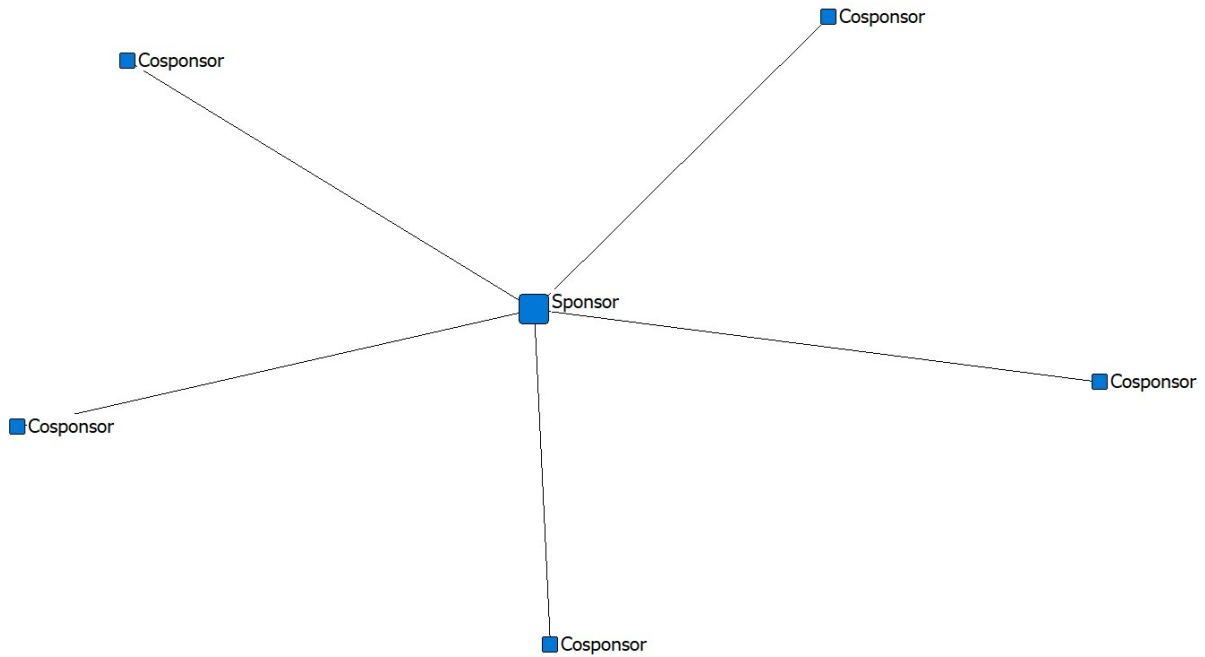


Figure 2. Cosponsorship Network Illustration of Actor (Legislator) Degrees

In general network terminology, degree centrality measures an actor's position in the network by considering the number of other actors this focal actor is tied to or connected to directly (Smith, et al., 2014). Actors that have high degree centrality are well-connected to other actors within the network (Scott, 2013). This feature is particularly important in legislative networks as a high degree centrality value compared to others in the network often indicates that the legislator (actor) is well-connected to other legislators which could improve access to resources the legislator needs or could allow for the legislator to supply to other legislators in the network. Consequently, the legislator with high-degree centrality can also constrain those resources (Smith, et al., 2014). For example, a well-connected legislator could withhold information, support, or others' support for a particular legislative proposal which could be more detrimental to the success of the proposal compared to a less-connected legislator (lower level of degree centrality) who might try to withhold information or support. Thus, we can expect that an actor with high degree centrality in a legislative network wields significant power. In cosponsorship networks, a legislator with a high degree centrality value, by way of receiving a large number of cosponsorship ties (known as in-degrees) or by giving a lot of cosponsorship ties (known as out-degrees) possesses a great deal of influence or power within the network. For the sponsoring legislator, a high degree centrality value signifies that the legislator, or the sponsored bill (or both), is receiving a great deal of support (or perhaps the bill itself garnered the support early in the policy cycle). In either case, the cosponsorship act, operationalized in network terms as a degree, has significant meaning within the framework of this study.

With directed data, it is appropriate to separate the degree centrality measure into *in-degree* centrality and *out-degree* centrality (Hanneman and Riddle, 2005). As the names imply, in-degree centrality is a measure of the number of ties an actor receives and out-degree centrality

measures the number of ties an actor gives.¹² Because this study focuses on ties (cosponsorships) received, the in-degree centrality measure will be employed; that is, the number of cosponsorships a sponsoring legislator receives on its bill from other legislators. This distinction is important for studies of legislative networks, as legislators who receive many ties are not only located in favorable structural positions in the network for resource access purposes but receiving many ties can also indicate a legislator’s network prestige as other legislators seek to form ties with this prominent legislator (Hanneman and Riddle, 2005). This analysis reports the raw values of in-degree centrality to demonstrate the wide range of intensity levels in this relational measure. The formula for the raw scale in-degree centrality is:

$$C_1(i) = \sum_{j=1}^n (x_{ji}) \quad (1)$$

where C is the raw centrality score, x_{ji} is the value of the tie from actor j (the *cosponsor* in this case) to actor (*sponsor*) i (a value of either 0 or 1) and n represents the number of actors in the network.

Bonacich (Beta) Centrality (in lieu of Eigenvector Centrality)

Degree centrality is based on the premise that all actors (nodes) and ties are equal. While degree centrality provides valuable information related to general actor access to resources and immediate contacts within a network, the importance of an actor can fluctuate based on the relative strength and importance of the connections (immediate and peripheral) of those nodes that the focal actor is connected to. Eigenvector centrality, as developed by Bonacich (1972), expands on degree centrality by accounting for the “sum of an actor’s connections to other actors, weighted by their (the other actors’) degree centrality” (Prell, 2012, p. 101). A higher

¹² In Figure 2, the Sponsor has a raw in-degree value of 5 while the Cosponsors have a 0 in-degree value. Likewise, the Cosponsors in this network diagram each have an out-degree value of 1 while the Sponsor has a 0 out-degree value.

eigenvector centrality metric connotes greater access to (and possibly more reliance on) other connections within a network through the adjacency of an actor to other high degree-centrality actors. For a legislative network, access to well-connected congressmembers may enhance the chances of legislative success. Yet, despite the use of the eigenvector centrality measure in prior legislative network research (most notably, Fowler 2006a,b), its use in this study is inappropriate. A significant limitation of eigenvector centrality is that it cannot adequately measure values for directed, asymmetric data (Borgatti, et al., 2013; Hanneman and Riddle, 2005). The data matrices utilized for this study are asymmetrical due to the use of directed, valued cosponsorship data. For example, in a situation where legislator A cosponsors five of legislator B's bills and legislator B cosponsors two of legislator A's bills, symmetry in the data is not present. Symmetry in the cosponsorship network data would be present if a cosponsorship tie between two legislators was valued as '1' regardless of the direction of the cosponsorship act (legislator A \rightarrow legislator B; legislator A \leftarrow legislator B) and regardless of the number of ties between the legislators. In other words, two legislators would be linked, in a symmetrical, non-directional manner, if just one in the pair of legislators cosponsored the other's sole bill during a legislative term. Furthermore, given the cosponsorship framework approach established for this analysis, where a relational tie is operationalized as a single act of cosponsorship for each bill, the application of the eigenvector method would assign a zero value to all cosponsors of a single bill since each one does not receive a cosponsorship in return, either from the sponsor or from any other legislator. But assigning a zero value to each cosponsor in this case would imply that no legislator has influence in this network; an implication without support from the prior scholarship.

A suitable alternative to eigenvector centrality in studies that incorporate directed, asymmetrical data used for this analysis is Bonacich power (or beta) centrality (Bonacich, 1987). A key feature of beta centrality, particularly for legislative networks, is that the presence of peripheral (rather than immediate) actors in the network can enhance or reduce the power centrality measure to better reflect the true power influence of a network actor (cosponsoring legislator). Unlike eigenvector centrality, beta centrality accounts for well- and less-connected peripheral actors in a systematic way (the measure values or devalues their network influence accordingly). Within this systematic approach, the network researcher is afforded the flexibility to choose the value of ‘beta’ or β to appropriately reflect the researcher’s conception of how each tie, direct or indirect, matters within the network (Borgatti, et al., 2013; Prell, 2012). The value chosen can be positive or negative. Positive relations or ties are not based on zero-sum exchanges; that is, a newly-established relation or tie does not result in another actor’s loss within the network (Prell, 2012). In many types of networks, such as communications and influence networks, exchanged information is usually received from others; in this case, the network would be considered positive and the researcher would design the beta-centrality approach with a positive β (Bonacich, 1987). Furthermore, according to Prell (2012), positive relations in influence networks, such as legislative and cosponsorship networks, are ones where actors receive more power as they become connected with other highly influential actors.¹³

This structural pattern, I argue, is like a cosponsorship network where cosponsorships are always received from other legislators (a positive system). It is true that cosponsorships can be withdrawn, but as the prior scholarship demonstrates, reneging a cosponsorship (a potential negative) can be detrimental to a legislator’s future relationships. Furthermore, as it has been

¹³ In network structures where relations are considered to be negative, power rests on a zero-sum basis and actors gain power and influence by connecting to the less-powerful actors within the network (Prell, 2012).

referenced in this paper, minority groups in legislatures are constantly seeking connections to other influential and well-connected legislators to further their interests and to help overcome their marginalized status. This behavior is indicative of the inherent characteristics of positive beta centrality. Therefore, based on Bonacich's (1987) portrayal, this study utilizes a positive β which allows for interpretation of legislators high in beta centrality as those tied to others who have high degree centrality and consequently have access to influence through their powerful (that is, well-connected) peripheral connections.

The formula for beta centrality is:

$$C_{\beta}(i) = \sum_{j=1}^n A_{i,j} (\alpha + \beta C_{\beta}(j)) \quad (3)$$

where $C_{\beta}(i)$ is the derived power centrality score for actor i , α is a parameter to normalize the measure (the beta centrality score), β is the value selected by the researcher to reflect the amount of dependence of actor i 's centrality on the centralities of the network actors to whom actor i is directly tied, and $A_{i,j}$ is the adjacency matrix using raw value data to better describe the wide range of intensity levels of this relational tie measure.¹⁴

Clustering Coefficient

The clustering coefficient metric reveals the level of transitivity in a network relationship (Borgatti, et al., 2013). In a legislative network, if legislator A and legislator B have a cosponsoring relationship, and legislator B and legislator C also have a relationship, it may be likely that legislator A and legislator C also have a cosponsoring relationship, thus forming a triad of the actors. The clustering coefficient metric reflects this relationship, representing the average fraction of a legislator's number of cosponsors who are also cosponsors with one another

¹⁴ The normalization parameter (α) is automatically selected by the UCInet software so that the square root of the sum of squares of the vertex (actor) centralities is the size of the network (Borgatti, et al., 2002; Bonacich, 1987).

(Tam Cho and Fowler, 2010). Higher clustering coefficients are indicators that a network is more stable and balanced than a network with lower proportions of transitivity (Tam Cho and Fowler, 2010). The scale for the clustering coefficient metric is continuous; a higher clustering coefficient indicates a more clustered network of legislators who have sponsored and cosponsored with each other. Consequently, higher clustering coefficient values imply high cooperation and support levels within a network (Scott, 2013). The formula for the clustering coefficient measure is:

$$C_i = \frac{2L_i}{k_i(k_i-1)} \quad (4)$$

where C_i is the derived clustering coefficient for actor i , k_i is the degree of actor i , and L_i is the number of ties between the k_i neighbors of actor i . For example, using the same graph from Figure 3, the clustering coefficient value for Actor 1 in the figure below (Figure 3) is 0.20 $[(2*2)/5(5-1)]$ while the clustering coefficient values for Actor 2 and Actor 6 are 1.00 and 0.00, respectively.

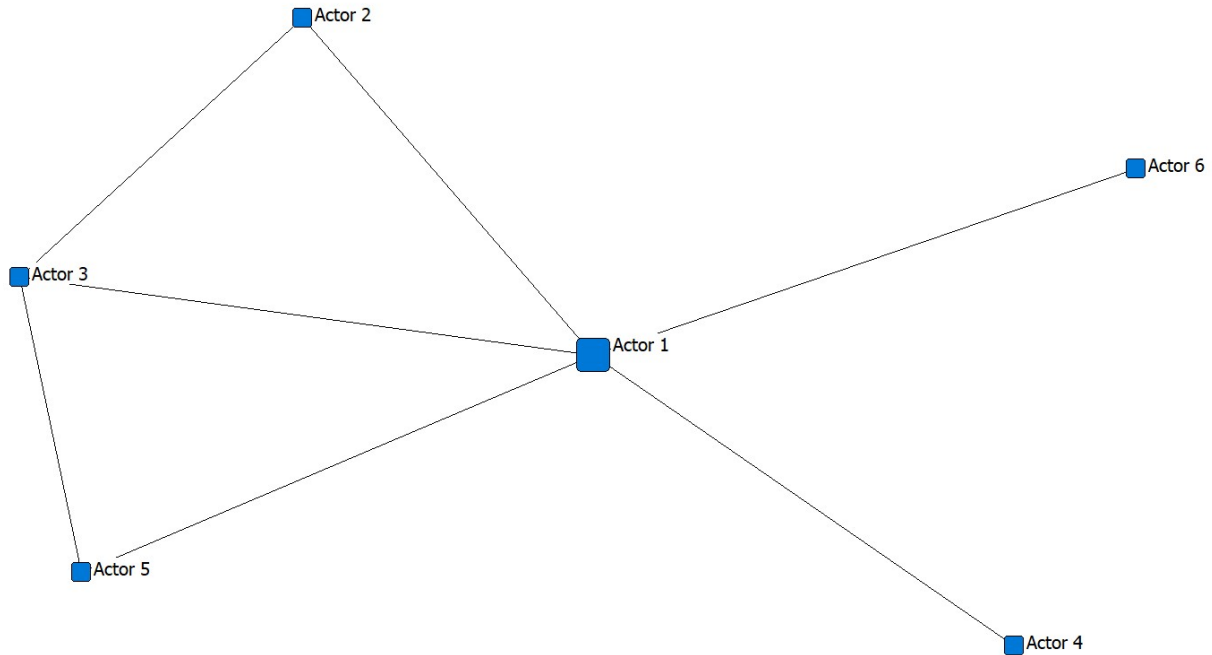


Figure 3. Network Illustration of Clustering Coefficient Measures

In network research, higher clustering coefficient metrics between actors often lead to the formation of dense local neighborhoods within a macro network structure or what are known in the social network literature as ‘small-world’ networks (Borgatti, et al., 2013; Scott, 2013; Tam Cho and Fowler, 2010; Hanneman and Riddle, 2005). To test whether a network is a small world one is to compare the clustering coefficient of the observed network to the clustering coefficient of a random graph (Borgatti, et al., 2013). If the observed network clustering coefficient is large relative to a random graph, there is evidence that the observed network is a small world one (Borgatti, et al., 2013). In their study of congressional cosponsorship networks, Tam Cho and Fowler (2010) found that small-world networks, measured by clustering coefficient metrics, are more effective at passing major legislation in Congress than less clustered networks. While Borgatti, et al. (2013) argue that the consequences of small-world networks are not well understood, in legislative and cosponsorship networks, higher clustering coefficients, and

consequently denser small-world networks, indicate the presence of active cosponsorship transitivity in Congress (Tam Cho and Fowler, 2010).¹⁵ I hypothesize that female legislators will demonstrate higher clustering coefficient values than their male counterparts, yet this outcome may not translate to legislative success due to prejudicial barriers faced by female legislators and the institutional rule framework of Congress as noted in previous sections of this paper.

Connectedness

The connectedness measure combines the number of cosponsors on each bill and the frequency of cosponsorship between any pair of legislators during a legislative term, whereas other legislative network measures consider only the number of cosponsors (Fowler, 2006a,b). Legislators who frequently cosponsor bills sponsored by the same legislator demonstrate a stronger relationship than those who rarely, or never, cosponsor (Fowler, 2006a,b). Through an examination of all types of legislation available to the House and the Senate, binding, ceremonial, and procedures-based, Fowler (2006a,b) found that the connectedness measure outperformed other traditional social network centrality measures (degree, closeness, betweenness, and eigenvector) in predicting legislator roll call vote choices on the House and Senate floors.

The connectedness network measure is not limited to sponsoring many bills; it also matters who one convinces to sign on to the legislation. Connectedness scores enable researchers to make stronger inferences about the social distance between legislators, and ultimately their level of influence within the congressional network (Fowler, 2006a,b). When employed in

¹⁵ In the context of cosponsorship networks, Tam Cho and Fowler (2010) state that the clustering coefficient metric measures the average fraction of a legislator's cosponsors who are also cosponsors with one another. Higher clustering coefficient values in a network illuminate the presence of fully linked triads of legislators, where legislators *a* and *b* cosponsor each other, legislators *b* and *c* cosponsor each other, then *a* and *c* cosponsor each other (Tam Cho and Fowler, 2010).

several bivariate and multivariate regression models, using cosponsorship data on all bills considered by Congress from 1973 through 2004, the connectedness measure was significant in its influence on a member's floor vote for an amendment and a member's chamber roll call votes, after controlling for ideology and partisanship (Fowler, 2006a,b). In other words, legislators are more likely to vote for final passage of bills that are sponsored by those legislators with high connectedness scores, despite ideological leanings or party membership (Fowler, 2006a,b). Because of these strong characteristics, the connectedness score of each legislator in this analysis is an important variable to consider. Despite its significance, the connectedness measure in this analysis will be limited to the 102nd through 108th Congresses (1991-2004) because Fowler stopped publishing his connectedness data as of 2004.¹⁶

E-I Index

By examining the ties between categories or groups of actors, such as by gender, the network researcher can determine when network actors are forming homophilous ties with those that are like themselves, or with those that are outside of their similarity preferences or group characteristics. The E-I index, developed by Krackhardt and Stern (1998), measures the tendencies of actors to embed themselves in macro-structures and the propensity of each individual to have ties within their group as well as external to dissimilar groups (Hanneman and Riddle, 2005). The E-I index is only concerned with connections to measure group closure (or openness); thus, directions of ties are ignored. The formula for the calculation of the E-I index is:

¹⁶ While Fowler's research provides the formula for calculating the connectedness measure, it does not fully explicate how the components of the formula are derived. Thus, it would be challenging and time-consuming to derive connectedness measures for the legislative terms included in this analysis after 2004. The author acknowledges this study limitation; however, it is a minor one. Connectedness is a control variable in this analysis; appropriate to include because of its relationship to network theory but not a central variable of interest in this study.

$$EI = \frac{b-a}{b+a} \quad (6)$$

where $E-I$ is the derived homophily value of the individual actor or group, and a and b are the number of ties to actors in each a group and each b group.

The E-I index provides an inverse measure of homophily; that is, it controls for the relative sizes of each group where large differences in group sizes can distort the measures of homophily (Borgatti, et al., 2013). This feature is important for this analysis as the proportion of male legislators in Congress is much higher than the proportion of females. For this analysis, I use the E-I Index to determine the number of female legislator ties within their own group as well as to the number of ties to male legislators. I anticipate that male legislators will be more likely to have within-group ties due to their dominant group status but this effect likely diminishes as more females are elected to both chambers of Congress. Likewise, I expect that female legislators, as the minority gender group, will form more out-group ties compared to male legislators to solicit as much support for their bills they can obtain and to overcome their marginalized status in Congress as discussed earlier in this paper. However, I expect that as more females are elected to Congress, the trend will shift as more ties are made within group.

Independent Variables (Legislator attribute-based)

The non-network variables associated with each legislator in this analysis are gender, party affiliation, majority party status, seniority, and power position held. These attribute-based variables are selected based on their demonstrated significance in prior research of legislative behavior and legislative networks. Based on this study's research question and hypotheses, gender of each legislative proposal's sponsor is the primary variable of interest with the other variables serving as control variables; however, there is discussion related to other significant variables within the context of prior scholarship. Congressional approval ratings for each

congressional term will not be included in the model; however, these ratings will be analyzed graphically to preliminarily determine if there are any trends between approval ratings and both legislative activity and network structures as suggested by Kirkland and Gross (2014). Detailed explanations of each variable, the measurement of each variable, and the reasoning supporting their inclusion are presented in the following sections.

Gender

Gender of each legislative proposal's sponsor is a categorical attribute and the primary variable of interest in this study. Within a social network analysis framework, gender is placed within the concept of homophily. Based on the literature review of legislative behavior and social network analysis, similarities between actors have been demonstrated as influential components underpinning the development of social connections in Congress; particularly relationships formed through the cosponsorship mechanism. While gender identification and the related public policy implications are burgeoning as significant issues in American society, this study will rely on the traditional social constructs of gender (identified at birth) to identify members of Congress: female and male. This categorical variable will be measured on a nominal scale with "1" representing a female sponsor and "0" representing a male sponsor.¹⁷

Party Affiliation

Much of the prior scholarship in legislative behavior and cosponsorship activity uses legislator party affiliation as a control variable due to its demonstrated significant relationship to legislative activity and effectiveness (see Harward and Moffett, 2010; Garand and Burke, 2006; Anderson et al., 2003; Burkett, 1999; Krehbiel, 1995; Schiller, 1995; Campbell, 1982). In some of these past studies as well as others, legislator ideology was employed as a variable of interest

¹⁷ For cosponsorship network analyses, "1" and "0" will also represent female and male cosponsors, respectively.

or control variable due to its demonstrated influence on roll-call voting (e.g., Poole and Rosenthal, 1991; Schneider, 1979). For this analysis, I exclude ideology for several methodological and demonstrated reasons. First, many ideology indices are constructed on prior roll call voting records that have traditionally followed party lines (Lewis, et al., 2020; Jackson and Kingdon, 1992). Second, the current definition of legislator ideology relies on left-right categories that generally follow the current two-party (major party) affiliation framework in the U.S. Congress (Lewis, et al., 2020; Peoples, 2008).¹⁸ Finally, prior research has demonstrated that party usually emerges as the strongest legislative vote determinant, with or without ideology measures (Peoples, 2008; Schiller, 1995; Weisberg, 1978).

The party affiliation categories for this analysis are Democrat and Republican. For the Senate, registered Independent legislators are considered as Democrats as all registered Independents in the Senate caucused as Democrats during the period of this analysis (Senate.gov, 2020). For the House, registered Independent legislators are considered as Democrats due to their voting records and sponsorship activity on legislation that had Democratic party-leaning content during the period of this analysis (Library of Congress, 2020). This categorical variable is measured on a nominal scale with “1” representing a legislator with a Democratic party affiliation and “0” representing a legislator with a Republican party affiliation.

Majority Party Membership

Related to party affiliation as an independent variable in this analysis is legislator membership in the majority party. It seems obvious that the political party in charge of each chamber, by virtue of its majority membership, has the upper hand in agenda setting and the

¹⁸ This characteristic may not explicitly hold in southern U.S. states where many registered Democrats have traditionally demonstrated a conservative voting record. However, the partisan lineage of conservative Democrats in the ‘Old South’ has been waning. Recent trends (1980s through the present time) indicate that more southern conservative voters are registering as Republicans than as Democrats (Valentino and Sears, 2005).

passing of legislation through its chamber. The scholarship in this domain has supported this notion empirically. Jeydel and Taylor (2003) found that legislative effectiveness in the House of Representatives is a function of membership in the majority party. Looking at solely one term of Congress (103rd), Anderson, et al. (2003) found majority party status as a significant predictor of legislative success within each chamber. Cox and Terry (2008), in their study of legislative success in both chambers of Congress (93rd through 105th Congresses), found that majority party membership is a highly significant predictor of which legislators would find success in having their bills passed through chamber roll call votes. The authors argue that rank-and-file majority party members obtain party leadership support for their legislative initiatives in exchange for their floor and caucus votes on other pieces of legislation sponsored by the majority part (Cox and Terry, 2008). This categorical variable is measured on a nominal scale with “1” representing a legislator in the majority party of its respective chamber and “0” representing a legislator in the minority party of its respective chamber. Because of the two-party system in the United States, there may not be enough variation between party membership and majority membership which could lead to high levels of correlation between the two variables. Therefore, tests of collinearity for these two variables, as well as other model variables, are conducted in this analysis.

Power Position

The power position attribute variable relates to certain party and committee leadership positions in each chamber considered by prior research to be influential in the agenda-setting process as well as floor vote success in each chamber (Volden, et al., 2013; Cox and Terry, 2008; Anderson, et al., 2003; Jeydel and Taylor, 2003). The question then becomes which leadership positions are the most influential to the policy process, particularly which ones have the most impact on the policy cycle and on successful floor votes. Cox and Terry (2008) find that majority party leaders are more successful at passing legislation than minority party leaders largely due to

access to more legislative resources (staff and parliamentary rights). Certain congressional committees have a tremendous amount of influence on which bills are heard and passed through committee before they reach a floor vote. For example, Volden et al. (2013) find that the most powerful House committees are Rules, Appropriations, and Ways and Means because they institute the funding and processes necessary for legislation to be successful both in the floor vote stage and when signed into law. In the Senate, the power committees are Appropriations, Finance, and Budget because these committees have the final say on the necessary funding to implement legislative policies and related programs (Volden, et al., 2013). Leadership positions in these committees are the chair and ranking member positions; committee chairs are chosen for this analysis because they control all items under consideration by their respective committees (Berry and Fowler, 2016) and ranking members assist chairs in committee regulation and lead on matters affecting a committee's minority membership (Congressional Research Service, 2009).

For this analysis, Senate party leadership positions include Majority Leader, Majority Whip, Chief Deputy Whip, Conference Chair, Conference Vice Chair, Senatorial Committee Chair, Policy Committee Chair, Minority Leader, Chief Deputy Minority Whip, Caucus Chair, and Steering and Outreach Chair. For the House, party leadership positions include Speaker, Majority Leader, Majority Whip, Majority Chief Deputy Whip, Senior Deputy Whip, Conference Chair, Policy Committee Chair, Minority Leader, Minority Whip, Chief Deputy Minority Whip, Caucus Chair, and Steering and Policy Committee Chair.

Standing committee chair and ranking member positions for the following standing committees are included: House Rules, House Appropriations, House Ways and Means, Senate Appropriations, Senate Finance, and Senate Budget. Standing committees are permanent panels that have legislative jurisdiction within their respective congressional chamber (Heitshusen,

2017). Select, special, and joint committees are not considered in this analysis because these bodies conduct ‘housekeeping’ duties or are established for a unique and specialized purpose and are ephemeral (Senate.gov, 2020). This power position control variable is measured on a nominal scale with “1” representing a legislator occupying any of the above listed power positions and “0” representing a legislator not occupying any of the listed power positions.

Seniority

The seniority variable is operationalized as the number of 2-year congressional legislative terms each legislator has served in Congress during the study period. While U.S. Senators serve 6-year terms, congressional legislative terms are always measured in two-year increments. Thus, a Senator serving a full term serves in three successive legislative terms in Congress. A legislator serving a partial term is considered in this analysis as having served a full term. This control variable will be measured on a continuous (count data) scale with “1” representing one 2-year term (or partial 2-year term) served by a legislator, with “2” representing two 2-year legislative terms served by a legislator, and so on.

Congressional Approval Ratings

Including congressional approval ratings by each legislative term in this analysis, as provided by Gallup/Newsweek Congress and the Public Poll (2020), comports with prior findings by Kirkland and Gross (2014). Their research showed that, as congressional approval declines, legislators tend to collaborate and support each other at greater rates (Kirkland and Gross, 2014). This finding was derived using the clustering coefficient network measure which is also included in this analysis. Kirkland and Gross (2014) found that, when popular opinion of Congress declines, legislator-to-legislator conflict wanes, leading to a breakdown of small, restricted cosponsorship clusters. Consequently, legislators expand outside of otherwise stable clustered networks resulting in declining partisanship among legislators. In these environments,

legislators tend to work more cooperatively together, including reaching across the aisle to conduct legislative business.

The Gallup/Newsweek Poll (2020) measures the American public's approval rating of the U.S. Congress. The monthly poll asks Americans who are likely voters in national elections to assess the job that Congress is doing (Gallup/Newsweek Poll, 2020). Approval and disapproval ratings, measured in percentage terms, are reported on the Gallup Poll's website (2020) from 1974 through the current legislative term. Because Kirkland and Gross (2014) used only the approval ratings in their analysis, this study will also employ only the congressional approval ratings. The ratings will not be included in the regression models used in this analysis because this study does not characterize Congress as a whole network as did Kirkland and Gross (2014). Instead, this analysis will employ graphical representations of the comparison of congressional approval ratings and gender group social network metrics by each legislative term in each chamber. The purpose of this analysis is to determine if there are any similarities or differences in the trend in ratings (if any) over time and the trends (if any) in mean network metrics by gender group within each chamber.

Interaction Terms

The use of interaction terms is common in political science as well as other social sciences as researchers attempt to understand the influence that two or more variables have on a particular phenomenon when those variables are interacted (Berry, et al., 2010). However, the literature directly relevant to this analysis rarely considers interactions between independent variables of interest. One reason may be that independent variable interaction in a model increases the likelihood of multicollinearity within the model. The presence of collinear independent variables would then suggest dropping one of the affected independent variables.

Another compelling reason for exclusion of product terms relates to the difficulty in the interpretation of the interaction term outputs in a logistic regression model, which is the model choice for this analysis. The computation and interpretation of the interaction effects are more complicated in non-linear models than in their linear counterparts. According to Berry, et al. (2010), Norton, et al. (2004), and Ai and Norton (2003), the coefficient of an interaction term in non-linear models cannot be evaluated the same way as in linear models for several reasons. First, the sign of the coefficient of the interacted term in a non-linear model may not represent the sign of the interaction effect due to the potential for different signs associated with different values of covariates (Allison, 2021; Berry, et al., 2010; Ai and Norton, 2003). Second, we know that magnitude of effect of a product term and the magnitude of effect of the uninteracted variables in non-linear models are conditional on a model's other independent variables (Ai and Norton, 2003; Norton, et al., 2004). However, the marginal effect of a change in both of the model's interacted variables is not the same as the marginal effect of changing the interacted term (Norton, et al., 2004). Third, the interaction effect's statistical significance cannot be tested using simple t-tests and the significance cannot be determined from the reported z-statistic (Ai and Norton, 2003; Norton, et al., 2004).

Due to the difficulty in calculating the correct marginal effects (and standard errors) of a change in two interacted variables in logit analysis, applied researchers have either misinterpreted the coefficient of the interaction term or have omitted interaction terms in their models (Norton, et al., 2004; Ai and Norton, 2003).¹⁹ To address these interpretation challenges, Norton, et al., (2004) developed a command in Stata ('*inteff*') that correctly computes the

¹⁹ Ai and Norton (2003) reviewed 13 economics journals from 1980 through 1999 searching for articles that employed interaction terms in non-linear models. They found 72 articles that met this criterion. Of these articles, only 1 study correctly interpreted the coefficient on the interaction term.

interaction effect and standard errors for logit models. Unfortunately, this Stata command will not allow for time-series operators to be included in the regression model, a limitation for this longitudinal analysis which includes the use of such operators.

For these reasons, interaction terms are not included in this analysis; their omission is not a significant flaw. Literature reviewed for this analysis has not made a compelling case to include such terms. The non-network independent variables included in this study's models are well-tested as single variables that have demonstrated statistically significant influences on the dependent variables in the models of relevant prior scholarship. In other words, these variables, when treated as non-interacted variables, are significant on their own and do not depend on other independent variables. Furthermore, to this author's knowledge, social network variables are not included in interaction terms.

Variables Summary

While there are likely other variables that directly or indirectly influence legislative productivity and success, the variables proposed for this analysis are specified in prior theories and research at the intersection of the domains of congressional legislative behavior, cosponsorship activity, and social network analysis, thus enhancing construct validity. Variables in this analysis are measured using routine indices or levels. Table 2 presents a summary of the designation of all variables included in this analysis. The methods section of this chapter describes the models used in this analysis and what variables, from the list presented in Table 2, will be employed for each model.

Congressional Data

This analysis includes data related to congressional legislation, sponsorship and cosponsorship activity, and congressional and legislator attribute data of the U.S. Senate and

Table 2. Variable Measurement, Scale, and Anticipated Sign Direction

<i>Variable</i>	<i>Dependent (DV) or Independent (IV)</i>	<i>Measurement</i>	<i>Scale</i>	<i>Expected Sign Directions</i>
Bill Pass: Y/N	DV	A significant bill passes or fails at chamber floor vote	Nominal (1=Pass, 0=Fail)	N/A
Gender	IV	Legislator gender	Nominal (1=Female, 0=Male)	-
Party	IV	Legislator party affiliation	Nominal (1=Democrat, 0=Republican)	N/A
Majority Party	IV	Legislator in chamber majority	Nominal (1=Majority Party, 0=Minority Party)	+
Seniority	IV	Number of legislative terms legislator has served (full or partial term)	Continuous [1 - ∞]	+
Party Leader (Power)	IV	Legislator is a majority party leader	Nominal: 1=Party Leader; 0=Not a Party Leader	+
Committee Chair (Power)	IV	Legislator is chair of an influential chamber committee	Nominal: 1=Committee Chair or Ranking Member; 0=Not a Committee Chair or Ranking Member	+
Congressional Approval Rating	Not used in models. Graphical analysis only.	Gallup/Newsweek Poll approval rating of Congress during a legislative term	Continuous [0% - 100%]	N/A
Network: In-Degree Centrality	IV	Number of in-degree ties presented as raw values	Continuous [0 - ∞]	+
Network: Beta Centrality	IV	Number of ties to others who have high in-degree centrality presented as raw values	Continuous [0 - ∞]	+
Network: Clustering Coefficient	IV	Average fraction of a legislator's number of cosponsors who are also cosponsors with one another	Continuous [0 - ∞]	+
Network: Connectedness	IV	A combination of the number of cosponsors on each bill and the frequency of cosponsorship between any pair of legislators during a term	Continuous [0 - ∞]	+
Network: E-I Index	Not used in models. Graphical analysis only.	Normalized on a scale of 0 to 1, with 1 indicating highest level of ties external to own-group of legislators (female/male)	Continuous [-1 to 1]	N/A

House Chambers of the 102nd Congress through the 114th Congress (1991 – 2016). The database constructed for this analysis includes more than 100,000 pieces of legislation (public bills and joint resolutions) introduced in Congress during the study period and all cosponsorship acts associated with each legislative proposal. All members of the House and Senate chambers during the study period are included in the database, whether they served full or partial legislative terms. The volume of accessible data (data sources listed in this section) and their relatively error-free reporting status provide a great deal of confidence that the resulting study inferences are reliable and valid.

There are two main reasons to include the 102nd through 114th legislative terms in the analysis. From a quantitative perspective, the 103rd Congress experienced the crossing of a ten-percent threshold of female legislators in Congress. This Congress included fifty-four voting female legislators, the first time that more than ten percent of a US Congress was represented by females (Manning and Brudnick, 2020).²⁰ As described in more detail in this section, the 103rd Congress will be analyzed to determine if crossing the ten-percent membership mark is statistically and substantively meaningful. The trend in current Congresses suggests that female membership in both chambers will continue to increase (Manning and Brudnick, 2020). If this trend continues, researchers in this area should continue to study the effects on legislative behavior and success because of greater female descriptive representation. The second reason to start this analysis with the 102nd Congress is a purely symbolic one. The national elections of November 1992 were deemed by many in the media as “The Year of the Woman” (Senate.gov, 2021). This election witnessed a huge jump in the number of females elected to the House (29 in the 102nd Congress to 47 in the 103rd Congress) and an increase in the number of female Senators from three to seven (Manning and Brudnick, 2020). Interestingly, for the first time in the history of the Senate, two female candidates were elected from the same state (California Senators Dianne Feinstein and Barbara Boxer).

Data Sources

Adler and Wilkerson (2020) and Fowler (2006a,b) are the primary data sources for the study period.²¹ The source datasets are organized by legislative term, legislator identification,

²⁰ 47 females in the House of Representatives and 7 females in the Senate.

²¹ On his personal website, Fowler acknowledges that the original sources of the congressional data are THOMAS.gov, the now-defunct Library of Congress online legislative information system and GovTrack.com’s deprecated congressional bulk raw data files. There are likely to be some discrepancies between these data sources and the Fowler data files due to data collection and scraping errors on the part of all sources.

legislative measure, and the sponsor and cosponsors of each measure. These datasets also indicate if a measure passed a chamber floor vote or not, which is the dependent variable of interest. These archival cosponsorship data are structured and relational; that is, the ties between legislators are determined by the act of cosponsorship, leaving no misinterpretation of the relational tie itself. In a social network context, archival sources of data for studying social networks are advantageous compared to qualitative methods because the datasets are often longitudinal in nature which allows for the study of network dynamics and outcomes (Borgatti, et al., 2013). Legislator relationships and outcomes are dynamic across legislative sessions for a variety of reasons, including, but not limited to, changes in national agenda interests, party influence, and prior legislative outputs and their resulting outcomes. Any attempts to generalize findings regarding the formation and evolution of legislative networks over time will be particularly difficult within a survey framework (Kirkland and Gross, 2014). A richer comparison of relationships measured through cosponsorship activity and their emergent outcomes over time enhances the generalizability of the study results.

The following sources for this analysis provide additional data related to the variable development in the analysis. The following sources will be accessed:

- Congressional Bills Project. This source provides a relational database of over 400,000 public and private bills introduced in the U.S. House and Senate since 1947. The data of interest in this database are additional sponsorship and cosponsorship data not found in the Fowler datasets, bill topic codes, legislator committee information, and legislator majority/minority party status (Adler and Wilkerson, 2020).
- PIPC Roll Call Dataset, Carl Albert Center, University of Oklahoma. This source maintains voting information datasets for each term of Congress that will be utilized to

access sponsorship, cosponsorship, and other data that is not included in the Fowler or Congressional Bills Project datasets (Roberts, et al., 2020).

- Voteview.com. This source allows users to view every congressional roll call vote in American history for Senators and Representatives (Lewis, et al., 2021).
- Congress and the Public, Gallup Poll. This source provides monthly polling data related to congressional approval ratings for the study period (Gallup, 2020). This analysis uses the average of the monthly ratings over the course of each legislative term.
- Congressional Committees, Modern Standing Committees, 102nd to 114th Congresses. This source contains membership information on all congressional committees for the periods covered in the study. The dataset is updated periodically from the Congressional Record (Stewart and Woon, 2020).

Data Analysis and Methods

This section presents the methods used to evaluate each of the hypotheses established in this study. Hypotheses 1 and 2 are motivated by legislative behavior theory, social network theory, and prior research at the intersection of legislative behavior and structural analysis. These hypotheses are evaluated by standard social network analysis software (UCInet) and standard statistical software for descriptive statistics (Stata). Hypothesis 3 is motivated by gender and legislative behavior theory as well as prior research findings and are evaluated with Stata (and use variables generated via UCInet).

The study design is an observational longitudinal analysis of the thirteen legislative terms (102nd to 114th). The dataset for the longitudinal analysis is in the format of a pooled cross-section where each bill in each term is unique and where congressmembers can differ across terms. There are many legislators who were members of Congress during the entire study period;

however, many others were not present in Congress due to retirement, death, or failed re-election efforts. Longitudinal data within a pooled cross-sectional format provides researchers the ability to control for individual heterogeneity and to identify and measure effects that may not be detectable in pure cross-sectional datasets (Allison, 2021; Baltagi, 2008). In this case, longitudinal data provides for estimation of the over-time dynamics of adjustment in legislative behavior, relationships, and success within and between legislators. The multiple observations in the full study-period dataset allows for estimates of the variation *within* each legislator and the repeated measurements provides the ability to control for time-invariant, unobservable differences *between* legislators. For example, legislator relationships and legislative output may change with a change in majority party status or a change in congressional approval ratings. These changes and their effects can be estimated within each legislator as well as between legislators.

Common limitations of longitudinal data methods are attrition of individuals over time, missing data, and statistical dependence among multiple observations from the same individual (Allison, 2021). For this analysis, missing data is not an issue as all legislator cosponsorship acts and attribute-based characteristics are present in the datasets. The attrition in legislators is common in longitudinal analyses of legislative behavior because legislators are elected, and many who appear at one point in time lose their seats in the future due to failed re-election efforts. The most concerning limitation for this analysis is statistical dependence of repeated observations on each individual; that is, they are likely to be positively correlated thus violating the assumption of independence. The consequences of this dependence are estimated standard errors that tend to be too low which lead to test statistics that are too high, p -values that are too low, and an increased likelihood of committing Type I errors (Allison, 2021).

For the network analysis process, each legislative term dataset and the full study period dataset are constructed as matrices where each column i and each row j represents a legislator. Valued matrices will incorporate cell entries that contain the total number of bills that legislator i sponsors that are cosponsored by legislator j .²² The matrix format for this analysis is considered “directed” because the direction of each tie (the act of cosponsoring) is asymmetric and proceeds in the same direction in each case; that is, legislator j sends the cosponsoring act (tie) to the bill sponsor, legislator i . The UCINET software package generates the network measures utilized in this analysis based on the data contained in each matrix for each chamber of Congress in each legislative term.

To test Hypothesis 3, I use logistic regression models because the dependent variable is a binary outcome (each significant bill passes or fails to pass a chamber floor vote).²³ Logistic regression is an appropriate method to test hypotheses related to legislative success because the method provides a probability measure for assessing the likelihood of a bill passing given certain

²² The other category of matrices in social network analysis is the binary matrix. In a binary matrix, each cell contains a 1 or a 0 to denote whether a tie between actors exists (or existed) or not, regardless of the number of times a tie formed or a relational event occurred between the two actors. For this analysis, each cosponsorship given by legislator A to legislator B would be counted as one tie. If legislator A cosponsored legislator B ten times in a term, the value of the cell connecting A and B would be 10. If this analysis considered the use of a binary matrix instead of a valued matrix, only a 1 would be inputted into the cell connecting the two legislators, regardless of the 10 cosponsorship acts from A to B.

²³ Other approaches for the dependent variable in this analysis would be to use legislator “hit rates” or the percentage of bills sponsored by a legislator that had a successful floor vote, or to use count data; that is, the number of bills each legislator sponsored that passed a floor vote. Because this analysis measures legislative success in terms of bills passing or not passing, a count data approach could skew the meaning of the results. For example, Legislator A might sponsor 3 bills in a term and have all 3 pass floor votes whereas Legislator B might also have 3 of her bills pass but she sponsored 12 bills in the term. Both members experienced success by having 3 bills pass but Legislator B was much less successful overall during the term. For similar reasons, hit rate measures are not used in this analysis because of these inherent weighting inaccuracies. For example, if Legislator A sponsors only one bill and that bill passes a floor vote, she would have a hit rate of 100% whereas Legislator B may sponsor 10 bills and have 8 of those pass a floor vote, with a hit rate of 80%. Given the context of this analysis in measuring legislative success, while Legislator A had 100% of their bills pass and may, *prima facie*, seem to be more successful, Legislator B was more active in sponsoring legislation, more active in securing cosponsorship ties, and achieved legislative success 7 times more than Legislator A. For these reasons, a binary outcome on each bill a legislator sponsors provides a more robust measure of legislative success.

factors. Prior scholarship in this domain has used the following models: Poisson or negative binomial regression (NBR) because they employ count data as their dependent variable (e.g. Cox and Terry, 2008; Fowler, 2006a,b; Anderson, et al., 2003),²⁴ logistic or probit regression due to the use of a binary outcome as the dependent variable (e.g. Harward and Moffett, 2010; Wilson and Young, 1997), or linear regression with ordinary least squares (OLS) estimation (e.g. Tam Cho and Fowler, 2010; Mayhew, 1991). Linear regression with OLS estimation is the least common method employed largely due to the prevalent use of count data with a characteristic excess of zeroes in the dependent variable data or with studies that use a dichotomous outcome variable.²⁵ Tam Cho and Fowler (2010) employ the OLS method because they were replicating Mayhew's (1991) analysis within their analytical context of small-world properties of Congress.

This analysis uses the *binary* logistic regression method, as opposed to ordinal logistic regression or multinomial logistic regression, because the dependent variable is dichotomous; that is, it refers to a variable that is coded as either 1 or 0 and cannot take on any value other than these two values. Due to the use of a dichotomous dependent variable, OLS estimation would not be appropriate because of the inherent violation of several required assumptions that would lead to inefficient estimation. Transforming the dichotomous response variable into a logit overcomes this inefficiency (Pampel, 2000). However, the interpretation of the regression coefficients with

²⁴ In these studies, the Poisson regression model could not be used because the data were overdispersed; that is, the dependent variable's conditional variance was greater than its mean. Consequently, both standard errors and p-values can be too low (Allison, 2012). When faced with overdispersed data, researchers can employ the alternative model, NBR, which can accommodate overdispersion by introducing a dispersion parameter. This approach yields smaller standard errors and p-values and can mitigate the potential validity threat that a Poisson model would otherwise introduce in these cases (Anderson, et al., 2003).

²⁵ The data used in this analysis demonstrates the problem of excess zeroes in the dependent variable if the unit of analysis is the legislator and is a primary factor in avoiding a Poisson model in this analysis. In the data utilized for this analysis, a majority of legislators did not experience a single instance of a bill passing a floor vote.

logistic regression is less intuitive than is the case with the OLS technique²⁶ and can lead to spurious results if caution is not exercised. The challenging interpretation elements stem from the fact that the dependent variable is a step-function and non-linear. A key assumption of the logit estimation technique is the estimation of the unobservable probability of the event occurring or not occurring and can be represented as a curvilinear form. These characteristics of logistic regression shift coefficient interpretation from changes in the original metric of the variables, or from changes in probabilities, to changes in logged odds (Pampel, 2000). Fortunately, the raw coefficients, measured as log odds, can be converted (more precisely, exponentiated) to an odds ratio metric which can then be interpreted as predicted odds of the effect of an independent variable (as a function of other variables). The ease of interpreting the tests of significance is enhanced by statistical software, such as Stata, by dividing the regression coefficients by their respective standard errors and evaluating with the z distribution (Pampel, 2000).

Model Characteristics

The logistic regression models specified for this analysis are appropriate for longitudinal datasets. For the analysis, I correct for the over-time dependence on repeated observations using two primary methods: 1) a generalized linear model (GLM) applying the generalized estimating equation (GEE) estimation procedure and 2) a random (mixed) effects model (ME). I apply robust standard errors to both models as they are robust to disturbances of heteroskedasticity and non-normality. In the ME model, the use of ‘cluster id’ command in Stata employs cluster-robust standard errors for model robustness to additional correlation between repeated observations over time (the GEE model is also robust to serial correlation). These standard error approaches

²⁶ Coefficients generated by count data methods, such as Poisson or negative binomial regression, can also be challenging to interpret but certain techniques in statistical software programs can often overcome these difficulties similar to logistic regression.

are recommended for large datasets similar to that of this analysis (Allison, 2021). Robust standard errors have the additional advantage over “model-based” standard errors because, unlike model-based standard errors, robust standard errors are not sensitive to the correlation structure of a model (Allison, 2021).

GLMs assume independence of observations; violation of this assumption will introduce bias and lead to incorrect inferences. In longitudinal data analyses with repeated measures, observations within each case (here, legislator) are likely to be interdependent between time points in the data. To account for the likely similarities within cases over time, Liang and Zeger (1986) proposed an extension of GLM which utilizes estimating equations to produce consistent estimates of the regression parameters and their variances. This approach is called Generalized Estimating Equations, or GEE which is a population-level approach based on a quasi-likelihood function (rather than a maximum likelihood or ordinary least squares estimation procedure) providing population-averaged estimates of the parameters (Wang, 2014). By using the GEE procedure in this analysis, I model the estimated marginal effect of independent variables on bill passage. By using the gender-based independent variable, the GEE estimates for gender will apply to each gender group rather than to each legislator.

The ME model estimates the model’s parameters using maximum-likelihood estimation. Unlike GEE, it is a subject-specific, or conditional, model. ME models allow researchers the ability to estimate different regression parameters for each subject in the data. Because the ME model has a likelihood function, it can be subjected to goodness of fit tests such as Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), whereas GEE cannot be subject to these tests (Allison, 2021). This is a minor limitation to this study: I cannot compare models using common goodness of fit tests; however, the primary purpose of this analysis is to

determine the effect of gender on legislative success, considering other variables, rather than comparing model fit.

Another critical distinction between the GEE and ME approaches is the interpretation of the coefficients in each model's outputs. The ME method produces subject-specific coefficients while the GEE method produces population-averaged coefficients. The outcome from a one-unit change in the RE model's regressor applies to fixed individuals within the dataset while the outcome from a one-unit change in the GEE model's regressor is applied across all the individuals in the dataset. Given that a primary purpose of this analysis is to test the hypothesis that female legislators, in the aggregate, are less successful in passing their bills than their male counterparts, in the aggregate, I am more interested in the population-based outcomes rather than individual-level outcomes. A further limitation of this approach, however, is that subject-specific coefficients are typically more accurate estimates of underlying causal mechanisms (Allison, 2021; Gardiner, et al., 2009).

Despite these differences, the primary model presented and discussed in the body of this paper is the GEE model. I chose GEE as the primary method over the ME method for several reasons, some of which were mentioned earlier. First, the GEE approach produces population-averaged coefficients. I am specifically interested in the average outcomes for the groups of female legislators in Congress as opposed to individual legislator effects. The datasets used in this analysis do not include the entire population of Congress as that would require data for every Congress since its inception, a nearly impossible task. I refer to the word 'population' because my interest is focused on female legislative groups, and, within each of the 13 terms of Congress in this study, every female legislator is included in the analysis. Second, the GEE method can handle a large number of clusters and is computationally faster compared to the ME approach,

which tends to generate convergence issues in statistical software packages (Allison, 2021). Finally, the GEE method can test for different correlation structures which is an important factor in achieving estimation efficiency. According to Hu, et al. (2015), identifying the appropriate model correlation structure enhances both estimation efficiency within longitudinal data analyses and valid statistical inferences for large-size clustered data. To fit the GEE model for this analysis with thirteen (13) time points and a large number of correlations between error terms at different points in time, I chose an exchangeable structure where all observations over time have the same correlation (assumes a constant time dependency). As a robustness check, I conduct the ME model analysis and report the results in the same section as the GEE results for comparison purposes.

I chose ME and GEE models over a fixed effects (FE) model for several reasons. First, time-invariant variables are absorbed by the intercept in FE models whereas ME and GEE models can include time-variant and time-invariant variables (Allison, 2021). This is a critical aspect for this analysis as the predictor variable of interest is time-invariant (gender) while all but one (party affiliation) of the remaining regressors are time-variant.²⁷ Second, in ME models, the unobserved heterogeneity across individuals in the dataset is assumed to be random and uncorrelated with the predictor variables (Greene, 2008). An FE model will control for time-invariant characteristics of individuals, but it will not produce coefficient estimates for the associated time-invariant predictors (Allison, 2021). In ME models, time-invariant variables are allowed to become predictor variables in the model; this is a critical issue for this analysis as a central aspect of the hypotheses is that there are variations across individual legislators,

²⁷ An argument could be made that party affiliation is time-variant as legislators have been known to switch parties from one legislative term to the next. However, only a small handful of legislators have switched parties during the study period which suggests that party affiliation is relatively fixed.

particularly across female and male legislators, that have at least some influence on the dependent variable (legislative success).

Model Specifications

The conventional cross-sectional logit model as summarized by Pampel (2000) is specified in Equation 7 as:

$$L = \ln\left(\frac{P}{1-P}\right) = \beta_1 + \beta_2 X_2 \quad (7)$$

where L is the logit, $\ln\left(\frac{P}{1-P}\right)$ is the natural log of the probability of the outcome of interest, β_1 is the parameter for the intercept, β_2 is the regressor parameter, and X_2 is the regressor. For longitudinal analyses, the conventional model would incorporate a time component for each element on both sides of the equation. Unlike a conventional linear regression model, a conventional logistic regression model does not contain an error term because the dependent variable is an expected value of the outcome of interest (Allison, 2021). To facilitate understanding of the results, the analysis output tables report the odds ratio for each variable in the models. In general, the odds ratio describes the odds of a specified outcome occurring given a 1-unit change in a regressor. In this analysis, the odds ratio describes the odds of legislative success occurring given a change in a regressor. Most of the regressors in this model are dummy variables; therefore, the odds ratio describes the odds of legislative success given a regressor changing from one state (e.g., male, and coded '0') to another state (e.g., female, and coded '1').

The following section presents the models in functional form used for this analysis. The GEE logistic model is presented in Equation 8 and the ME logistic model is presented in Equation 9 as follows:

$$L_{it}(BillPass) = \ln\left(\frac{P_i}{1-P_i}\right) f(\beta_{it}, Gender_{it}, Party_{it}, MajorityParty_{it}, Seniority_{it}, \\ PartyLeader_{it}, CommitteeChair_{it}, InDegree_{it}, BetaCentrality_{it}, ClusteringCoeff_{it}, \\ Connectedness_{it}, LegislativeTerm_{it}) \quad (8)$$

$$L_{it}(BillPass) = \ln\left(\frac{P_i}{1-P_i}\right) f(\beta_{it}, Gender_{it}, Party_{it}, MajorityParty_{it}, Seniority_{it}, \\ PartyLeader_{it}, CommitteeChair_{it}, InDegree_{it}, BetaCentrality_{it}, ClusteringCoeff_{it}, \\ Connectedness_{it}, LegislativeTerm_{it}, \alpha_{it}) \quad (9)$$

where β_{it} is the Intercept and α_{it} represents all the estimated observed and unobserved causes of the response variable that vary across legislators but do not vary across time.

Model Formats by Congressional Chamber

Tables 3 and 4 present the models for the analyses, for the House and Senate chambers, respectively. The analyses for each chamber include the 102nd through 108th Congresses and 102nd through 114th Congresses. The reason for the different time-periods is that the Fowler (2006a,b) connectedness measure is only available through the 108th Congress. As described earlier, higher connectedness scores have been demonstrated in at least two published social network/legislative behavior literature sources as an influential measure of strong relational ties in Congress but also as a precursor to legislative success.²⁸

²⁸ Omitting a potentially influencing variable such as connectedness in legislative terms 109 through 114 may introduce omitted variable bias to the analysis of the 102nd through 114th legislative terms. This is certainly a limitation to the analysis; however, connectedness has primarily been utilized by Fowler in his studies of cosponsorship networks in Congress and not as widely utilized in other studies at the intersection of network analysis and legislative behavior. Its restricted use as a meaningful variable, while deemed to be significant, is not as harmful to the analysis as the omission of other well-tested legislative variables such as majority party status and seniority.

Table 3. House Chamber Models

House Chamber; Logistic Regression; Dependent Variable: Bill Pass Y/N		
<i>Variables</i>	<i>102nd-108th Congresses</i>	<i>102nd-114th Congresses</i>
All Variables	X	
All Variables except Connectedness		X

Table 4. Senate Chamber Models

Senate Chamber; Logistic Regression; Dependent Variable: Bill Pass Y/N		
<i>Variables</i>	<i>102nd-108th Congresses</i>	<i>102nd-114th Congresses</i>
All Variables	X	
All Variables except Connectedness		X

Research Design and Methodologies Summary

This chapter describes the research methods used in this study to answer the research questions and test the stated hypotheses. This chapter includes a discussion of the research design, the data collection process and data sources, the model variable construction, model characteristics, and method techniques used in the analysis. Theory and prior scholarship informed the research design, data, models, and methods employed in this analysis within a quantitative framework. The elements of the research design and methodologies enhance the study's external and internal validity and strengthen confidence in the resulting inferences. The goal of the next chapter is to present the study findings resulting from the methodologies described in this chapter.

Chapter 4: Analysis and Results

This section presents the results of the methods described in Chapter Three to analyze the congressional data and to test the study hypotheses. The results are presented by social network structures, descriptive statistics, and regression methods as related to the study hypotheses.

Patterns between each temporal model within each chamber, between regression methods used, and between congressional chambers are examined at the appropriate sections of this chapter.

The results of the gender variable of interest are summarized at the end of the chapter.

Network Structures

Due to the large number of ties (cosponsorship acts) in each term, graphical illustrations of the congressional social networks are visually very dense. From these dense perspectives, it can be difficult to visualize the micro-patterns of behavior between legislators. However, by looking at the changing patterns of the networks *based solely on female cosponsorship acts* over time, a definite trend emerges. The following network representations of each chamber in the 102nd Congress and the 114th Congress (Figures 4 through 7) demonstrate the changing patterns of female cosponsorship network representations from earlier to more current legislative terms. The changes are largely due to the increased presence of female members of Congress over this study period.

Figure 4 shows the female legislator cosponsorship network of ties for binding, force-of-law bills in the House chamber during the 102nd Congress. In this figure, red (circle) nodes are female legislators acting as cosponsors while blue (square) nodes represent both females and males receiving cosponsorship ties (bill sponsors). Nodes not connected by ties (meaning that females did not cosponsor these House members) are considered in network terminology as isolates and are represented as blue nodes placed to the left of the main graph. In this graph, there

are 29 (red) nodes (female legislators who cosponsored at least one bill during this term), 397 legislator nodes receiving at least one tie, 50 isolates, and 10,855 ties (cosponsorship acts).

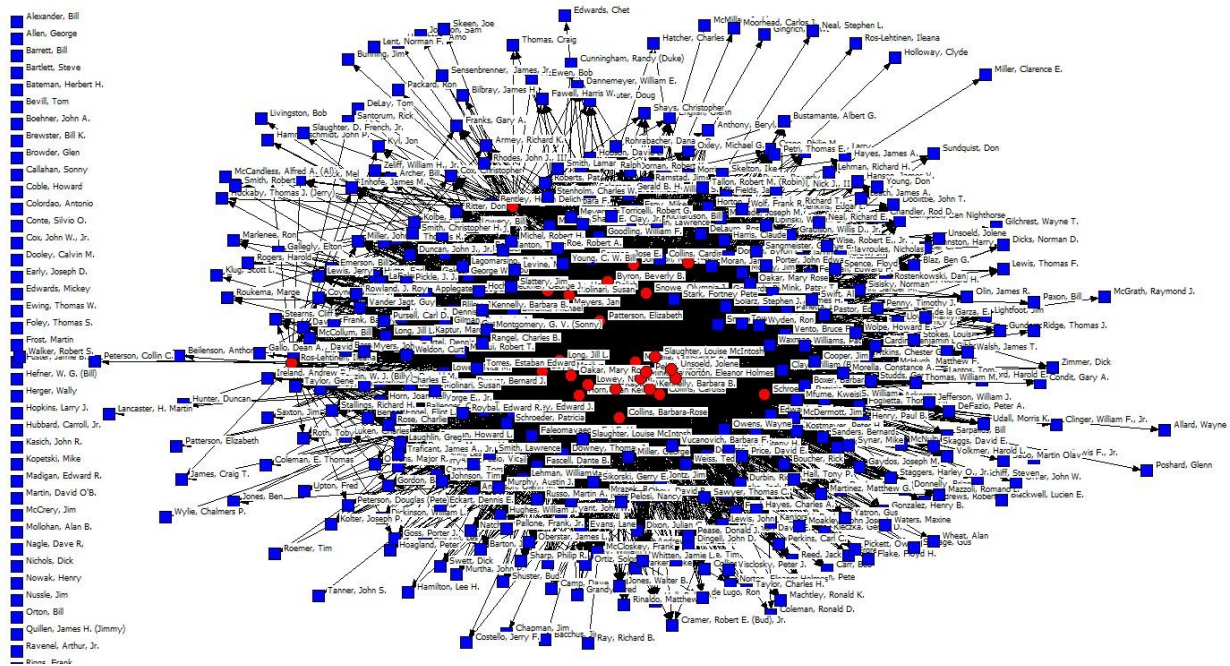


Figure 4. House Chamber Female Cosponsorship Network, 102nd Congress

As female membership in the House increased since the 102nd Congress, the number of cosponsorship ties from female legislators, in the aggregate, also increased. It is important to note that this result does not suggest that the frequency of ties per legislator increased as will be demonstrated in the next section. The increase in aggregate female ties results in a very dense graphical representation of the female cosponsorship network as shown in Figure 5 (90 cosponsoring nodes, 435 legislator nodes receiving at least one tie, 11 isolates, and 25,388 ties (cosponsorship acts). While it is difficult to derive much meaning from this illustration, the main point of the graph comparison between the 102nd Congress and 114th Congress is to illustrate that the female cosponsorship network becomes denser, in the aggregate, as the number of female legislators increases, assuming the per-female legislator tie frequency does not decrease. In

addition, the graphical representation of the 114th Congress House network shows fewer isolates than presented in the 102nd Congress House network. As more females entered the House during this study period, there were more opportunities for increased cosponsorship acts for female-sponsored legislation.

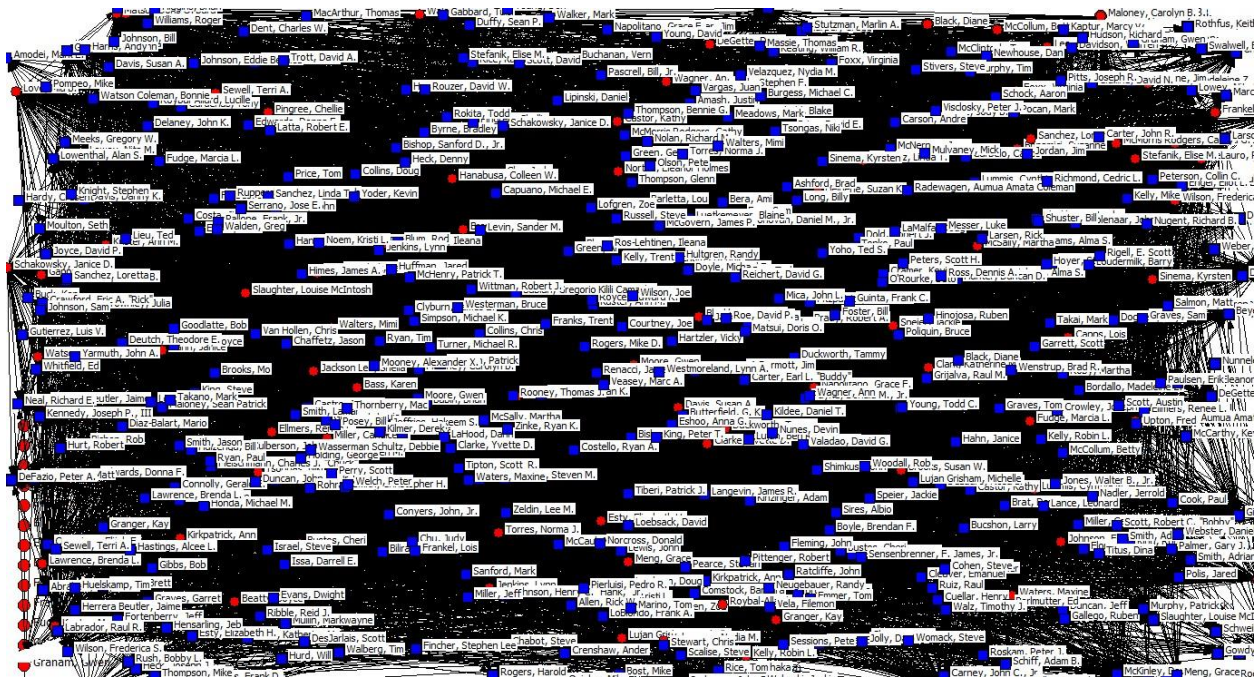


Figure 5. House Chamber Female Cosponsorship Network, 114th Congress

A similar pattern as that demonstrated in the House emerged in the Senate from the 102nd Congress to the 114th Congress. Figures 6 and 7 present the female cosponsorship networks for the Senate Chamber in the 102nd Congress and the 114th Congress, respectively. In the Senate 102nd Congress graph, there are 3 (red) nodes (female legislators who cosponsored at least one bill during this term), 95 legislator nodes receiving at least one tie, 7 isolates, and 623 ties (cosponsorship acts). In the Senate 114th Congress graph, there are 20 cosponsoring nodes, 100 legislator nodes receiving at least one tie, 0 isolates, and 4,689 ties. Like the House pattern, as more females entered the Senate, the female cosponsorship network became denser. In addition,

the 114th Congress Senate network yields no isolates, meaning that each member of the Senate received at least one cosponsorship tie from a female Senator during this term.

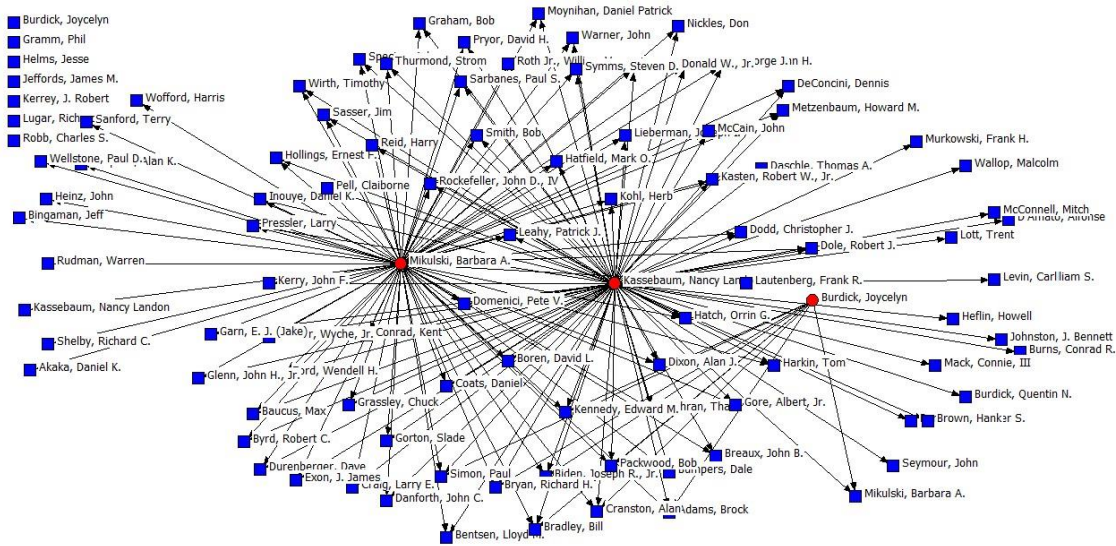


Figure 6. Senate Chamber Female Cosponsorship Network, 102nd Congress

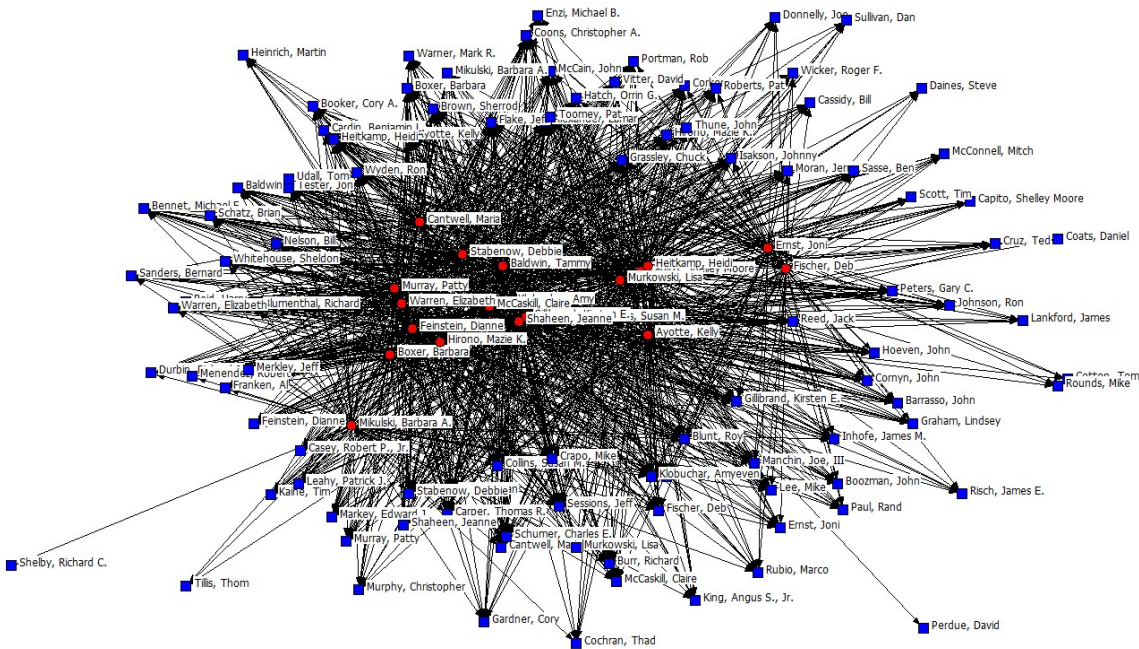


Figure 7. Senate Chamber Female Cosponsorship Network, 114th Congress

Descriptive Statistics

Tables 5 and 6 present the descriptive statistics for the House and Senate, respectively. These tables show the number of binding legislative proposals considered for each model time period, the number of those proposals that passed a chamber floor action, and those that failed to secure passage. Below the bill information is a listing of dichotomous variables categorized by gender group and their number of observations for all terms in each study period.

Table 5. House Chamber Descriptive Statistics – Bills and Dichotomous Variables

<i>Variables</i>	H102-108	H102-114
	<i>Obs</i>	<i>Obs</i>
Total Bills	39,321	79,438
Bills Passed	4,395	8,604
Bills Failed	34,926	70,834
<i>Dichotomous Variables</i>		
Female Sponsored Bills	4,978	12,632
Male Sponsored Bills	34,343	66,806
Female Democrat	70	134
Male Democrat	405	540
Female Republican	33	62
Male Republican	392	598
Female is Party Leader	9	19
Male is Party Leader	33	64
Female is Committee Leader	0	2
Male is Committee Leader	15	23

Table 6. Senate Chamber Descriptive Statistics – Bills and Dichotomous Variables

<i>Variables</i>	S102-108	S102-114
	<i>Obs</i>	<i>Obs</i>
Total Bills	21,172	43,647
Bills Passed	2,408	3,664
Bills Failed	18,764	39,983
<i>Dichotomous Variables</i>		
Female Sponsored Bills	2,034	6,609
Male Sponsored Bills	19,138	37,038
Female Democrat	11	20
Male Democrat	80	117
Female Republican	6	10
Male Republican	86	127
Female is Party Leader	1	10
Male is Party Leader	22	46
Female is Committee Leader	0	1
Male is Committee Leader	10	15

Tables 7 and 8 present the descriptive statistics for the House and Senate continuous variables, respectively. For these variables, the means, standard deviations, minimum, and maximum values are presented.

Table 7. House Chamber Descriptive Statistics – Continuous Variables

<i>Continuous Variables</i>	102nd -108th Congresses				102nd -114th Congresses			
	<i>Mean</i>	<i>Std Dev</i>	<i>Min</i>	<i>Max</i>	<i>Mean</i>	<i>Std Dev</i>	<i>Min</i>	<i>Max</i>
Sponsor Seniority (# of terms)	6.236	4.181	1	27	6.229	4.450	1	30
Congressional Approval	0.392	0.097	0.25	0.55	0.298	0.122	0.14	0.55
Connectedness	0.171	0.043	0.00	0.276	N/A	N/A	N/A	N/A
In-Degree	354.9	354.5	0.00	3719.0	343.9	323.6	0.00	3719.0
In-Beta	345291.8	326078.2	0.00	2118355.0	329081.1	315774.8	0.00	2118355.0
Clustering Coefficient	0.790	0.197	0.34	4.667	0.815	0.196	0.34	4.667
E-I Index	-0.582	0.482	-1.00	0.927	-0.490	0.488	-1.00	1.000

Table 8. Senate Chamber Descriptive Statistics – Continuous Variables

<i>Continuous Variables</i>	102nd -108th Congresses				102nd -114th Congresses			
	<i>Mean</i>	<i>Std Dev</i>	<i>Min</i>	<i>Max</i>	<i>Mean</i>	<i>Std Dev</i>	<i>Min</i>	<i>Max</i>
Sponsor Seniority (# of terms)	7.160	4.729	1	24	6.831	4.885	1	25
Congressional Approval	0.392	0.097	0.25	0.55	0.298	0.122	0.14	0.55
Connectedness	0.998	0.206	0.00	1.613	N/A	N/A	N/A	N/A
In-Degree	227.2	172.1	0.00	910.0	234.2	161.2	0.00	910.0
In-Beta	225548.2	177979.5	0.00	1010154.0	232821.5	172988.9	0.00	1010154.0
Clustering Coefficient	1.908	0.488	0.90	3.745	1.965	0.395	0.90	6.333
E-I Index	-0.667	0.477	-1.00	0.980	-0.518	0.519	-1.00	0.980

Table 9 presents the sponsorship and cosponsorship activity categorized by gender of legislator in the House from the 102nd Congress through the 114th Congress. The results show that female representatives had higher mean sponsorship and cosponsorship rates than male representatives, thus demonstrating more active legislative output and greater support and collaboration levels within the female networks compared to the male networks in the House during the study period. The exception to this statement is the level of sponsorship rates in the 112th Congress where male representatives sponsored at a slightly greater rate than their female counterparts, 15.3 bills to 14.8 bills, respectively.

Table 9. House Chamber Membership and Sponsorship and Cosponsorship Activity by Gender Group by Term

<i>Legislative Term (Years)</i>	<i># of Representatives</i>		<i>Mean Bills Sponsored by Each Representative ²</i>		<i>Mean Bills Cosponsored by Each Representative</i>	
	<i>Female ¹</i>	<i>Male</i>	<i>Female</i>	<i>Male</i>	<i>Female</i>	<i>Male</i>
102 (1991-1992)	29 (6.5%)	418	18.1	15.0	374.3	303.0
103 (1993-1994)	49 (11.0%)	397	14.2	12.7	259.3	225.6
104 (1995-1996)	49 (11.0%)	396	11.1	10.1	167.9	145.8
105 (1997-1998)	55 (12.2%)	394	11.4	11.1	230.6	187.2
106 (1999-2000)	58 (13.1%)	384	13.6	13.1	309.1	230.4
107 (2001-2002)	62 (13.9%)	385	15.1	12.9	326.1	220.7
108 (2003-2004)	63 (14.2%)	381	13.0	12.4	289.6	223.7
109 (2005-2006)	71 (16.0%)	374	16.2	14.4	268.4	228.1
110 (2007-2008)	79 (17.5%)	373	18.2	16.1	321.3	263.9
111 (2009-2010)	80 (17.7%)	371	17.9	14.1	279.7	232.0
112 (2011-2012)	78 (17.3%)	372	14.8	15.3	230.4	206.7
113 (2013-2014)	84 (18.8%)	363	13.6	13.4	264.2	223.5
114 (2015-2016)	90 (20.4%)	356	15.3	14.7	282.1	239.0
	<i>Mean for All Terms</i>		<i>14.9</i>	<i>13.5</i>	<i>275.4</i>	<i>225.5</i>

1. Percentages in parentheses indicate female membership percentage in the House.

2. "Bills" includes public bills and joint resolutions. Private bills, amendments, resolutions, and concurrent resolutions are omitted for reasons described in this paper.

Table 10 presents the sponsorship and cosponsorship activity categorized by gender of legislator in the Senate from the 102nd Congress through the 114th Congress. Unlike the House results, male senators sponsored at greater rates than female senators in the first three terms of the study period (102nd Congress – 105th Congress) and cosponsored more frequently than female senators in the 102nd and 104th Congresses. In the subsequent legislative terms, female senators sponsored and cosponsored at greater rates than their male counterparts, thus demonstrating more active legislative output and greater support and collaboration levels similar to the House results.

Table 10. Senate Chamber Membership and Sponsorship and Cosponsorship Activity by Gender Group by Term

Legislative Term (Years)	# of Senators		Mean Bills Sponsored by Each Senator ²		Mean Bills Cosponsored by Each Senator	
	Female ¹	Male	Female	Male	Female	Male
102 (1991-1992)	3 (2.9%)	99	20.0	37.1	207.7	259.9
103 (1993-1994)	7 (6.9%)	94	19.4	28.4	183.7	168.4
104 (1995-1996)	9 (8.8%)	93	20.8	22.3	87.3	93.2
105 (1997-1998)	9 (9.0%)	91	25.3	27.3	162.7	125.1
106 (1999-2000)	9 (8.8%)	93	34.3	32.6	234.4	173.9
107 (2001-2002)	13 (13.0%)	87	41.1	31.1	223.4	150.8
108 (2003-2004)	14 (14.0%)	86	41.4	29.0	217.7	150.7
109 (2005-2006)	14 (13.9%)	87	48.6	40.0	244.8	172.4
110 (2007-2008)	16 (15.7%)	86	49.5	34.8	289.6	191.0
111 (2009-2010)	18 (16.5%)	91	49.2	35.3	202.8	146.8
112 (2011-2012)	17 (16.8%)	84	47.6	35.2	189.9	162.5
113 (2013-2014)	20 (19.2%)	84	33.0	28.7	199.1	165.4
114 (2015-2016)	20 (20.0%)	80	37.5	35.5	234.5	182.9
	Mean for All Terms		39.1	32.1	212.0	165.2

1. Percentages in parentheses indicate female membership percentage in the Senate.

2. "Bills" includes public bills and joint resolutions. Private bills, amendments, resolutions, and concurrent resolutions are omitted for reasons described in this paper.

Using UCINet, I calculated the descriptive statistics for centrality, cohesion, connectedness, and group-related network measures for each legislator in each legislative term within each chamber. I used Stata to develop the aggregate functions of each measure (mean, standard deviation, minimum, and maximum) by gender group for each term. The results of these analyses are presented in Tables 11 through 16.

Table 11 shows the House centrality measures of in-degree centrality and in-beta centrality. As demonstrated in the table, there are wide ranges of values and high standard deviations for each measure by gender group within each term. These characteristics are not surprising in social networks where relationships are constantly changing, evolving, or devolving, particularly in legislative bodies where each election cycle may end one legislative

career and start a new one.²⁹ For the in-degree measure, the mean values for females were greater than male values in each term. The overall mean for the study period for this measure was significantly higher for the female group than for the male group. A similar pattern existed for the in-beta measure with the exception of the 104th legislative term where the male group mean was slightly higher, in percentage terms, than the female group mean. Like the results of the in-degree centrality measure analysis, the overall mean for the female group for the in-beta centrality measure was significantly higher for the female group than for the male group.

Table 11. House Chamber Centrality Measures by Gender Group by Term

Legislative Term (Years)	In-Degree Centrality						Beta Centrality					
	Female			Male			Female			Male		
	Mean ¹	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max
102 (1991-1992)	489 (403)	3	1,459	295 (339)	0	3,719	526,354 (439,123)	5,218	1,548,700	283,520 (309,982)	0	1,880,933
103 (1993-1994)	282 (254)	3	918	223 (245)	0	1,441	304,029 (286,994)	5,579	1,175,567	213,786 (251,426)	0	1,525,737
104 (1995-1996)	171 (216)	0	1,078	145 (165)	0	976	144,720 (200,450)	0	1,055,503	149,962 (187,364)	0	1,107,531
105 (1997-1998)	227 (254)	0	995	188 (196)	0	963	231,969 (267,969)	0	1,164,193	183,133 (195,376)	0	980,170
106 (1999-2000)	309 (361)	1	2,057	231 (229)	0	1,423	314,058 (373,433)	525	2,118,355	228,000 (230,929)	0	1,375,982
107 (2001-2002)	319 (310)	4	1,342	222 (241)	0	1,615	317,257 (321,044)	2,234	1,434,265	204,154 (227,177)	0	1,368,829
108 (2003-2004)	283 (264)	0	1,246	225 (220)	0	1,254	276,802 (281,380)	0	1,347,477	200,860 (203,392)	0	1,244,969
109 (2005-2006)	292 (293)	0	1,362	224 (210)	0	1,281	285,287 (297,055)	0	1,390,503	208,111 (202,700)	0	1,272,141
110 (2007-2008)	345 (330)	0	1,536	259 (260)	0	1,500	348,723 (401,941)	0	1,917,939	214,863 (283,624)	0	1,780,336
111 (2009-2010)	300 (290)	0	1,280	228 (235)	0	1,355	305,107 (327,693)	0	1,533,300	186,708 (247,552)	0	1,467,142
112 (2011-2012)	233 (230)	0	1,077	206 (191)	0	1,408	231,864 (231,773)	0	1,022,807	186,202 (174,136)	0	1,247,869
113 (2013-2014)	252 (234)	0	1,259	227 (231)	0	1,677	248,550 (242,828)	0	1,341,822	213,137 (219,827)	0	1,395,375
114 (2015-2016)	278 (275)	0	1,406	240 (222)	0	1,346	270,775 (266,508)	0	1,408,371	221,754 (212,143)	0	1,422,961
Mean for All Terms	284 (288)			224 (236)			284,436 (308,659)			207,580 (232,018)		

1. Numbers in parentheses indicate standard deviations.

Table 12 presents the Senate chamber aggregate function analysis for in-degree and in-beta centrality measures. Similar to the Senate pattern of sponsorship and cosponsorship activity levels for the two gender groups, the centrality means for female senators were lower than for male senators in the earlier terms of the study period with females exhibiting higher mean values than males in the mid to later stages of the study period. Like the House results, the overall mean

²⁹ It is not surprising that the Senate standard deviations were smaller relative to the House figures as senators enjoy longer terms than do representatives.

of both centrality measures for the female Senate group were higher than for the male Senate group, however the percentage differences were greater in the House than in the Senate.

Table 12. Senate Chamber Centrality Measures by Gender Group by Term

Legislative Term (Years)	In-Degree Centrality						Beta Centrality					
	Female			Male			Female			Male		
	Mean ¹	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max
102 (1991-1992)	185 (221)	0	429	261 (197)	3	910	197,925 (232796)	0	454,409	258,010 (206312)	4,069	1,010,154
103 (1993-1994)	130 (83)	44	249	172 (140)	0	706	127,901 (70,020)	52,274	215,740	171,169 (148,308)	0	769,415
104 (1995-1996)	95 (112)	0	338	92 (101)	1	761	85,793 (109,528)	0	314,589	88,630 (105469)	1,073	821,981
105 (1997-1998)	91 (49)	11	192	132 (120)	9	581	83,889 (49,488)	14,097	180,529	133,142 (125,767)	8,087	609,388
106 (1999-2000)	161 (98)	38	278	181 (128)	0	533	163,674 (103,377)	41,174	288,227	181,611 (130,109)	0	586,731
107 (2001-2002)	186 (112)	50	399	156 (131)	1	630	183,461 (109,127)	45,367	382,480	149,963 (136,957)	227	697,255
108 (2003-2004)	214 (128)	49	475	151 (119)	7	607	207,863 (114,803)	44,395	424,361	146,894 (117,957)	7,872	582,479
109 (2005-2006)	192 (158)	25	539	181 (124)	12	529	190,438 (154,702)	22,015	540,398	173,968 (118,416)	9,254	489,111
110 (2007-2008)	255 (187)	42	736	197 (172)	3	896	242,217 (205,253)	21,507	764,570	180,546 (193,198)	324	1,005,585
111 (2009-2010)	190 (109)	32	481	149 (137)	0	639	186,813 (108,740)	33,143	403,973	139,324 (152,840)	0	629,299
112 (2011-2012)	187 (87)	61	342	163 (106)	6	497	191,116 (108,789)	34,524	430,865	147,199 (131,695)	2,160	633,191
113 (2013-2014)	181 (100)	49	422	170 (126)	0	521	192,589 (108,787)	28,454	446,056	158,023 (148,774)	0	581,627
114 (2015-2016)	221 (83)	79	385	186 (121)	10	551	222,925 (91,350)	83,003	410,372	178,556 (118,158)	9,454	545,265
Mean for All Terms	186 (122)			169 (140)			184,899 (126,036)			162,619 (148,862)		

1. Numbers in parentheses indicate standard deviations.

Tables 13 and 14 present the House and Senate cohesion measure of clustering coefficient and Fowler’s centrality-based connectedness measure, respectively. Unlike the results of the traditional network centrality measure analysis, the range of values and standard deviations of clustering coefficient and connectedness is smaller in each term for each chamber and gender group.³⁰ The mean values in each term for both measures are relatively similar for both gender groups in both chambers. In the House, the overall mean of the clustering coefficient measure for the female group (0.90) is slightly higher than the overall mean for the male group (0.85) and the overall mean of the connectedness measure is the same for each group (both at 0.15). In the Senate, the overall mean of the clustering coefficient measure for the female group (1.96) is slightly lower than the overall mean for the male group (1.98) and the overall mean of

³⁰ This difference may be due to how cosponsorship ties are measured in each network metric and the scales with which they are measured.

the connectedness measure is slightly higher for the female group (0.93) than for the male group (0.92).

Table 13. House Chamber Clustering Coefficient and Connectedness Measures by Gender Group by Term

Legislative Term (Years)	Clustering Coefficient						Connectedness ²					
	Female			Male			Female			Male		
	Mean ¹	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max
102 (1991-1992)	1.00 (0.20)	0.72	1.45	1.03 (0.20)	0.00	1.98	0.16 (0.04)	0.05	0.21	0.15 (0.05)	0.05	0.27
103 (1993-1994)	0.88 (0.19)	0.59	1.21	0.85 (0.19)	0.00	1.54	0.13 (0.04)	0.03	0.20	0.14 (0.04)	0.01	0.22
104 (1995-1996)	0.65 (0.15)	0.34	1.10	0.65 (0.15)	0.33	1.14	0.13 (0.05)	0.02	0.21	0.14 (0.05)	0.00	0.24
105 (1997-1998)	0.81 (0.18)	0.45	1.46	0.75 (0.19)	0.00	1.75	0.13 (0.04)	0.03	0.20	0.13 (0.04)	0.01	0.22
106 (1999-2000)	0.87 (0.16)	0.56	1.33	0.85 (0.17)	0.56	1.60	0.17 (0.04)	0.02	0.25	0.16 (0.05)	0.02	0.28
107 (2001-2002)	0.90 (0.19)	0.55	1.26	0.88 (0.28)	0.52	4.67	0.15 (0.04)	0.04	0.22	0.16 (0.04)	0.02	0.24
108 (2003-2004)	0.87 (0.19)	0.53	1.49	0.82 (0.17)	0.51	1.48	0.17 (0.05)	0.05	0.26	0.17 (0.05)	0.00	0.28
109 (2005-2006)	0.88 (0.27)	0.54	2.77	0.81 (0.16)	0.00	1.40	N/A	N/A	N/A	N/A	N/A	N/A
110 (2007-2008)	1.07 (0.32)	0.62	2.05	0.94 (0.23)	0.56	2.42	N/A	N/A	N/A	N/A	N/A	N/A
111 (2009-2010)	0.99 (0.33)	0.56	3.17	0.89 (0.25)	0.42	3.33	N/A	N/A	N/A	N/A	N/A	N/A
112 (2011-2012)	0.84 (0.18)	0.50	1.47	0.81 (0.20)	0.48	2.50	N/A	N/A	N/A	N/A	N/A	N/A
113 (2013-2014)	0.90 (0.19)	0.54	1.91	0.85 (0.18)	0.52	1.73	N/A	N/A	N/A	N/A	N/A	N/A
114 (2015-2016)	0.97 (0.34)	0.60	3.50	0.87 (0.18)	0.00	1.64	N/A	N/A	N/A	N/A	N/A	N/A
Mean for All Terms	0.90 (0.26)			0.85 (0.22)			0.15 (0.05)			0.15 (0.05)		

1. Numbers in parentheses indicate standard deviations.

2. Connectedness data only available for the 102nd through 108th terms.

Table 14. Senate Clustering Coefficient and Connectedness Measures by Gender Group by Term

Legislative Term (Years)	Clustering Coefficient						Connectedness ²					
	Female			Male			Female			Male		
	Mean ¹	Min	Max	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max
102 (1991-1992)	2.73 (0.14)	2.63	2.83	2.83 (0.22)	2.55	3.75	0.54 (0.49)	0.00	0.97	0.84 (0.18)	0.49	1.23
103 (1993-1994)	2.04 (0.23)	1.77	2.32	1.96 (0.21)	1.64	3.00	0.71 (0.07)	0.60	0.79	0.78 (0.18)	0.04	1.20
104 (1995-1996)	1.26 (0.34)	0.96	2.11	1.24 (0.22)	0.90	2.11	0.76 (0.31)	0.00	0.99	0.88 (0.17)	0.43	1.58
105 (1997-1998)	1.56 (0.11)	1.43	1.74	1.57 (0.18)	1.26	2.01	0.81 (0.18)	0.48	0.99	0.89 (0.18)	0.48	1.36
106 (1999-2000)	1.97 (0.19)	1.78	2.31	1.97 (0.18)	1.74	2.93	0.98 (0.20)	0.69	1.19	0.97 (0.17)	0.55	1.36
107 (2001-2002)	1.94 (0.24)	1.63	2.26	1.90 (0.25)	1.52	2.65	1.14 (0.22)	0.86	1.46	1.05 (0.21)	0.63	1.61
108 (2003-2004)	1.77 (0.13)	1.60	1.96	1.87 (0.18)	1.57	2.42	1.11 (0.19)	0.63	1.31	1.03 (0.19)	0.57	1.43
109 (2005-2006)	2.02 (0.14)	1.83	2.28	2.03 (0.18)	1.79	2.89	N/A	N/A	N/A	N/A	N/A	N/A
110 (2007-2008)	2.40 (0.29)	2.03	3.08	2.34 (0.30)	1.56	3.48	N/A	N/A	N/A	N/A	N/A	N/A
111 (2009-2010)	1.92 (0.25)	1.61	2.47	1.99 (0.61)	1.17	6.33	N/A	N/A	N/A	N/A	N/A	N/A
112 (2011-2012)	1.89 (0.19)	1.68	2.23	1.91 (0.21)	1.61	2.68	N/A	N/A	N/A	N/A	N/A	N/A
113 (2013-2014)	2.03 (0.22)	1.74	2.49	2.00 (0.34)	1.66	4.36	N/A	N/A	N/A	N/A	N/A	N/A
114 (2015-2016)	2.15 (0.17)	1.94	2.50	2.14 (0.22)	1.89	3.07	N/A	N/A	N/A	N/A	N/A	N/A
Mean for All Terms	1.96 (0.34)			1.98 (0.46)			0.93 (0.29)			0.92 (0.20)		

1. Numbers in parentheses indicate standard deviations.

2. Connectedness data only available for the 102nd through 108th terms.

Tables 15 and 16 present the trends over time of the characteristics of intra- and inter-group relational ties within Congress via cosponsorships between legislators as measured by the social network term, E-I Index. While not a variable included in the regression analyses, it is informative to summarily examine the frequency of ties between gender groups as more females enter Congress. In the earlier terms of this study period, the mean E-I Index for male legislators was highly negative while the mean value for female legislators was highly positive.³¹ As more females entered Congress during the study period, the positive female group E-I Index values decreased in value toward zero while the male group E-I Index values increased toward zero.

Table 15. House Chamber External-Internal Group Index Measures by Gender Group by Term

<i>Legislative Term (Years)</i>	<i>E-I Index</i>					
	<i>Female</i>			<i>Male</i>		
	<i>Mean</i> ¹	<i>Min</i>	<i>Max</i>	<i>Mean</i>	<i>Min</i>	<i>Max</i>
102 (1991-1992)	0.83 (0.03)	0.72	0.87	-0.85 (0.03)	-0.96	-0.71
103 (1993-1994)	0.67 (0.22)	-0.77	0.82	-0.77 (0.10)	-1.00	0.85
104 (1995-1996)	0.69 (0.12)	0.36	0.89	-0.78 (0.09)	-0.94	-0.33
105 (1997-1998)	0.70 (0.08)	0.72	0.87	-0.76 (0.08)	-0.94	-0.50
106 (1999-2000)	0.67 (0.07)	0.49	0.88	-0.73 (0.07)	-0.91	-0.55
107 (2001-2002)	0.59 (0.24)	-0.77	0.84	-0.70 (0.11)	-1.00	0.66
108 (2003-2004)	0.64 (0.17)	-0.59	0.84	-0.70 (0.10)	-0.87	0.78
109 (2005-2006)	0.56 (0.25)	-0.59	0.79	-0.65 (0.17)	-0.83	0.69
110 (2007-2008)	0.56 (0.09)	0.25	0.74	-0.60 (0.17)	-0.80	0.77
111 (2009-2010)	0.55 (0.10)	0.20	0.78	-0.62 (0.15)	-0.83	0.73
112 (2011-2012)	0.59 (0.10)	0.41	0.79	-0.67 (0.10)	-0.90	-0.20
113 (2013-2014)	0.52 (0.12)	0.14	1.00	-0.62 (0.16)	-0.84	0.78
114 (2015-2016)	0.50 (0.10)	0.25	0.81	-0.61 (0.14)	-0.89	0.71
Mean for All Terms	0.60 (0.16)			-0.70 (0.14)		

1. Numbers in parentheses indicate standard deviations.

³¹ As described in Chapter 3, the E-I Index utilized in this analysis is measured on a -1 to 1 scale. As the measure proceeds from negative to positive on a scale, the indication is that members of one group reach out more often to members of the other group in comparison to ties formed within group. Conversely, if members were to solely form ties within their own group, their corresponding E-I Index value would be -1.

Table 16. Senate Chamber External-Internal Group Index Measures by Gender Group by Term

Legislative Term (Years)	E-I Index					
	<i>Female</i>			<i>Male</i>		
	Mean ¹	Min	Max	Mean	Min	Max
102 (1991-1992)	0.97 (0.02)	0.96	0.98	-0.96 (0.01)	-1.00	-0.92
103 (1993-1994)	0.86 (0.02)	0.83	0.89	-0.86 (0.03)	-0.94	-0.77
104 (1995-1996)	0.77 (0.07)	0.60	0.85	-0.83 (0.05)	-1.00	-0.69
105 (1997-1998)	0.80 (0.03)	0.75	0.84	-0.82 (0.05)	-1.00	-0.70
106 (1999-2000)	0.82 (0.02)	0.78	0.84	-0.82 (0.03)	-0.91	-0.74
107 (2001-2002)	0.72 (0.03)	0.67	0.75	-0.72 (0.05)	-0.86	-0.62
108 (2003-2004)	0.72 (0.02)	0.65	0.76	-0.69 (0.03)	-0.75	-0.58
109 (2005-2006)	0.73 (0.03)	0.66	0.77	-0.72 (0.03)	-0.85	-0.64
110 (2007-2008)	0.68 (0.02)	0.65	0.71	-0.67 (0.04)	-0.84	-0.60
111 (2009-2010)	0.61 (0.04)	0.52	0.68	-0.61 (0.08)	-0.86	-0.33
112 (2011-2012)	0.64 (0.04)	0.55	0.73	-0.64 (0.07)	-0.84	-0.44
113 (2013-2014)	0.56 (0.06)	0.44	0.70	-0.61 (0.09)	-0.82	-0.36
114 (2015-2016)	0.58 (0.04)	0.47	0.64	-0.59 (0.07)	-0.75	-0.36
Mean for All Terms	0.68 (0.10)			-0.74 (0.12)		

1. Numbers in parentheses indicate standard deviations.

Prior scholarship has demonstrated a connection between congressional approval ratings and legislative activity and collaboration (Kirkland and Gross, 2014). Specifically, as congressional approval declines, legislators tend to collaborate and support each other at greater rates; in network terms, legislators expand outside of otherwise stable clustered networks (Kirkland and Gross, 2014). Congressional approval ratings are not included in the regression analyses because the unit of analysis is at the bill level rather than at the level of the entire body of Congress and the variable of interest in this study is related to gender, not Congress as a whole. However, I include a light, graphical treatment of the potential effects of approval ratings on the network measures for perspective in this analysis and for stimulating further extensions of this work and that of Kirkland and Gross (2014).

Figures 8 through 13 present comparisons of congressional approval ratings as presented by Gallup (2020) and the legislative cosponsorship network measures by gender group of in-degree centrality, clustering coefficient, and connectedness. An interesting result of this graphical analysis is that for each network measure in each chamber, female and male legislator network measures generally follow the same pattern. For the in-degree measure, there seems to be no clear relationship between in-degree values for each group in each chamber and congressional approval ratings as demonstrated in Figures 8 and 9. The pattern of in-degree values in the House seems to be consistent from the 106th Congress to the 114th Congress while, in the Senate, in-degree values seem to steadily increase from the 104th Congress to the 114th Congress. In both chambers, in-degree values sharply decline from the 102nd Congress to the 104th Congress and then proceed to levels above those found in the 104th Congress.

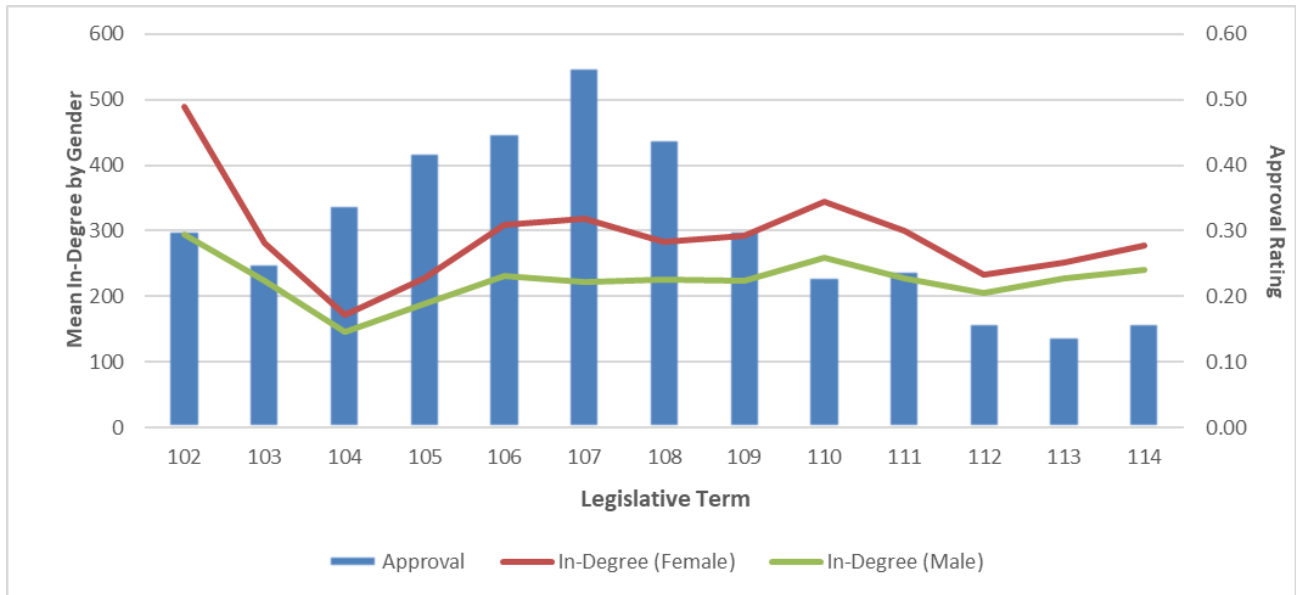


Figure 8. Congressional Approval Ratings and Group-based In-Degree Centrality Comparisons, House Chamber 102nd - 114th Congresses

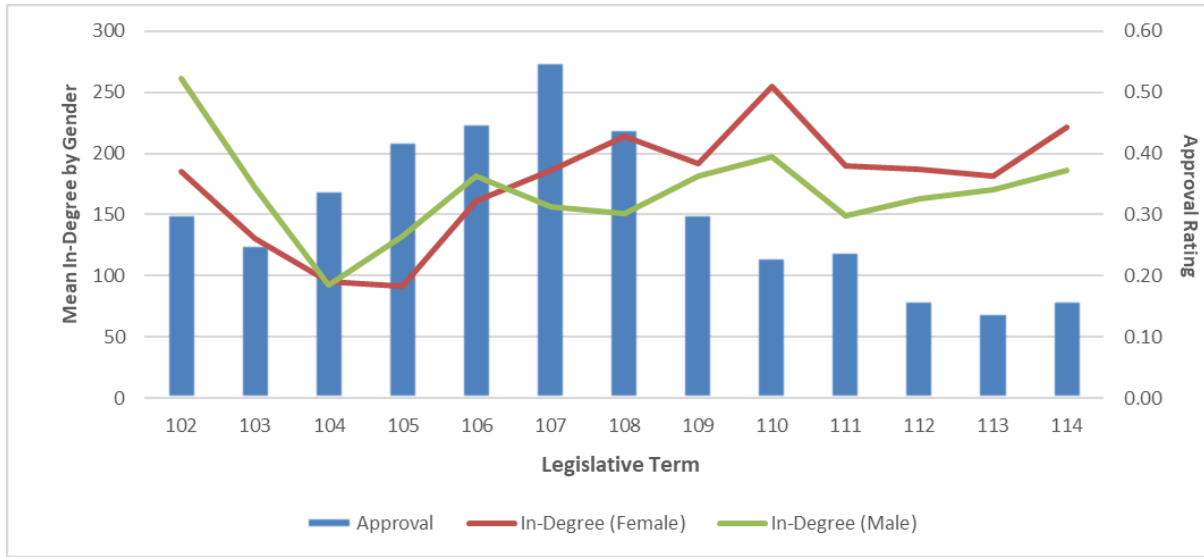


Figure 9. Congressional Approval Ratings and Group-based In-Degree Centrality Comparisons, Senate Chamber 102nd - 114th Congresses

Figures 10 and 11 illustrate the pattern of clustering coefficient values compared to approval ratings for the House and Senate, respectively. Female group and male group clustering coefficient values are roughly similar in both chambers and exhibit similarities with the in-degree measure; that is, step declines from the 102nd Congress to the 104th Congress followed by an increasing trend from the 105th to 114th Congresses.

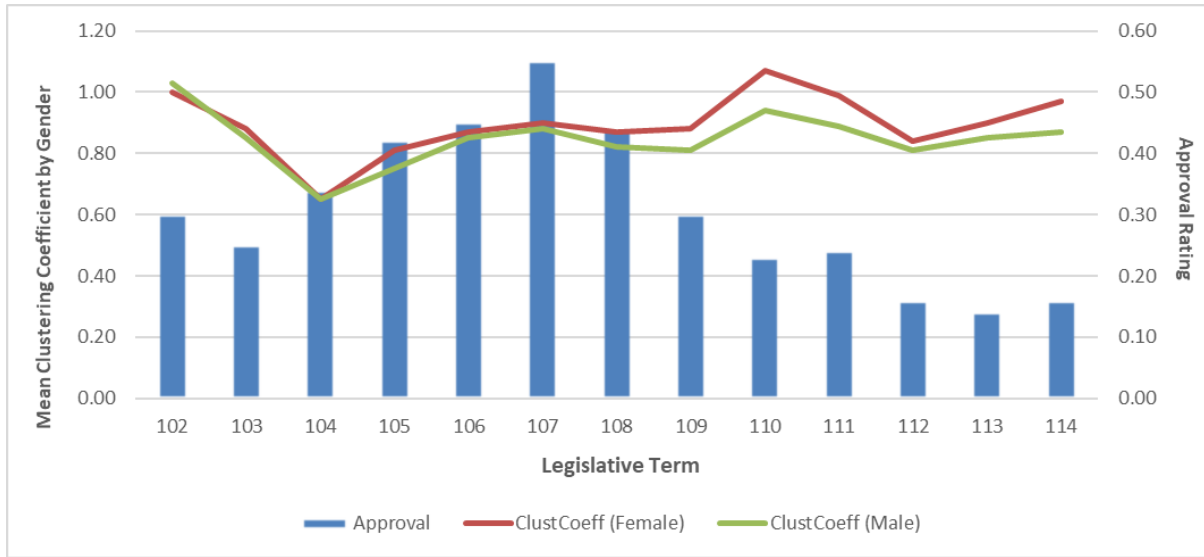


Figure 10. Congressional Approval Ratings and Group-based Clustering Coefficient Comparisons, House Chamber 102nd - 114th Congresses

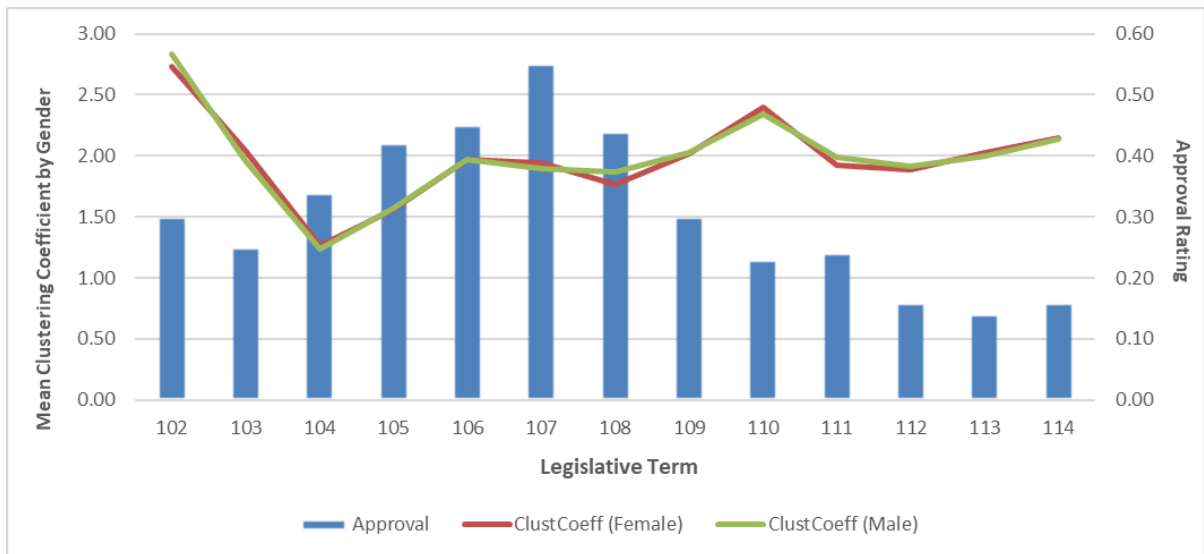


Figure 11. Congressional Approval Ratings and Group-based Clustering Coefficient Comparisons, Senate Chamber 102nd - 114th Congresses

Figures 12 and 13 illustrate the pattern of connectedness values compared to approval ratings for the House and Senate from the 102nd Congress through the 108th Congress. Both figures demonstrate that connectedness values generally rise and fall with approval ratings. There are no remarkable differences in the female and male values over time in the House;

however, the Senate graph shows a significant gap in connectedness values between the two groups starting in the 102nd Congress with female connectedness values much lower than males. The gap tends to close after the 102nd Congress and the patterns of values follow each other through the 108th Congress.

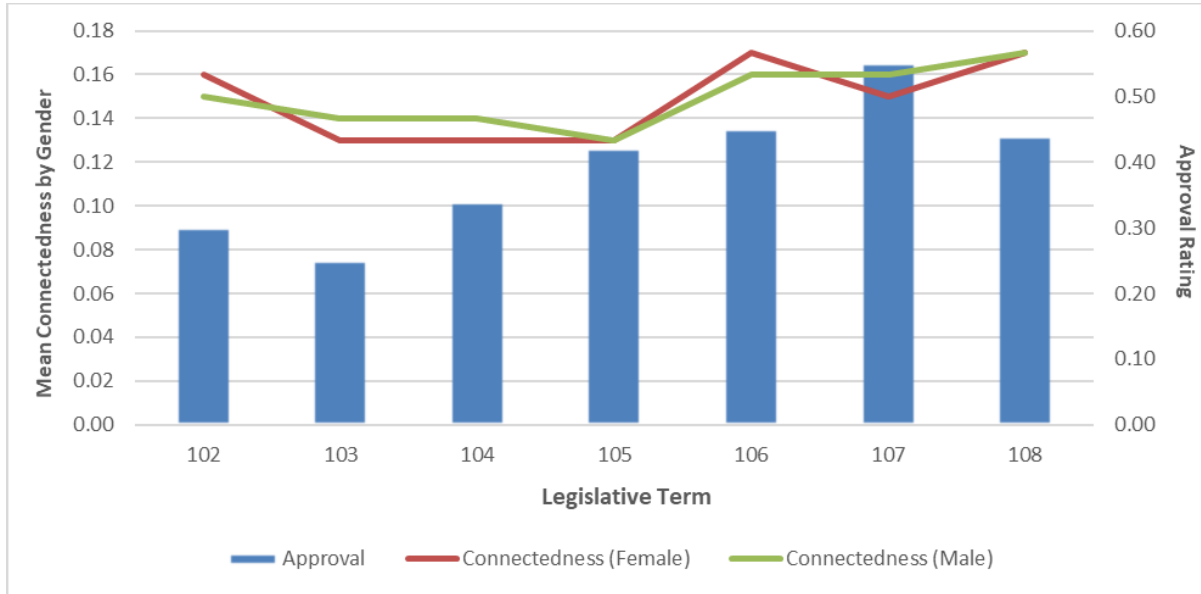


Figure 12. Congressional Approval Ratings and Group-based Connectedness Comparisons, House Chamber 102nd - 108th Congresses

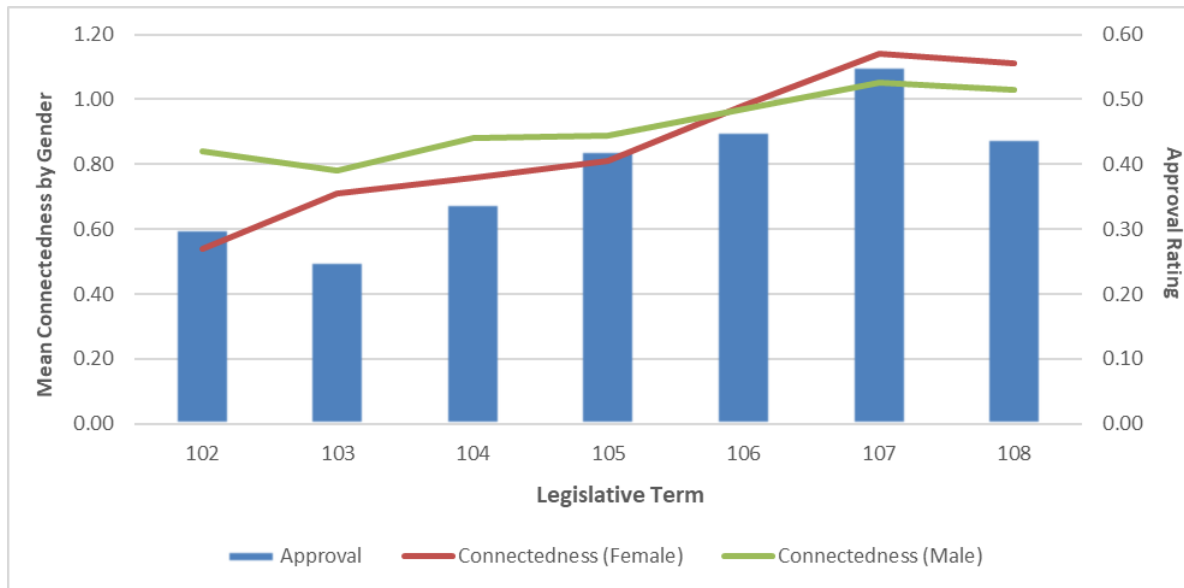


Figure 13. Congressional Approval Ratings and Group-based Connectedness Comparisons, Senate Chamber 102nd - 108th Congresses

Sponsorship and Cosponsorship Activity – Testing Hypothesis 1

I hypothesized that female legislators within both chambers of Congress exhibit greater rates of sponsorship and cosponsorship activity, on average, on binding, force-of-law congressional measures than do their male counterparts. The previously discussed observational data support Hypothesis 1, however, the more rigorous empirical results only partially support this hypothesis. Further discussion and interpretation of these results are provided in the next chapter.

Hypothesis 1 is based on studies that demonstrate that female legislators are more active legislators than male legislators for several compelling reasons. First, their increased legislative activity is a direct result of their minority gender group status in Congress (Barnes, 2016). In Congress, minority group status is an incentive for individuals in these groups to sponsor and cosponsor frequently to both establish long-term relationships within group and with majority group members as well as to enhance their chances of legislative success on their sponsored

legislation and of those they cosponsor (Craig et al., 2015). Second, increased legislative activity is viewed by female legislators as a means to increase substantive representation of females in the United States (Swers, 2005). Finally, prior scholarship has demonstrated that junior members typically sponsor at greater rates to build reputations in specific policy areas (Swers, 2005; Burkett, 1999). In most of the terms of the study period for this analysis, the average tenure of female representatives and senators was smaller than for the male legislators.³²

As shown in Figures 4 through 7, female cosponsorship networks grew significantly denser in both chambers of the 102nd through 114th Congresses. Tables 9 and 10 presented the mean sponsorship and cosponsorship rates by gender group for each legislative term in each chamber. Based on the observational data alone, female legislators in the House on average out-sponsored male legislators in every term of the study period except the 112th term. The female mean for the entire period (14.9 sponsorships) was roughly 10 percent higher than the male mean (13.5 sponsorships). The female cosponsorship mean in each term was higher than the male mean in the same term and the female mean for the entire period (275.4 cosponsorships) was roughly 22 percent higher than the male mean (225.5 cosponsorships). There were similar patterns in the Senate with a few exceptions. Male senators on average out-sponsored female legislators in the 101st through 105th Congress and females out-sponsored males from the 106th Congress through the 114th Congress. The female mean for the entire period (39.1 sponsorships) was roughly 22 percent higher than the male mean (32.1 sponsorships). Cosponsorship activity followed a similar pattern as that found in sponsorship activity. Male cosponsorship activity was higher on average than female activity from the 101st through 104th Congresses. For the study

³² In the 114th Congress, average female tenure in the House was slightly higher than average tenure for males, and similar to that of men in the Senate.

period, the female mean (212.0 cosponsorships) was roughly 28 percent higher than the male mean (165.2 cosponsorships).

While the observational data show that females in both chambers were more active sponsors and cosponsors than males, on average, during the study period, statistical testing demonstrated that the gender group differences were mixed. Table 17 presents the results of an independent sample t-test analysis to determine if the differences between gender groups in the House were statistically significant. The sponsorship differences between females and males in both time periods were not statistically significant ($p < 0.05$). Therefore, I cannot reject the null hypothesis that the observed differences in mean sponsorship activity between gender groups in the House are legitimate; that is, the observed differences for the study period are likely due to random factors. However, the cosponsorship differences between the two gender groups were statistically significant ($p < 0.05$). Therefore, I can reject the null hypothesis that the differences are due to chance and can confidently conclude that the differences in the House cosponsorship data for the study period are meaningful. In the Senate, the gender group differences in sponsorship activity *and* in cosponsorship activity were found not to be statistically significant, as shown in Table 18. Therefore, only part of Hypothesis 1 is supported; females in the House have statistically significant differences in cosponsorship activity than do males, yet the differences in observational data for House sponsor activity and Senate sponsor and cosponsorship activity between the two gender groups are not significantly different and are likely due to unobserved random factors.

Table 17. House Chamber Independent Sample T-Test – Sponsorship and Cosponsorship Activity

Description	Independent Sample t-test (House)							
	102nd-108th Congresses				102nd-114th Congresses			
	T	DF	P	Mean Diff (M-F)	T	DF	P	Mean Diff (M-F)
<i>Legislative Activity</i>								
Sponsorships	-0.872	125.257	0.385	-4.547	-1.082	237.464	0.280	-6.638
Cosponsorships	-2.683	126.466	0.008	-191.749	-2.311	238.006	0.022	-206.022

Table 18. Senate Chamber Independent Sample T-Test - Sponsorship and Cosponsorship Activity

Description	Independent Sample t-test (Senate)							
	102nd-108th Congresses				102nd-114th Congresses			
	T	DF	P	Mean Diff (M-F)	T	DF	P	Mean Diff (M-F)
<i>Legislative Activity</i>								
Sponsorships	-0.060	19.491	0.953	-1.511	-1.619	33.240	0.115	-62.691
Cosponsorships	1.014	22.900	0.321	95.377	-1.675	35.823	0.103	-258.520

Network Structures – Testing Hypothesis 2

I hypothesized that female legislators within both chambers of Congress form better networks than male legislators with respect to greater network centrality, cohesion, and connectedness values, on average, on binding, force-of-law congressional measures than their male counterparts. The previously discussed observational data as well as the empirical testing results partially support Hypothesis 2. Further discussion and interpretation of these results are provided in the next chapter.

Hypothesis 2 is based on studies demonstrating that female legislators are more collaborative and supportive than male legislators (Barnes, 2016; Craig, et al., 2015; Swers, 2005). In the context of social networks, females form better cosponsorship networks as

operationalized through relational cosponsorship ties as this study has shown. These ties form the basis of the cosponsorship networks and are measured in this study through centrality and cohesion metrics: *in-degree*, *in-beta*, *clustering coefficient*, and *connectedness*. Tables 11 through 14 presented these metrics by each legislative term in the House and the Senate.

In the House, mean female legislator in-degree and in-beta centrality measures were higher than mean male legislator measures except for the 104th Congress where the mean male in-beta centrality measure was slightly higher than the female one (male – 149,962; female – 144,720). The overall study period female legislator means for both the in-degree and the in-beta centrality measures were higher than the male ones. The mean female in-degree value was at 284 and the male mean was at 224 and the mean female in-beta value was at 284,436 and the male mean was at 207,580. According to Hanneman and Riddle (2005), network actors with high in-degree centrality measures generally occupy favorable structural positions in the network in terms of resource access and network prestige. Where in-degree centrality gives equal weighting to all incoming ties to an actor, the in-beta centrality measure weights these ties based on the structural position of the actor giving the tie. Ties to well-connected actors receive greater weight than ties to less-connected actors. In this analysis, legislators with high in-beta centrality values have a greater degree of power centrality; that is, they are directly and indirectly tied to other well-connected (powerful) actors within the cosponsorship network. These ties afford the actor the ability to more easily access powerful network actors compared to actors with lower in-beta centrality values. The results of the mean in-beta centrality analysis demonstrate that, on average, female House members have more cosponsorship ties to well-connected legislators than do male legislators, on average.

In the Senate, mean female legislator centrality measures were higher than mean male legislator measures in most legislative sessions and the study period mean for the female group was higher for both centrality measures. Female legislator in-degree values were higher than male legislator values in 9 of the 13 terms and female in-beta values were higher in 8 of the 13 terms. In both cases, male legislator centrality measure values were higher earlier in the study period with the trends reversing as more women became members of Congress later in the study period. Similar to the House centrality results, as more women entered the Senate, they received more cosponsorship ties than men, on average, and those ties were generally to more well-connected senators than what was experienced by male senators. These results indicate that for the majority of the study period, female senators occupied favorable structural positions in the cosponsorship network in terms of resource access, network prestige, and power through their ties to other well-connected senators.

In the House, there were no distinguishable differences between mean connectedness values for female and male legislators within each term or over the aggregated study period. The study period mean for both gender groups was 0.15. However, different results were evident in the connectedness measure analysis for the Senate gender group during the study period. Mean connectedness values for female legislators were higher from the 106th through 108th Congresses, whereas male legislators in the prior Congresses exhibited higher mean connectedness values. The aggregate mean was slightly higher for female senators than for male senators, at 0.93 and 0.92, respectively, and far surpass the means evident in the House analysis. Given that each gender group's connectedness measures utilized in this analysis are similar within each chamber, it is difficult to draw the conclusion that female legislators form better networks based on the connectedness measure alone.

In the House, the mean female legislator clustering coefficient cohesion measures were higher than mean male legislator measures except for the 102nd Congress, where the mean male value (1.03) was slightly higher than the female one (1.00), and the 104th Congress, where both male and female values were identical (0.65). For the entire study period, the female legislator mean was higher than the male mean (0.90 versus 0.85). Senate clustering coefficient values show a different trend compared to the House. Female values were higher than male values in 6 of the 13 terms, male values were higher in another 6 terms, and in the 106th Congress, the value was the same for both female and male legislators. The advantages that each gender group experienced did not fit a pattern as they were equally spread throughout the study period.

In the House, the observational data show that females had higher mean centrality and clustering coefficient measures than did males. Statistical testing through an independent sample t-test supports the observational data for the centrality measures but the results for the clustering coefficient measure were mixed depending on the time period tested (see Table 19). The differences in both centrality measure means between the two gender groups were statistically significant ($p < 0.05$). Therefore, I rejected the null hypothesis that the differences are due to chance and conclude with confidence that House females had higher centrality means than did males. The t-test performed on the clustering coefficient measure yielded mixed results as the means between the two gender groups were significant for the H102-114 time period ($p > 0.05$) but not for the H102-H108 period (see Table 19). Testing for the connectedness measure yielded non-significant results for the H102-108 time period, thus mirroring the conclusions drawn from the observational data for this network measure.

Table 19. House Chamber Independent Sample T-Test – Network Measures

Description	Independent Sample t-test (House)							
	102nd-108th Congresses				102nd-114th Congresses			
	T	DF	P	Mean Diff (M-F)	T	DF	P	Mean Diff (M-F)
<i>Network Metrics</i>								
In-Degree Centrality	-4.098	429.138	0.000	-67.430	-5.776	1046.670	0.000	-60.415
In-Beta Centrality	-4.553	418.360	0.000	-78933.060	-6.917	1013.980	0.000	-76855.680
Clustering Coefficient	-1.272	492.309	0.204	-0.014	-5.998	1052.800	0.000	-0.057
Connectedness	-0.504	454.276	0.615	-0.001	N/A	N/A	N/A	N/A

Like the results found in the House, the Senate observational data show that female senators had higher mean centrality measures than did male senators. Statistical testing through an independent sample t-test, for the most part, does not support the observational data (see Table 20). The results for the in-degree centrality measure indicate no statistically significant difference in means between the gender groups, while the results for the in-beta centrality measure are only statistically significant for the S102-114 time period ($p < 0.05$). For the clustering coefficient and the connectedness measures, the observational data indicate that the means for each measure between gender groups were similar. The t-test performed on the clustering coefficient measure indicated no significant difference between gender groups in the S102-108 time period but there was a meaningful difference in the S102-114 time period ($p < 0.05$). Like the House result, the testing for the connectedness measure for the Senate group means yielded non-significant results for the S102-108 time period, thus mirroring the conclusions drawn from the observational data for this network measure.

Table 20. Senate Chamber Independent Sample T-Test – Network Measures

Description	Independent Sample t-test (Senate)							
	102nd-108th Congresses				102nd-114th Congresses			
	T	DF	P	Mean Diff (M-F)	T	DF	P	Mean Diff (M-F)
<i>Network Metrics</i>								
In-Degree Centrality	0.569	84.338	0.571	8.816	-1.647	238.198	0.101	-16.856
In-Beta Centrality	0.636	87.079	0.526	9733.424	-2.094	242.114	0.037	-22279.680
Clustering Coefficient	2.457	87.026	0.016	0.124	0.691	267.124	0.490	0.020
Connectedness	-0.478	69.563	0.634	-0.018	N/A	N/A	N/A	N/A

Therefore, only part of Hypothesis 2 has been supported; females in the Senate have statistically significant differences in the in-beta centrality measure than do males for the S102-114 time period, yet the differences in the in-degree centrality measure were not meaningful for either time period. In addition, the results of testing for the clustering coefficient and connectedness measures yielded no legitimate differences in the means between Senate gender groups. This result was also evident in the House; however, the testing results for the House centrality measures demonstrated that females did have significant differences in means compared to males for both time periods. The general conclusions drawn from these findings indicate that females generally formed better networks than males in the House as measured through centrality metrics, yet the same results were not evident in the Senate. In fact, when including the clustering coefficient and connectedness measures, females did not exhibit better networks overall compared to males in the Senate.

Regression Analysis and Results – Testing Hypothesis 3

I hypothesized that despite sponsoring and cosponsoring at greater rates and forming better networks as measured, female legislators are less successful in passing their binding, force-of-law bills in both chambers of the United States Congress than their male counterparts,

considering other variables (Hypothesis 3). This section presents the House and Senate logistic regression results for the models including the 102nd through 108th Congresses and the 102nd through 114th Congresses. Analyses of longitudinal repeated-measures data typically use statistical methods that include the general estimating equation method (GEE), fixed effects (FE) modeling, random effects (RE) modeling, and mixed effects (ME) modeling (Allison, 2021; Gardiner, et al., 2009). The statistical method used for this longitudinal analysis is logistic regression employing the GEE method followed by a ME model as a robustness check. Further discussion and interpretation of the results of the analyses are discussed in the next chapter.

Results of Logistic Regression Employing the General Estimating Equation (GEE) Method for the House of Representatives

For the primary analysis of the House of Representatives, I chose the GEE method developed by Liang and Zeger (1986) as an extension of generalized linear models when analyzing longitudinal data. Use of the approach provides researchers with consistent estimates of model parameters and standard errors when analyzing repeated measures with non-normal response variables (Liang and Zeger, 1989). The GEE logistic regression model estimates the same model as found in standard logistic regression, however, the GEE method allows for dependence within group clusters, such as those found in longitudinal data (Allison, 2021). A benefit of the GEE method is the ability to obtain population-averaged parameter estimates rather than subject-specific coefficients typically modeled in FE and RE approaches. This characteristic is important to my analysis since my primary interest are the consequences of gender, as a group characteristic, on bill passage in each chamber of Congress. In addition to these advantages, the GEE method accounts for correlations between binary outcomes across time within the same individual and allows for specification of time-variant and time-invariant variables often found in variable-rich models such as the ones for this analysis (Allison, 2021).

When using the GEE method, the researcher must specify a working correlation structure to estimate regression parameters more efficiently, particularly for datasets that have a larger number of time points, generally more than five (Allison, 2021; Westgate and Burchett, 2017; Wang and Carey, 2003; Liang and Zeger, 1986). Correct specification leads to more reliable statistical inference. For this analysis, I specified an exchangeable correlation structure which is suitable for repeated measures data (Allison, 2021). This type of structure allows for correlation of observations within each subject and for clustered observations irrespective of the timing of the observations and that the correlations between values of the response variable at any two points in time is the same (Allison, 2021). According to Shults, et al., (2009) the exchangeable structure is a satisfactory approach where the researcher expects little decay in the correlation of measurements despite the increase in separation in time (Shults, et al., 2009). In this analysis, I do not expect there to be substantial decreasing correlations within clusters between consecutive measurements (by term) as the number of terms increase. If this were the case, I would consider employing the AR correlation structure.

The results of the House logistic regression models using GEE methods for the 102nd – 108th Congresses and 102nd – 114th Congresses are presented in Table 21. The models include robust standard errors to address potential problems with error terms not being identically distributed (standard errors are robust to heteroskedasticity). I report the results in terms of odds ratios rather than the logit coefficients as the coefficients returned by logit are difficult to interpret intuitively. Odds ratios are multiplicative which means that an odds ratio of 1.00 indicates no effect, an odds ratio that is greater than 1 indicates a positive effect, and negative effects are indicated by odds ratios between 0 and 1 (Long and Freese, 2014).

Table 21. Logistic Regression Generalized Estimating Equation (GEE) Models, House Chamber (Dependent Variable: Bill Pass or Fail Floor Vote)

Variables	102nd -108th Congresses						102nd -114th Congresses					
	Odds		z	Sig.	95% C.I. Bounds		Odds		z	Sig.	95% C.I. Bounds	
	Ratio	S.E. ¹			Lower	Upper	Ratio	S.E. ¹			Lower	Upper
Gender	0.765	0.097	-2.12	0.034	0.596	0.980	0.865	0.064	-1.97	0.049	0.749	0.999
Party	1.028	0.086	0.34	0.736	0.874	1.211	0.856	0.056	-2.39	0.017	0.753	0.972
Majority Party	3.622	0.256	18.23	0.000	3.154	4.159	2.724	0.124	22.02	0.000	2.491	2.978
Seniority	1.060	0.009	6.52	0.000	1.042	1.079	1.038	0.007	5.26	0.000	1.024	1.053
Party Leader	1.351	0.216	1.88	0.060	0.988	1.847	1.436	0.127	4.10	0.000	1.208	1.708
Power Comm. Chair	1.947	0.434	2.99	0.003	1.258	3.013	2.590	0.391	6.31	0.000	1.927	3.481
In-Degree Centrality	1.000	0.000	-1.64	0.100	0.999	1.000	1.000	0.000	-0.59	0.556	0.999	1.000
In-Beta Centrality	1.000	0.000	1.82	0.069	1.000	1.000	1.000	0.000	0.67	0.500	1.000	1.000
Clustering Coefficient	0.765	0.156	-1.31	0.190	0.513	1.142	0.746	0.153	-1.43	0.154	0.498	1.116
Connectedness	0.220	0.151	-2.20	0.028	0.057	0.847	N/A					
Term												
103rd	0.795	0.061	-2.98	0.003	0.684	0.924	0.835	0.061	-2.46	0.014	0.724	0.964
104th	1.005	0.128	0.04	0.968	0.784	1.289	0.923	0.103	-0.72	0.473	0.743	1.148
105th	1.005	0.115	0.04	0.966	0.803	1.258	0.951	0.093	-0.52	0.603	0.785	1.151
106th	1.257	0.123	2.34	0.019	1.038	1.522	1.161	0.092	1.89	0.059	0.995	1.356
107th	1.036	0.103	0.36	0.722	0.852	1.260	0.973	0.084	-0.31	0.754	0.821	1.153
108th	1.220	0.125	1.94	0.052	0.998	1.490	1.111	0.098	1.19	0.234	0.934	1.321
109th							0.858	0.075	-1.76	0.078	0.723	1.017
110th							1.250	0.094	2.97	0.003	1.079	1.449
111th							0.959	0.080	-0.50	0.618	0.815	1.129
112nd							0.637	0.062	-4.64	0.000	0.527	0.771
113th							0.903	0.080	-1.16	0.246	0.759	1.073
114th							0.990	0.089	-0.11	0.913	0.831	1.180
Constant	0.055	0.015	-10.85	0.000	0.033	0.093	0.074	0.016	-11.71	0.000	0.048	0.115
N (# of bills):	39,321						79,438					
Model: Wald χ^2 (522.25), Prob > χ^2 (0.000)							Model: Wald χ^2 (982.42), Prob > χ^2 (0.000)					

1. Robust standard errors.

For both models presented in Table 21, gender has a statistically significant effect on legislative success at $p < 0.05$, considering the other independent variables. During the 102nd through 108th terms, the odds of legislative success for female House members were 23.5 percent *lower* than the odds for male House members. During the 102nd through 114th terms, odds for legislative success for females appear to improve compared to males but the odds were still lower. In this model, the odds of legislative success for female House members were 13.5 percent *lower* than the odds for male House members. This result may suggest that female House

members in the 109th through 114th Congresses began to enjoy more legislative success than they did in earlier terms of the study period.

While the variable of interest in this analysis is gender, it is interesting to briefly report the results of the other predictor variables with respect to their effects (or lack thereof) on legislative success. Not surprisingly, majority party status, seniority, and being a power committee chair were highly statistically significant at $p < 0.01$. These results support findings from prior literature (Volden, et al., 2013; Cox and Terry, 2008; Jeydel and Taylor, 2003; Anderson, et al., 2003; Swers, 2002). Of particular note in this analysis, the magnitude of significance and the odds ratios for majority party status in both models were remarkable (e.g. the odds of legislative success for House members in the majority party were 262 percent higher than the odds for minority party House members in the 102nd through 108th Congresses). These results are not surprising given that the majority party in the House largely controls what items progress to the decision agenda, what items pass through committee, and what items are considered on the House floor.

The surprising results were the lack of statistical significance of the social network measures of in-degree, in-beta, and clustering coefficient in both models. The connectedness measure was statistically significant at $p < 0.05$; however, the direction of the odds ratio in the 102nd – 108th terms model was surprising. I expected that legislators with high connectedness values would exhibit more legislative success than those with lower connectedness values; however, this was not the case in this model. For a one unit *increase* in connectedness value, the odds of legislative success were expected to *decrease* by a factor of 0.22, considering other variables in the model. This result differs from Fowler's (2006a,b) finding that higher connectedness scores suggested higher rates of legislative success. The contradictory findings

may be due to differences in study focus and methodology, types of bills analyzed (Fowler considered all measures rather than binding bills), and temporal periods examined.

House GEE Post-estimation analyses

The first post-estimation I performed was a global test of the time effect to determine if the dummies for each term were equal to 0 or if the resulting coefficients were significantly different from each other. For both GEE models, there was a significant difference in the coefficients for each year in both models (House 102nd–108th Congresses: $X^2 = 36.66$, $prob > chi2 = 0.0000$; House 102nd-114th Congresses: $X^2 = 137.08$, $prob > chi2 = 0.0000$). My original assumption that each legislative term should be included in each model was supported as time fixed effects should be included in both models.

The second post-estimation command I employed was the development of the within-subject (legislator) correlation matrix to examine the correlation structure estimated by the model and ultimately to detect the presence of autocorrelation. As discussed in the regression results, the correlation structure of the GEE is exchangeable. Due to the nature of exchangeable structures, the correlation coefficients in the correlation matrices are the same, meaning that the correlation of observations within each legislator is constant. High coefficient values translate to high correlations between responses within each legislator from one legislative term to the next resulting in incorrect parameter estimates (Allison, 2021). The weighted correlation command in Stata generates correlations between responses (legislative success) in each legislative term within subjects, adjusting for the dependence on the explanatory variables. The correlations estimated by the House 102nd to 108th Congresses (H102-108) GEE model and the 102nd to 114th Congresses (H102-114) model, are 0.048 and 0.041, respectively. Both outputs indicate very low correlations between responses in one legislative term to the next within each legislator. These

results suggest that, in this analysis, each legislator response could be treated as an independent observation regardless of the number of responses each legislator exhibits between terms.

The final post-estimation test for this analysis was used to test for the presence of high collinearity among the data. High collinearity (also known as multicollinearity) can be a cause for concern in linear and non-linear models and is commonly found in longitudinal data (Gujarati and Porter, 2009). Models that exhibit high, or in rare cases, perfect, collinearity contain regression coefficients with larger standard errors and wider confidence intervals thus increasing uncertainty around the coefficient estimates (Bashir, 2015; Gujarati and Porter, 2009). However, there are situations where high collinearity can be ignored. According to Allison (2012), high collinearity is not a problem if one or more of the following conditions are present: 1) the highly collinear variables are control variables rather than variables of interest, 2) if the high collinearity is caused by the inclusion of powers or products of other variable, or 3) in the case of categorical predictor dummy variables that contain three or more categories. For this analysis, the variable of interest is gender (referring to point 1 above); thus, if gender is found to be highly collinear with other predictor variables, there might be cause for concern for the gender coefficient estimates.

Fortunately, high collinearity can be diagnosed in logistic regression models in the same manner as those utilized for linear regression models. Through the use of correlation matrix and variance inflation factor (VIF) analyses, I tested for the presence of high collinearity in the models. The H102-108 GEE model correlation matrix output for the main variable of interest, gender, showed low correlation values between gender and all other control variables and the VIF analysis output for gender was low at a 1.26 value. There was substantially high collinearity between the in-degree centrality and in-beta centrality variables (0.92). The VIF analysis output also demonstrated high collinearity for each variable (in-degree at 10.46 and in-beta at 11.44).

However, because these variables are not of primary interest to this study, I retained them in the model.³³ The H102-114 GEE model correlation matrix output for gender also showed low correlation values between gender and all other control variables and the VIF analysis output for gender was low at a 1.32 value. Similar to the H102-108 model, there was substantially high collinearity between the in-degree centrality and in-beta centrality variables (0.92). The VIF analysis output also demonstrated high collinearity for each variable (in-degree at 23.20 and in-beta at 25.60). While the presence of multicollinearity does not bias the coefficient estimates, it does cause the estimates to be unstable with large standard errors. While larger standard errors could be a factor behind unexpected results for the estimated coefficients of variables that are highly correlated, in-degree centrality and in-beta centrality variables in both models did not have high standard errors. For this reason and the same reasons listed for the H102-108 model, these variables remained in the H102-114 model.

House GEE Margins Analysis

A margins analysis was conducted after the logistic regression analysis to add further information to the regression analysis and results. Margins analyses generate the average predicted probabilities of each gender group's legislative success during the study periods. Table 22 presents the results of the margins analyses which show that the predicted probability of legislative success is lower for female legislators in the House than it is for male legislators. Illustrations of the predictive probabilities and their related 95 percent confidence intervals from Table 22 are presented in Figures 14 and 15.

³³ Including each of these variables separately in the model did not have a material effect on the *gender* variable z-score and p-value.

Table 22. House Chamber GEE Model Margins Analysis, Probability of Bill Passing Floor Vote

Gender	102nd -108th Congresses						102nd -114th Congresses							
	Obs ¹	Margin	S.E. ²	z	Sig.	95% C.I. Bounds		Obs ¹	Margin	S.E. ²	z	Sig.	95% C.I. Bounds	
						Lower	Upper						Lower	Upper
Female	4,978	0.098	0.010	9.40	0.000	0.077	0.118	12,632	0.107	0.006	16.54	0.000	0.094	0.119
Male	34,343	0.123	0.004	32.84	0.000	0.116	0.130	66,806	0.121	0.003	42.37	0.000	0.115	0.126

1. Number of sponsored bills by gender of sponsor.

2. Delta Method.

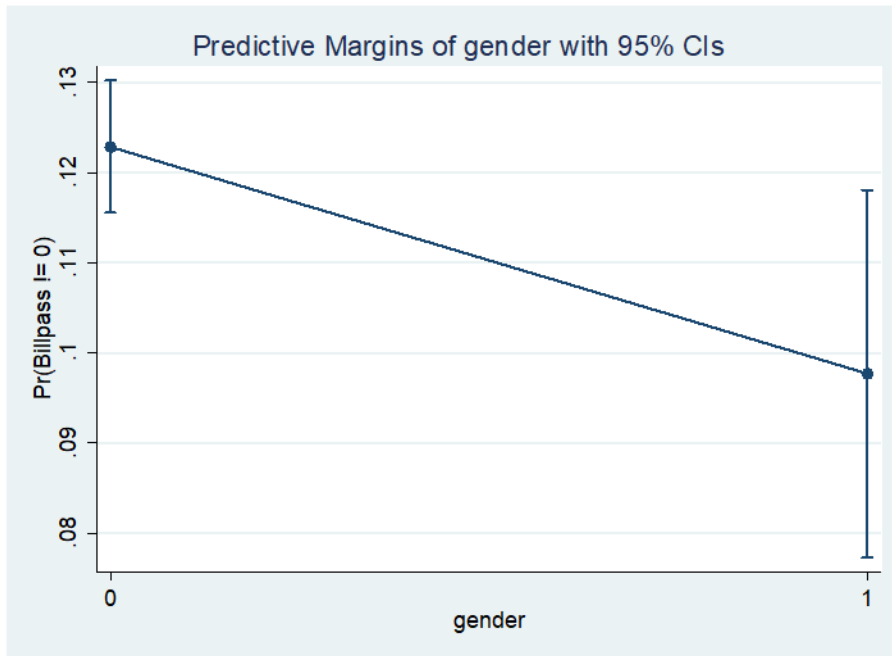


Figure 14. GEE Model Predictive Margins Plot, Probability of Bill Passing Floor Vote by Gender of Legislator, House Chamber 102nd - 108th Congresses (1 = Female, 0 = Male)

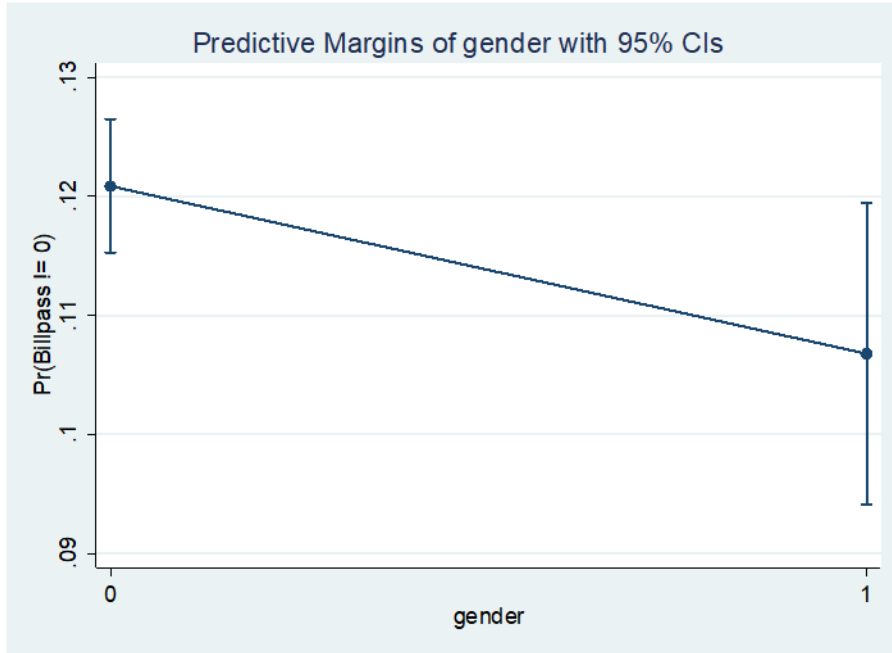


Figure 15. GEE Model Predictive Margins Plot, Probability of Bill Passing Floor Vote by Gender of Legislator, House Chamber 102nd - 114th Congresses (1 = Female, 0 = Male)

Results of Mixed Effects (ME) House of Representatives Models

Mixed effects logistic regression incorporates variations in independent variables in a population when the response variable is binary and also accounts for repeated measures within individuals when working with longitudinal data (Allison, 2021). Mixed effects modeling also has the advantage of accounting for time-variant and time-invariant data and variables (Allison, 2021). Furthermore, mixed models allow researchers the ability to produce cluster-robust standard errors that are robust to disturbances being heteroskedastic and autocorrelated (Allison, 2021). These characteristics and advantages are reasons I chose to employ a mixed effects model as a robustness check to the primary model (GEE) for this analysis. It is important to reiterate here that the GEE method produces population-based coefficients whereas the ME method produces subject-specific coefficient results.

Table 23 presents the results of the logistic regression ME models for the House chambers for the 102nd through 108th Congresses and the 102nd through 114th Congresses. Like the GEE models, results are reported in the odds ratios format.

Table 23. Logistic Regression Mixed Effects (ME) Models, House Chamber (Dependent Variable: Bill Pass or Fail Floor Vote)

Variables	102nd -108th Congresses						102nd -114th Congresses					
	Odds		z	Sig.	95% C.I. Bounds		Odds		z	Sig.	95% C.I. Bounds	
	Ratio	S.E. ¹			Lower	Upper	Ratio	S.E. ¹			Lower	Upper
Gender	0.730	0.093	-2.45	0.014	0.568	0.939	0.876	0.073	-1.59	0.112	0.745	1.031
Party	0.937	0.088	-0.69	0.489	0.780	1.126	0.867	0.062	-2.01	0.044	0.754	0.996
Majority Party	3.982	0.314	17.50	0.000	3.411	4.649	3.301	0.179	22.03	0.000	2.969	3.672
Seniority	1.076	0.011	7.08	0.000	1.054	1.098	1.050	0.007	7.66	0.000	1.037	1.064
Party Leader	1.541	0.234	2.85	0.004	1.145	2.075	1.531	0.163	3.99	0.000	1.242	1.887
Power Comm. Chair	1.491	0.416	1.43	0.152	0.863	2.576	2.181	0.489	3.48	0.001	1.406	3.385
In-Degree Centrality	1.000	0.000	-0.90	0.366	0.999	1.000	1.000	0.000	0.10	0.924	0.999	1.000
In-Beta Centrality	1.000	0.000	0.47	0.642	1.000	1.000	1.000	0.000	-1.17	0.241	0.999	1.000
Clustering Coefficient	0.665	0.165	-1.64	0.101	0.409	1.082	0.753	0.143	-1.49	0.136	0.518	1.093
Connectedness	0.057	0.053	-3.09	0.002	0.009	0.349	N/A					
Term												
103rd	0.801	0.077	-2.30	0.021	0.664	0.968	0.864	0.071	-1.79	0.074	0.736	1.014
104th	0.975	0.145	-0.17	0.867	0.729	1.305	0.937	0.112	-0.54	0.587	0.742	1.184
105th	0.979	0.126	-0.17	0.867	0.761	1.259	0.937	0.100	-0.61	0.541	0.760	1.155
106th	1.300	0.137	2.48	0.013	1.057	1.599	1.176	0.111	1.71	0.087	0.977	1.415
107th	0.989	0.108	-0.10	0.922	0.800	1.224	0.906	0.090	-0.99	0.323	0.745	1.102
108th	1.238	0.135	1.95	0.051	0.999	1.533	1.054	0.105	0.53	0.596	0.867	1.282
109th							0.812	0.081	-2.08	0.038	0.668	0.988
110th							1.263	0.105	2.81	0.005	1.073	1.486
111th							0.968	0.086	-0.37	0.711	0.814	1.151
112nd							0.636	0.068	-4.26	0.000	0.517	0.784
113th							0.969	0.093	-0.33	0.744	0.804	1.169
114th							1.121	0.106	1.20	0.229	0.931	1.350
Constant	0.068	0.023	-7.97	0.000	0.035	0.132	0.059	0.013	-13.22	0.000	0.039	0.089
N (# of bills):	39,321						79,438					
Model: Wald χ^2 (524.63), Prob > χ^2 (0.000)							Model: Wald χ^2 (763.88), Prob > χ^2 (0.000)					

1. Robust standard errors.

There were mixed results in this analysis for the gender variable. In the 102nd – 108th model, gender had a statistically significant effect on legislative success at $p < 0.05$, considering other independent variables. During the 102nd through 108th terms, the odds of legislative success for female House members were 27 percent *lower* than the odds for male House members. The effect of gender on legislative success in the 102nd – 114th Congress model was not statistically

significant at $p < 0.05$. Similar to the suggestion I offer for the GEE model of the 102nd – 114th Congresses, this non-significant result may support the notion that female House members in the 109th through 114th Congresses began to enjoy more legislative success than they did in earlier terms of the study period.

In both ME models, majority party status, seniority, and being a party leader were highly statistically significant at $p < 0.01$. Being a power committee chair was not statistically significant in the H102-108 model but was significant at $p < 0.01$ in the H102-114 model. Like the results found in the GEE models, the magnitude of significance and the odds ratios for majority party status in both ME models were remarkable (the odds of legislative success for House members in the majority party were 298 percent higher than the odds for minority party House members in the 102nd through 108th Congresses and 230 percent higher than the odds for minority party House members in the 102nd through 114th Congresses).

In the ME models, the social network measures of in-degree, in-beta, and clustering coefficient were not statistically significant. Like the GEE H102-108 model, the connectedness measure in the ME H102-108 model was statistically significant at $p < 0.05$ with the direction of the odds ratio indicating a negative effect. In the ME model, a one unit *increase* in connectedness value resulted in the odds of legislative success to *decrease* by a factor of 0.057, considering other variables in the model.

House ME Post-estimation analyses

I conducted a similar post-estimation testing process for the House ME models as the one used for the House GEE models with the exception of the weighted correlation structure analysis. Mixed-effects (ME) models in Stata allow for the use of the ‘cluster’ command to produce standard errors that are robust to disturbances being heteroskedastic and autocorrelated. Furthermore, Stata does not support the weighted correlation structure command in ME

models.³⁴ I conducted the global test of the time effect to determine if the dummies for each term were equal to 0 or if the resulting coefficients were significantly different from each other. For both ME models, there was a significant difference in the coefficients for each year in both models (House 102nd-108th Congresses: $X^2 = 34.36$, $prob > chi2 = 0.0000$; House 102nd-114th Congresses: $X^2 = 114.09$, $prob > chi2 = 0.0000$). My original assumption that each legislative term should be included in each model was supported as time fixed effects should be included in both models.

The final post-estimation test for this analysis was used to test for the presence of high collinearity within the data. For the ME model analysis, I conducted correlation matrix and variance inflation factor (VIF) analyses similar to the GEE analyses. The H102-108 ME model correlation matrix output for the main variable of interest, gender, showed low correlation values between gender and all other control variables and the VIF analysis output for gender was low at a 1.26 value. There was substantially high collinearity between the in-degree centrality and in-beta centrality variables (0.95). The VIF analysis output also demonstrated high collinearity for each variable (in-degree at 21.17 and in-beta at 24.80). In contrast to the House GEE models, the clustering coefficient and connectedness variables exhibited high VIF values of 12.55 and 20.68, respectively. For reasons described in the GEE model analyses, I retained all four variables in the model. The H102-114 ME model correlation matrix output for gender also showed low correlation values between gender and all other control variables and the VIF analysis output for gender was low at a 1.32 value. Similar to the H102-108 model, there was substantially high collinearity between the in-degree centrality and in-beta centrality variables (0.93). The VIF analysis output also demonstrated high collinearity for each variable (in-degree at 23.20 and in-

³⁴ GEE models in Stata do not accept the 'cluster' command, thus the reasoning for employing the structure analysis in that model.

beta at 25.60). In addition, the clustering coefficient VIF value was 11.01. For the same reasons listed for the H102-108 model, these variables remained in the H102-114 model.

House ME Margins analysis

A margins analysis was conducted after the logistic regression analysis to add further information to the regression analysis and results. Table 24 presents the results of the margins analyses which show that the predicted probability of legislative success is lower for female legislators in the House than it is for male legislators. Illustrations of the predictive probabilities and their related 95 percent confidence intervals from Table 24 are presented in Figures 16 and 17.

Table 24. House Chamber ME Model Margins Analysis, Probability of Bill Passing Floor Vote

Gender	102nd -108th Congresses						102nd -114th Congresses							
	Obs ¹	Margin	S.E. ²	z	Sig.	95% C.I. Bounds		Obs ¹	Margin	S.E. ²	z	Sig.	95% C.I. Bounds	
						Lower	Upper						Lower	Upper
Female	4,978	0.086	0.009	9.26	0.000	0.068	0.105	12,632	0.098	0.007	14.77	0.000	0.085	0.111
Male	34,343	0.113	0.004	30.07	0.000	0.106	0.121	66,806	0.110	0.003	38.51	0.000	0.104	0.115

1. Number of sponsored bills by gender of sponsor.
 2. Delta Method.

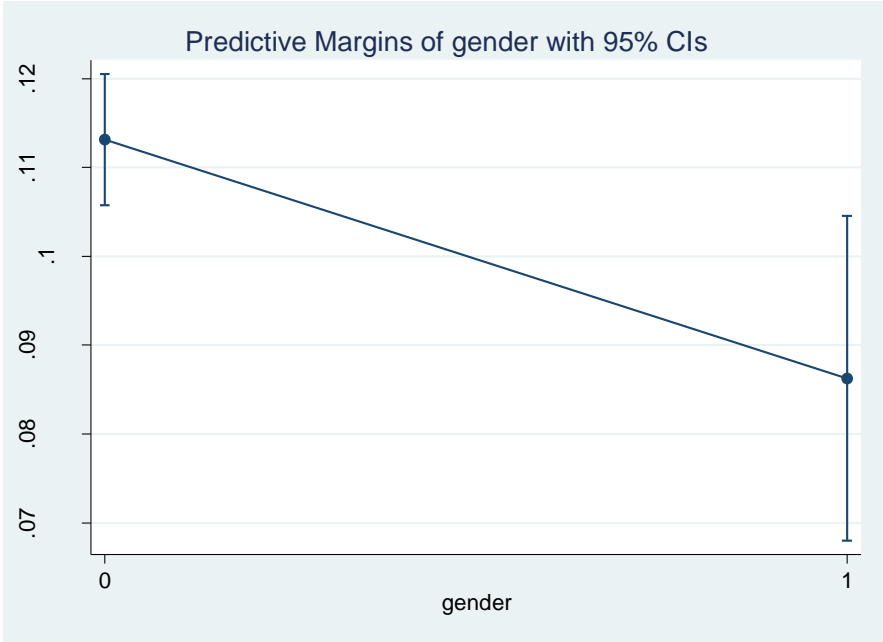


Figure 16. ME Model Predictive Margins Plot, Probability of Bill Passing Floor Vote by Gender of Legislator, House Chamber 102nd - 108th Congresses (1 = Female, 0 = Male)

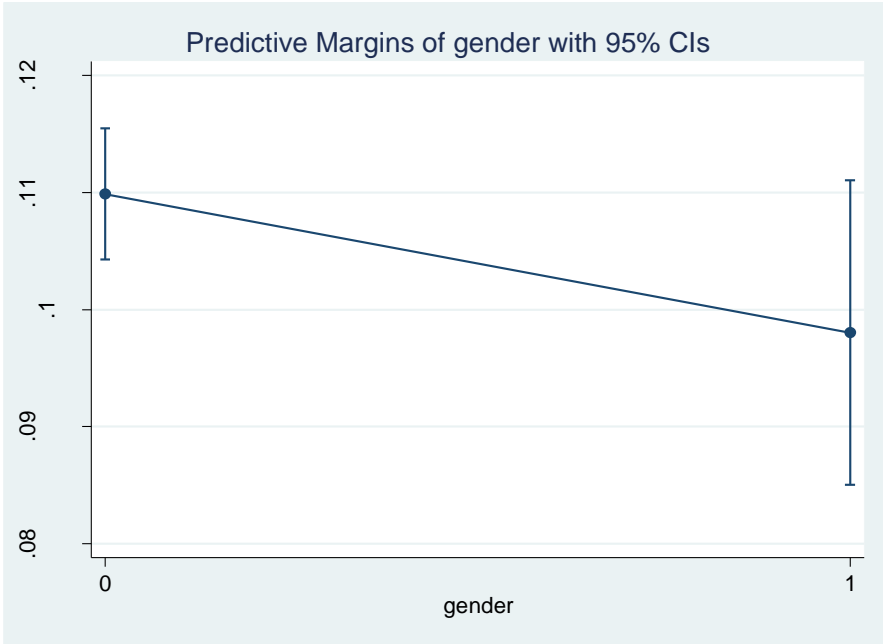


Figure 17. ME Model Predictive Margins Plot, Probability of Bill Passing Floor Vote by Gender of Legislator, House Chamber 102nd - 114th Congresses (1 = Female, 0 = Male)

Results of Logistic Regression Employing the General Estimating Equation (GEE) Method for the Senate

Like the House analysis, the primary model for the Senate analysis is logistic regression utilizing the GEE method of estimation with an exchangeable working correlation structure. The results of the logistic regression models for the Senate chamber in the 102nd – 108th Congresses and 102nd – 114th Congresses are presented in Table 25. The models include robust standard errors to address potential problems with error terms not being independent and identically distributed (standard errors are robust to heteroskedasticity).

Table 25. Logistic Regression Generalized Estimating Equation (GEE) Models, Senate Chamber (Dependent Variable: Bill Pass or Fail Floor Vote)

Variables	102nd -108th Congresses						102nd -114th Congresses					
	Odds		z	Sig.	95% C.I. Bounds		Odds		z	Sig.	95% C.I. Bounds	
	Ratio	S.E. ¹			Lower	Upper	Ratio	S.E. ¹			Lower	Upper
Gender	1.026	0.127	0.21	0.837	0.805	1.307	1.024	0.107	0.23	0.818	0.835	1.257
Party	0.740	0.072	-3.07	0.002	0.611	0.897	0.071	0.065	-3.74	0.000	0.597	0.851
Majority Party	1.690	0.123	7.22	0.000	1.465	1.947	1.682	0.109	8.03	0.000	1.482	1.910
Seniority	1.058	0.012	4.85	0.000	1.034	1.082	1.051	0.009	5.70	0.000	1.033	1.069
Party Leader	1.093	0.162	0.60	0.550	0.817	1.461	1.113	0.111	1.08	0.280	0.916	1.353
Power Comm. Chair	0.716	0.106	-2.25	0.024	0.535	0.958	0.769	0.097	-2.09	0.037	0.602	0.984
In-Degree Centrality	0.997	0.001	-2.21	0.027	0.995	1.000	0.999	0.001	-1.29	0.199	0.997	1.000
In-Beta Centrality	1.000	0.000	2.89	0.004	1.000	1.000	1.000	0.000	1.75	0.081	1.000	1.000
Clustering Coefficient	0.847	0.221	-0.64	0.524	0.508	1.412	0.792	0.137	-1.35	0.178	0.564	1.112
Connectedness	0.499	0.127	-2.73	0.006	0.303	0.822	N/A					
Term												
103rd	0.845	0.218	-0.65	0.514	0.510	1.401	0.830	0.154	-1.00	0.317	0.577	1.195
104th	0.587	0.263	-1.19	0.235	0.244	1.413	0.504	0.157	-2.20	0.028	0.273	0.928
105th	0.728	0.270	-0.86	0.392	0.351	1.507	0.642	0.166	-1.71	0.087	0.386	1.067
106th	0.781	0.207	-0.94	0.350	0.465	1.312	0.681	0.128	-2.04	0.041	0.471	0.985
107th	0.525	0.149	-2.28	0.023	0.302	0.915	0.429	0.091	-3.99	0.000	0.283	0.650
108th	0.931	0.267	-0.25	0.805	0.531	1.635	0.764	0.016	-1.32	0.188	0.512	1.140
109th							0.500	0.096	-3.62	0.000	0.344	0.728
110th							0.344	0.055	-6.71	0.000	0.252	0.470
111th							0.270	0.057	-6.16	0.000	0.178	0.410
112nd							0.241	0.052	-6.63	0.000	0.158	0.367
113th							0.315	0.062	-5.84	0.000	0.214	0.464
114th							0.325	0.057	-6.39	0.000	0.231	0.459
Constant	0.225	0.182	-1.84	0.065	0.046	1.100	0.161	0.083	-3.53	0.000	0.058	0.443
N (# of bills):	21,172						43,647					
Model: Wald χ^2 (308.20), Prob > χ^2 (0.000)							Model: Wald χ^2 (720.43), Prob > χ^2 (0.000)					

1. Robust standard errors.

Unlike the results of the House GEE models, gender does not have a statistically significant effect on legislative success in either of the Senate GEE models. While this finding is contrary to the finding in the House models, the effects of majority party, seniority, and being a power committee chair are statistically significant in both Senate GEE models, consistent with both House GEE models. The social network measures of in-degree, in-beta, and connectedness measures were statistically significant at $p < 0.05$ in the S102-108 model but in-degree and in-beta were not significant in the S102-114 model. Similar to the H102-108 GEE model, connectedness in the S102-108 suggests a negative effect on legislative success with a high degree of magnitude (OR = 0.499, $p < 0.01$), which is in contrast to Fowler's (2006a,b) findings. The term fixed effects in the S102-114 model yielded interesting results. In nine of the terms, the legislative term had an effect on legislative success compared to the reference term (102nd Congress). This result is markedly different than the findings of the H102-114 GEE model where only three terms demonstrated a statistically significant effect on legislative success compared to the 102nd term.

Senate GEE Post-estimation analyses

The first post-estimation I performed was a global test of the time effect to determine if the dummies for each term were equal to 0 or if the resulting coefficients were significantly different from each other. For both GEE models, there was a significant difference in the coefficients for each year in both models (Senate 102nd–108th Congresses: $X^2 = 30.37$, $prob > chi2 = 0.0000$; Senate 102nd-114th Congresses: $X^2 = 212.26$, $prob > chi2 = 0.0000$). My original assumption that each legislative term should be included in each model was supported as time fixed effects should be included in both models.

The second post-estimation command I employed was the development of the within-subject (legislator) correlation matrix to examine the correlation structure estimated by the model

and ultimately to detect the presence of autocorrelation. As discussed in the regression results, the correlation structure of the GEE is exchangeable. Due to the nature of exchangeable structures, the correlation coefficients in the correlation matrices are the same, meaning that the correlation of observations within each legislator is constant. High coefficient values translate to high correlations between responses within each legislator from one legislative term to the next resulting in incorrect parameter estimates (Allison, 2021). The weighted correlation command in Stata generates correlations between responses (legislative success) in each legislative term within subjects, adjusting for the dependence on the explanatory variables. The correlations estimated by the Senate 102nd to 108th Congresses (S102-108) GEE model and the 102nd to 114th Congresses (S102-114) model, are 0.025 and 0.015, respectively. Both outputs indicate very low correlations between responses in one legislative term to the next within each legislator. These results suggest that in this analysis, each legislator response could be treated as an independent observation regardless of the number of responses each legislator exhibits between terms.

The final post-estimation test for this analysis was used to test for the presence of high collinearity among model independent variables. As discussed earlier, high collinearity is not a concern for this the highly collinear variables are used solely as control variables rather than as variables of interest. The S102-108 GEE model correlation matrix output for the main variable of interest, gender, showed low correlation values between gender and all other control variables and the VIF analysis output for gender was low at a 1.27 value. There was substantially high collinearity between the in-degree centrality and in-beta centrality variables (0.97). The VIF analysis output also demonstrated substantially high collinearity for each variable (in-degree at 104.86 and in-beta at 101.28). In addition, VIF values for the connectedness and clustering coefficient variables were 49.34 and 15.10, respectively. However, because these variables are

not of interest to this study, I retained them in the model.³⁵ The S102-114 GEE model correlation matrix output for gender also showed low correlation values between gender and all other control variables and the VIF analysis output for gender was low at a 1.29 value. Similar to the S102-108 model, there was substantially high collinearity between the in-degree centrality and in-beta centrality variables (0.98). The VIF analysis output also demonstrated high collinearity for each variable and were the same values as those found in the S102-108 analysis (in-degree at 68.50 and in-beta at 66.97). In addition, the clustering coefficient had a high VIF value (9.10). For the same reasons listed for the S102-108 model, these variables remained in the S102-114 model.

Senate GEE Margins Analysis

Although gender did not have an effect on legislative success in the Senate GEE models, I conducted a margins analysis after the logistic regression analysis to give additional perspective to the regression analysis and results. Table 26 presents the results of the margins analyses which indicate that the predicted probabilities of legislative success were approximately similar for female and male legislators. Illustrations of the predictive probabilities and their related 95 percent confidence intervals from Table 26 are presented in Figures 18 and 19.

Table 26. Senate Chamber GEE Model Margins Analysis, Probability of Bill Passing Floor Vote

<i>Gender</i>	102nd -108th Congresses						102nd -114th Congresses							
	<i>Obs</i> ¹	<i>Margin</i>	<i>S.E.</i> ²	<i>z</i>	<i>Sig.</i>	<i>95% C.I. Bounds</i>		<i>Obs</i> ¹	<i>Margin</i>	<i>S.E.</i> ²	<i>z</i>	<i>Sig.</i>	<i>95% C.I. Bounds</i>	
						<i>Lower</i>	<i>Upper</i>						<i>Lower</i>	<i>Upper</i>
Female	2,034	0.118	0.012	9.64	0.000	0.094	0.143	6,609	0.088	0.008	11.44	0.000	0.073	0.103
Male	19,138	0.116	0.005	22.08	0.000	0.106	0.126	37,038	0.086	0.003	24.71	0.000	0.080	0.093

1. Number of sponsored bills by gender of sponsor.
 2. Delta Method.

³⁵ Including each of these variables separately in the model did not have a material effect on the *gender* variable z-score and p-value.

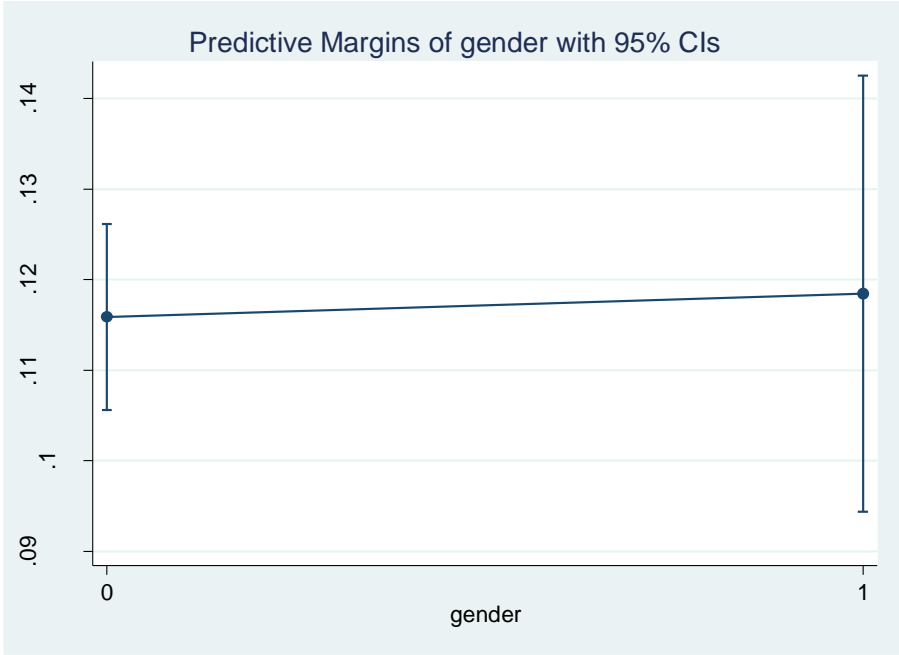


Figure 18. GEE Model Predictive Margins Plot, Probability of Bill Passing Floor Vote by Gender of Legislator, Senate Chamber 102nd - 108th Congresses (1 = Female, 0 = Male)

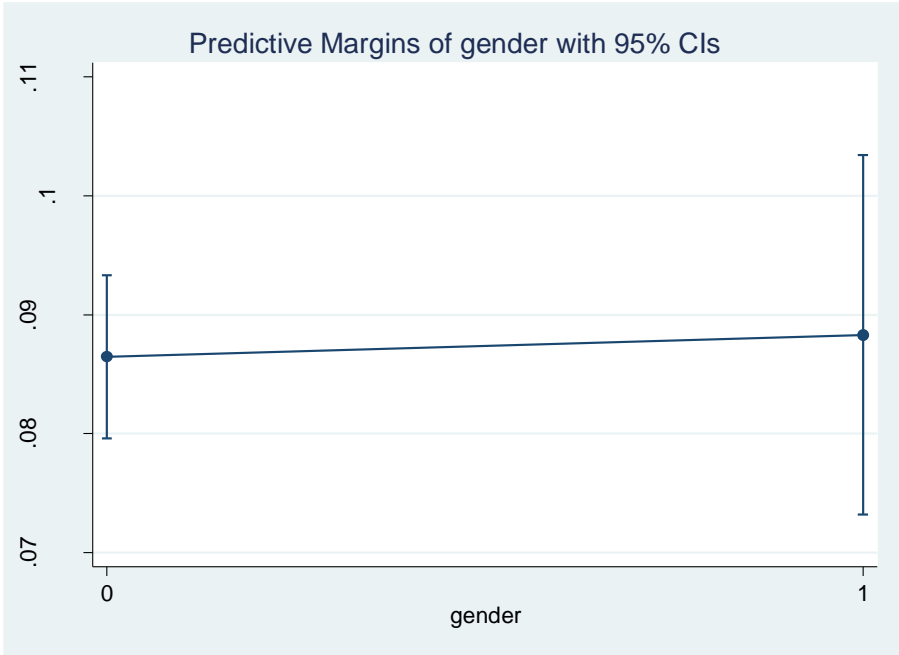


Figure 19. GEE Model Predictive Margins Plot, Probability of Bill Passing Floor Vote by Gender of Legislator, Senate Chamber 102nd - 114th Congresses (1 = Female, 0 = Male)

Results of Mixed Effects (ME) Senate Models

Table 27 presents the results of the logistic regression ME models for the Senate chambers for the 102nd through 108th Congresses and the 102nd through 114th Congresses. Like the GEE models, results are reported in the odds ratios format.

Table 27. Logistic Regression Mixed Effects (ME) Models, Senate Chamber (Dependent Variable: Bill Pass or Fail Floor Vote)

Variables	102nd -108th Congresses						102nd -114th Congresses					
	Odds		z	Sig.	95% C.I. Bounds		Odds		z	Sig.	95% C.I. Bounds	
	Ratio	S.E. ¹			Lower	Upper	Ratio	S.E. ¹			Lower	Upper
Gender	0.879	0.142	-0.80	0.424	0.641	1.210	0.981	0.114	-0.17	0.866	0.780	1.232
Party	0.745	0.078	-2.79	0.005	0.606	0.916	0.751	0.073	-2.94	0.003	0.621	0.910
Majority Party	1.802	0.149	7.14	0.000	1.533	2.120	1.824	0.136	8.20	0.000	1.580	2.110
Seniority	1.039	0.013	3.14	0.002	1.014	1.063	1.051	0.011	4.63	0.000	1.030	1.074
Party Leader	1.065	0.172	0.39	0.697	0.776	1.461	1.061	0.112	0.56	0.575	0.862	1.310
Power Comm. Chair	0.612	0.122	-2.47	0.013	0.414	0.903	0.639	0.095	-3.01	0.003	0.478	0.855
In-Degree Centrality	0.999	0.001	-1.26	0.207	0.996	1.000	1.000	0.001	-0.48	0.628	0.998	1.001
In-Beta Centrality	1.000	0.000	1.76	0.079	1.000	1.000	1.000	0.000	0.59	0.556	1.000	1.000
Clustering Coefficient	0.729	0.212	-1.09	0.278	0.412	1.290	0.714	0.148	-1.63	0.104	0.477	1.071
Connectedness	0.602	0.170	-1.79	0.073	0.346	1.048	N/A					
Term												
103rd	0.749	0.216	-1.00	0.316	0.426	1.317	0.727	0.156	-1.48	0.139	0.478	1.109
104th	0.470	0.232	-1.53	0.127	0.178	1.239	0.411	0.152	-2.40	0.016	0.199	0.849
105th	0.589	0.239	-1.30	0.193	0.265	1.310	0.534	0.163	-2.06	0.039	0.293	0.970
106th	0.711	0.205	-1.18	0.237	0.403	1.252	0.632	0.141	-2.06	0.039	0.409	0.978
107th	0.466	0.148	-2.40	0.016	0.250	0.869	0.378	0.097	-3.80	0.000	0.229	0.624
108th	0.854	0.272	-0.49	0.621	0.458	1.594	0.702	0.172	-1.44	0.149	0.435	1.135
109th							0.442	0.101	-3.57	0.000	0.282	0.692
110th							0.328	0.058	-6.29	0.000	0.232	0.464
111th							0.232	0.600	-5.69	0.000	0.140	0.384
112nd							0.214	0.054	-6.16	0.000	0.131	0.350
113th							0.296	0.067	-5.35	0.000	0.190	0.462
114th							0.325	0.064	-5.68	0.000	0.221	0.479
Constant	0.310	0.283	-1.28	0.200	0.052	1.857	0.207	0.126	-2.59	0.009	0.063	0.681
N (# of bills):	21,172						43,647					
Model: Wald χ^2 (241.59), Prob > χ^2 (0.000)							Model: Wald χ^2 (620.54), Prob > χ^2 (0.000)					

1. Robust standard errors.

Allowing for fixed and random effects in the Senate ME models yielded similar results as the Senate GEE models in terms of the analysis on the gender variable. In the Senate ME models, gender does not have a statistically significant effect on legislative success. The effects of majority party, seniority, and being a power committee chair are statistically significant in

both Senate ME models, consistent with the Senate GEE models. Contrary to the S102-108 GEE model, the social network measures of in-degree, in-beta, and connectedness measures were not statistically significant at $p < 0.05$ in the S102-108 ME model.

Senate ME Post-estimation analyses

I conducted a similar post-estimation testing process for the Senate ME models as the one used for the Senate GEE models with the exception of the weighted correlation structure analysis. I conducted the global test of the time effect to determine if the dummies for each term were equal to 0 or if the resulting coefficients were significantly different from each other. For both ME models, there was a significant difference in the coefficients for each year in both models (Senate 102nd-108th Congresses: $X^2 = 37.61$, $prob > chi2 = 0.0000$; Senate 102nd-114th Congresses: $X^2 = 203.28$, $prob > chi2 = 0.0000$). My original assumption that each legislative term should be included in each model was supported as time fixed effects should be included in both models.

In the final post-estimation test for the ME model analysis, I conducted correlation matrix and variance inflation factor (VIF) analyses. The S102-108 ME model correlation matrix output for the main variable of interest, gender, showed low correlation values between gender and all other control variables and the VIF analysis output for gender was low at a 1.27 value. There was substantially high collinearity between the in-degree centrality and in-beta centrality variables (0.96). The VIF analysis output also demonstrated high collinearity for each variable (in-degree at 104.86 and in-beta at 101.28). In contrast to the Senate GEE models, the clustering coefficient and connectedness variables exhibited high VIF values of 15.10 and 49.34, respectively. For reasons described in the GEE model analyses, I retained all four variables in the model. The S102-114 ME model correlation matrix output for gender also showed low correlation values between gender and all other control variables and the VIF analysis output for gender was low at

a 1.29 value. Similar to the S102-108 model, there was substantially high collinearity between the in-degree centrality and in-beta centrality variables (0.97). The VIF analysis output also demonstrated high collinearity for each variable (in-degree at 68.50 and in-beta at 66.97). In addition, the clustering coefficient VIF value was 9.10. For the same reasons listed for the previous House and Senate models, these variables remained in the S102-114 model.

Senate ME Margins Analysis

Table 28 presents the results of the margins analyses related to the Senate ME models. In the S102-114 model, the predicted probabilities of legislative success were approximately similar for female and male legislators. However, in the S102-108 model, female legislators exhibited slightly lower predicted probabilities of success compared to males, although the confidence interval for females is large enough to question this finding. Illustrations of the predictive probabilities and their related 95 percent confidence intervals from Table 28 are presented in Figures 20 and 21.

Table 28. Senate Chamber ME Model Margins Analysis, Probability of Bill Passing Floor Vote

Gender	102nd -108th Congresses						102nd -114th Congresses							
	Obs ¹	Margin	S.E. ²	z	Sig.	95% C.I. Bounds		Obs ¹	Margin	S.E. ²	z	Sig.	95% C.I. Bounds	
						Lower	Upper						Lower	Upper
Female	2,034	0.102	0.014	7.31	0.000	0.075	0.130	6,609	0.083	0.008	10.22	0.000	0.067	0.099
Male	19,138	0.115	0.005	22.35	0.000	0.105	0.125	37,038	0.084	0.003	24.23	0.000	0.077	0.091

1. Number of sponsored bills by gender of sponsor.
 2. Delta Method.

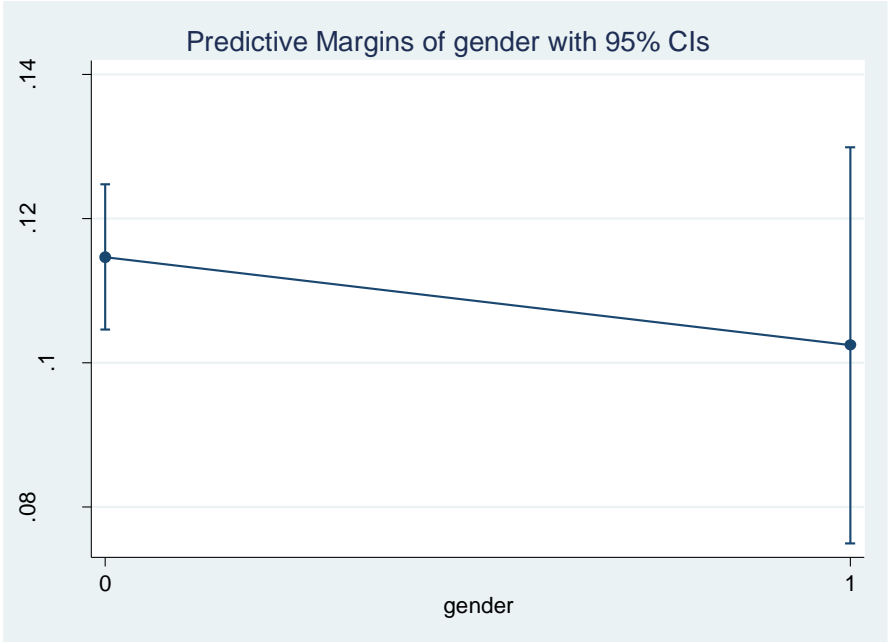


Figure 20. ME Model Predictive Margins Plot, Probability of Bill Passing Floor Vote by Gender of Legislator, Senate Chamber 102nd - 108th Congresses (1 = Female, 0 = Male)

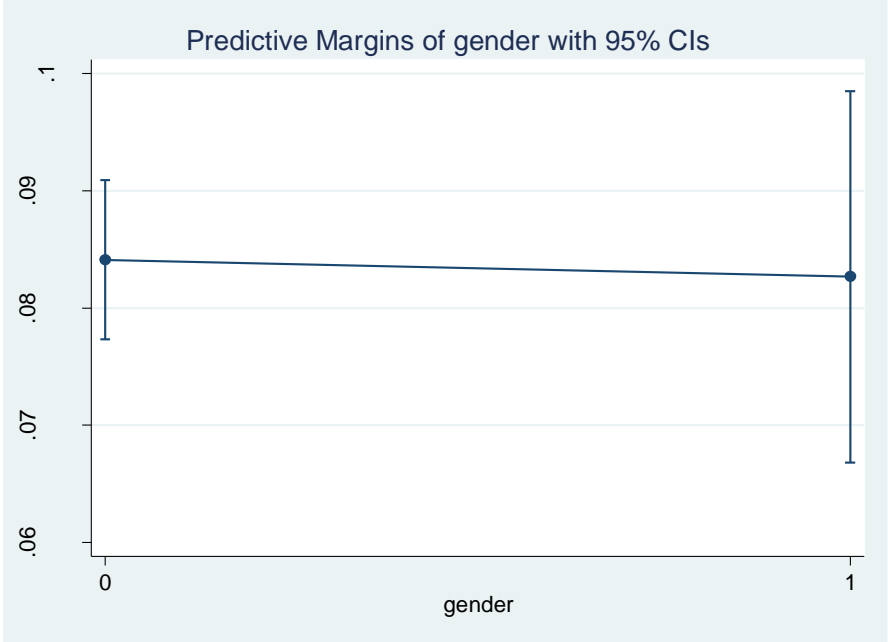


Figure 21. ME Model Predictive Margins Plot, Probability of Bill Passing Floor Vote by Gender of Legislator, Senate Chamber 102nd - 114th Congresses (1 = Female, 0 = Male)

Summary Table of Logistic Regression Results

Table 29 presents a summary of the logistic regression findings by model. The Discussion chapter will provide an assessment of the results with respect to the study hypotheses and interpretations of the results.

Table 29. Summary of Results of GEE and ME Models by Congressional Chamber, Odds of Female-sponsored Bills Passing Floor Votes

<i>Models</i>	House						Senate					
	<i>Odds</i>		<i>z</i>	<i>Sig.</i>	<i>95% C.I. Bounds</i>		<i>Odds</i>		<i>z</i>	<i>Sig.</i>	<i>95% C.I. Bounds</i>	
	<i>Ratio</i>	<i>S.E.</i> ¹			<i>Lower</i>	<i>Upper</i>	<i>Ratio</i>	<i>S.E.</i> ¹			<i>Lower</i>	<i>Upper</i>
GEE 102-108	0.765	0.097	-2.12	0.034	0.596	0.980	1.026	0.127	0.21	0.837	0.805	1.307
GEE 102-114	0.865	0.064	-1.97	0.049	0.749	0.999	1.024	0.107	0.23	0.818	0.835	1.257
ME 102-108	0.730	0.093	-2.45	0.014	0.568	0.939	0.879	0.142	-0.80	0.424	0.641	1.210
ME 102-114	0.876	0.073	-1.59	0.112	0.745	1.031	0.981	0.114	-0.17	0.866	0.780	1.232

1. Robust standard errors.

Chapter 5: Discussion

This study is the product of the concern with low levels of female descriptive and substantive representation in the United States Congress as well as biased attitudes toward female legislators that may limit their legislative success. Female representation in both chambers is well below that of the population of females in the United States. Minority group status for females in Congress presents challenges to descriptive representation but also negatively affects substantive representation. This paper has cited prior work that women in many organizational settings face biases that limit their productivity and success in their given settings. In Congress, biased attitudes toward women have manifested themselves in a variety of ways including women facing greater rates of interruption during floor debates than those encountered by men, encountering limitations within the congressional committee selection process, facing hostile speech patterns, and experiencing male segregation within gendered group settings.

To attempt to overcome their marginalized status in Congress, I argue that female legislators collaborate more and exhibit greater rates of legislative productivity than do male legislators. This claim is supported by other scholars such as Barnes (20016), Swers (2002), and Volden, et al. (2013). Unlike these scholars, however, I test these arguments by examining sponsorship and cosponsorship data across many legislative terms in combination with a unique set of variables. Furthermore, I argue that female legislators in both chambers of Congress are less successful than men in passing their binding, force-of-law measures despite greater rates of collaborative and legislative activity. I emphasize the study of binding measures because many scholars of legislative behavior and relational characteristics focus on all forms of legislative proposals, including ceremonial and rules- and procedures-based measures. I believe that studies of legislative activity should place more emphasis on binding measures because these legislative

proposals have the most direct and long-lasting policy impacts on the general public and this country.

Summary of Findings

My first hypothesis (H1), that female legislators in both chambers of Congress are more active sponsors and cosponsors than male legislators, was partially supported. In the House, the female legislator group had higher mean sponsorship activity than males in all but one congressional term and higher mean cosponsorship activity than males over all terms of the study period. However, hypothesis testing demonstrated that this observation held only in the House with respect to cosponsorship activity. In the Senate, the testing results showed no evidence that female mean cosponsorship activity was significantly different than male cosponsorship activity. Furthermore, hypothesis testing showed no statistically significant difference between female and male mean sponsorship activity in either chamber. These results certainly cast a shadow on the findings of prior literature that suggest female legislators, as a group, are more active sponsors and cosponsors in Congress, with respect to binding legislation. Only the House cosponsorship findings can provide this support.

My second hypothesis (H2), that female legislators in both chambers form better networks than males, was partially supported. Hypothesis testing on the House data indicated that the female legislator group had statistically significant higher mean in-degree centrality and in-beta centrality measures than male legislators. In the Senate, the testing results showed no evidence of significant mean differences in these measures except for the in-beta measure during the S101-114 time period. Furthermore, hypothesis testing showed no statistically significant difference between female and male mean clustering coefficient and connectedness measures in either chamber, with the exception of the clustering coefficient measure in the House during the

102nd-114th Congress study period. It appears that females in the House form better networks with respect to certain centrality measures but not with respect to clustering coefficient and connectedness measures. The Senate results seem to indicate that females, for the most part, do not form better networks than do their male counterparts.

The results of the gender differences in terms of legislative success on binding, force-of-law measures were split between the two chambers. My third hypothesis (H3) argued that, despite females being more active sponsors and cosponsors than males and forming better networks than males, female legislators were less successful in passing their binding, force-of-law measures in both chambers of the United States Congress than their male counterparts, considering other variables. As the primary regression analyses (GEE method for H102-108 and H102-114) presented in the prior chapter showed, female House members were less successful than their male counterparts in getting their bills passed. The results were mixed for the ME models where female House members were less successful in the H102-108 model but there was lack of statistical significance for the gender variable in the H102-114 model. All Senate regression models indicated that gender did not have a statistically significant effect on legislative success during the study period, controlling for other variables.

Interpretation of Results

The observational data preliminarily indicated that females sponsor and cosponsor more than males in both chambers of Congress on binding, force of law legislation. In the period examined for this study, female sponsorship and cosponsorship activity levels began to exceed those of males when female membership reached near or at the 10 percent level in each chamber. These data combined with the results of the E-I index analysis suggest that female legislators began to increase their relationship building within their gender group as more females entered

Congress while still maintaining, or possibly exceeding, their rates of cosponsorship activity with male legislators. However, when the data were subjected to statistical testing, the mean differences between females and males were only significant for cosponsorship activity in the House. These results provide a measure of disagreement with the prior scholarship of Craig, et al., (2015) and Swers (2002) that argued that female legislators are more active sponsors and cosponsors than male legislators. However, it is important to note that these prior studies considered all congressional legislation while my analysis focused solely on binding legislation.

Why are these results important for female legislators and their legislative success? They are critical because the act of cosponsoring, in and of itself, as well as a proxy for social relations, is meant to influence other legislators, particularly in chamber roll call voting, even after controlling for legislative attributes (Peoples, 2008; Kessler and Krehbiel, 1996).

Cosponsoring demonstrates that a legislator wishes to collaborate with other legislators, build coalitions, and establish long-term influential relationships (Barnes, 2016; Craig, et al. 2015; Swers, 2002; Campbell, 1982). These objectives are of utmost importance to female legislators as means to overcome their marginalization as the minority gender group in Congress and become more effective and successful legislators (Barnes, 2016).

Scholars of legislative behavior have demonstrated that the level of cosponsorship activity is a general predictor of legislative success (Kessler and Krehbiel, 1996). Bills with more cosponsors receive more consideration in committee and have greater chances of passing through committee and achieving success in chamber floor votes than bills with few or no cosponsors (Fowler, 2006a,b; Koger, 2003; Wilson and Young, 1997). Therefore, being more active in the legislative process, by cosponsoring more than males and gaining more cosponsors on their sponsored legislation, should enhance female influence in Congress and provide female

legislators greater chances of legislative success on their sponsored legislation. However, the results of this analysis show that greater cosponsorship activity does not work well for females, particularly in the House of Representatives.

An important aspect of enhancing influence and achieving individual and group goals and objectives is to develop meaningful and long-lasting relationships within one's environment. As presented in this paper, relational ties form networks between actors within a particular setting. These ties can take many forms and developed for many purposes. Within the setting of the U.S. Congress, there are a wide variety of networks. The focus of this analysis has been gender-based cosponsorship networks within both chambers of Congress. My second hypothesis that women form better cosponsorship networks in both chambers of Congress than men was partially supported.

The findings confirm that females have better cosponsorship networks with respect to centrality measures of in-degree and in-beta, but only in the House. Centrality is a good measure of power through association with powerful others within a network (Bonacich, 1987). Referring to the work of Hanneman and Riddle (2005), the centrality findings in this analysis suggest that females in the House occupied favorable structural positions in the cosponsorship networks in terms of resource access, network prestige, and power through their ties to other well-connected legislators. As women make up a greater percentage of the House membership, the results of the centrality means testing and the observational data provide support to the argument that women in Congress will continue to gain more favorable structural positions as their membership in the institution grows. However, it must be considered that high degree and beta centrality measures suggest distinct types of positional standing. Power, resource access, and prestige are different concepts, and each can yield different benefits to those who exhibit high centrality values. While

females in Congress do have higher centrality measures than males, it may not lead directly to power and influence itself. These findings may suggest that women have more connections to powerful others, but this may only demonstrate that women in Congress have higher prestige or easier access to resources that do not necessarily translate to influence within the legislative process, namely in committee consideration and chamber floor action. The empirical results in this study may support this proposition. Except for the S102-108 ME model, the results of the regression analyses indicate that higher in-degree and in-beta centrality measures do not have a statistically significant influence on legislative success, by either gender group. Surprisingly, the sign on the in-degree coefficients in seven of the eight models were negative which may suggest that higher in-degree metrics, rather than promoting legislative success, actually lead to legislative failure.

The analysis of the sole cohesion metric, clustering coefficient, yielded different results for the House (as compared to the House centrality analysis) but was consistent with the results of the Senate centrality analysis. The observational data showed higher mean clustering coefficient values for the female group in the House but not in the Senate. The House means between the two gender groups, when tested, were not significantly different during the H102-108 time period but were during the H102-114 time period. Prior literature argues that higher clustering coefficient values indicate the presence of ‘small-world networks’ suggesting that actors in these networks are more likely to know a majority, or all, of the other actors in the network (Borgatti, et al., 2013; Tam Cho and Fowler, 2010; Hanneman and Riddle, 2005; Watts and Strogatz, 1998). As described earlier, in legislative and cosponsorship networks, higher clustering coefficients, and consequently denser small-world networks, indicate the presence of active cosponsorship transitivity in Congress (Tam Cho and Fowler, 2010). These properties

demonstrate balanced and stable networks. The consequence of these types of networks, as measured through cosponsorship ties, is a higher level of legislative productivity and success (Tam Cho and Fowler, 2010).

During the study period, female House and Senate members may have exhibited high degrees of small world properties, but their group means were not significantly different than the male means. During the study periods, the findings suggest that the House and Senate female networks were similarly balanced and stable compared to House and Senate male groups. For House females, these findings suggest that female House members should enjoy legislative success during this study period. However, the results of the regression analysis do not support this contention, at least on binding, force-of-law legislative proposals. The regression analyses show that higher clustering coefficient metrics do not have a statistically significant influence on legislative success in both chambers, by either gender group. Furthermore, the signs for the clustering coefficient variable in all models were negative which may suggest that higher clustering coefficient metrics hurt *both* gender groups when trying to get sponsored legislation successfully through chamber floor votes.

Fowler (2006b) argues that his derived connectedness measure outperforms other, more established centrality measures in terms of predicting legislative productivity and success. I tested this measure in the same manner as the other centrality measures and the cohesion measure of clustering coefficient. In the House, there were no distinguishable or statistically significant differences between mean connectedness values for female and male legislators within each term or over the aggregated study period. The study period mean for both gender groups was 0.15. Based on the observational data for the Senate, the mean connectedness values for female senators were higher from the 106th through 108th Congresses, whereas male

legislators in the prior Congresses (102-105) exhibited higher mean connectedness values. The aggregate mean was similar for female senators than for male senators, at 0.93 and 0.92, respectively, and far surpass the means evident in the House analysis. Statistical testing of the mean differences yielded no support that the differences are meaningful. Given that each gender group's connectedness measures utilized in this analysis are similar within each chamber and are not significantly different, it is difficult to draw the conclusion that female legislators in both chambers form better networks based on the connectedness measure alone. And given the regression results, it appears that forming better networks as measured through the connectedness measure has either no positive influence on legislative success or it may stifle it.

Prior studies demonstrate that greater legislative activity, measured through sponsorship and cosponsorship efforts, and better networks, measured in terms of centrality and cohesion metrics, enhance the chances of legislative success. The findings of this study confirm that female members of the House are more active than males with respect to cosponsorship activity and form better networks with respect to centrality measures utilized in this analysis when considering binding, force-of-law legislation. Therefore, the inference could be made that female House members should be more successful in having their legislation pass House chamber floor votes. However, in this case, the hypothesis that female House members would be less successful than male House members despite these traits was confirmed. The same hypothesized association was made for females in the Senate; however, the results of my analysis could not support this hypothesis. Why would this be the case? Perhaps, these results suggest that the institutional designs of the chambers of Congress matters when it comes to legislative success. This notion certainly has merit for the Senate given its smaller size relative to the House and its longer electoral terms. These institutional characteristics promote more collegiality among

senators and may help minority groups integrate with the dominant group quicker and easier than may occur in the House.

Volden, et al. (2013) found that women are more effective lawmakers than men but only when females are in the minority party in their respective chamber. While this analysis did not specifically test minority party female legislators and includes a smaller subset of legislation than that considered in Volden, et al. (2013), the House findings in the analysis suggest that, when considering other variables, including majority party and party status, females are not more effective lawmakers than men. The House regression findings suggest that high centrality measures for women do not influence legislative success despite prior scholarship suggesting that higher centrality connotes greater influence and power within a network. Furthermore, the small world network property of clustering coefficient is not indicative of legislative success as offered by Tam Cho and Fowler (2010) if the networks are analyzed by gender grouping. Finally, despite scholarship indicating that higher levels of cosponsorship connotes legislative success (Barnes, 2016; Fowler, 2006a,b; Koger, 2003; Wilson and Young, 1997; Kessler and Krehbiel, 1996), females in the House were less successful than their male counterparts despite their greater cosponsorship activity than men.

The results of the Senate analyses yielded no statistically significant gender differences in sponsorship and cosponsorship activity, network characteristics, and legislative success. So, the inference of the hypotheses testing is that women are less successful at getting their bills passed in the House but the findings do not support the same inference in the Senate. A logical follow-up question is why are there differences for female legislative success, or lack thereof, between the two legislative chambers of Congress? The following section addresses this question with several potential reasons.

Could the inter-chamber differences relate to differences in the number of women in both chambers, and furthermore, will electing more women to Congress help close the success gap evidenced in the House analysis? During the study period of this analysis, female membership rates in both chambers were approximately similar to each other in each legislative term. In reviewing Tables 9 and 10, the reader will notice that these percentages for each chamber were not substantially different from each other. Tables 9 and 10 illustrate that each term experienced an increasing trend of female membership in roughly the same percentage point proportion. Therefore, the differences in legislative success findings between the two chambers likely cannot be explained by significant differences in female membership profiles.

Will electing more women to Congress affect their legislative success rates? Electing more women will not only enhance descriptive representation in Congress but it could stimulate more collaboration in both chambers and, by increasing membership, could make substantive impacts to current patterns of legislative behavior, activity, and outcomes. During the study period, as more women began to occupy Congress, the characteristics of the female cosponsorship networks changed in both chambers (see Figures 4 and 5). The network graph representations of the House of the 114th Congress House network shows fewer isolates³⁶ than those evident in the 102nd Congress House network. As more females entered the House during this study period, there were more opportunities for representatives to secure cosponsorship acts for their legislation. The findings were similar in the Senate (see Figures 6 and 7) except that there were no isolates evident in the 114th Congress whereas there were several in the female Senate network within the 102nd term. A lack of isolates in the Senate 114th term network is

³⁶ In this analysis, an isolate refers to a legislator, male or female, who did not receive a cosponsor tie from a female legislator. A cosponsorship network with no isolates indicates that each legislator received at least one cosponsorship tie from a female legislator during the term.

likely the result of more female senators reaching out to all senators and being able to reach out to all senators due to the smaller size of the chamber membership.

Ibarra (1992) has shown that females in organizations dominated by males tend to form more heterophilous ties than do males. The results of the E-I Index analysis shown in Tables 15 and 16 provide some measure of support for this finding. In both the House and the Senate, E-I values of women became less negative (which demonstrates greater rates of relationship building within group) and male E-I values became less positive (which demonstrates greater rates of relationship building outside of group) over time in a convincing trend. As more females entered Congress during the study period, the negative female group E-I Index values increased in value toward zero while the male group E-I Index values decreased toward zero. These results suggest that, as female membership in Congress increased rather significantly in percentage terms from the 102nd Congress to the 114th Congress, female within-group ties (more homophily) increased in the aggregate (with a likely corresponding decrease in the rate of ties with male members). Conversely, as more females entered Congress, male members increased their number of ties with female legislators (more heterophily) corresponding with a likely decrease in the number of ties within group. These findings, coupled with the network measure analyses presented in this paper, suggest that women in the House and Senate, on average, collaborate with and support both women and men to a greater degree than do men. In addition, as more females entered the House during this study period, there were more opportunities for representatives to secure cosponsorship acts for their legislation, thus developing more complete networks and leaving potentially fewer isolates in the network.

More Women in Congress Does Matter

Electing more women to Congress has the potential of impacting current patterns of legislative behavior, activity, and outcomes, to the benefit of women in Congress. As discussed

earlier in this paper, critical mass theorists posit that increasing the presence of women in organizations changes the operating dynamics of the organizations themselves; similar results occur in legislative bodies. Paxton, et al., (2007) contend that female membership in the 15 to 30 percent range is the threshold required for women to make substantive impacts in legislative bodies. The female legislative success results of the House regression analyses found in Table 21 may support this finding. As more women entered the House in the latter terms of the study period, the magnitude of the odds of being less successful for female representatives decreased. During the 102nd through 108th terms, the odds of legislative success for female House members was 23.5 percent lower than the odds for male House members. During the 102nd through 114th terms, the odds for legislative success for females improved compared to males; that is, the odds of legislative success for female House members was 13.5 percent lower than the odds for male House members. This result may suggest that female House members in the 109th through 114th Congresses began to enjoy more legislative success than they did in earlier terms of the study period. The combination of these findings provide support to the claims that increasing the presence of women in Congress will lead to greater frequency of collaboration between the gender groups and may enhance the chances of female legislative success (at least in the House based on the results of the regression analysis).

Another suggestion for the inter-chamber differences in findings for female legislative success is the difference in characteristics of the chambers themselves. Differences in rules and procedures, party constraints, effect of seniority and member access to powerful others, and the size of both chambers may be obstacles to female success in one chamber but not the other. According to Barnes (2016), female legislators are more likely to collaborate when there are weak party constraints. This notion is particularly true in the Senate where party constraints are

weaker compared to in the House. Party constraints have been particularly evident in the House during the study period, most notably during the 104th Congress when Republicans took control of the House after 40 years of Democratic rule. According to Swers (2002), a significant number of conservative female and male freshmen representatives joined the House in 1994 which changed the direction of the institutional agenda from being moderate to a more conservative one. One major effect of this change was that moderate Republican women who were promoting female-oriented legislation and working with other moderates on both sides of the aisle in the 103rd Congress were now constrained by the new conservative agenda in the 104th Congress (Swers, 2002). Moderate Republican women were disincentivized by conservative party leaders from pursuing policy interests beyond the conservative party platform (Barnes, 2016). These party constraints were muted in the Senate so that female Senators had more autonomy to work across party lines and to collaborate on and advance a wide variety of policy issues, particularly women-oriented legislation (Barnes, 2016). This is not surprising as other researchers have demonstrated that senators tend to form strong bonds with each other, despite party and gender differences (Uslaner and Zittel, 2011; O'Connor, et al., 2004).

Another substantive difference between the House and the Senate is the effect that seniority has on legislator relationships. Based on the findings of the regression analyses in this study, seniority had a statistically significant effect on legislative success in both chambers for all years, however the effect was slight. The statistically significant result supports the findings of Peoples (2008) and Swers (2002) but contradicts that of Campbell (1982). In this analysis, the average tenure of females in both chambers increased as the number of women entering Congress increased. In the 102nd Congress, the average tenure for female representatives was 4.6 terms and for female senators the average tenure was 3.7 terms. In the 114th Congress, female

representative average tenure was 5.3 terms and female senator average tenure was 5.5 terms. Male legislators had longer average tenures in both chambers in the 102nd Congress but by the 114th Congress, average female tenure was longer than that of men in the Senate, and the same in the House. By this simple analysis, it seems that as more women enter Congress, their seniority levels increase.

Legislator seniority is closely associated with ascension to power positions in Congress. According to Swers (2002), greater seniority can translate to party leadership positions and committee chair positions. Longer tenure affords legislators the opportunities for power positions in Congress, either as party leaders or as committee chairs. Seniority is also a key factor in terms of access and influence, at least in the Senate. According to Campbell (1982), junior senators have an easier time connecting to senior senators as compared to junior representatives' access to senior representatives in the House. The reason for this, according to Campbell (1982), is due to the size of the Senate. It is easier to meet and collaborate with senior senators when faced with a body of 100 rather than a body of 435 as found in the House. With respect to female senators, Barnes (2016) found that senior women in the Senate facilitate collaboration with junior colleagues both within their party *and* within the opposition party. Senior female senators collaborate through mentoring, informal meetings, and joint efforts to develop legislation; these efforts are not as commonplace with longer tenured male senators (Barnes, 2016). These Senate dynamics, that is, greater collaboration between senior and junior members and easier access to more senior and influential senators than that found in the House, suggest why there was no finding of a gender effect on legislative success in the Senate.

A final consideration for the differences in legislative success is the simple fact that the Senate is a smaller institution than the House and senators enjoy longer terms than

representatives. Tam Cho and Fowler (2010) emphasized these characteristics in their findings on the effects of small-world networks on legislative success. These fundamental differences between the two legislative bodies may explain why gender had a significant effect in the House models but not in the Senate models. The Senate has a smaller membership body and member terms are three times as long as representative terms. The intimate size of the Senate and the greater service term length are conducive to developing stronger, more intimate relationships than legislators in the House enjoy. The Senate characteristics facilitate access to a greater percentage of the Senate body for idea transfer, legislative support, and collaboration. These characteristics may overcome gender differences and potential biases that are inferred in the House.

Implications of Results

Within the context of cosponsorship activity and social network analysis, this study broadens existing knowledge of female group legislative support and collaboration processes and their influence on legislative outputs in the U.S. Congress. Furthermore, the research design and statistical analyses described in this paper present a new understanding of the relationship between gender and legislative success in the U.S. Congress measured through cosponsorship ties and resulting networks. The research design is unique to the field given the combination of the network metrics employed as control variables along with more traditional measures found in prior studies of legislative behavior in order to measure female legislative success in Congress over 13 legislative terms.

The purpose of using cosponsorship data in this analysis stems from prior scholarship findings that a cosponsorship act is a mechanism for women to gain influence in the policymaking process and to increase substantive representation for females in the United States

(Barnes, 2016; Swers, 2005, 2002). This paper and prior research referenced in the paper do provide evidence of highly active female sponsoring and cosponsoring efforts in Congress, and with respect to cosponsoring activity, more so than demonstrated by men. And yet, according to this analysis, greater levels of legislative activity do not necessarily translate to legislative success. This paper has offered that one potential obstacle leading to this outcome is that there are simply not enough females in Congress. The results of this analysis, at least in the House where females are less successful than males, provide support to the claim that more women in Congress will improve legislative success rates for female sponsors.

These research findings and interpretations have broad implications for how we think about the passage of female-specific legislation such as wage equality and reproductive rights. Others' research shows that female legislators are more aggressive advocates for female interests; they sponsor and cosponsor female-oriented legislation at much higher rates than male legislators (Rouse, et al., 2013; Volden, et al., 2013). Therefore, the inference derived from this analysis is that diminished legislative success experienced by female congressmembers, at least in the House, leads to fewer opportunities for the passage of female-oriented legislation. What is the impact of this inference with respect to female equality, and other forms of equality, in the United States? Carroll and Sanbonmatsu (2013) suggest that women's political equality may be needed to achieve equality in other domains. Can we then draw the conclusion that if women are more successful in passing legislation in Congress that gains will be made in women's equality? And what is the impact of women's equality on the state of democracy in the United States? According to Barnes (2016), "collaboration improves democracy by better representing the views of out-of-power groups." (p. 216). Therefore, the implication of Barnes' statement is that, as more women enter Congress, and by extension of my analysis achieve more legislative

success, particularly for female-oriented legislation, greater collaboration within Congress will further promote democratic principles. However, as Barnes (2016) has cautioned, weak party constraints may be the key context for women to succeed in overcoming their marginalization and thus stimulating collaboration among gender groups. So, it seems that the House of Representatives, if it were to demonstrate weak party constraints as has been found in the Senate, would promote greater collaboration across party lines and greater female legislative success which would lead to greater female substantive representation, thus promoting equality and enhancing democracy in the U.S. What is not clear is whether or not both weak party constraints and more women in Congress have to exist for democracy to improve through greater collaboration. Further research in these areas may provide more information.

Limitations of the Study

Like most studies in social science, there are limitations and qualifications associated with this analysis that should be described. This analysis considers 13 terms of Congress. This number of terms is positioned between the number of terms analyzed in the related studies cited in this paper; some studies examine 1 to 2 terms while others look at 30 or more. The 13 terms incorporated periods of majority party change in both chambers, changes in the party of the President (although not measured in the analysis), changes in the intensity of party polarization in Congress (also not measured), varying degrees of congressional approval ratings, and changes in the economic, political, and societal condition in the United States. Furthermore, employing 13 terms of sponsorship and cosponsorship data provided the opportunity to assess the degree to which cosponsorship acts and the resulting network dynamics influenced legislative activity and effectiveness by gender group. Despite these benefits, which give me confidence that the findings are generalizable with respect to many of the variables included in the regression

models, the primary variable of interest in this analysis is gender of the legislative proposal sponsor and the related effect that gender has on legislative success. It is in this focus where there is a limitation to the generalizability of the findings of gender's effect on success in Congress. The simple fact is that this analysis was limited by the small number of females in Congress during the study period (10 percent to a maximum of 20 percent). Clearly, future similar studies will benefit from a larger female presence in both chambers, in terms of confidence levels in the inferences generated. Furthermore, the findings of this analysis and prior research show that influential positions in powerful committees and party leadership posts are associated with greater rates of legislative success. During this study period, no females occupied power committee chair positions and relatively few party leadership posts compared to men. These characteristics provide support to my initial claim that females face prejudices by the male dominant group which manifest themselves in many different ways. For purposes of this analysis, until women begin to occupy these posts, the true effects of the female legislator on success rates cannot be fully measured.

Data management was a difficult task for this study. Even though the analysis focused on binding legislation (public bills and joint resolutions), 13 terms of congressional bill data produced over 120,000 pieces of binding legislation complete with bill data and member information. The data sources used in the analysis and referenced in this paper contained mistakes. The mistakes in the published data were not substantial in number; where they were identified I researched and corrected them. Despite my best efforts, it is likely that some mistakes still remain and should be considered as noise within the datasets.

Finally, there is a fundamental challenge of applying traditional inferential formulas (in this case, logistic regression) to network measures as these measures are typically based on

interdependence of relational ties and, depending on how they are used, can often be scale-free (Hanneman and Riddle, 2005). These characteristics may result in poor estimation of the true sampling variability (Hanneman and Riddle, 2005). This final limitation is not as concerning in this analysis as it would be in models that apply network measures as the primary variables of interest or as the response variable. This analysis includes network measures as one test of the study hypotheses, but in the regression analyses they are used as control variables rather than as main variables of interest.

Future Research and Analysis

To elucidate the implications of these results, future research should consider similar studies when female membership in both chambers exceeds the 30 percent threshold discussed by Paxton, et al., (2007). The authors claim that female membership in the 15-to-30-percent range is the threshold required for women to make substantive impacts in legislative bodies. The results of my analysis suggest that as more women entered the House in the latter terms of the study period the magnitude of the odds of being less successful for female representatives decreased. By employing the same analysis for the House as female membership exceeds 30 percent, results may show that the gap narrows further or even that there is no significant difference between the two gender groups with respect to legislative success.

Adding to this suggestion, future studies could focus on the success rates of women of different races and ethnicities as more women in different racial and ethnic groups become members of Congress. As Swers (2002) correctly notes, all women have some shared experiences and interests; however, women of different races and ethnicities also have their separate and distinct experiences and policy interests. Their backgrounds and experiences help form their individual and group-based legislative behaviors, interests, and activities; from a

social-network perspective, these influence their network relationships and activity levels within network.

From a substantive representation perspective, future studies could focus on legislative success rates of women's legislation in both chambers, rather than on all binding legislation as analyzed here. Prior scholarship has shown that success rates on female-oriented legislation are paltry compared to legislation in other policy areas (Barnes, 2016; Volden, et al., 2013; Swers, 2002). As more women enter Congress, the results may show an improvement in success rates for specifically female-based legislation. A further nuance for such an analysis would be to compare success rates for this type of legislation sponsored by female legislators and those sponsored by male legislators.

As more females increase their influential positional standing in the House and the Senate, particularly in influential positions within party leadership and influential committees like those included in this analysis, future studies should consider these variables as well as their interactions with gender. Few women during the study periods of this analysis were members of the powerful positions in their respective parties and no women were chairs of the power committees included. Standing in institutional positions is influential to policymaking process (Cox and Terry, 2008; Swers, 2002). If women increasingly occupied powerful committee chair seats and party leadership posts, there may be more positive impacts on female legislative success rates and potentially on female-specific legislation.

Finally, future research in legislative behavior that is concerned with policy implications should consider data related to binding, force-of-law legislation. The literature reviewed for this analysis is void of disaggregated legislation types apart from Mayhew (1974) and Tam Cho and Fowler (2010) who focused solely on landmark legislation. This is an important distinction as

legislators are concerned about their reputations, chamber standing and prestige, and their chances for re-election (Fenno, 1973). Reputations and electoral security are based on legislative activity on measures that have significance for home states and districts as well as the country. Non-binding ceremonial and procedure-based legislative efforts often have ephemeral impacts, and, in the case of rules-based legislation, most citizens have little to no interest. With respect to studying legislative activity and policy impacts, what useful inferences can the research community glean from studies of non-binding legislation? Furthermore, studies using relational data should only consider binding legislation because it can provide strong measures of the strength of the legislator-to-legislator relationship. Finally, future research in legislative behavior that is concerned with policy implications should consider data related to binding, force-of-law legislation. The literature reviewed for this analysis is void of disaggregated legislation types apart from Mayhew (1974) and Tam Cho and Fowler (2010) who focused solely on landmark legislation.

Chapter 6: Conclusion

This study extends our knowledge from the questions and findings of past studies using intersections of several domains such as cosponsorship/legislative activity and success, gender/legislative activity and success, and social network analysis/cosponsorship/legislative activity and success. This study is unique in that it examines gender-based cosponsorship networks in Congress through the lens of social network analysis over thirteen relatively recent terms of Congress. Within the context of cosponsorship activity and social network analysis, this study broadens knowledge of gender, the value of network theory, legislative support and collaboration processes, and their influence on legislative outcomes. Equally unique is that the cosponsorship data and the networks and results derived from an analysis of these data are based solely on binding legislation; this feature is important because binding, force-of-law legislative proposals are the products that directly affect large segments of the US population, and, in many cases, affect the entire country.

The findings described in this paper suggest that female legislators in the House of Representatives were less successful than their male counterparts at getting their sponsored legislation passed during floor votes from 1992 through 2016. These difficulties were evident despite female House members exhibiting significantly higher cosponsorship activity levels than men as well as better network centrality metrics than men. However, as more women entered Congress during the study period, the gap in success rates between female and male House members narrowed suggesting that as more women take seats in the House, female legislative success rates will improve. In the Senate, females also were active legislatively but not significantly different than males and their network formation statistics were similar to their male counterparts. Unlike the House, there were no statistically significant differences in legislative success rates between the two gender groups in the Senate. These results suggest that the

institutional characteristics of the Senate chamber matter and perhaps they matter more so than the House characteristics when examining the intersection of legislative success and gender.

Despite these inconsistent inter-chamber findings, there are key elements to consider from this research that I hope will benefit future studies in this area. The House findings suggest that as more women enter the House, and, presumably, occupy more influential positions within the chamber, the gap in legislative success rates will likely diminish over time. The research findings of Barnes (2016) and Swers (2005, 2002) support this projection and I am certain future scholarship will bear out these results. A change in legislative success rates may not be the only outcome we experience as more women enter Congress. There are likely to be dynamic shifts in other aspects of legislative behavior that reflect the characteristics of female legislators. One such potential change could be an institutionalization of collaboration among and between all gender groups and even racial groups within Congress as suggested by Barnes (2016). I am looking forward to these future contributions to expand our knowledge of women's legislative experiences and continued research into the relational aspects of legislative behavior.

Appendix A. Social Network Analysis Glossary

Actors

Entities that make up a social system of relationships among the actors. Actors may be individual persons or collectivities such as informal groups and formal organizations. Also known as nodes. (Borgatti, Everett, and Johnson, 2013; Knoke and Yang, 2008).

Attribute data

Data relating to the attitudes, opinions, and behavior of agents. (Scott, 2013).

Average Path Length

An average of the geodesic path lengths in a network as an indicator for how close together actors are to one another. (Prell, 2012)

Centrality

A property of a node's (or group of nodes) position in a network. Centrality can be considered in many ways, such as the contribution the node makes to the structure of the network or the advantage that accrues to a node by virtue of its position in the network (Borgatti, Everett, and Johnson, 2013).

Centrality (Beta; In-Beta)

A measure of the total amount of potential influence a node can have on all other nodes via direct and indirect channels, where indirect channels are weighted (inversely) by their length. The beta (β) parameter in the beta centrality equation controls how much the longer walks in the network are counted. In-beta centrality only considers the in-degree centrality measures. (Borgatti, Everett, and Johnson, 2013).

Centrality (Degree; In-Degree)

A simple measure of centrality which is the number of ties of a given type that a node has in a network. In-degree centrality focuses on the ties received by an actor from other network actors. (Borgatti, Everett, and Johnson, 2013).

Centrality (Eigenvector)

A variation of degree centrality in which the number of nodes adjacent to a given node is counted but each adjacent node is weighted by its centrality. A node with high eigenvector centrality is connected to nodes that are themselves well connected. (Borgatti, Everett, and Johnson, 2013).

Clustering Coefficient

A measure of the density of ties in each node's own, or ego, network; that is, the density of ties among nodes connected to a given node. (Borgatti, Everett, and Johnson, 2013).

Cohesion

A concept of dense intimate relations among members embedded in a social group or closed social circle. A cohesive subgroup consists of actors connected through many direct reciprocated choice relations that enable them to act collectively. (Knoke and Yang, 2008).

Connectedness

A centrality-based measure that accounts for the weighted number of bills cosponsored and the number of cosponsors per bill to estimate the strength of each tie. (Fowler, 2006a,b).

Density

The number of ties in a network, expressed as a proportion of the number of ties possible in the network. (Borgatti, Everett, and Johnson, 2013).

Directed/Undirected Graph

Graphs may be directed or undirected. In a directed graph, the ties or relations between nodes have a sense of direction. In undirected graphs, the ties or relations have no direction; that is, the direction does not make sense or logically must always be reciprocated. (Borgatti, Everett, and Johnson, 2013).

E-I Index

A measure of group embedding based on comparing the numbers of ties within groups and between groups. The E-I (external - internal) index takes the number of ties of group members to outsiders, subtracts the number of ties to other group members, and divides by the total number of ties. (Hanneman and Riddle, 2005).

Isolate

A node with no connection to other nodes. (Borgatti, Everett, and Johnson, 2013).

Network

A way of thinking about social systems that focus our attention on the relationships among the entities that make up the system. The entities are called actors or nodes. (Borgatti, Everett, and Johnson, 2013).

Path

A path is a walk in which each other actor and each other relation in the graph may be used at most one time. The single exception to this is a closed path, which begins and ends with the same actor. (Hanneman and Riddle, 2005).

Relational Data

Concerning the contacts, ties, and connections, and the groups attachments and meetings that relate one actor to another and that cannot be reduced to the properties of the individual actors themselves. (Scott, 2013).

Small World Networks

A type of network structure where the mean shortest path length in the network is significantly smaller than the mean-shortest path length in a random graph of the same size, and the average

level of clustering is significantly higher than it is in a corresponding random graph. (Tam Cho and Fowler, 2010).

Social Network Analysis

A method with foundations in network and graph theory used to describe the structure of a network or capture aspects of an actor's position in the network. (Borgatti, Everett, and Johnson, 2013; Scott, 2013).

Ties

The relational connections between actors or nodes. Ties are also known as links, edges, arcs, or lines. (Borgatti, Everett, and Johnson, 2013).

Valued Data/Binary Data

Numerical measurement of relational data. Values indicate the strength of a relation whereas binary data describes the mere presence of a relation. (Scott, 2013).

Walk

The most general form of connection between two actors in a network. A walk is an unrestricted sequence of actors and relations that begins and ends with actors. A walk can involve the same actor or the same relation multiple times. (Hanneman and Riddle, 2005).

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