Predicting Partnerships: Congressional Issue Agreement and Legislative Collaboration*

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Abstract

Congress is a collaborative institution. But how do members form these collaborative relationships? While existing literature points to social ties and common traits as links by which members establish working relationships, we suggest that a key connection is yet overlooked: policy-level agreement. In this project, we uncover the extent to which agreement on expressed issue-level positions translates to legislative collaboration. Specifically, we determine how positions members take during their campaigns predict their likelihood of working with other members who hold similar stances on a given issue. We find that the degree to which members express similar issue-level policy goals is predictive of their likelihood to collaborate on that particular issue, even across party lines. This project provides a policy-level explanation for how members identify legislative collaborators and explains partnerships that otherwise might remain surprising — particularly those that bridge the ideological divide.

Keywords: Bipartisanship, Collaboration, Campaigns, Text-as-Data

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On July 29th, 2021, Representative Suzanne Bonamici (D-Ore.) and Representative Cathy McMorris Rodgers (R-Wash.) joined forces to introduced H.R. 4786, the "RISE Act of 2021." The bill sought to reduce barriers students with disabilities face in higher education by easing documentation requirements when seeking accommodations in college.[1] While this bill was relatively straightforward in its content, the partnership behind this legislation, however, was less obvious. Bonamici and McMorris Rodgers represent different parties, different states, entered Congress in different years, and did not serve on any committees together. The two members also rarely saw eye-to-eye when it comes to policy: Rep. Bonamici was a member of the Congressional Progressive Caucus and strongly advocated for more progressive policies, including campaigning to protect a woman's right to choose, supporting labor unions, increasing the Social Security tax cap, and paid family leave. Meanwhile, McMorris Rodgers was a member of the conservative Republican Study Committee, a former member of the House Republican leadership, and supported more right-leaning policies, including repealing and replacing the Affordable Care Act, reining in government spending, and supporting the Pro-Life Caucus.

To most onlookers, the type of collaboration observed here — between Representatives Bonamici and McMorris Rodgers — remains surprising. This type of collaboration between ideologically distant members, however, is hardly rare. Among the 9,430 bipartisan bills introduced into the 116th, 117th, and 118th Congresses, over half of these bipartisan bills (5,102) featured at least one co-author whose absolute value of their DW-NOMINATE score is greater than 0.5, a criterion which 30% of members meet. Moreover, nearly 10% (841) of bipartisan bills include at least one co-author from each party whose absolute value of their DW-NOMINATE score is greater than 0.5.

How, then, do these members with deep political disagreements come to collaborate on legislation? Scholarly literature points to shared traits and experiences as sources of relationship formation in Congress. Members from the same state (Craig 2023), those entering

[1] H.R. 4786, 117th Congress, introduced July 29th, 2021. See `https://www.congress.gov/bill/117th-congress/house-bill/4786`.

Congress in the same cohort, those with similar ideological dispositions (Bratton and Rouse 2011), those who have had the same staff work for them at different points in time (Ommundsen 2027), those who have traveled together abroad (Curry and Roberts 2023), and even those who attended the same university (Battaglini, Sciabolazza and Patacchini 2020; Cohen and Malloy 2014) tend to be disposed to collaborate as legislative partners. These explanations largely identify the characteristics or experiences of legislators as deterministic of whether a particular pair of lawmakers is more likely to work together in general. Existing scholarship suggests that a pair of members holding some feature or experience in common should lend to a broad collaborative relationship. While important, this perspective fails to address two important questions. First, why do legislative partnerships emerge between members who lack the shared traits, experiences, or broad ideological alignment typically associated with collaboration? And second, why do members who are generally disposed to collaborate work together on some policy issues but not others?

In this paper, we add to the scholarly literature on collaboration in Congress by suggesting that trait- or experience-based commonalities do not fully explain the formation of these working relationships or the policy areas in which they emerge. We conceptualize legislative collaboration as an issue-specific — rather than a member-level — phenomenon and identify a new avenue through which potential collaborators can be identified. Other work has demonstrated that members of Congress vary their propensity to engage in bipartisan lawmaking not at the member level, but rather at the issue level (Case, Ommundsen and Porter N.d.). We follow a similar logic and contend that members identify legislative collaborators not only through shared traits, experiences, or the overall ideological alignment that is typically associated with collaborative relationships, but rather at the granular level of a particular issue. Furthermore, these policy-level commonalities explain why members who are otherwise inclined to work together collaborate on some issues but not others. We refer to this policy-level commonality as "expressed issue agreement," or the extent to which two members publicly articulate similar positions within the same issue area.

Bonamici and McMorris Rodgers' collaboration on H.R. 4786 illustrate this possibility. Despite their disagreements on other issues, Bonamici and McMorris Rodgers largely agreed on education policy. In 2020, Bonamici campaigned on the need for America's education system to serve students "regardless of background and ability" from pre-kindergarten through college. McMorris Rodgers similarly emphasized her position regarding the need to "increase educational opportunities" for individuals with disabilities and help them fulfill their abilities and ambitions. In this manner, policy-level agreement provides a basis for collaboration among otherwise unlikely partners, while also explaining why members who have pre-existing relationships work together on some issues but not others.

Others have acknowledged that agreement on policy is critical for collaboration (e.g., Craig 2023), yet this issue-based link has remained empirically untested. We seek, however, to test this precise concept. To measure expressed issue agreement, we rely on policy commitments articulated by members of the U.S. House of Representatives on their campaign websites from 2018 to 2022. Using these statements, we employ text embeddings to calculate the semantic similarity between the policy positions expressed by every possible pair of members within the same issue area. With member-to-member, dyadic measures of policy-level similarity, we then uncover the extent to which agreement on an issue translates to legislative collaboration on that issue.

To determine whether similar policy goals translate to legislative collaboration, we estimate a series of random- and fixed-effects models relating the similarity of a pair of members' policy statements to their likelihood of collaborating within the same policy area. Our primary specifications include member-dyad fixed effects, allowing us to compare collaboration across issues within the same pair of legislators, while holding constant all stable characteristics of that relationship. This design evaluates whether members are more likely to collaborate on the particular issues where they express greater policy agreement. While scholars often look to similar voting records as a proxy for congressional relationships, we argue — in line with recent work (e.g., Curry and Roberts 2023) — that original cosponsor-

ship provides a more direct indicator of legislative partnership. Because House rules permit only one formal sponsor on a piece of legislation, original cosponsorship serves as a signal of co-authorship and collaboration prior to a bill's introduction. We use original cosponsorship, therefore, as our primary outcome to evaluate whether expressed issue agreement translates into legislative action.

Our results provide strong evidence that expressed issue agreement predicts legislative collaboration. Holding constant all stable characteristics of a pair of members through member-dyad fixed effects, as well as differences across policy areas and years, members are significantly more likely to collaborate on issues where their publicly expressed policy goals are more similar. This relationship is especially pronounced among bipartisan pairs: the association between expressed issue agreement and legislative collaboration is significantly stronger for members from opposing parties than for members of the same party.

Together, these findings demonstrate that legislative collaboration is not simply a product of broad ideological similarity, common traits, or enduring member-level relationships. Policy-level agreement helps explain why the same pair of legislators collaborates on some issues but not others, and how members who might otherwise appear unlikely to work together can nevertheless identify opportunities for legislative partnerships.

Identifying Potential Collaborators

Recent scholarship has endeavored to quantify what congressional insiders have long known to be true: productive, working relationships are essential for a functioning Congress. Legislators who approach the lawmaking process from a collaborative lens — particularly, those who take a bipartisan approach — are far more productive than those who attempt to go at it alone, or who remain insular to their own party (Harbridge-Yong, Volden and Wiseman 2023). Accordingly, the vast majority of legislation that successfully navigates the legislative process does so with the initial backing of a team of legislators, rather than a sole advocate

(Ommundsen 2027). Knowing that lawmaking is a collaborative effort, a strategic member of Congress who is serious about achieving a policy goal will seek out at least one partner as they strive toward lawmaking success. Scholars have sought to uncover, then, how these teams of lawmakers identify each other and what potential sources of interpersonal connections might exist that lend to legislative collaborations.

Social ties are a critical avenue by which member-to-member connections are formed. This is not a new phenomenon, as scholars in the mid-twentieth century pointed toward the congressional boardinghouse as a crucial source of personal connections for lawmakers in the early Congresses. Legislators in the early- to mid-1800s who lived in close proximity to one another had more similar voting patterns than legislators who lacked this shared experience (Young 1966). Scholars also determined, observing the same early Congresses, that common traits can influence voting records. Bogue and Marlaire (1975) found that lawmakers who hailed from the same home state were even more likely to vote in a similar manner than those who lived together in boardinghouses. It is clear, then, that social connections and shared traits have long been an influential source in lawmakers' decision making. What scholarship has capitalized on more recently is a variety of new data sources by which to identify the root of these interpersonal relationships, as well as a handful of new metrics by which the effect of these relationships can be measured.

While the congressional boardinghouse is a relic of the 19th century, the notion of common experiences or traits inspiring congressional action is very much alive and well. Recent work has re-affirmed the influence a common trait can have on collaborative efforts (Craig 2023). Further, shared experiences gained by traveling abroad on official congressional trips (Curry and Roberts 2023) or attending the same undergraduate institution (Battaglini, Sciabolazza and Patacchini 2020; Cohen and Malloy 2014), for example, also contribute to the establishment of connections between members of Congress. Scholars have demonstrated that these common experiences spur legislative partnerships, which can be observed through co-signing

Dear Colleague letters (Craig 2023) and co-authoring legislation (Curry and Roberts 2023, 2025).[2]

While social ties and shared traits are a convenient foundation upon which relationships can be established, we suggest that these connections are neither necessary for relationship formation, nor do they provide a complete understanding of how members of Congress go about identifying collaborators. Personal connections are certainly useful in narrowing the pool of potential collaborators to whom a member might turn, yet not every social tie will result in legislative collaboration. This leaves unanswered the question of why some social ties prompt collaboration and others do not. Further, we suggest that pre-existing ties are not necessary in establishing a connection. We contend, therefore, that there exists an additional, yet empirically overlooked, factor that is a precondition to congressional collaboration. This factor, put simply, is policy-level agreement.

As lawmakers consider which of their colleagues they might turn to as legislative partners, they certainly will rely on their social connections and colleagues with shared traits as a familiar starting point. What we argue, however, is that narrowing the pool of potential collaborators in this way is not sufficient to establishing a partnership. A necessary step in forming a relationship as legislative collaborators, rather, is identifying a partner with whom a member agrees on a policy level. This policy-aligned partner might be found in a subset of colleagues with social connections or shared traits, yet might still be found in a broader pool of members of Congress with whom a member has no personal characteristics or experiences in common. While Representatives Elise Stefanik (R-N.Y.) and Katherine Clark (D-N.Y.), for example, both have degrees from Harvard University and represent portions of the same state, we would not expect these ideologically distant members to identify each other as potential collaborators simply because of these commonalities, nor would we expect them to constrain their pool of potential collaborators to their fellow Harvard graduates or New

[2]As will be discussed in greater detail in subsequent sections, co-authors are determined to be any sponsor or original cosponsor of a piece of legislation.

Yorkers. Ultimately, we contend that the critical link that is necessary to any legislative relationship is agreement on a particular piece of legislation.

Previous work evaluating collaboration typically operationalizes member-level agreement through the absolute difference in DW-NOMINATE scores for a pair of members (e.g. Curry and Roberts 2023). Employing the absolute difference in DW-NOMINATE scores to identify similarly aligned members presumes a certain degree of ideological homogeneity across a given member's issue positions. There is strong evidence, however, of heterogeneity in members' positions across issues — both during campaigns (Case and Porter 2026) and in legislative behavior (Yoshinaka and Grose 2011) — and their disposition toward collaboration across issues (Case, Ommundsen and Porter N.d.). Representatives Bonamici and McMorris Rodgers certainly do not have similar overall ideological outlooks, as exemplified by their DW-NOMINATE scores being 0.837 points apart in the 118$^{\text{th}}$ Congress, yet they found a particular issue on which they agreed: removing barriers to education for those with disabilities. Observing similarities at the issue level allows for a more granular identification of agreement in a set of members, rather than expecting members to hold similar positions across an entire platform of issues. Members might rely on shared experiences or identities to spur conversation and learn something about their peers' issue positions, yet ultimately, issue agreement is critical in establishing an observable legislative relationship.

As we explain in greater detail in the sections that follow, we use issue-level statements found on members' campaign websites as a source of expressed policy preferences to determine how aligned a given pair of members is on any particular issue. We do not suggest that members consult each others' campaign websites to learn which of their colleagues think like them on a given topic, yet we argue that campaign websites serve as a valuable source of publicly expressed statements that constrain members' behavior.

Members use campaign websites to signal to both voters and donors how they might behave and what issues they will advocate for if elected to Congress (Druckman, Kifer and Parkin 2009; Herrnson 2015). While members might not have their future colleagues in

mind when making issue-level statements on their campaign websites, these statements do serve as a constraint of their future behavior in the sense that it is a publicly expressed statement (Sulkin 2009, 2011; Case, Ommundsen and Porter N.d.). Members of the voting and donating publics can hold members accountable if they deviate substantially from their previously expressed policy preferences. We can, therefore, interpret the issue statements a member publishes on her campaign website as an accurate and binding representation of her policy preferences. It is from these observable issue-level positions that we suggest we can best identify a member's pool of potential legislative collaborators. Members who express similar issue-level goals should be more likely to form a relationship for the purposes of enacting that policy. While shared experiences and traits can be helpful in building social connections, it is this issue-level agreement — which we observe via campaign websites — that ought to spark the greatest amount of legislative collaboration.

Observing Legislative Partnerships

Having established the necessity of issue-level agreement in fostering legislative partnerships, we observe the presence of these relationships through early-stage legislative collaboration. While some scholars have looked to similar voting records as an indication that members may be closely aligned (e.g., Young 1966; Bogue and Marlaire 1975), others have attempted to identify member-level partnerships through co-signed Dear Colleague letters (Craig 2023). We follow a handful of recent works, however, that identify partnerships through joint participation in the drafting and introduction of legislation in Congress (e.g. Curry and Roberts 2023, 2025; Porter, Harden and Dobson 2025; Ommundsen 2027; Case, Ommundsen and Porter N.d.).

While similar voting patterns can signal a certain level of agreement between two members, we contend that voting records do not display the presence or absence of a relationship between two members. Members' votes are constrained by the list of bills leadership

schedules for a vote, and members' choices are confined to voting for a bill, opposing it, or abstaining. These limiting factors do not allow for a careful observation of congressional relationships; similar voting records, rather, simply depict similar choices by two individuals in a constrained environment. Members co-signing Dear Colleague letters, on the other hand, would signify an active partnership between two or more members. Yet the focus of many of these letters, however, is not legislative. While many Dear Colleague letters are circulated in hopes of building support for legislation, as discussed by Craig (2023), nearly half of these co-signed letters do not have an express legislative purpose. Members distribute Dear Colleague letters to invite colleagues and staff to briefings and events, to request members' support on a future letter, or to seek support on some policy request. Because we are primarily interested in how legislative partnerships are formed, observing sets of co-signers on the full scope of Dear Colleague letters does not allow us to identify these legislative relationships. We argue, then, that the most appropriate method by which to observe legislative collaborations is through original cosponsorship.

As is explained in greater detail in the sections that follow, we consider members to have formed a legislative relationship when they serve as part of a sponsorship/original cosponsorship team. As both the U.S. House of Representatives and Senate allow just one member to be listed as a sponsor of a given bill, members who worked closely with the sponsor during the drafting stage denote their co-authorship in the form of original cosponsorship. This signal of co-authorship not only denotes an active, working relationship between a team of members, but as the product of this relationship is a piece of legislation, we are able to observe how agreement on a particular issue translates to legislative collaboration on that precise issue in Congress.

We expect that members who express similar issue-level stances on their campaign websites will be most likely to collaborate as original cosponsors. Representatives Bonamici and McMorris Rodger's collaboration is evidence of the fact that collaborators need not agree on all policies, just the one on which they are co-authoring. While we do not expect issue-level

agreement to replace shared-trait explanations of partnership formation, we contend that policy agreement adds to the existing story and explains cases in which members collaborate yet do not have experiences or qualities in common.

> **H1 Expressed Issue Agreement:** A pair of members who express similar stances on an issue will be more likely to collaborate on that issue than a pair of members who do not share similar issue positions.

While we hold that common member-level features are not necessary for establishing partnerships, we expect the effect of issue-level agreement to vary based on the conditions under which members collaborate. Members of the same party, for example, are more likely to possess preexisting social ties, share broader ideological commitments, and benefit from the general expectation that copartisans will work together. Bipartisan pairs of members, on the other hand, are less likely to benefit from these same partisan and social foundations. Working with an out-partisan may also require greater coordination and political justification. Issue-level agreement, then, should be especially important when a potential partnership cannot rely as readily on other established foundations for collaboration. Under these conditions, agreement on an issue provides a more valuable substantive basis for collaboration. Agreement reduces uncertainty about what the members can jointly support and helps justify the time and political capital required to form the partnership. While we anticipate that issue-level agreement will spur copartisan partnerships, we expect the effect of issue-level agreement to be particularly pronounced when it comes to prompting bipartisan partnerships.

As is explained below, our analyses focus on the U.S. House of Representatives. While the contemporary U.S. Senate operates under a variety of super-majoritarian procedures requiring greater levels of bipartisan agreement, the House remains a majoritarian institution. In nearly all cases, House leaders can operate without the consent of the minority, meaning that members do not face the same procedural need to identify bipartisan partners. Bipartisan collaboration in the House is, therefore, a more difficult and potentially more costly form

of partnership than collaboration among copartisans. Out-partisans such as Representatives Bonamici and McMorris Rodgers do not see eye-to-eye on the vast majority of policies, lack the shared partisan incentives that ordinarily facilitate collaboration, and may have fewer established social ties on which to rely. Yet they do collaborate. We argue that agreement on the particular issue under consideration provides the substantive foundation needed to overcome these barriers. Expressed issue agreement should therefore matter for both partisan and bipartisan partnerships, but it should be especially important when members cross party lines.

> **H2 Bipartisan Collaborators:** The effect of expressed issue similarity on legislative collaboration will be greater for bipartisan pairs of members than partisan pairs of members.

Following similar logic regarding the effect of member-level traits, the final dimension on which we expect issue-level agreement to vary is on a member's seniority. Knowing that social ties develop over time as members gain opportunities to interact and establish working relationships, first-term members, by construction, have fewer opportunities to form these connections than their more senior colleagues. Returning members may, therefore, be able to draw upon established relationships when identifying collaborators because of those social ties. First-term members, on the other hand, cannot rely as readily on these alternative foundations for collaboration. In the absence of established social ties, agreement on the relevant issue should provide a more important basis for identifying a potential partner and determining whether collaboration is likely to occur. As a result, we expect expressed issue agreement to be positively associated with legislative partnerships at all levels of seniority, but we anticipate that the effect of agreement will be particularly pronounced when a pair of legislators includes a freshman member.

> **H3 Freshmen Effect:** The effect of expressed issue similarity on legislative collaboration will be greater for pairs of members in which at least one member

is a freshman than pairs of members in which both are returning members of Congress.

Data and Measurement

To test our hypotheses, we rely on a dataset of expressed issue commitments from members of the U.S. House of Representatives during their most recent campaign, spanning from 2018 to 2022. With these data, we measure the relative similarity of two members' issue-level commitments, which we term "expressed issue agreement." Using these dyadic data reflecting the level of similarity between two members' stances on a given issue, we then rely on bill-level data to examine whether agreement on a particular issue translates into realized legislative collaboration on that same issue. Each of our data sources and measurement strategies is described in detail below.

Measuring Expressed Issue Agreement

An inherent challenge in evaluating whether members' agreement predicts their legislative collaboration is measuring the degree to which two legislators see eye-to-eye on a particular issue. Rather than relying on a generic measure of ideological agreement across all issues (such as the absolute difference in DW-NOMINATE), we evaluate similarity at the level of a particular policy area. When it comes to our application, this issue-level variation is critical because it suggests that two members might agree on healthcare policy but disagree on immigration policy. As a result, we capture issue-specific expressed agreement between members on particular policy areas, as stated on their congressional campaign websites.

To compile a dataset of issue-specific statements made on congressional campaign websites, we rely on CampaignView, collected by Porter, Case and Treul (2025) across the 2018, 2020, and 2022 congressional elections. Campaign websites are a particularly valuable source of expressed positions because they provide detailed statements across a wide range of issues

prior to the start of a Congress. We do not suggest that members of Congress or their staffs actively consult each other's campaign websites when identifying potential collaborators. Rather, we argue that campaign websites provide a record of candidates' publicly expressed issue positions before they enter the upcoming Congress. Other sources of member communication could be used to measure expressed agreement, including e-newsletters, speeches, press releases, and social media posts. We focus, however, on campaign websites for two reasons.

First, campaign website statements are observed before members have the opportunity to collaborate legislatively in the Congress to which they are elected. Porter, Case and Treul (2025) collect these issue statements during the week leading up to a member's primary election, ensuring that the rhetoric we analyze precedes the legislative activity on which we focus later. This temporal aspect is critical because it ensures that our measure of expressed agreement is not shaped by subsequent collaboration or by statements about legislation members are already working on together in the subsequent Congress, which other data sources of expressed statements likely capture. Our goal, moreover, is not to recover the "true" underlying policy agreement between two members. Instead, we seek to capture the extent to which members' publicly expressed commitments signal agreement between legislators, and therefore identify potential areas of future collaboration. To the extent that campaign rhetoric reflects genuine policy priorities, greater similarity in these statements should be associated with subsequent legislative collaboration once members enter office.

Second, campaign websites provide a broader and more systematic presentation of candidates' policy positions than many other forms of political communication. Communications produced during the legislative session likely respond to the issues dominating the political agenda at a particular moment, rather than revealing the fuller set of issues members prioritize and the positions they hold on them. Campaign websites, by contrast, typically include structured issue pages that allow candidates to articulate positions across multiple policy areas at once. Although these statements are still shaped by the electoral context and issue

salience in a given campaign year (Sachleben and Treul 2026), that salience is tied to the election rather than to the legislative calendar and leaders' agendas. As a result, campaign websites provide the most systematic representation of the policy positions that candidates bring into office.

Given our goal of measuring expressed agreement within specific policy areas, we begin by identifying which policy area or areas candidates discuss on their campaign websites, according to categories defined by the Congressional Research Service (CRS). We do so at the paragraph level, using paragraphs drawn from CampaignView "platform points" as the text unit for classification. This choice is important because CampaignView's researcher-assigned labels operate at the document level and capture only the general topic of a platform point. Platform points, however, often contain multiple paragraphs that address different policy areas, making a single label too broad and failing to capture the variation in policies discussed.[3] Additionally, several CampaignView policy labels lack specificity, as a handful correspond to multiple CRS bill categories. We, therefore, construct our own paragraph-level policy labels, allowing us to (1) recover narrower policy areas than those provided by CampaignView, reflecting the more precise CRS policy codes; (2) measure issue-specific agreement using the text that is most directly relevant to a given topic; and (3) assign multiple policy labels to a single paragraph, when necessary, acknowledging that many paragraphs discuss a variety of policy areas rather than a single topic.[4]

To assign these labels, we rely on a supervised machine learning pipeline to classify whether each paragraph on a campaign website discusses any of the 32 policy topic codes the Congressional Research Service uses to classify bills. To create our training data, a graduate research assistant used a CRS-provided codebook to label a sample of 7,750 campaign paragraphs across all 32 CRS policy areas.[5] While we label all 32 categories, we drop policy

[3] In our subsequent classification, we find that 34% of CampaignView platform points address more than one policy topic.

[4] 14% of paragraphs address multiple policy topics, justifying our choice of allowing multiple policy areas to be assigned per paragraph while also defining a narrow text unit.

[5] `https://www.congress.gov/help/field-values/policy-area`

areas from our data that appeared in fewer than 1% of campaign statement paragraphs.[6] For the remaining policy areas, we train a separate supervised classifier for each category to identify whether a paragraph discusses that issue. Full details on labeling, the model training process, and models used for the classifier can be found in Appendix A. After training the models, we use a held-out dataset of 750 statements to validate the out-of-sample performance of our classifiers. A full overview of our validation can be found in Appendix A.3. In total, eleven of our policy areas had F1 Scores of greater than 0.8 and all twenty-one exhibited performance above 0.7, suggesting strong performance.[7] This validation performance is on par or better than other multi-policy area classifications (e.g., Case and Porter 2026). Across the 21 policy areas included in our analysis, members discuss an average of 10.1 issues, or 48.1% of the possible categories, with an inter-quartile range of seven to 13. Nearly all members discuss multiple policy areas: more than 93% discuss at least five, and 16% discuss 15 or more. Healthcare and economics are the most commonly discussed policy areas (>75% of members discuss) while housing, families, and trade and finance are discussed much less frequently (<20% of members). In Appendix A.4, we present descriptive statistics on the issues discussed by members of Congress.

Having identified which policy topic(s) are discussed within a given paragraph, we use these issue statements to measure the degree of expressed agreement between pairs of members within a given policy area. In other words, we identify which members make similar statements on a particular issue. Importantly, we calculate agreement scores only for pairs of members who both discuss a particular issue during the campaign. Members who do not discuss a given topic, therefore, do not receive a score indicating their level of agreement with other members on that particular issue.[8]

[6]These policy areas include Animals; Arts, Culture, Religion; Congress; Emergency Management; Finance and Financial Sector; Law; Native Americans; Public Lands and Natural Resources; Social Sciences and History; Sports and Recreation; and Water Resources Development.

[7]The F1 score is the balance of precision and recall, summarizing how well a classifier balances false positives and false negatives, with higher values indicating better performance. Scores have a minimum of 0 and a maximum of 1.

[8]This means that our subsequent analyses are limited to cosponsorship among members who discuss a given issue during the campaign. This makes for a more difficult empirical test of our theory. Previous work

We operationalize expressed agreement as the similarity in meaning between two members' statements for a given policy area. It is important to note that this approach is agnostic to ideological placement within an issue area. Our goal is not to scale members from liberal to conservative, moderate to extreme, or along any other single ideological dimension. Rather, our goal is to capture the extent to which two members articulate similar policy commitments and "agree" on those commitments within an issue area. This is advantageous because it allows us to identify common ground across a diverse set of policy positions, including issue areas that do not map cleanly onto a typical left-right scale. This also allows us to explicitly identify members who take similar positions on an issue, rather than just occupying the same position on a left-right scale.

Previous work measuring text agreement often relies on cosine similarity computed from representations (e.g., document feature representations) that are heavily dependent on word overlap. While useful and straightforward, these approaches can struggle to capture semantic similarity when two politicians express comparable policy commitments using different words, phrases, or rhetorical styles.[9] To overcome these measurement hurdles, we rely on text embeddings generated by OpenAI's text-embedding-3-large model through the OpenAI API, whose training includes contrastive learning tasks (Neelakantan et al. 2022).[10] In contrastive embedding models, document embeddings are encoded into a shared vector space such that semantically related documents are located closer together, and documents that are less semantically similar are located farther apart. More specifically, the model encodes

shows that campaign discussion of policy topics is itself predictive of future legislative activity (Sulkin 2009, 2011). Our analyses, therefore, focus on the subset of members already predisposed to engage with an issue and evaluate whether similarity in their expressed positions structures whether and how they build coalitions in Congress, rather than treating the choice not to discuss an issue as an expression of relative disagreement.

[9]More recent work improves on this by using cross-encoders to estimate semantic similarity directly, particularly for short political texts (Lin 2025). Cross-encoders jointly process two texts and can provide precise similarity estimates. However, most commonly used cross-encoder implementations remain constrained by transformer input-length limits (typically 256-512 tokens), and longer sequences are truncated once they exceed the model's maximum input window.

[10]While models such as OpenAI's text-embedding-3-large model exhibit state-of-the-art performance, they do have the limitation of eventual "digital decay." We can only generate the embeddings through the API, and while the output is consistent across time, our access to the model depends on OpenAI continuing to maintain access to the API. We found OpenAI's text-embedding-3-large model greatly outperformed open-source contrastive transformer models, such as Nomic, so we chose OpenAI despite digital decay concerns.

each text input independently into a dense numerical vector, allowing texts to be compared using cosine similarity. This approach is especially useful for our purposes because it allows us to compare campaign statements based on semantic meaning rather than simple word overlap, while also making it computationally feasible to represent each paragraph once and reuse its embeddings across many comparisons.

To construct our measure of expressed issue agreement, we first take a weighted average of the paragraph embeddings for each member within a given policy area for a given election. Paragraph embeddings are weighted by word count. This produces a single embedding for each member-Congress-policy area combination discussed. The resulting embedding reflects the overall semantic content of a candidate's issue text within that policy area. Using these overall issue embeddings, we take the cosine similarity between members who both discuss the same policy topic in the same election year. This subsequent measure captures to which members' overall rhetoric on a policy area is semantically similar, and thus captures expressed agreement on an issue area. We then operationalize this variable to have a mean of zero and standard deviation of one within a policy area to aid with interpretation across policy domains.

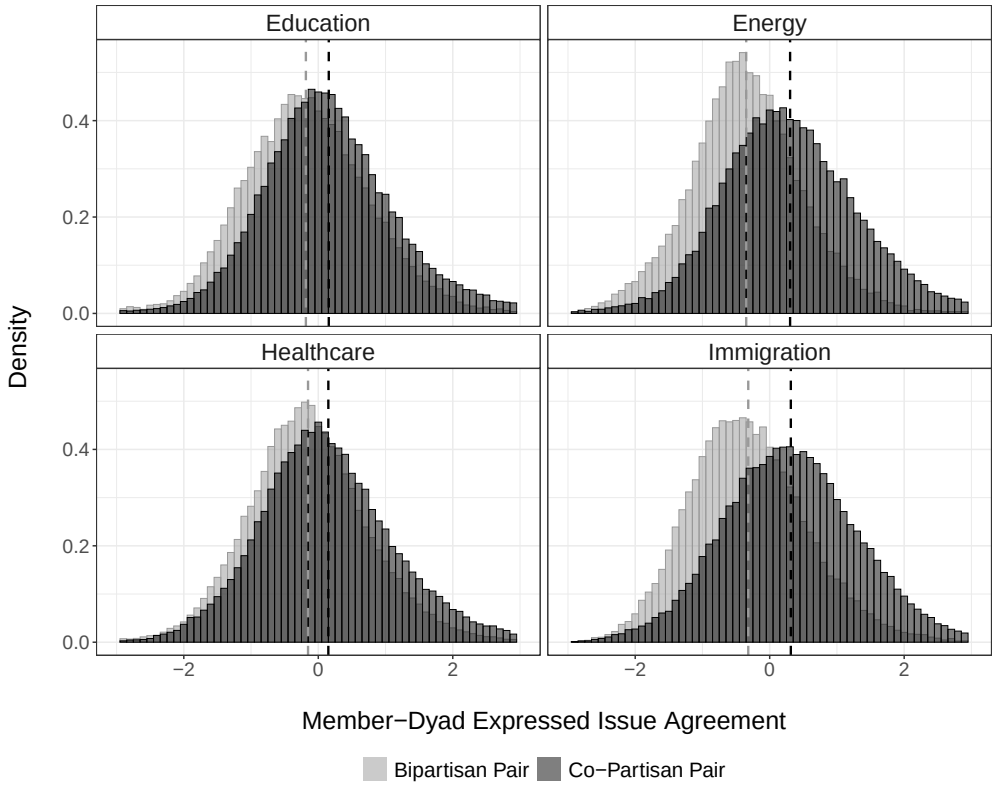
We also conduct a human validation of our expressed issue agreement measure to ensure the measure actually captures expressed issue agreement (see Appendix C for full details of the validation task). In our validation test, a graduate research assistant completed 500 paired-comparison tasks in which they selected which of two campaign statements expressed a position more similar to a reference statement from the same policy area. The statement receiving the higher similarity score is also selected by the coder in 73.1% of the comparisons. Agreement remains nearly identical when the party of the member making the reference statement is the same as the party of both members making the comparison statements (72.7%), indicating that the similarity measure captures more than simply differences across parties. The coder also becomes substantially more likely to select a statement as most similar to the reference as its empirical similarity advantage over the other statement grows

($\beta = 1.400$, $p < 0.001$). These results provide strong evidence that our measure captures differences in the substantive positions members express within the same policy area.

A central component of our argument is that expressed agreement between two members of Congress at the issue level can deviate from the broader ideological similarity between members. Because our measure is designed to capture agreement within particular policy areas, we expect it to be related to members' overall ideological dispositions, but only weakly so. For example, two members who are ideologically distant overall — such as Reps. Bonamici and McMorris Rodgers — might still express similar policy positions on a particular issue, such as a particular education policy. Consistent with our argument, the correlation between two members' expressed issue agreement and the absolute distance between those members' DW-NOMINATE scores is only -0.247. This correlation indicates that pairs of members who have more distinct DW-NOMINATE scores tend to have lower expressed agreement, but this relationship between these variables is relatively weak.

Figure 1 provides a broader view of how these overall similarity scores are distributed across member-dyads for four issue areas: education, energy, healthcare, and immigration. A higher value corresponds to an instance in which two members have high levels of agreement on a particular issue, whereas a negative score represents dissimilar issue-level statements. We see that, on average, co-partisan pairs of members have higher expressed agreement than bipartisan pairs. There remain many cases, however, where issue agreement is high for a subset of bipartisan pairs. We also see that, in general, there is a greater spread between bipartisan pairs than co-partisan pairs. This spread among the four issues is greatest among energy and immigration but substantially smaller for education and healthcare. This trend is further demonstrated in the distribution of all 21 issue areas, which can be found in Appendix B. With this measure of expressed issue agreement, we now turn to evaluating whether members who make similar issue-level statements do, in fact, identify one another as viable collaborators and take steps to implement their policy goals through legislative action.

Figure 1: Distribution of Member-Dyad Overall Similarity Scores



Note: Figure plots the distribution of member-dyad overall issue similarity separately for bipartisan and co-partisan pairs across four policy areas: education, energy, healthcare, and immigration. Histograms are scaled to density within each panel, with a mean similarity score of zero and a standard deviation of one. Vertical dashed lines indicate the mean similarity for bipartisan and co-partisan pairs. See Appendix B for the distribution of overall similarity scores across all 21 issue areas.

Measuring Legislative Issue Collaboration

To determine whether expressed agreement on an issue is associated with actual legislative collaboration in Congress in that same policy area, we measure legislative collaboration through bill sponsorship and original cosponsorship. While only one member can be listed as the sponsor of an introduced piece of legislation, members frequently sign on to a bill as an original cosponsor to indicate their participation in the bill's development. It is commonly held that members who are original cosponsors are actively involved in a bill's creation, and are seen as close collaborators or even "equal partners" in the legislative process (Curry and Roberts 2023). Therefore, when two members appear together in a bill's sponsorship/original

cosponsorship coalition, this provides a direct indicator of legislative collaboration on that bill between a pair (or team) of members.[11]

We collect bill cosponsorship data through the Congress.gov API for all bills introduced in the House of Representatives in the 116th, 117th, and 118th Congresses.[12] We follow previous work (e.g. Curry and Roberts 2023, 2025; Porter, Harden and Dobson 2025; Case, Ommundsen and Porter N.d.) and define original cosponsors for a piece of legislation as either the sponsor who introduced the legislation or the cosponsors who joined the bill on the day it was introduced. In addition to cosponsorship data, we collect the policy-area classification assigned to each bill by the Congressional Research Service. This allows us to connect our measure of expressed policy agreement to meaningful legislative collaboration within the same issue area. This variable of legislative collaboration equals 1 if the two members were part of the sponsorship/original cosponsorship coalition on at least one bill in that issue area during the relevant Congress, and 0 otherwise. We focus on a binary indicator rather than a count of legislative ties for both theoretical and empirical reasons. Substantively, our interest is in whether a collaborative tie emerges at all within an issue domain, not how many times a particularly active pair introduces legislation together. Empirically, original cosponsorship occurs in a minority of member-issue pairs. Among pairs of members we have campaign website data for, only 22.6% of member-dyad-issue pairs in the 116th Congress, 25.7% in the 117th Congress, and 21.8% in the 118th Congress involve at least one collaborative tie. The binary indicator, therefore, provides a direct measure of legislative collaboration on an issue area with enough meaningful variation, without placing more weight on a small number of dyads that are especially active in an issue area.

[11] There is no limit to the number of original cosponsors a bill may have, resulting in some pieces of legislation with a large number of original co-sponsors. The median bill, however, has three original cosponsors and the average bill has more than eight. To ensure our results reflect close collaboration and not a messaging effort coordinated across a caucus, for example, we estimate models including only bills with fewer than eight original cosponsors and find similar results to the full set of original cosponsorship teams. Results are presented in Appendix E.

[12] We limit our analyses to House bills and drop all simple, joint, and concurrent resolutions.

Table 1: Average Rate of Legislative Collaboration by Campaign Issue Discussion

	Proportion of Dyads with Legislative Collaboration		
	116^{th} Congress	117^{th} Congress	118^{th} Congress
All Member-Dyad-Issue Observations	0.226	0.257	0.218
Neither Member Discusses Issue	0.145	0.176	0.146
One Member Discusses Issue	0.225	0.239	0.210
Both Members Discuss Issue	0.322	0.367	0.313

Note: Entries report the proportion of member-dyad-issue observations in which the pair was part of the sponsorship/original cosponsorship coalition on at least one bill within the relevant issue area in the specified Congress. The first row pools all levels of campaign issue discussion. The remaining rows distinguish whether neither member, one member, or both members discussed the issue on their campaign websites. The sample is restricted to pairs for which campaign website data are available for both members. Full details on the sample used in our analyses can be found in Appendix D.

Importantly, the average rate of legislative collaboration increases with the number of members in a pair who discuss the issue during the campaign. As Table 1 demonstrates, across all three Congresses, the rate of collaboration is more than twice as high among pairs in which both members discuss an issue as among pairs in which neither member discusses it. The rate of collaboration is also between 43% and 54% higher than among pairs in which only one member discusses the issue. These patterns provide important context for our subsequent analyses. As noted above, we can measure expressed issue agreement only when both members articulate positions on the same issue. These patterns reflect that the subset of members-dyad-issue observations our analysis focuses on are the pairs with shared issue attention and the highest observed likelihood of collaborating within that policy area. Our subsequent analyses evaluate whether, within this pool, similarity in members' expressed policy goals further distinguishes which pairs collaborate. In other words, we evaluate whether expressed agreement structures collaboration among pairs that have already demonstrated shared issue attention, rather than treating the choice not to discuss an issue as evidence of disagreement.

Modeling Legislative Collaboration

To evaluate whether expressed agreement on an issue is associated with greater legislative collaboration in Congress on that issue, we utilize two complementary modeling approaches. A distinctive feature of our data is that for each member-dyad, we observe repeated potential collaboration ties (observed via joint original cosponsorship) across the set of policy areas both members discuss during their campaigns. In other words, the same two members can be connected via multiple issue areas within a single Congress. We leverage this structure using both fixed- and random-effects models. Together, these approaches allow us to evaluate whether expressed issue agreement predicts legislative collaboration both across differing sets of members and across policy areas within the same set of members. For each set of analyses, we estimate separate models for the 116^{th}, 117^{th}, and 118^{th} Congresses, reflecting the fact that the chamber's membership changes across Congresses, resulting in many dyads appearing in some Congresses and not others. Our primary independent variable of interest across all model specifications is expressed issue agreement. This measure varies across policy areas within the same member-dyad, allowing us to evaluate whether greater agreement on a particular issue is associated with collaboration on that same issue.

Our first modeling approach uses member-dyad fixed effects that rely exclusively on variation across policy areas within the same pair of members. This approach holds constant all observed and unobserved characteristics of a member-dyad that remain stable within a Congress, allowing us to evaluate whether the same pair of legislators is more likely to collaborate on issues where they express greater agreement than on issues where their expressed positions are less similar. Because characteristics such as whether members belong to opposing parties or whether a dyad includes a freshman member do not vary across policy areas within a Congress (the relationships addressed in hypotheses two and three), their direct effects are absorbed by the member-dyad fixed effects. We are still able, however, to estimate whether the relationship between expressed issue agreement and collaboration differs across these types of member pairings by interacting each characteristic with our measure of ex-

pressed issue agreement. We also include policy-area fixed effects and cluster standard errors at the member-dyad level across all fixed-effect models to account for repeated observations of the same pair of legislators across policy areas.

Our second approach uses random-effects models that retain variation across member-dyads. Unlike the fixed-effects models, the random-effects models retain all member-dyads in the analytic sample, including pairs that do not collaborate in any of the policy areas both members discuss.[13] This approach allows us to account directly for observable characteristics that make some pairs of legislators more or less likely to collaborate in general, regardless of the particular policy area. Specifically, we account for whether members are from the same state, whether they serve on a committee together, whether they entered Congress in the same cohort, whether they belong to opposing parties, whether at least one member is a freshman, and the ideological distance between the two members (measured using DW-NOMINATE). Including these characteristics also allows us to benchmark the substantive relationship between expressed issue agreement and legislative collaboration against established predictors of collaborative relationships. Additionally, we include a random intercept for each member-dyad, which captures persistent, unobserved differences across pairs of members in their general propensity to collaborate. Finally, the model also includes policy-area fixed effects to account for differences in the overall propensity for collaboration across issue areas.[14]

[13]The member-dyad fixed-effects models require within-dyad variation in legislative collaboration and therefore exclude pairs for which the outcome is constant across observed policy areas. In practice, this excludes pairs that do not collaborate in any policy area.

[14]An alternative approach would be to estimate a network model given the nature of the data. Specifically, a repeated-observation additive and multiplicative effects (AME) network model that accounts for broader dependence in legislative relationships across dyads and the fact that members' collaborative ties are embedded within a larger congressional network. However, given the size of our network, this model is computationally intensive and takes several days to run a single model, making it infeasible with little added analytic value over the approaches we detail here.

Results

We begin by evaluating whether expressed issue agreement is associated with a greater likelihood of legislative collaboration. Table 2 presents results from our fixed- and random-effects models separately for the 116$^{\text{th}}$, 117$^{\text{th}}$, and 118$^{\text{th}}$ Congresses. Across both modeling approaches and all three Congresses, we find consistent support for our first hypothesis: expressed issue agreement is positively and significantly associated with legislative collaboration. In other words, pairs of members who express more similar stances on the same issue are more likely to collaborate on that issue than members who do not express similar views. Consistent with previous work on legislative collaboration, our random-effects models also indicate that members are significantly more likely to collaborate when they serve on the same committee or represent the same state, while greater ideological distance and belonging to opposing parties are associated with significantly lower levels of collaboration across all three Congresses.

Previous work has demonstrated that common experiences and institutional ties can provide an important foundation for legislative relationships (e.g., Craig 2023; Curry and Roberts 2023, 2025). Knowing that shared committee membership provides members with repeated opportunities to interact and work together on policy and is predictive of legislative partnerships, we use it as a benchmark for evaluating the substantive magnitude of our measure of expressed issue agreement. The coefficient for expressed issue agreement is substantively meaningful relative to this established predictor of legislative collaboration. In our random-effects models, the coefficient associated with a one-standard-deviation increase in expressed issue agreement is approximately 71% of the size of the coefficient for shared committee membership in the 116$^{\text{th}}$ Congress, 51% in the 117$^{\text{th}}$ Congress, and 84% in the 118$^{\text{th}}$ Congress. Thus, while serving together on the same committee is more strongly associated with collaboration across all three Congresses, expressed agreement on a particular issue exhibits a somewhat similar effect to a clear institutional factor affecting collaboration.

Table 2: Expressed Issue Agreement & Legislative Collaboration

	Dependent variable: Legislative Collaboration					
	116^{th} Congress		117^{th} Congress		118^{th} Congress	
Expressed Issue Agreement	0.30^{***}	0.21^{***}	0.23^{***}	0.20^{***}	0.22^{***}	0.26^{***}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Bipartisan Dyad		-1.53^{***}		-1.92^{***}		-1.52^{***}
		(0.04)		(0.04)		(0.04)
Freshman Dyad		-0.45^{***}		-0.95^{***}		-0.44^{***}
		(0.02)		(0.02)		(0.02)
Ideological Distance		-2.67^{***}		-2.55^{***}		-3.13^{***}
		(0.05)		(0.05)		(0.05)
Shared Committee		0.30^{***}		0.39^{***}		0.30^{***}
		(0.02)		(0.02)		(0.02)
Same Cohort		0.03		-0.11^{***}		0.02
		(0.02)		(0.02)		(0.03)
Same State		1.05^{***}		0.98^{***}		1.06^{***}
		(0.03)		(0.03)		(0.03)
Constant		-0.35^{***}		-0.49^{***}		0.31^{***}
		(0.06)		(0.05)		(0.05)
Observations	252,109	389,497	357,996	463,275	259,640	420,631
Member-Dyad FEs	✓		✓		✓	
Member-Dyad REs		✓		✓		✓
Policy Fixed Effects	✓	✓	✓	✓	✓	✓

Note: Coefficients are logistic regression coefficients with standard errors in parentheses. Dyad-level characteristics are absorbed by the member-dyad fixed effects and are therefore estimated only in the random-effects models. Standard errors for fixed-effects models are clustered by member-dyad. The fixed-effects models include only member-dyads with within-dyad variation in legislative collaboration, while the random-effects models retain all member-dyads in the analytic sample. Full sample details are found in Appendix D. *p<0.1; **p<0.05; ***p<0.01.

To provide further substantive context for these results, Figure 2 plots the predicted probability of legislative collaboration across levels of expressed issue agreement for each Congress and modeling approach. We hold all other model components at their observed values and vary expressed issue agreement from two standard deviations below to two standard deviations above the mean.[15] Across the fixed-effects models, moving from the mean level of

[15]The levels of the predicted probabilities in Figure 2 also reflect the observations included in each modeling approach. As Table 1 demonstrates, our analyses focus on policy areas that both members discuss during their campaigns, where the average rate of legislative collaboration is higher than across all member-dyad-issue observations. The fixed-effects models further exclude pairs that do not collaborate in any of the policy areas both members discuss, while the random-effects models retain these pairs. This difference contributes to the higher predicted probabilities in the fixed-effects models. We therefore focus on how the

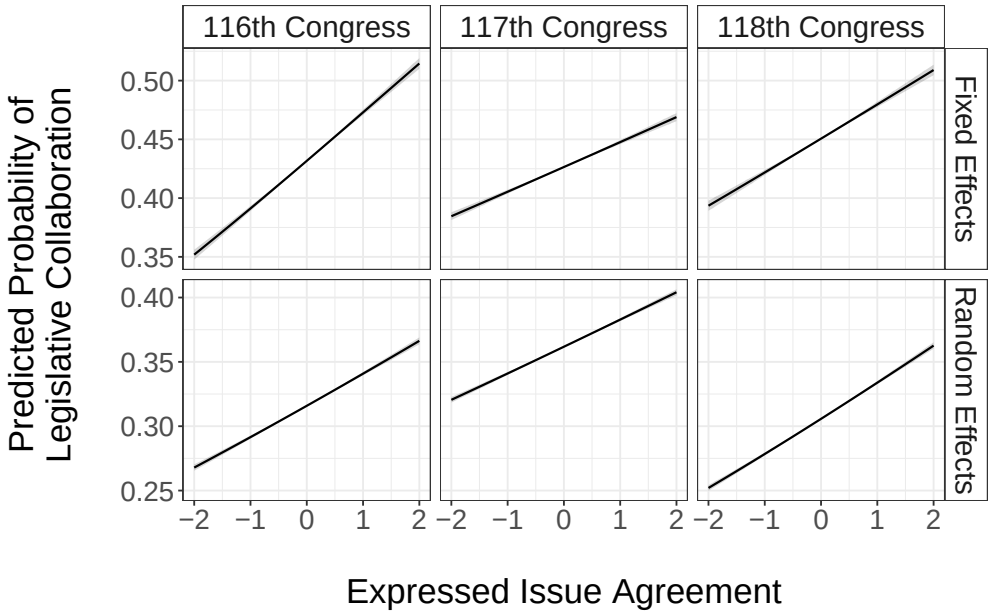
expressed issue agreement to one standard deviation above the mean is associated with a 4.1 percentage-point increase in the predicted probability of collaboration in the 116$^{\text{th}}$ Congress, a 2.1 percentage-point increase in the 117$^{\text{th}}$ Congress, and a 2.9 percentage-point increase in the 118$^{\text{th}}$ Congress. Relative to the predicted probability of collaboration at the mean level of agreement, these changes represent increases of 9.6%, 5.0%, and 6.5%, respectively. We observe similar substantive changes in the random-effects models, where a one-standard-deviation increase in expressed issue agreement is associated with increases in the predicted probability of collaboration of 2.5, 2.1, and 2.8 percentage points, or relative increases of 7.9%, 5.8%, and 9.2%, across the three Congresses. These results demonstrate that, across both modeling approaches, moving from an average level of expressed issue agreement to one standard deviation above the mean is associated with a substantively meaningful increase in the probability of legislative collaboration.

Next, we evaluate whether the relationship between expressed issue agreement and legislative collaboration differs between co-partisan and bipartisan dyads. Table 3 presents results from our fixed- and random-effects models separately for the 116$^{\text{th}}$, 117$^{\text{th}}$, and 118$^{\text{th}}$ Congresses. Across the fixed-effects models, we find consistent support for our second hypothesis: the relationship between expressed issue agreement and legislative collaboration is significantly stronger among bipartisan dyads than co-partisan dyads in all three Congresses. The random-effects models provide similar, although somewhat less consistent, evidence. The interaction between expressed issue agreement and bipartisan status is positive and significant in the 116$^{\text{th}}$ and 118$^{\text{th}}$ Congresses, but is small and not statistically significant in the 117$^{\text{th}}$ Congress.

The inconsistent results from the 117$^{\text{th}}$ Congress can perhaps be explained by the events that unfolded on January 6$^{\text{th}}$, 2021, at the start of the 117$^{\text{th}}$ Congress. As Curry and Roberts (2025) find, several bipartisan relationships were damaged by many Republican members'

predicted probability of collaboration changes across levels of expressed issue agreement within each modeling approach rather than comparing the absolute probability levels across the fixed- and random-effects models. See Appendix D for more details.

Figure 2: Predicted Probability of Legislative Collaboration by Expressed Issue Agreement



Note: Figure plots the predicted probability of legislative collaboration across levels of expressed issue agreement for the 116$^{\text{th}}$ (left column), 117$^{\text{th}}$ (middle column), and 118$^{\text{th}}$ Congresses (right column). Predictions are shown separately for member-dyad fixed-effects (top row) and random-effects models (bottom row). Predicted probabilities are calculated using observed values for all other model components while varying expressed issue agreement from -2 to 2 standard deviations. Shaded regions indicate 95% confidence intervals. Full model results can be found in Table 2.

decision to object to the certification of the 2020 presidential election results. Accordingly, when a bipartisan collaboration might otherwise have been expected due to expressed issue agreement, the events that marked the beginning of the 117$^{\text{th}}$ Congress might explain some of the discrepancies in relationship formation in this particular Congress.

Taken together, these results provide evidence that expressed issue agreement generally exhibits a stronger relationship with legislative collaboration among members from opposing parties, although this pattern does not emerge across every model specification.

Table 3: Expressed Issue Agreement, Bipartisanship, & Legislative Collaboration

	Dependent variable: Legislative Collaboration					
	116^{th} Congress		117^{th} Congress		118^{th} Congress	
Expressed Issue Agreement	0.28^{***}	0.20^{***}	0.21^{***}	0.21^{***}	0.19^{***}	0.24^{***}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Bipartisan Dyad		-1.53^{***}		-1.92^{***}		-1.52^{***}
		(0.04)		(0.04)		(0.04)
Agreement x Bipartisan	0.13^{***}	0.05^{***}	0.06^{***}	-0.02	0.16^{***}	0.05^{***}
	(0.02)	(0.01)	(0.02)	(0.01)	(0.02)	(0.01)
Freshman Dyad		-0.45^{***}		-0.95^{***}		-0.44^{***}
		(0.02)		(0.02)		(0.02)
Ideological Distance		-2.66^{***}		-2.55^{***}		-3.12^{***}
		(0.05)		(0.05)		(0.05)
Shared Committee		0.30^{***}		0.39^{***}		0.30^{***}
		(0.02)		(0.02)		(0.02)
Same Cohort		0.03		-0.11^{***}		0.02
		(0.02)		(0.02)		(0.03)
Same State		1.05^{***}		0.97^{***}		1.06^{***}
		(0.03)		(0.03)		(0.03)
Constant		-0.35^{***}		-0.49^{***}		0.31^{***}
		(0.06)		(0.05)		(0.05)
Observations	252,109	389,497	357,996	463,275	259,640	420,631
Member-Dyad FEs	✓		✓		✓	
Member-Dyad REs		✓		✓		✓
Policy Fixed Effects	✓	✓	✓	✓	✓	✓

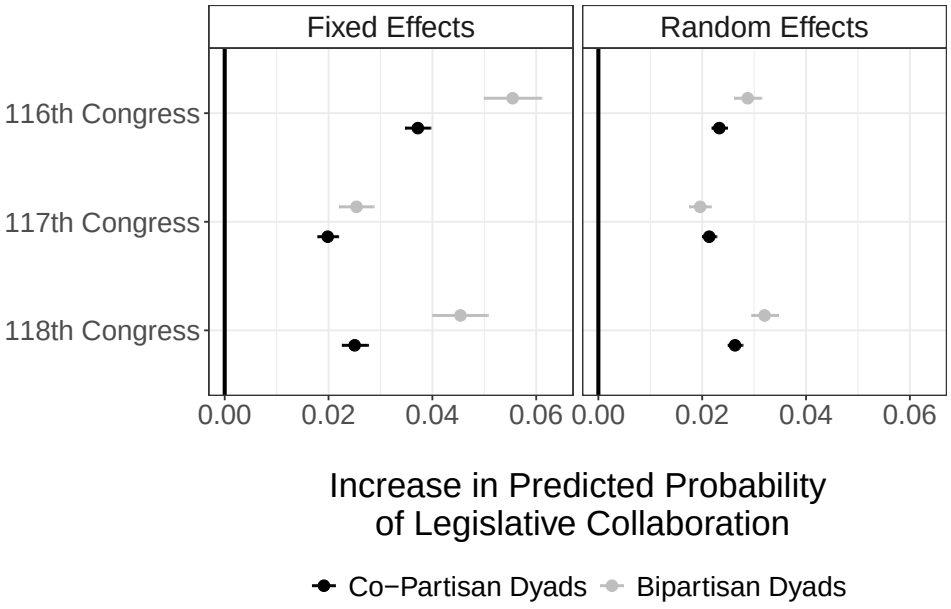
Note: Coefficients are logistic regression coefficients with standard errors in parentheses. Dyad-level characteristics are absorbed by the member-dyad fixed effects and are therefore estimated only in the random-effects models. Standard errors for fixed-effects models are clustered by member-dyad. The fixed-effects models include only member-dyads with within-dyad variation in legislative collaboration, while the random-effects models retain all member-dyads in the analytic sample. Full sample details are found in Appendix D. *p<0.1; **p<0.05; ***p<0.01.

To provide substantive context for this interaction, Figure 3 plots the change in the predicted probability of legislative collaboration associated with a one-standard-deviation increase in expressed issue agreement for co-partisan and bipartisan dyads (0 to 1). Consistent with the interaction results, the fixed-effects models show a larger increase in the probability of collaboration among bipartisan dyads in each Congress. Moreover, the interaction effect is substantively meaningful, as increases in expressed issue agreement are associated with

noticeably larger increases in the probability of legislative collaboration among bipartisan dyads than among partisan dyads.

This difference is most pronounced in the 116th and 118th Congresses. In the 116th Congress, a one-standard-deviation increase in expressed issue agreement is associated with a 5.5 percentage-point increase in the probability of collaboration among bipartisan dyads compared to a 3.7 percentage-point increase among co-partisan dyads. So while expressed issue agreement is associated with higher levels of collaboration for all types of member dyads (Hypothesis 1), we find support for our second hypothesis suggesting that the effect of issue-level agreement is particularly pronounced for bipartisan pairs of members. Relative to the predicted probability of collaboration at the mean level of agreement, these correspond to increases of 12.8% and 8.6%, respectively. Similarly, in the 118th Congress, the corresponding increase is 4.5 percentage points among bipartisan dyads compared to 2.5 percentage points among co-partisan dyads, representing relative increases of 10.1% and 5.5%, respectively. The random-effects models show a similar, though more modest, pattern in the 116th and 118th Congresses, while the estimated changes for co-partisan and bipartisan dyads are nearly identical in the 117th Congress. Taken together, these results provide further evidence that expressed issue agreement is particularly consequential for collaboration across party lines, although the strength of this relationship varies across Congresses and modeling approaches.

Figure 3: Change in Predicted Probability of Legislative Collaboration by Bipartisan Status



Note: Figure plots the change in the predicted probability of legislative collaboration associated with a one-standard-deviation increase in expressed issue agreement for partisan and bipartisan dyads (0 to 1). Results are shown for the 116th, 117th, and 118th Congresses using member-dyad fixed-effects models (left panel) and random-effects models (right panel). We calculate co-partisan and bipartisan effects from the same observed-value baseline within each model. Horizontal lines indicate 95% confidence intervals.

Finally, we evaluate whether the relationship between expressed issue agreement and legislative collaboration is stronger among dyads that include at least one member in her first term (Hypothesis 3). Table 4 provides inconsistent support for our third hypothesis. In the fixed-effects models, the interaction between expressed issue agreement and freshman status is negative and significant in the 116th and 117th Congresses and statistically insignificant in the 118th Congress. The random-effects models produce a different pattern, with a positive and significant interaction in the 116th and 118th Congresses but a negative and significant interaction in the 117th Congress. Taken together, these results do not provide evidence that expressed issue agreement is more strongly associated with collaboration among dyads that include freshman members.

Table 4: Expressed Issue Agreement, Freshman Status, & Legislative Collaboration

	Dependent variable: Legislative Collaboration					
	116^{th} Congress		117^{th} Congress		118^{th} Congress	
Expressed Issue Agreement	0.32^{***}	0.20^{***}	0.25^{***}	0.21^{***}	0.22^{***}	0.24^{***}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Freshman Dyad		-0.45^{***}		-0.96^{***}		-0.44^{***}
		(0.02)		(0.02)		(0.02)
Agreement × Freshman	-0.05^{***}	0.03^{**}	-0.13^{***}	-0.04^{***}	0.00	0.05^{***}
	(0.02)	(0.01)	(0.03)	(0.01)	(0.02)	(0.01)
Bipartisan Dyad		-1.53^{***}		-1.92^{***}		-1.52^{***}
		(0.04)		(0.04)		(0.04)
Ideological Distance		-2.67^{***}		-2.55^{***}		-3.13^{***}
		(0.05)		(0.05)		(0.05)
Shared Committee		0.30^{***}		0.39^{***}		0.30^{***}
		(0.02)		(0.02)		(0.02)
Same Cohort		0.03		-0.11^{***}		0.02
		(0.02)		(0.02)		(0.03)
Same State		1.05^{***}		0.98^{***}		1.06^{***}
		(0.03)		(0.03)		(0.03)
Constant		-0.35^{***}		-0.49^{***}		0.31^{***}
		(0.06)		(0.05)		(0.05)
Observations	252,109	389,497	357,996	463,275	259,640	420,631
Member-Dyad FEs	✓		✓		✓	
Member-Dyad REs		✓		✓		✓
Policy Fixed Effects	✓	✓	✓	✓	✓	✓

Note: Entries are logistic regression coefficients with standard errors in parentheses. Dyad-level characteristics are absorbed by the member-dyad fixed effects and are therefore estimated only in the random-effects models. Standard errors for fixed-effects models are clustered by member-dyad. The fixed-effects models include only member-dyads with within-dyad variation in legislative collaboration, while the random-effects models retain all member-dyads in the analytic sample. Full sample details are found in Appendix D. *p<0.1; **p<0.05; ***p<0.01.

In general, our results demonstrate that expressed issue agreement helps explain when and with whom members of Congress collaborate. Consistent with our first hypothesis, we find that members are more likely to form legislative partnerships on issues where they express similar policy goals and, in support of our second hypothesis, we find that this relationship is particularly pronounced among bipartisan pairs. These results help explain how members who otherwise appear unlikely to work together — including members who

are ideologically distant and disagree on many other policies — can nevertheless identify opportunities for legislative collaboration.

Conclusion

Interpersonal relationships are crucial for congressional action and legislative success. While most scholars point to common traits or shared experiences as the spark that ignites a relationship between two members of Congress, we demonstrate that there exists another key factor that both explains and motivates legislative relationships: policy-level agreement.

With data on members' expressed policy statements, as found on their campaign websites, we create a new measure of policy-level similarity for every possible combination of two members in a given Congress. Using text embeddings, we calculate the level of similarity between two members across 21 policy areas. This measure of similarity allows us to employ a variety of models to evaluate the effect of issue-level similarity on a the propensity of a pair of members to collaborate as original cosponsors on a piece of legislation in that particular policy area. We find support for our theory, suggesting that issue-level agreement adds to the explanation of why a pair of members would collaborate. In general, we find that expressed issue agreement is a positive and statistically significant predictor of legislative collaboration. In other words, pairs of members who express similar policy-level statements are more likely to establish a partnership for the purposes of legislating on that topic.

Additionally, we find support for our expectation that the effect of issue agreement varies based on the partisan composition of the partnership. We find that the effect of expressing a similar policy preference is stronger in predicting bipartisan collaborations than co-partisan collaborations. This suggests that while members of the opposing party likely do not see eye-to-eye on the vast majority of issues facing Congress, they can and do come together to form partnerships for the purpose of co-authoring legislation on a particular issue when they find common ground.

We do not find evidence to suggest that the effect of issue agreement varies based on the freshman status of a pair of members. We anticipated that while members in their first term will have had fewer opportunities to build social connections on Capitol Hill they might be more likely to rely on expressed issue statements to identify potential collaborators. We do not, yet, find evidence of this trend, suggesting that members in their first term face higher hurdles to find collaborators.

While common experiences, including travel, or shared traits, such as a common home state or congressional cohort, do shed light on how many congressional relationships are formed, we add to this story to suggest that these factors are not necessary, nor are they sufficient in explaining why a pair of members might collaborate. If a set of members is to co-author a piece of legislation, this necessarily presumes that these members agree on the policy content of the bill they plan to introduce. We demonstrate that all else equal, members who express similar issue-level preferences are more likely to collaborate as legislative partners. This result sheds light on how and why members identify their collaborators, and even explains many otherwise unexpected bipartisan partnerships.

References

Battaglini, Marco, Valerio Leone Sciabolazza and Eleonora Patacchini. 2020. "Effectiveness of Connected Legislators." *American Journal of Political Science* 64(4):739–756.

Bogue, Allan G. and Mark Paul Marlaire. 1975. "Of Mess and Men: The Boardinghouse and Congressional Voting, 1821-1842." *American Journal of Political Science* 19(2):207–230.

Bratton, Kathleen A. and Stella M. Rouse. 2011. "Networks in the Legislative Arena: How Group Dynamics Affect Cosponsorship." *Legislative Studies Quarterly* 36(3):423–460.

Carlson, David and Jacob M Montgomery. 2017. "A pairwise comparison framework for fast, flexible, and reliable human coding of political texts." *American Political Science Review* 111(4):835–843.

Case, Colin R., Emily Cottle Ommundsen and Rachel Porter. N.d. "Bipartisan Campaign Messages are Credible Policymaking Signals." Working Paper.

Case, Colin R. and Rachel Porter. 2026. "Strategic Heterogeneity in Issue Positioning:Evidence from Congressional Campaigns.".
URL: *https://doi.org/10.31219/osf.io/zhrmv*$_v$5

Cohen, Lauren and Christopher J. Malloy. 2014. "Friends in High Places." *American Economic Journal: Economic Policy* 6(3):63–91.

Craig, Alison W. 2023. *The Collaborative Congress: Reaching Common Ground in a Polarized House*. Cambridge University Press.

Curry, James M. and Jason M. Roberts. 2023. "Inter-Personal Relationships and Legislative Collaboration in Congress." *Legislative Studies Quarterly* 48(2):333–369.

Curry, James M. and Jason M. Roberts. 2025. "Interpersonal Relationships, Bipartisanship, and January 6th." *American Political Science Review* 119(3):1542–1548.

Druckman, James N., Martin J. Kifer and Michael Parkin. 2009. "Campaign Communications in U.S. Congressional Elections." *American Political Science Review* 103(3):343–366.

Harbridge-Yong, Laurel, Craig Volden and Alan E. Wiseman. 2023. "The Bipartisan Path to Effective Lawmaking." *The Journal of Politics* 85(3):1048–1063.

Herrnson, Paul S. 2015. *Congressional Elections: Campaigning at Home and in Washington*. CQ Press.

Lin, Gechun. 2025. "Using cross-encoders to measure the similarity of short texts in political science." *American Jounral of Political Science* 69(4):1600–1616.

Neelakantan, Arvind, Tao Xu, Raul Puri, Alec Radford, Jesse Michael Han, Jerry Tworek, Qiming Yuan, Nikolas Tezak, Jong Wook Kim, Chris Hallacy, Johannes Heidecke, Pranav Shyam, Boris Power, Tyna Eloundou Nekoul, Girish Sastry, Gretchen Krueger, David

Schnurr, Felipe Petroski Such, Kenny Hsu, Madeleine Thompson, Tabarak Khan, Toki Sherbakov, Joanne Jang, Peter Welinder and Lilian Weng. 2022. "Text and Code Embeddings by Contrastive Pre-Training." *arXiv* .

Ommundsen, Emily Cottle. 2027. "Social Capital on Capitol Hill: Congressional Staff and Legislative Networks". In *New Directions in Congressional Politics*, ed. Jamie L. Carson and Michael S. Lynch. 3 ed. Routledge.

Park, Ju Yeon and Jacob M Montgomery. 2025. "Toward a framework for creating trustworthy measures with supervised machine learning for text." *Political Science Research and Methods* pp. 1–17.

Porter, Rachel, Colin R Case and Sarah A Treul. 2025. "CampaignView, a database of policy platforms and biographical narratives for congressional candidates." *Scientific data* 12(1):1237.

Porter, Rachel, Jeffrey J. Harden and Mackenzie R. Dobson. 2025. "Electing amateur politicians reduces cross-party collaboration." *Proceedings of the National Academy of Sciences* 122(41).

Sachleben, Audrey and Sarah A. Treul. 2026. "Issue Attention in Congressional Primary Elections." Working paper.

Sulkin, Tracy. 2009. "Campaign Appeals and Legislative Action." *Journal of Politics* 71(3):1093–1108.

Sulkin, Tracy. 2011. *The Legislative Legacy of Congressional Campaigns*. Cambridge University Press.

Yoshinaka, Antoine and Christian R Grose. 2011. "Ideological hedging in uncertain times: Inconsistent legislative representation and voter enfranchisement." *British Journal of Political Science* 41(4):765–794.

Young, James Sterling. 1966. *The Washington Community, 1800–1828*. Columbia University Press.

Predicting Partnerships: Congressional Issue Agreement and Legislative Collaboration

Supporting Information

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A Supervised Machine Learning Pipeline

A.1 Hand Labeling Process

To train our supervised classifiers, we first constructed a hand-labeled set of campaign website paragraphs using the Congressional Research Service's policy area framework. A graduate research assistant labeled 7,750 campaign paragraphs using the CRS policy area codebook provided at `https://www.congress.gov/help/field-values/policy-area`. These labels covered all 32 policy areas used by CRS.

Applying the CRS framework to campaign text required judgment in some cases, as the descriptions in the CRS codebook do not always map cleanly onto how candidates discuss policy on their websites, or are not specific enough to make a determination. When the appropriate policy area was not clear from the codebook alone, we identified substantively similar legislation on Congress.gov and used the policy area assigned to that legislation to resolve the ambiguity. This procedure allowed us to align our labeling decisions with how the CRS framework is applied in practice. It also ensured that our labeled categories correspond with legislation, which is our ultimate goal with this classification.

Although we labeled paragraphs across the full set of 32 CRS policy areas, not all categories appeared frequently enough in campaign text to support downstream classification. After hand labeling, we therefore dropped policy areas that appeared in fewer than 1% of campaign statement paragraphs.[1] We retained the remaining policy areas for the supervised machine learning pipeline.

A.2 Supervised Machine Learning Classification

We next used the hand-labeled paragraphs to train a supervised machine learning classifier for each of the twenty-one CRS policy areas. For every policy area, we estimated a separate binary classifier in which the outcome indicated whether a paragraph belonged to that topic. This approach allowed a paragraph to be evaluated independently for each policy area rather than a single multiclass assignment.

Before model fitting, we pre-processed paragraph text by converting all characters to lowercase, removing punctuation, and removing English stop words. We then transformed the text into a term frequency–inverse document frequency (tf-idf) matrix, which served as the feature input for all supervised models.

We split our labeled data into 7,000 observations for model training and 750 observations for held-out validation after the training process. Using the training data, we fit and tuned a common set of classifiers for each policy area. Specifically, for every topic, we estimated support vector machine, decision tree, random forest, gradient boosting, lasso logistic regression, ridge logistic regression, and XGBoost models. We selected hyperparameters through five-fold cross-validation on the training data. Table A1 reports the full set of tuning parameters considered in the grid search.

After selecting the best-performing specification for each model, we re-fit the tuned classifier on the full training set and generated predictions for the training data, the held-out test

[1] Animals, Arts, Congress, Emergency, Finance, Law, Native Americans, Public Lands, Social Studies and History, Sports, and Water.

Table A1: Model Tuning Parameters

Model	Tuning Parameter	Values
Support Vector Machine	Regularization	0.1, 1, 10, 100
	Gamma	1, 0.1, 0.01, 0.001
	Kernel	linear, rbf
Decision Tree	Max Depth	None, 10, 20, 30
	Min Samples Split	2, 5, 10, 20
	Min Samples Leaf	1, 2, 4, 8
Random Forest	Number of Estimators	50, 100, 200, 300
	Max Depth	None, 10, 20, 30
	Min Samples Split	2, 5, 10, 20
Gradient Boosting	Number of Estimators	50, 100, 200
	Learning Rate	0.01, 0.1, 0.2
	Max Depth	3, 5, 7
Lasso Logistic Regression	Regularization	0.01, 0.1, 1, 10, 100
Ridge Logistic Regression	Regularization	0.01, 0.1, 1, 10, 100
XGBoost	Number of Estimators	50, 100, 200
	Learning Rate	0.01, 0.1, 0.2
	Max Depth	3, 5, 7
	Scale Position Weight	1, 2, 5

set, and the full set of unlabeled campaign paragraphs. We also constructed a stacking classifier for each policy area. The stacking model used the tuned base classifiers as component learners and a logistic regression model as the final estimator. This procedure allowed us to compare the performance of individual algorithms to an ensemble approach that combines information across models.

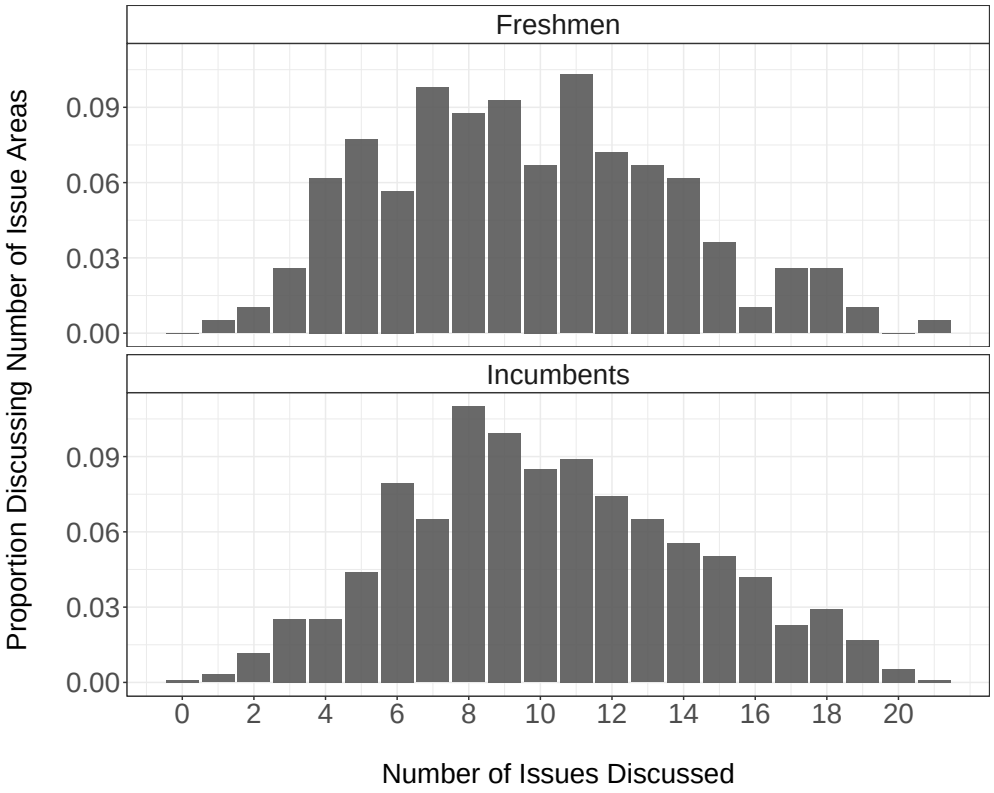
A.3 Issue Classification Validation

We validate our supervised classification approach using the held-out test set, which was not used at any stage of model tuning (Park and Montgomery 2025). For each retained policy area, we compared the out-of-sample performance of all candidate classifiers and selected the final model based on its held-out F1 score. Validation results indicate that the classifiers perform well overall on unseen campaign text. Across the 21 retained policy areas, held-out accuracy averages 0.985 and ranges from 0.961 to 0.997, while F1 scores average 0.814 and range from 0.714 to 0.961. No single model dominated across all policy areas. Ridge logistic regression produced the best held-out performance for seven policy areas, stacking for six, support vector machines for three, XGBoost for two, and gradient boosting, lasso, and random forest for one policy area each. We report policy-specific held-out accuracy, precision, recall, and F1 scores for the selected model in Table A2.

Table A2: Held-Out Validation Performance for Final Policy Area Classifiers

Policy Area	Final Model	Accuracy	Precision	Recall	F1 Score
Agriculture and Food	SVM	0.989	0.857	0.667	0.750
Armed Forces & National Security	Ridge	0.983	0.889	0.903	0.896
Civil Rights & Liberties	Ridge	0.961	0.821	0.867	0.843
Commerce	SVM	0.989	1.000	0.579	0.733
Crime & Law Enforcement	Ridge	0.975	0.781	0.676	0.725
Economics & Public Finance	Ridge	0.975	0.702	0.868	0.776
Education	Ridge	0.980	0.875	0.933	0.903
Energy	SVM	0.989	0.875	0.875	0.875
Environmental Protection	XGBoost	0.987	0.826	0.760	0.792
Families	Stacking	0.993	0.875	0.636	0.737
Foreign Trade	Gradient Boosting	0.995	1.000	0.556	0.714
Government Operations and Politics	Stacking	0.989	0.813	0.722	0.765
Health	Stacking	0.963	0.916	0.858	0.886
Housing & Community Development	Stacking	0.997	1.000	0.818	0.900
Immigration	Stacking	0.995	1.000	0.925	0.961
International Affairs	Lasso	0.981	0.815	0.710	0.759
Labor & Employment	Random Forest	0.973	0.718	0.757	0.737
Science, Technology, Communications	XGBoost	0.995	1.000	0.667	0.800
Social Welfare	Ridge	0.991	0.889	0.762	0.821
Taxation	Ridge	0.992	0.810	0.895	0.850
Transportation & Public Works	Stacking	0.993	1.000	0.783	0.878

Figure A1: Number of Issue Areas Discussed by Incumbency Status



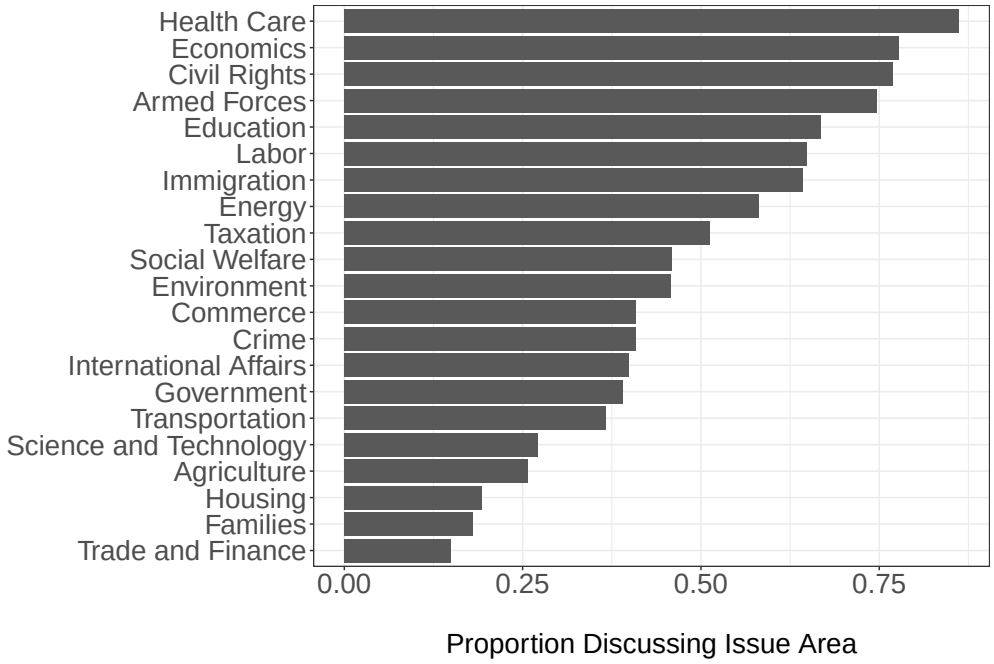
Note: Figure plots the proportion of incoming freshmen members (top facet) and incumbent members (bottom facet) by the number of issue areas they discuss on their campaign websites, ranging from 0 to 21. Members without a website or without an issue page are excluded.

A.4 Policy Discussion Descriptive Statistics

Overall, members vary considerably in the breadth of policy discussion on their campaign websites. Across the 21 policy areas included in our analysis, members discuss an average of 10.1 issues, or 48.1% of the possible categories, with an inter-quartile range of seven to 13. Nearly all members discuss multiple policy areas: more than 93% discuss at least five, and 16% discuss 15 or more. Figure A1 shows the distribution of the number of policy areas discussed, separately for freshmen and returning incumbents. The two groups look quite similar. Freshmen discuss an average of 9.62 policy areas, compared with 10.3 policy areas for returning members, suggesting that incoming legislators enter office with broadly comparable levels of issue breadth in their campaign communications, regardless of whether it was their first campaign or not.

Beyond the number of policy areas a candidate mentions, candidates also vary substantially in which policy areas they choose to discuss. Figure A2 plots the proportion of incoming members discussing each of the 21 retained CRS policy areas, excluding those without issue pages on their campaign websites. Some policy areas appear on a large majority of websites; Health Care (86%), Economics and Public Finance (78%), Civil Rights and Liberties (77%), and Armed Forces and National Security (75%) are each discussed by more than 70% of incoming members. Other topics are much less common; fewer than 30% of members discuss

Figure A2: Proportion of Incoming Members Discussing Each Policy Category

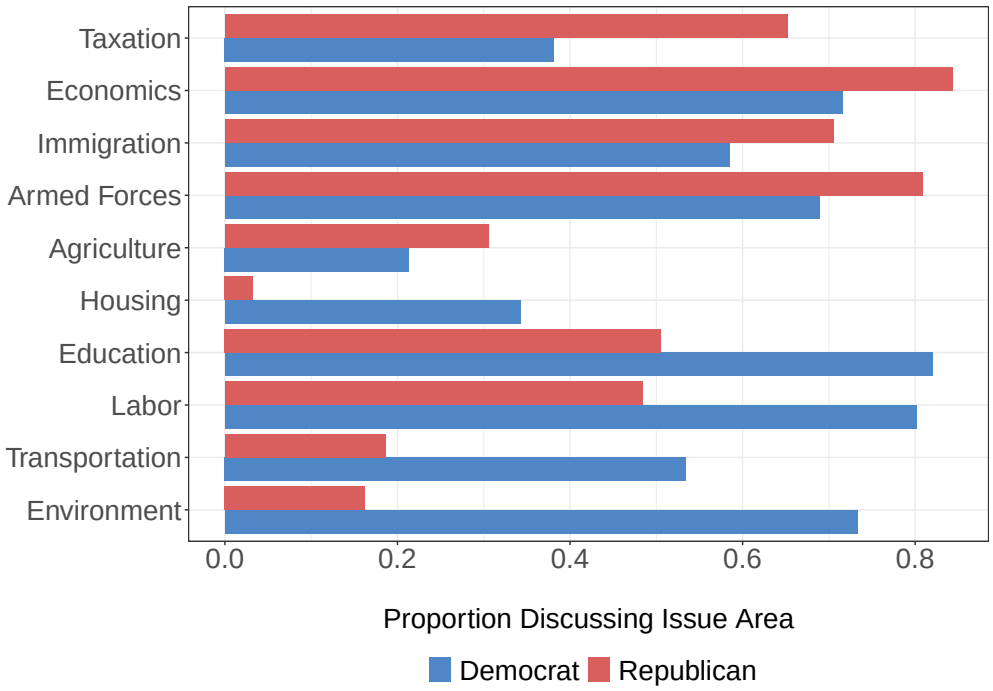


Note: Figure plots the proportion of incoming members with campaign website issue pages who discuss each of the 21 retained CRS policy areas.

Science and Technology (27%), Agriculture and Food (26%), Housing (19%), Families (18%), and Trade and Finance (15%). This uneven distribution reinforces the value of our issue-specific measurement: opportunities for expressed agreement are not equally likely across policy areas because members are not equally likely to articulate positions on every issue.

Discussion of policy areas is also strongly structured by party. Figure A3 plots the five issues with the largest Democratic advantage and the five with the largest Republican advantage in the share of candidates discussing the issue. Consistent with prior research on party-issue ownership in campaigns (e.g., Sachleben and Treul 2026), Republicans are more likely than Democrats to discuss Taxation (difference = 0.27), Economics and Public Finance (0.13), Immigration (0.12), Armed Forces and National Security (0.12), and Agriculture and Food (0.09). Democrats, by contrast, are substantially more likely to discuss Environmental Protection (difference = 0.57), Transportation and Public Works (0.35), Labor and Employment (0.32), Education (0.31), and Housing and Community Development (0.31). These patterns are broadly consistent with the issue emphases identified in CampaignView and in recent work on party-issue ownership in congressional campaigns. More importantly for our purposes, they show that expressed agreement is conditioned not only by how similarly two members talk about an issue, but also by whether members of each party choose to discuss that issue at all.

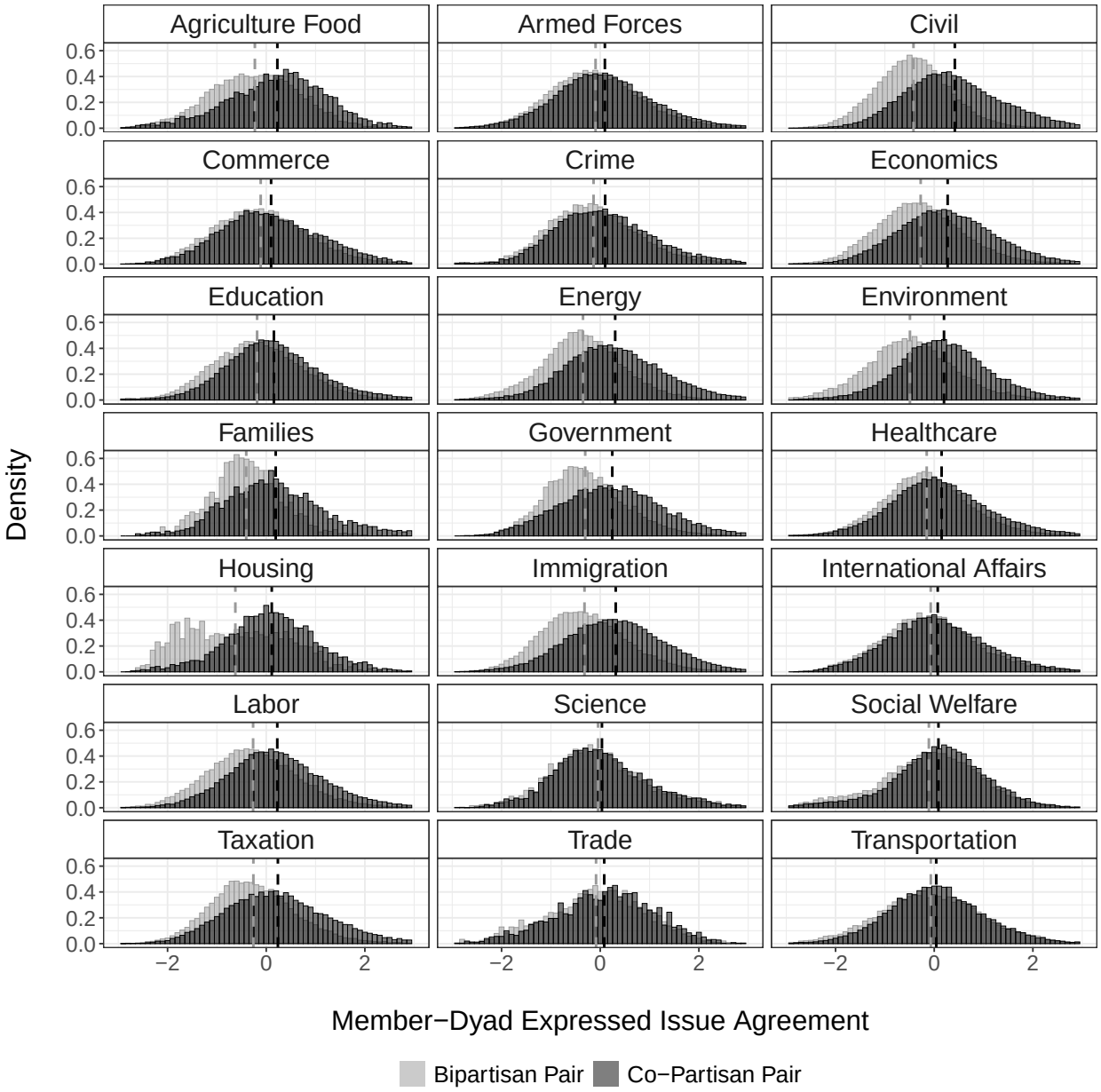
Figure A3: Proportion of Incoming Members Discussing Policy Areas, by Party



Note: Figure plots the five policy areas with the largest Democratic advantage and the five with the largest Republican advantage in the proportion of incoming members discussing the issue on their campaign websites.

B Similarity Measurement Distribution by Policy Area

Figure A4: Distribution of Member-Dyad Overall Similarity Scores



Note: Figure plots the distribution of member-dyad similarity separately for bipartisan and partisan pairs. Histograms are scaled to density within each panel, with a mean similarity score of zero and a standard deviation of one. Vertical dashed lines indicate the mean similarity for bipartisan and co-partisan pairs, respectively.

C Similarity Measurement Validation

To validate our measure of expressed issue agreement, we use a paired-comparison task. For each task, a graduate research assistant reads three campaign website statements from the same policy area: one reference statement and two comparison statements. The coder selects which comparison statement expresses a policy position that is more similar to the position expressed in the reference statement. Pairwise comparisons reduce the demands placed on coders by replacing an absolute rating with a relative judgment, which can improve consistency and produce more reliable hand-labeled data (Carlson and Montgomery 2017). We instruct coders to focus on substantive policy outcomes, government actions, and policy goals rather than shared words, writing style, general ideology, or discussion of the same topic. Because all three statements address the same policy area, the task evaluates whether our measure distinguishes between the substantive positions members express within an issue.

We compare these human judgments with the rankings produced by our similarity measure. We first calculate the percentage of comparisons in which the statement with the higher similarity score is also the statement selected by the human coder. We then use the actual similarity scores to evaluate whether a coder becomes more likely to select a statement as its measured similarity relative to the other comparison statement increases. The first analysis evaluates whether our measure produces the same relative ranking as the human coders. The second evaluates whether the magnitude of the difference between the two similarity scores provides additional information about the human choice. We describe the validation sample, coding procedure and results in the following subsections.

C.1 Validation Sample and Coding Procedure

To construct the validation sample, we begin with the set of unique member-policy-year observations represented in our dyadic data. We randomly sample 500 of these observations to serve as reference statements. For each reference statement, we identify all other members who discussed the same policy area during the same election year. We then randomly select two distinct members from this pool to provide the two comparison statements. For each member included in a task, we collect all campaign website paragraphs classified into the relevant policy area and combine them into a single issue statement. The coder therefore evaluates the full set of campaign website text used to characterize each member's expressed position within that policy area. Below provides our full coding instructions for this validation task.

This coding task evaluates whether the measure of **expressed issue agreement** accurately captures similarities in the substantive policy positions expressed by members of Congress. You will engage in a **paired comparison** where you determine which of two comparison statements expresses a policy position more similar to a reference statement. The focus of this task is on **substantive policy agreement**, not similarity in wording, writing style, general ideology, or simply discussing the same topic.

Expressed issue agreement is the extent to which two statements communicate compatible substantive policy positions within the same policy area. Statements exhibit greater expressed issue agreement when the speakers:

- Want similar policy outcomes.
- Support or oppose similar government actions or policy changes.
- Express compatible substantive policy goals.
- To a lesser extent, identify similar policy problems that should be addressed.

Agreement does not require identical wording or identical proposals. Two statements can use very different language but exhibit high agreement if they advocate similar policy outcomes. Likewise, two statements can discuss exactly the same topic but exhibit low agreement if they advocate conflicting outcomes.

Example: Same Topic, Disagreement
Statement A: "Congress should increase funding for additional Border Patrol agents."
Statement B: "Congress should reduce funding for immigration enforcement and redirect those resources toward processing asylum claims."

Both statements concern immigration enforcement, but they advocate conflicting government actions. They therefore exhibit **low expressed issue agreement**.

Example: Different Wording, High Agreement
Statement A: "Medicare should be allowed to negotiate directly with pharmaceutical companies to reduce prescription drug prices."
Statement B: "We can lower the cost of medicine by giving Medicare the authority to negotiate drug prices."

These statements use different wording but advocate essentially the same policy. They therefore exhibit **very high expressed issue agreement**.

General Decision Rules:

Focus on substantive policy content. Consider what policymakers should do, what outcomes they want government to pursue, and what policies they support or oppose.

Consider the direction of the position. Pay particular attention to whether a speaker wants to expand, reduce, eliminate, prohibit, protect, increase, decrease, require, permit, fund, or defund something.

Consider the entire statement. Longer statements may contain several relevant policy positions. Do not base your judgment only on one matching or conflicting sentence if additional relevant information appears elsewhere in the text. Repeated agreement or disagreement across multiple substantive parts of the statements should receive greater weight.

At the same time, **do not mechanically count matching positions**. Consider both how much of the substantive content agrees and how important those areas of agreement or disagreement are. Longer statements should not automatically receive higher agreement simply because they contain more individual policy claims.

Distinguish goals from policy mechanisms. Two statements may agree on a broad goal while proposing different ways to achieve it. This represents some agreement, but usually less than when both statements endorse the same policy response. If the proposed approaches could reasonably be pursued together, they indicate more agreement than approaches that conflict with one another.

Do not infer positions that are not expressed. A statement identifying a problem does not necessarily endorse a particular solution. For example:

Statement A: "The high cost of prescription drugs is hurting families across the country."
Statement B: "Congress should allow Medicare to negotiate prescription drug prices."

The statements share a concern about prescription drug costs, but Statement A does not tell us whether the speaker supports Medicare negotiation. They therefore exhibit less agreement than two statements that both explicitly endorse Medicare negotiation.

Do Not Base Your Coding On:

- Shared words or phrases.
- Similar writing style or tone.
- Simply discussing the same broad issue or subissue.
- General liberal, conservative, Democratic, or Republican positions.
- Praise or criticism of the same politician, party, or political group.
- Outside knowledge about the politicians making the statements.

Code only the policy content contained in the statements you are shown.
In the coding task, you will see:

1. **Reference Statement**
2. **Comparison Statement 1**
3. **Comparison Statement 2**

Determine which comparison statement expresses a policy position that is **more similar to the policy position expressed in the reference statement**.
Compare each statement with the reference based on:

- Desired policy outcomes.
- Supported or opposed government actions.
- Substantive policy goals.
- Compatibility of the positions expressed throughout the statements.

Report:

1 — Comparison Statement 1 is more similar
2 — Comparison Statement 2 is more similar

Some comparisons will be difficult. In these cases, make your best judgment using the criteria above. Select the statement that exhibits greater substantive policy agreement with the reference even when the difference is relatively small.

C.2 Validation Results

We first calculate the percentage of comparisons in which the statement receiving the higher similarity score is also selected by the coder. Across the 500 paired-comparison tasks, the similarity measure and the human coder produce the same ranking in 72.4% of the comparisons. This rate is substantially greater than the 50% agreement expected by chance. We also calculate agreement among tasks in which the reference member and both comparison members are co-partisans. The similarity measure and the human coder produce the same ranking in 71.3% of these comparisons. The similar rates indicate that the overall correspondence is not driven by comparisons between members of different parties.

We next evaluate whether the difference between the two similarity scores predicts which comparison statement the coder selects. The dependent variable equals one when the coder selects Comparison Statement 1 and zero when the coder selects Comparison Statement 2. We subtract the similarity score for Comparison Statement 2 from the similarity score for Comparison Statement 1. Positive values therefore indicate that the similarity measure ranks Comparison Statement 1 as more similar to the reference statement, while negative values indicate that it ranks Comparison Statement 2 as more similar.

The difference between the two similarity scores strongly predicts the coder's selection. The coefficient on the similarity difference is positive and statistically significant ($\beta = 1.33$, $SE = 0.13$, $p < 0.001$). Together, these results show that the similarity measure frequently produces the same ranking as the human coder and that the coder becomes increasingly likely to select a statement as its measured similarity difference grows.

D Model Sample Information

Our main analyses evaluate whether pairs of members are more likely to collaborate on issues where their publicly expressed policy positions are more similar. Because expressed issue agreement can be measured only when both members articulate positions within the same policy area, these analyses necessarily focus on member-dyad-issue observations characterized by shared issue attention. This appendix describes how this requirement, along with CampaignView coverage and the requirements of fixed-effects estimation, determines the samples used in the main text. We then estimate a supplementary set of models that includes policy areas discussed by only one or neither member. These models allow us to evaluate whether our results depend on using only jointly discussed issues to estimate the broader structure of legislative collaboration.

For each Congress, we begin with the 435 House members elected at its start and the twenty-one policy areas included in our analysis. Pairing each member with every other member once produces 94,395 unique member-dyads. Observing each dyad across all twenty-one policy areas yields 1,982,295 potential member-dyad-issue observations in each Congress. Table **??** presents the sequential construction of the estimation samples from this full set of potential observations.

We first require CampaignView issue-page data for both members in a dyad. These data are available for 369 members elected to the 116$^{\text{th}}$ Congress, 393 elected to the 117$^{\text{th}}$ Congress, and 384 elected to the 118$^{\text{th}}$ Congress. This requirement removes all observations associated with dyads in which one or both members lack issue-page data. Among the remaining dyads, we retain policy areas in which both members articulate positions. Expressed issue agreement cannot be measured when only one or neither member discusses the issue because there are not two expressed positions to compare. Excluding these observations therefore avoids treating the absence of a campaign statement as evidence of either agreement or disagreement.

These restrictions leave 389,497 member-dyad-issue observations in the 116$^{\text{th}}$ Congress, 463,275 in the 117$^{\text{th}}$ Congress, and 420,631 in the 118$^{\text{th}}$ Congress. These observations constitute the samples available to the random-effects models, which retain dyads regardless of whether they exhibit within-dyad variation in legislative collaboration.

The member-dyad fixed-effects models impose an additional requirement. Legislative collaboration must vary across the retained policy areas for a given dyad. Dyads that collaborate on none or all of the issues both members discuss are perfectly predicted by the member-dyad fixed effect and therefore do not contribute to estimation of the remaining coefficients. This restriction also excludes dyads observed in only one jointly discussed policy area because the outcome cannot vary within the dyad. It removes 137,388 observations in the 116$^{\text{th}}$ Congress, 105,279 in the 117$^{\text{th}}$ Congress, and 160,991 in the 118$^{\text{th}}$ Congress. The resulting fixed-effects samples contain 252,109, 357,996, and 259,640 observations, respectively.

These samples allow us to evaluate whether expressed agreement distinguishes collaboration among pairs that have already demonstrated shared attention to an issue. This restriction follows directly from our measurement strategy: agreement between two expressed positions is defined only when both positions are observed. It also means, however, that the member-dyad and policy-area effects in the main models are estimated using a particular

Table A3: Construction of the Legislative Collaboration Estimation Samples

Congress	116th	117th	118th
Full potential sample	1,982,295	1,982,295	1,982,295
Excluded: one member lacks issue pages	-556,479	-364,707	-438,039
Excluded: only one member discusses the issue	-578,190	-672,026	-644,012
Excluded: neither member discusses the issue	-458,129	-482,287	-479,613
Random-effects sample	**389,497**	**463,275**	**420,631**
Share of full potential sample	19.6%	23.4%	21.2%
Excluded (FE Only): no within-dyad outcome variation	-137,388	-105,279	-160,991
Fixed-effects sample	**252,109**	**357,996**	**259,640**
Share of full potential sample	12.7%	18.1%	13.1%

Note: The random-effects sample includes all member-dyad-issue observations for which both members have CampaignView issue-page data and discuss the same policy area. The fixed-effects sample further excludes dyads without within-dyad variation in legislative collaboration across the retained policy areas.

subset of potential collaboration opportunities. As Table 1 demonstrates, pairs are more likely to collaborate on issues that both members discuss than on issues discussed by only one or neither member. We therefore conduct an additional analysis to determine whether restricting the estimation sample to jointly discussed issues drives our substantive conclusions.

For this supplementary analysis, we return to the full set of policy areas for member-dyads in which both members have CampaignView issue-page data. The expanded data therefore include policy areas discussed by both members, only one member, or neither member. Before fixed effect exclusions, this produces 1,425,816 member-dyad-issue observations in the 116$^{\text{th}}$ Congress, 1,617,588 in the 117$^{\text{th}}$ Congress, and 1,544,256 in the 118$^{\text{th}}$ Congress. Including these observations allows policy areas without shared issue attention to contribute to the estimation of members' general propensity to collaborate, differences across policy areas, and the relationship between campaign issue discussion and legislative collaboration.

Expressed issue agreement remains unobserved when fewer than two members discuss an issue. To retain these observations, we assign expressed issue agreement a value of zero when only one or neither member discusses the issue. We preserve the issue-specific standardization used in the main analysis and do not recalculate the mean or standard deviation after adding these observations. Among observations for which agreement is measured, zero therefore continues to represent the average level of expressed agreement within that policy area, and a one-unit increase represents a one-standard-deviation increase in observed agreement. For the added observations, however, zero serves only as a common reference value that permits their inclusion in the model. It does not indicate that the members hold average positions or that they agree with one another.

We also include campaign issue discussion as a categorical predictor distinguishing whether neither member, one member, or both members discuss the policy area. These indicators allow the baseline likelihood of collaboration to differ across the three levels of issue discussion. Thus, assigning agreement a value of zero does not require observations without shared issue discussion to have the same expected probability of collaboration as observations with

an average level of measured agreement. At the same time, the coding necessarily treats all observations without two expressed positions as equivalent along the agreement dimension. The model cannot recover variation in underlying agreement when that agreement is not expressed by both members.

Because expressed issue agreement equals zero whenever fewer than two members discuss the issue, those observations do not directly identify the agreement coefficient after controlling for whether neither or one member discussed the issue. The coefficient continues to be estimated from variation in observed agreement among policy areas that both members discuss. The expanded observations can nevertheless affect this estimate by contributing to the member-dyad effects, policy-area effects, discussion-status coefficients, and other model components. The supplementary analysis therefore evaluates whether the relationship observed in the main text persists when the remaining policy areas are allowed to inform the broader model of legislative collaboration.

We follow the same sequence of models used in the main text. The first specification estimates the overall relationship between expressed issue agreement and legislative collaboration while accounting for whether neither member, one member, or both members discuss the issue. The second interacts expressed issue agreement with bipartisan status, and the third interacts expressed issue agreement with freshman status. In the latter two specifications, we also interact campaign issue discussion with the corresponding dyad characteristic.

These additional interactions are important because the relationship between shared issue attention and collaboration may differ across the types of dyads represented in our hypotheses. Without them, the model would require the difference in collaboration across levels of campaign issue discussion to be the same for co-partisan and bipartisan dyads, or for returning-member and freshman dyads. Because expressed issue agreement varies only when both members discuss the issue, imposing this restriction could require the agreement interaction to account for differences associated with both agreement and the broader relationship between issue discussion and collaboration. Allowing campaign issue discussion to vary by dyad type accounts for these group-specific differences in shared issue attention. The interaction between expressed issue agreement and the relevant dyad characteristic can therefore more directly capture whether the relationship between observed agreement and collaboration differs within the set of policy areas both members discuss. Results for our baseline models, bipartisan interaction models, and freshman interaction models are presented in the following tables. Across models, the full sample models are largely consistent with the results in the body of the paper.

Table A4: Expressed Issue Agreement, Campaign Issue Discussion, & Legislative Collaboration: Full Sample

	Dependent variable: Legislative Collaboration					
	116^{th} Congress		117^{th} Congress		118^{th} Congress	
Expressed Issue Agreement	0.22^{***}	0.20^{***}	0.17^{***}	0.18^{***}	0.18^{***}	0.21^{***}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
One Member Discusses	-0.34^{***}	-0.33^{***}	-0.20^{***}	-0.23^{***}	-0.36^{***}	-0.37^{***}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Neither Member Discusses	-0.61^{***}	-0.63^{***}	-0.37^{***}	-0.44^{***}	-0.59^{***}	-0.63^{***}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Bipartisan Dyad		-1.61^{***}		-2.01^{***}		-1.60^{***}
		(0.03)		(0.03)		(0.03)
Freshman Dyad		-0.48^{***}		-0.68^{***}		-0.50^{***}
		(0.01)		(0.01)		(0.01)
Ideological Distance		-2.46^{***}		-2.51^{***}		-3.13^{***}
		(0.04)		(0.03)		(0.04)
Shared Committee		0.33^{***}		0.38^{***}		0.30^{***}
		(0.02)		(0.01)		(0.01)
Same Cohort		-0.03		-0.05^{***}		0.03
		(0.02)		(0.02)		(0.02)
Same State		1.18^{***}		1.02^{***}		1.21^{***}
		(0.03)		(0.02)		(0.02)
Constant		-0.71^{***}		-0.59^{***}		0.29^{***}
		(0.02)		(0.02)		(0.02)
Observations	1,144,563	1,425,816	1,434,783	1,617,588	1,148,238	1,544,256
Member-Dyad FEs	✓		✓		✓	
Member-Dyad REs		✓		✓		✓
Policy Fixed Effects	✓	✓	✓	✓	✓	✓

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

Table A5: Expressed Issue Agreement, Bipartisanship, & Legislative Collaboration: Full Sample

	Dependent variable: Legislative Collaboration					
	116^{th} Congress		117^{th} Congress		118^{th} Congress	
Expressed Issue Agreement	0.20^{***}	0.19^{***}	0.19^{***}	0.20^{***}	0.18^{***}	0.20^{***}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Bipartisan Dyad		-1.62^{***}		-1.80^{***}		-1.43^{***}
		(0.03)		(0.03)		(0.03)
Agreement × Bipartisan	0.07^{***}	0.03^{***}	0.01	-0.03^{***}	0.07^{***}	0.04^{***}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.01)
One Member Discusses	-0.34^{***}	-0.32^{***}	-0.10^{***}	-0.15^{***}	-0.29^{***}	-0.32^{***}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Neither Member Discusses	-0.62^{***}	-0.65^{***}	-0.25^{***}	-0.36^{***}	-0.50^{***}	-0.57^{***}
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
One Discusses × Bipartisan	−0.02	-0.03^{*}	-0.43^{***}	-0.31^{***}	-0.38^{***}	-0.27^{***}
	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)
Neither Discusses × Bipartisan	0.02	0.09^{***}	-0.57^{***}	-0.37^{***}	-0.56^{***}	-0.36^{***}
	(0.02)	(0.02)	(0.02)	(0.02)	(0.03)	(0.02)
Freshman Dyad		-0.48^{***}		-0.68^{***}		-0.50^{***}
		(0.01)		(0.01)		(0.01)
Ideological Distance		-2.46^{***}		-2.50^{***}		-3.12^{***}
		(0.04)		(0.03)		(0.04)
Shared Committee		0.33^{***}		0.38^{***}		0.30^{***}
		(0.02)		(0.01)		(0.01)
Same Cohort		−0.03		-0.05^{***}		0.03
		(0.02)		(0.02)		(0.02)
Same State		1.18^{***}		1.02^{***}		1.21^{***}
		(0.03)		(0.02)		(0.02)
Constant		-0.71^{***}		-0.67^{***}		0.24^{***}
		(0.02)		(0.02)		(0.02)
Observations	1,144,563	1,425,816	1,434,783	1,617,588	1,148,238	1,544,256
Member-Dyad FEs	✓		✓		✓	
Member-Dyad REs		✓		✓		✓
Policy Fixed Effects	✓	✓	✓	✓	✓	✓

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

Table A6: Expressed Issue Agreement, Freshman Status & Legislative Collaboration: Full Sample

	Dependent variable: Legislative Collaboration					
	116^{th} Congress		117^{th} Congress		118^{th} Congress	
Expressed Issue Agreement	0.20***	0.18***	0.17***	0.18***	0.17***	0.19***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Freshman Dyad		−0.42***		−0.90***		−0.42***
		(0.01)		(0.02)		(0.02)
Agreement × Freshman	0.04***	0.05***	−0.06***	−0.03***	0.04***	0.06***
	(0.01)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)
One Member Discusses	−0.32***	−0.32***	−0.26***	−0.29***	−0.33***	−0.35***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
Neither Member Discusses	−0.52***	−0.55***	−0.47***	−0.53***	−0.53***	−0.59***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
One Discusses × Freshman	−0.05***	−0.02*	0.34***	0.27***	−0.11***	−0.10***
	(0.01)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
Neither Discusses × Freshman	−0.25***	−0.20***	0.48***	0.40***	−0.23***	−0.18***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Bipartisan Dyad		−1.61***		−2.00***		−1.60***
		(0.03)		(0.03)		(0.03)
Ideological Distance		−2.46***		−2.52***		−3.13***
		(0.04)		(0.03)		(0.04)
Shared Committee		0.33***		0.38***		0.30***
		(0.02)		(0.01)		(0.01)
Same Cohort		−0.03		−0.06***		0.03
		(0.02)		(0.02)		(0.02)
Same State		1.18***		1.02***		1.21***
		(0.03)		(0.02)		(0.02)
Constant		−0.73***		−0.54***		0.27***
		(0.02)		(0.02)		(0.02)
Observations	1,144,563	1,425,816	1,434,783	1,617,588	1,148,238	1,544,256
Member-Dyad FEs	✓		✓		✓	
Member-Dyad REs		✓		✓		✓
Policy Fixed Effects	✓	✓	✓	✓	✓	✓

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

E Alternative Specification: Restricted Co-sponsorship Bills

Table A7: Expressed Issue Agreement & Legislative Collaboration: Small Cosponsorship Teams

	Dependent variable: Legislative Collaboration					
	116^{th} Congress		117^{th} Congress		118^{th} Congress	
Expressed Issue Agreement	0.24^{***}	0.22^{***}	0.21^{***}	0.20^{***}	0.23^{***}	0.22^{***}
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Bipartisan Dyad		1.17^{***}		0.93^{***}		1.27^{***}
		(0.15)		(0.14)		(0.14)
Freshman Dyad		-0.18^{***}		-0.23^{***}		-0.35^{***}
		(0.06)		(0.06)		(0.06)
Ideological Distance		-2.52^{***}		-2.47^{***}		-2.92^{***}
		(0.21)		(0.19)		(0.19)
Shared Committee		0.97^{***}		0.87^{***}		0.91^{***}
		(0.07)		(0.06)		(0.06)
Same Cohort		0.30^{***}		0.20^{**}		0.16^{*}
		(0.08)		(0.08)		(0.09)
Same State		1.42^{***}		1.37^{***}		1.53^{***}
		(0.10)		(0.09)		(0.10)
Constant		-7.61^{***}		-6.73^{***}		-6.25^{***}
		(0.19)		(0.14)		(0.13)
Observations	37,012	389,497	47,470	463,275	43,412	420,631
Member-Dyad FEs	✓		✓		✓	
Member-Dyad REs		✓		✓		✓
Policy Fixed Effects	✓	✓	✓	✓	✓	✓

Note: Sample of collaborating members limited to those who sponsored/originally cosponsored legislation with fewer than eight original cosponsors. *p<0.1; **p<0.05; ***p<0.01.

Table A8: Expressed Issue Agreement, Bipartisanship, & Legislative Collaboration: Small Cosponsorship Teams

	Dependent variable: Legislative Collaboration					
	116^{th} Congress		117^{th} Congress		118^{th} Congress	
Expressed Issue Agreement	0.21^{***}	0.21^{***}	0.16^{***}	0.16^{***}	0.20^{***}	0.19^{***}
	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)
Bipartisan Dyad		1.16^{***}		0.89^{***}		1.25^{***}
		(0.15)		(0.14)		(0.14)
Agreement × Bipartisan	0.12^{**}	0.06	0.20^{***}	0.18^{***}	0.10^{*}	0.13^{***}
	(0.05)	(0.04)	(0.05)	(0.04)	(0.05)	(0.04)
Freshman Dyad		-0.18^{***}		-0.23^{***}		-0.34^{***}
		(0.06)		(0.06)		(0.06)
Ideological Distance		-2.51^{***}		-2.44^{***}		-2.90^{***}
		(0.21)		(0.19)		(0.19)
Shared Committee		0.97^{***}		0.87^{***}		0.91^{***}
		(0.07)		(0.06)		(0.06)
Same Cohort		0.31^{***}		0.20^{**}		0.16^{*}
		(0.08)		(0.08)		(0.08)
Same State		1.42^{***}		1.37^{***}		1.53^{***}
		(0.10)		(0.09)		(0.10)
Constant		-7.61^{***}		-6.73^{***}		-6.24^{***}
		(0.19)		(0.14)		(0.13)
Observations	37,012	389,497	47,470	463,275	43,412	420,631
Member-Dyad FEs	✓		✓		✓	
Member-Dyad REs		✓		✓		✓
Policy Fixed Effects	✓	✓	✓	✓	✓	✓

Note: Sample of collaborating members limited to those who sponsored/originally cosponsored legislation with fewer than eight original cosponsors. *p<0.1; **p<0.05; ***p<0.01.

Table A9: Expressed Issue Agreement, Freshman Status, & Legislative Collaboration: Small Cosponsorship Teams

	Dependent variable: Legislative Collaboration					
	116^{th} Congress		117^{th} Congress		118^{th} Congress	
Expressed Issue Agreement	0.21^{***}	0.19^{***}	0.22^{***}	0.21^{***}	0.24^{***}	0.24^{***}
	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Freshman Dyad		-0.19^{***}		-0.23^{***}		-0.34^{***}
		(0.06)		(0.06)		(0.06)
Agreement × Freshman	0.08	0.08^{**}	-0.05	-0.03	-0.07	-0.11^{**}
	(0.05)	(0.04)	(0.06)	(0.05)	(0.06)	(0.04)
Bipartisan Dyad		1.18^{***}		0.93^{***}		1.26^{***}
		(0.15)		(0.14)		(0.14)
Ideological Distance		-2.52^{***}		-2.47^{***}		-2.92^{***}
		(0.21)		(0.19)		(0.19)
Shared Committee		0.97^{***}		0.87^{***}		0.91^{***}
		(0.07)		(0.06)		(0.06)
Same Cohort		0.30^{***}		0.20^{**}		0.16^{*}
		(0.08)		(0.08)		(0.08)
Same State		1.42^{***}		1.37^{***}		1.52^{***}
		(0.10)		(0.09)		(0.10)
Constant		-7.60^{***}		-6.73^{***}		-6.25^{***}
		(0.19)		(0.14)		(0.13)
Observations	37,012	389,497	47,470	463,275	43,412	420,631
Member-Dyad FEs	✓		✓		✓	
Member-Dyad REs		✓		✓		✓
Policy Fixed Effects	✓	✓	✓	✓	✓	✓

Note: Sample of collaborating members limited to those who sponsored/originally cosponsored legislation with fewer than eight original cosponsors. *p<0.1; **p<0.05; ***p<0.01.