The Political Ideologies of Organized Interests & Amicus Curiae Briefs:

Large-Scale, Social Network Imputation of Ideal Points*

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Abstract

Interest group ideology is theoretically and empirically critical in the study of American politics, yet our measurement of this key concept is lacking both in scope and time. We provide a novel measure of ideology for organized interests by leveraging network science and ideal point estimation. Our Interest Group Network (IGNet) scores cover more than 12,000 unique groups across 95 years, providing the largest and longest measure of interest group ideologies to date. In addition, our approach allows us to score Supreme Court amicus curiae briefs on the same ideological scale. The scores reveal a polarized network of interest groups before the Court, and that giving to campaigns is more common among the ideologically extreme groups. The macro-ideology of briefs show early dominance from the liberal side until the 1980s, with ideological representation virtually even after then.

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Central to the study of American democracy is the study of factions. Among them, interest groups are both foundational and pervasive, impacting the function of every branch. There is evidence of interest group efforts on Congress (e.g., Berry, 1999; Wawro, 2001; Fellowes and Wolf, 2004; Esterling, 2007), the executive (e.g., Baumgartner et al., 2011), the courts, (e.g., Caldeira and Wright, 1988; Collins Jr, 2007), the bureaucracy (Drope and Hansen, 2004; Kelleher and Yackee, 2006), as well as in state and local politics (e.g., Miller, 2008). Underlying these and related works are expectations about interest groups' preferred lobbying strategies and political outcomes. Thus, core to the study of interest groups, both theoretically and empirically, is the ideology of the group. However, for the vast majority of active interests relatively little is known on this front.

While frequently implied or assumed, missing from many studies of interest group influence is an *a priori* objective measure of their ideologies. Such an absence makes understanding interest group preferences at a large-scale and over multiple issues, events or periods nearly impossible. Likewise, the ability to predict political outcomes under the influence of interest groups is severely hampered. Scholars must either make (educated) guesses toward interest group ideology based on in-depth knowledge, or else infer their ideological leanings from their political activity. Further complicating large-scale inferences about and from interest group activity is that the population of such interest groups is unknown. Indeed, substantial portions of those actively lobbying in the American political system do not formally register as lobbyists (LaPira and Thomas, 2014). In short, many organizations, associations and corporations actively pursue political outcomes, but do not meet the high bar to formally register and have political leanings that are generally unknown, and are therefore largely left to exert influence in the shadows.

We propose to address these deficiencies by estimating interest group ideal points for the entire population of entities engaged in a crucial form of interest group lobbying: signing and submitting *amicus curiae* briefs to the Supreme Court. Across nearly 100 years of activity, over 15,000 organizations from a wide range of industry sectors have signed these briefs (see, e.g., Box-Steffensmeier and Christenson, 2012). By utilizing the full set of amicus-filing organizations we expand the realm of known interest groups beyond those with histories of donating to campaigns or registering lobbying activities.

In what follows, we begin by situating our work in the context of those that have constructed related measures for interest groups, broadly construed. In doing so, we find a lasting need for a measure of this nature that is comprehensive, both in terms of time and breadth. We next introduce our methodology that couples political donation ideal points (Bonica, 2014) with a network analysis of the amicus cosigning strategies of groups. In contrast to traditional unsupervised methods, the availability of a set of starting estimates in our methodology pegs the probability of a relational tie to some known value, substantially improving the end results. Our approach makes use of cross-validation both to establish internal validity and, ultimately, as the estimated ideal points, which we call Interest Group Network (IGNet) scores. An additional feature of our approach is the ability to provide scores for amicus curiae briefs as well.

The IGNet scores uncover a number of substantive insights into the behavior of organized interests before the Court. Foremost, we find that the amicus curiae cosigning network is ideologically polarized. However, interest groups across the ideological spectrum employ different coalition strategies, with moderate groups acting as bridges among more extreme groups, leading to a network that is relatively well-connected overall. The scores also show historically greater representation of liberal briefs that has given way to virtually equal representation since the 1980s. Finally, by comparing our measure across interest groups, we find support for the expectation that ideological extremity and campaign donations are correlated. Yet, these results only scratch the surface of insights available with a comprehensive measure of organized interest ideology. IGNet scores open the door to investigate a host of questions involving interest group influence beyond the Court and across institutional branches and levels of government, not to mention in campaigns and public opinion.

1 The Importance of Interest Group Ideology

In recent decades, a substantial increase in lobbying activity—be it of the legislative, executive or judicial branch—points to the importance of this practice for both public officials as well as special interests. Whether it is to gain policy favors at a "low cost" (e.g., Ansolabehere and John M De Figueiredo, 2003), to capture legislators' attention and efforts (e.g., Hall and Wayman, 1990), or to persuade supporters and counteract the effects of opponents (e.g., Hansen, 1991), interest groups direct a substantial amount of resources to influence policy outcomes.

Studies of interest groups have generated a wealth of information about how and when lobbyists attempt to influence public policy, as well as the conditions under which they choose to join coalitions. Scholars have pursued the decision of interests to lobby on particular issues and amidst competition (e.g., Gray and Lowery, 1996*b*,*a*; Leech et al., 2005; Holyoke, 2009) and, if so, whether to collaborate (e.g., Hall and Deardorff, 2006; Baumgartner et al., 2009) and with whom (Box-Steffensmeier and Christenson, 2014). As they work for the attention of policymakers, they cultivate patterns of competition and cooperation that define their organizational identity. At the heart of this identity is their ideological alignment with institutional actors, as well as among each other. However, linking the preferences of interest groups with that of policy-makers, requires a reliable measure of their policy preferences and, ultimately, ideological orientation.

At the same time, a wealth of methodological advances in social network analysis and the estimation of political actors' ideological positions has occurred. Leveraging these two methodological approaches is critical for our work. Improvements in ideal point estimation have preceded bursts of research productivity in political science, starting with the NOMINATE models (Poole and Rosenthal, 1985*a*).[1] While originally developed to measure the ideology of members of Congress, it has expanded to include ideal point estimates for a wide range of political actors. The most current, DW-NOMINATE, relies on co-voting behavior between Members of Congress (Lewis et al., 2019), acknowledging the fundamental network structure across legislators and bills.

Following Poole and Rosenthal (1985*a*), scholars have developed ideal point estimates for presidents (e.g., Bertelli and Grose, 2011), judges (e.g Martin and Quinn, 2001; Bailey and Maltzman, 2011; Lauderdale and Clark, 2012) and bureaucrats (e.g., Clinton et al., 2012). These works have made substantial contributions to understanding the political preferences and relationships of political actors and interest groups. However, there are still challenges to obtaining a wide-ranging reliable measure of interest group ideology. For instance, despite its massive contributions, the primary limitation of DW-NOMINATE is its narrow focus: only individuals who have voted on bills on the floor of Congress can be easily scaled.

Recent efforts to expand the scope of ideological scaling include Bonica (2013, 2018), who uses co-donating behavior among US citizens from campaign finance records. While this approach is able to capture information even for those unsuccessful candidates or less effective interest groups, one of the shortfalls is that not all interest groups (or their employees) make donations. Barberá (2015) scales Twitter co-followers of elected officials, candidates, and organizations. A major benefit of this study is that it allows ideal point estimates across polities for recent times, should they have a sizeable enough presence on Twitter to extract their ideological position.

Making further use of the DW-NOMINATE scores, McKay (2008) uses 72 interest groups'

[1]The analysis of roll-call voting has a long history, going back at least to Rice (1924) with advances made by MacRae (1958), Clausen (1967), Weisberg (1968), Morrison (1972), among others.

expressed preferred votes on select bills to map them ideologically. In a similar vein, CROSSON, FURNAS and LORENZ (2020) uses interest group positions on post-2004 legislation from Maplight with roll-call votes to locate 2,646 groups in ideological space. A more direct approach is offered by Thieme (2018), who is able to map state-level groups in three states due to their declaration of principal lobbying positions required by law. Finally, and also utilizing amicus curiae briefs, Hansford and Depaoli (2015) estimate the ideal points of 192 of the most active organizations by linking them to justices' ideologies who voted in the same direction as they desired on a case. Each with their own strengths and invaluable insights, we build on these advances to expand the estimation of ideal points to more interest groups—and amicus curiae briefs—and over a longer time period than has been done so far.

2 Amicus Cosigning Behavior

While the most notable studies of interest group ideology rely on campaign contributions (Bonica, 2014) and roll call votes (Poole and Rosenthal, 1985*b*), a substantial amount of influence comes from groups and organizations that are not formally registered as lobbyists and do not make campaign contributions. In this research, we utilize network structure and a novel imputation procedure to capture ideal points for nearly all organizations that have cosigned amicus curiae briefs before the US Supreme Court.

In an increasingly crowded advocacy environment, interest groups have continuously resorted to forming coalitions, be it to share information, resources, or build a critical mass in support of an issue (Berry, 1997; Hula, 1999; Hojnacki, 1998). Individuals, groups and organizations lobbying the Supreme Court rely on cosigning amicus briefs to convey legal, technical or social scientific information to the court in support of the petitioning or responding party, or sometimes to take a neutral position (Kearney and Merrill, 2000; Collins, 2008).

In the process of crafting each brief, which includes selection of content and signatories, the cosigning parties publicly declare their position towards the question being reviewed by the court. Moreover, this coordinated declaration is an indication that the cosigning groups share some overlapping opinion on the issue at hand (Box-Steffensmeier and Christenson, 2014). Even if the intent of cosigning an amicus brief is limited to specific court cases and issues, there is evidence that groups may join an amicus brief specifically to build and maintain relationships with similar groups (Wasby, 1995; Clark, 2011).

As an expressive method of sharing interest through a written document, amicus briefs also contrast the behavior of groups lobbying the legislature. First, amicus brief cosigners provide a clear signal of directionality, not only through their support for the litigant parties, but also in their rejection or acceptance of ideas put forward by the litigants. Second, in contrast to the behavior of donor interests, we have no reason to believe that amici's expressive behavior may be strategic, as there is no gain from misrepresenting their interests to persuade other groups or the justices. Hence, regardless of which side they support, these qualities of the amicus cosigning process make it an excellent measure of "purposive, coordinated action" (Box-Steffensmeier and Christenson, 2014), and hence useful for quantifying a group quality such as ideology.[2]

We put forth a contextually novel methodology to analyze a network that is historical, large and relatively sparse—many organizations have filed amicus briefs, but the average number of briefs

[2] In terms of future substantive work with these data, we note here that we do not assume that interest group behavior is identical across the branches of government, yet, in the context of the interest group community as a whole, we expect that the behavior and relationships are similar (see also Caldeira and Wright, 1988; Collins Jr, 2007; Box-Steffensmeier, Christenson and Craig, 2019).

any one organization has signed is small (the average for all 15,446 is 19.9 and the median is five amicus briefs). Our approach leverages network structure more directly to expand the estimates and insights from common-space DIME scores (Bonica, 2014) to the thousands of politically active organizations before the Court and other branches, the vast majority of which are without donor histories and therefore without DIME scores. Importantly, our estimation is not limited to groups that meet the criteria of lobbying laws at the state or federal levels, or the groups that are the most active, or only those active in recent years; it does not require groups to take positions on roll call votes or any legislation, nor does it ask groups to express or recall their outcome preferences in subsequent interviews—and they do not even have to have donated to a candidate. The reach here is truly broad.

3 Combining Network Science with Ideal Point Estimation

Our methodological challenge is to estimate ideal points for amicus-signing organizations. We leverage three sources of data in doing so: 1) the inherent network structure of amicus brief cosigning (Box-Steffensmeier and Christenson, 2014), 2) accompanying case-level metadata from the Supreme Court Database (Spaeth et al., 2015); and 3) ideal point scores for a subset of amicus signers (Bonica, 2012).

We begin with a database on interest groups culled from the aforementioned expressive behavior of signing amicus curiae briefs (Box-Steffensmeier and Christenson, 2012; Box-Steffensmeier, Christenson and Hitt, 2013; Box-Steffensmeier and Christenson, 2014). Our data consist of 14,329 amicus briefs signed by 15,446 organizations from 1917 to 2012. We structure this cosigning behavior into a bipartite (rectangular) adjacency matrix, such that for every organization the presence of (co)signing onto one or more amicus briefs is denoted with a one and zero otherwise. This matrix forms the network structure component of our data. Of these briefs, 36.1% are cosigned among two or more organizations; the average number of signers for a brief is 2.41.

Secondly, we identify 2,898 organizations in the amicus curiae network who also occur in the DIME dataset (Bonica, 2014) We arrive at matches through a combination of exact matching and hand-validated fuzzy string matching (see Kaufman and Klevs, 2020). These organizations act as training labels in our network, or the ideal point component. We assume that ideologically proximate organizations are more likely to cosign amicus briefs than ideologically distant ones. As we discussed above, since all organizations who sign briefs are required to take a side in the case—i.e., in support of the petitioner, respondent, or neither—and case decisions can be measured as ideologically liberal or conservative (Spaeth et al., 2015), we have a high level of confidence in this assumption.[3] Leveraging this assumption, we can use an unlabeled organization's network proximity to those of labeled organizations to infer its ideology on the same scale as ideal point estimates from campaign donations. In the methodology section directly below, we refer to organizations whose ideal points we derive from Bonica (2014) as *origin* score nodes, or as the training set, and the remainder as *imputed* or endogenous score nodes, or the test set.

3.1 Network Modeling & Estimation

Having built an amicus signing network of 15,446 organizations, of which 2,898 are labeled, and 14,329 briefs are cosigned, we establish a procedure for imputing ideology labels for all the organi-

[3] A justice's vote on ideological lines is one of the most prevalent variables in the empirical study of judicial behavior (Epstein et al., 2013, 2005).

zations in the data.[4] We develop a novel weighted averaging procedure, which we show is equivalent to optimizing an exponential loss function. In particular, we impute a set of ideal points such that organization i's ideal point is the average of its briefs' ideal points, and brief b's ideal point is the average of its cosigners' ideal points.

While many tools exist for estimating underlying or unobserved social space in networks, our approach offers important advantages in this context. In particular, an important approach to learning about the similarities in nodes from only the network structure comes from latent space models (e.g., Hoff, Raftery and Handcock, 2002; Ward, Ahlquist and Rozenas, 2013). Broadly speaking, these unsupervised methods utilize embedding mechanisms of "latent low-dimensional feature representations for the nodes or links in a network" (Arsov and Mirceva, 2019, p. 1). Our approach, drawn from work in computational biology and epidemiology (Warde-Farley et al., 2010; Gligorijević, Barot and Bonneau, 2018), improves upon these methods by including a subset of labeled data, the DIME scores for select organizations (see Figure 1). Incorporating pre-labeled data offers a number of critical features: it greatly reduces computation time, improves the quality of estimation, enables us to estimate scores for briefs as well as organizations, and binds our ideology estimates to commonly-used, pre-existing measures (Figure 3).[5]

3.2 Estimation Procedure

Let there be a set of amicus writing organizations O that have written a set of briefs B, some co-authored and some not. We think of O and B as together being a set of nodes constituting a bipartite graph G. Let $p(v, 0)$ be the initial position of each vertex in the graph. Let $N(v)$ be the neighborhood of v. Then we assume that the co-signers of brief b (formally, $N(b)$) negotiate the content of the brief so that its position reflects the average of their preferred positions, perhaps with some noise $p(b, 1) = \frac{1}{|N(b)|} \sum_{v \in N(b)} p(v, 0) + \epsilon_{b1}$. Organizations come in two types. Some organizations have "known" positions, in which case $p(o, 1) = p(o, 0) = p(o)$ is fixed and constant. Alternatively, some organizations o have "unknown" positions. In this case, we assume that the average position of the briefs o signed is a noisy estimate of its position. More formally, $p(o, 1) = \frac{1}{|N(o)|} \sum_{v \in N(o)} p(v, 1) + \epsilon_{o1}$ where $\epsilon_{o1} \sim N(0, \sigma_1^2)$. Since $p(o, 1)$ is a noisy estimate of o's position, $p(b, 1)$ no longer reflects the average position of the organizations that co-signed it. To address this issue, we focus on finding the expected "steady state" of this system, where the updating from $t-1 \to t$ follows the same rule as from $0 \to 1$. In such a state, all briefs reflect a fair bargain between co-signers based on their ideology and the average of the briefs an organization signs is a noiseless estimate of their ideology. In fitting the estimates, we may ignore the noise which will eventually drop out, and prefer to callibrate the uncertainty associated with these estimates through bootstrapping and cross-validation.

To calculate the state, note first that we can formalize the brief update step through a matrix $\mathbf{B}$ whose entry b_{ij} is the number of briefs co-signed by i and j divided by the total number of briefs that i has signed, unless $i = j$ in which case $b_{ij} = 0$. Let $\vec{p}$ be a vector where p_i is i's original ideology score if available.[6] Then the value after the first brief step is $\mathbf{B}p + \vec{\epsilon}_{1b}$. Similarly, we can construct a matrix O to describe the organizational updatestep, and note that the estimate of

[4] We perform this imputation regardless of each organization's total number of briefs signed. Many ideology estimates limit their support to individuals or groups above a certain threshold of activity (e.g., Bonica, 2014; Barberá, 2015; Desmarais, La Raja and Kowal, 2015), but we elect to include all organizations, so as to expand the reach of the measure as broadly as possible.

[5] To illustrate these points, we compare our methods to those in the `latentnet` R library (Krivitsky and Handcock, 2008), a popular and flexible network embedding tool, in the Appendix.

[6] If i has no origin score available, p_i can be anything

ideology after the org step is $\mathbf{OB}\vec{p} + \mathbf{O}\vec{\epsilon}_{1b} + \vec{\epsilon}_{1o}$. The scores evolve as follows:

$$\mathbf{OBOB}\vec{p} + OBO\vec{\epsilon_{1b}} + OB\vec{\epsilon_{1o}} + O\vec{\epsilon_{2b}} + \vec{\epsilon_{2o}}$$
$$\mathbf{OBOBOB}\vec{p} + \mathbf{OBOBO}\vec{\epsilon_{1b}} + \mathbf{OBOB}\vec{\epsilon_{1o}} + \mathbf{OBO}\vec{\epsilon_{2b}} + \mathbf{OB}\vec{\epsilon_{2o}} + \mathbf{O}\vec{\epsilon_{3b}} + \vec{\epsilon_{3o}}$$
$$(\mathbf{OB})^n\vec{p} + \sum_{i=1}^{n}\left\{(\mathbf{OB})^{n-i}\mathbf{O}\vec{\epsilon_{ib}} + (\mathbf{OB})^{n-i}\vec{\epsilon_{io}}\right\}$$

Under suitable assumptions about the variance of the noise as the system evolves, $\lim_{n\to\infty}\sum_{i=1}^{n}\left\{(\mathbf{OB})^{n-i}\mathbf{O}\vec{\epsilon_{ib}} + (\mathbf{OB})^{n-i}\vec{\epsilon_{io}}\right\}$ is also Gaussian with finite variance and expected value 0. Therefore, we may focus our attention on the value of $\lim_{n\to\infty}(\mathbf{OB})^n\vec{p}$, which is the expected steady state of the system.

To see how we may calculate this value analytically, let $\mathbf{M} = \mathbf{OB}$ and note that $\mathbf{M}$ is a valid transition matrix for a Markov process on the digraph of briefs and organizations. Nodes with origin scorse are "absorbing states," in the sense that if one were to transition to these states one would never leave. All other nodes represent transient states. If we reorder the nodes so that organizations with origin scores are first, we may write

$$\mathbf{M} = \begin{bmatrix} \mathbf{I} & 0 \\ \mathbf{S} & \mathbf{Q} \end{bmatrix}$$

Here $\mathbf{S}$ contains the transition probabilities of an node without a score to a node with an origin scor**e,** while$\mathbf{Q}$ contains the transition probabilities between nodes lacking scores. Put differently, $\mathbf{S}$ represents the probabilities of going to an absorbing state on the digraph when starting from a transient state, while $\mathbf{Q}$ represents the transition probabilities of going from one transient state to another. Further, block matrix multiplication shows

$$\mathbf{M^k} = \begin{bmatrix} \mathbf{I} & 0 \\ \mathbf{S}(\mathbf{I} + \mathbf{Q} + \mathbf{Q^2} + \ldots + \mathbf{Q^k}) & \mathbf{Q^k} \end{bmatrix}$$

Let us describe what happens to each block in turn as $k \to \infty$. Clearly, the probability of being outside an absorbing state goes down with k, and must eventually become 0.[7] As a result, $\lim_{k\to\infty}\mathbf{Q^k}$ =0. Further we have the identity $(\mathbf{I} + \mathbf{Q} + \mathbf{Q^2} + \ldots + \mathbf{Q^k} + \ldots)(\mathbf{I} - \mathbf{Q}) = \mathbf{I}$ therefore $\mathbf{S}(\mathbf{I} + \mathbf{Q} + \mathbf{Q^2} + \ldots + \mathbf{Q^k} + \ldots) = \mathbf{S}\left(\mathbf{I} - \mathbf{Q}\right)^{\mathbf{-1}}$, if $(\mathbf{I} - \mathbf{Q})$ is invertible. Since the eigenvalues of $\mathbf{Q}$ are strictly less than 1 for $\lim_{k\to\infty}\mathbf{Q^k}$ =0, the inverse of $(\mathbf{I} - \mathbf{Q})$ must exist. Therefore we have

$$\mathbf{M}^\infty = \begin{bmatrix} \mathbf{I} & 0 \\ S\left(\mathbf{I} - \mathbf{Q}\right)^{-1} & \mathbf{0} \end{bmatrix}$$

Let $\tilde{p} = \mathbf{M}^\infty\tilde{\mathbf{p}}$. Then $\mathbf{M}\tilde{p} = \mathbf{M}\cdot\mathbf{M}^\infty\vec{p} = \mathbf{M}^\infty\vec{p} = \tilde{p}$ so the weighted average of neighbor property will obtain for those nodes which are not given exogneously. Further, by construction, $\tilde{p}_i = \vec{p}_i$ if i is an absorbing state/origin node.

Clearly, the term $\mathbf{S}\left(\mathbf{I} - \mathbf{Q}\right)^{-1}$ is the key one for estimation. It reflects the weights ultimately given to each of the nodes with origin scores for each of the nodes we estimate. Potentially, these weights are also of interest, and could be useful to researchers. For example, if the exogenous

[7] We assume that all transient nodes are connected somehow to an absorbing node. A node that is not connected to some node with an origin score is one to which we are unable to assign an ideology score, and so we may eliminate all these prior to estimation.

ideal point measures are not estimated with certainty, then they can be used to efficiently impute confidence intervals around the endogenous measures, for example by sampling. Alternatively, they could be used for sensitivity analysis. Another important point about the formulation above is that we have implicitly assumed that all nodes without origin scores were connected by some degree to one with an origin score. If it were not, then we would have no basis for ever imputing its ideology purely on the basis of its neighbors. Finally, the block nature of the matrix $\mathbf{M}^\infty$ gives some insight into why it does not matter what values are initially supplied for the nodes without origin scores. In the expected steady state, the estimated scores depend only on the origin scores.

3.3 Illustration of Iterative Weighted Average with Toy Network

To illustrate how the imputation strategy works in the iterative weighted average approach, we provide here a small-scale example with a toy network. Suppose there were three organizations in the network X, Y, and Z, who have cosigned briefs XY1, XY2, YZ, and XYZ. X and Z are origin score nodes. This network is visualized in Figure 1.

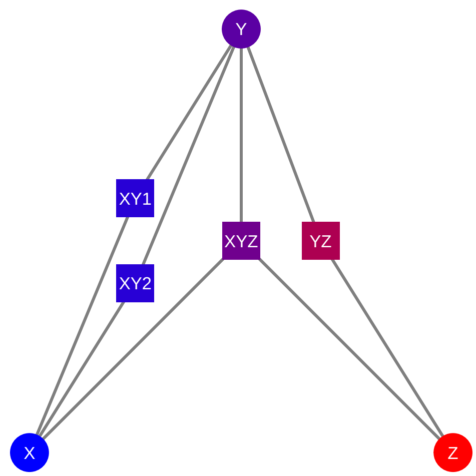


Figure 1: Hypothetical Amicus Cosigning Network. *Origin score nodes are on the bottom row. Organization nodes are circles while brief nodes are squares. Node colors indicate their scores from blue to red.*

This seven-node network has the following scaled adjacency matrix[8]:

$$\begin{bmatrix} 0 & 0 & 0 & 1/3 & 1/3 & 0 & 1/3 \\ 0 & 0 & 0 & 1/4 & 1/4 & 1/4 & 1/4 \\ 0 & 0 & 0 & 0 & 0 & 1/2 & 1/2 \\ 1/2 & 1/2 & 0 & 0 & 0 & 0 & 0 \\ 1/2 & 1/2 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1/2 & 1/2 & 0 & 0 & 0 & 0 \\ 1/3 & 1/3 & 1/3 & 0 & 0 & 0 & 0 \end{bmatrix}$$

Rows 1 and 3 are our origin nodes—those with known ideology estimates. To estimate ideology for the remaining nodes, we perform the iterative weighted average approach.

[8]In Appendix 0.1, this matrix is $\mathbf{M}$.

We begin with Figure 2, Panel A. In the first iteration, only nodes X and Z have scores, and so we can only calculate the scores for the four briefs; node Y receives no score since all of its briefs are unscored (Figure 2, Panel B). However, in the second iteration, the four briefs have estimated ideology scores, so we can assign Y a score based on the weighted average of the four briefs it cosigns (Panel C). In the third iteration, all seven nodes have assigned scores, but the four briefs' neighboring nodes look different: whereas before the briefs received their scores only from X and Z, now node Y also has a score, so we use node Y's score to update the scores for the four briefs (Panel D). Next, since the briefs have updated scores, we can update node Y's score (Panel E). We repeat this process until the scores for all initially-unscored nodes change very little from iteration to iteration[9].

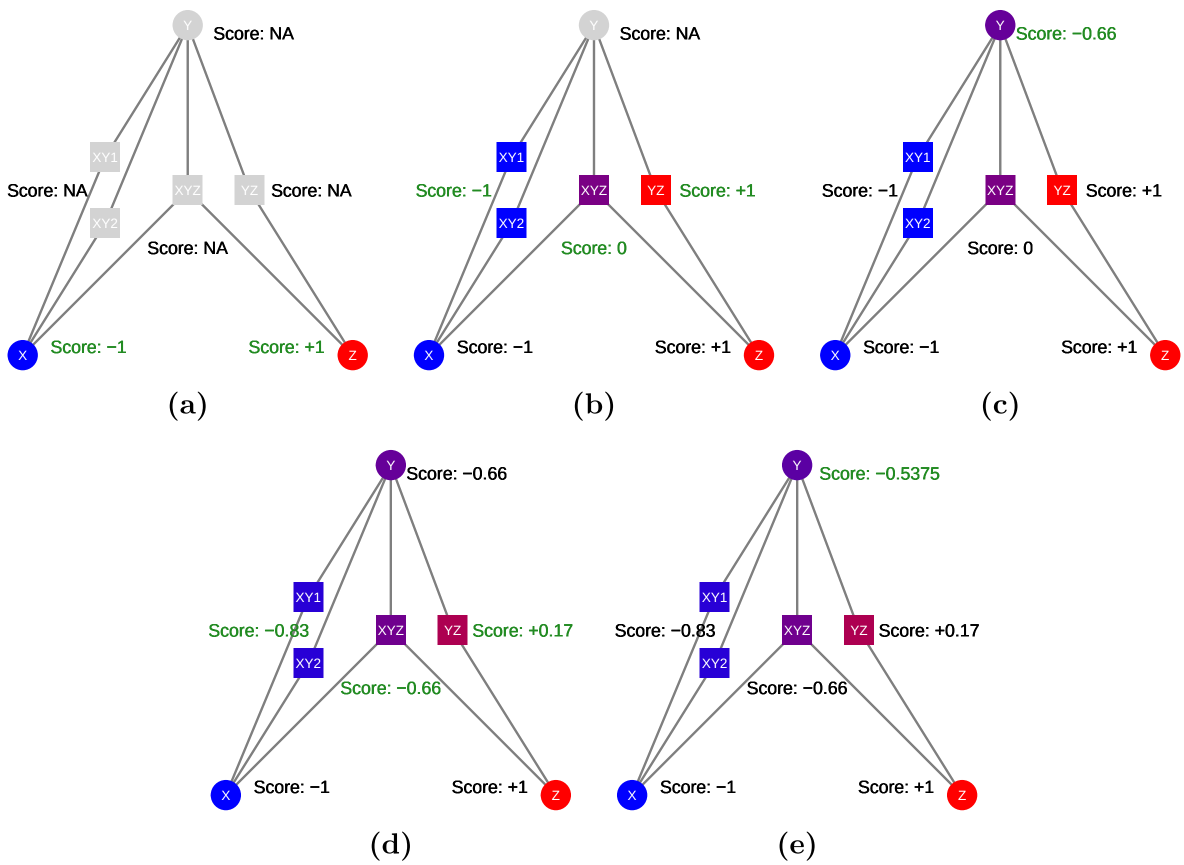


Figure 2: An illustration of our iterative weighted averaging procedure in five steps. Circle nodes are organizations and square nodes are briefs. Node color indicates ideology score from −1 (blue) to +1 (red). Each iteration's updated ideology scores are indicated in green, starting with Organizations X and Z on the bottom..

This iterative process converges to a two-by-five matrix where each row corresponds to an unscored node and each column corresponds to a training-set node[10]:

[9] This is equivalent to calculating $\mathbf{M}^{\text{inf}}$; see Appendix 0.1.

[10] In Appendix 0.1, this matrix is $(\mathbf{I}-\mathbf{Q})^{-1}\,\mathbf{S}$

$$\begin{bmatrix} 8/13 & 5/13 \\ 21/26 & 5/26 \\ 21/26 & 5/26 \\ 4/13 & 9/13 \\ 7/13 & 6/13 \end{bmatrix}$$

In this matrix, the top row indicates that node Y's final score is an average of nodes X and Z with weights $\frac{8}{13}$ and $\frac{5}{13}$. Node X has signed more briefs with Y than node Z has, so it is reasonable that its weight is higher. Indeed, X has larger weight in every imputed ideal point than Z except brief YZ. In particular, although brief XYZ signed with all three organizations, X has more weight in its ideal point because X signed more with Y than Z did, and that influence propagates through the network.

3.4 Internal Validity

Although our procedure for estimating ideal points described above has strong intuitive appeal, we nevertheless verify that the outputs are sensible. In particular, it is important that the outputs are robust to measurement error in the training labels. The scores produced by Bonica (2014) that we use as our ground truth are imperfect (Enamorado, Fifield and Imai, 2019), and we ensure that our model's outputs are valid despite any noise the training labels may induce.

Our approach to establishing internal validity of these estimates, and to account for measurement error in the training labels, is to use cross-validation. Like all cross-validation, we randomly partition our training data into twenty equally sized folds, $k \in 1, 2, ..., 20$. We then conduct our iterative weighted averages procedure using all our data *except* the observations in the kth fold. Next we estimate the ideal points for the observations in the kth fold, pretending for the moment that we do not observe them from the training labels. In comparing the scores we estimate with the scores provided in the training data, we can assess the validity of our measures: if there is little deviation between our estimates and the training data, we can be confident that *all* our estimates are valid.

Quantile	MAD	Side Agreement	Stability	
1st Quart.	0.532	0.420	0.658	0.991
Median	0.563	0.501	0.692	0.992
3rd Quart.	0.599	0.544	0.710	0.995

Table 1: Performance Metrics for the Cross-Validation Exercise

Since we conduct 20-fold cross-validation, we obtain 20 cross-validation estimates. Table 1 presents the inter-quartile range for 3 different metrics, calculated across the 20 folds of our cross-validation results.[11] The first set of performance statistics we consider, mean absolute deviation

[11] It is worth noting that the number of organizations that obtain scores does depend somewhat on the cross-validated sample. Using 90% of the data (exogenous scores from approximately 2,700 organizations selected at random), we consistently find that about 9% of organizations that sign briefs are unscorable. The figure is only slightly larger than the 8.4% that cannot be scored given the entirety of the exogenous data. An increase in the number of unscorable organizations is expected with less data, because some organizations exist in small, isolated network components. If we used five-fold cross-validation, the number of unscorable organizations would typically be

(MAD), is a standard target of cross-validation. In comparing the estimated ideologies for withheld organizations to their ideologies as measured by Bonica (2014), the MAD between these scores is between 0.55 and 0.59 on a standardized normal distribution.[12]

A second performance statistic dichotomizes ideology into +1 (conservative) and -1 (liberal). When we consider only whether an organization's ideology is less than zero or greater than zero, we find that our model estimates an organization's ideology to be on the same side of the political spectrum as our withheld labels for between 67 and 72% of organizations.

Finally, we report a measure capturing uncertainty in our estimates. In a standard cross-validation procedure, a model trained on $k-1$ folds is used to predict the outcomes only for the kth fold of training data. In our procedure, however, we predict the outcomes for the kth fold as well as all our remaining test set organizations due to the networked nature of our data (Li, Levina and Zhu, 2016). As such, we produce k predictions for each organization in our test data. By comparing these scores trained on $k-1$ folds to the scores produced by our full model trained on all k folds, we can gauge the uncertainty associated with our predictions (Snijders and Borgatti, 1999). We find that even when withholding a sample of our training observations, our ideal point estimates correlate with our full results in a range from 0.98 to 0.99, indicating that our estimates are stable to noise in our training labels.

No. Orgs	No. Unique Score Orgs	No. Pairs	Same Name Corr.	MAD	Side Agreement
1,982	597	116,102	0.341	0.681	0.654

Table 2: Performance Metrics for the Within DIME Score Comparisons

How confident should we be in light of our cross-validation results? We benchmark our results by leveraging the fact that many organizations in the DIME database have multiple entries. We suppress this multiplicity in our estimation procedure by taking a weighted average of scores with weights determined by the number of reports used for the estimation. Nevertheless, to evaluate the reliability of our measures we examine the relationship between the various scores in the DIME database for any single organization. 1,385 organizations have at least two distinct scores within the DIME database, allowing us to calculate similar performance statistics as in Table 1. For example, if we observe two entries for "JP Morgan Chase" in the DIME database, we can calculate both the difference in DIME scores between those entries, and whether those scores are on the same side of zero. Table 2 collects these statistics. The mean absolute deviation between two scores for the same amicus-signing organization in DIME is 0.656, the correlation is 0.373, and the dichotomous classification is the same 64% of the time. That is, our cross-validation procedure predicts DIME scores better than other DIME scores: it produces lower mean absolute deviation, and produces scores on the same size of zero more regularly.

This is less surprising than it sounds: many of the DIME estimates are measured with error, and by leveraging the network we amplify the signal within DIME itself. An important source for that error is that the DIME data set includes record linkage inaccuracies whereby organizations are linked to incorrect FEC contributions. A second source is that interest groups may engage in heterogeneous behavior, in so far as they may behave differently with regards to their political donation activity than they do in amicus cosigning—a possibility we address in more detail below.

larger, while if we used twenty-fold cross-validation it would be smaller.

[12] For comparison, a "model" which always guesses an ideology of 0 has a MAD of 0.79.

For both these reasons we neither expect nor desire a perfect accuracy with the DIME scores.

Ideology is a complex and multifaceted concept (see, e.g., Conover and Feldman, 1981; Feldman and Johnston, 2014; Jost, Federico and Napier, 2009), broad enough to allow for such variance in behavior. But for the sake of our measure of interest group ideology, we prefer not to propagate errors arising from the limitations above, and to avoid conflating donation-based ideology with amicus-derived ideology. Therefore, to ensure an internally consistent measure of ideology, our final ideology estimates do not include any raw DIME scores from Bonica (2014). Rather, we take the scores for all interest groups—regardless of whether the organization is in the training data—from our cross-validation estimates. Thus, while our scores for the organizations in the test set derive from a model trained on the full training data, our scores for the organizations in the training set derive from the model trained on $k-1$ folds. This choice has an additional benefit related to mean reversion. Our iterative weighted average procedure renders our imputed nodes less overdispersed than the training nodes; by selecting our cross-validated estimates for training nodes rather than their original labels, we ensure that our training nodes and imputed nodes have equivalent mean-reversion.

4 The Ideologies of Organized Interests

Our network estimation procedure leads to new ideal points—i.e., IGNet scores—for 12,602 unique interest groups and 11,794 briefs over 95 years.[13] As a first step in illustrating the IGNet scores of organized interests, we display the ideal points for a small collection of benchmark organizations alongside familiar political representatives. In Figure 3, circles indicate entities already scored by Bonica (2014), though they have been overwritten with our IGNet scores—unless they are individuals, in which case it is a true DIME score, since the amicus curiae network only includes organizations and briefs. Squares are entities we score for the first time using our network imputation and cross-validation approach—i.e., they do not exist in the DIME database. The Figure shows that the interest groups Gun Owners of America and the Family Research Council are of similar conservative ideologies to former Attorney General Jeff Sessions and Senator Mitch McConnell. At the moderate level we find National Public Radio (NPR) and Hewlett Packard (HP). Interestingly, large media corporations like the *NY Times* and the *LA Times* are shown to be moderate, with ideal points just a touch right of center. More liberal groups include Common Cause and the Center for Reproductive Rights, which are about as liberal as Senator Charles Schumer.

Looking across the full range of ideology scores for all the organizations (i.e., beyond the figure), we find that the most liberal organizations are a series of law schools including Yale and Vermont, animal rights organizations such as Jews for Animal Rights, book stores like Half Price Books and Harvard Book Store Inc, students' or veterans' advocacy groups such as the Children's Defense Fund of Ohio and the American Military Retirees Association. The most conservative are corporations or corporate advocacy groups like the Ohio Valley Coal Company, hospital and healthcare provider conglomerates like Wellness Lifestyles Inc, and conservative social policy groups, like the Oklahoma Family Policy Council and the Christian Advocates Serving Evangelism. In sum, the imputed organizations pass a test of face validity, given that those we expect to be liberal, moderate and conservative turn out to be so in the IGNet scores.

[13] Our measure is temporally static. That is, a group's ideal point is time-invariant. However, one could plausibly use the method we propose here on a specific time period or a moving window, which we leave for future research.

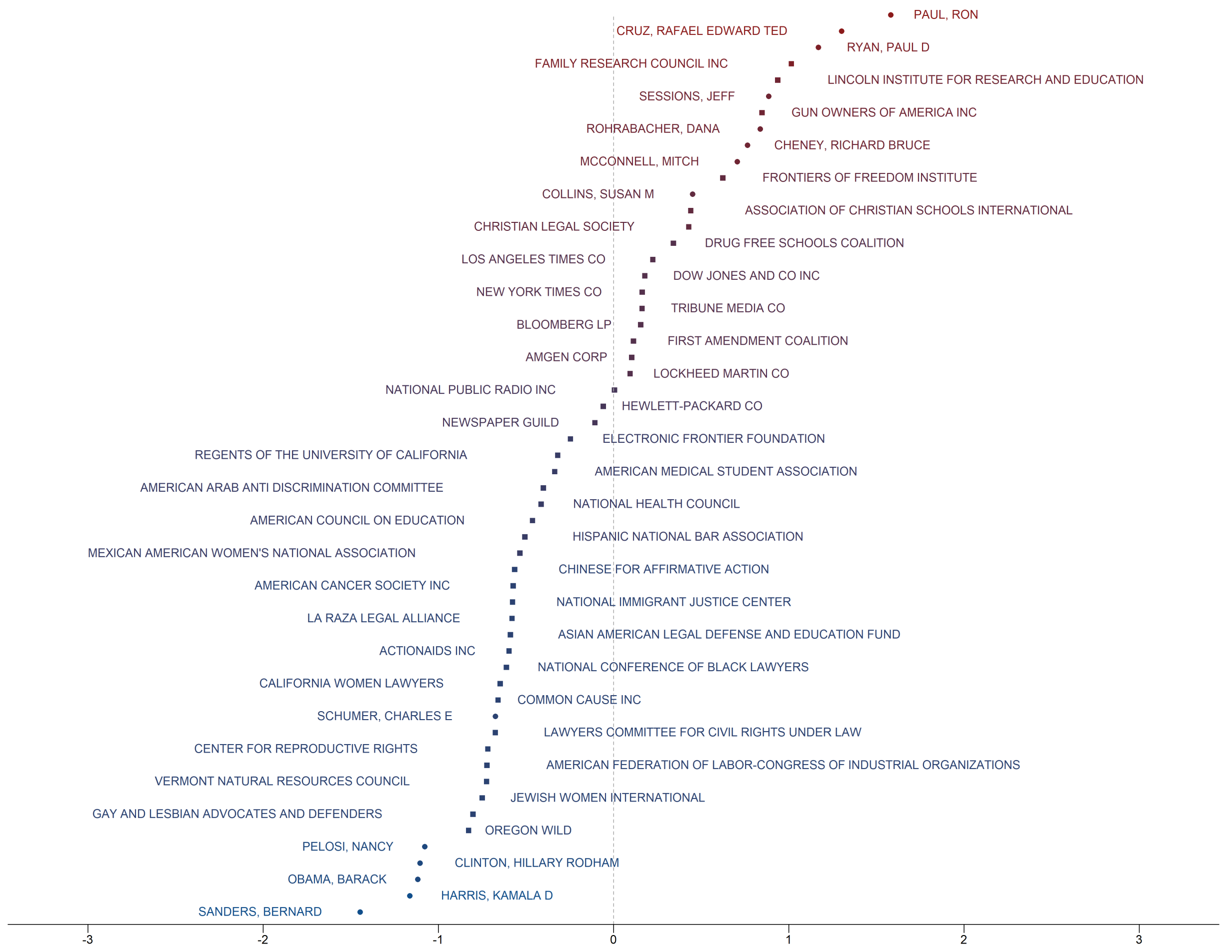


Figure 3: Ideal Points of Selected Interest Groups and Political Elites. *Circles indicate organizations or individuals with DIME scores, and squares indicate organizations without them. Nodes are colored and ordered by ideology from liberal (left and blue) to conservative (right and red).*

4.1 Interest Group Coalition Strategies

IGNet scores provide a window not only into the degree of ideological heterogeneity in organized interests before the Court, but also into their coalitional strategies. Combining both their ideology and networks allows us to see whether particular interest groups work largely with other groups that are ideologically similar. For example, we might expect, given the polarization of national politics in the US, that liberal organizations will predominantly cosign with other liberal organizations, and that conservative organizations will do the same. Alternatively, we might anticipate that the signaling value of an amicus brief signed by a bipartisan coalition of organizations would carry more weight, providing incentives for organizations to cosign broadly and across the ideological spectrum.

To this end, we graph a one-mode projection of the ties of every interest group in the data in Figure 4. We add to the plot the IGNet scores in the form of node shapes and colors. Circles indicate organizations that begin with a DIME score and squares indicate organizations without one. Nodes are colored by the estimated IGNet scores from liberal and blue to conservative and red, with more moderate organizations as purple. The 3,029 organizations without IGNet scores are colored light gray. Again, in all cases, the IGNet score is determined by the cross-validation process, and thus may not match the DIME score.

Immediately evident from the graph are two dense networks in the center surrounded by several small cliques and isolates in the periphery. The coloring suggests that much like other political networks (e.g., Adamic and Glance, 2005; Barberá, 2015), what we see before the Court is a polarized network of two ideological communities, the conservative and the liberal. Also apparent is the larger size and increased density among the liberal organizations, whereas the conservative groups are broken into a few tighter-knit communities. The periphery of the graph also conveys the relatively greater number of conservative groups working alone or in very small coalitions. However, at the center of the graph, we note the appearance of a non-trivial number of purple organizations with substantial ideological overlap. In all, the network suggests that interest group coalitions before the Court are largely but not exclusively polarized, with a small collection of groups working with both sides of the ideological spectrum.

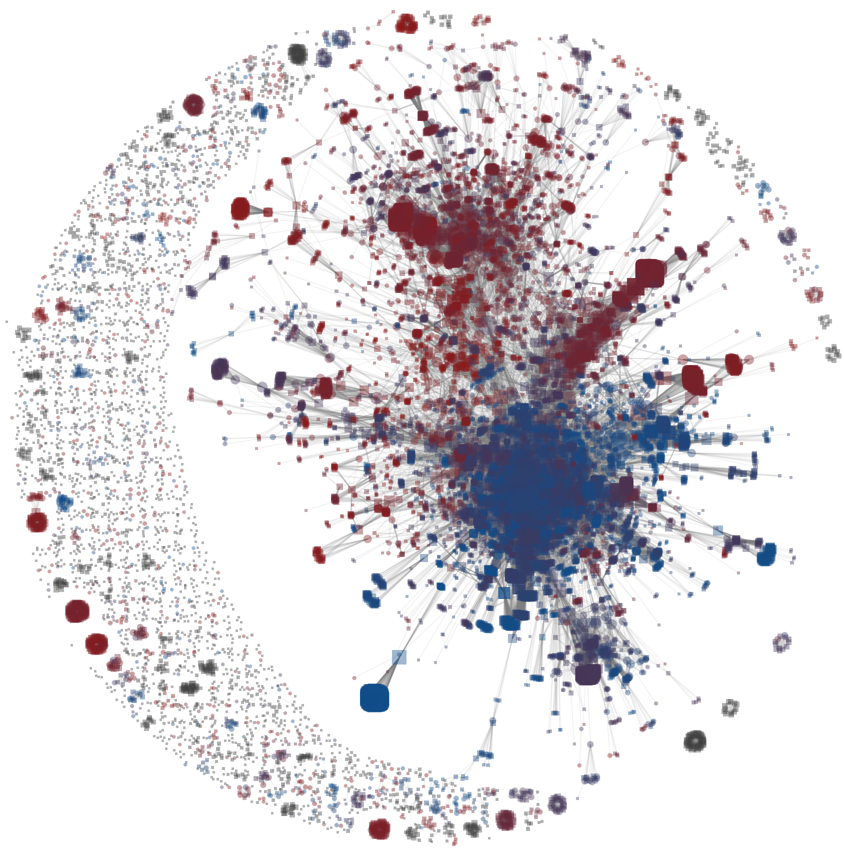


Figure 4: Amicus Curiae Network. *Circles indicate organizations in the training set, and squares indicate organizations in the test set. Nodes are colored by ideology from liberal (blue) to conservative (red). Nodes with no scores are light grey.*

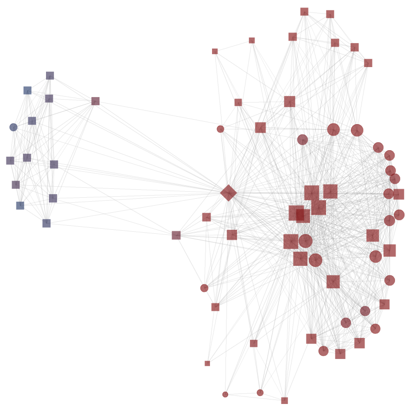
Organization	Org Ideology	Ego Network Ideology
Gun Owners of America	0.67	0.85
Free Speech Defense and Education Fund	0.88	0.95
New York Times	0.14	0.10
Johnson & Johnson	0.14	0.16
Feminist Majority Foundation	-0.80	-0.90
NARAL Pro-Choice America	-0.63	-0.61
Unweighted and degree-weighted means	-0.15	-0.30

Table 3: Ideologies of Ego-Networks of Prominent Amicus-Filing Organizations

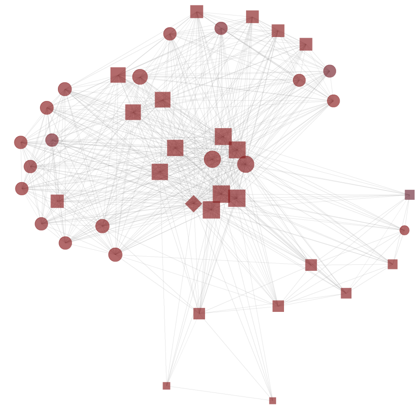
We can look more closely into the coalition structure of particular interest groups with their egocentric networks, or egonets. Egonets present all the organizations that have cosigned with an organization, the ego, and the cosigning links between those organizations. Thus, they can provide insights into the diversity of strategies particular nodes play within their own networks. While interest groups have been shown to employ mixed strategies before the Court—for example, acting as equal teammates, or leaders, as well as avoiding coalitions altogether (Box-Steffensmeier and Christenson, 2014; Box-Steffensmeier et al., 2018), the role of ideology in these coalitions are largely unexplored.

In Figure 5, we observe six prominent amicus cosigning organizations: two conservative (Gun Owners of America and the Free Speech Defense and Education Fund), two moderate (New York Times and Johnson & Johnson Co.), and two liberal (Feminist Majority Foundation and NARAL Pro-Choice America). As in all the figures, all of these organizations' IGNet scores were imputed based on the network. We also provide these organizations' ideal points and the average ideal points of their ego networks in Table 3. The first column indicates the ideology or IGNet score of the ego. The second column indicates the average ideology of all organizations in the organization's ego network. Substantial differences between the ego's ideology and their cosigners' ideologies suggest an ideologically heterogeneous strategy, whereas similar scores suggest a homogenous one. The final row indicates the average ideology of all organizations in the data, and the *degree-weighted* average ideology of all organizations in the data, to give an idea of how different these six groups are from the rest of the network.

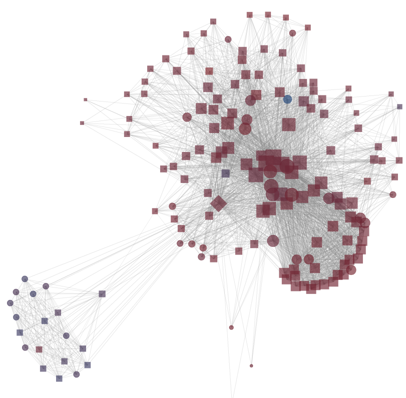
Careful examination of these six ego networks reveals important facets of their organizations' legal strategies. Foremost—and just as it appeared in the full network plot (Figure 5)—the egonets show that interest groups generally work with organizations of similar ideological backgrounds. The ego ideologies in Table 3 are similar to the average in their networks. Of course, Figure 5 also shows that some of these groups work in more ideologically heterogeneous networks than others. The Feminist Majority Foundation and the Free Speech Defense and Education Fund primarily cosign with dense, highly connected groups of co-ideological organizations. These groups largely work as equal teammates, situated among groups that work with one another and agree ideologically. By contrast, the Gun Owners of America and NARAL Pro-Choice America have two almost wholly disconnected subgroups, meaning that they act as leaders and information brokers, bringing together groups that would be otherwise disconnected. The Gun Owners of America has a subnetwork of conservative cosigners and one subnetwork of strongly liberal co-signatories. Of the two clusters of NARAL Pro-Choice America cosigners, one is a diverse array of liberal



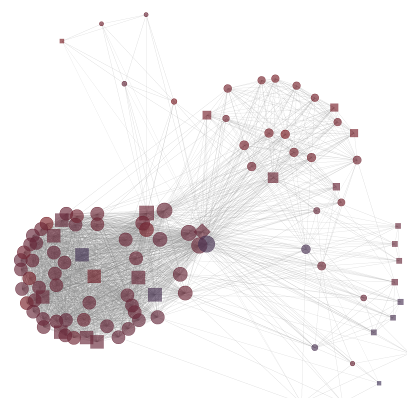
(a) Gun Owners of America



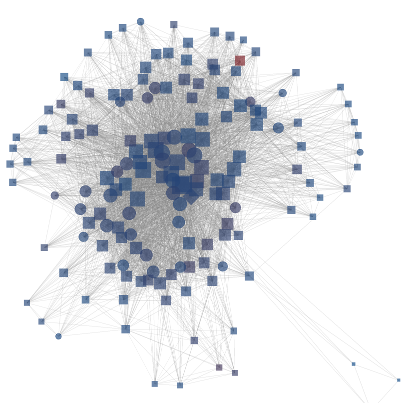
(b) Free Speech Defense and Education Fund



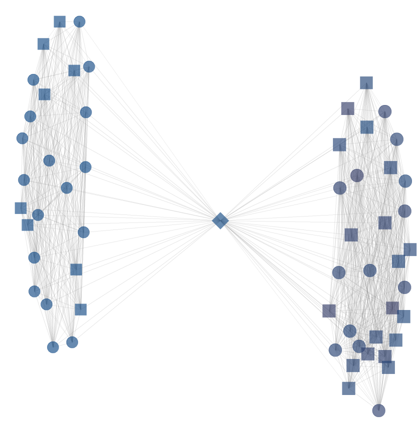
(c) New York Times



(d) Johnson & Johnson Co.



(e) Feminist Majority Foundation



(f) NARAL Pro-Choice America

Figure 5: Ego-Networks of Prominent Amicus-Filing Organizations. *Circles indicate organizations or individuals in the Bonica (2013) database, and squares indicate organizations that are not in it. Diamonds indicate the central node. Nodes are colored by ideology.*

interest groups while the other consists exclusively of state-specific NARAL chapters. Located at the center of the ideological spectrum, the *New York Times* and Johnson & Johnson Co both cosign with a highly diverse and interconnected group of organizations from across the political spectrum. Ultimately, the egonets not only suggest support for mixed coalition strategies, but also that few exist in perfectly homogenous ideological networks. While polarization is the norm, interest groups, particularly moderate ones, seek out partnerships with ideologically diverse groups from time to time, creating a relatively dense network of the population of interest groups.

5 The Ideologies of Amicus Curiae Briefs

Our method maintains the useful properties that an organization's score is the average of the briefs it cosigns and a brief's score is the average of the organizations that cosign it. As such, our approach provides an additional feature in the form of ideal point estimates for 11,794 amicus curiae briefs.[14] That is, in addition to scores for interest groups, we arrive at the first large-scale measure of ideology for amicus curiae briefs. These ideal points are on the same scale as the DIME and IGNet scores, allowing for ideological comparisons across organizations, individuals and briefs.

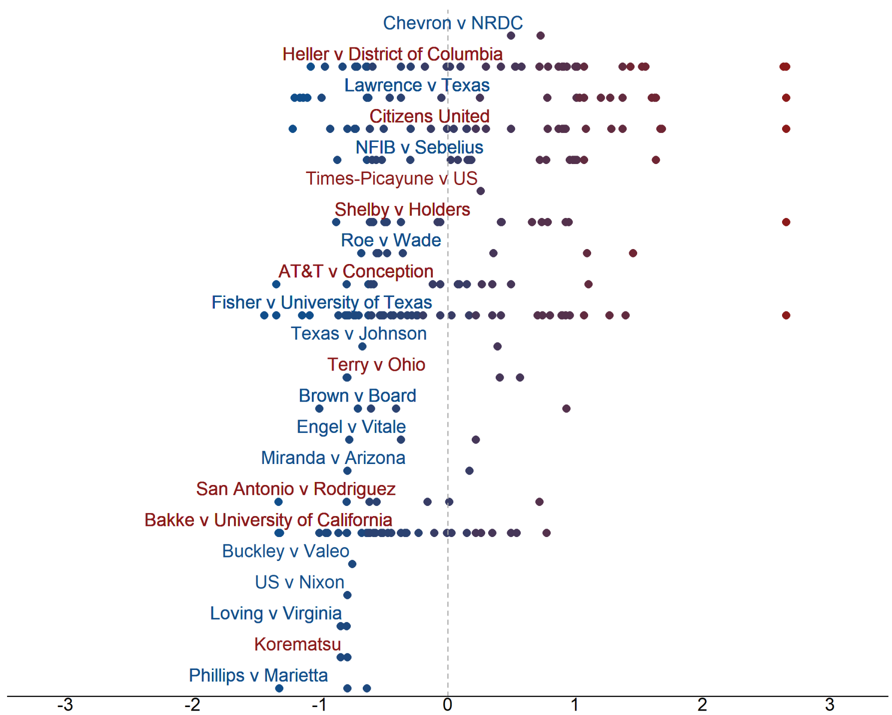


Figure 6: The ideology of amicus curiae briefs submitted in prominent US Supreme Court cases.

In Figure 6 we show the ideological distribution of amicus curiae briefs submitted for a number of prominent Supreme Court cases. As discussed above, there are often many amicus briefs for a single case, especially among prominent cases. Thus, each point here represents a single brief on a case named above it. The x-axis refers to the IGNet score; briefs farther to the left (and bluer)

[14]We are unable to score 2,535 briefs, since these are signed by groups without IGNet scores.

are more liberal and those farther to the right (and redder) are more conservative. In terms of the y-axis, we have ordered the cases from the top with the highest mean IGNet score across the briefs (most conservative) to the bottom with the lowest mean IGNet scores (most liberal). The names of the cases that are in blue were decided by the Supreme Court in a liberal direction and those in red were in a conservative direction (as determined by Spaeth et al. (2015)).

While only a snippet of these data, the figure provides an overall picture of the various ideological components present in each case, and how they potentially interact with each other. For instance, it is notable that for cases addressing highly controversial issues there is a high number of briefs, and a greater number of briefs at the extremes of the ideological scale. For instance, in *District of Columbia v. Heller*, 554 U.S. 570 (2008), there were a total of 40 amicus briefs, 12 in support of the petitioner (liberal) and 28 in support of the respondent (conservative). The most liberal and most conservative amicus briefs have an IGNet score of -1.076, and 2.655, respectively. This wide range of ideological scores is consistent with the controversial nature of the case, especially for conservative groups such as the National Rifle Association. The figure shows a similar pattern for other highly controversial cases such as *Lawrence v. Texas*, 539 U.S. 558 (2003), *Citizens United v. FEC*, 558 U.S. 310 (2010), and *NFIB v. Sebelius*, 567 U.S. 519 (2012), *Shelby County v. Holder*, 570 U.S. 529 (2013).

In contrast, in cases addressing less controversial questions, we observe a smaller number of briefs with less extreme ideological scores. This is especially true for cases of criminal procedures such as *Terry v. Ohio* 392 U.S. 1 (1968) or *Miranda v. Arizona* 384 U.S. 436 (1966), or political questions, such as *US v. Nixon*, 418 U.S. 683 (1974). For instance in Terry v Ohio, there were a total of 4 amicus briefs, 2 in support of the petitioner (liberal) and 2 for the respondent (conservative). In contrast to more controversial cases, the most liberal brief has a score of -0.797, and the score of the most conservative brief is 0.565. A similar pattern is observed for the other two cases. Overall, the consistency in the number of briefs and their ideological spread with the type of cases presented in Figure 6 serves as a qualitative validity measure for the IGNet scores.

5.1 The Ideological Drivers of Amicus Filing

Are some cases, courts or times more attractive targets for interest groups of one ideological persuasion or the other? Moreover, do some cases bring together more ideologically diverse groups than others? O'Connor and Epstein (1983) find that, between 1969 and 1980, conservative groups chose amicus briefs as their preferred method of participation in judicial proceedings at a significantly higher rate than liberal groups. However, this is not necessarily an indication that conservative groups find amicus briefs to have greater value or even file in greater number. But it does further reinforce the notion that interest groups have important heterogeneous capabilities and interests that compel further research. If we are to better understand their influence on the courts and beyond (e.g., Collins, 2008; Kearney and Merrill, 2000), we need to uncover how ideology shapes interest groups' decisions to file amicus briefs, and the sides they choose during this process.

In Figure 7 we graph the IGNet scores for each brief in our data set, along with a smoothed estimate of the conditional mean and confidence interval from a generalized additive model. Such provides a (simple) measure of the dynamics of interest group macro-ideology before the Court that has largely escaped the discipline. In doing so, we find that the average is below zero for most of history. Filing amicus briefs is a strategy that, historically, has been employed by more liberal than conservative organizations. That is, there is a fairly consistent though small left-wing bias to amicus representation before the Court. The bias is particularly evident in the 1960s, before it shrank in the 1970s. Since the mid-1980s any bias has remained small to non-existent. Indeed, in

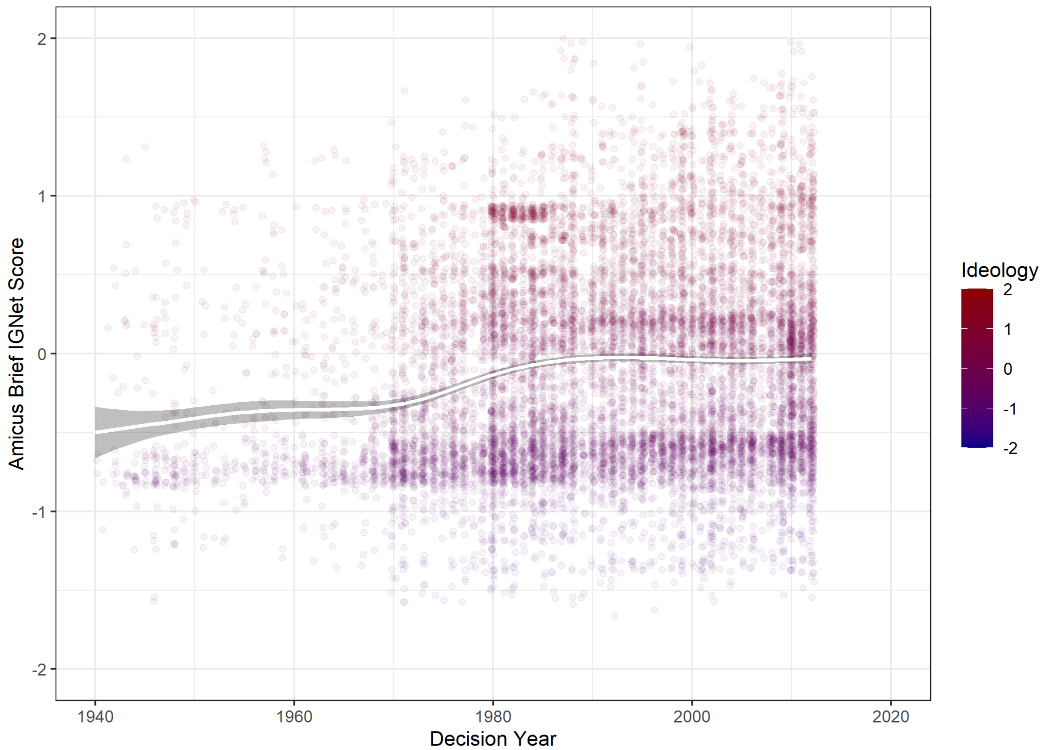


Figure 7: Macro-Ideology Dynamics of Interest Groups

the 1910s, the average ideology score of organizations that submitted an amicus brief was -0.792. By the end of our data in 2012, the ideology score of organizations that submitted an amicus brief was -0.142, a substantial change. The volatility of the mean ideology of an amicus signing organization has also decreased over-time. Much of this decline in volatility is attributable to the increasing frequency of organizations joining amicus briefs, which has grown at roughly 6% per year since the end of the Second World War. Interestingly, this increase in activity has come at the same time the Court has taken fewer and fewer cases.

6 Discussion: The Import of the Measure

Our measure of interest group ideologies opens the door to investigate a host of issues surrounding representation before the Supreme Court and in politics at large. This work makes three major contributions to the study of American politics. Foremost, we introduce a measure of ideology for more interest groups than ever before and across a longer timeframe. We demonstrate that the measure is valid, using cross-validation tests and comparing our imputed scores to those of known individuals and groups. Second, we make methodological and measurement contributions in extending donation based ideal points to non-donors based on social network analysis that can be applied to other substantive contexts. Finally, we provide empirical work that is central to theories in American politics that highlights the import of the measure.

By describing the dynamics of interest group macro-ideology over 95 years, we arrive at unique insights into the ideological context surrounding Supreme Court cases and issues. In addition, we show that interest groups before the Court are neatly, though imperfectly, divided based on ideology. While they are more likely to work most closely with groups of similar ideology, few groups are entirely disconnected to ideologically different ones by virtue of either a cosigner or a case that does not fall neatly along partisan lines. In turning to campaign finance, we find support for two expectations about interest group donation behavior. Interest groups that donate to campaigns are more ideologically extreme than non-donor groups and more conservative.

The IGNet scores provides an unprecedented glimpse into fundamental actors in the American democracy—and into a largely invisible web of influence in our political system. Our exposition demonstrates how the measure can shed light into the overall ideological composition of special interests in the United States and over time. Of course, such findings are only tips of proverbial icebergs, and we hope the work here inspires a number of avenues for further research. The measure provides a sense of the ideological direction of the active population of interest groups across several decades that could be used, for example, to better understand the relationships between public and elite attitudes. The measure also opens up the ability to explore the effects of asymmetric ideological influences on elite behavior across all branches of government.

In the realm of judicial politics, we ask—and can answer with this data: do different legal cases result in different kinds of ideological collections on each side of a case? By analyzing the collections of interest groups on each side of a case, petitioner or respondent, one can identify the cases that involve "strange bedfellows," politically speaking, and those that involve the homogenous collections of interest groups that are expected from a partisan political perspective. Moreover, are organizations that give to political candidates ideologically different than those that do not? Ansolabehere, Snyder Jr and Tripathi (2002) find a strong relationship between lobbying and campaign contributions. Interest groups active in lobbying give more equally across the ideological spectrum, while those less active appear more partisan in their giving. We heed their important call for "more careful study of the heterogeneity of groups" (p. 152).

Given the broad and seemingly increasing influence of special interests in American democracy, future studies will likely benefit from this measure of interest group ideology for thousands of politically active organizations, including those that have not donated to campaigns and sometimes not even formally registered as actively lobbying.

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