Competing for the Platform: How Organized Interests affect Party Positioning in the United States

Jennifer Nicoll Victor
George Mason University

Gina Yannitell Reinhardt
University of Essex

Abstract

What explains which groups are included in a party coalition in any given election cycle? Recent advances in political party theory suggest that policy demanders comprise parties, and that the composition of a party coalition varies from election to election. We theorize three conditions under which parties articulate an interest group’s preferred positions in its quadrennial platform: when groups are ideologically proximate to the party median, when groups display party loyalty, and when groups are flush with resources. Using computer-assisted content analysis on a unique and rich data source, we examine three cycles of testimony that 80 organized groups provided to the Democratic Party. The analysis compares group requests with the content of Democratic and Republican National Committee platforms in 1996, 2000, and 2004. Results show that parties reward loyal groups and those that are ideologically proximate to the party, but offer no confirmation of a resource effect.

Keywords: interest groups, Democratic Party, platforms, content analysis, USA
During the 1996 GOP Convention, Presidential candidate Bob Dole met conflict with pro-life advocates. The Platform Committee had adopted a strongly pro-life plank in the platform, but Dole favored a statement of tolerance that might appeal to party moderates. Though trying to foster a sentiment of compromise, Dole confronted a platform committee stacked with grassroots activists from the Christian Coalition, and his efforts ultimately failed (Rozell et al 2012).

Studying the complexities of the relationship between political parties and organized interests has generated scholarship that describes these entities as distinct (Key 1964), competing (Sabato 1981), dependent (Kolodny & Dulio 2003), or fully enmeshed (Cohen et al 2008). These arguments, in light of stories such as above, lead us to explore the US platform-drafting process and ask: Under what conditions will a party include a group in its coalition via the party platform?

American political parties publicly articulate their ideological positions in quadrennial platforms, adopted in presidential nominating conventions. Organized groups seek to join the party coalition by having their interests articulated via platform planks. Parties may use these platforms to appeal to undecided voters (ideological moderates), or to boost enthusiasm (and therefore turnout) from a party’s ideological base. While Downs (1957) tells us parties use platforms only for the former, the ‘extended party network’ (EPN) theory of parties, and a variety of anecdotal evidence, suggest parties regularly use conventions and platforms for the latter. We contend that platforms can be tools for either, depending on group characteristics.

We seek to further the understanding of the relationship between groups and parties by exploring their interaction during the platform-drafting process. We hypothesize conditions under which parties respond to organized groups, and test these expectations using platform-
drafting hearing testimony. Using automated text analysis we find evidence of parties negotiating
with groups for inclusion in their coalition. We find political parties responding to organized
groups that show loyalty and ideological similarity to the mainstream of the party, but no
evidence that parties bend to those with greater resources.

Our work contributes to and furthers our knowledge of the party-group interaction
empirically, theoretically, and substantively. Empirically, we utilize exclusive transcripts of
platform hearing testimony given to the Democratic Party in 1996, 2000, and 2004. These data
are not public, and are unavailable to the academic community except through our research.
They provide a window into the direct negotiations between parties and groups. Rather than
being restricted to insights inferred from observational data, we have empirical evidence of the
interaction between these potential coalition partners.

We also employ recent methodological advances in the form of automated text analysis.
This technique is relatively new and commonly utilized by a select group of scholars of
comparative party preferences (Laver et al 2003; Slapin & Proksch 2008). By employing these
tools to scale differences in platform text with automated text analysis, we facilitate the
discussion between Comparative and American Politics.

Theoretically, our findings help advance debate on the birth-order of parties and groups
(e.g. which came first?). We provide an important update to the group-party literature by
demonstrating that money and resources are less influential in group-party relationships than one
might expect. We also speak to ongoing concerns raised in popular literature about the corruptive
power of wealthy groups on political action. Our results are consistent with recent evidence that
shows ideas precede parties (Noel 2014) and our findings dampen heightened anxiety that
political parties are purchased by highest bidders. Instead, we show that loyalty to a party gains more attention than absolute dollars.

Substantively, we demonstrate how party platforms can matter to both parties and groups. Though criticized for lacking efficacy (Truman 1993) or embodying ‘nothing more than the momentary sentiments of a majority of party activists,’ (Rozell et al 2006), the very fact that groups mobilize to testify at platform hearings indicates that American party platforms are valuable. Platforms may not be the most important documents in American history, but they are possibly the single most representative document of group influences on the central parties.

Political parties and organized interests

Scholars often conceptualize organized interests as groups external to political parties. Thought of as natural combatants in some instances, or ‘symbiotic adversaries’ (Fine 1994) in others, their goals may vacillate between competing and complimentary. More recent research re-conceptualizes this framework by acknowledging that political parties are ultimately, at least in part, comprised of organized interests (Bawn et al 2012; Cohen et al 2008; Karol 2009; Noel 2014). In this view parties are loose coalitions of intense policy demanders who seek some common goal (Masket 2016). Prior work has established the overlapping individual memberships of groups and parties as ranging from intertwined to indistinguishable (Grossmann & Dominguez 2009; Heaney et al 2012; Herrnson 2009; Koger et al 2009; Kolodny & Dwyre 1998; Skinner et al 2012).

Our idea of a dynamic negotiation between parties and groups is consistent with the Extended Party Network (EPN) theory, which assumes parties are comprised of groups. (Noel 2014) argues that parties and ideologies are distinct but related phenomena, where ‘parties
choose the ‘who’ that they unite by considering what those people want’ (24). Ultimately, a party’s primary objective is to maximize the number of seats won in a given election. A party therefore strategizes to create a coalition that will maximize the probability of attaining that goal.

Organized interests, on the other hand, have multiple goals, and success is often self-defined and dynamic (Brunell 2005). Groups demonstrate partisan affiliation (Koger et al 2009; Koger et al 2010) with respect to legislative activity (Grossmann & Dominguez 2009; Masket 2011) and candidate selection (Cohen et al 2008; Miller & Schofield, 2003). Some groups seek specific policy implementation, and would be unsatisfied with anything less than policy or social change. Other groups, however, may be pleased with the opportunity to voice, to clearly and vigorously express, their preferred policies; taking advantage of the opportunity to be heard would be sufficient cause for celebration.

What does this mean about the interaction between parties and groups? A group’s ability to mobilize and convince blocks of individual votes gives that group bargaining leverage with the party and its positioning (Harvey 1998; Miller & Schofield 2003; Truman 1993). A group can promise to support a party or candidate, or to mobilize out-group voters in supplement to the party campaign (Esterling 2007). A group might also credibly threaten to exit a two-party system, either by not voting, or by voting for a third party. These organized groups of ideological thinkers have little reason to compromise (Noel 2014).

Parties, meanwhile, have many incentives to compromise. One party’s calculus can change from one election to the next, and it is not uncommon for parties to change issue positions over time. Karol (2009), for example, explains how US Democrats and Republicans switched positions on trade policy in the 20th Century because party leaders valued organized labor as coalition partners more than they valued a consistent position on trade. (Wolbrecht
2000) shows that the parties switched positions on women’s issues during the same time period largely because of the groups included in each party’s coalition—women for Democrats, and religious conservatives for Republicans. In both cases, parties opted to maintain coalitions by changing policy positions.

This literature suggests elasticity in party coalitions, with organized groups moving in and out. We see bargaining across issues and groups where coalitions (e.g. parties) and their potential partners negotiate about which interests (e.g. groups) to include and which issues to favor. Party leaders settle on an arrangement of interests that maximizes the ability to win elections. This process is fluid, and results in party coalitions that change between election cycles. We suspect it does so in predictable ways.

Why platforms?

The platform-drafting process is only one element of party building, and some regard it as entirely symbolic. The extant literature on the value of party platforms in the United States contrarily finds platforms to be both vapid (Truman 1993) and useful (Maisel 1993; Pomper & Lederman 1980; Snyder & Ting 2002). We argue that it is a suitable juncture at which to examine group-party coalition formation for several reasons.

First, the platform-drafting process is time and labor intensive for both parties and groups. In 2004, for example, the Democratic Party’s platform-writing process spanned six months and four cities. It began with the appointment of a small Platform Drafting Committee, which drafted an initial document. Any individual or group could submit statements, comments, or requests to testify in response to the document (Democratic National Convention 2004). An official Platform Committee, made up of party leaders and ‘rising stars,’ then conducted hearings
in Portland, OR, Baton Rouge, LA, and Santa Fe, NM. Ultimately 193 entities from around the
country testified in person at the hearings. The Committee then revised the platform and
submitted it to the full Convention for discussion, debate, and adoption by delegate vote.

This activity highlights the utility of platform drafting to parties and groups, which is the
second reason for our focus. Groups see platforms as a tool to voice interests and broadcast
preferences nationally, while parties use platforms to bargain with groups for the ultimate
electoral prize: votes. Rozell, Wilcox, and Franz argue groups ‘assign symbolic importance to
the creation of platforms,’ and ‘believe that candidates do ultimately heed platforms to some
degree’ (2012: 46-8). They support their view with evidence from 2008, when the Republican
platform offered immigration and abortion positions more conservative than McCain’s and
included his name only once, due to group influence (Rozell et al 2012).

Finally, platform drafting is a direct and observable negotiation between those drafting an
official statement of the party and those seeking to influence that statement. It demonstrates the
bargaining process leading to a party coalition, wherein groups commit support in exchange for
interest articulation, and party leaders offer platform input based on the ability to deliver votes.
Whether resulting in policy change or not, the interaction captures the behavior of ‘intense policy
demanders’ (Bawn et al., 2012; Cohen et al 2008), those who have a strong preference for
particular policy outcomes and, in this case, influence over platform creation.

Hypotheses

We assume that parties are instrumental and strategic about building coalitions, and that
parties are dominated by elites who drive their broad decision processes. We theorize that parties
court groups into their coalition in an attempt to maximize votes in an election. If we consider
parties and groups to be related, overlapping, and perhaps even wholly enmeshed, we can think of the negotiation over platform content as a strategic game. The final outcome (i.e. the platform) is a Nash Equilibrium representing each entities’ best response to the other (see Reinhardt & Victor 2013). These observations beg our question: under what conditions will a party include a group in its coalition via the party platform? Based on the above insights we see three characteristics of groups as critical determinants of the final outcome: party loyalty, ideological proximity, and group resources.

First, we expect parties to include groups that can either promise or mobilize voters (Adkins & Dowdle 2004). Groups with a large membership base or substantial financial resources (Gilens 2012; Schattschneider 1975) may find it easier to mobilize large numbers of voters. We therefore expect that all else being equal parties will seek to incorporate more resourceful groups into their coalitions.

H1: Groups with greater resources for mobilization are more likely to be included in the party coalition than groups with fewer resources.

Second, Karol (2009) and Wolbrecht (2000) show that parties are willing to shift issue positions to appeal to loyal groups. Those groups that have expressed interest in a variety of parties across time may not be able to compel one party to switch positions, while consistently loyal groups may be more likely to persuade a party to reconsider its position. We therefore expect parties to reward and protect groups showing loyalty to their coalition, as opposed to that of another party.

H2: Groups that display greater loyalty towards one party are more likely to be included in the party coalition than groups that show less loyalty.
Third, the basic Downsian model emphasizes the importance of spatial proximity (Downs 1957). Groups are not likely to seek out party coalitions ideologically distant from their ideal point, and parties are unlikely to court groups ideologically opposite from the rest of the party coalition. We therefore expect parties to seek to include those groups in their coalition that are nearest to the median position of the party coalition. While that median point may shift as groups move in and out of the coalition, all else being equal we expect the probability of a group being included in a party’s coalition to increase as the ideological distance between the party median and the group median declines.iii

H3: Groups with median ideology closer to the existing party coalition median are more likely to be included in the party coalition than groups that are ideologically more distant.

Data and methods

Platform hearings provide a venue for groups to articulate their views of the party platform, and offer an excellent source from which to estimate the positions of groups trying to influence platform creation.iv Our unit of analysis is a group-year, accounting for each group that testified at a DNC platform hearing in 1996, 2000, or 2004 (N=80). Our empirical strategy is to examine what groups request, and compare this to what parties produce in platform negotiations. We expect to systematically explain the group interests that are incorporated into the party coalition (platform) using group ideology, loyalty, and resources.

Our dependent variable is the overlap between the group’s testimony and the final DNC platform. We derive this by analyzing the content of the testimonies and platform using Wordscores, described fully below (Laver et al 2003). Our data includes the complete population
of groups that jockeyed for platform position during these three election cycles; however, groups that do not participate are unobserved. We therefore note that our data has a selection bias and do not draw inference on the population of all groups, but only those in a position to be included by parties in the first place. While this limits our inference, our approach increases our understanding of the competition for party attention among this class of groups, which has not been previously understood.

**Using text as data**

We began with the full (hardcopy) texts of the Democratic Party platform hearings from 1996, 2000, and 2004. We digitized the information into plain text, extracting testimony and question responses for each participating interest group. We obtained the full text of final party platforms from the websites of the DNC and RNC.

Analyzing text to proxy actors’ positions relative to one another generally includes two possible strategies. One approach is to hand code text. This strategy involves developing a series of categories and codes from the substance of the text and using humans to apply codes to segments of the text. Error can be minimized by using inter-coder reliability checks, though the increase in reliability comes with increases in labor costs as well (see for example Budge 2001a, 2001b).

An alternative approach is to use computer-assisted coding. This strategy involves some human coding to develop categories and codes on a sample of text, and then using software to apply these codes to remaining text. It allows one researcher to code large quantities of text (see for example (Laver & Garry 2000). Each of these modes of text analysis involves tradeoffs. Generally, the researcher trades some measurement error in exchange for efficiency.
A third strategy is computer-assisted text analysis. Developed by Laver, Benoit, and Garry (2003), it does not treat text as substantive prose meant to be dissected, analyzed, and comprehended. Rather, these scholars approach text with naïve agnosticism and assume that individual words, and short strings of words, convey information. Their approach treats texts as a chaotic ‘bag of words’ where information about speakers’ positions is contained in the frequency of word choice, rather than in the meaningful substance of sentences and paragraphs. This strategy is efficient and reliable. The approach is easy to implement, fully replicable, and not prone to measurement error, or to human coding error or variance. It does, however, trade some precision and nuance in favor of efficiency and replicability.

Laver, Benoit, and Garry (2003) argue that one can ascertain the policy positions of political actors by analyzing texts the actors have written. They show that treating text as data for the purpose of revealing actor’s policy positions is sometimes advantageous over alternatives. For example, let’s say one seeks to evaluate congressional policy preferences. Legislative roll call voting indicates one’s choice from dichotomous options, but is only observed at the end of a long process, and likely masks strategic behavior. Alternatively, one might use surveys or interviews, but costly methods can include measurement error due to participant guardedness. Analyzing the texts produced by political actors can provide an objective, easy to replicate, inexpensive, and transportable metric of actors’ policy positions.

There are two key requirements to make the Laver, et al. approach work. First, the technique requires a known and quantified ‘reference text’ against which to measure all other texts. The reference text must have a known position in ideological space. The original research on this technique, for example, uses the Comparative Manifestos Project, which hand-codes multiple party manifestos in several countries to develop a common ideological score for each.
This score, and the word frequencies associated with it, act as a quantitative anchor from which to compare new unscored ‘virgin’ documents about which no ideological information is known. The algorithm in this technique, known as Wordscores, compares the word frequencies in the virgin text to those in the previously-scored reference text to produce a score for the virgin text. Therefore, a known, verifiable, meaningful, and quantifiable score for the reference text is fundamentally necessary.

Second, the texts used in Wordscores must be appropriate texts for the technique in that they can be interpreted on a common spatial scale. Such a scale is common in the study of politics, legislatures, and parties where for several decades scholars have used Euclidean distances to estimate ideological positions. In such cases the technique is flexible enough to analyze texts and actors such as activists, judges, commentators, bloggers, lobbyists, legislators, candidates, etc. Yet one would be misadvised to compare a party manifesto to a series of appliance manuals.

We employ the Wordscores technique for three reasons. First, party platforms provide known and quantified reference texts to which we can compare the ‘virgin’ texts of interest group platform testimonies. Since groups try to influence the platform the texts have a direct relationship. Second, the texts we have are appropriate. It is common to quantify party platforms and to assume that they can be placed in a Euclidean ideological space. It is equally common to assume that political actors, such as those that represent organized interests, can be placed in a similar space. Third, we are ultimately only interested in estimating the overlap in policy positions between the party and groups and have no expectations regarding specific planks or policies. We seek efficiency, accuracy, and scientific replicability over substantive nuance of particular groups’ requests. Wordscores therefore provides the best option for evaluating our
expectations about the conditions under which parties will incorporate group interests into their platforms.

More technically, we give Wordscores two collections of reference texts—a series of Democratic Party platforms (from 1996, 2000, and 2004) and a series of Republican Party Platforms (from 1996, 2000, and 2004). We concatenate each party’s platforms into one document, yielding one Democratic reference text and one Republican reference text. Next we provide an a priori score to these reference documents of -1 (Democrat) and 1 (Republican), akin to the scale commonly used in ideological space.\textsuperscript{vi}

The algorithm in Wordscores observes a word (or two-word or three-word clusters, depending on the parameters provided) in a reference text and calculates the probability that the word came from a particular reference text based on word frequencies. This probability is multiplied by the a priori ideological anchoring score we provide, and the result is a ‘score’ for each word in the reference texts. Then we can compare individual words in the virgin texts to the scored words in the reference texts using the same logical procedure. First, the software calculates the relative frequency of each word in the virgin texts, and multiplies that frequency by the weighted score of the word from the reference texts. An overall wordscore for the entire virgin text is then the average weighted scores of its words. For our purposes, individual words uttered by testifiers are weighted and aggregated to produce a testimony score that places the group in the same ideological policy space as the party platform (see Appendix A for a technical description of Wordscores). As Laver, et al (2003) state:

Scoring words in this way replaces the predefined deterministic coding dictionary of traditional computer-coding techniques. It gives words policy scores, not having determined or even considered their meanings in advance but, instead, by treating words purely as data associated with a set of reference texts whose policy positions can be confidently estimated or assumed (313).
If we take the pre-defined ideological or policy space score of the reference texts as meaningful, the Wordscores technique allows us to use the frequency with which groups used particular words to estimate party proximity without evaluating their meaning or intent.

A skeptical reader may question the wisdom of stripping words of meaning and calculating organizational policy positions based on word frequencies. Yet counter-intuitively, the blindness of this technique gives us confidence in its estimates. The procedure is immune to bias, personal interpretations, preset expectations, or other cognitive limitations of human coding, which makes our work both replicable and falsifiable. We therefore accept the trade-offs.

The Wordscores technique has been utilized (Baum & Zhukov 2012) and criticized (Lowe 2008). A primary critique is that Wordscores generates outputs that do not have interpretable magnitude. This is a serious shortcoming, if interested in generating point estimates. In our case, however, we seek only to draw an inference on the relationship between group inclusion in a party platform and the characteristics of a group that are predictive of its inclusion. Wordscores provides us the invaluable tool of quantifying party and group interests in a single space, with information about the relative positions of each player rather than the magnitude of causal effects.\textsuperscript{vi}

\textit{Dependent Variable}

To calculate the extent to which an interest group is included in the platform, we use the transformed Wordscore for each group-year as an indication of group proximity to the Democratic and Republican platforms. Values closer to -1 are nearer the Democratic platforms, while those closer to 1 are nearer the Republicans’ platforms. We make this calculation on
‘unigrams,’ or the overlap in single words, as well as ‘bigrams,’ and ‘trigrams,’ the overlap in groups of two and three words, respectively. The literature suggests that counting small groups of words, rather than single words, provides a greater degree of sensitivity of overlap between texts; however, one must tradeoff degrees of freedom and power to make this exchange. Figures 1A and 1B show the relative positions of the groups in our sample to the party platforms for unigrams (Figure 1A) and bigrams (Figure 1B). The reader may notice the DNC position (at -1) and the RNC position (at 1), which more or less splits the population into thirds, with most groups falling between the two parties. There is similarity between the arrangements of groups between the two figures, giving us confidence in the method.

[Figures 1A, 1B]

Substantively, the transformed Wordscore value for each group represents the group’s proximity to each party, or the extent to which each party included the group’s interests in their platforms, as measured by the overlap in word frequencies. The arrangement of groups along this scale shows a reasonable left-right logic. On the left we see traditional Democratic groups such as labor unions and civil rights organizations, while on the right we see veterans’ organizations and business interests. Table 1 shows the summary breakdown of the texts used to create the figures.

[Table 1]

Independent Variables

Interest group ideology is operationalized using Bonica’s (2014) measure of group ideology. This score is developed from observations of campaign contribution behavior from groups, PACs, and associated individuals (e.g. employees), and has been shown to provide a good approximation of group ideology. We must accept some missingness to use this variable
because not all of our group testifiers appear in the Bonica data (Table 2 offers summary statistics).

In measuring groups’ resources we seek an indicator of potential to mobilize voters. We create a standardized index for each group based on two characteristics known to affect their ability to mobilize voters (Kollman 1998): number of members and reported budget. Each measure is standardized among groups, summed, and standardized again. Formally, resources is the sum of the standardized count of the number of members a group has and the group’s standardized budget. The sum is standardized again:

\[ Resources = \text{std} \left( \text{std}(M_t) + \text{std}(B_t) \right), \]

where: \( M_t \) is the reported number of members in the group in electoral cycle \( t \), \( B_t \) is the group’s reported budget in cycle \( t \), and \( \text{std} \) redistributes the variable to a standard Normal distribution.

We measure loyalty as the percentage of campaign contributions made by each group’s Political Action Committee, or by individual employees of the group, to the Democratic Party during the two-year campaign cycle of the testimony. We weight the percentage by the total amount of money the group gave to Democratic candidates in the same cycle, and take the natural log of the result. Most of the testifying groups give heavily to Democrats. Twenty-four have no PAC or employee contributions tracked by the Federal Elections Commission. Formally:

\[ Loyalty = \ln \left( \frac{C_{Dt}}{C_t} \right) * A, \]

where: \( C_t \) is the total contributions made by a group in cycle \( t \), \( C_{Dt} \) is the group’s total contributions to Democratic candidates in cycle \( t \), \( A \) is the total amount donated.
Loyalty and ideology are both derived from campaign contribution behavior, though this should not cause concern. While the initial data is the same, the algorithms convert the observed behavior into two different metrics. They are correlated at $r = 0.2$.

[Table 2]

**Results and Analysis**

We estimate a linear regression model. We cluster the error term on groups, as several groups are represented multiple times in this short cross-sectional time series. With 80 observations$^{ix}$ spanning three time periods, $(N=80, T=3)$, our data do not fit the $T>N$ restriction desired for standard cross-sectional time series analysis (Beck & Katz 1995). We therefore insert time-wise fixed effects for each platform year, excluding 1996, the reference year (appropriate for short panels, see (Arellano 2003; Wooldridge 2010). We estimate standard errors with bootstrapping because our dependent variable is itself the product of an estimation procedure. The statistical model is:$^{x}$

$$Platform\ Inclusion_{it} = \alpha + \beta_1 Ideological\ Congruence_{it} + \beta_2 Loyalty_{it} + \beta_3 Resources_{it} + \beta_4 D_{it2} + \beta_5 D_{it3} + \epsilon_{it}$$

[Table 3]

We estimate this model separately for unigrams, bigrams, and trigrams (Table 3 provides results).

We note that the unigram and bigram models perform similarly to each other, while the trigram model performs poorly. We suspect the increased sensitivity of the trigram is not worth
the sacrifice of statistical power, so we focus instead on the bigram model (Model 2), combining statistical power and sensitivity.

We find no support for H1 that group resources will be positively associated with platform inclusion. Though unexpected, this finding is consistent with previous research suggesting that group monetary resources are not particularly predictive of group behavior or success (McKay 2012). Moreover, it suggests that parties do not necessarily rely on constituent groups for external voter mobilization. This may be because parties have sophisticated internal machineries using micro targeting and ‘smart’ campaigning (Issenberg 2013). The platform drafting process and coalition building between parties and groups either sits external to this process, occurs in a different timeframe, or remains unobserved using our methods. Either way, our finding dampens concerns about groups buying their way into the Democratic Party’s favor.

Loyalty is negative (-0.775) and statistically significant ($p<0.01$) in Model 2. Results for loyalty are thus consistent with our expectation (H2) that groups showing more loyalty to the Democratic Party are more likely to be included in the Democratic platform (recall that inclusion is represented by a transformed Wordscore nearer to the Democratic platform (-1)).

The positive and statistically significant coefficient on Ideological Congruence is consistent with our expectation (H3) that groups ideologically closer to the party’s status quo position are more likely to be included in the platform. Recall that the dependent variable and ideology are measured on the same scale (-1, 1), which is equivalent to (Poole & Rosenthal, 2011) NOMINATE scales. The coefficient is positive, relatively large given the distribution of the data (1.1), and statistically significant ($p<0.05$).

Discussion
We have used the Wordscores technique to gauge the relative positions of parties and groups, and to engage in a basic test of our hypotheses. From our results, we infer that ideology and loyalty are significant predictors of group inclusion in a party coalition (as measured by the platform), while resources are not. Overall, our analysis casts a shadow on the role of group resources in influencing party platforms, though we do not interpret these findings to suggest generally that group resources do not influence party behavior.

Our inference is limited in three important ways. First, we have temporal and ideological limitations because our specialized data includes only the Democratic Party’s platform drafting process in 1996, 2000, and 2004. In addition to being denied access to Republican platform testimony in 1996-2004, both parties changed their platform drafting process in 2008, so comparable data for later elections does not exist.

Second, our sample only includes groups that testified before the platform drafting committee, who are presumably a subset of groups who requested to testify. It is likely that the Democratic Party would seek input from their most loyal activists, and if so, our loyalty measure is biased due to the sample on which we make observations. We have no information on groups that might have sought to influence the process but were not granted access, and it is possible that well-funded groups influenced the process without testifying at the hearings.

Yet these are limitations of the research design, not of the empirical model. We have opted to utilize this rare and valuable data to gain insight into the Democratic Party’s process during the time period under study, and to conduct an analysis with novel and superior measures of group-party interactions. Even with limitations, our results show that among testifying groups, group resources do not predict inclusion in a platform, while group loyalty does.
Third, we have limited ability to substantively interpret coefficients or relative magnitudes. The substantial transformation of text to data is compelling because it allows us to quantify a previously unmeasured process, but also somewhat dissatisfying because the values of the measures are not necessarily substantively meaningful. If one is persuaded by the critiques, a downside of our empirical strategy is that we cannot reasonably interpret the relative size of the effects of group characteristics on platforms—only whether such associations exist.

We measure the groups of policy demanders who attempt to join the party coalition through the platform-drafting mechanism. Limitations notwithstanding, our work represents the first systematic window into this closed-door interaction between groups and parties. Our approach allows us to measure the characteristics of groups that seek to become part of a party coalition in a given election cycle. The opportunity to observe and directly compare organized groups’ requests about the party and its platform to the final document is unique and valuable.

Our results suggest that groups and parties engage in a strategic interaction to negotiate a platform, where the platform represents the aggregation of group policy interests that dictate a party organization’s agenda in a given election cycle. By analyzing the population of testifying groups, and identifying the characteristics of those with successfully articulated interests, we provide a creative and conservative test of how groups achieve interest articulation in party platforms. Testifying groups that demonstrate higher degrees of party loyalty through campaign contributions, and those with ideological preferences closer to the party, are more likely to see their interests articulated in the platform.

Conclusions

We set out to investigate party-group coalition building during the platform-drafting process. We develop three testable expectations: (1) parties reward loyal interest groups with
platform inclusion, (2) parties seek to include groups that are ideologically near the existing party median, and (3) parties are more likely to reward groups that have greater resources to mobilize voters. Our text analysis of party platforms helps probe the make-up of the final coalition of ‘policy demanders’. Our evidence furthers extended party network (EPN) theory’s view that parties represent extended coalitions of organized interests and that these interests jockey with one another to build a party coalition during each election cycle.

We use unique data to generate these results. Automated text analysis of the transcripts from three cycles of testimony provided to the DNC’s platform writing committee helps determine how much congruence there is between what groups request and what they receive in the final platform. Word frequencies and Wordscores technology produce reasonable estimates of overlap between groups and parties. Our empirical findings generally support our expectations: groups ideologically closer to the party, and those more loyal to the party, are more likely to be included in the platform.

Substantively, our paper offers first steps toward a greater understanding of party platforms, often thought to be useless, and neglected in the agenda of American politics. If parties use platforms to mobilize voters vis-à-vis interest groups, the study of those platforms and the groups participating in their construction has implications for the analysis of networks and party-building (Koger et al 2009). Can weakly connected groups use platform-drafting hearings to gain better network positions? Do the relative connections between groups and parties predict meaningful behavior from parties (e.g. which candidates to nominate) and groups (e.g. which candidates to support financially)? Platform-drafting politics can provide insight into broader cleavages within a party that may reveal new insights about party positions, candidate strategies, and policy goals.
Despite shortcomings in our research design, we offer two clear, consistent findings: political party platforms are responsive to organized interests that are ideologically similar to the party status quo, and to those who have demonstrated loyalty to the party. Moreover, the composition of parties changes across time in systematic ways. We look to future scholarship to improve our ability to measure group actions, incentives, and resources with respect to parties.

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ii This number differs from our N (below) because it includes elected officials, private citizens, and individuals representing organizations that are not organized interests.

iii We acknowledge the potential for conditional effects among the three variables. Rather than fully develop theory and expectations here, we report exploratory statistical results in Appendix B and find no statistically significant interaction effects.

iv We assume groups reveal sincere preferences in their hearing testimony.

v The Republican National Committee denied us access to their hearing testimony.

vi We also estimated models with un-concatenated platforms and Comparative Manifestos Project scores for each party-year. Those models are not substantively different from the models below, which we present because the concatenated reference texts include a larger corpus of words and generate more precise estimates.

vii While there is no way to verify that parties directly adopt groups’ demands, a direct link between group requests and party drafting is not necessary for our purpose. If the final platform draft more closely mirrors the requests of Group X over Group Y, the party is more inclusive of Group X than Group Y.

viii PAC data for 1996 were not available so in those cases we used contribution data from 1998.

ix Due to missingness in the covariates, n<80; we employ casewise deletion rather than imputation.

x The models are robust to variations in specification.
References


### Table 1 Summary of Texts

<table>
<thead>
<tr>
<th>Year</th>
<th>DNC Platform word count</th>
<th>RNC Platform word count</th>
<th>Number of Groups</th>
<th>Group Testimony Average Unigrams (percent scored)</th>
<th>Group Testimony Average Bigrams (percent scored)</th>
<th>Group Testimony Average Trigrams (percent scored)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1996</td>
<td>18,032</td>
<td>27,160</td>
<td>24</td>
<td>800 (95%)</td>
<td>454 (54%)</td>
<td>132 (16%)</td>
</tr>
<tr>
<td>2000</td>
<td>23,964</td>
<td>34,503</td>
<td>26</td>
<td>852 (93%)</td>
<td>458 (50%)</td>
<td>132 (15%)</td>
</tr>
<tr>
<td>2004</td>
<td>17,821</td>
<td>42,076</td>
<td>30</td>
<td>1332 (94%)</td>
<td>712 (51%)</td>
<td>199 (15%)</td>
</tr>
<tr>
<td>TOTAL</td>
<td>59,817</td>
<td>103,739</td>
<td>80</td>
<td>1016 (94%)</td>
<td>288 (52%)</td>
<td>157 (15%)</td>
</tr>
</tbody>
</table>
### Table 2 Summary Statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean (Standard Dev.)</th>
<th>Range</th>
<th>Definition</th>
<th>Source</th>
</tr>
</thead>
<tbody>
<tr>
<td>Platform Inclusion- Unigrams (DV1)</td>
<td>0.0185 (1.41)</td>
<td>(-2.7 – 3.43)</td>
<td>Transformed Wordscores values, where DNC (-1) and RNC (1) platforms, concatenated for 1996, 2000, 2004 are reference texts, and group testimonies are virgin texts.</td>
<td>Interest group testimony to DNC platform drafting committees and texts of 1996, 2000, and 2004 DNC and RNC platforms.</td>
</tr>
<tr>
<td>Platform Inclusion - Bigrams (DV2)</td>
<td>0.0199 (1.41)</td>
<td>(-2.6 – 4.2)</td>
<td>Transformed Wordscores values, where DNC (-1) and RNC (1) platforms, concatenated for 1996, 2000, 2004 are reference texts, and group testimonies are virgin texts.</td>
<td>Interest group testimony to DNC platform drafting committees and texts of 1996, 2000, and 2004 DNC and RNC platforms.</td>
</tr>
<tr>
<td>Ideology</td>
<td>-0.437 (0.597)</td>
<td>-1.19 – 1.02</td>
<td>Ideological spatial position estimated from campaign contributions of group’s PAC or donations of its members.</td>
<td>Adam Bonica Database on Ideology, Money in Politics, and Elections (2013)</td>
</tr>
<tr>
<td>Loyalty</td>
<td>10.6 (3.02)</td>
<td>5.3 – 14.6</td>
<td>The natural log of the sum of all donations made to candidates by the group’s PAC or its employees, multiplied by the percentage of donations made to Democrats.</td>
<td>Federal Election Commission campaign contribution data, as compiled by Opensecrets.org</td>
</tr>
<tr>
<td>Resources</td>
<td>0 (1)</td>
<td>-0.75 – 5.2</td>
<td>Standardized index for each group based on two characteristics known to affect their ability to mobilize voters (Kollman 1998): number of members and reported budget. Each measure is standardized among groups, then summed and standardized again.</td>
<td>Galenet’s Encyclopedia of Associations (1996, 2000, 2004); Colgate, National Trade and Professional Associations of the United States (1996, 2000); Gale Encyclopedia of Business and Professional Associations 1996-7; Congressional Quarterly Inc., Public Interest Group Profiles (1996-7, 2000-1); GuideStar (2008); Foundation Center (2008); Associations Unlimited (2008); OpenSecrets.org (2008); Campaign Money (2008); the Federal Elections Commission (2008); groups’ webpages and archived webpage.</td>
</tr>
</tbody>
</table>
### Table 3 Linear Regression Results

**Regression Estimates for Interest Group Wordscores**  
Relative to Party Platforms (-1 = Dem / +1 = Repub)

<table>
<thead>
<tr>
<th></th>
<th>Unigrams</th>
<th>Bigrams</th>
<th>Trigrams</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Model 1</td>
<td>Model 2</td>
<td>Model 3</td>
</tr>
<tr>
<td>Ideology (-1 = D/ +1 = R)</td>
<td>0.907*</td>
<td>1.116**</td>
<td>0.988***</td>
</tr>
<tr>
<td></td>
<td>(-0.372)</td>
<td>(-0.341)</td>
<td>(-0.317)</td>
</tr>
<tr>
<td>Dem. Loyalty</td>
<td>-0.882***</td>
<td>-0.775***</td>
<td>-0.435</td>
</tr>
<tr>
<td></td>
<td>(-0.247)</td>
<td>(-0.178)</td>
<td>(-0.260)</td>
</tr>
<tr>
<td>Resources</td>
<td>0.34</td>
<td>0.317</td>
<td>0.069</td>
</tr>
<tr>
<td></td>
<td>(-0.284)</td>
<td>(-0.198)</td>
<td>(-0.222)</td>
</tr>
<tr>
<td>Year 2000</td>
<td>0.078</td>
<td>-0.133</td>
<td>-0.338</td>
</tr>
<tr>
<td></td>
<td>(-0.460)</td>
<td>(-0.407)</td>
<td>(-0.490)</td>
</tr>
<tr>
<td>Year 2004</td>
<td>0.597</td>
<td>0.443</td>
<td>0.049</td>
</tr>
<tr>
<td></td>
<td>(-0.416)</td>
<td>(-0.513)</td>
<td>(-0.507)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.027</td>
<td>0.373</td>
<td>0.566</td>
</tr>
<tr>
<td></td>
<td>(-0.371)</td>
<td>(-0.387)</td>
<td>(-0.321)</td>
</tr>
<tr>
<td>Adj R-squared</td>
<td>0.266</td>
<td>0.283</td>
<td>0.178</td>
</tr>
<tr>
<td>N</td>
<td>46</td>
<td>46</td>
<td>46</td>
</tr>
<tr>
<td>Pr (Chi)</td>
<td>0.000</td>
<td>0.000</td>
<td>0.019</td>
</tr>
</tbody>
</table>

*Bootstrapped standard errors clustered on groups in parentheses.*
Figure 1A Wordscores Estimates for Unigrams with Confidence Intervals:

Appendix A: Wordscores Technical Information

The Wordscores technique begins by using known information about a set of reference texts, $R$, and each reference text’s ($r$) known dimensions, $d$. In our case, the known reference texts are party platforms for Democrats and Republicans from various years, and their known dimensions are each platform’s exogenously assigned ideological score from the Comparative Manifestos Project ($d_r$). Wordscores calculates the frequency of each word stem ($F_{wr}$), as a proportion of the total number of words in the reference text, $r$. Given a set of reference texts, one can then compute the probability that any given word ($w$) is from a particular reference text ($r$): $P(r|w) = \frac{F_{wr}}{\sum F_{wr}}$, called $P_{wr}$. Next, Wordscores uses this probability to calculate a weighted average score for each word in the reference texts: $S(d|w) = \Sigma(P_{rw} * d_r)$, called $S_{wd}$. Then, Wordscores calculates the proportional word frequencies ($F_{wv}$) in the ‘virgin’ texts to be analyzed using the same technique as with the reference texts. For us, the virgin texts are group testimony and mission statements. Each word in a virgin text, $v$, is assigned a score by multiplying the word frequency ($F_{wv}$) by the dimensional weight, $S_{wd}$. The score for the entire text, $S_{vd}$, is simply the average of all the individual weighted word scores: $S_{vd} = \Sigma(F_{wv} * S_{wd})$. This number represents the expected position of the virgin text on the known dimension of the reference text.
### Appendix B: Results of interactive models

| Regression Estimates for Interest Group Wordscores Relative to Party Platforms (-1 = Dem / +1 = Repub) |
|-----------------------------------------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|
| | Unigrams | | | | Bigrams | | | | Trigrams | | | |
| | Model 4 | Model 5 | Model 6 | Model 7 | Model 8 | Model 9 | Model 10 | Model 11 | Model 12 | Model 10 | Model 11 | Model 12 |
| **Ideology (-1 = D/+1 = R)** | 0.902* | 0.757 | 0.875** | 1.112** | 1.190** | 1.077** | 0.928** | 1.009* | 0.961** | 0.928** | 1.009* | 0.961** |
| | (-0.354) | (-0.537) | (-0.309) | (-0.344) | (-0.369) | (-0.357) | (-0.360) | (-0.416) | (-0.317) | (-0.360) | (-0.416) | (-0.317) |
| **Dem. Loyalty** | -0.918* | -0.876*** | -0.822** | -0.801* | -0.778*** | -0.704* | -0.859 | -0.436 | -0.384 | -0.481 | -0.231 | (-0.424) |
| | (-0.401) | (-0.239) | (-0.278) | (-0.405) | (-0.203) | (-0.309) | (-0.481) | (-0.231) | (-0.424) | (-0.481) | (-0.231) | (-0.424) |
| **Resources** | 0.337 | -0.041 | 0.452 | 0.315 | 0.506 | 0.451 | 0.033 | 0.122 | 0.165 | 0.033 | 0.122 | 0.165 |
| | (-0.351) | (-0.897) | (-0.331) | (-0.219) | (-1.027) | (-0.336) | (-0.283) | (-0.762) | (-0.375) | (-0.283) | (-0.762) | (-0.375) |
| **Year 2000** | 0.085 | 0.068 | 0.065 | -0.128 | -0.128 | -0.15 | -0.256 | -0.336 | -0.35 | -0.256 | -0.336 | -0.35 |
| | (-0.398) | (-0.420) | (-0.501) | (-0.363) | (-0.383) | (-0.368) | (-0.382) | (-0.472) | (-0.534) | (-0.382) | (-0.472) | (-0.534) |
| **Year 2004** | 0.607* | 0.591 | 0.516 | 0.45 | 0.446 | 0.346 | 0.167 | 0.05 | -0.02 | 0.167 | 0.05 | -0.02 |
| | (-0.268) | (-0.392) | (-0.518) | (-0.325) | (-0.465) | (-0.399) | (-0.504) | (-0.471) | (-0.442) | (-0.504) | (-0.471) | (-0.442) |
| **Loyalty X Ideology** | -0.056 | -0.041 | -0.657 | (-0.444) | (-0.462) | (-0.524) | | | | | | |
| **Resources X Ideology** | -0.522 | 0.259 | 0.072 | (-1.203) | (-1.364) | (-1.032) | | | | | | |
| **Resources X Loyalty** | -0.127 | -0.152 | -0.108 | (-0.266) | (-0.318) | (-0.375) | | | | | | |
| **Constant** | 0.019 | -0.068 | 0.102 | 0.367 | 0.419 | 0.463 | 0.475 | 0.579 | 0.631 | 0.475 | 0.579 | 0.631 |
| | (-0.340) | (-0.497) | (-0.390) | (-0.293) | (-0.323) | (-0.264) | (-0.393) | (-0.302) | (-0.367) | (-0.393) | (-0.302) | (-0.367) |
| **Adj R-squared** | 0.248 | 0.253 | 0.256 | 0.265 | 0.266 | 0.277 | 0.19 | 0.157 | 0.163 | 0.19 | 0.157 | 0.163 |
| **N** | 46 | 46 | 46 | 46 | 46 | 46 | 46 | 46 | 46 | 46 | 46 | 46 |
| **Pr (Chi)** | 0.000 | 0.000 | 0.006 | 0.000 | 0.000 | 0.023 | 0.002 | 0.002 | 0.022 | 0.002 | 0.002 | 0.022 |

Bootstrapped standard errors clustered on groups in parentheses.