Political Discourse and Waves of New Political Advocacy Organizations in the United States

Darren R. Halpin
Australian National University
Darren.Halpin@anu.edu.au

Michael T. Heaney
University of Glasgow and University of Michigan
michaeltheaney@gmail.com

Abstract: The determinants of founding new political advocacy organizations has long been a central topic in the study of American politics. Less attention has been given, however, to the question of what relevance new cohorts of organizations have when they arrive on the scene. Drawing on a rich tradition of scholarship in organizational theory – particularly the concepts of organizational imprinting and liability of newness – this study considers the distinctiveness of new advocacy organizations in American political discourse in the immediate aftermath of the election of Donald J. Trump as President of the United States. The paper relies on Exponential Random Graph Models (ERGMs) to analyze the common language used on Twitter by 22 new and 22 already established political advocacy organizations. The analysis provides some support for the hypothesis that new organizations share a common lexicon that is associated with their contribution to political discourse.

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In his classic treatise, *The Semisovereign People*, political scientist E. E. Schattschneider (1960, p. 30) wrote that "organization is itself a mobilization of bias in preparation for action" (italics removed from original). In making this claim, Schattschneider stressed that the formation of political organizations reveals which interests are well situated to exert pressure on decision makers and which are not. The groups that get organized have opportunities to shape many (but not all) policy outcomes, while those that fail to organize are much less likely to exert political influence (Gilens and Page 2014). Consequently, questions of who gets organized – and why and how they do so – have long been central to the study of American politics.

Prior research provides extensive insight on the factors that enable or obstruct the formation of new advocacy organizations. David Truman (1951) exposed the role of social, economic, and technological changes in generating "wavelike" patterns of organizational foundings following "disturbances" to prevailing logics of association (Truman 1951, p. 107). Mancur Olson (1965) and Robert Salisbury (1969) stressed the importance of incentives for membership – and the organizational entrepreneurs who craft those incentives – to the sustainability of collective action by groups. Jack Walker (1983) and David Lowery and Virginia Gray (1995) revealed how advocacy organizations depend on resources from their political environments. Theda Skocpol (2003) discerned the hand of new technology – especially direct mail – in influencing what kinds of organizations thrive. Kathleen Blee (2012) expounded on the fragility of new organizations and recounted the many ways that they can dissolve – or radically alter their purpose – in the earliest stages of their development. These, and other studies in the extant literature, provide clear expectations about when and how new political advocacy organizations are likely to become a part of the American political landscape.

The question of what cohorts of new advocacy organizations do once they arrive on the scene has been the subject of significant case studies, but it has received less systematic attention than has the founding of the organizations themselves. These studies exposed the transformative effects that new advocacy organizations have had on fields such as medicine (Starr 1982), agriculture (Hansen 1991), labor (Clemens 1997), citizen advocacy (Berry 1999), and business (Drutman 2015). For example, John Mark Hansen (1991) documented how the rise of the Farm Bureau benefitted congressional re-election efforts, thus pushing the organization to the center of policy debates. These insights encourage us to address the more general question of how the rise of new advocacy organizations is associated with the evolution of political discourse.

We argue that a critical element in appreciating the impact of emerging organizations lies in understanding the organizational imperatives of the groups themselves. In doing so, we build on a tradition that highlights the value of organizational theory to the study of interest group politics (Halpin 2014; Heaney 2004; Young 2010). We invoke the insights of Arthur Stinchcombe (1965) with respect to organizational *imprinting*, which is the idea that the early period after the formation of an organization is pivotal to the type of organization that it ultimately becomes (see also Johnson 2007). During this time, the organization engages in formative exchanges with other actors in its environment, which has a strong hand in shaping the types of people that it hires, the ways that it is structured organizationally, the technologies that it relies on, the tactics that it deploys, and the nature of its goals. As a result of the intense organization-environment interactions during the founding period, organizations founded at the same time (or close in time to one another) are likely to bear persistent similarities over their lives. To this end, we examine the nascent cohort of national political advocacy organizations founded in the aftermath of Donald J. Trump's election as President of the United States. We explore the distinctive ways that the members of this cohort engaged in political discourse and, thus, shed light on the potentially enduring ways that these organizations may contribute to American politics.

Our methodological approach focuses on the need to study organizations at the earliest conceivable stage of their existence. New organizations suffer from an acute *liability of newness* that threatens their existence mostly severely in the immediate aftermath of their founding (Stichcombe 1965). Organizational mortality is unlikely to be a random event because conformity (or lack thereof) with the selective pressures of the environment is a strong predictor of organizational survival (Nownes and Lipinski 2005; Halpin and Thomas 2012). Thus, if the study of new organizations is delayed by months or years after their founding, then surviving organizations – available to the researcher for investigation – may differ systematically from the population of all founded organizations. In short, substantial selection bias is expected. Moreover, as Blee (2012) observed, political organizations may undergo sometimes astounding transformations in the early moments of existence, making it critical to observe organizational foundings as soon as possible.

To study the emergence new political organizations at the earliest moment of founding, we turn to Twitter as a source for detecting these groups. Of course, we cannot possibly ensure that all new political organizations are mentioned in some way on Twitter. Prior research by Ana Langer and her colleagues (2019) demonstrates that a fair about of the content of advocacy campaigns is exposed through digital platforms. In this vein, we argue that examining mentions of new organizations on Twitter is a good way to identify a wide range of new, nationally focused, advocacy organizations. Organizations need not have their own Twitter accounts to be swept up in such an analysis; they merely need be mentioned by others who do have Twitter accounts.

We mined a large sample of tweets generated in the five months following the 2016 election to identify new organizations. We matched each new organization to an already existing political advocacy organization on a related topic. We then collected the mission statements of these organizations from Twitter, as well as tweets in which they were mentioned, over a one-year period. This paper considers the lexical similarity – or differences – among groups as a fruitful means of exploring imprinting processes. Following the insights of Leifeld (2016), we modelled new and established organizations as a discourse network using Exponential Random Graph Models (ERGMs). The results of our analysis provide some support for the proposition that new political advocacy organizations adopt a shared common lexicon that distinguishes them from already established organizations.

Organizational Imprinting and the Liability of Newness

The interest groups literature has tended to view organizational formation as an *event*. Events may be summarized as dates in directories, founding stories on group websites, and historical accounts in case studies. In contrast, Douglas Imig and Jeffrey Berry (1996, p. 149) viewed formation as a *process* whereby individuals (or groups of individuals) strategize over the question of "what kind of organization should we be?". Along these lines, they suggested that scholars focus on how the organizations operate during their formative periods.

The urge to focus on the process of formation is important because this is the context in which organizational imprinting occurs. Truman (1951, p. 115) pointed out that organizational features that were important in their formative period may no longer seem to resonate with contemporary conditions, "yet their impress upon the organizational structure of the group may continue". As Stinchcombe (1965, p. 154) put it "organizations formed at one time typically have a different social structure from those formed at another time". Organizations may be imprinted with something akin to an organizational date stamp. Imprinting effects may encourage conformance: organizations formed at the same time, facing the same conditions, may resort to similar recipes or blueprints.

A rival hypothesis to imprinting is one of little variation across like-groups. This expectation might usefully be restated as a test of the rather straightforward isomorphism proposition, that populations of like-groups manifest the same form. Organizational isomorphism is operationalized in the organizational studies literature as “the [degree of] similarity of a set of organizations at a given point in time” (Deephouse 1996, p. 1024). For example, this perspective would hold the expectation that organizations inhabiting the same policy niche would be relatively more similar to one another than newly founded organizations would be to one another.

Interest group scholars implicitly draw on the idea of imprinting when they make period-based arguments. For instance, in her analysis of the development of US advocacy, Skocpol (2003) contended that traditional groups established themselves around face-to-face meetings, local branches, and federated structures. She reported that these organizations were replaced by new generations of groups where members where remote and agendas were staff driven. As Skocpol (2003, p. 275) explained, the new generation of group entrepreneurs “let their imaginations roam and look for ways to reinvent membership organizations along new lines suited to today’s constituencies and technologies”. Some entrepreneurs imagined new, internet-mediated groups, where there is no formal bricks-and-mortar organization, as a third group generation (Karpf 2012).

Advocacy organizations trying to establish themselves do so against an institutional context that shapes – or even constrains – choice. Stinchcombe (1965) explained that new organizations face a multitude of hurdles in finding a foothold in the existing organizational landscape, which means that new endeavours are overly disposed to failing (and early). Research in this tradition specifies the dependent variable as the success of “*attempted foundation* of an organization” (Stinchcombe 1965, p. 143, italics in original). This idea has proven highly influential in organizational science. Organizations that follow proven organizational recipes – mimic forms that are established and thus deemed legitimate – are more likely to succeed. This logic creates an expectation that new generations of groups either coalesce around a novel *shared* form (thus *building* legitimacy) or instead mimic pre-existing forms in the field (thus *borrowing* legitimacy). On the one hand, organizations face incentives to mimic (where possible) existing and accepted (legitimate) organizational forms, perhaps even cloaking new claims in traditional forms. On the other hand, leaders may utilize long-accepted models of organization in unique ways. Alternatively, leaders may pursue utterly unique forms of organization, but enacting them confronts a significant liability-of-newness problem.

Interest group scholars have spent relatively little time considering this question. Aggregate studies of group fields – such as Anthony Nownes' (2004) study of gay and lesbian groups in the United States – report that the density of groups is low in the early stages of the population's development but rises over time. This density-dependent model of population development is one way to understand legitimacy, and hence the outcome of group struggles with the liability of newness. There are, however, few studies that look at how this liability is managed by groups as they are in the process of being created.

Research Design

The pluralists, like Truman (1951), held that disturbances would create ripples or waves of mobilization and counter-mobilization in the group system (McFarland 2004). Likewise, from a population ecology perspective, the energy term in growth models points to the likely positive impact that disturbances may play in the prospects of group formation (Gray and Lowery 1995). Our study takes place at a specific historical juncture, which may have its own independent impact on the patterns of organizational creation. The election of any new president constitutes a significant moment in the development of American political life. Yet, the recent election of Donald J. Trump as the 45th President of the United States, has mobilized the US citizenry in unprecedented ways (Heaney 2018).

Trump's agenda, style, and vernacular has antagonized and energized a range of constituencies. For progressives, Trump's agenda is viewed as a threat to values, rights, and cherished institutions. It is potentially a rollback of hard-won gains. For some conservatives, Trump offers hope of the return of glorious times now past, for others, the securing of American values and identity and, for still others, the re-instatement of entitlements. Our study probes whether the specific political juncture that provided the focal point for new organizations – the election of Donald J. Trump – is reflected in their participation in public discourse, as compared to existing groups operating in the same political field.

Contemporary studies of advocacy group formation tend to rely on data sources that render early detection of formation difficult. Reflecting on the widely used *Encyclopedia of Associations*, Shaun Bevan and his colleagues (2013, p. 1752) explained "In a perfect world all new associations would be instantly recognized by the publisher of the [*Encyclopedia of Associations*], changes to association descriptions would be made in real time, and associations that fail would be removed from the directory immediately". Yet, as they outlined, for most groups there is a four-year lag between their self-reported creation date and the date they are first entered in the directory. The implications are three-fold. Researchers may only find out about creation many years after an organization is launched, we may only see the entries for groups that succeeded in being created (if they form and fail within the four years, they presumably are never afforded an entry) and, finally, we may be provided with a creation date but not details on the lead up to this founding.

The problems we note in the group literature are an instance of a more general problem identified in the social-scientific study of organizations. While the dependent variable in Stinchcombe's early work was conceptualized the success of "*attempted foundation* of an organization" (1965, p. 143, italics in original), scholars have noted that most work investigating this proposition has tested it incorrectly. As Howard Aldrich and Tiantian Yang (2012, p. 3) explained "researchers have never properly tested Stinchcombe's original propositions because they have mostly focused on *registered new firms* rather than *emergent* ones." Just as Bevan et al. (2013) noted in respect to group studies, students of organizational emergence have relied on directories that tend only to enumerate those who already have a firm organisational footing and provide cursory organizational details in yearly snapshots. Alrdich and Yang (2012, p. 1) pointed out that "almost all research has examined organizations that have already gone through the early period of struggle that most concerned Stinchcombe". They likewise noted that the reliance on directories leads to left-truncation which means that "they will have left out the cases terminated earlier than when their observations starts" (Aldrich and Yang 2012, p. 6). They advised that Stinchcombe's "argument would seem to require a research design that captures aspiring entrepreneurs in the process of constructing emerging organizations, rather than entrepreneurs running already established organizations" (Adrich and Yang 2012, p. 2). We diagnose and address this lacuna in our paper.

Our research questions required us to identify organizations *as they were being created*. We pioneer an approach that leverages the immediacy of social media platforms, specifically Twitter, for this task. As a source of timely notifications of efforts at group formation, social media platforms avoid the problems with lags between formation and notification that are inherent to directory and other heavily curated or edited sources. Instead, when an individual references a new group – or effort to start a new group – on social media the communication is both immediate and largely unmediated.

We are mindful that the use of social media data for our purpose is not wholly unproblematic. For one, the sheer volume of communications on the platform means that we need to identify strategies to help us economically locate tweets that are relevant to group formation. In addition, our specific choice of Twitter is no doubt an issue: there is likely to be some platform bias in our search. Some organizers will decide not to use Twitter, yet we reason that while initial founders might make such a choice, the media and activists may not repeat that choice. As such, we used Twitter to identify self-reports of creation from activist communities online to compile a list of efforts.

To navigate the vastness of the content on Twitter, we implemented a form of hashtag analysis, which is now a standard form of analysis among social media communications scholars (Small 2011). Rather than selecting the content of specific @accounts, hashtag analysis extracts all tweets that use the same #*hashtag*, regardless of account. To do this, one first needs to identify the #*hastags* of interest. To identify hashtags, we turned to Sysomos, a commercial service that provides access to social media data from platforms such as Twitter, Facebook, Youtube, Instagram, and online news blogs. Sysomos allows searching full text, handles, and hashtags. Our strategy was to create a comprehensive library of hashtags associated with liberal and conservative discussions of the election of Donald J. Trump; and, thereafter uses these hashtags to construct a corpus of tweets that we searched for the notification of new group formation.

Our initial step was to identify the top 10 hashtags on Twitter pertaining to the search "Trump" for each month from November 2016 to March 2017. From this list of 50 hashtags, we distilled a list of 31 unique hashtags. We took the 31 unique hashtags and repeated the search so that we found the top 10 hashtags for each of these original hashtag terms over the period. From this list of 310 hashtags, we distilled a list of 119 unique hashtags. To ensure that our hashtags were relevant, we had two independent coders examine the Twitter feeds of each of the 119 unique hashtags. They indicated whether or not they have high relevance to the formation of a new advocacy organization. We determined that intercoder reliability was satisfactory (Krippendorff's $\alpha = 0.83$) and after discussing differences among the coders, added 57 new hashtags. We again took these 57 new hashtags and repeated the search so that we found the top

10 hashtags for each of these terms. We identified 97 new hashtags, which integrated into our list, yield a final list of 216 hashtags. We examined and rated then as leaning conservative, neutral, or liberal. We then identified 40 conservative and 40 liberal hashtags for further search. Our final corpus of tweets was constructed by searching for all tweets using these 80 hashtags.

These hashtags allowed us to locate the Twitter conversations that would be most relevant to the communities debating the election of Donald J. Trump – from both conservative and liberal perspectives. But we then needed to identify tweets relevant to any efforts at group formation. To do so, we created a series of search terms, intended to identify new organizations. The organizational terms we used were: group, cause, advocacy, association, movement, meeting, organization, lobby, grassroots, interest, coalition, and protest. To denote novelty, we used the following terms: new, founded, launched, and established. We used these terms to conduct a systematic search of all tweets between November 2016 and March 2017 that included one of the 80 hashtags, one of the organization terms, and one of the novelty terms.

To identify newly established organizations, the authors manually inspected the corpus of tweets for evidence of new interest groups formed in the immediate aftermath of the 2016 presidential election. This procedure identified 22 new national advocacy organizations, 16 of which were liberal leaning and 6 of which were conservative leaning. Note that the liberal bias of our sample is not merely an artifact of our research design but is a substantive finding of the research. The liberal bias is to be expected because of the events of the period were an existential threat to liberal interests, thus stimulating grassroots mobilization (Hansen 1985). Moreover, group formation is more common as a political strategy on the left side of the political spectrum than on the right side (Grossmann and Hopkins 2016). Thus, we are confident that this set of organizations well reflects the nascent organizing in early Trump period.

Given that we wish to assess whether newly formed groups differ from those already established, we matched each of these organizations to one existing interest group, founded at least five years earlier, and that was similar to the organization in terms of its political niche. We conducted the matching using organizations' issue profiles, ideology, and tactical approach. Our argument is not that there is a uniquely determined match for each organization but, rather, that our choices provide plausible comparisons for the purposes of research. These 44 organizations constitute the empirical basis of our study (see Table 1 and the Appendix).

INSERT TABLE 1 HERE

This list of organizations provided in Table 1 sheds light on both continuity and change in the advocacy community. For example, the March for Science emerged recently as a grassroots version of the American Association for the Advancement of Science. The Women's March is the 21st century edition of the National Organization for Women. The Resistance is a modern incarnation of MoveOn, which is now 20 years old (Fisher 2019). America First Policies is the Trump era's answer to Tea Party Patriots. These comparisons reflect how certain issue concerns are enduring even though modes of organizing and style of advocacy evolve.

Having identified 44 organizations for analysis, we assessed their use of common language via network analysis. In this paper, we examine two networks. The first is a Twitter *mission network*. This network is constructed by analyzing the content of the mission that each group had on its Twitter account in January 2018. An edge exists in this network when two organizations share words in their respective missions. The second is a Twitter *text network*. Here the edges are constructed where groups share words in the tweets that they respectively authored or were mentioned in. In both networks, the ties that bind these groups are conceived via shared language. Node attributes (coded at the organizational level) in our analysis include generation (new or established), ideology (liberal or conservative), and matched policy niche.

The authors collected the data on group mission manually in January 2018. The Twitter text network was constructed by creating a text corpus from the tweet content of each individual group (which amounted to thousands of tweets for some groups). Using the TM package in R, we constructed a text corpus of all tweets for each group (Feinerer, Hornik and Meyer 2008). Pre-processing of text included removing stop words, whitespaces, and other Twitter-related characters (#, @, http, etc.). We subsequently extracted a list of unique words for each of our groups and generated frequencies for each word. The top 10 words for each group account for the annual period May 1, 2017 to May 1, 2018 constitute the data from which we composed the network.

Data Analysis

The network of common language used by the 44 organizations in our study is reported in Figure 1 (mission statements) and Figure 2 (top 10 words). Each node represents an organization, with shape and color denoting the organization's generation and ideological lean. Visualization was performed using the spring-embedding algorithm – which positions nodes close to one another in a way that minimizes the tension on the graph – in Netdraw 2.162 (Borgatti, Everett, and Freeman 2018; Kamada and Kawai 1989). The thickness of the edges reflects the number of words that two organizations have in common.

INSERT FIGURES 1 AND 2 HERE

Since the threshold for two organizations to have a connection is only one word in common, the structure of the network is less revealing than it might have been if a higher threshold had been adopted (e.g., requiring two or three words in common to draw a tie). For instance, 19 of the 44 organizations included the word "America" in their mission statement, with half of these uses partly accounted for by the fact that "America" is in the organizational name. This element assumes connections between new and established – as well as liberal and conservative – organizations that might not otherwise have much else in common. Inspecting the thickness of links in the graphs is more informative. In Figure 1, the close connections among liberal organizations such as MoveOn, United to Protect Democracy, and Democracy 21 are apparent. In Figure 2, close ties between Indivisible, the Resistance, and the Women's March stand out. On the other hand, less frequent Twitter users, such the Constitution Society, the American Immigration Control Foundation, and Friends of NASA, are isolated in one or both of the graphs.

Viewing the network graphs helps to provide some intuition for what may be happening in discourse networks. However, a more rigorous statistical approach is necessary in order to draw inferences confidently about the network processes. To do so, we employ an Exponential Random Graph Model (ERGM) approach. Use of the ERGMs enables us to account for specified network dependencies in the data (Frank and Strauss 1986; Cranmer and Desmarais 2011).

In an ERGM framework, we can model a network by describing how it is composed of endogenous local structures and how its structure is additionally co-determined by exogenous covariates, such as nodal attributes, that increase or decrease the tie probability of a connected dyad. This model captures both the dependencies between observations as well as covariate effects. Two interpretations of ERGMs are: (1) a global interpretation where the probability of an observed network over the networks one could have observed is considered; and, (2) a local interpretation where the same probability governs whether any particular edge in the network is realized. In an ERGM, the probability of an observed network topology over the networks one could have observed is

$$P(N, \boldsymbol{\theta}) = \frac{\exp\{\boldsymbol{\theta}' \boldsymbol{h}(N)\}}{\sum_{N^* \in \mathcal{N}} \exp\{\boldsymbol{\theta}' \boldsymbol{h}(N^*)\}}$$

where N is a matrix representing the observed network, $\boldsymbol{\theta}$ are the coefficients that need to be computed, $\boldsymbol{h}(N)$ is a vector of statistics to be included in the model (including the endogenous dependencies and exogenous covariates), and N^* refers to a particular permutation of the topology of the network from the set of all possible permutations of the topology, denoted as $\mathcal{N}$ (Cranmer and Desmarais 2011). The denominator is a normalizing constant that scales the probability between 0 and 1. ERGMs are typically estimated by Markov Chain Monte Carlo Maximum Likelihood Estimation (MCMC MLE) because the denominator contains a sample space that is too large to be evaluated using exhaustive optimization algorithms. We performed this estimation using the ergm package in R (Hunter et al. 2018).

The standard ERGM allowed us to estimate models in which ties between nodes are specified as 1 or 0, as is the case in a binary logit model. Hence, we estimated three standard ERGMS for both networks, using one word, two words, and three words in common to set thresholds for ties. An alternative approach is possible in which the *count* of words in common is modelled. This specification requires modifying the sample space to allow for a range of positive integers and the addition of a reference distribution to the normalizing constant in order account for assumptions about the distribution of the count (Krivitsky 2012). In our case, we used Poisson as our reference distribution and estimated the models using the ergm.count package in R (Krivitsky 2018). Thus, we report results for two count ERGMs in addition to the six binary ERGMs in Table 2 and Table 3.

INSERT TABLE 2 AND TABLE 3 HERE

The ERGM results reported in Table 2 yield some evidence of imprinting. This hypothesis is tested using the *Both Organizations are New* variable. A positive and significant coefficient on this variable indicates that organizations that are both part of the post-2016 cohort of organizations are more likely to use common language in their mission statements than are organizations that are not both part of this cohort. Significance appears when the dyad of organizations has at least three words in common, but not when there are fewer words in common or when the count is considered. Insignificance on this coefficient when there are one or two words in common may be a result of some words – such as "America", discussed above – being frequently used. The ERGM results reported in Table 3 also contain some evidence of imprinting. Significant coefficients in Model (6) – two words in common – and Model (4) – a count of the words in common.

Although not all of the models suggest the relevance of imprinting, none of the models indicated the opposite: that more established organizations were more likely to share common language than were other dyads. In fact, contrary to this possibility, Model (5) showed that established organizations were less likely to use one word in common than were new organizations. This aversion makes sense given that we selected established organizations that had been formed across more than a century and a half; formation during different periods likely imprinted them with divergent concerns, thus pushing their discourses apart.

Analysis of mission statements documented that conservative organizations were significantly and consistently more likely to use common language than were liberal dyads or conservative-liberal dyads. This finding is consistent with prior research stressed the ways that conservative organizations have deliberately relied on language to exert political influence (Smith 2007). However, similar evidence is not present in models of common language in Top 10 words examined in Table 3.

Finally, our analysis produced consistently significant coefficient on *Organizations were Matched with Respect to Topic* in all seven models in which it was possible to estimate this parameter. Given that these dyads were deliberately selected due to their similarity, these results should be interpreted as a test of the validity of our research design. Positive, significant coefficients mean that the assigned dyads were more likely to share common language than were dyads that were not systematically paired. Had these results not held, we would have questioned whether our matching exercise had relied on reasonable criteria for pairing the organizations.

Discussion

Our analysis of Twitter mission statements and Top-10 words provides some preliminary support for the hypothesis that new cohorts of organizations are imprinted with a common lexicon during the process of their founding. While the use of common words, such as "America", attenuate our findings, the diffusion of more distinctive words – such as "resist" and "resistance" – weigh in the direction of a tendency toward imprinting. In fact, we never observed "resist" or "resistance" in the missions or Top-10 words of established organizations but detected them in the language of four new organizations. Imprinting theory predicts that the concept of resistance, for example, will persist in the lexicon and the logic of these organizations – if they survive to adolescence – even after Donald Trump leaves the political stage.

Given that this paper is a first effort to use Twitter data to examine questions related to organizational founding and imprinting, we plan to undertake more work before reaching firmer conclusions. In particular, we plan a new round of modelling that relies on all words used in tweets, rather than just mission statements and top-10 words. This approach would provide a richer basis for analysis. We believe that it would increase the efficiency of the ERGM count models and, thus, strengthen the conclusions that can be draw from this analysis. Accounting for time in these models could also be fruitful step, especially given that our events-as-process perspective is consistent with the idea that the effects of imprinting may change over time.

Examining the characteristics of the words used, in addition to organizational characteristics, could potentially enhance what is learned from these data. Doing so would require the use of two-model network models, which are prevalent in the study of policy advocacy networks (Brieger 1974; Heaney 2014; Heaney and Leifeld 2018). Such an analysis would allow us to explicitly distinguish between the effects of common words like "America" and more distinctive words like "resist". It may also be fruitful to parse the data among organizing words that are likely to be adopted in both liberal and conservative circles (e.g., alliance, endorse, unite), ideologically specific terminology (e.g., MAGA, intersectionality, originalism), and topical words (e.g., environment, immigration, health). At the same time, two-mode models may suffer disadvantages from comparatively lower parsimony, which could potentially obscure imprinting effects.

Conclusion

Interest group research speaks richly to the complexities of forming and maintaining advocacy organizations. Yet it tells us less about the roles that cohorts of these organizations play after they come into existence. It is well known that the stock of advocacy organizations continues to accumulate in Washington, DC (Leech et al. 2005), in state capitals, and around the world. Our analysis suggests the value of not thinking of these organizations as a homogenous set but as intricately layered, temporally connected communities that are the residues of battles past. To the extent that imprinting is operative – and our results suggest that it is – aspects of these battles may continue on into contemporary politics.

Our analysis documents the effects of imprinting on discourse networks. Such networks are a critical element of recognizing the relevance of discourse to policy change (Leifeld 2016). At the same time, this is only one of multiple possible types of imprinting effects. Imprinting is likely also relevant to organizational tactics, management structures, goals, and other elements of organizational behavior. Our work raises new questions about how these elements may be linked through common organizational histories.

This study illustrates the value to interest group research of drawing upon insights from the rich literature in organizational theory. Arthur Stichcombe's (1965) ideas – as well as those of his intellectual progeny – have been applied extensively to research on business organizations. Yet their relative neglect by political scientists is puzzling. Future interest group scholarship could benefit from greater attention to how the organizational features of advocacy groups matter not only to the way that they are managed, but also to their political identities and policy impacts.

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Table 1. New and Matched Established Advocacy Organizations

New Advocacy Organization	*Matched Established Organization (Year Founded)*
Liberal Organizations	
Action Together Network	Progress Now (2005)
American Oversight	Center for Public Integrity (1989)
Boycott Patriots	Green America (1982)
Democratic National Redistricting Committee	Democracy 21 (1997)
Draft Bernie for a People's Party	Democracy for America (2004)
Indivisible	Progressive Democrats of America (2004)
Let America Vote	FairVote (1992)
March for Science	American Association for the Advancement of Science (1848)
Medical Society Consortium on Climate & Health	Center for Health, Environment & Justice (1971)
Rogue NASA	Friends of NASA (2008)
Run for Something	She Should Run (2007)
The Resistance	MoveOn (1998)
Trans Relief	National Center for Transgender Equality (2003)
United to Protect Democracy	Project on Government Oversight (1981)
Untwisting It	Union of Concerned Scientists (1969)
Women's March	National Organization for Women (1966)
Conservative Organizations	
1776 Restoration	Constitution Society (1994)
America First Policies	Tea Party Patriots (2009)
Conservatives for Environmental Reform	ConservAmerica (1995)
Great American Alliance	Eagle Forum (1972)
Stand Up Republic	John Birch Society (1958)
The Minutemen	American Immigration Control Foundation (1983)

Table 2. Predictors of Common Language in Twitter Mission Statements, January 2018

	(1) *At Least One Word in Common*	(2) *At Least Two Words in Common*	(3) *At Least Three Words in Common*	(4) *Count of Words in Common*
Independent Variable				
Both Organizations are New (=1)	-0.013	0.198	1.204 *	0.080
	(0.174)	(0.259)	(0.583)	(0.110)
Both Organizations are Established (=1)	0.008	0.158	1.074	0.078
	(0.171)	(0.262)	(0.592)	(0.111)
Both Organizations are Conservative (=1)	0.732 *	0.672 *	1.953 *	0.483 *
	(0.278)	(0.334)	(0.652)	(0.149)
Both Organizations are Liberal (=1)	-0.204	-0.038	0.467	-0.077
	(0.147)	(0.224)	(0.555)	(0.097)
Organizations were Matched with Respect to Topic (=1)	1.332*	1.280 *	N/A	0.560 *
	(0.482)	(0.537)		(0.220)
Endogenous Parameter				
Edges	-0.648 *	-2.758 *	-5.039 *	
	(0.153)	(0.229)	(0.601)	
Two Edgewise Shared Partners	-0.166	0.835 *	N/A	
	(0.207)	(0.182)		
Nonzero Dyads				-0.408 *
				(0.141)
Sum of Dyad Values				-0.564 *
				(0.119)
Model Information				
Akaike Information Criterion (AIC)	1219	593	N/A	-337
Bayesian Information Criterion (BIC)	1253	627	N/A	-303
Estimator	Standard Binary ERGM	Standard Binary ERGM	Standard Binary ERGM	Count ERGM (Poisson)

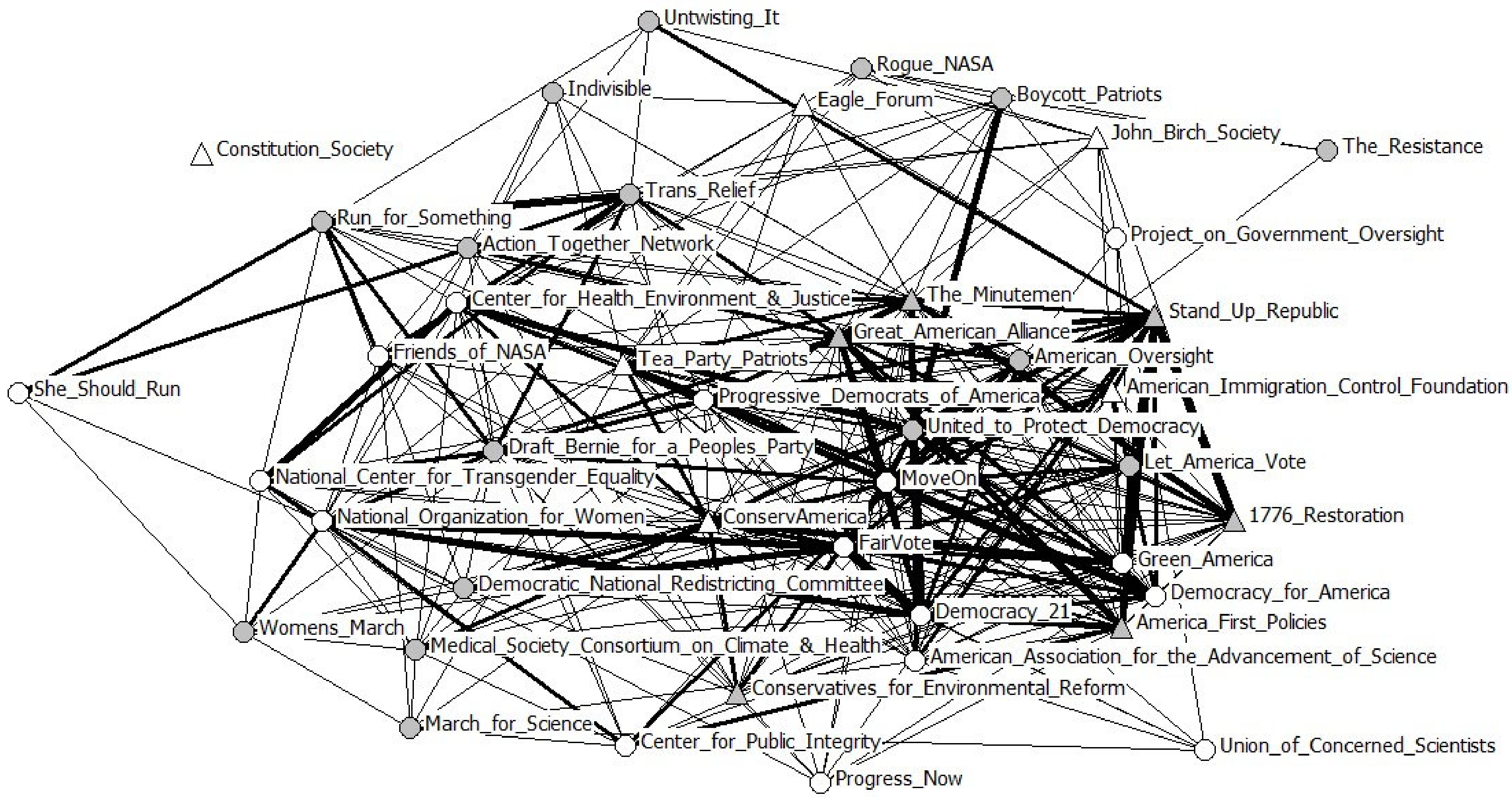
Note: * $p \leq 0.05$.

Table 3. Predictors of Common Language in Top-10 Words Used in Tweets, 2017-2018

	(5) *At Least One Word in Common*	(6) *At Least Two Words in Common*	(7) *At Least Three Words in Common*	(8) *Count of Words in Common*
Independent Variable				
Both Organizations are New (=1)	0.311	0.979 *	0.715	0.309 *
	(0.195)	(0.397)	(0.707)	(0.144)
Both Organizations are Established (=1)	-0.487 *	0.509	N/A	-0.285
	(0.248)	(0.479)		(0.190)
Both Organizations are Conservative (=1)	-0.227	0.596	N/A	-0.026
	(-0.411)	(0.707)		(0.293)
Both Organizations are Liberal (=1)	0.571 *	0.800	0.878	0.480 *
	(0.185)	(0.423)	(0.818)	(0.145)
Organizations were Matched with Respect to Topic (=1)	1.728 *	2.844 *	2.894 *	1.129 *
	(0.458)	(0.625)	(0.846)	(0.222)
Endogenous Parameter				
Edges	-1.666 *	-4.793 *	-5.253 *	
	(0.186)	(0.475)	(0.785)	
Two Edgewise Shared Partners	-0.722 *	1.845 *	N/A	
	(0.209)	(0.247)		
Nonzero Dyads				-0.957 *
				(0.205)
Sum of Dyad Values				-1.172 *
				(0.210)
Model Information				
Akaike Information Criterion (AIC)	841	263	N/A	-885
Bayesian Information Criterion (BIC)	875	297	N/A	-851
Estimator	Standard Binary ERGM	Standard Binary ERGM	Standard Binary ERGM	Count ERGM (Poisson)

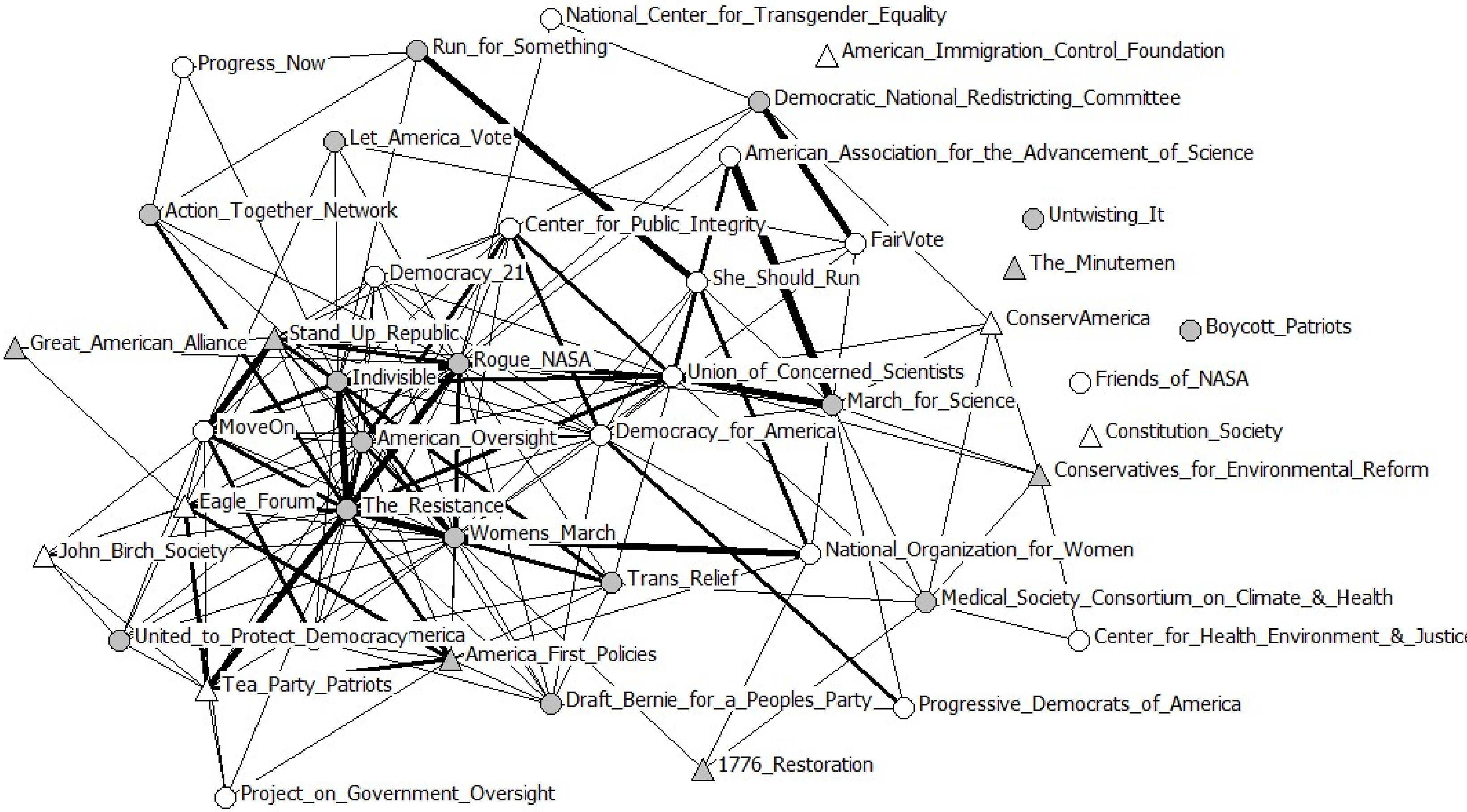
Note: * $p \leq 0.05$.

Figure 1. Network of Common Language in Twitter Mission Statements, January 2018



Note: Gray circles are new liberal organizations. White circles are established liberal organizations. Gray triangles are new conservative organizations. White triangles are established conservative organizations.

Figure 2. Network of Common Language in Top-10 Words Used in Tweets, 2017-2018



Note: Gray circles are new liberal organizations. White circles are established liberal organizations. Gray triangles are new conservative organizations. White triangles are established conservative organizations.

Appendix. Brief Sketches of New Advocacy Organizations

1. Liberal Organizations

Action Together Network was formed to share lessons and strategies among a pre-existing set of local networks to oppose President Trump.

American Oversight was formed as a 501c(3) organization by ex-staffers in the previous Democratic administration – including the Department of Justice and the White House – and designed to file Freedom of Information Act requests on federal agencies, seek investigations, and bring lawsuits. It cited ethical concerns with the Trump Administration as a rationale for its establishment.

Boycott Patriots was established to crowdsource ideas for – and encourage the use of – consumer boycotts to protest Trump Administration policies. Its origins appear to have been in the Women's March. It attempted to harness that momentum for a specific style of political action – namely, consumer boycotts. The founders were not identified, yet the Facebook page administrator accounts point to individuals with little, if any, direct paid political experience.

Democratic National Redistricting Committee was created to address the Democratic Party's disadvantage in drawing of congressional district boundaries. Its strategy was to provide information to support redistricting and to assist in winning races that would allow Democrats to influence the redistricting process to its advantage for 2021. It was chaired by the former Attorney General, Eric Holder, was a professionally staffed organisation, and was registered as a 527 organisation.

Draft Bernie for a People's Party set out to raise money to coax Bernie Sanders into forming a new political party. This effort was subsidised by another existing non-profit organization, People for a Working Democracy.

Indivisible. In the wake of President Trump's election, the head of a national non-profit organization and his wife, drafted a manual on how those seeking to resist the new administration could effectively lobby Congress. The draft was circulated through Resistance-related social media groups. The popularity of the manual forged hundreds of local groups. In turn, this group emerged to service the new nascent organisation.

Let America Vote was established by a young, Democratic ex-Secretary of State from Missouri. It aimed to challenge voter suppression laws. Its approach was to fundraise and develop a grassroots campaign to mobilize against such laws.

March for Science set out to advocate for greater federal funding of science and use of science in policy decision making.

Medical Society Consortium on Environment and Health was established to leverage the status and authority of existing state and national medical societies – and their members – to campaign on issues of environment and health. They were hosted by the Center for Climate Change Communication at George Mason University and funded by a handful of large corporate donors.

Rogue NASA. This organization was one of a number of Twitter handles in the genre (@rogue_agency_name), that set out to discuss the difficulties for public employees within federal departments and agencies under the Trump Administration. It was not possible to ascertain who runs this account, or whether it is in fact disaffected government employees. There was no parallel website or organising effort.

Run for Something was established to promote individuals under the age of 35 to run for office. Its primary strategy was to develop a bank of progressive minded young people and to provide them with the support to get on the ballot in all types of elections. It was founded by two individuals, one was a former staff member who worked for Bill and

Hillary Clinton – and was a fundraiser for America for Hillary. The other founder was a progressive activist and management consultant with experience on Democratic campaign.

The Resistance assisted and coordinated the actions of groups in a range of progressive issue areas. The Resistance emerged as a hashtag and a loose movement of groups that identified online as being part of the resistance to newly elected President Trump.

Trans Relief Project. Working in partnership with Trans United 501(c)3, this organization set out to provide material assistance to ensure that trans individuals have correct documentation

United to Protect Democracy was established as a left-of-center litigation and advocacy organization created to oppose the policies of President Donald Trump.

Untwisting It was formed to work toward "untwisting" the truth in national politics.

Women's March was formed to raise the voices of women in American politics. It was an immediate response to Trump's election.

2. Conservative Organizations

1776 Restoration was created to promote the reinvigoration of early constitutional principles of government in the United States.

America First Policies was led by Brad Pascale, former Digital Director the Trump presidential campaign and head of a digital communications firm.

Conservatives for Environmental Reform was established by a university student with a background in Republican politics (specifically the Mitt Romney campaign). It was a Political Action Committee with the aim of supporting a new generation for young Republicans with solutions on environmental issues. It envisaged electoral work particularly at the state level.

Great American Alliance was a spin-off from the Great American Political Action Committee that worked to support Trump's presidential campaign. It was a 501(c)(4) organization, created to support Trump in office. It claimed to be the largest outside group to support Trump's agenda.

Stand Up Republic was founded by Ewan McCullin who ran as an independent conservative presidential candidate in the 2016 election.

The Minutemen set out as a movement of Trump supporters.