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Community Structure in Federal Election Donation Networks, 1980-2008

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In this paper, I analyze Federal Election Commission donation data from the 1980-2008 election cycles using the tools of social network analysis. I construct two separate networks for each election cycle. In the first, political committees are networked based on the number of individual donors from whom they each receive funds. In the second, committees and candidates are connected based on monetary transfers among each other. Having constructed these networks, I employ a community detection algorithm in an attempt to derive the community structure of the donation networks. Identifying the relevant communities in each donation network, and the strength with which they are defined, provides insight into the partisan nature of campaign contributions and their relationship to partisan polarization.

1 Introduction

Studies of campaign finance in United States federal elections have primarily focused on identifying the conditions under which campaigns receive money from various actors, how much money they receive, when they receive it, how these contributions impact the outcomes of elections, and the extent to which they influence the behavior of elected officials. These studies are generally conducted using aggregate data on contributions to campaigns over the course of an election cycle from particular sources, with particular attention to the actions of party organizations, individual contributors, and political action committees.

Starting with the 1979-1980 electoral cycle, the Federal Election Committee (FEC) maintains a comprehensive database of contributions data for these actors, both aggregated and itemized, making large-scale longitudinal analysis possible. Still, the majority of analyses have concentrated on small subsets of the available data, often limited to particular election cycles, particular actors, and aggregated rather than itemized contributions data. As such, we know a great deal less than we might about the overall structure of campaign contributions in federal elections. In particular, we know little about how this structure has evolved, and how it influences or is influenced by, for example, changes in political institutions, partisan control of government, campaign finance laws, and partisan polarization. The increasing popularity of network analysis methodologies in political science, however, provides with appropriate tools to analyze the structure of itemized FEC contributions data, visualize and measure changes in this structure over time, and estimate the influence of structural change on variables of interest.

This paper takes the first step in that process by assembling itemized contributions data for each federal election, from 1980-2008, into networks. I assemble two networks for each election. In the first, which employs data on individual contributions, weighted links are drawn between pairs of political committees, with weights equal to the number of individual contributors that have donated to both. In the second, which employs data on contributions among committees and candidates, weighted links are drawn between pairs of committees/candidates, with weights equal to the amount of the contribution. To find the structure of these networks, we require a way of dividing the nodes of the network (in this case committees and candidates) into discrete communities, and a way of assessing the quality of that division.

I use an algorithm that maximizes a network science statistic called modularity (Newman & Girvan 2004, Newman 2006*b*). Modularity measures the quality of a community partition for a given network by comparing the number and weight of connections that occur within a community to the number and weight of connections that occur between communities. Modularity increases as the ratio of in-community to between-community edges increases. The community partition that maximizes modularity, therefore, gives us the network structure that best divides the nodes based on their contribution activity. Compared to colloquial definitions of community, this measure makes intuitive sense. Communities are routinely defined based on shared behavior. In this case that behavior is a political contribution. The modularity statistic not only allows us to locate community structures within electoral cycles, but also allows us to compare the strength of community divisions across electoral cycles. This gives us the opportunity to analyze the conditions under which communities of donors coalesce, when they break down, and how these changes are associated with important political variables.

Though these networks have many potential scholarly uses, this paper focuses primarily on the relationship between community structure and modularity in donation networks and partisan polarization. Examining the membership of the largest communities in each network, I find that these communities are, for the most part, highly partisan. This is coupled with the finding that, over time, modularity increases dramatically in both network types, suggesting that increasing partisan divisions may be causing donors to choose sides, thus reducing the number of between-community links. Interestingly, modularity does not spike in both network types at the same time. In the networks of committee and candidate contributions, modularity spikes in the 1987-1988 electoral cycle, whereas in the networks of individual contributions, modularity does not spike until the 2001-2002 electoral cycle. This suggests that donations among elite political actors polarized some 14 years prior to donations from individual contributors.

The plan of the paper is as follows. Section 2 provides a brief review of the study of community structure in campaign contributions, as well as the use of community detection methods in political networks, generally. Section 3 describes the construction of the network datasets. Section 4 provides a more complete definition of modularity and the other methods used in this analysis. Section 5 analyzes the results of the community detection process. Section 6 concludes.

2 Background

Despite considerable interest in the study of campaign contributions generally speaking, very little work has been done concerning the community structure of donations in federal elections. Some attention, however, has been paid to the relationship between campaign contributions and partisan polarization.

One branch of research concerns the contribution behavior of political action committees. PACs have been shown to primarily spend money primarily on incumbent candidates, and candidates who have held seats on committees relevant to their business (Herrnson 2004, Jacobson 2004). Despite this regularity, there is some evidence that PACs have ideological leanings, or at least act as if they do. Poole and Romer (1985, 1987), for example, demonstrate that PAC contributions to Congressional races can be explained with a spatial model, and that PACs rarely donate to candidates who occupy opposite extremes of the political spectrum.

A second branch concerns the contributions of party organizations to Congressional candidates. Numerous studies have shown that parties distribute funds based on the perceived competitiveness of campaigns, with an eye towards maximizing seat shares in Congress, and that comparatively little attention is paid to party loyalty (Jacobson 1985-1986, Herrnson 1989, Damore & Hansford 1999). There is some evidence that the Democratic Party has used campaign funding as a reward for loyalty (Leyden & Borreli 1990). However, no clear relationship has been established between party funding and future loyalty in voting (Cantor & Herrnson 1997).

Generally speaking, the connections between campaign contributions and partisan polarization remain difficult to establish empirically. With the use of community detection algorithms on FEC contribution data, however, we are able to measure the strength of community divisions within contribution networks, and chart the development of these divisions and their strength over time. Community detection algorithms have previously been employed in the study of committees (Porter, Mucha, Newman & Warmbrand 2005, Porter, Mucha, Newman & Friend 2007), cosponsorships (Zhang, Friend, Traud, Porter, Fowler & Mucha 2008) and roll-call voting in Congress (Waugh et al. 2010). In each set of Congressional data, the authors found evidence of increased partisan polarization over time.

3 Data

In this section, I describe the data and processes used to assemble the donation networks. I begin by discussing the FEC data generally, and subsequently describe issues particular to the creation of each of the two network types employed.

3.1 Dataset Assembly

The networks analyzed in this paper were assembled using data made available online by the FEC (www.fec.gov). For each federal election, 1980-2008, the FEC maintains two datasets. The first contains itemized contributions from individuals to federal committees. The second contains itemized contributions from federal committees to candidates. Additionally, for the 1986-2008 elections, the FEC maintains a third dataset, containing itemized transactions between any two federal committees. I employ these data to create two network types for each election. The first network type, which I term *shared individual donations*, employs the individual contributions dataset. The second, termed *monetary transfers*, employs the data on contributions from committees to candidates and committees to committees. In all networks I exclude contributions less than $200. Committees/candidates are not required by law to report contributions less than $200, and indeed they are not regularly reported, making data on these small contributions unreliable. The nodes in these networks consist of federal committees and candidates, which are given unique identification codes by the FEC.

3.2 Shared Individual Donations as Weighted, Undirected Networks

In the shared individual donation networks, an undirected edge is drawn between two nodes if those nodes both receive money from the same individual donor. The weight of the edge is equivalent to the number of individual donors that the two nodes share. Theoretically, a heavily weighted edge between two nodes should indicate similarity between these nodes in the eyes of individual donors.

Unfortunately, identifying the number of shared individual donors between two nodes using the FEC data proves to be a non-trivial task. Individual contributors, unlike candidates and committees, are not given unique identification. Furthermore, FEC does not keep a master list of individual contributors. Rather, each individual contribution is identified by the name, address, and occupation of the contributor. Many individuals donate to multiple candidates/committees and therefore appear multiple times in the itemized datasets. Irregularities in the coding of identifying variables make the generation of unique donor lists difficult. I decided to combine the name and zip code variables for the individual contributions and used this combination to generate unique individual donor lists for each electoral cycle. Certainly, this process is not without error, as two individuals with the same name in the same zip code will be coded as one person, and individuals who donate money and then change zip codes will be counted as two separate people, but given the available data, it is unclear that a better option was available.

Having assembled unique donor lists, I then identified all of the committees/candidates to which each individual contributed using the FEC data, and assembled the finished networks in R using the *igraph* package (Csardi & Nepusz 2006). The finished networks, it should be noted, do not contain all of the committees/candidates that took part in a given election cycle. Rather, they contain only those that share an individual donor with at least one other committee/candidate.

3.3 Monetary Transfers as Weighted, Directed Networks

In the monetary transfer networks, a directed edge is drawn between two nodes, A and B, if node A transfers money to node B. The weight of the edge $A \rightarrow B$ is equal to the amount of money transferred. Frequently, there are multiple transfers from one node to another in this network. Since these transfers vary in date, amount, and type, among other interesting variables kept by the FEC, I chose to allow multiple edges to remain, rather than collapsing them into a single edge and summing the weights. Though these variables are not analyzed in this paper, they will be the subject of future work.

Assembling the monetary transfer networks was relatively straightforward. Each itemized transfer over $200 in the FEC committee-candidate and committee-committee datasets was simply added as an edge in a network, again using the igraph package in R. At this point, the monetary transfer networks were ready for community detection with no further data processing.

4 Methods

In this section, I describe the network science concept of modularity, which I use to evaluate community structures in the federal election donation networks. I then describe the algorithm used to find the community structure that maximizes modularity. Finally, I review the techniques used to evaluate the identified communities.

4.1 Using Modularity to Evaluate Community Structure

We begin our discussion of community structure by defining a community partition. In a community partition, every node in a given network is assigned to precisely one community, with no overlap between communities. In order for a community partition to be meaningful, however, we must have a criterion for evaluating its quality.

Modularity provides a conceptually simple way to evaluate the quality of a given community partition using the information contained in the edges of the network (Porter, Onnela & Mucha 2009, Newman & Girvan 2004, Newman 2006*b*, Fortunato 2010). In a network, however constituted, nodes relate to one another through the presence or absence of shared edges. Modularity assumes that nodes in the same community should share more ties with each other (intra-community ties) than with nodes in other communities (extra-community ties) (Newman & Girvan 2004, Newman 2006*b*).

Considering a contribution network, this assumption makes intuitive sense. Suppose we partitioned a contribution network into Democratic and Republican communities. Under normal circumstances we would expect Democratic committees to contribute money almost exclusively to other Democratic committees, and would believe the community structure to be quite strong. If, however, we encountered a situation in which Democratic and Republican committees were regularly sharing money with one another, we might question the value of the party label as an informative cue, and consider the party communities to be weaker. In either case, the modularity score of such a community partition would reflect our intuition. Importantly, however, the modularity score is calculated based solely on the presence or absence of network connections, and is agnostic to other assumptions about the structure of the political system. This allows us to calculate the modularity statistic for any hypothesized community partition.

More formally, for a given community partition, modularity Q represents the fraction total tie strength m contained within the specified communities minus the expected total strength of such ties. The expected strength depends on an assumed null model. I use the standard Newman-Girvan null model that posits a hypothetical network with the same expected degree distributions as the observed network (Newman 2006*b*, Newman 2006*a*), yielding the equation

$$Q = \frac{1}{2m} \sum_{ij} \left[A_{ij} - \frac{k_i k_j}{2m} \right] \delta(g_i, g_j) \,, \tag{1}$$

where $m = \frac{1}{2}\sum_i k_i$ is the total strength of ties in the network, $k_i = \sum_j A_{ij}$ is the weighted degree (i.e., the strength) of the ith node, g_i is the community to which i belongs, and $\delta(g_i, g_j) = 1$ if i and j belong to the same community and 0 if they do not. If the community partition is strong, a greater percentage of the total tie strength of the network will be contained in the communities than would be expected by chance, and the modularity score will be large and positive.

4.2 Community Detection Using Modularity Maximization

The modularity statistic gives us an intuitively satisfying criterion for evaluating the quality of a given community partition. Given the assumption about community strength that underlies modularity, it follows that the best community partition for a network is the one that maximizes the modularity score. Modularity optimization, however, is an NP-complete problem (Brandes, Delling, Gaertler, Goerke, Hoefer, Nikoloski & Wagner 2008), so identifying the correct partition requires the use of a computational heuristic, several of which have been developed for this purpose (Danon, Diaz-Guilera, Duch & Arenas 2005, Porter, Onnela & Mucha 2009, Fortunato 2010).

In this paper, I use the *walktrap* algorithm (Pons & Latapy 2005), as implemented in the R package *igraph* (Csardi & Nepusz 2006). This implementation is particularly useful because it allows the use of weighted edges, and can also process the directed edges and multiple connections present in the monetary transfer networks.

The walktrap algorithm starts by partitioning the network into n communities, which each contain a single node. It calculates a measure of the distance between each pair of communities and begins merging groups by taking short random walks between them, operating under the principle that such walks should connect closely tied nodes and identify relevant communities. After each merging step, one calculates the modularity score for the current partition. The algorithm finishes after n?1 steps when the nodes have been merged into a single community consisting of the full network. Although the algorithm always begins with n communities and ends with a single community, it returns the community partition with the highest modularity value it was able to find.

4.3 Modularity Over Time

Using the modularity values derived from the walktrap algorithm, I examine the strength of community partitions in federal election donation networks over time. The data span 15 federal election cycles from 1980-2008. Because the two network types I examine rely on different types of data, one using shared individual donors, and the other using monetary transfers among committees and candidates, I am able to separately examine the evolution of modularity on two different aspects of donation network structure.

In the shared individual donor networks, increases in modularity reflect a world in which the individual donors themselves are divided. The communities in the network (i.e. political committees) become more strongly defined as more individuals choose to donate explicitly to committees within that community as opposed to outside it. To the extent that these communities are divided on a partisan basis, increases in modularity suggest that individual donors themselves are becoming more partisan.

Interpretation of the monetary transfer networks is more straightforward, and follows directly from the definition of modularity. In these networks, increases in modularity reflect increased intra-community transfers of funds and decreased extra-community transfers. By comparing the evolution of modularity in the two network types, therefore, we have the capacity to understand when and why the donation communities of political elites, as opposed to individual donors, become more consolidated.

4.4 Analysis of Communities

In addition to analyzing the evolution of modularity, I examine the size and composition of the largest communities in each network over time. The relative sizes of the largest communities in each network provide insight into the number of relevant divisions in each donation network. The composition of these communities also offers a number of insights. I am able to identify, for example, which communities lean Republican and Democratic, and what types of PACs Republican- and Democratic-dominated communities tend to contain.

5 Findings

Results from the longitudinal analysis of modularity in the donation networks are presented in Figure 1. Comparison of the modularity in the monetary transfers network to that in the shared individual donors network reveals that both networks have become dramatically more modular over time, and in both cases the increase in modularity occurred almost entirely over the course of a single electoral cycle. In the monetary transfer network, the leap in modularity occurred in the 1987-1988 electoral cycle, whereas in the shared individual donors network the leap occurred in the 2001-2002 electoral cycle.

The time disparity between the modularity increases in the two time series is of particular interest in this case, as it suggests that political elites (party committees, PACs, and candidates) developed and sustained consolidated group structures some 14 years before individual donors. To the extent that these group structures reflect partisan separation, this finding suggests that groups of elite actors in the campaign contributions network polarized (in the sense that they began donating more exclusively to one party), long before individual donors did. This provides some evidence supporting the theory that partisan polarization in the United States is elite-driven, and not the product of increasing polarization at the grass-roots level (Jacobson 2006). In order to examine this possibility more fully, however, we must examine the size and composition of the communities in these networks.

Figure 2 plots the size difference (as a percentage of total nodes) between the two largest communities in each network. Two observations are noteworthy. First, the two largest communities in the shared individual donor networks are approximately the same size in every electoral cycle save three: 1980, 2000 and 2008. Interestingly, each of these elections resulted in a switch in the party controlling the Presidency. Second, the two largest communities in the monetary transfer networks start out vastly different in size in the early 1980s, but this difference nearly disappears in the 1987-1988 electoral cycle; the same cycle in which modularity skyrocket. This suggests that the modularity increase in the monetary transfer network is associated with a balancing of community sizes in the network, which could also be evidence of increased partisan polarization in contributions. The modularity spike in the individual donor network also occurs simultaneously with a balancing of group size, but the change is not nearly as dramatic, relative to the increase in modularity.

In order to confirm the relationship between these findings and partisan polarization in the donation networks, it is important to understand who belongs to these communities. Table 1 provides information on the membership of the two largest communities in each of the monetary transfer networks, while Table 2 provides the same information for the shared individual donor networks. These tables list the size of each community, along with the percentage of its membership that is Democratic and Republican. Since many of the committees in these networks are non-partisan, the tables also list the percentage of each communitys membership occupied by corporate, labor, trade, and membership PACs.

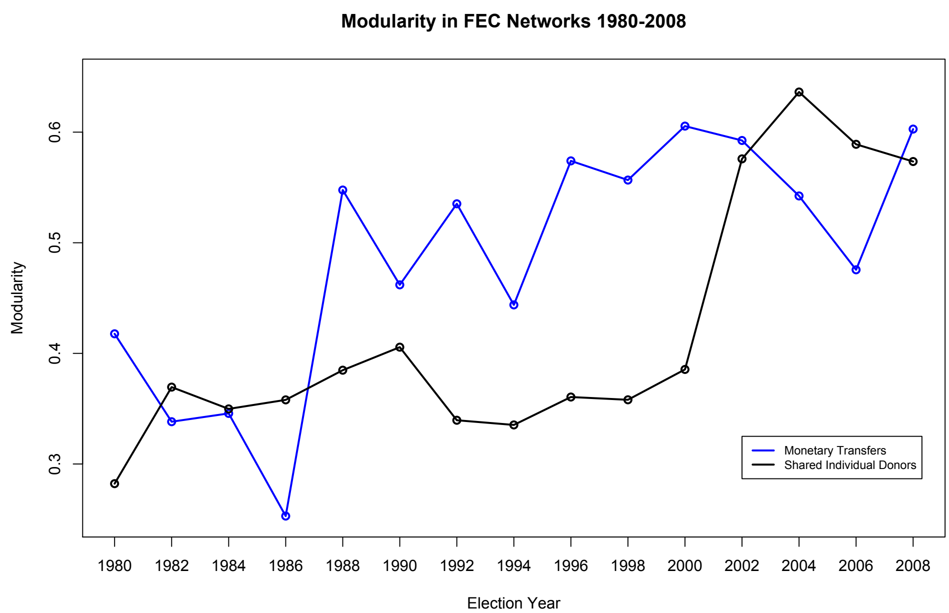

Figure 1: Modularity in FEC Networks, 1980-2008

5.1 Community Analysis in Monetary Transfer Networks

It is immediately apparent from looking at these tables that, in the vast majority of cases, the largest communities are extremely divided on a partisan basis. In the monetary transfer networks, however, the emergence of partisan divisions follows a different course than in the shared individual donor

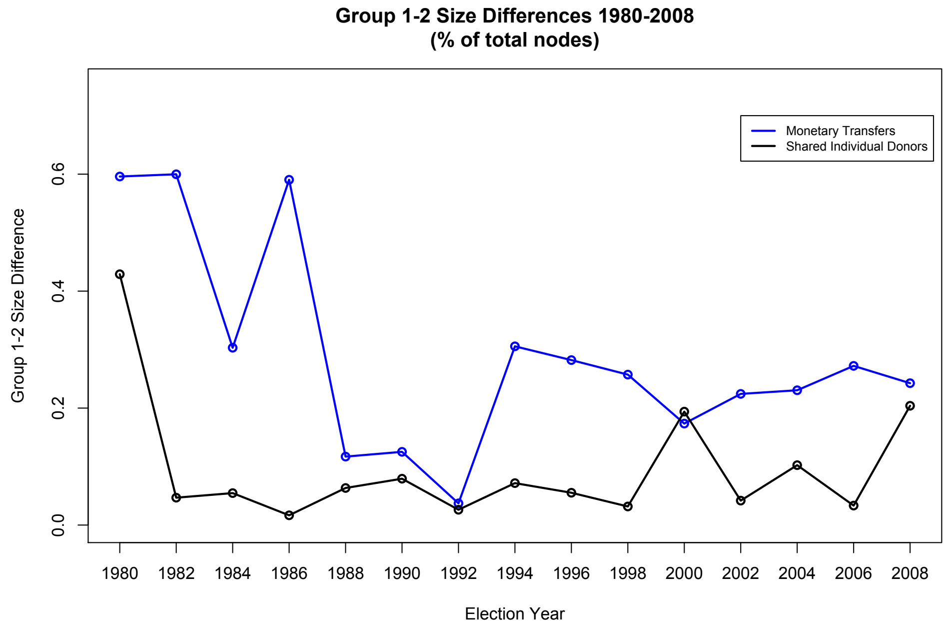

Figure 2: Group 1-2 Size Differences, 1980-2008

networks. As shown in Figure 2, the monetary transfer networks from 1980-1986 are characterized by the presence of dominant largest communities. In each of these electoral cycles, the largest community contains roughly similar numbers of Republican of Democratic nodes, with between party differences ranging from 0.8% to 3.7%, and neither party holding a consistent advantage in membership. This community structure may reflect the divided status of Congress during these years, in which Republicans held the Senate and Democrats held the House.

In the 1987-1988 electoral cycle, however, which would see the Democrats regain unified control of Congress, the community structure changes drastically. The largest community shrinks from 3918 to 2242 nodes, while the second-largest community grows from 302 to 1420 nodes. This shift appears to be driven by a mass-exodus of Democratic nodes from the largest community, which shrinks from 14.9% Democratic in 1986 to 4.7% in 1988. Republican nodes in the largest community open up a 5.9% membership advantage over Democratic nodes in 1988, and maintain an advantage ranging from 3.4% to 12.8% for the rest of the time series. The second-largest community, meanwhile, remains predominantly Democratic from 1988 onward, never containing more than 5.4% Republican nodes. It appears that the basic partisan structure of campaign contributions in the monetary transfer network remains stable from 1988-2008.

The shift in community structure that occurs in 1988 also appears to be influenced by changing donation behaviors on the part of corporate and labor PACs that take place over a longer period of time. From 1984 onward, at least 10% of the second-largest community is composed of labor PACs. This is no surprise, given the long history of association between organized labor and the Democratic Party. More surprising is the changing behavior of corporate PACs. When the Democratic nodes first split off from the largest community in 1988, the second-largest community contains a roughly equal balance of corporate and labor PACs (16.1% and 12.5% respectively). The second-largest community maintains this balance until the 1993-1994 electoral cycle. Here, corporate PACs make up only 8.6% of the second-largest community compared to labors 15.9%. Interestingly, this is also the electoral cycle that saw the Democrats lose control of both chambers of Congress. The second-largest community obtains greater than 10% corporate PAC membership only one time after 1992 13.8% in the 2000 electoral cycle. Even when the Democrats retook Congress in 2006, and the Presidency in 2008, the second-largest community fails to realize meaningful gains in corporate PAC membership.

5.2 Community Analysis in Shared Individual Donor Networks

The shared individual donor networks begin to show highly partisan community divisions starting with the 1981-1982 electoral cycle, suggesting that individual donors have a long history of favoring either one political party or the other. In each electoral cycle the after 1980, the two largest communities are both skewed toward one party or the other, and in each case both the Democrats and Republicans are represented in one of the two largest communities. Compared to the monetary transfer networks, the two largest communities are also much closer in size. Furthermore, in every electoral cycle save 1993-1994, the largest community is dominated by affiliates of the party that went on to win control of the House of Representatives.

Despite the prevalence of party divisions in the communities throughout the time series, however, modularity does not increase dramatically until the 2001-2002 electoral cycle. Examining the two largest communities alone in the 1999-2000 and 2001-2002 electoral cycles does not suggest an adequate explanation for this change. Figure 3 plots the sizes of the six largest communities in each of these two cycles in an attempt to further understand the structural changes at work. Table 3, in turn, provides the membership information for these communities. Figure 3 shows that while the 1999-2000 network has only 3 communities of 100 nodes or more, the 2001-2002 network has 5 such communities. In this case, the increase in modularity appears to be driven by the breaking down of large, weakly constituted communities into smaller communities that are better defined.

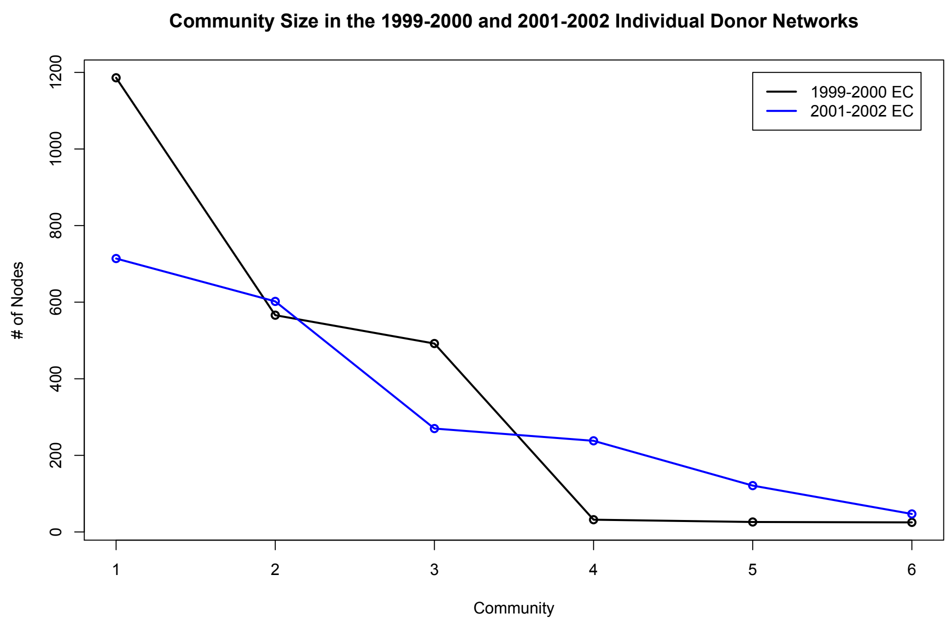

Figure 3: Community Size in 1999-2000 and 2001-2002 Shared Individual Donor Networks

Table 3 shows that in 1999-2000 the largest community is predominantly Republican, whereas the next two communities are predominantly Democratic. In 2001-2002, however, Republicans are divided over three large communities, and the Democrats remain in two large communities. It is tempting to attribute this change in community structure to the midterm election. We might expect, for example, that the presence of a presidential election inspires more individuals to donate money, and that these individuals are generally less-partisan than those who donate in midterm elections, and thus are more likely to split their donations between parties, resulting in weaker ratios of intra-community to extra-community ties during presidential election years. This would explain the presence of a large and weak Republican community in 1999-2000, presumably assembled from Bush donors. In a midterm election, with fewer, more partisan donors forming edges in the network, we might expect smaller and stronger communities. Unfortunately, this reasoning does not explain the further increase in modularity observed in the 2003-2004 election cycle, or the fact that community structure remains fairly constant with respect to party in 2003-2004, with Republicans once again occupying three large communities and the Democrats occupying two.

6 Conclusion

In this paper, I have constructed two sets of networks for each electoral cycle from 1980-2008 using data available from the FEC. Using a computational heuristic, I derive the community structure for each network that maximizes a network science statistic called modularity. Examining these networks over time, I find that both sets demonstrate large increases in modularity, and that these increases are likely related to increased partisan polarization in the United States.

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Tables

Year	Size	% Dem	% Rep	% Corp	% Labor	% Member	% Trade
80	3247	0.157	0.180	0.308	0.058	0.048	0.128
80	234	0.709	0.256	0.004	0.000	0.009	0.000
82	3854	0.163	0.126	0.315	0.063	0.079	0.129
82	355	0.025	0.817	0.023	0.003	0.017	0.000
84	2553	0.076	0.084	0.468	0.042	0.078	0.169
84	607	0.489	0.023	0.049	0.148	0.082	0.028
86	***3918***	***0.149***	***0.121***	***0.353***	***0.052***	***0.092***	***0.143***
86	***302***	***0.894***	***0.053***	***0.000***	***0.007***	***0.013***	***0.000***
88	***2242***	***0.047***	***0.106***	***0.485***	***0.016***	***0.087***	***0.177***
88	***1420***	***0.320***	***0.026***	***0.161***	***0.125***	***0.118***	***0.079***
90	1931	0.042	0.076	0.492	0.016	0.082	0.197
90	1136	0.316	0.017	0.129	0.150	0.124	0.074
92	2411	0.041	0.124	0.414	0.013	0.064	0.158
92	2119	0.272	0.054	0.168	0.107	0.075	0.103
94	3219	0.058	0.128	0.390	0.027	0.055	0.169
94	958	0.376	0.021	0.086	0.159	0.066	0.047
96	3062	0.048	0.138	0.398	0.019	0.046	0.183
96	976	0.414	0.023	0.059	0.175	0.058	0.046
98	2752	0.033	0.133	0.427	0.014	0.042	0.182
98	1071	0.327	0.012	0.090	0.173	0.063	0.073
00	2531	0.019	0.135	0.407	0.009	0.042	0.180
00	1329	0.309	0.015	0.138	0.148	0.057	0.084
02	2534	0.031	0.151	0.392	0.011	0.037	0.185
02	1039	0.382	0.017	0.086	0.154	0.055	0.056
04	2834	0.028	0.156	0.399	0.014	0.029	0.179
04	1108	0.429	0.053	0.059	0.142	0.032	0.055
06	3203	0.030	0.154	0.377	0.013	0.026	0.185
06	1143	0.456	0.040	0.062	0.128	0.025	0.044
08	3001	0.036	0.128	0.392	0.021	0.024	0.183
08	958	0.459	0.004	0.065	0.114	0.020	0.058

Table 1: Membership of Two Largest Communities in Monetary Transfers Network

Year	Size	% Dem	% Rep	% Corp	% Labor	% Member	% Trade
80	1599	0.197	0.248	0.196	0.002	0.081	0.085
80	577	0.383	0.355	0.014	0.000	0.005	0.014
82	394	0.058	0.439	0.079	0.000	0.124	0.056
82	320	0.450	0.050	0.047	0.006	0.163	0.038
84	860	0.392	0.088	0.088	0.002	0.147	0.063
84	764	0.050	0.432	0.182	0.001	0.113	0.077
86	289	0.083	0.450	0.087	0.000	0.142	0.066
86	261	0.456	0.080	0.088	0.000	0.080	0.034
88	520	0.419	0.042	0.065	0.008	0.169	0.056
88	397	0.136	0.320	0.108	0.000	0.108	0.106
90	656	0.441	0.026	0.085	0.003	0.143	0.072
90	471	0.159	0.299	0.104	0.000	0.066	0.119
92	933	0.375	0.015	0.083	0.009	0.105	0.055
92	848	0.021	0.327	0.137	0.000	0.071	0.118
94	795	0.414	0.026	0.075	0.005	0.096	0.060
94	576	0.019	0.438	0.118	0.000	0.056	0.122
96	1267	0.032	0.393	0.161	0.002	0.040	0.127
96	1085	0.456	0.032	0.079	0.007	0.069	0.063
98	872	0.080	0.347	0.128	0.000	0.028	0.153
98	779	0.449	0.018	0.068	0.013	0.073	0.054
00	***1186***	***0.015***	***0.347***	***0.152***	***0.001***	***0.041***	***0.141***
00	***566***	***0.329***	***0.081***	***0.104***	***0.004***	***0.048***	***0.101***
02	***714***	***0.111***	***0.464***	***0.069***	***0.004***	***0.031***	***0.094***
02	***602***	***0.510***	***0.023***	***0.050***	***0.003***	***0.058***	***0.065***
04	933	0.139	0.371	0.085	0.001	0.029	0.102
04	609	0.537	0.005	0.074	0.013	0.049	0.061
06	996	0.518	0.030	0.053	0.005	0.037	0.070
06	885	0.024	0.416	0.116	0.000	0.019	0.136
08	1282	0.461	0.027	0.105	0.009	0.030	0.086
08	515	0.008	0.443	0.130	0.000	0.019	0.138

Table 2: Membership of Two Largest Communities in Shared Individual Donors Network

Year	Size	% Dem	% Rep	% Corp	% Labor	% Memb	% Trade
00	1186	0.015	0.347	0.152	0.001	0.041	0.141
00	566	0.329	0.081	0.104	0.004	0.048	0.101
00	492	0.445	0.004	0.063	0.016	0.087	0.043
00	32	0.219	0.219	0.156	0.000	0.031	0.031
00	26	0.000	0.654	0.115	0.000	0.038	0.038
02	714	0.111	0.464	0.069	0.004	0.031	0.094
02	602	0.510	0.023	0.050	0.003	0.058	0.065
02	270	0.019	0.363	0.111	0.000	0.022	0.156
02	238	0.374	0.046	0.042	0.008	0.088	0.063
02	121	0.058	0.364	0.058	0.000	0.025	0.231

Table 3: Membership of 5 Largest Communities in 2000 and 2002 Shared Individual Donors Network