Network Centralities and Subgraph Communities Among

Political Committee Financial Exchanges

By
Dave Lobue

Thesis Project
Submitted in partial fulfillment of the Requirements for the degree of
Master of Science in Data Science
March 2022
Moses Boudourides, First Reader
John McNutt, Second Reader

Table of Contents

Abstract

Political campaign finance laws have undergone several changes over the past two decades resulting in a massive influx of funds from individuals, organizations, and labor groups intending to influence election outcomes for Presidential, Senate, and House races. Over $24 billion in donations were made during the 2020 two-year election cycle, creating a complex network of financial exchanges among donors and committees. This research explores the structure of this network through applications of graph data science including centrality scoring, subgraph communities, and relationships between financial connectedness and election success.

By converting traditional relational databases to a weighted, directed graph comprising all active political committees and donors for the 2020 election cycle, donors/committees (nodes) and their financial exchanges (edges) can be examined as a single network. Node centrality scores for Eigenvector, HITS Authority, and PageRank suggest dominance among the presidential candidate committees and national fundraising committees WinRed and ActBlue. Looking down ballot at House races in particular, candidates who scored higher on these measures relative to opponents were strong indicators of successful election outcomes. Within House races, candidates with primary committees scoring higher on centrality scores relative to opponents won 93% of the time in the case of Eigenvector and 85% when scoring higher on PageRank. Subgraph community detection with greedy modularity maximization suggests Democrats may be better organized relative to Republicans, with a modularity score of 0.52 compared to Republicans 0.27. Additional investigations into assortativity and reciprocity also yield further distinguishing traits among the subgraphs analyzed.

List of Tables, Figures, and Graphs

Introduction

The study of network science has delivered widespread applications of web search, fraud detection, transportation logistics, and the spread of disease, to name a few. Recently, social networks have provided new opportunities to study massive quantities of network data, however challenges still persist in terms of complexity management and computational processing speed. In many cases, network complexity prohibits or greatly delays compiling a complete set of interactions that can in turn be studied. The network that has n nodes and m edges can have as many as $\binom{n}{2}$ node pairs with potential edges and $\binom{\binom{n}{2}}{m}$ ways of placing the m edges (Newman 2017, 342). The benefits of distilling complex interactions into more manageable connected sets of information can be seen in the inception of many recent tech companies that are fundamentally based on applications understanding network structure and node interactions.

The data collected and provided by the Federal Election Commission (FEC) provides a computationally manageable, complete set of network interactions in the focused area of financial contributions to political committees and their disbursements. Since political contributions are legally regulated in the United States, this dataset is considered complete in as far as the reporting guidelines are followed, however, it still requires a number of pre-processing steps in order to structure the data as a network of interactions. As such, it requires a fully integrative data science pipeline to extract, process, and analyze the data in order to derive insights about this very important, complex subject area. This in turn produces a rich data source of network interactions with multiple avenues of fresh exploration using modern techniques.

In a given two-year election cycle, contributions (*receipts*, see appendix II) can be made from individuals, lobbyists, corporations, and labor organizations (via Separate Segregated Funds or SSFs), as well as other political committees. While financial contributions from individuals can only flow in one direction, the exchanges of financial flows among registered committees creates a dynamically changing network involving campaign strategy management. Further, recent Supreme Court rulings have altered the dynamics in which campaign funds can be raised/spent. This has fueled a massive increase in donations (Figure 1) from large corporations and mega-donors, resulting in over $24 billion in overall donations for the 2020 election cycle (Federal Elections Commission, 2021).

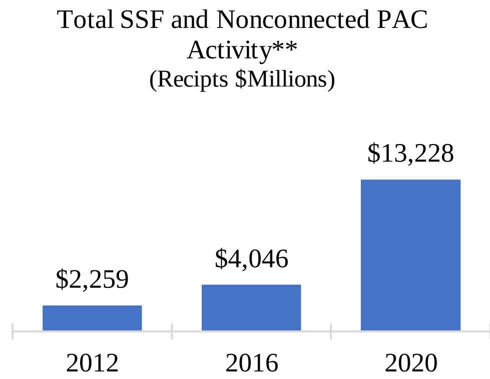


Figure 1. Historical SSF and Nonconnected PAC Receipts

Campaign Finance Historical Context

To date, there is a lack of full and systematic analysis of the FEC political campaign financial network data. While financial contributions to political campaigns have always been a part of United States elections, modern legal developments including the 1971 Federal Election Campaign Act (FECA) and recently the Citizens United v. FEC Supreme Court ruling have drastically changed how federal election campaigning is approached and managed. In 1971, FECA modernized the legal requirements for finance disclosures for federal candidates, political parties, and political action committees (PACs). This act was further strengthened in 1972 as Congress set limits on contributions by individuals, political parties, and PACs (Federal Election Comission, n.d.a).

More recently, the Bipartisan Campaign Reform Act (BCRA) of 2002 initially restricted the influence of money in politics by preventing corporations and labor unions from using funds to finance electioneering communications within 60 days before general elections and 30 days of primaries. However, the Citizens United decision in 2010 determined this act placed prohibitions on campaign communications that violated the First Amendment, overruling these restrictions so long as reporting and disclaimer requirements were followed. This decision along with EMILY's List v FEC (Federal Election Commission, n.d.c) and Carey v FEC (Federal Election Commission, n.d.d) represent a fundamental shift in political campaign financing and strategy as to how candidates and committees raise and spend their money in federal elections. The influence of entities such as corporations and labor unions has given rise to Super PACs, otherwise known as independent expenditure-only political committees, which can engage in unlimited spending for/against candidates.

Receipts $Millions (24-month period)				**∆ Change as %**	
	2012	**2016**	**2020**	**'12- '16**	**'16- '20**
Presidential	$1,379.8	$1,539.1	$4,073.9	*12%*	*165%*
Congress	$1,878.8	$1,644.3	$4,005.3	*-12%*	*144%*
Party Committees	$1,609.4	$1,629.4	$3,196.8	*1%*	*96%*
Independent Exp	$1,250.5	$1,631.0	$3,143.7	*30%*	*93%*
Independent Expenditure-Only Political Committees	$824.0	$1,807.0	$3,427.2	*119%*	*90%*
Committees with non-contribution accounts	$179.4	$783.3	$7,786	*337%*	*894%*
Total SSF and Nonconnected PAC Activity	**$2,259.1**	**$4,046.3**	**$13,227.9**	***79%***	***227%***

Table 1. Historical two-year presidential cycle (full twenty-four-month period) receipts by committee type in millions. (Federal Elections Commission 2021; Federal Elections Commission 2013; Federal Elections Commission 201)

Statement of the Problem

The massive influx of financial contributions since the legal rulings of 2009-2011 referenced above has resulted in an increase in Separate Segregated Funds[1] (SSF) and Nonconnected PAC receipts from approximately $2.2 billion (2012) to $13.2 billion in the 2020 2-year election cycle (table 1). The number of corresponding active PACs has changed relatively modestly from 7,311 to 8,855 over this period; meaning the number of registered entities hasn't changed as dramatically as the money flowing in. This creates a network of campaign finance exchanges that can be strategically navigated to exert influence on federal and local elections through means of traditional media of print, cable, digital, and direct mail communications.

As social media and digital outlets have enabled new methods of highly targeted advertisements and engagement in recent years, it's increasingly important to follow political committee financial exchanges and their end destinations as either disbursements or independent expenditures through these channels. There is currently a low level of transparency due to the internal complexity of this committee network. For many ordinary voters, active engagement and awareness of candidate positions and policies isn't enough to understand the full picture of connected committees. Initial donations once aggregated can be disbursed or re-allocated to small concentrations of entities with sophisticated influencing power to sway public opinions regarding local and national candidates and policies.

The current research focuses on these linkages of funds across the campaign financing network. Connections between individual contributors and campaign committees (directional in

[1] Separate Segregated Funds are defined by the FEC as: A political committee established, administered or financially supported by a corporation or labor organization, popularly called a Corporate or Labor Political Action Committee (PAC) (Federal Elections Commission n.d.e.)

only) and among the committees themselves (can be bi-directional) is best approached through graph data science theory. After initial financial contributions are made, disbursements and expenditure allocations are at the discretion of committees, making it highly relevant to understand relationships between committee entities and how/where funds are ultimately spent.

Justification/Addressing the Problem

This problem has been presented as a network of financial interactions among contributions/receipts and disbursements/expenditures; therefore, it is best tackled through a number of graph algorithms. This research focuses on three core areas of network exploration, each of which provide unique insights in efforts to gain deeper understanding of this important problem. The most fundamental objective addresses the question of "what is this network?" by providing overall graph descriptive statistics and characterization of the underlying properties through measures such as node count, edges, degree, density, reciprocity, transitivity, etc. This starting point provides the basis for examination of network communities, centrality measurement, and node attributes as related to assortativity measurement.

Understanding communities is another major focus, which involves identifying behavior patterns of committee nodes that distinguish groups of nodes from those external within the broader overall network. Three community detection algorithms assist in exposing committee relationships that may otherwise remain unknown to outside donors. Community detection through modularity maximization (Newman 2018, 204) is utilized among directed subgraphs of committee-to-committee exchanges, since individual contributors who can only make single-directional transactions are less relevant for addressing this type of problem. Here, the directed relationships among the committees are examined to understand the composition of communities within the two dominant parties of Republicans and Democrats. By comparing across algorithms applied to each party-affiliated committee subgraph, we can understand characteristics about how the major parties manage connected finances across offices, regions and at a national level.

Lastly, identification of the most powerful (Bonacich 1987) or otherwise centrally connected nodes provides insights as to the integration of individual political committees, whether candidate, party, or independently associated. However, since individual committees are subject to disbursement and expenditure restrictions based on their legal classification type, measures of prominence (in-degree or prestige) and influence (out-degree) do not tell the full story of their connectedness. As a result, the more restrictive node relationships (dollar amount in/out, Appendix I) in this context do not fit squarely into previously defined measures of 'power' or 'influence' and therefore in certain cases are referred to more broadly in this context as synchronized committees. Here, committee interactions are considered in sync as financial partners for collective party ambitions (e.g., Republican, Democrat majorities). This generalization aims to avoid confusion with direct comparison of the naming conventions (e.g., 'power') used in the explicit context of the network applications in which they were originally applied.

Centrality measures provide meaningful insights in this context as they can inform donors which entities or types of committees are more broadly connected across the networks' various party-specific, regional, national, or other uniquely affiliated committees. In many cases, funds are exchanged a number of ways across region, elected office, and organizational types thus creating unique sets of interactions among committees on both the receiving and distributing end. For example, a presidential committee may distribute funds to a state party committee to support efforts to elect themselves as well as local in-party candidates seeking other offices. To better distill this information, eigenvector centrality, PageRank, and HITS authority algorithms are applied as tools for quantifying individual node scoring.

In addition to these focal areas, graph visualizations of these relationships greatly improve our understanding of the committees that are closely related and their corresponding organizational types or other attributes. Colorized visuals are presented where relevant, however the number of nodes in this network make condensed visualization challenging and only a subset can be meaningfully displayed here with additional data and figures provided online in a consolidated, centralized source (Data Science Quarterly 2022). Instead, focus is placed on community detection through modularity optimization, node interactions through centrality scoring, and other network quantification measures.

Literature Review

The number of published articles and journal entries focused on graph or network theory and their applications has increased significantly in recent decades to become one of the more popular sub topics of data science. While this rising popularity can in part be attributed to machine learning and other graph neural network applications, many original network algorithms and models for community detection and centrality yield fresh applications and discoveries today.

Specific to community detection, Newman published *Fast Algorithm for Detecting Community Structure in Networks* (Newman 2004), where he presents a greedy optimization of modularity. Modularity is detailed thoroughly in the Physical Review article *Finding and Evaluating Community Structure in Networks* (Girvan and Newman 2004) and is a key measure of the division of communities within a network and can be broadly defined as:

Q = (fraction of edges within communities) – (expected fraction of such edges)

This definition relies on a calculation of the number of expected edges, which can be achieved through the configuration model of a graph, with a given degree sequence derived from the degree sequence of the original underlying network. In contrast to random graphs, which are created in essence by selecting at random a simple graph among the set of all possible simple graphs with exactly *n* nodes and *m* edges, or the $\binom{\binom{n}{2}}{m}$ ways of placing *m* edges. In *Fast Algorithm* (Newman 2004) proposes the following modularity function: $Q = \sum(e_{ij} - a_i^2)$ where e_{ij} is the fraction of edges in the network connecting vertices in group *i* to group *j* and $a_i = \sum e_{ij}$. This "greedy" approach starts with each node as a single member of a community and repeatedly joins communities to reach the largest overall increase in modularity through each combination of pairs. This also falls under the broad category of aggregative hierarchical clustering.

Since the above approach and exhaustive modularity optimization in general is a NP complete problem, this creates computational challenges for the set of all possible graphs of size *x*. When dealing with complex networks that have hundreds of thousands to millions of nodes and their corresponding edge relationships, the tradeoff between algorithm selection/optimizations and computational processing speed becomes a critical factor in determining the best approach analyzing most graphs. Subsequently, *Finding Community Structure in Very Large Networks* (Clauset et al. 2004), co-published with Clauset and Moore, delivered a more efficient computational approach to achieving identical results as the previous

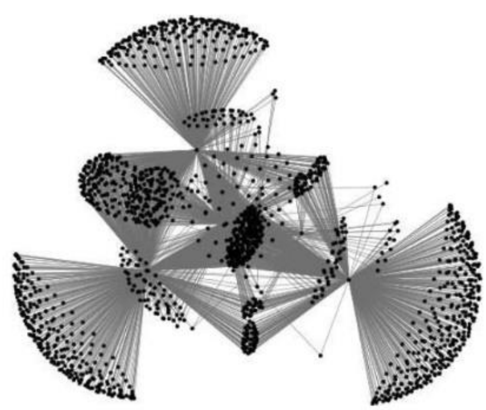


Figure 2. Visualization of the community structure at maximum modularity (Clauset, et al. 2004)

paper. The latter focuses on "hierarchical agglomeration algorithm for detecting community structures that is faster than many competing algorithms: its running time on a network with *n* vertices and *m* edges is O(*md*log*n*) where d is the depth of the dendrogram describing the community structure" (Clauset et al. 2004).

As both approaches depend on adjacency matrix calcluations, the improved algorithm is computationally simplified as it stores only the delta modularity matrix instead of both the originating adjacency matrices between updates in the greedy algorithm process in addition to the modularity change. As noted in the paper, the original process "wastes a good deal of time and memory space on the storage and merging of matrix elements with value 0, which is the vast majority of the adjacency matrix" (Clauset et al. 2004). This produces an improvement in both speed and memory demands and thus a superior overall process for identifying community structures. This type of approach is not only of relevance for the results it produces but also as a demonstration of underlying process improvements that can make computations much more feasible and realistic with more broadly available computer processors and memory constraints.

Modularity optimization approaches can focus on directed or undirected networks, which in the latter case, would require naïve transformation of the directed graph here in order to perform any underlying analysis (not a part of this research). In identifying shortcomings of undirected transformations, *Community Structure in Directed Networks* (Leicht and Newman, 2008), proposes an extension of the underlying model to account for valuable edge directionality data. The modularity calculation within the configuration model framework where: $k_i k_j/2m$ is the probability of an edge between two vertices *i* and *j* where k_i is the degree of vertex *i* and m is the total number of edges is:

$$Q = \frac{1}{2m}\sum_{ij}\left[A_{ij} - \frac{k_i k_j}{2m}\right]\delta c_i c_j$$

A_{ij} is an element of the adjacency matrix, δ_{ij} is the Kronecker delta symbol, and c_i is the label of the community to which vertex *i* is assigned. Accounting for the directionality of the edges, this equation becomes:

$$Q = \frac{1}{m}\sum_{ij}\left[A_{ij} - \frac{k_i^{in}k_j^{out}}{m}\right]\delta c_i c_j$$

The resulting community assignment improvements are clearly noticeable when compared side by side with the undirected version of the modularity algorithm. Due to the exploratory nature of these processes, there can often be no exact or pre-defined 'perfect' solutions to these types of community assignment problems. We can benefit from data visualizations (figure 3) to better understand real-world performance, or as Newman demonstrated, explore algorithm performance in the context of alternate applications such as word adjacency matrix from text corpus that demonstrate clustering of word-relationships.

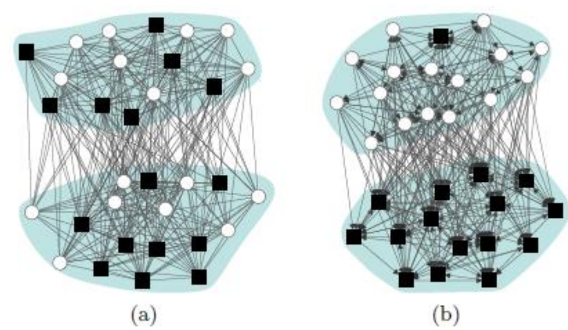


Figure 3. Improved modularity. (a) a standard undirected modularity maximization which ignores edge direction and (b) algorithm (Leicht and Newman 2008)

Phillip Bonacich's, *Power and Centrality: A Family of Measures* (Bonacich 1987) details centrality scores as they relate to 'power' and proposes a solution to the limitations of basic degree centrality in the context of social psychology applications. Degree centrality is based on the notion that a node is more powerful depending on whether or not it has more connections to other nodes. However, as Bonacich proposes, a better centrality scoring mechanism incorporating eigenvectors through "a function of the statuses of those to whom he or she is connected…in a power hierarchy, one's power is a positive function of the powers of those one has power over" (Bonacich 1987). There are two separate thoughts here, the first of which Bonacich extrapolates nodes are considered more central when having more connections in a local network and power is increased through connections to other high-status nodes. In other words, being connected to other highly connected nodes in turn increases power. This approach takes into account not only the immediate relationships among nodes but also the secondary relationships of those connected nodes as well. The second concept is presented in the context of *bargaining*, where he notes it is better to be connected to those nodes with few connections, as these nodes are lacking alternatives and therefore it is easier to exert influence given the relative dependency on that node. These concepts broadened earlier definitions of centrality to include eigenvectors and provides a useful alternative for measuring individual node power within a network that has seen wide application over time.

Another key contribution in the topic of centrality was introduced by Jon Kleinberg in *Authoritative Sources in a Hyperlinked Environment*, which extrapolated the hyperlink-induced topic search or HITS algorithm. The paper details concept of hubs and authorities as a method for organizing hyperlinks, a design for optimizing web search. While this approached proved less than optimal in widespread webpage search engine context (compared with PageRank), it does provide a solid basis for understanding key node relationships in complex networks based on their underling in and out degrees, which is relevant for the current network. Kleinberg's hub and authority model states:

> Authoritative pages relevant to the initial query should not only have large in-degree; since they are all authorities on a common topic, there should also be considerable overlap in the *sets* of pages that point to them. Thus, in addition to highly authoritative pages, we expect to find what could be called *hub pages*: these are pages that have links to multiple relevant authoritative pages. It is these hub pages that "pull together" authorities on a common topic, and allow us to throw out unrelated pages of large in-

> degree…. Hubs and authorities exhibit what could be called a *mutually reinforcing relationship*: a good *hub* is a page that points to many good authorities; a good *authority* is a page that is pointed to by many good hubs. (Kleinberg 1999)

Since this approach can induce a circular logic, the method of breaking free from this trap is accomplished through an iterative algorithm storing the weights for each node at each pass. The method follows: "If p points to many pages with large x-values, then it should receive a large y-value; and if p is pointed to by many pages with large y-values, then it should receive a large x-value*"* (Kleinberg 1999). Each iteration updates the weights in turn until an overall equilibrium is reached. The utility of this algorithm has seen application adoption in some web searches and provides a useful measurement for understanding the nature of underlying graphs as it pertains to these concepts of overlapping hubs and authorities. Of relevance in this work is the identification of top-ranking authority nodes, which provide insight as to the more important or involved committees within political parties.

Arguably one of the most popular and widely applied centrality measures today is PageRank, which was originally introduced in the paper "The Anatomy of a Large-Scale Hypertextual Web Search Engine" (Brin and Page 1998) and became central to Google's web ranking methodology. This system of ranking web pages overcame many shortcomings of earlier centrality measures like Katz and eigenvector centrality that had limitations in webpage ranking applications. PageRank was able to overcome the inherent bias of single web pages with thousands of links out (e.g., Amazon) that justifiably score high centrality, but in turn pass on high centrality scores to connected nodes due to link association. PageRank's methodology dealt with in-link scoring bias by normalizing the number of links on a given page and not counting all links out equally. As defined in the original paper:

> We assume page A has pages T1...Tn which point to it (i.e., are citations). The parameter d is a damping factor which can be set between 0 and 1. C(A) is defined as the number of links going out of page A. The PageRank of a page A is given as follows:
> PR(A) = (1-d) + d (PR(T1)/C(T1) + ... + PR(Tn)/C(Tn))
> Note that the PageRanks form a probability distribution over web pages, so the sum of all web pages' PageRanks will be one. (Brin and Page 1998)

The critical element of this algorithm that found highly effective utility in the web search network where approaches like HITS failed, was the incorporation of dividing by the page out-degree, which mitigates the effect of large hubs with disproportionally high out-degree links.

Still, the PageRank method has some similarities with Kleinberg's HITS algorithm, where a page can receive higher scores by having many pages link to it, or if a small number of pages with high PageRank (similar to authorities) point to it, but with the upgrade of an added mitigation factor. Newman provides a comparison grid of PageRank with other centrality measures and how out-degree division and constants influence each ranking:

	With constant term	Without constant term
Divide by out-degree	$x = (I-\alpha AD^{-1})^{-1}1$ PageRank	$x = AD^{-1}x$ Degree Centrality
No division	$x = (I-\alpha A^{-1})\,1$ Katz Centrality	$x = K^{-1}Ax$ Eigenvector Centrality

Table 2. Comparison of centrality measures. (Newman 2018, 167)

Building off these approaches to modularity presented above by Newman et al. and hyperlink importance attribution from PageRank, a novel approach to identifying communities in directed networks is presented by Youngdo Kim, Seung-Woo Son, and Hawoong Jeong in "LinkRank: Finding Communities in Directed Networks" (Kim et al. 2010). The objective of this algorithm is to generalize modularity in directed networks to exploit certain "trap regions" (figure 4) where a random walker can enter a directed path and is more likely to stay due to limited out-edges. Consistent with some earlier directed graph methods listed above, this approach proposes that links with opposite directions should be considered differently in community node assignment. There have been many successful applications of LinkRank in citation/reference networks, where the algorithm's focus on pattern-based clusters (edge relationships over nodes) produces a distinct set of clusters that won't necessarily be defined through more traditional undirected node to node linkages.

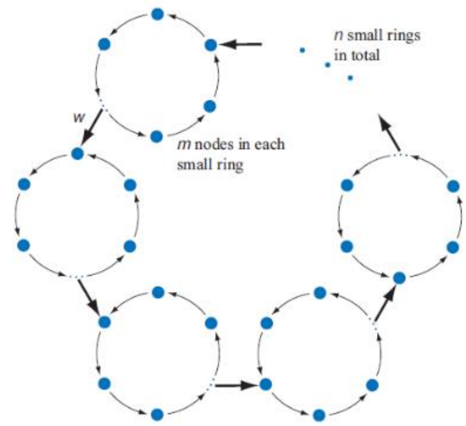


Figure 4. Example model network to demonstrate LinkRank method (Kim et al. 2010)

Methods

Data Collection and Processing

The data used in this research for network analysis was sourced directly from the Federal Elections Commission (FEC), an independent government agency created by Congress in 1974. The FEC's website, FEC.gov, provides bulk data downloads as well as developer access to all campaign contribution and spending data through a RESTful API that is accessible programmatically after signing up for a developer key. The bulk datasets used for this analysis include candidate, committee, receipts, and disbursements. In order to capture the full network dynamics of financial contributions and expenditures, data had to be merged across each of these sources. Python programming language was used for data extraction and cleaning processes, including the Python libraries Numpy and Pandas for formatting, merging, and grouping of relevant fields for storage and aggregating financial transactions by the contributing/receiving entities.

Since all committee-contribution data flows into the network as receipts, this data file was largest in size, which for the two-year election cycle ending in 2020 was 18.5GB comprising 96,400,963 transaction records. This data covers eighteen ‘transaction types’ across subcategory breakouts of contributions, earmarks, and refunds subtypes (e.g., individual, Native American tribe, convention receipts). Per FEC reporting, this data includes qualifying contributions such as “election cycle-to-date amount is over $200 for contributions to candidate committees, or the contribution’s calendar year-to-date amount is over $200 for contributions to political action committees (PACs) and party committees” (Federal Elections Commission, n.d.f). In order to format the data into the required network node, edge relationships required for analysis and contribution/earmark records were grouped by individual PII based on defining feature values, resulting in a compressed/grouped dataset of 34,188,013 records. A driver of this compression is largely due to source data records being provided with transfer timestamps, resulting in multiple contributions by single individuals/organizations to the same committee over time. Since time-relationship dynamics were not a focus of this network analysis, the timestamps were not relevant and therefore repeated donor-to-receiver transactions were aggregated to a cumulative sum about for the full election cycle. This produced a single record for each individual or committee to committee donation/disbursement exchange.

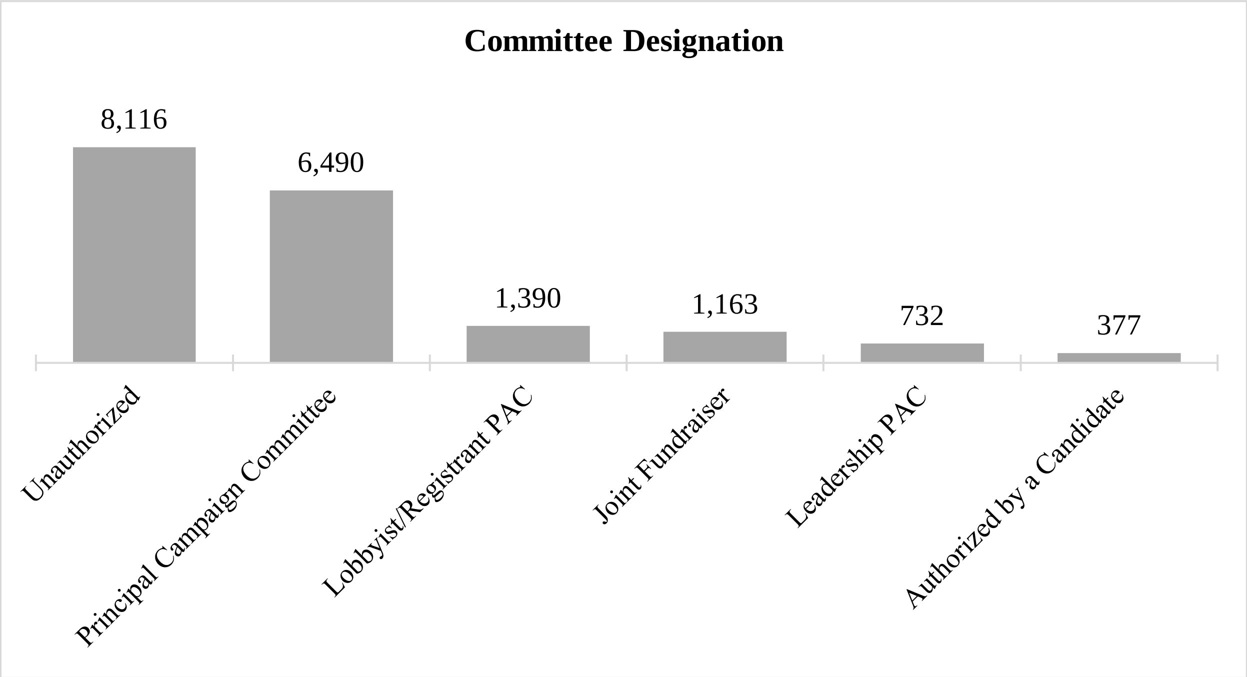


Figure 5. Distribution counts of active committees (2020 election cycle) by broad category type

In addition to the transaction receipts dataset detailing individual contributions, a disbursement data set comprising itemized committee-to-committee financial exchanges for the 24-month 2019-2020 election cycle are included to capture the network flow of funds between/across committees. This raw dataset included 7,454,172 records, which was grouped into 253,254 unique committee: committee financial exchanges. In order to consistently categorize these and the individual receipt data files, committee names were joined using the committee_id key from the committee master dataset, which included 18,273 unique committee names by designation (Figure 5) that were registered for the 2019-2020 election cycle (although not all had an affiliated transaction).

Committee Type	DEM	REP	IND	LIB	Other	Total	%
House	2,180	2,086	184	89	477	**5,016**	*27%*
Independent Expenditor (person or group)					652	**652**	*4%*
PAC - Nonqualified	51	26	2	6	3,390	**3,475**	*19%*
Independent Expenditor-only (Super PACs)	6	1	1		2,268	**2,276**	*12%*
Presidential	300	161	202	55	372	**1,090**	*6%*
PAC - Qualified	35	40			3,184	**3,259**	*18%*
Senate	326	397	74	30	213	**1,040**	*6%*
Single-candidate Independent Expenditure	2	6			137	**145**	*1%*
PAC: non-contribution account/ nonqualified	3	1			441	**445**	*2%*
PAC: non-contribution account/ qualified	1				75	**76**	*0%*
Party - Nonqualified	131	86	3	18	117	**355**	*2%*
Party - Qualified	109	121	1	4	16	**251**	*1%*
Communication/Electioneering/Delegate					188	**188**	*2%*
Grand Total	**3,144**	**2,925**	**467**	**202**	11,535	**18,273**	
%	*17%*	*16%*	*3%*	*1%*	*63%*		

Table 3. List of 2020 election cycle committee types (count) broken out by primary party affiliation

Network Analysis Setup

For network analysis, Python package NetworkX (Hagberg, Schult, and Swart 2008) was the primary tool used as well as visualization-package dependencies from matplotlib. From the above-mentioned preprocessed data, individual network nodes are defined as the total number of unique individuals, organizations, and committees who either made contribution(s), received contribution(s), or both made and received contributions. This produced an overall network structure (directed, weighted graph) composed 7,968,732 nodes and 17,579,862 edges. Among these nodes, 7,965,842 are *donors/distributors* (which include individual contributions from private citizens, organizations, or company SSFs as well as official committees making disbursements) and 10,036 *receivers* (which are official committees registered with the FEC that file incoming receipts). The number of nodes functioning as both donors/receivers is 7,146.

This graph was stored as a NetworkX object with weights defined as the financial exchange amounts between nodes. The nodal attributes were stored as a Python dictionary structure assigning each unique name of the committee or anonymized individual to a key value. The values of this Python dictionary were the corresponding committees receiving contributions/expenditures sourced from the key values. Moreover, the defining characteristics of these committees (including designation, type, and party affiliations) were added as additional values of the dictionary.

An important distinction in the development of the financial flow network structure is the categorization of "earmarked" contributions, which are identified in the receipts-source data using transaction type '15E'. These records present a unique case in that the explicit network flow of funds is decided by an originating node (e.g., individual) before passing through an intermediary node (conduit) to reach its intended destination. Since the purpose of the current research is to analyze the explicit network flow of funds, all conduit/intermediary nodes are included in the network path structure despite the *intent* being for the money to reach a separate node.

The alternative argument to this position of explicit network linkages would be based on exchange *intent*, considering the network edge between A, B, and C is not decided explicitly by B (figure 6), whereas other network interactions are each individual nodes' decision as to how/where funds are transferred to another node. This therefore impacts the underlying relationship of the network structure, which is addressed later in the further research opportunities section. This mechanism of creating indirect bonds in graphs is usually referred to as transitive or triadic closure (Newman 2018, 421).

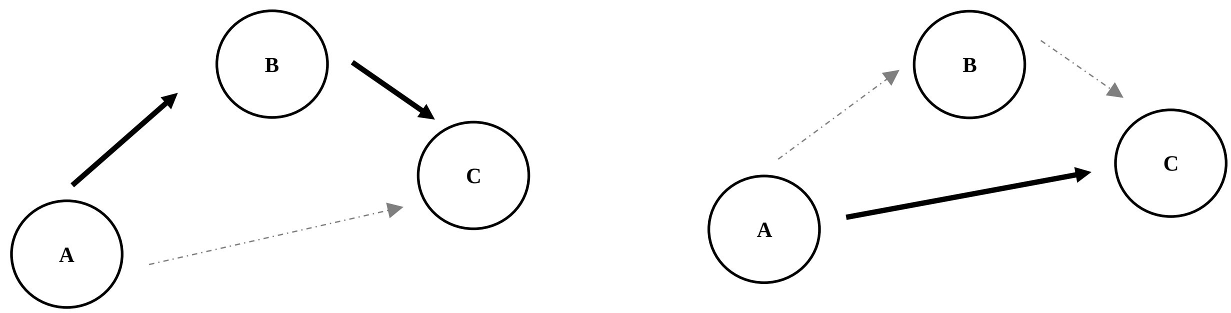


Figure 6. Explicit network flow (left) where every node involved (A, B, C) in a financial exchange gives rise to a transitive indirect bond between A and C, when compared with intent (right) as the conduit node B is the intermediary in the indirect transaction from A to B to C

Graph – Theoretic Methods

Since the primary focus of this research is to extract key features of the 2020 election financial exchange network, graph algorithms are examined across centrality index computations and community detection methods. Within centrality measures, the primary algorithms explored are eigenvector (Newman 2018, 159-169), HITS (Kleinberg 1999), and PageRank (Brin and Page 1998). These approaches are evaluated on the network as a whole, then again separately as a comparison against the subset of individual head-to-head candidates for Senate, House races. Here, the focus is to first identify the most influential nodes of the entire election cycle and then second, to evaluate how these scoring systems perform on alignment with election outcome successes.

Separately, this work focuses on gaining understanding of the inherent community structures among the primary committees themselves (excluding individual/ 'person' nodes). By focusing on modularity maximization, several community detection algorithms are considered including Girvan-Newman (Hagberg, Schult, and Swart 2008; Girvan and Newman 2004), greedy modularity maximization (Hagberg, Schult, and Swart 2008; Newman 2018, 224; Clauset et al. 2004), and asynchronous label propagation (Hagberg, Schult, and Swart 2008; Parés et al. 2017). This network analysis provides insights into the differences between the Democrat and Republican party committee organization/coordination across regions up to the national level and the committees financially independent of other in-party committees.

Results

Overall Graph Statistics

The overall graph diagnostics provide details about the entire network, and later sections focus on subgraphs broken out based on official party affiliation or committee type. The entire FEC donor/receiver or disbursement/receipt network consists of 7,968,732 nodes and 17,579,862 edges. For the purposes of this research, edges between nodes do not differentiate between 'receipt' and 'disbursement', as they both generalize to represent a transfer of funds from one node to another. In many cases, committees transfer funds to themselves in a circular loop, which is disregarded here and focus is placed on exchanges between separate nodes. Both concepts present opportunity for further research beyond this paper's focus.

With this context, the graph is a directed, weighted, simple graph and not strongly connected with 7,962,806 strongly connected components with the largest strongly connected component of the graph has 5,839 nodes and 224,773 edges. The graph is also not weakly connected and has 773 weakly connected components (Newman 2018, 135). The largest weakly connected component has 7,965,405 nodes and 17,577,300 edges. The graph has no isolates and has a density of 0.000000277, transitivity of 0.0883, and reciprocity of 0.0043.

Committee Node	P	In Deg
WinRed	R*	2,321,689
ActBlue	D*	1,871,811
Trump Make America Great Again Committee	R	1,261,132
Donald J. Trump for President, Inc	R	867,231
Republican National Committee	R	734,192
NRSC	R	450,184
NRCC	R	351,644
Perdue for Senate	R	338,696
Georgians for Kelly Loeffler	R	329,933
Team Graham, Inc.	R	317,107

Committee Node	P	Out Deg
NRCC	R	1,020
DCCC	D	850
Scalise for Congress	R	822
National Association of Realtors PAC	U	811
Comcast Corp. & NBCUniversal PAC - Federal	U	692
National Air Traffic Controllers Assoc. PAC	U	668
AT&T Inc/Warner Media Federal PAC	U	651
NRSC	R	633
American Bankers Association Pac	U	610
Planned Parenthood Votes	U	592

Table 4. Top 10 committees overall ordered by number of in-node and out-node degrees. P (party) affiliations are R: Republican, D: Democrat, U: Unaffiliated. *Indicates unofficial affiliation

In terms of individual node measurements, one of most fundamental approaches is the indices of node in/out centrality (Newman 2018, 159), as represented in a directed network as each node's normalized in-degree and out-degree counts. The node with the largest in-degree is WinRed, which has 2,321,689 edges in and NRCC is the network's largest out-degree node with 1,020 edges out. As expected, committee nodes on average have significantly more nodes-in than nodes-out. Among all active transacting committees, the average ratio of in-out degree is 74:1 with differences distinguishable by party (Rep 51:1, Dem: 35:1), and office (President: 52:1, Senate: 42:1, House: 28:1).

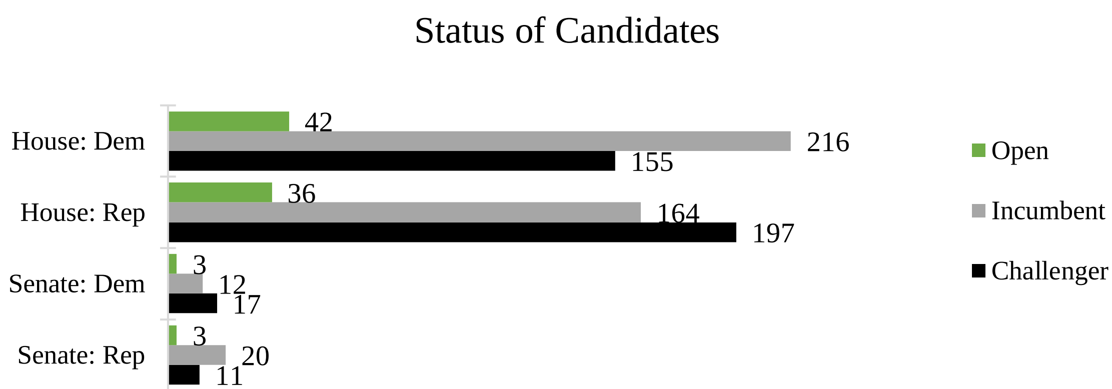


Figure 7. Candidate Status by office, party among open/incumbent/challengers.

Among the House and Senate seats contested, an important consideration in election outcomes is whether or not a seat is currently filled with an incumbent seeking reelection, otherwise the office is considered 'open'. In addition, the position of candidates being either incumbent or challenger can influence respective campaign strategies and financing connections. Relevant for centrality and influence scores evaluated later on in this paper, the breakdown of candidates by status is detailed in Table 5.

	Challenger	Incumbent	Open	Grand Total
House	**352**	**380**	**78**	**810**
DEM	155	216	42	413
REP	197	164	36	397
Senate	**28**	**32**	**6**	**66**
DEM	17	12	3	32
REP	11	20	3	34
Total	**380**	**412**	**84**	**876**

Table 5. Candidates by seat (House/Senate) in positions of challenger /incumbent/ open.

Network Centrality

Applications of centrality within this network focus on the full contribution/disbursement graph, which is considerably larger than the individual party committee subgraphs, since it also includes contributions from private individuals (in-only). The largest number of edges plays a role but is not necessarily the *most important* factor to understand how committees are linked across the network. Here, the connectedness measures place additional focus on how connected neighboring nodes behave, with and without weighting factors. All nodes and corresponding edges are considered in these measures, which include individual,

	Count (nodes)	In Degree	Out Degree
Authorized by a candidate			
House	115	476	2
Senate	33	177	1
Joint fundraiser			
House	129	34	4
PAC - nonqualified	723	2,486	11
PAC - qualified	5	386	41
Senate	81	62	4
Leadership PAC			
PAC - nonqualified	277	100	22
PAC - qualified	355	226	84
Lobbyist/Registrant PAC			
Independent expenditure-only (Super PACs)	23	26	21
PAC - nonqualified	139	18	13
PAC - qualified	1,126	437	96
PAC with non-contribution account - qualified	6	915	102
Principal committee: Candidate			
House	2,434	1,083	6
PAC - qualified	3	29	45
Presidential	112	12,043	8
Senate	409	8,802	12
Unauthorized			
Independent expenditor (person or group)	287	14	3
Independent expenditure-only (Super PACs)	1,057	250	4
PAC - nonqualified	972	129	5
PAC - qualified	1,545	227	24
PAC with non-contribution account - nonqualified	210	21,141	6
PAC with non-contribution account - qualified	57	2,922	45
Party - nonqualified	188	28	2
Party - qualified	232	9,306	39

Table 6. Average node in/out degree by committee designation and type.

organizational donations to PACs, candidate committees, candidates contributing to their own committees, Party committee transfers, and disbursement exchanges, to name a few relationships.

The network measures of node in/out degree provide overall details of the most active committees as they relate to receiving and distributing funds. Among these, the two nonqualified national PACs with non-contribution account committees, WinRed (2,321,689) and ActBlue (1,871,811), have the most in-degrees, followed by Donald Trump's PAC Make America Great Again (1,261,132) and principal campaign committee, Donald J. Trump for President (867,231). Interestingly, WinRed is not within the top thirty-five rankings ordered by out-degree committees. The out-degree top 100 ranked committee-nodes tells a very interesting story, which is dominated by 72 Lobbyist/ Registrant PACs (e.g., Comcast, AT&T, Amazon, Walmart, Google) and has just 4 Candidate Principal Campaign Committees. The four candidate committees are Scalise for Congress, Kevin McCarthy for Congress, Perdue for Senate, and Texans for Senator John Cornyn. The major party committees (NRCC, DCCC, NRSC, DSCC) are all in the top 20.

Several insights emerge when looking at averages among the committee type and designations, including the large in-degree among Joint-Fundraiser and Unauthorized PACs (non-qualified). Also of note is the large in-degree among Principal Candidate Committees: Presidential committees (12,043), with relatively few out-degrees (8) as well as for Senate candidates having on average 8,802 in-degree and 12 out-degrees. Table 6 summarizes these larger groups of committee types and their corresponding in/out degrees with the number of committee nodes represented.

Focusing on the subset of House and Senate races contested during the 2020 election where both Democratic and Republican candidates ran for office (excludes uncontested), a number of additional insights emerge. Among winning House candidates, Republican winners averaged 6,512 in-degree compared with 3,502 for those who lost their respective district races. Democrats also had notable differences with winning candidates averaging 1,115 in-degree compared to 695 among those who lost races. Elections for Senate seats were consistent among Democratic candidates, with those winning election having an average of 28,153 in-degrees compared to 22,801 among losing candidates. Republican Senate candidates overall had a slightly different outcome, with in-degrees among winning candidates at 62,405 and those losing races having 79,406. However, this later relationship among Republicans is largely driven by the GA, MI, and AZ races where four of the top six (including top two) candidates ranked based on incoming nodes lost their respective elections (Table 7).

Candidate	Primary Committee	Party	Node In	Node Out	Result	State	Position
David Perdue	Perdue for Senate	R	338,696	374	L	GA	Incumbent
Kelly Loeffler	Georgians for Kelly Loeffler	R	329,933	144	L	GA	Incumbent
Martha McSally	McSally for Senate, Inc.	R	226,163	76	L	AZ	Incumbent
John James	John James for Senate, Inc.	R	157,283	15	L	MI	Challenger

Table 7. Notable election losses among Republican Senate candidates with high in degree measures.

Comparing the impact of these network relationships among winners and losers across additional centrality scores allows for a deeper understanding of how these interactions or levels of synchronization across committees can contribute to or align with political victories in Senate and House elections.

Eigenvector Centrality

By focusing on a more traditional measure of node influence that is a level deeper than node degree centrality, the eigenvector centrality scores (Hagberg, Schult, and Swart 2008; Bonacich 1987) for the overall network are not necessarily surprising, with Presidential candidate affiliated committees receiving six of the top ten highest scores (Table 8). The two major fundraising committees WinRed and ActBlue are in the top spots while the Republican National Committee and Senate Leadership Fund also score in the top ten. Further research outside the scope of this work focusing on longitudinal studies can inform us whether the 2020 results are consistent with historical performance among other presidential candidates during the presidential year election cycles.

Node	Eigenvector
WinRed	0.5219
ActBlue	0.3785
Biden for President	0.3414
Donald J. Trump for President, Inc.	0.3072
Mike Bloomberg 2020, Inc.	0.2776
Biden Victory Fund	0.2389
Trump Make America Great Again Committee	0.2344
Republican National Committee	0.2204
Trump Victory	0.1854
Senate Leadership Fund	0.1052

Table 8. Top ten eigenvector centrality scores among all network committees.

Focusing specifically on election success in House and Senate races for the two major parties, winning candidates had higher eigenvector scores relative to their losing opponents in 93% of the House races contested. For Senate seats, the relationship is less pronounced, with just 72% of candidates with higher eigenvector scores winning their races vs. opponents with lower scores on the same measure (figure 8).

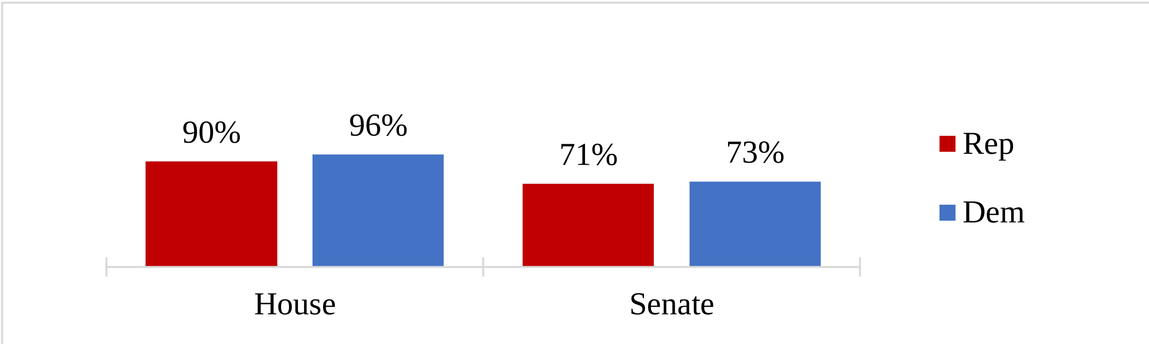


Figure 8. Percent winning with higher eigenvector centrality scores (Bonacich 1987) compared with opponent among Democratic, Republican candidate committees for House and Senate seats.

HITS

The second measure evaluated for node centrality scoring is the HITS hyperlink induced topic search algorithm (Hagberg, Schult, and Swart 2008; Kleinberg 1999). This method has relevant application in this context since it separates the concepts of authorities and hubs, which are conceptually relevant for donor/ distributor hubs and the authorities on the receiving end. Interestingly, the top ten authorities are all Democratic affiliated or associated committees. Four Joe Biden affiliated committees are ranked in the top five as well as the DNCC and four state specific Democratic party committees for Pennsylvania, Georgia, Michigan, and Florida (Table 9). It is

Node	Authority
Mike Bloomberg 2020, Inc	0.99508
Biden Victory Fund	0.00165
Biden Action Fund	0.00071
Biden for President	0.00029
Biden Fight Fund	0.00023
Democratic Executive Committee of Florida	0.00019
Pennsylvania Democratic Committee	0.00017
Georgia Federal Elections Committee	0.00013
2020 Dem. National Convention Committee	0.00013
Michigan Dem. State Central Committee	0.00012

Table 9. Top ten HITS authority scores.

of note that Mike Bloomberg scored high as a Presidential candidate that gave over $1 Billion dollars to his own campaign, dramatically influencing his score (a weakness of this algorithm).

The performance among major party candidates in down ballot races comparing HITS authority scores (Hagberg, Schult, and Swart 2008) is mixed compared to Eigenvector score for the two major parties. Winning candidates had higher HITS authority scores relative to their losing opponents in 73% of the House races contested and 59% among Senate seats. All Senate Democrats with higher scores won their respective races (Figure 9).

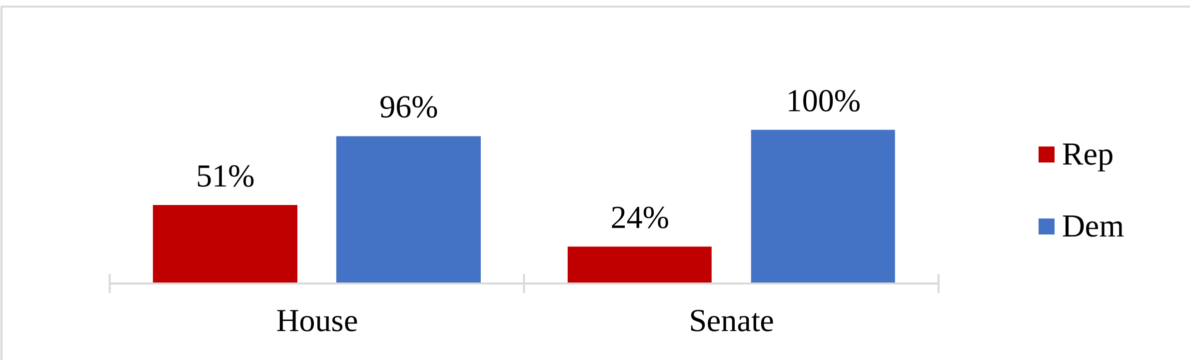


Figure 9. Percent wins with higher HITS authority scores (Kleinberg 1999) compared to opponent among Dem, Rep candidate committees for House, Senate seats.

PageRank

The third and final node centrality measurement considered is PageRank (Hagberg, Schult, and Swart 2008; Brin and Page 1998), which provides additional insights beyond the earlier measures of in/out degree, eigenvector, and even HITS. Compared to the previous centrality measures, the major fundraising committees, WinRed and ActBlue place in the top spots, which also score high on Eigenvector centrality (table 10). The PageRank results also score the primary presidential committees relatively high, similar to Eigenvector scoring, and capture the main party committees, RNC, NRSC, DSCC, and NRCC. In fact, only presidential and national party committees, all of which have wide reach and notably large in-degrees, are scored in the top ten. While the earlier mentioned algorithm scoring presents unique insights based on neighborhood nodes and hub-relationships, the PageRank top results are more in sync with what one might expect among the most popular/commonly known contributions to committees.

Node	Score
WinRed	0.2002
ActBlue	0.1624
Trump Make America Great Again Committee	0.0762
Republican National Committee	0.0466
Donald J. Trump for President, Inc.	0.0422
Biden Victory Fund	0.0141
NRSC	0.0132
DSCC	0.0103
NRCC	0.0096
Biden For President	0.0084

Table 10. Top ten PageRank scores among all committees.

Again, by focusing on candidate-committee performance as related to centrality scoring and the eventual win/loss of a given election, it is evident the PageRank performance in general is a comparable indicator of likelihood to win a House race relative to eigenvector scores. Winning candidates had higher PageRank scores relative to their losing opponents in 85% of the House races contested and 66% among Senate seats (figure 10).

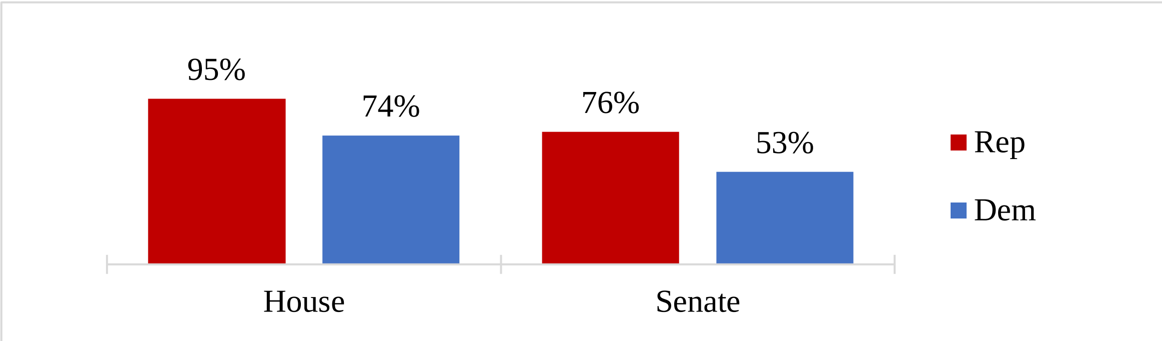


Figure 10. Percent winning with higher PageRank scores (Brin and Page 1998) compared with opponent among Democratic, Republican candidate committees for House and Senate seats.

While these results do not determine any causal influence on overall election outcome, they do suggest a consistent pattern that higher degree of committee connectedness or being in sync with other in-party network committees is a likely indicator in increased chances of election success (Table 11). Perhaps worthy of further investigation is the skew across parties with

Success Indicators: House	Rep	Dem	Total
Eigenvector	90%	96%	93%
PageRank	95%	74%	85%
HITS – Authorities	51%	96%	73%

Table 11. Head-to-head comparison of centrality scores, percent of House candidates winning when having higher score than opponent.

PageRank strongly aligned with Republican House victories and the HITS authority scoring aligned with 96% and 100% of Democrat House and Senate victories, respectively. Because house races are contested every two years with 435 open seats vs the rotating 100 Senate seats among six-year terms, committee connectedness and centrality can vary relative to office and candidate tenure. As many house candidates are often newly running, they may not have the established resources and connections to support a winning campaign vs. a seasoned, networked opponent. Here, increased centrality and being in sync with the broader party can open up resources and financial support to potentially sway close elections.

Attribute Assortativity

The network nodes each have four key committee attributes associated: party affiliation, type, interest group, and designation. In addition, committees with an associated candidate have attributes for the state the elected office represents, district, and election result (win/loss). The four key committee attributes enable the study of assortativity, to understand the nodes' tendency to be connected with other similar nodes (Newman 2018, 203) within the overall network and subgraphs. The assortativity coefficient (A.C.) ranges from -1 to 1 where 1 represents a perfectly assortative mixing pattern (homophily) and -1 is a completely dissasorted network (heterophily). When applied to the network as a whole, the assortativity coefficients for these attributes are low < +/- 0.1, however looking at the subgraphs broken out based on party affiliation provide some differentiation among these attributes.

	Republican	Democrats	All Other
Type	0.20	0.23	0.14
Designation	0.10	0.18	-0.23
Interest Group	-0.00	-0.00	-0.31
Office	0.18	0.31	0.00

Table 12. Four committee attributes assortativity coefficients in network subgraphs: Republican, Democrat affiliated and all other.

In the Republican and Democrat subgraphs, assortativity coefficient for committee type (e.g., House, Senate, Presidential, PAC, Party, etc.) is 0.20 and 0.23, respectively (Table 12). The committee designation A.C. (e.g., leadership PAC, principal campaign committee, lobbyist

PAC, etc.) is low among Republicans, 0.1, and slightly higher for Democrats at 0.18. Consistent with the communities identified above, there is a stronger assortativity coefficient for candidate office (House, Senate, President) for both parties at 0.31 Democrat and 0.18 Republican, as many House committees tend to have increased associations. Collectively, Democrats scored higher on A.C. relative to Republicans, although not by consistently large margins. Also interesting is the assortativity coefficients among nondemocratic or Republican affiliated committees for 'Interest Group' (e.g., corporation, labor organization, trade association, etc.) which are -0.31, or more dissasortive as well as for designation at -0.23.

Secondarily, at the corresponding mixing matrices to identify joint probabilities of occurrence among attribute pairs within these subgraphs, a number of notable occurences arise. Republicans and Democrats both have highest percentages of connections within House to House committee types with 53% and 48% of occurences, respectively. Separately, principal campaign committees (committee designation attribute) are more likely to be connected to other principal campaign committees (59% Rep 57% Dem). Among the committees that are neither officially affiliated with Democrats or Republicans, qualified PACs (committee type) are more likely to be connected to other qualified PACS (59%) and among committee designations, Leadership PACs and Lobbyist/Registrant PACs have above average connection probability at 25%. Lower, yet still positive probabilities also exist among Republican committees: Unauthorized committees linked to Principal Campaign Committees (20%), Party committees linked to House Committees (9%) and PACs-qualified linked to House (7%). Additional notable joint Democrat probabilities pairs also include Unauthorized committees with Principal Campaign Committees (18%), Party committees with House (10%), and Party to Party (6%).

Community Detection

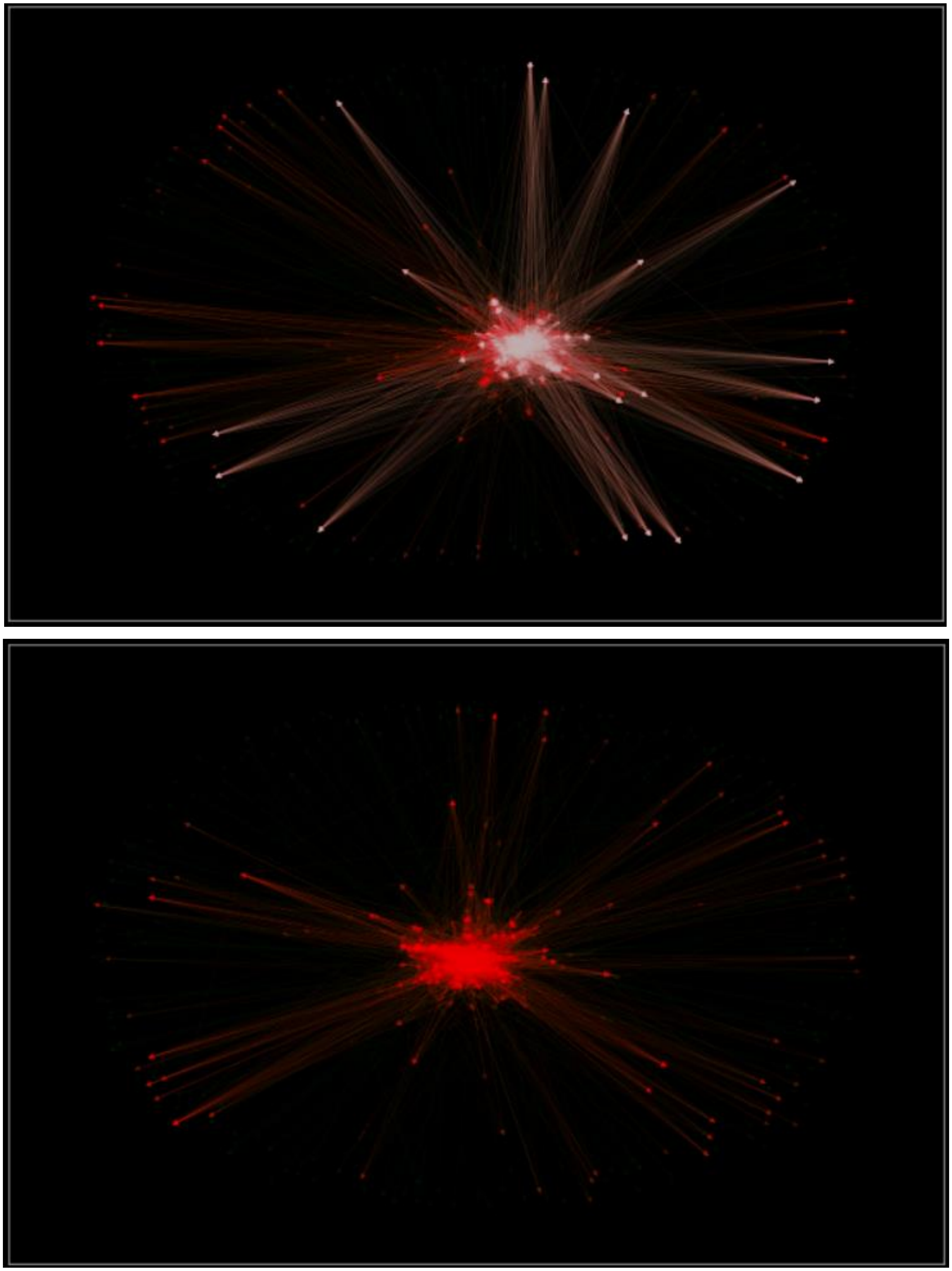
A small number of the two dominant party-affiliated committees engage in exchanges across party lines (7%) so in order to find the most relevant communities within the network, focus is placed on the separate official party-affiliated committee subgraphs. Here, relationships emerge within the two parties that indicate how coordinated or fragmented they are by region, seat, type, etc. Table 13 provides a condensed comparison across four subgraphs after removing individual contributors (private citizens) of how committees interact with each other based on density (ratio of actual vs potential connections), transitivity (ratio of closed triplets), and reciprocity (likelihood to be mutually linked). Standout measures here include strong reciprocity in general, especially within the non-Dem/Rep affiliated committee subgraph.

	Nodes	**Edges**	**Density**	**Transitivity**	**Reciprocity**
Full Graph	7,968,732	17,579,862	0.00000028	0.0883	0.0043
No Individuals	20,695	250,311	0.0006	0.0417	0.3010
Republicans	1,754	6,746	0.0022	0.0490	0.2416
Democrats	1,625	9,061	0.0034	0.0520	0.2715
All Other Affl. (no Rep/Dem)	17,316	61,919	0.0002	0.0184	0.7659

Table 13. Summary comparison of the entire network and 4 subgraph breakouts after removing individual private citizen donors. *No Individuals* represents all nodes excluding private citizen donors, Republicans is the subgraph among *No Individuals* for committees with official Republican affiliation. Democrats is the subgraph among *No Individuals* for committees with official Democrat affiliation. All other is the sugraph among *No Individuals* for committees with neither Rep/Dem affiliation.

Among Republican affiliated committees, the resulting subgraph is a directed, simple, weighted graph with 1,754 nodes and 6,746 edges. The graph is not strongly connected and has 1,178 strongly connected components, with the largest strongly connected component having 547 nodes and 5,292 edges. The graph is also not weakly connected and has 792 weakly connected components. Among these, the largest weakly connected component has 939 nodes and 6,717 edges. The density of the Republican subgraph is 0.0022, the transitivity is 0.0490 and the reciprocity is 0.2416. By comparison, the Democrat committee subgraph is also a directed, simple, weighted graph and has 1,625 nodes with 9,061 edges. The graph is not strongly connected and has 1,001 strongly connected components, with the largest strongly connected component having 621 nodes and 7,505 edges. The graph is also not weakly connected and has 618 weakly connected components. Among these, the largest weakly connected component has 996 nodes and 9,049 edges. The density of the Democrat subgraph is 0.0034, the transitivity is 0.0520, and the reciprocity is 0.2715. The number of isolates for these subgraphs are 768 (Republican) and 606 (Democrat).

One of the core functions used to evaluate network communities as they are distinguishable from a random placement of edges is modularity, which is as described: ("if the number of within-community edges is no better than random, we will get Q=0. Values approaching Q=1, which is the maximum, indicate networks with strong community structure. In practice, values for such networks typically fall in the range from about 0.3 to 0.7. Higher values are rare," (Newman 2004). With this context in mind, the algorithm approaches for greedy modularity maximization, asynchronous label propagation, and Girvan-Newman method are performed on party subgraphs to evaluate the strength of connected communities within the official party-affiliated Republican and Democrat committees.



Figures 11-12: Colored visualizations of subgraph comparisons using K-cores degree threshold (all degrees: green; 3+: red; 25+ silver for Democrat (top) and Republican (bottom)

Greedy Modularity Maximization

For understanding underlying communities within the respective party committees, the greedy modularity maximization algorithm returned the highest modularity scores: Republicans 0.27, Democrats: 0.52 among the respective directed, weighted subgraphs. A defining characteristic of both parties is the large number of single node communities: Dem: 607, 37% of nodes, Rep: 770, 44% of nodes. The independent assignment of these nodes appears intuitive since these groups were dominated by committees with very few or no out-degrees for both parties. The bulk of these committees were also principal campaign committees (93% Rep, 94% Dem), particularly among House candidates. Senate committees made up roughly ~10% of these Republican and Democrat communities.

The three largest communities (Figure 13) dominate in size with the top three combined representing 49% across both parties and when added to the single-node communities, reaches 89%+ of all committee assignments for both party subgraphs. Both parties have a single largest community dominating assignment, accounting for 36% of all Democratic committees and 29% of Republican.

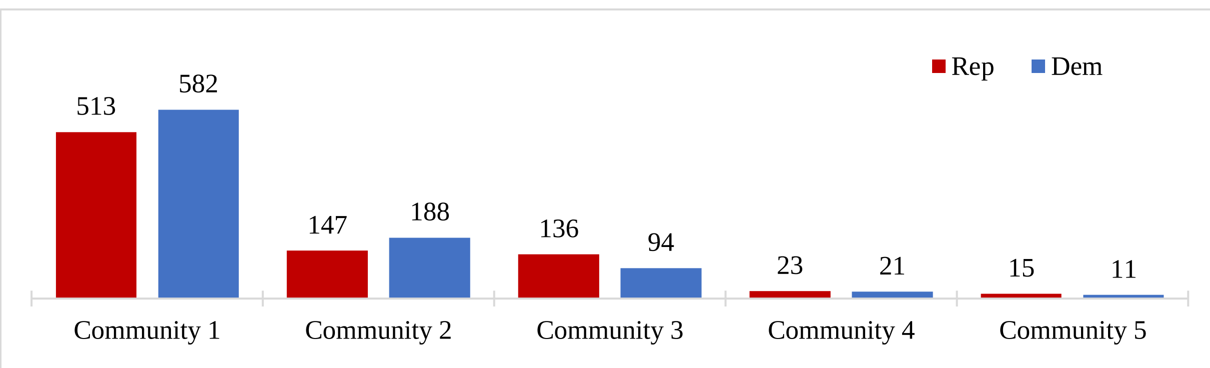
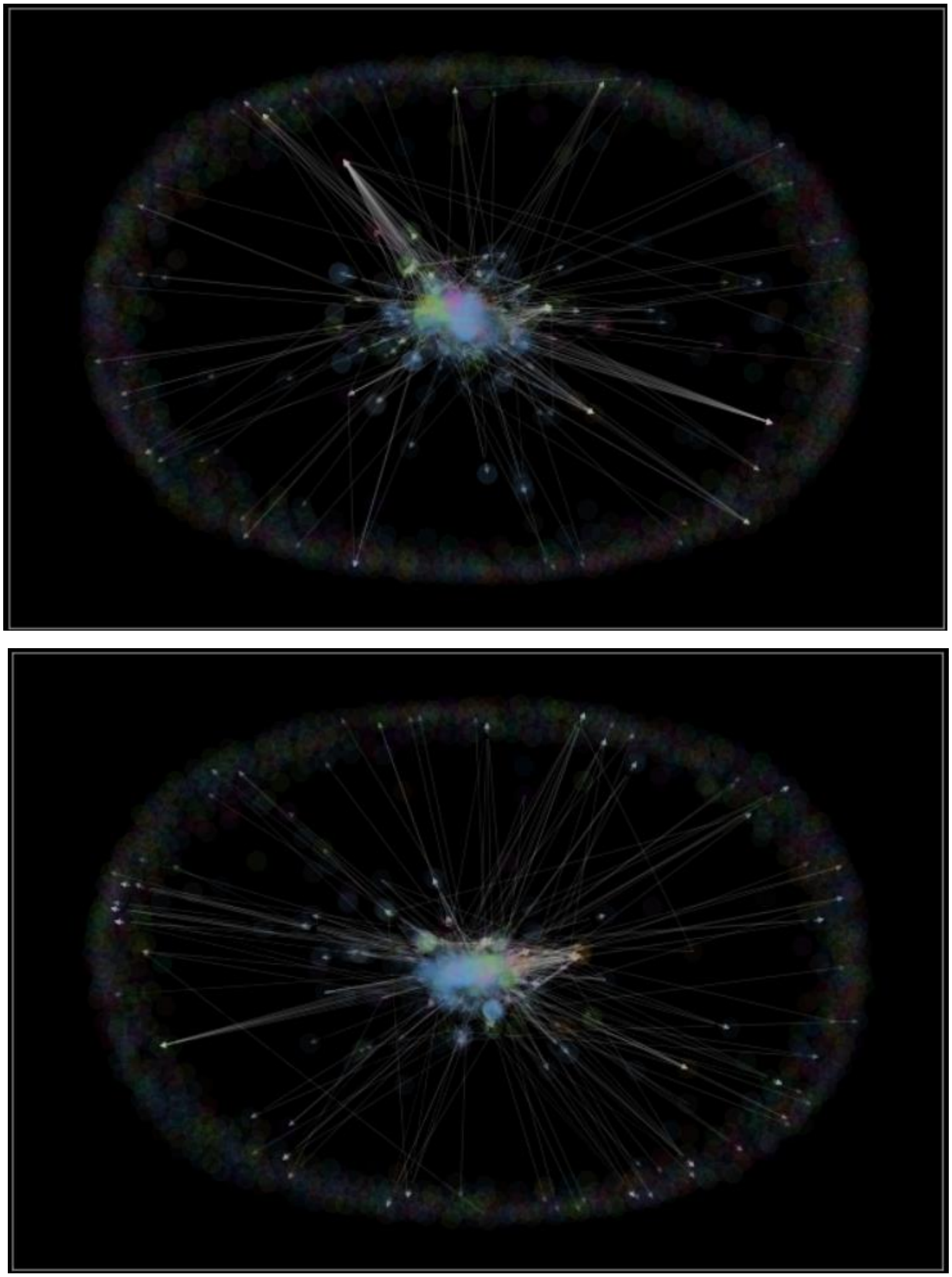


Figure 13. Republican, Democrat subgraph community assignments (counts) for greedy modularity maximization algorithm: top 5 communities by committee size

The largest community for Republicans has on average 4,416 in-nodes and 18 out-nodes comprised of 79% house committees, 12% party committees, 5% PACs, and 3% Senate committees. Comparably, the largest Democrat community has fewer average in-nodes at 938 with 16 average out-nodes. The composition is also dominated by house committees at 76% with 13% party committees, 6% PACs, and 4% Senate committees. Among the next largest communities, Republican community 2 has less House dominance at 45% and higher Senate committee representation at 38% (PACs comprise just 6% and party committees 9%). The third largest Republican community has increased Party committee representation at 39%, with House and Senate committees representing ~36% and ~20%, respectively. The other subgraph among Democratic committees produced a second largest greedy modularity maximization community with 28% party committee representation and 48%, 18% for House and Senate, respectively (PACs represented just 3%). The third largest Democratic community had increased Senate presence at 37% with 16% party and 12% PAC (House represented 32%). Also of note is the presidential committee presence in this case was 4%, which the Democratic primaries with multiple candidates played a contributing factor.

The largest communities for both subgraphs using the greedy modularity maximization algorithm exhibit distinguishing characteristics both within party and across party lines. While House committees dominate the overall largest community, there are associations between senate committees with Party and PACs, separately. Republican community #3 has a dominant House

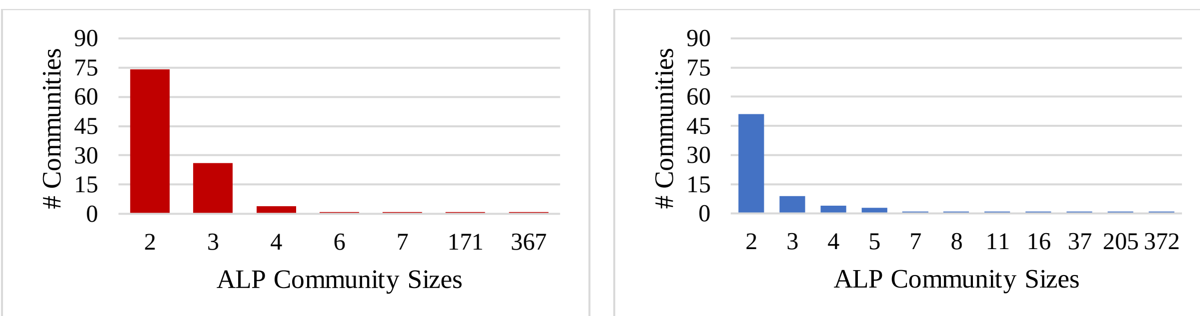
Senate-Party representation while Democrat community #3 has more even distribution among House-Senate-Party-PAC committees.



Figures 14-15. Colored visualizations of the Republican (top) and Democrat (bottom) committee communities using greedy modularity maximization.

Asynchronous Label Propagation

Application of the asynchronous label propagation (ALP) algorithm (Hagberg, Schult, and Swart 2008; Raghavan et al. 2007) to the same party subgraphs produced slightly varied results from the greedy modularity maximization detailed above. Modularity scores for ALP were lower at 0.15 for Republican and 0.47 for Democrat weighted, directed subgraphs. Fragmentation of single-node communities was a consistent outcome here as well, with 961 Republican committee nodes falling into these types of communities (Figure 16) and 810 Democratic single-node communities (figure 17). Otherwise, a smaller share of two, three committee communities were detected with largest community for Republicans having 367 nodes and for Democrats, 372 nodes. Next largest number of communities for Republicans and Democrats, respectively, were 171 and 205.



Figures 16-17. Asynchronous Label Propagation (ALP) number of distinct communities identified by community size (excludes communities of size 1) Rep left, Dem right.

As seen above, Republican communities' splinter into a number of smaller communities including 74 of size 2-nodes and 26 3-nodes. Democratic communities' group into additional collection sizes comprised of 37, 16, and 11 committees before fragmenting into smaller single-digit communities, including nine 3-nodes and fifty-one 2-nodes. Overall, the communities of the Democratic affiliated committees form more varied distribution compared to Republicans across the mid-sized communities such as those with 8, 11, 16, and 37 committees.

Girven-Newman Method

Applying the Girvan-Newman algorithm (Hagberg, Schult, and Swart 2008; Girvan and Newman 2004), which relies on iterative elimation of edges to optimize within-community edge betweeness, the two major parties exhibit similar performance with low modularity scoring through 50 iterations. Both iterations on these subgraphs selecting edges based on weights and weights using hightest betweenneess centrality were applied but returned comparably low modularity results.

Future Research

Several topics have been suggested throughout this research for future areas of study as this work will hopefully serve as a starting point for complementary and expanded analysis. Since this work focused on a single election cycle of 2020, an additional area of exploration is a longitudinal survey over multiple presidential election and off-year cycles. Separately, an examination of the co-donation and co-receiving committees as it pertains to the 2020 election cycle would provide valuable additional insights regarding committee relationships and the various underlying patterns of financial exchanges. It was also mentioned that this analysis focuses on explicit network flow of funds, regardless of ‘intent’. An alternate graph composition would take into account this intent or flow of disbursed funds through conduit committees and what effect that has on centrality scoring or community detection.

In addition, this research focused solely on individual contributions and committee disbursements as provided through the FEC.gov bulk data access endpoints. There is a much larger volume of data available through the FEC API that includes donations lower than the $200 thresholds included here. With this more comprehensive data source, there is also the potential to expand network attributes to account for refund types and other types of financial exchanges as defined by transaction type variable in the source data. Further exploration of assortativity measures across disbursement types, committee characteristics, and candidate profiles is also another interesting area of exploration, including cross-party interactions.

Conclusion

The findings presented here provide insights into an area of research that has not yet been widely explored. While summary tables can be retrieved online directly though the FEC.gov websites, a public comprehensive network analysis has not been undertaken to date. This work serves three purposes: 1. present an overall summary of the FEC campaign contribution donation/disbursement network as a graph data science problem with relevant high-level network statistics for the 2020 election year, 2. identify the nodes or committees that are highly connected through in/out degree and other centrality measures across overall network exchanges and the underlying attribute characteristics of these identified committees, 3. explore communities among the subgraph of primary political party affiliated committees, identifying underlying characteristics unique to each party subgraph.

Through the application and comparison of community detection algorithms and centrality scoring measures, the complex network of the 2020 election year political campaign financing network has been summarized to deliver a more concise and accessible set of insights to the general population. Barriers to this type of analysis have included massive data files organized by transaction type/date over time and the computational processing requirements for data at this scale. The traditional relational database approach is adapted here to form a network structure capable of graph data science. Thus, the approach presented here has identified the dominant committees, explored nuances of communities within dominant parties, and provided a summary of the various relationships within this overall network. With the insights here, individuals can have a deeper and more comprehensive understanding of the internal dynamics of how political committees operate and exchange funds across the various committees within-party and those unaffiliated (e.g., super PACs).

References

Aric A. Hagberg, Daniel A. Schult and Pieter J. Swart. Aug 2008. "Exploring network structure, dynamics, and function using NetworkX." In *Proceedings of the 7th Python in Science Conference* (SciPy2008), edited by Gäel Varoquaux, Travis Vaught, and Jarrod Millman, 11–15. Pasadena, CA, USA.

Blondel, Vincent D. et al. 2008. "Fast unfolding of communities in large networks." In *Journal of Statistical Mechanics: Theory and Experiment*.

Bonacich, Phillip. 1987. "Power and Centrality: A Family of Measures." In *American Journal of Sociology* 92, no. 5:1170–82.

Brin, Sergey and Page, Lawrence. 1998. "The anatomy of a large-scale hypertextual Web search engine." In *Computer Networks and ISDN Systems* 30, no. 1-7:107-117.

Clauset, Aaron, Mark E. J. Newman and Cristopher Moore. 2004. "Finding community structure in very large networks." *Physical review. E, Statistical, nonlinear, and soft matter physics* 70 no. 6 *Pt 2 (2004): 066111.*

Data Science Quarterly. Accessed Jan 31 2022. https://www.data-science-quarterly.io/.

Federal Elections Commission. 2013. "FEC Summarizes Campaign Activity of the 2011-2012 Election Cycle." Press Release, April 19, 2013. https://www.fec.gov/updates/fec-summarizes-campaign-activity-of-the-2011-2012-election-cycle/.

Federal Elections Commission. 2017. "FEC Summarizes Campaign Activity of the 2015-2016 Election Cycle." Press Release, March 23, 2017. https://www.fec.gov/updates/statistical-summary-24-month-campaign-activity-2015-2016-election-cycle/.

Federal Elections Commission. 2021. "FEC Summarizes Campaign Activity of the 2019-2020 Election Cycle." Press Release, April 2, 2021. https://www.fec.gov/updates/statistical-summary-24-month-campaign-activity-2019-2020-election-cycle.

Federal Elections Commission. n.d.a. "Mission and history." Accessed Jan 5, 2022. https://www.fec.gov/about/mission-and-history/.

Federal Elections Commission. n.d.b. "FEC 40th Anniversary Timeline," Accessed Jan 5, 2022. https://transition.fec.gov/pages/40th_anniversary/40th_anniversary.shtml.

Federal Elections Commission. n.d.c. “EMILY’s List v. FEC,” Accessed Jan 5, 2022. https://www.fec.gov/legal-resources/court-cases/emilys-list-v-fec/.

Federal Elections Commission. n.d.d. “Carey v. FEC,” Accessed Jan 5, 2022. https://www.fec.gov/legal-resources/court-cases/carey-v-fec/.

Federal Elections Commission. n.d.e. “OpenFEC.” Accessed Jan 5, 2022. https://api.open.fec.gov/developers/.

Federal Elections Commission. n.d.f. “Federal Elections Commission Bulk Data.” https://www.fec.gov/data/browse-data/?tab=bulk-data.

Fortunato, Santo. 2010. “Community detection in graphs.” In *Physics Reports* 3-5, no. 486: 75-174.

Kim, Youngdo et al. 2010. “LinkRank: Finding communities in directed networks.” In *Physical review. E, Statistical, nonlinear, and soft matter physics* 81, no. 1: Pt 2.

Kleinberg, Jon M. 1999. “Authoritative sources in a hyperlinked environment.” In *Journal of the ACM* 46, no. 5.: 604–632.

Leicht E, Newman M. 2008. “Community structure in directed networks.” *Physical Review Letters* 100, no. 11 (2008 Mar 21): 118703. doi: 10.1103/PhysRevLett.100.118703.

Malliaros, Fragkiskos & Vazirgiannis, Michalis. 2013. “Clustering and Community Detection in Directed Networks: A Survey.” *Physics Reports* 533, no. 4 (2013): 95-142.

Newman, Mark 2018. *Networks*. Second edition. Oxford: Oxford University Press.

Newman, Mark 2004. “Fast algorithm for detecting community structure in networks.” In *Physical review. E, Statistical, nonlinear, and soft matter physics* 69, no. 6: Pt 2.

Newman, Mark and Michelle Girvan. 2004. “Finding and evaluating community structure in networks.” In *Physical review. E, Statistical, nonlinear, and soft matter physics* 69, no. 2: Pt 2.

Parés F., Garcia-Gasulla D. et al. 2017. “Fluid Communities: A Competitive and Highly Scalable Community Detection Algorithm.” In *6th International Conference on Complex Networks and Their Applications*.

Raghavan, Usha Nandini, Réka Albert, and Soundar Kumara. 2007. "Near linear time algorithm to detect community structures in large-scale networks." In *Physical review. E, Statistical, nonlinear, and soft matter physics* 76, no. 3.

Appendix I: Top 100 Committees Rank-ordered by in-degree

Committee / Node	P	Committee Type	Eigen-vector	Author -ities	Page Rank	In Deg	Out Deg
WinRed		PAC with non-contribution account - nonqualified	0.522	1.1E-10	0.2002	2,321,689	430
ActBlue		PAC with non-contribution account - nonqualified	0.378	1.4E-08	0.1624	1,871,811	217
Trump Make America Great Again Committee		PAC - nonqualified	0.234	5.4E-09	0.0762	1,261,132	35
Donald J. Trump For President, Inc.	R	Presidential	0.307	1.3E-06	0.0422	867,231	262
Republican National Committee	R	Party - qualified	0.220	2.2E-08	0.0466	734,192	162
NRSC	R	Party - qualified	0.093	6.5E-10	0.0132	450,184	633
NRCC	R	Party - qualified	0.061	3.5E-10	0.0096	351,644	1,020
Perdue For Senate	R	Senate	0.064	2.1E-08	0.0062	338,696	374
Georgians For Kelly Loeffler	R	Senate	0.048	1.0E-08	0.0062	329,933	144
Team Graham, Inc.	R	Senate	0.029	4.9E-09	0.0076	317,107	72
Biden Victory Fund		PAC - nonqualified	0.239	1.7E-03	0.0141	245,733	212
Mcconnell Senate Committee	R	Senate	0.025	6.5E-10	0.0034	237,086	166
Mcsally For Senate Inc	R	Senate	0.031	1.4E-08	0.0049	226,163	76
DSCC	D	Party - qualified	0.053	2.2E-05	0.0103	185,824	522
Biden For President	D	Presidential	0.341	2.9E-04	0.0084	161,657	267
Dnc Services Corp / Democratic National Committee	D	Party - qualified	0.103	1.3E-05	0.0082	159,501	169
John James For Senate, Inc.	R	Senate	0.022	3.3E-09	0.0025	157,283	15
DCCC	D	Party - qualified	0.052	7.7E-05	0.0075	129,174	850
Jon Ossoff For Senate	D	Senate	0.061	3.8E-08	0.0035	121,782	40
Joni For Iowa	R	Senate	0.032	2.4E-08	0.0011	119,947	155
Steve Daines For Montana	R	Senate	0.022	1.5E-08	0.0015	118,829	81

Team Scalise		PAC - nonqualified	0.009	3.4E-11	0.0013	117,871	2
Jaime Harrison For Us Senate	D	Senate	0.027	6.7E-07	0.0023	92,069	26
Tim Scott For Senate	R	Senate	0.003	2.8E-12	0.0005	88,065	3
Mark Kelly For Senate	D	Senate	0.027	2.5E-07	0.0025	85,105	35
Kevin Mccarthy For Congress	R	House	0.007	1.7E-11	0.0009	84,730	438
Scalise For Congress	R	House	0.013	3.7E-11	0.0012	84,596	822
Warnock For Georgia	D	Senate	0.043	3.5E-08	0.0022	84,410	36
Cory Gardner For Senate	R	Senate	0.012	1.2E-09	0.0009	80,906	279
Collins For Senator	R	Senate	0.024	4.6E-08	0.0011	80,751	218
Amy Mcgrath For Senate, Inc.	D	Senate	0.015	1.0E-09	0.0030	79,332	20
Thom Tillis Committee	R	Senate	0.033	3.3E-08	0.0008	76,035	92
Lacy Johnson For Congress	R	House	0.002	6.4E-13	0.0006	72,637	12
Warren For President, Inc.	D	Presidential	0.019	4.9E-09	0.0024	72,114	36
Bernie 2020	D	Presidential	0.024	7.7E-09	0.0023	71,048	12
Elise For Congress	R	House	0.003	2.8E-11	0.0006	70,394	49
Jim Jordan For Congress	R	House	0.003	1.0E-11	0.0006	70,335	73
The Lincoln Project		Independent expenditure-only (Super PACs)	0.014	1.5E-09	0.0041	65,324	30
Devin Nunes Campaign Committee	R	House	0.005	6.3E-12	0.0015	65,148	92
Sara Gideon For Maine	D	Senate	0.027	4.1E-07	0.0017	63,960	44
Texans For Senator John Cornyn Inc.	R	Senate	0.015	1.0E-07	0.0012	63,565	352
Kim Klacik For Congress	R	House	0.002	5.8E-12	0.0005	61,359	1
National Victory Action Fund		PAC with non-contribution account - nonqualified	0.005	3.5E-10	0.0005	59,829	9
Stop Republicans		PAC with non-contribution account - nonqualified	0.013	1.5E-08	0.0011	58,381	2

Progressive Turnout Project		PAC with non-contribution account - qaualified	0.012	2.4E-07	0.0015	49,063	118
Win The Era Pac	D	PAC - nonqualified	0.017	5.3E-09	0.0017	46,404	44
Amy For America	D	Presidential	0.008	1.8E-09	0.0021	46,199	31
Fair Fight		PAC with non-contribution account - nonqualified	0.019	4.1E-08	0.0024	45,601	29
SMP		Independent expenditure-only (Super PACs)	0.085	4.3E-08	0.0024	45,177	71
Cotton For Senate, Inc.	R	Senate	0.002	4.2E-12	0.0004	44,419	31
Emily's List		PAC - qualified	0.011	2.4E-08	0.0033	42,687	113
Cal For NC	D	Senate	0.040	4.5E-08	0.0009	41,499	44
Peters For Michigan	D	Senate	0.021	3.4E-08	0.0013	40,380	45
Joe Collins For Congress	R	House	0.001	2.9E-12	0.0004	38,640	4
Montanans For Bullock	D	Senate	0.022	1.2E-08	0.0008	38,637	27
Moveon.Org Political Action		PAC with non-contribution account - qualified	0.003	8.4E-10	0.0023	38,186	97
Friends Of Andrew Yang	D	Presidential	0.005	1.8E-09	0.0014	37,570	13
Kamala Harris For The People	D	Presidential	0.007	3.8E-07	0.0014	37,006	38
Jason Lewis For Senate	R	Senate	0.003	5.7E-11	0.0004	35,864	6
Theresa Greenfield For Iowa	D	Senate	0.030	1.6E-08	0.0007	35,394	42
Mike Garcia For Congress	R	House	0.004	7.3E-09	0.0003	35,203	4
Cawthorn For NC	R	House	0.001	3.5E-11	0.0002	35,015	1
Congressional Leadership Fund		Independent expenditure-only (Super PACs)	0.041	7.8E-10	0.0002	34,933	135
Senate Conservatives Fund		PAC - qualified	0.002	1.5E-12	0.0006	33,314	21

Dan Crenshaw For Congress	R	House	0.003	9.9E-11	0.0009	32,556	14
Young Kim For Congress	R	House	0.002	7.2E-10	0.0003	32,554	8
Senate Georgia Battleground Fund		PAC - nonqualified	0.027	2.6E-10	0.0010	32,267	222
Hickenlooper For Colorado	D	Senate	0.014	6.4E-08	0.0007	31,458	35
End Citizens United		PAC - qualified	0.005	7.7E-07	0.0007	30,108	301
John Kennedy For Us	R	Senate	0.001	3.8E-12	0.0002	29,543	2
Burgess 4 Utah	R	House	0.003	2.5E-09	0.0002	29,458	4
Hunt For Congress	R	House	0.003	2.7E-10	0.0003	27,654	7
Zeldin For Congress	R	House	0.003	1.7E-09	0.0002	27,023	29
Americans For Parnell Committee	R	House	0.001	1.8E-11	0.0002	26,709	6
Marco Rubio For Senate	R	Senate	0.001	1.0E-11	0.0003	26,178	21
Nancy Mace For Congress	R	House	0.003	3.6E-09	0.0002	25,488	6
Van Drew For Congress	R	House	0.003	4.0E-10	0.0002	25,449	9
Trump Victory		PAC - nonqualified	0.185	6.1E-09	0.0017	25,313	147
Mast For Congress	R	House	0.001	4.5E-11	0.0002	25,167	30
Jaime For Congress	R	House	0.001	1.2E-09	0.0002	23,849	25
House Freedom Fund		PAC - qualified	0.002	4.8E-13	0.0006	23,833	87
Ted Cruz For Senate	R	Senate	0.002	7.6E-12	0.0007	23,450	48
National Democratic Training Committee Pac		PAC with non-contribution account - nonqualified	0.003	1.2E-08	0.0003	22,711	13
Tuberville For Senate, Inc.	R	Senate	0.003	2.0E-09	0.0003	21,560	7
Bollier For Kansas	D	Senate	0.012	1.2E-08	0.0005	21,271	26
Anna Paulina Luna For Congress	R	House	0.001	4.9E-13	0.0002	20,919	2
Alaskans For Dan Sullivan	R	Senate	0.006	2.4E-09	0.0003	20,619	56
Michelle Steel For Congress	R	House	0.004	3.1E-09	0.0002	20,087	5
Cory 2020	D	Presidential	0.005	2.0E-09	0.0010	19,417	47
Doug Jones For Senate Committee	D	Senate	0.006	2.4E-08	0.0004	19,122	32
Ashley Hinson For Congress	R	House	0.002	2.0E-09	0.0002	19,091	5

Ann Wagner For Congress	R	House	0.003	4.5E-09	0.0002	19,026	5
Brian Fitzpatrick For Congress	R	House	0.002	8.7E-11	0.0001	18,963	35
Friends Of Hagedorn	R	House	0.002	2.9E-09	0.0001	18,351	14
Valadao For Congress	R	House	0.003	4.9E-09	0.0002	18,132	17
Lauren Boebert For Congress	R	House	0.001	2.4E-09	0.0001	18,092	1
Tenney For Congress	R	House	0.000	2.6E-12	0.0000	18,055	2
Ditch Fund		PAC with non-contribution account - nonqualified	0.002	1.9E-10	0.0004	17,273	7
Rodimer For Congress	R	House	0.002	2.4E-09	0.0001	17,245	2
Jim 2020 Committee	R	House	0.001	9.3E-12	0.0001	17,018	6

Appendix II: Core Definitions

Sourced from FEC.gov

Candidate
An individual running for a seat in the Senate or the House of Representatives or for President of the United States becomes a candidate when he or she raises or spends more than $5,000 in contributions or expenditures. Federal candidates must designate a principal campaign committee. This campaign committee takes in contributions and makes expenditures for the candidate's campaign. Candidates may designate additional authorized campaign committees to help raise and spend funds, but only a principal campaign committee is required.

Committee
An entity that meets one of the following conditions: 1. An authorized committee of a candidate (see definition of candidate) 2. Any club, association or other group of persons that receives contributions or makes expenditures, either of which aggregate over $1,000 during a calendar year 3. A local unit of a political party (except a state party committee) that: (1) receives contributions aggregating over $5,000 during a calendar year; (2) makes contributions or expenditures either of which aggregate over $1,000 during a calendar year or (3) makes payments aggregating over $5,000 during a calendar year for certain activities that are exempt from the definitions of contribution and expenditure 4. Any separate segregated fund upon its establishment.

Receipts
Receipts are anything of value (money, goods, services or property) received by a political committee. Authorized committees take in all receipts for a candidate's campaign. Receipts include both contributions and other forms of support. Once the treasurer (or authorized agent) receives a receipt, he or she must deposit it within 10 days. Contributions not deposited within 10 days must be returned to their donors.

Disbursements
An expenditure is a purchase, payment, distribution, loan, advance, deposit or gift of money or anything of value to influence a federal election. "**Disbursement**" is a broader term that covers both expenditures and other kinds of payments (those not made to influence a federal election). All disbursements are reportable by the campaign. *Disbursements must be made by check or similar draft drawn on an account maintained at the committee's designated depository*.
Campaign-related expenses: By definition, the Federal Election Campaign Act allows campaign funds to be used for purposes in connection with the campaign to influence the

federal election of the candidate. Disbursements related to the campaign include payments for day-to-day expenses, such as staff salaries, rent, travel, advertising, telephones, office supplies and equipment, fundraising, etc. Day-to-day operations, Transfers between a candidate's committees, Campaign fundraisers, Using the facilities or resources of corporations or labor organizations, Fundraising notices for campaigns, Joint fundraising with other candidates and political committees, Travel, Advertising and disclaimers, Recounts
Noncampaign expenses: Campaign funds may be used for certain purposes that are not related to the candidate's campaign for federal office. Using campaign funds for personal use is prohibited. Noncampaign expenses for travel, transfers and donations, making contributions to other candidates, supporting tax-exempt organizations, fundraising for other candidates, committees and organizations, Personal use

Independent Expenditures
An independent expenditure is an expenditure for a communication, such as a website, newspaper, TV or direct mail advertisement that: 1. Expressly advocates the election or defeat of a clearly identified candidate; and 2. Is not made in consultation or cooperation with, or at the request or suggestion of any candidate, or his or her authorized committees or agents, or a political party committee or its agents Individuals, groups, corporations, labor organizations and political committees (including separate segregated funds (SSFs), party committees and nonconnected committees) may support or oppose candidates by making independent expenditures. Independent expenditures are not contributions and are not subject to limits. *All independent expenditures require a disclaimer. Communications paid for by an individual, a group, a political committee, a corporation, or a labor organization, but not authorized by a candidate or a candidate's campaign, must contain a disclaimer notice identifying who paid for the communication and indicating whether any candidate or candidate's committee authorized the communication.*

Committee Distinctions	
Authorized Committee	Presidential, House and Senate candidates must designate a campaign committee. This "authorized committee" takes in contributions and make expenditures on behalf of the campaign. A political committee that has been authorized by a candidate to accept contributions or make expenditures on his or her behalf, or one that accepts contributions or makes expenditures on behalf of a candidate and has not been disavowed by the candidate.
Political Party Committee	Political party committees represent a political party at a local, state or national level. Examples of political party committees include the Democratic National Committee, the Green Party of the United States, the Libertarian National Committee and the Republican National Committee.

	Political party committees can take in contributions and make expenditures to influence federal elections.
Corporations and Labor Organizations	Corporations and labor organizations can't make contributions to federal candidates, but they can establish and administer a special kind of political committee, called a separate segregated fund (SSF). SSFs can solicit contributions from a limited group of people. They can make contributions to candidates and make expenditures that are coordinated with candidates.
Political action committees (PACs)	Popular term for a political committee that is neither a party committee nor an authorized committee of a candidate. PACs directly or indirectly established, administered or financially supported by a corporation or labor organization are called separate segregated funds (SSFs). PACs without such a corporate or labor sponsor are called nonconnected PACs. Groups that want to set up a PAC and aren't a candidate's authorized committee, a political party committee or an SSF can set up a type of PAC called a nonconnected committee. Nonconnected committees can take in contributions and make expenditures to influence federal elections. There are several types of nonconnected committees, including the following: (1) Hybrid PACs (2) Leadership PACs (3) Super PACs (also called independent expenditure committees) As committees that solicit and accept **unlimited** contributions from individuals, corporations, labor organizations and other political committees, **Super PACs and Hybrid** PACs** do not make contributions to candidates. ***from its non-contribution account*
Nonconnected Committee	*Any committee that conducts activities in connection with an election, but is not a party committee, an authorized committee of any candidate for federal election, or a separate segregated fund.*
Other filers	Every person, group of persons or organization, other than a political committee, that makes certain communications may be required to file certain disclosure forms with the FEC, as well as comply with disclaimer requirements for specific types of communications. Host committees, convention committees and inaugural committees must register and file specific disclosure forms with the FEC regarding their activities.

Sources of Funds	Notes by Contributor Type

Individuals	An individual may make contributions to candidates and their authorized committees, subject to limitations.
Single Member LLC's and Partnerships (not corporations)	Single member LLC contributions will be attributed to the member. Partnerships are permitted to make contributions according to special rules. In addition, a contribution from a partnership also counts proportionately against each participating partner's own limit with respect to the same candidate.
Indian tribes	In past advisory opinions and enforcement cases, the Commission has determined that an unincorporated tribal entity can be considered a "person" under the *Federal Election Campaign Act* (the Act)
Political party committees	Party committees may support federal candidates in a variety of ways, including making contributions.
Political action committees	**Separate segregated funds (SSFs)** may make contributions to candidates and to their authorized committees. **Nonconnected PACs**: May make contributions to influence federal elections, subject to the Act's limitations and reporting requirements. As nonconnected committees that solicit and accept unlimited contributions from individuals, corporations, labor organizations and other political committees, Super PACs and Hybrid PACs do not make contributions to candidates.
Other federal campaigns	A candidate's authorized committees may accept a contribution of up to $2,000 per election from the authorized committee of another federal candidate
State PACs, unregistered local party orgs, nonfederal campaign committees	State PACs, unregistered local party organizations and nonfederal campaign committees (nonfederal committees) may, under certain circumstances, contribute to federal candidates.
The Candidate	When candidates use or loan their personal funds for campaign purposes, they are making contributions to their campaigns. Unlike other contributions, these candidate contributions are not subject to any limits.

Contribution Limits for 2019-2020 Election Cycle

DONORS	RECIPIENTS				
	Candidate Committee	PAC[1] (SSF and Nonconnected)	State/District/ Local Party Committee	National Party Committee	Additional National Party Committee Accounts[2]
Individual	$2,800* per election	$5,000 per year	$10,000 per year (combined)	$35,500* per year	$106,500* per account, per year
Candidate Committee	$2,000 per election	$5,000 per year	Unlimited Transfers	Unlimited Transfers	
PAC Multicandidate	$5,000 per election	$5,000 per year	$5,000 per year (combined)	$15,000 per year	$45,000 per account, per year
PAC Nonmulticandidate	$2,800* per election	$5,000 per year	$10,000 per year (combined)	$35,500* per year	$106,500* per account, per year
State/District/Local Party Committee	$5,000 per election (combined)	$5,000 per year (combined)	Unlimited Transfers		
National Party Committee	$5,000 per election[3]	$5,000 per year			

Contributions A contribution is anything of value given, loaned or advanced to influence a federal election.	
Direct monetary contributions and loans	A contribution of money may be made by check, cash (currency), credit card or other written instrument. A loan, including a loan to the campaign from a member of the candidate's family, is considered a contribution to the extent of the outstanding balance of the loan. (Bank loans, however, are not considered contributions if made in the ordinary course of business and on a basis that assures repayment.)
In-kind contributions	**Goods and services**: Goods (such as facilities, equipment, supplies or mailing lists) are valued at the price the item or facility would cost if purchased or rented at the time the contribution is made. Services (such as advertising, printing or consultant services) are valued at the prevailing commercial rate at the time the services are rendered. **Advances of personal funds:** When an individual uses personal funds (or personal credit) to pay for a campaign expense, that payment is generally an in-kind contribution from that individual. **Coordinated communications:** When a committee, group or individual pays for a communication that is coordinated with a campaign or a candidate, the communication is either an in-kind contribution or, in some limited cases, a coordinated party expenditure by a party committee.
Earmarked contributions	An earmarked contribution is one which the contributor directs (either orally or in writing) a clearly identified candidate or the candidate's authorized committee through an intermediary or conduit. Earmarking may take the form

	of a designation, instruction or encumbrance and may be direct or indirect, express or implied, written or oral. Earmarked contributions require additional disclosure.
Lobbyist bundled contributions	A bundled contribution is any contribution that is either: Forwarded to a reporting committee by a lobbyist/registrant or lobbyist/registrant PAC; or Received by the reporting committee and credited to a lobbyist/registrant or lobbyist/registrant PAC through "records, designations, or other means of recognizing that a certain amount of money has been raised." Bundled contributions do not include contributions made from the personal funds of the lobbyist/registrant who forwards or is credited with raising those contributions and the personal funds of that person's spouse. Likewise, contributions made from committee funds of a lobbyist/registrant PAC that forwards or is credited with raising those contributions are not bundled contributions.
Joint contributions	A joint contribution is a contribution that is made by more than one person using a single check or other written instrument. Although each individual has a separate contribution limit, joint contributors may combine their contribution limits by contributing a joint contribution (for example, a check for $5,600 for a candidate's primary election) as long as both sign the check (or an attached statement).
Joint fundraising	Joint fundraising is election-related fundraising conducted jointly by a political committee and one or more other political committees or unregistered organizations.
Transfers	Transfers of funds and assets between federal committees authorized or established by the same candidate are generally unlimited because the committees are considered affiliated committees. However, an authorized committee of a federal candidate may not accept any transfers of funds or assets from a committee established by the same candidate for a nonfederal election.
Proceeds from sales	The entire amount paid to attend a political fundraiser or other political event or to purchase a fundraising item sold by a political committee is a contribution and counts against the individual's contribution limit.

Transfers Between a Candidate's Committees
In general, funds may be transferred between authorized committees of the same candidate (for example, from a previous campaign to a current campaign committee) without limit as long as the committee making the transfer has no net debts outstanding. This section covers when committees can make or receive transfers from other authorized committees of the candidate. Keep in mind that not all receipts or disbursements to other committees are transfers. The following are not transfers: 1. Contributions to or from other candidates (federal or

nonfederal), 2. Contributions to or from PACs, 3. Contributions from party committees, although an authorized committee may make unlimited transfers to party committees
<u>Transfers between a candidate's committees for the same office</u> **Transferring in the same election:** Funds and assets may be transferred without limit between a candidate's principal campaign committee and the candidate's other authorized committees for the same office during the same election. However, an authorized committee may not transfer funds to another authorized committee of the same candidate if the transferring committee has net debts outstanding. **Transferring between primary and general election campaigns in the same election cycle:** Funds that went unused in the primary election may be transferred without limit to a candidate's general election campaign.

	Who Can't Contribute
Campaigns are prohibited from accepting contributions from certain types of organizations and individuals.	➢ Corporations, including nonprofit corporations (although funds from a corporate separate segregated fund are permissible) ➢ Labor organizations (although funds from a separate segregated fund are permissible) ➢ Federal government contractors ➢ Foreign nationals
Corporations, labor organizations, national banks	Campaigns may not accept contributions from the treasury funds of corporations, labor organizations or national banks. This prohibition applies to any incorporated organization, including a nonstock corporation, a trade association, an incorporated membership organization and an incorporated cooperative. A campaign may, however, accept contributions from PACs established by corporations, labor organizations, incorporated membership organizations, trade associations and national banks. Moreover, the Act permits corporations, labor organizations, incorporated membership organizations, trade associations and national banks to use their treasury funds for certain election-related activities that benefit candidates.
Professional corporations	Although law firms, doctors' practices and similar businesses are often organized as partnerships, some of these businesses may instead be professional corporations. Unlike a partnership, a professional corporation is prohibited from making any contributions because contributions from corporations are unlawful.
Partnerships or LLCs with corporate partners or members	Because contributions from corporations are prohibited, a partnership or LLC with corporate partners or members may not attribute any portion of a contribution to the corporate partners or members. A partnership or LLC composed solely of corporate partners or members may not make any contributions.
Partnerships or LLCs with foreign national members	Similarly, because contributions from foreign nationals are prohibited, a partnership or LLC may not attribute any portion of a contribution to a partner who is a foreign national.
Personal funds from a candidate employed by prohibited source	A candidate's salary or wages earned from bona fide employment are considered his or her personal funds. However, compensation paid to a candidate in excess of actual hours worked, or in consideration of work not performed, is generally considered a contribution from the employer. If the employer is a corporation, federal government contractor, or another prohibited source, the excess payment would result in a prohibited contribution under the regulations applicable to that employer.
Churches and other charitable organizations	Incorporated charitable organizations—like other corporations—are prohibited from making contributions in connection with federal elections. Unlike most other corporations, charities face additional restrictions on political activity under provisions of the Internal Revenue Code.

Federal government contractors	Campaigns may not accept or solicit contributions from federal government contractors. A federal government contractor is a person who enters into a contract, or is bidding on such a contract, with any agency or department of the United States government and is paid, or is to be paid, for services, material, equipment, supplies, land or buildings with funds appropriated by Congress. Since corporate contributions are already prohibited, the government contractor ban applies primarily to contributions from a partnership (or a limited liability company) with a government contract. It also applies to the personal and business funds of: (1) Individuals under contract to the federal government; and (2) Sole proprietors of businesses with federal contracts. The spouses of individuals and sole proprietors who are federal government contractors and employees of federal government contractors, however, may make contributions from personal funds.
Partnerships or LLCs with federal government contracts	A partnership or LLC that is negotiating a contract with the federal government or that has not completed performance of such a contract is prohibited from making contributions. However, an individual partner in such a firm may make contributions from personal funds (rather than from funds drawn on the partnership's account). Also, an individual, who is, in his or her own right or as a sole proprietor, a federal government contractor or negotiating a contract with the federal government may not make contributions using any funds (business or personal) under his or her control. Note that the spouse of such an individual is not prohibited from making a personal contribution in his or her own name (as long as he or she is not otherwise prohibited from making contributions in connection with a federal election).
Foreign nationals	Campaigns may not solicit or accept contributions from foreign nationals. Federal law prohibits contributions, donations, expenditures and disbursements solicited, directed, received or made directly or indirectly by or from foreign nationals in connection with any election — federal, state or local. This prohibition includes contributions or donations made to political committees and building funds and to make electioneering communications. Furthermore, it is a violation of federal law to knowingly provide substantial assistance in the making, acceptance or receipt of contributions or donations in connection with federal and nonfederal elections to a political committee, or for the purchase or construction of an office building. This prohibition includes, but is not limited to, acting as a conduit or intermediary for foreign national contributions and donations.
Contributions in the name of another	A contribution made by one person in the name of another is prohibited. For example, an individual who has already contributed up to the limit to the campaign may not give money to another person to make a contribution to the same candidate. Similarly, a corporation is prohibited from using bonuses or other methods of reimbursing employees for their contributions.