

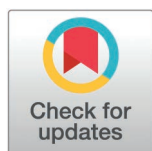
RESEARCH ARTICLE

Structural modeling of campaign finance decisions in the U.S. House of Representatives

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Abstract

Computational modeling and quantifying the drivers of modern political campaign finance is an emerging area of interest among researchers, policymakers, and the general public alike. In a federal legislative body like the U.S. House of Representatives, campaign finance decisions or “money flows” between party members are legal and common practice among both political parties for allocating resources and influence. Using extensive data from the Federal Election Commission, we model these money flows as complex networks and explain their formation using exogenous factors, previously only discussed qualitatively, such as seniority, non-coordinated SuperPAC expenditures, and House leadership status. Our results show that these factors have significant and persistent effects on both parties. These findings provide an empirical basis for ongoing debates about term limits in Congress and the role of unlimited independent expenditures by SuperPACs.

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Data availability statement: All data underlying the results of this study are publicly available at <https://github.com/yidans/Campaign-Finance>. The repository includes the compiled dataset, consisting of directed edge lists representing money flow networks, node-level attributes, and covariate data across seven election cycles (2009–2022), along with

Author summary

Campaign finance in the United States is often studied through donations from individuals, political action committees, and outside groups, but less attention has been paid to how members of Congress financially support one another within the same party. These internal transfers can reveal how parties allocate resources, reward influence, and respond to competitive elections. In this study, we examine campaign contributions exchanged among members of the U.S. House of Representatives from 2009 to 2022. We represent these contributions as directed networks and use statistical network models to test how structural processes and member characteristics relate to contribution patterns. We find clear differences between the two major parties. Democratic contribution networks remain relatively stable and centralized over time, while Republican networks change more substantially, becoming less centralized and more locally clustered. Seniority, leadership status, and SuperPAC activity are also associated with which members are more likely to give or receive support. These findings

replication scripts and detailed documentation. The dataset was compiled from public Federal Election Commission (FEC) bulk data and official rosters published by the Clerk of the U.S. House of Representatives. Files are provided in CSV format to support accessibility and reproducibility.

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show that campaign finance within Congress is not random, but reflects broader organizational features of party politics and changing electoral pressures.

Introduction

Especially since the *Citizens United* decision of the United States (U.S.) Supreme Court [1], political campaign finance has increased in both influence and complexity and become a contentious topic of debate [2–5]. Congressional candidates in the 2023–2024 election cycle reported raising approximately \$3.80 billion [6], a historically high total similar to the previous cycle and roughly 60 percent higher than in 2014 [7,8]. While not definitive, a candidate's ability to raise funds is often considered a prerequisite by political observers both for achieving electoral success and for subsequent legislative influence once elected [9,10].

An increasingly important but relatively understudied aspect of this system is the contribution of campaigns *between* members of Congress. Since the early 2000s, driven in part by the Bipartisan Campaign Reform Act of 2002, representatives have increasingly used their own campaign and leadership PAC funds to support the electoral efforts of party colleagues, both to aid competitive races and to build political influence within the party [11]. For example, during the 2021–2022 cycle, House Republican Leader Kevin McCarthy's Majority Committee PAC raised about \$7.20 million [12], and reportedly contributed \$4 million to House Republicans facing difficult reelection contests and another \$7 million to the National Republican Congressional Committee to support the party's 2024 efforts [13].

Such contributions made through leadership PACs are highly visible and frequently reported due to their explicit purpose and disclosure requirements, whereas those from personal campaign committees or other affiliated entities, though equally reportable under FEC regulations, receive less public attention. These internal contributions between members of Congress represent only a small fraction of total fundraising [15], yet they can signal party strategies for supporting selected candidates and prioritizing competitive races. For example, Fig 1 shows that in every cycle from 2009–2010 to 2021–2022, contributions from both leadership PACs and personal campaign committees (including other affiliated committees) rose sharply in the months preceding the general election, indicating that both parties concentrate resources on key contests in the final months as a deliberate strategy.

In addition to strategic timing, previous studies show that incumbents and members seeking leadership positions are more likely to contribute to other representatives in competitive or high-priority races to strengthen their standing within the party and improve prospects for committee assignments [16,17]. For instance, during the four years preceding her election as House Minority Leader in 2003, Nancy Pelosi contributed nearly \$2 million to fellow House campaigns, more than any other Democrat at the time [9]. While such cases are well documented, systematic analysis of the structure and determinants of contributions between members remains limited. Most campaign finance research has focused on donations from individuals, PACs,

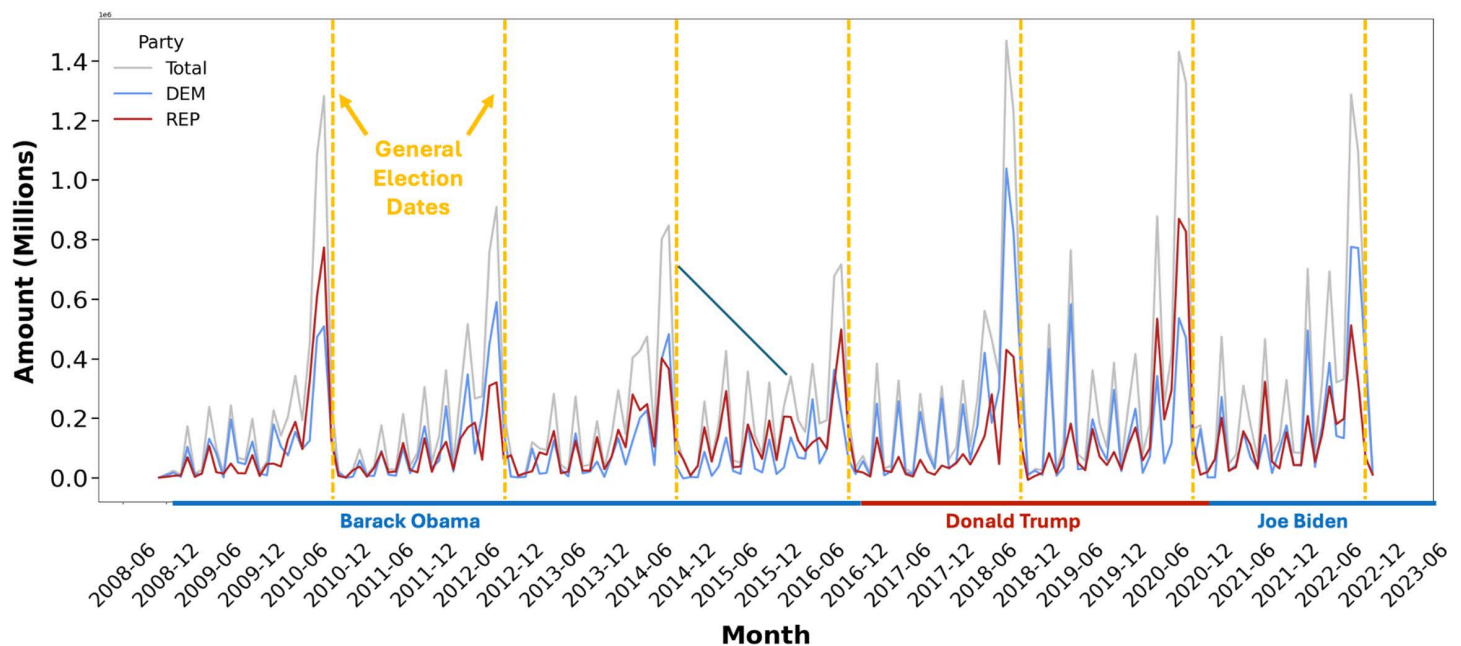


Fig 1. Aggregate total monthly contributions (y-axis; in millions of dollars) from one U.S. House representative to another between the seven two-year election cycles spanning 2009–2022, based on Federal Election Commission (FEC) data on contributions from committees to candidates [14]. The figure shows the monthly aggregated money flow between representatives, with the red line representing contributions from Republican representatives and the blue line representing contributions from Democratic representatives. Ticks on the x-axis are at every six months, with yellow vertical dashes marking the general election dates. The x-axis is also labeled with the corresponding President in office during each period.

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or outside groups, leaving unresolved questions about whether members direct support toward other representatives who already receive substantial internal contributions, whether resources are concentrated among a few recipients or distributed more broadly, and how often contributions are reciprocated rather than one-directional.

Besides these internal party strategies, the rise of *SuperPACs* introduces a major external factor influencing how members allocate campaign funds. SuperPACs, formally known as independent expenditure-only committees, can raise and spend unlimited amounts to support or oppose candidates, but are legally prohibited from coordinating directly with campaigns [18]. They have become a central component of federal campaign finance [19–21], with expenditures reported publicly in near real time. During the 2020 election cycle, for example, the *Congressional Leadership Fund* reported more than \$140 million in outside spending in House races, and the *House Majority PAC* spent over \$160 million, primarily defending vulnerable Democratic incumbents and contesting competitive Republican seats [22]. Such large-scale, visible activity may signal electoral vulnerability or strategic importance, prompting members to adjust their contribution behavior accordingly [23,24]. While prior research has examined how SuperPAC spending affects voters and candidate messaging [25], its relationship to financial transfers between members remains largely untested. Theories of donor signaling and decentralized party coordination suggest that external spending, despite the absence of formal coordination, could shape internal resource allocation within parties [17]. Yet it remains unclear whether supportive and oppositional SuperPAC spending has comparable effects or whether these responses differ by party organization. To our knowledge, few studies have systematically examined whether members alter their giving or receiving behavior in response to SuperPAC expenditures directed at themselves or their co-partisans.

Motivated by these observations and gaps, this article proposes *quantitative* network analysis of campaign finance data to examine how members of the U.S. House of Representatives direct contributions to other members over time.

We begin by constructing a set of *money flow networks* (MFNs) using campaign finance data from the Federal Election Commission (FEC) [14]. Each MFN represents the directional flow of contributions between members during a two-year election cycle, spanning 2009–2022. We focus on this period because SuperPACs as an entity only became legal around 2010; therefore, there is sufficient data to study their association with the campaign finance strategies of representatives. For each election cycle, we construct separate Democratic and Republican money-flow networks. Across the two-party networks, all 435 elected House members are represented, with one node for each representative and a directed link from a “sender” to a “receiver” if the sender made a campaign contribution to the receiver during that cycle. Although network science has been applied in political science to study international conflict, committee influence, cosponsorship, interest group activity, caucus formation, and legislative behavior [26–32], there has been less emphasis on candidate-to-candidate campaign finance networks.

However, mapping a money flow network is only the first step in understanding its structure. Equally important is developing a model that explains network formation and the non-random effects of exogenous factors. To do this, we employ *exponential random graph models* (ERGMs) [33,34], which specify a joint probability distribution over all possible ties. These models can account for node-level covariates such as seniority and leadership status but, just as importantly, also incorporate endogenous structural terms such as reciprocity (whether contributions are mutual), transitivity (whether members tend to contribute within small, interconnected groups), and degree heterogeneity (whether some members consistently give to or receive from many others), all of which cannot be explained by individual-level characteristics alone. These terms can indicate whether money flows are shaped by strategic coordination, coalition building, or hierarchical concentration beyond what would be expected from individual attributes. This framework also enables systematic comparison between parties, such as whether Democrats and Republicans differ in the breadth of support, the degree of hierarchical concentration, or the extent to which leaders act as donors.

Using these models, we focus on three research questions:

- (1) How did the structure of contributions among House members change over time, specifically with respect to reciprocity (mutual ties), transitivity (group clustering), and degree heterogeneity (centralization of giving and receiving)? And do these features differ systematically between Democrats and Republicans?
- (2) How do representatives with high *internal status*, such as seniors and those holding leadership positions (e.g., House Speaker and committee chairs), participate in allocating campaign funds, and do these regularities vary between the Democratic and Republican parties?
- (3) Externally, are representatives targeted by SuperPAC spending activity more (or less) likely to contribute to, or receive contributions from, their co-partisans, and how do these effects depend on the candidate’s party affiliation and on the SuperPAC’s expenditures being supportive or oppositional to the candidate’s agenda?

Existing research in political science has described campaign contributions exchanged among members of Congress but has not systematically accounted for endogenous network structures such as reciprocity and transitivity alongside contextual factors such as shared state representation that shape these decisions. Our analysis incorporates these factors to examine how internal transfers of campaign funds link individual fundraising to collective party objectives and interact with independent spending to shape the flow of electoral resources within Congress.

Methods

Overview

Our analysis proceeds in five main steps: (1) compiling and validating raw campaign finance data from the FEC; (2) identifying elected House representatives for each two-year cycle; (3) extracting member-to-member contributions via their affiliated committees; (4) constructing directed money flow networks (MFNs); and (5) fitting and analyzing Exponential

Random Graph Models (ERGMs) to evaluate the role of exogenous and endogenous predictors. Detailed implementation procedures are provided in [S1 Method](#).

Data sources and processing

We analyze campaign contributions between U.S. House members using publicly available data from the Federal Election Commission (FEC) covering seven two-year election cycles from 2009–2022 [14]. The analysis draws on four core FEC datasets: the *Candidate Master* file, which records each candidate's name, identifier, party, and principal campaign committee; the *Candidate—Committee Linkage* file, which records all political committees officially associated with each candidate; the *Committee Master* file, which records every registered political committee and its classification; and the *Contributions from Committees to Candidates and Independent Expenditure* file, which reports all committee-to-candidate contributions and independent expenditures by political committees. Because these datasets are released separately for each election cycle, we compiled and processed 28 files in total. Each dataset was cross-checked by candidate and committee identifiers to ensure that all records referred to valid, active entities during the corresponding cycle.

For each two-year cycle, we next identified the 435 seats filled through regular general elections to the U.S. House of Representatives and matched them to the winning candidates who began serving in the subsequent Congress (for example, winners of the 2020 general election who entered the 117th Congress in January 2021). We focused on elected members at the end of each cycle because campaign funds raised and distributed during that period are intended to support service in the upcoming Congress. The elected members were identified using FEC election results [35] and verified against official House rosters published by the Clerk of the U.S. House [36]. In most cases, the two sources listed the same members. When discrepancies occurred—for instance, when a candidate died, resigned, or declined to assume office before being seated—we retained the individual who originally won the election rather than the successor who later filled the seat, since fundraising during a given cycle was directed toward the elected candidate's campaign, not their replacement.

Finally, we identified contributions made by one member of Congress to another through their affiliated political committees using the *Contributions from Committees to Candidates and Independent Expenditure* file, which records all contributions by political committees to candidates and all independent expenditures made in support of or opposition to a candidate. Under FEC rules, members of Congress may contribute funds to one another through committees formally linked to them, including their principal or secondary campaign committees and their Leadership Political Action Committees (Leadership PACs) [37]. These committees are subject to contribution limits and public reporting requirements, and their affiliations are specified in the *Candidate—Committee Linkage* file. When a member was associated with multiple committees, all linked committees were aggregated by the member. We excluded personal donations made by one representative to another in an individual capacity because the dataset does not reliably identify the donor's congressional status and would require uncertain name matching. Such personal donations are generally small and symbolic rather than strategic. For these reasons, the analysis includes only verified transfers made through officially registered political committees affiliated with elected House members.

Detailed procedures for data compilation and validation are provided in [S1 Method](#).

Network construction

We constructed separate directed money-flow networks (MFNs) for Democratic and Republican members in each election cycle, based on both theoretical and empirical considerations. Contributions across parties are extremely rare—often absent in several cycles—whereas within-party transfers serve as the principal channel through which members coordinate fundraising, allocate resources, and organize electoral support [11,38,39]. Partitioning the data by party also improves comparability across cycles and reduces estimation difficulties that can arise from extreme sparsity, near-disconnected components, or unstable ERGM behavior, as discussed in the modeling section below [33,40–42].

Accordingly, all contributions between members of different parties were excluded. The few cross-party contributions observed involved members who subsequently changed party affiliation. At the time these contributions occurred, the members were still officially registered with their original party and are coded accordingly in the dataset. Such cross-party contributions constitute less than 0.50% of all records and are insufficient for reliable statistical estimation. Although the House permits candidates to serve as *Independents*, none were elected during the study period. Two members of the 116th Congress—Justin Amash (MI) and Paul Mitchell (MI)—were elected as Republicans and later declared Independent status. Each is coded as a Republican for the cycle in which they were elected, and neither sought nor won re-election as an Independent.

After applying these exclusions, we defined each party-specific MFN as a directed graph $G_p = (V_p, E_p)$, where $p \in \{\text{Democratic, Republican}\}$. V_p is the set of nodes representing all elected House members from party p in a given cycle. A directed edge from node i to node j is present if representative i , through an affiliated committee, contributed to representative j during that cycle. Together, the Democratic and Republican networks include all 435 elected members in each cycle. To maintain consistency across parties and time, all members, including those who neither gave nor received contributions, are retained as nodes in the corresponding networks.

Detailed procedures for network construction, including data validation and aggregation rules, are provided in the [S1 Method](#).

Exponential Random Graph Models (ERGMs)

We model tie formation in the money-flow networks (MFNs) using Exponential Random Graph Models (ERGMs) [34]. ERGMs specify a probability distribution over all possible networks of a given size, where the likelihood of observing a particular network depends on specified structural and covariate-based features. Formally, the probability of observing a network y is:

$$P(Y = y \mid \theta) = \frac{\exp(\theta^\top \mathbf{s}(y))}{\kappa(\theta)},$$

where $\mathbf{s}(y)$ is a vector of sufficient statistics representing the network features included in the model, θ is the corresponding vector of parameters, and $\kappa(\theta)$ is a normalizing constant that ensures probabilities sum to one over all possible networks. Each term k corresponds to a network statistic $s_k(y)$ with parameter θ_k , indicating the strength and direction of its association with the probability of observing y .

Factors in an ERGM are either *exogenous*, derived from attributes external to the network, or *endogenous*, defined by structural dependencies among ties (e.g., reciprocity, triadic closure, and in-degree centralization). In the MFNs constructed earlier, an example of an exogenous factor is *state homophily*, which tests whether two House members from the same state are more likely to exchange contributions than those from different states. This term is exogenous because it derives from a nodal attribute rather than the network structure, and dyadic because it is defined for pairs of nodes. Node-level factors are also included, such as a representative's leadership status, which tests whether individual characteristics are associated with the probability of giving or receiving contributions. The ERGMs estimated in this study include both node-level and dyadic terms, exogenous and endogenous, to model the formation of money-flow networks across all seven election cycles.

Analogous to logistic regression, each coefficient θ_k represents the change in the log-odds of a tie forming associated with a one-unit increase in the corresponding statistic $s_k(y)$, conditional on all other factors in the model. A positive value of θ_k indicates that the presence or greater magnitude of factor k increases the probability of observing a tie, whereas a negative value indicates a decrease in that probability. For example, a positive estimate for the *state homophily* term implies that representatives are more likely to contribute to co-partisans from the same state, whereas a negative estimate

implies a tendency toward cross-state giving. Hence, ERGM coefficients can be interpreted as conditional log-odds ratios for tie formation, analogous to logistic regression parameters.

ERGMs have become increasingly common in political network analysis [41,43,44]. Much of this work has examined international relations [45,46] and policy networks [47–49]. For example, Henry et al. [49] used ERGMs to analyze how policy beliefs and social capital influence collaborative ties among policymakers. For an applied example, Desmarais and Cranmer (2012) introduce a resampling approach for MPLE uncertainty and a temporal ERGM, and apply it to U.S. Senate cosponsorship networks [50]. Despite these advances, to our knowledge, ERGMs have not yet been used to study contribution ties within the U.S. House of Representatives.

Model specification

Endogenous terms

All models include four endogenous structural terms: *edges*, *mutual*, *gwesp*(0.50), and *gwidegree*(0.50), representing baseline tie propensity, reciprocity, triadic closure, and in-degree centralization, respectively. Each term quantifies a specific structural dependence that influences the probability of a tie. Below, we describe the interpretation of each term and its relevance for the money-flow networks (MFNs) analyzed in this study.

Edges: This term serves as the model intercept and represents the baseline log-odds of a tie forming between two randomly selected representatives, conditional on all other factors. A strongly negative coefficient, common in empirical applications, indicates a sparse network, meaning that the observed number of ties is far smaller than in a random graph of equivalent size. Because the *edges* coefficient is typically large and negative in such sparse settings, its corresponding odds ratio is well below one; other coefficients are therefore interpreted relative to this low baseline probability of a tie.

Reciprocity (*mutual*). This term tests whether directed ties are reciprocated. In MFNs, it measures whether a contribution from member *i* to member *j* increases the probability of a contribution from *j* to *i*. Prior studies show that reciprocal exchanges often occur in leadership contests or among active fundraisers seeking to reinforce alliances [51]. In this model, an odds ratio (OR) below 1 for the *mutual* term indicates lower conditional odds of reciprocation; the presence of a contribution in one direction reduces the conditional odds of a reciprocal contribution.

Triadic closure (*gwesp*(0.50)). This term tests whether two members are more likely to form a tie when both are linked to a common third member, thereby forming a closed triad. In MFNs, it measures whether representatives who share a contribution partner are also more likely to exchange contributions. The *gwesp*(0.50) statistic (geometrically weighted edgewise shared partners, with a fixed decay of 0.50) quantifies how the probability of a tie increases with the number of shared partners while allowing the marginal effect of each additional partner to decline geometrically [40]. Comparable transitive structures have been identified in legislative cosponsorship networks, where shared partners are associated with a higher probability of tie formation [50].

In-degree centralization (*gwidegree*(0.50)). This term measures concentration in the in-degree distribution (receiver centralization) by up-weighting configurations in which some members receive contributions from many co-partisans, with diminishing marginal influence as in-degree increases [40,52]. In sparse directed networks, this term helps represent heterogeneity in incoming ties. Because *gwidegree* is a curved term, its coefficient does not admit a simple one-to-one interpretation in odds-ratio units across networks; we therefore interpret its direction and relative magnitude qualitatively and report the estimate primarily as a structural control rather than a stand-alone substantive effect.

For curved terms (*gwesp*(0.50)/*gwidegree*(0.50)), ORs reflect a one-unit change in the change statistic and are not comparable to simple covariates; we report them for completeness and interpret direction/magnitude qualitatively.

Exogenous covariates

Exogenous covariates are included at both the node and dyadic levels to represent members' institutional positions, electoral environments, and financial linkages within the campaign finance system.

State Homophily (dyadic). This binary variable equals one if two members represent the districts within the same state and zero otherwise. It tests whether representatives are more likely to contribute to representatives from their own state, given that members sharing a state often draw on overlapping donor networks, participate in joint fundraising events, and maintain shared political alliances [38,53].

Seniority (House Terms Served) (node). The data used for constructing this variable was obtained from the congress-legislators dataset maintained by The United States Project [54], which provides authoritative historical records of U.S. Congress members, including bioguide identifiers, term start dates, and complete service histories. This source was selected because of its comprehensive coverage, consistent maintenance, and direct linkage between Congressional records and FEC candidate identifiers, enabling reliable matching of representatives to their career service data. Each representative's seniority is defined as the cumulative total number of House terms served throughout their entire congressional career, as of the election cycle in question. This count includes both consecutive and non-consecutive terms served, regardless of when they began service. For example, in the 2021–2022 cycle, a member who first served in 1955 and completed 27 terms (including any gaps in service) would have a seniority value of 27. Importantly, this definition is invariant across election cycles: seniority always represents cumulative career service measured on the same scale, differing only in realized values as members accrue additional terms over time. Separate sender and receiver effects ($Seniority_{\text{Sender}}$ and $Seniority_{\text{Receiver}}$) test whether longer-serving members are more likely to give or receive contributions. Prior research shows that senior members generally have greater fundraising capacity and institutional visibility [16,50].

Leadership (node). Binary indicators identify whether a member holds or will hold a leadership position, including Speaker, party leader, whip, caucus or conference chair, and committee chair or ranking member. Leadership positions are determined in party caucus elections held after each general election, and members' chances of selection generally depend on fundraising performance and established relationships from prior cycles [44,51]. Leaders were identified from official caucus and committee rosters and cross-checked against Congressional archival sources to confirm timing and officeholders.

Two sets of variables are included. $Leadership(\text{Next})_{\text{Sender}}$ and $Leadership(\text{Next})_{\text{Receiver}}$ indicate members who will hold a leadership position in the *next* Congress (the Congress convening after the election cycle), while $Leadership(\text{Current})_{\text{Sender}}$ and $Leadership(\text{Current})_{\text{Receiver}}$ indicate those who hold such positions during the *same* Congress. The “Next” indicators test whether members who later enter leadership contribute more before assuming office, whereas the “Current” indicators test whether sitting leaders contribute more or receive fewer contributions while in office. Because many leaders serve consecutive terms, the two sets are highly collinear; therefore, they are estimated in separate model specifications. We report results for the “Next” specification in the *Results* section, as most redistribution occurs in the cycle preceding leadership selection.

SuperPAC Activity (node). Four node-level covariates measure whether the number of SuperPACs making independent expenditures for or against a representative is associated with their contribution activity. Committees are classified as SuperPACs when identified by the FEC as independent-expenditure-only committees, consistent with Advisory Opinions 2010–09 and 2010–11. Support and opposition are identified via transaction type codes 24E (support) and 24A (oppose) in the independent-expenditure records (detailed in [S1 Method](#)). For each election cycle, we count the number of distinct SuperPACs making expenditures supporting or opposing each member. The covariates $SuperPAC(\text{Support Count})_{\text{Sender}}$ and $SuperPAC(\text{Support Count})_{\text{Receiver}}$ test whether representatives supported by more SuperPACs are more likely to give or receive contributions, respectively, and $SuperPAC(\text{Oppose Count})_{\text{Sender}}$ and $SuperPAC(\text{Oppose Count})_{\text{Receiver}}$ test the same for oppositional spending. These variables evaluate whether independent expenditures signal electoral strength or vulnerability in ways that influence internal fund allocation [17,55–57]. In a sensitivity analysis, we replace SuperPAC counts with total expenditure amounts (in \$100,000) to assess robustness to the use of spending levels rather than counts.

Model variants

We estimate three ERGM specifications (one main model and two variants) that differ in their inclusion of exogenous covariates (Table 1). All three models include the four endogenous structural terms described above, and each also includes State Homophily as a control variable.

Model (1) serves as the main specification and incorporates factors for both House terms served and leadership. For each, we estimate separate sender and receiver effects, as the likelihood that a member gives contributions may differ from the likelihood of receiving them. Model (1) uses the *next Congress* leadership specification ($Leadership(Next)_{Sender}$ and $Leadership(Next)_{Receiver}$), testing whether contribution activity is associated with attaining leadership in the next Congress.

Two sensitivity analyses extend this baseline model. Model (1a) replaces the leadership covariates with the *current Congress* specification ($Leadership(Current)_{Sender}$ and $Leadership(Current)_{Receiver}$), testing whether sitting leaders differ from other members in how they give and receive contributions. Model (1b) retains the *next Congress* leadership terms but replaces the number of distinct SuperPACs with the total dollar amount of SuperPAC expenditures for each representative, testing whether the results are robust when using expenditure amounts instead of counts.

Unless otherwise noted, the *Results* section reports findings from Model (1). Results from Models (1a) and (1b) are referenced explicitly where relevant to assess the robustness of the main findings.

Estimation and analysis

All models were estimated using the *ergm* package in R [33] with Markov Chain Monte Carlo Maximum Likelihood Estimation (MCMLE). MCMLE is required for models with structural dependence terms such as *mutual*, *gwesp*, and *gwidegree*. The method approximates the full likelihood by drawing samples from the distribution of networks implied by the ERGM and computing parameters that maximize the expected log-likelihood.

Goodness-of-fit (GOF) diagnostics were computed for all fitted models using the *ergm* package. These diagnostics compare networks simulated from the fitted parameters with the observed data across key auxiliary statistics, including in-degree, out-degree, geodesic distance, and edgewise shared partners. Each model was evaluated using 100 networks simulated from the fitted parameters. Across election cycles, the fitted models reproduce the sufficient statistics closely; while some deviations appear in auxiliary distributions (e.g., higher-order shared-partner counts), the observed statistics generally remain within the range of simulated values [58]. We distinguish between in-model statistics—those explicitly

Table 1. ERGM model terms included in Models (1), (1a), and (1b). A ✓ indicates inclusion of a term.

Term Category / Factor	Model (1)	Model (1a)	Model (1b)
Endogenous Terms			
edges, mutual, gwesp(0.50), gwidegree(0.50)	✓	✓	✓
Dyadic Covariate			
State Homophily	✓	✓	✓
Node-Level Covariates			
Seniority (House Terms Served) (Sender / Receiver)	✓	✓	✓
Leadership (Next) (Sender / Receiver)	✓		✓
Leadership (Current) (Sender / Receiver)		✓	
SuperPAC Counts (Support / Oppose, Sender / Receiver)	✓	✓	
SuperPAC Amounts (Support / Oppose, Sender / Receiver)			✓

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included as sufficient statistics for parameter estimation—and auxiliary diagnostics, which characterize residual features not directly constrained by the model [59]. While our inferences rely on the stable recovery of the former, we report the latter in [S1 Fig](#) for transparency. To ensure model validity, we monitor for *degeneracy*, defined as the near-concentration of probability mass on extreme graphs or MCMC behavior that fails to explore the distribution, which was not observed in any of the final models reported here [60,61].

Our model specification is theory-driven: endogenous terms control for well-documented structural dependencies in directed networks, while exogenous covariates correspond directly to the hypotheses under investigation. We prioritize a consistent specification across all seven election cycles to preserve the cross-cycle comparability of effect estimates that is central to our analytical design. We nevertheless evaluated alternative structural specifications aimed at improving auxiliary GOF, including additional degree-based terms and specifications without *mutual*. Across cycles, these alternatives frequently produced poor MCMC mixing or unstable MCMLE updates and were therefore unsuitable for a comparative analysis requiring reliable estimation in every cycle. The retention of the current specification was not driven by selection on substantive results, but by the requirement that the model converge reliably across all seven cycles. We use GOF diagnostics to verify that the model adequately recovers its sufficient statistics and is free from degeneracy, rather than as a criterion for specification search. Details of these sensitivity checks are reported in [S2 Table](#).

To summarize effects across election cycles, we conducted random-effects meta-analyses using the *metafor* package in R [62]. For each model term, we extracted estimated log-odds and standard errors across the seven cycles as inputs to independent random-effects models. A random-effects framework is adopted because true effect sizes may vary across cycles due to differences in political context, membership composition, and external influences [63]. For each term, the meta-analysis estimates the pooled effect size, standard error, 95% confidence interval, and p-value. In *Results*, we report odds ratios (exponentiated coefficients) with 95% confidence intervals.

Full parameter estimates, standard errors, and model diagnostics are provided in [S5 Table–S10 Table](#). Detailed procedures for data construction and model estimation are provided in [S1 Method](#).

Ethics statement

This study did not involve human subjects research as defined by institutional review board standards. All data analyzed were publicly available campaign contribution records from the Federal Election Commission. No identifiable private or sensitive information was collected, and the research adhered to all relevant ethical standards regarding the use of public data.

Results

We estimated Model (1) separately for each party in each of the seven Money Flow Networks (MFNs) spanning 2009–2022. [Table 2](#) reports pooled odds ratios (ORs) by party; cycle-specific estimates for all Model (1) terms are reported in [S5 Table–S6 Table](#). Each MFN represents contributions from one member to another within a two-year cycle, and all models were fit independently. [Fig 2](#) shows the ORs for each model term by party and cycle. Summary statistics for the MFNs spanning all election cycles are provided in [S1 Table](#).

Structural characteristics of contributions between members

We examined four structural properties of contribution networks: edges (how frequently contribution ties formed overall), reciprocity (whether contributions tended to be returned), triadic closure (whether members who shared contribution partners were more likely to contribute to one another), and in-degree centralization (whether incoming ties were concentrated among a small number of recipients). Throughout the *Results* section, “contributing” and “receiving” refer to the presence of a contribution tie between two members (i.e., whether any contribution was made). For triadic closure and in-degree centralization, the odds ratios do not have the same straightforward interpretation as those for simple covariates such as

Table 2. Pooled odds ratio (OR) estimates from Model (1), across all seven Money Flow Networks (MFNs), for the two parties (described and specified fully in *Methods*). 95% confidence intervals (CIs) of ORs are in parentheses. Unpooled estimates for each of the seven cycles for the Democratic and Republican parties are reported in [S5 Table–S6 Table](#). Random-effects pooling was used. *, **, and * indicate ORs significantly different from unity at the 99%, 95%, and 90% confidence levels, respectively.**

	Democrats	Republicans
Structural characteristics:		
Edge	0.03 (0.02, 0.04)***	0.02 (0.02, 0.03)***
Reciprocity (mutual)	0.23 (0.17, 0.32)***	0.31 (0.15, 0.64)***
Triadic closure (gwsesp, $\tau = 0.50$)	1.36 (1.15, 1.62)***	1.91 (1.63, 2.23)***
Degree centralization (gwidegree, $\tau = 0.50$)	0.01 (0.00, 0.02)***	0.06 (0.02, 0.22)***
Odds of a representative making a contribution (sender) based on:		
Each additional term served by the sender	1.05 (1.04, 1.06)***	0.99 (0.96, 1.03)
Sender holds a leadership position in the upcoming term	1.49 (1.07, 2.06)**	2.11 (1.81, 2.46)***
Each additional SuperPAC supporting the candidate	0.53 (0.32, 0.87)**	0.76 (0.72, 0.79)***
Each additional SuperPAC opposing the candidate	0.54 (0.38, 0.77)***	0.58 (0.42, 0.79)***
Odds of a representative receiving a contribution (receiver) based on:		
Each additional term served by the receiver	0.95 (0.93, 0.97)***	0.95 (0.93, 0.96)***
Receiver holds a leadership position in the upcoming term	0.96 (0.87, 1.05)	0.71 (0.66, 0.77)***
Each additional SuperPAC supporting the candidate	1.25 (1.12, 1.41)***	1.19 (1.14, 1.24)***
Each additional SuperPAC opposing the candidate	1.41 (1.24, 1.61)***	1.31 (1.22, 1.41)***
Odds of forming a tie between representatives who:		
Are from the same state	2.10 (1.78, 2.47)***	2.75 (2.28, 3.32)***

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seniority or leadership; we report them to compare direction and relative magnitude across cycles. The edge term implies very low baseline tie probabilities in both parties (see [S5 Table–S6 Table](#)), consistent with highly sparse networks.

Contribution ties between House members were infrequent in both parties and generally unidirectional. Among Republicans, reciprocity—the tendency for a member who received a contribution to give one in return, measured as the conditional odds of a reciprocal tie—declined from 0.70 (95% CI: 0.45–1.11) in 2009–10 to 0.03 (95% CI: 0.01–0.09) in 2021–22, with some fluctuation across intermediate cycles. Among Democrats, reciprocity remained consistently low, with odds ratios ranging from 0.13 to 0.34 across cycles (see [S5 Table–S6 Table](#) for cycle-level estimates).

Contribution ties among Republicans were more likely to form within locally interconnected groups—a structural property known as triadic closure, in which members who shared contribution partners had higher conditional odds of forming a tie with one another. This tendency was present in both parties but stronger among Republicans (pooled OR = 1.91, 95% CI: 1.63–2.23) than among Democrats (pooled OR = 1.36, 95% CI: 1.15–1.62).

In-degree centralization reflects whether incoming contribution ties were concentrated among a small number of recipients. (Values further below 1 indicate stronger centralization; values closer to 1 indicate weaker centralization.) Among Republicans, in-degree centralization weakened overall from 2009–10 (OR = 3.90×10^{-3} , 95% CI: 2.60×10^{-3} – 5.80×10^{-3}) to 2021–22 (OR = 1.08, 95% CI: 0.63–1.87), where the estimate was not statistically different from 1, with some fluctuation across intermediate cycles. Among Democrats, in-degree centralization remained strong across all cycles (OR consistently far below 1), indicating persistent concentration of incoming ties among a small subset of recipients. Full estimates are provided in [S5 Table–S6 Table](#).

In summary, reciprocity among Republicans generally declined over time, and incoming ties shifted from being concentrated among a few recipients toward a more even distribution. Republicans also showed stronger evidence of triadic

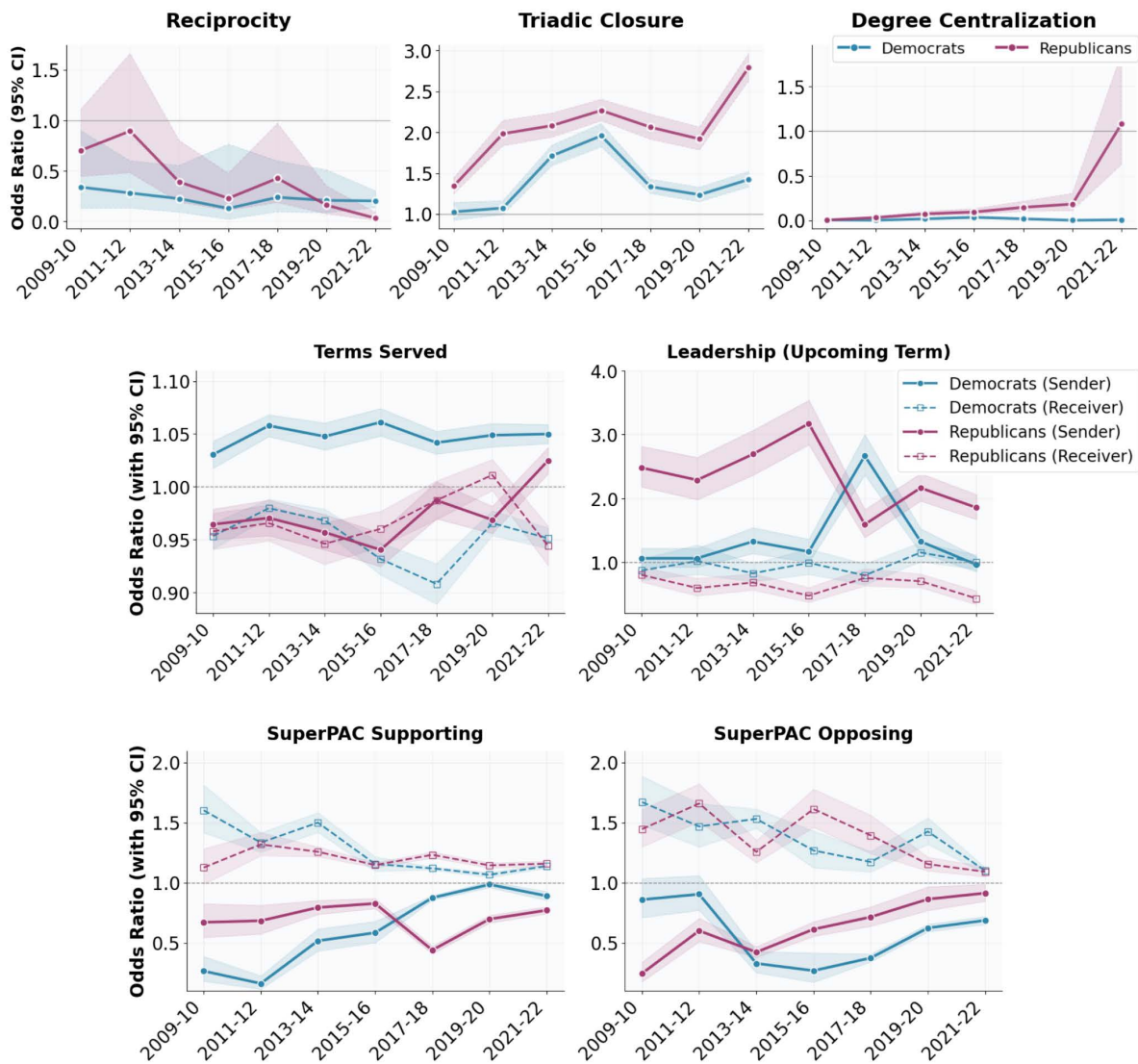


Fig 2. Estimated odds ratios (ORs) for all terms in Model (1), estimated separately for Democrats and Republicans in each election cycle from 2009 to 2022 across the seven Money Flow Networks (MFNs). For each cycle and party, the figure shows ORs with 95% confidence intervals for both structural characteristics (reciprocity, triadic closure, and in-degree centralization) and individual or external factors, including party leadership, seniority (measured as House terms served), and SuperPAC involvement. *Note:* For structural terms, higher ORs indicate stronger reciprocity or triadic closure, whereas smaller ORs indicate greater centralization of contributions.

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closure. Among Democrats, ties remained infrequent and mostly unidirectional, with persistent concentration of incoming ties among a small subset of recipients across cycles.

Effects of Seniority and leadership status on internal contributions

Seniority (measured as cumulative House terms served) showed different associations with giving and receiving across parties. Among Democrats, each additional term was associated with higher conditional odds of contributing (OR = 1.05, 95% CI: 1.04–1.06, $p < 0.001$) and lower odds of receiving (OR = 0.95, 95% CI: 0.93–0.97, $p < 0.001$). Among Republicans, seniority was also negatively associated with receiving (OR = 0.95, 95% CI: 0.93–0.96, $p < 0.001$), but the pooled

association with contributing was not statistically significant (OR = 0.99, 95% CI: 0.96–1.03, $p > 0.05$). Cycle-specific sender estimates were generally below 1 from 2009–10 to 2019–20 and exceeded 1 in 2021–22, indicating heterogeneity over time in the seniority–giving association.

Beyond seniority, leadership status—defined as holding a formal position in the *next* Congress (Speaker, majority or minority leader, whip, caucus or conference chair, or committee chair or ranking member)—was strongly associated with giving and receiving, particularly among Republicans. Republican leaders had higher odds of contributing than non-leaders (OR = 2.11, 95% CI: 1.81–2.46, $p < 0.001$) and lower odds of receiving (OR = 0.71, 95% CI: 0.66–0.77, $p < 0.001$). Among Democrats, leaders also had higher odds of contributing on average (OR = 1.49, 95% CI: 1.07–2.06, $p = 0.02$), but showed no significant pooled association with receiving (OR = 0.96, 95% CI: 0.87–1.05, $p > 0.05$).

A key question is whether members gain leadership positions by building support through contributions, or whether leaders use contributions to sustain influence once in office. To address this, we re-estimated Model (1a) with leadership status defined for the *same* Congress in which contributions occurred, so that leadership reflects positions held at the time of contributing. While this does not establish causality, the results show that leaders in both parties had higher conditional odds of contributing. Republican leaders had lower odds of receiving (OR = 0.63, 95% CI: 0.49–0.82, $p < 0.001$) and higher odds of contributing (OR = 2.26, 95% CI: 1.74–2.93, $p < 0.001$). Democratic leaders had higher odds of contributing (OR = 1.45, 95% CI: 1.17–1.80, $p < 0.001$) and did not differ significantly in receiving (OR = 1.01, 95% CI: 0.95–1.07, $p > 0.05$). Full results for both specifications are reported in [S7 Table–S8 Table](#).

As a complementary descriptive analysis, we compared centrality distributions by leadership status ([Fig 3A–B](#)). [Fig 3C](#) illustrates within-cycle directionality: leaders frequently give to non-leaders, whereas contributions from non-leaders to leaders are rare.

Effects of SuperPAC activity on internal contributions

Representatives targeted by a larger number of *distinct* SuperPACs making independent expenditures—supportive or oppositional—had lower conditional odds of contributing and higher conditional odds of receiving. Substantively, members targeted by more SuperPACs were more likely to receive contributions from co-partisans and less likely to contribute to others. For Democrats, each additional supportive SuperPAC was associated with a 47% decrease in the odds of contributing (OR = 0.53, 95% CI: 0.32–0.87, $p = 0.01$) and a 25% increase in the odds of receiving (OR = 1.25, 95% CI: 1.12–1.41, $p < 0.001$). For Republicans, each additional supportive SuperPAC corresponded to a 24% decrease in the odds of contributing (OR = 0.76, 95% CI: 0.72–0.79, $p < 0.001$) and a 19% increase in the odds of receiving (OR = 1.19, 95% CI: 1.14–1.24, $p < 0.001$).

Counts of distinct SuperPACs making oppositional expenditures were likewise associated with lower contributing and higher receiving in both parties. For Democrats, each additional opposing SuperPAC was associated with a 46% decrease in the odds of contributing (OR = 0.54, 95% CI: 0.38–0.77, $p < 0.001$) and a 41% increase in the odds of receiving (OR = 1.41, 95% CI: 1.24–1.61, $p < 0.001$). For Republicans, the corresponding estimates were a 42% decrease in the odds of contributing (OR = 0.58, 95% CI: 0.42–0.79, $p < 0.001$) and a 31% increase in the odds of receiving (OR = 1.31, 95% CI: 1.22–1.41, $p < 0.001$).

We find no direct correspondence between representatives' likelihood of giving or receiving contributions and the overall rise in SuperPAC activity during the study period. In fact, these internal contribution rates declined slightly in the final cycle even as SuperPAC activity remained high over the study period. [Fig 4](#) shows that in 2009–10, only about 16–17% of members in each party received SuperPAC support, but this proportion grew rapidly, exceeding 80% for Republicans by 2015–16 and nearly 90% for Democrats by 2017–18. Since then, more than half of all members in both parties have consistently received SuperPAC support. [Fig 4B](#) further distinguishes between opposing and supporting expenditures. Since 2011–12, Democrats have consistently had more SuperPACs supporting them than opposing them—a gap that has widened in recent cycles. In contrast, Republicans experienced more SuperPACs opposing them than supporting them in 2009–10, 2011–12, and 2019–20.

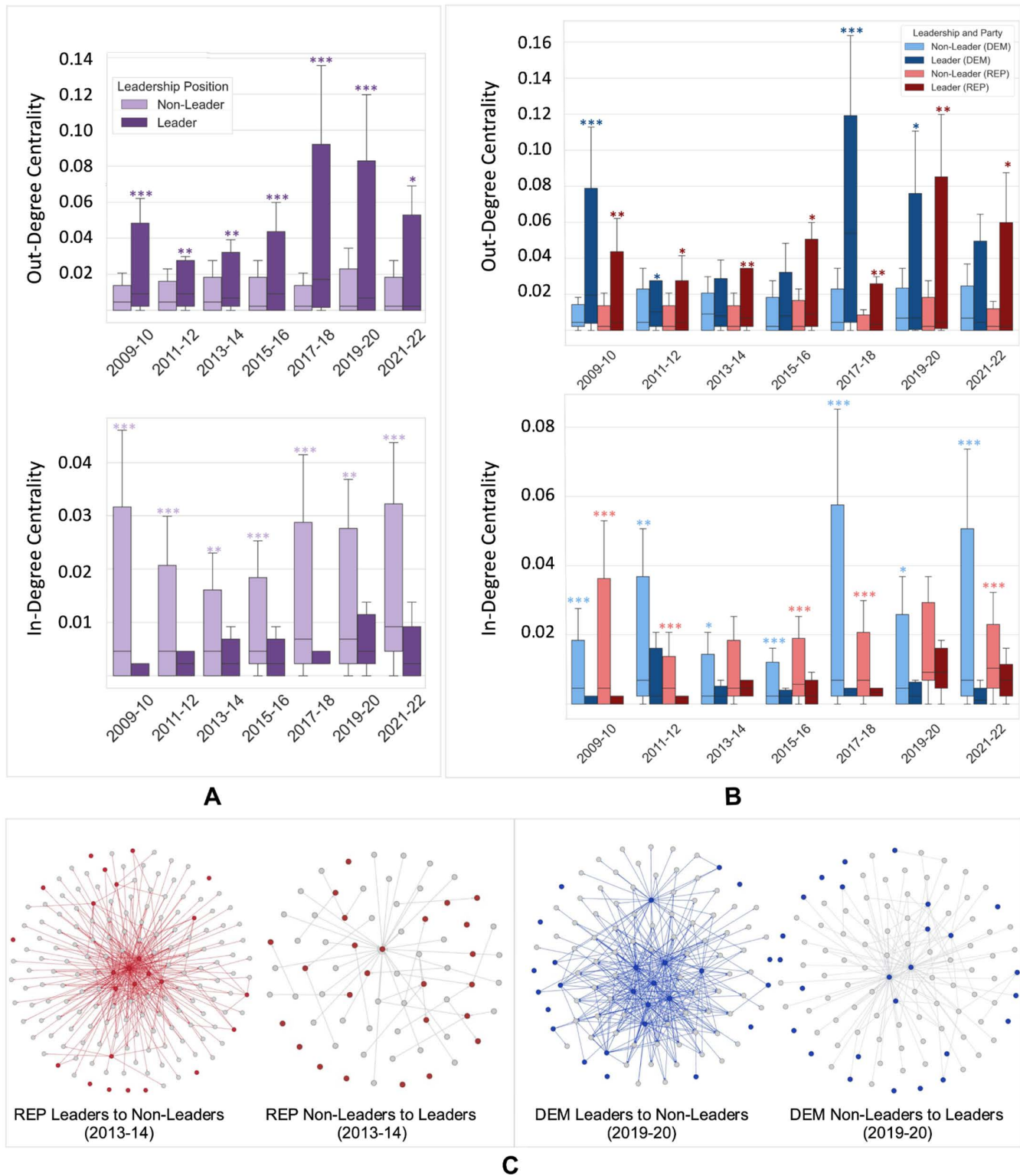


Fig 3. A comparison of centrality distributions and network structure for leaders and non-leaders. (A) Comparison of out-degree (top pane) and in-degree (bottom pane) centrality distributions between leaders and non-leaders for each election cycle. Using a one-sided Mann-Whitney U test, *, **, and *** indicate a significant shift in the centrality distributions between leaders and non-leaders at the 10%, 5%, and 1% levels, respectively. In each

boxplot, outliers were excluded, and whiskers extend to 1.5 times the interquartile range from the lower and upper quartiles. Detailed statistical test results underlying these significance markers are provided in S3 Table. **(B)** The same data as in **(A)**, but with the centrality distributions shown separately for representatives of the Democratic (DEM) and Republican (REP) parties. Similar to **(A)**, we compute and report significant differences in the centrality distributions between out-degree and in-degree for leaders and non-leaders, but for each party separately. Statistical tests for party-specific comparisons are reported in S3 Table. **(C)** A network illustration of contributions between Republican representatives during the 2013–2014 cycle (left pane) and Democratic representatives during the 2019–2020 cycle (right pane), when they each controlled the House. The left figure in each pane shows contributions from leaders to non-leaders, and the right figure shows contributions from non-leaders to leaders. Nodes not participating in contributions (singletons) are included only if they are leaders. Grey nodes represent non-leaders, while red and blue nodes represent leaders.

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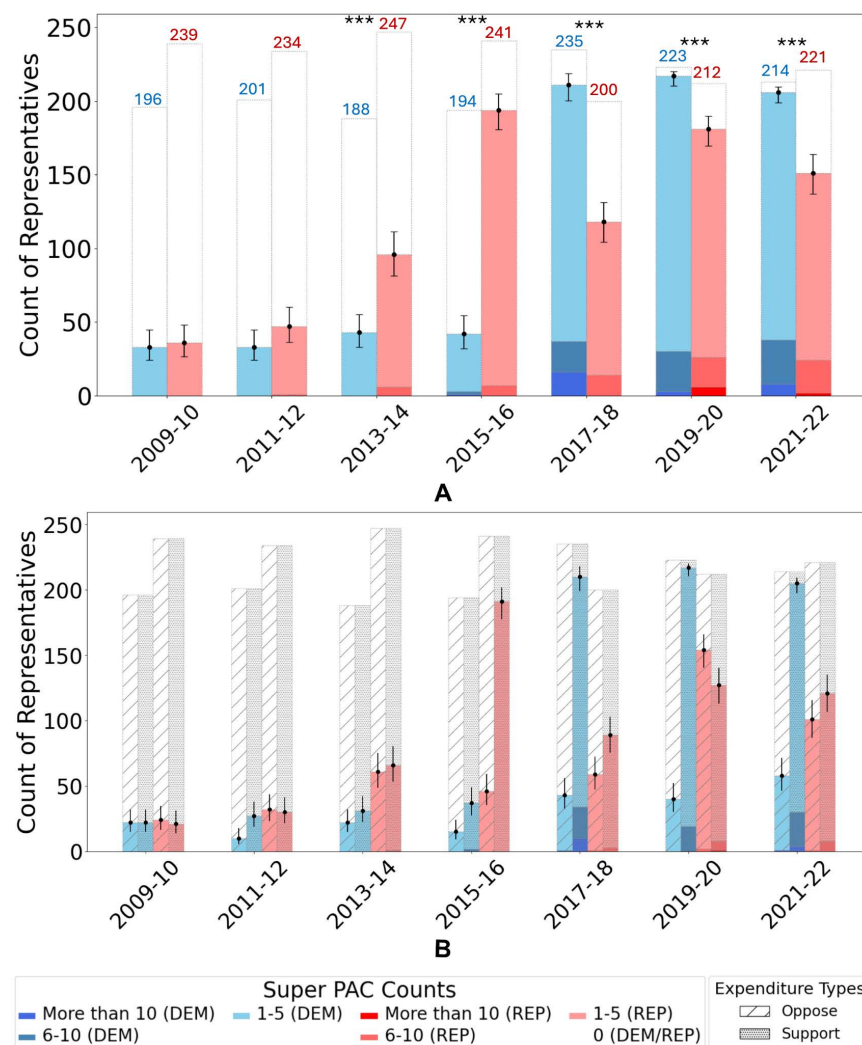


Fig 4. (A) Counts of “Super” Political Action Committees (SuperPACs) making independent expenditures for Democratic (DEM) and Republican (REP) representatives in each cycle. The total number of elected representatives from each party is shown at the top of each bar. Error bars represent 95% confidence intervals (CIs) for the share of representatives in each party for whom at least one SuperPAC made expenditures (nonzero SuperPAC count). Using a two-sample z-test of proportions, we find that starting from the 2013–2014 cycle, the proportions of Democratic and Republican representatives with nonzero SuperPAC counts are significantly different at the 99% confidence level ($p < 0.01$), indicated by ***. In the other two cycles, significant differences were not observed at the 90% confidence level or above. Detailed breakdowns by party and SuperPAC count and the underlying z-test statistics are provided in S4 Table. **(B)** Disaggregation of SuperPAC expenditures into those supporting or opposing candidates. For each election cycle, the number of SuperPACs spending money to support or oppose Democratic (DEM) and Republican (REP) representatives is displayed separately. Different textures differentiate between support and opposition expenditures. The corresponding tabular data stratified by expenditure type and party affiliation are provided in S4 Table.

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As a sensitivity analysis, we re-estimated Model (1b) using total SuperPAC expenditure (rescaled to \$100,000 units) instead of counts of distinct SuperPACs and pooled the estimates across cycles. The expenditure-based results matched the main specification in direction. For both parties, higher SuperPAC expenditure was associated with higher odds of receiving (Democrats: $OR_{support} = 1.07$, 95% CI: 1.065–1.073; $OR_{oppose} = 1.03$, 95% CI: 1.024–1.032; Republicans: $OR_{support} = 1.05$, 95% CI: 1.04–1.07; $OR_{oppose} = 1.07$, 95% CI: 1.068–1.079). Higher expenditure was also associated with lower odds of contributing (Democrats: $OR_{support} = 0.81$, 95% CI: 0.79–0.82; $OR_{oppose} = 0.99$, 95% CI: 0.987–0.993; Republicans: $OR_{support} = 0.67$, 95% CI: 0.57–0.78; $OR_{oppose} = 0.94$, 95% CI: 0.937–0.948). All pooled associations were statistically significant ($p < 0.001$). As in the main specification, the direction was consistent across cycles while magnitudes varied. Full results for this analysis are reported in [S9 Table–S10 Table](#).

Discussion

Our analysis of campaign contributions between House members from 2009 to 2022 shows persistent differences in intra-party contribution organization between Democrats and Republicans. Democratic contributions remain centralized, with senior members and party leaders more likely to give to electorally vulnerable colleagues. Republican contributions, in contrast, change over time from an initially centralized structure to one in which contributions are more evenly distributed across recipients and more likely to occur within locally connected groups of members who share contribution partners. These differences emerge during a period of sharply increased outside spending by SuperPACs and other independent groups and are consistent with parties adapting in different ways to a changing campaign finance environment. Taken together, the findings link intra-party contribution networks to broader questions about how parties sustain cohesion through financial interdependence [64–66].

In addressing our first research objective, we find that early in the study period, House Republican contributions were concentrated among a small number of recipients. Over time, contributions became more evenly distributed across recipients, and reciprocity generally declined, indicating that recipients rarely returned contributions to donors. At the same time, contributors who gave to the same recipients were also more likely to contribute to one another, indicating increased local clustering among donors. This change overlaps with the entry of Tea Party-aligned candidates and documented increases in intra-party factionalization [67–69]. A contextual interpretation, consistent with accounts of Tea Party-era organizational conflict, is that reduced reliance on leadership-centered giving coincided with more within-group coordination among ideologically aligned subsets. Empirically, the decline in recipient centralization together with stronger donor clustering indicates reduced overall centralization [65]. This is consistent with movement away from a more hierarchical contribution organization described in some accounts of conservative coalitional structures [70]. We treat these links as interpretive rather than causal, but the timing aligns with scholarship documenting asymmetric polarization and related organizational change within the Republican coalition [65,67].

Democratic contributions, by contrast, remain consistently centralized across all seven election cycles, with giving concentrated among a small group of recipients. This stability aligns with evidence that Democratic leaders and committee chairs coordinate contributions to support incumbents in competitive races as part of an organized electoral strategy [17,64,71]. Reciprocity within the Democratic caucus remained low and relatively stable across cycles, consistent with contributions flowing from more electorally secure members to those facing competitive contests. Unlike Republicans, Democrats show no indication of a shift toward decentralized or locally clustered contribution activity over time. The persistence of centralization indicates that, despite ideological heterogeneity within the Democratic caucus, the main features of intra-party giving remain stable over the study period.

Seniority effects (measured by the total House terms served) differ between the parties. Among Democrats, seniority is positively associated with contributing and negatively associated with receiving, consistent with a structure in which senior members are net donors to junior colleagues [66,72]. Among Republicans, seniority effects are weaker on average and vary more across cycles. This is consistent with documented challenges to seniority-based authority after 2010, including

the Tea Party movement and the emergence of the Freedom Caucus [73,74]. Across both parties, the modest size of seniority effects is also consistent with broader changes in congressional fundraising. Newer members can increasingly raise funds through national donor networks, including SuperPAC activity and digital fundraising, reducing any mechanical link between tenure and fundraising capacity [15,75]. In this setting, long service may confer less incremental advantage for fundraising than in earlier periods, and junior members may be less dependent on senior colleagues for financial support.

Leadership status shows stronger and more consistent associations than seniority, particularly among Republicans. The similar estimates when leadership is measured before versus during the contribution period indicate that future leaders already contribute at higher rates prior to holding office, consistent with leadership selection from among high contributors rather than contributions rising only after appointment [11,16]. These findings are consistent with prior work showing that politically secure members contribute to co-partisans in competitive races as part of party electoral strategy [38,39,51,76–78]. Leadership associations are stronger among Republicans, consistent with formal office being a more informative correlate of contribution activity in a party where the seniority–giving association is weaker or less stable. Among Democrats, seniority is more consistently associated with giving, so leadership adds less incremental association. Together with the less centralized Republican network structure in our first research objective, these results are consistent with leaders having higher giving activity within a more dispersed system, without implying that giving is organized through a single coordinating center [64]. The weaker and more variable leadership estimates among Democrats in recent cycles are consistent with a fundraising environment in which caucus committees and outside groups account for a larger share of party resources, reducing the marginal relevance of formal leadership for direct member-to-member transfers.

Our third objective examines how SuperPAC activity relates to member-to-member contributions. The direction of the association is consistent across cycles: members targeted by more SuperPACs tend to receive more contributions and make fewer contributions to others, although effect sizes vary across cycles. This is consistent with external spending correlating with electoral risk: when SuperPACs invest heavily in a race, co-partisans are more likely to direct contributions to the targeted candidate and less likely to allocate contributions elsewhere. These findings extend prior research on SuperPAC influence by linking outside spending to intra-party transfers [19,25,79–84]. We do not claim causality because electoral vulnerability can affect both SuperPAC targeting and intra-party giving [57,85,86]. The stable direction of the estimates across cycles, however, is consistent with members responding to publicly observable information associated with outside spending. Several mechanisms are compatible with this association: heavy outside spending may increase the salience of targeted races, party actors may use public spending information when prioritizing races, or both outside and internal actors may respond to the same underlying signals of competitiveness. Although our design cannot distinguish among these pathways, the consistency across cycles suggests that the informational role of outside spending is not limited to a single election.

This relationship persists despite legal restrictions on coordination from *Citizens United* and related rulings. Outside spending is consistent with an informal signaling role: members targeted by multiple opposing SuperPACs receive especially large increases in intra-party contributions despite coordination prohibitions. Outside expenditures often identify competitive or high-priority races [17,20,23,87]. For example, in 2020, outside spending reached approximately \$8.40 million in Spanberger’s VA-07 (\$0.83 million support, \$7.56 million opposition) and \$7.36 million in Valadao’s CA-21 (\$0.33 million support, \$7.04 million opposition) [88,89]. These results show that SuperPAC activity is associated with where intra-party contribution ties concentrate during competitive elections [90]. Internal contribution rates declined slightly in the final cycle even as outside spending remained historically high, which is consistent with a signaling interpretation rather than a simple volume-based correspondence. More generally, the results indicate that the boundary between “internal” transfers and “external” spending is less sharp in practice than in formal law: SuperPAC visibility creates a shared information environment in which members observe risk signals and incorporate them into allocation decisions.

Taken together, our findings across the three research objectives show systematic differences in how Democrats and Republicans organize member-to-member contributions. Democratic contributions remain centralized throughout the study period, with giving concentrated among a small set of recipients. This is consistent with a hierarchical structure in which seniority is associated with giving activity, and leadership adds a modest incremental association, directing funds from electorally secure members to those in competitive races. Republican contributions, by contrast, shift from a similarly centralized structure toward a more dispersed one, with ties more evenly distributed across recipients and increasingly clustered among members who share contribution partners. Leadership status is a stronger and more consistent correlate of contribution activity among Republicans than among Democrats, even as overall Republican centralization declines. Seniority effects are weaker and less stable among Republicans, and the association between seniority and giving/receiving weakens over time in both parties, consistent with broader changes in fundraising as new members gain access to national donor networks through digital platforms and outside spending [15,75]. Finally, SuperPAC spending is associated with lower rates of contributing and higher rates of receiving, consistent with members responding to publicly observable signals linked to electoral risk. Although these associations are descriptive rather than causal, they show that intra-party contribution networks change over time and that the two parties respond to institutional and financial pressures differently.

This analysis has several limitations, each of which also suggests directions for future research. First, we model member-to-member contributions but do not incorporate additional relational information that may shape contribution decisions, such as ideological proximity, caucus membership, committee overlap, or co-sponsorship ties. This omission is consequential because it leaves open a central interpretive question: whether the associations we observe reflect strategic allocation to maximize party electoral outcomes, ideological alignment, or both. Future work integrating ideological and relational data could help distinguish these mechanisms. Second, House terms served is measured as the cumulative number of House terms served as of each cycle (see *Methods*). While this definition is invariant across cycles and better matches the intended seniority construct, it remains a proxy for institutional experience and does not reflect informal influence or committee-specific seniority that may matter for fundraising. Third, fundraising capacity varies widely across members. Representatives from safe districts may contribute to co-partisans in competitive races, and majority-party members may face stronger incentives to finance priority contests [38,53,71,91]. Because House campaigns draw heavily on national donor networks rather than relying solely on district-level contributions, future work could develop standardized measures of donor-base breadth by combining member-level fundraising totals with the geographic distribution of contributors [15,38]. Fourth, we do not include electoral competitiveness as a covariate because it can both affect and be affected by intra-party transfers, making it a post-treatment variable; we therefore treat competitiveness as an outcome for future research. Finally, each election cycle is modeled as an independent cross-section. Hierarchical or temporal ERGMs [40,92], latent space models, or party-structured frameworks could represent cross-cycle dependence more directly and may improve fit and estimation stability in future work. Such models could also test whether the organizational divergence we document between the two parties has continued, stabilized, or reversed in cycles beyond our study period.

Supporting information

S1 Table. Network statistics for the Money Flow Networks (MFNs) spanning seven election cycles from 2009–2010–2021–2022.

(PDF)

S2 Table. Alternative model specifications tested and reasons for non-adoption.

(PDF)

S3 Table. Mann-Whitney U test results comparing centrality distributions between leaders and non-leaders across election cycles, with separate results by party affiliation.

(PDF)

S4 Table. Super PAC activity data across election cycles, including counts of Super PACs and their expenditure types (supporting or opposing) by party.

(PDF)

S5 Table. Full ERGM results for Model 1 fitted to Democratic money flow networks. Log odds estimates are reported; confidence intervals were calculated as $\exp(\text{est.} \pm 1.96 * \text{SE})$.

(PDF)

S6 Table. Full ERGM results for Model 1 fitted to Republican money flow networks. Log odds estimates are reported; confidence intervals were calculated as $\exp(\text{est.} \pm 1.96 * \text{SE})$.

(PDF)

S7 Table. ERGM results for Model 1(a) fitted to Democratic money flow networks, with leadership status defined contemporaneously.

(PDF)

S8 Table. ERGM results for Model 1(a) fitted to Republican money flow networks, with leadership status defined contemporaneously.

(PDF)

S9 Table. ERGM results for Model 1(b) fitted to Democratic money flow networks, using Super PAC expenditure amounts instead of counts.

(PDF)

S10 Table. ERGM results for Model 1(b) fitted to Republican money flow networks, using Super PAC expenditure amounts instead of counts.

(PDF)

S1 Fig. Goodness-of-fit diagnostics for Model 1 across parties and election cycles. For each party-cycle combination, the observed network statistic (black line) is compared to the distribution of 100 simulated networks (boxplots). Panels (a)–(g) show Democratic networks and panels (h)–(n) show Republican networks from 2009–2010 to 2021–2022. See text for discussion of panel (n), which shows estimation challenges for the 2021–2022 Republican network.

(PDF)

S1 Method. Detailed procedures for data compilation, network construction, ERGM specification and estimation, model diagnostics, and robustness checks.

(PDF)

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