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Abstract

How do parties' donor networks change over time, based on year and industry? This paper analyzes the networks made up of the top fifty donor contributions to California State Assembly and Senate campaigns between 2011 and 2016. We wanted to find out if polarization in the networks increased over time, and which industries were most likely to donate to which parties. We isolated the five most common donor groups (**Health**, **Labor**, **Finance and Real Estate**, **General Business**, and **Agriculture**) to find each cycle's most frequent pairings, conducted a community detection algorithm to determine polarization, and ran a network regression to determine the probability of two groups donating to the same candidate. We found that the networks for California State Assembly and Senate donors became more polarized in every election cycle. **Health** and **Labor** groups donated most often to Democratic candidates, and **Business** and **Agriculture** ones did to Republicans; two donors from the same group had a higher chance of donating to the same candidate.

Introduction

It has been reported that polarization, which will be defined as separation and unwillingness to connect, between the two major United States political parties is increasing in recent years. This trend has been confirmed by studies done on polarization in legislatures and party convention delegates (Heaney 1654, Neal 103). Since many aspects of politics in America have become more polarized over time, it makes sense to understand how the rising trend of polarization has extended to the campaign donation landscape. Individuals and groups donate to one party's candidates to help them defeat those of the other party in elections, and spread their message to voters through advertisements (Robbins 12). One way to understand how donations affect polarization is through social network analysis. Interest groups and individuals are tied to candidates for office through donations to their campaigns. Social network analysis can allow us to understand and visualize the partisan communities that campaign donations fall into, as well as how networks of donors have changed over time.

This paper focuses on the partisan networks of donors to California's State Assembly and Senate candidates. We created networks of the top fifty combined donations amongst any two organizations or individuals to state legislative races to understand which groups of industries donated to which parties, used a community detection algorithm to separate the donors into partisan communities, and conducted a network regression to determine the likelihood of two actors from the same group donating to the same candidates. We found that polarization in campaign donations for both chambers of the California state legislature has increased because groups donating to each party increased their ties with each other and decreased cross-party ties. Health and Labor groups donated mostly to Democratic candidates and the other groups (Business and Agriculture) donated to Republican candidates. Also, donors from the same group had a 45-50% higher chance of donating to the same candidates.

This paper contributes to the literature on polarization and relationships between parties and industries, by providing a focus on California and extending the time coverage. Some past papers on this topic have covered similar trends in federal House and Senate races. We wanted to only focus on California because it was an influential state with socioeconomic trends that are reflected in the donor networks. A past paper written by Jacob Apkarian et al. looked at the donor networks of political campaigns in California in 2004. We would like to extend their findings to the 2010s to understand if these trends still hold in a decade known for increased political polarization; one can assume that California campaign donations became even more polarized in the years leading up to the 2016 election.

Literature Review

This research paper focuses on the networks formed by the top fifty donor contributions to candidates for the California State Assembly and Senate between 2011 and 2016. These donors include local party committees, businesses, labor unions, and health, finance and real estate institutions, and agricultural companies. The goal of this paper is to understand the composition and evolution of these donor networks. We chose to study California because it is a majority-Democratic state, so we wanted to find out what partisan donation patterns existed in a dominant-party state. It is also a very wealthy and influential state with a large wealth gap, which might be reflected in donation patterns. One reason is that the groups that primarily donate to each party (such as unions and businesses) represent the needs of the different socioeconomic classes.

Polarization and Campaign Donations

Past research focused on the existence of polarization in the networks formed between candidates and campaign donors. Matt Grossmann et al.'s paper found two distinct endorsement subnetworks, one for Democrats and one for Republicans. Most of the ties are within each subnetwork, and there are fewer ties between the subnetworks; there is one actor in the center, the International Brotherhood of Teamsters, that forms multiple ties with members of either community (Grossmann 782). Gregory Koger et al.'s paper, using a study of the ties formed between political groups' mailing lists, found that "two distinct and polarized networks are revealed, which correspond to a more liberal Democratic group and a more conservative Republican group" (Koger 633). These papers support our theory because they give background to the trends of interactions between the party subnetworks.

Relationships between Political Parties and Interest Group Donations

Past studies found that some industries tend to donate to one political party over the other, and these donation trends changed over time. Suzanne Robbins and Grossmann et al. found that in the 2000 and 2002 elections, labor groups mostly donated to Democrats, while other groups such as corporations mostly donated to Republicans (Robbins 8, Grossmann 773-774). Thomas Brunell found that the same broad industry categories mentioned in Robbins' paper donated to each party, but these partisan donation habits changed over time. Corporations began to donate more often to Republican candidates and less often to Democrats after 1994 (Brunell 685). James Gimpel et al. found that even though almost all of their studied industries that donated to one party favored Republicans, there were many that "exhibit[ed] no partisan preference" (Gimpel 1059). These papers provide evidence for our theory, but also provide nuance to it because they look at donation patterns across different industries.

Applications of Previous Findings

Donation networks are important to study because they provide insights into donor motivations. Some groups, according to past research, might use their expenditures to elect candidates whose views match theirs, while others might do so to develop relationships with them after they take office. Jacob Apkarian et al. named two motivations for campaign donations: the advancement of a group's ideology and interests, and found that "donors that contribute for ideological purposes are likely to support one political party" (Apkarian 5, 9). They found that social organizations might donate to candidates for "more complex" reasons, while businesses mostly do so to advance their own interests (Apkarian 12). Oliver Wouters found that the pharmaceutical and health industries made donations to support ballot measures in California in 2005 and 2016 (Wouters 693). Brunell concluded that interest groups donate to candidates because they have a stake in who the majority party in Congress is (Brunell 681).

The findings from past papers support our theory. They endorse one of our hypotheses, that Democratic candidates' donations mostly come from labor groups and Republicans' donations come from businesses. They also support our expectation that the donor networks will change over time. Grossmann et al.'s paper endorses our other hypothesis, that the donation networks are polarized (Grossmann 781). We would like to understand how the donor networks to California State Assembly and Senate candidates changed over time between 2011 and 2016, to expand on past findings.

Expectations

As the years progress, we believe that there will be a higher level of polarization in how party affiliated groups and top donors contribute to campaigns, as certain donors, especially from the top echelon, will be consistent to one political party with little cross-party interactions. We believe that this will lead to a higher level of network modularity, which we will define as more ingoing ties than outgoing ones within the two communities, formed by separations based on party affiliations. Modularity is "the density of connections within a module or community" ("Modularity Optimization"). To find the modularity of our Assembly and Senate networks for each election cycle, we will use community detection algorithms, which calculate the communities in a specific network to "evaluate how groups of nodes are clustered or partitioned, as well as their tendency to strengthen or break apart" ("Community Detection").

Also, we hypothesize that the top Republican donors will come from financial and business groups, the agriculture sector, and party affiliated committees, which are represented in an increase of ties between these donor groups. On the other hand, we believe that the majority of the Democratic donor base will come from labor groups, the public health sector, and grassroots organizations, which are also more likely to have closer ties.

Research Design

The California Assembly and Senate Donor Network dataset from 2011-2016 contains an edge list in which two actors who share a tie both donated to the same political candidate. Kevin Reuning, who created the dataset, "use[d] data from the National Institute on Money in Politics (NIMP) to generate party donation networks," as "NIMP has aggregated donations in state legislative elections from 2000 to 2016" (Reuning 271). Our data is representative of the electoral donation network we were interested in, as the source itself came from an aggregate coverage of donations over a period of time from an accredited institution.

After wrangling our data, we were able to visualize the directed network of the top fifty aggregate contributions between any two donor connections in California for Democratic and Republican candidates in the Assembly and Senate races every electoral year from 2011-2016. The ties represent the sum of the money the two donors both gave to one candidate. Using this data, we colored the network's edges according to whether both actors donated over 50% of their contributions towards either the Democratic or Republican Party candidates where blue represents the former and red the latter. Afterwards, we applied an optimal community detection algorithm, which uses the combination of shared edges between the nodes, in order to form subgroups or communities intent on ensuring that the calculated network modularity is maximized. Network modularity scores calculate the proportion of ingoing ties actors share within various subgroups to outgoing ties between actors throughout the entire network. So, a higher modularity score means that our community detection algorithm was more successful in isolating the various sub-communities bolstered by the inherent structure of shared ties between donors in our entire network. Thus, our six visualizations for each respective State Assembly and Senate race from 2011-16 include the party affiliation of the candidate donors contributed to in any respective tie through the edge coloring along with groupings based on proximity and shared ties output from the optimal algorithm. Both visual elements allow us to determine whether there are any patterns among donor motivations per year and if they change as the years progress. Also, our purpose in choosing to combine both communities along with network modularity measures is to both explore sub-communities within the majority-Democratic state of California, considering the majority of the actors contributed towards Democratic candidates, as well as to see if donors displayed bipartisan behavior by funding candidates from both parties. Also, the formulated communities amongst the most influential donors lead us to investigate our second motivating question regarding the importance of donors sharing similar traits, such as industry categorization, as well as overall financial contributions in forming ties.

To address our second hypothesis in an exploration of descriptive statistical analysis, we isolated ties in our network that contained actors that came from these groups: **Health**, **Labor**, **Finance and Real Estate**, **General Business**, or **Agriculture**. We chose to isolate these five groups because they were the top 25% most frequent categories of donors across all five years who contributed overwhelmingly above 50% to either party, outside of uncoded groups or ones that were only prominent in one election cycle. Because we wanted to explore which groups were more likely to donate to either party, we decided to isolate the top two most frequently represented donor categories for both parties. Thus, we found that **Health** and **Labor** donors contributed mostly to Democratic candidates, while **General Business** and **Agriculture** groups donated more frequently to Republican candidates. On the other hand, our final group, **Finance and Real Estate**, was interestingly prominent among donors for both Democratic and Republican candidates, so we wanted to ensure that we would be able to determine the true impact of groups, party affiliations, and donor ties by including a group that was both a consistent and bipartisan donor as well.

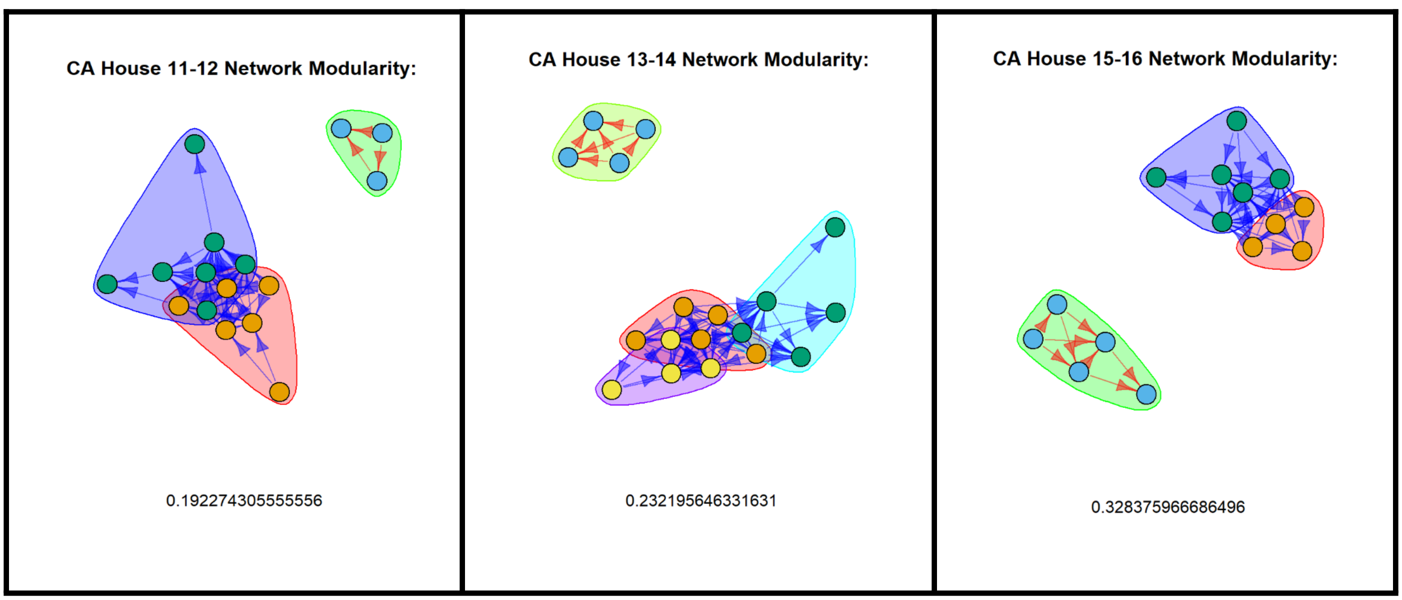
In order to understand how the majority of ties were formed across the five categories isolated above, we decided to create a probability matrix that displayed the proportion of a tie being present between any one pairing, such as **Agriculture-Agriculture** compared to **Agriculture-General Business**. Our twelve probability matrices are based on a single electoral year for both the Assembly and Senate election cycles from 2011-16, in which a higher numerical value represented a higher level of ties between two of the four groups, including ties between the same categories. There is a Democratic probability matrix that isolates the distribution of ties between categories of those who donated over 50% to Democratic candidates and one that likewise is reflective of those who donated over 50% to Republican candidates. However, our probability matrix was not able to determine the true frequency of all pairing between the five groups, as **Health-Labor** and **Labor-Health** were separated into different entries. Thus, we implemented a function that outputs a listed ranking of all fifteen possible pairings, which gives us the true representation of the most likely pairings per year. We decided to isolate the top five most frequent pairings per year, as we set a threshold of 0.10 to determine if a tie between groups was more significant. These matrices and rankings allowed us to take a closer look at the overall data and distribution of ties present amongst the donor base, especially if the groups we claimed were more likely to donate to either group were, in fact, the most frequent contributors prominent in the top five pairings.

Finally, we decided to implement a network regression model in order to find tangible results to determine if donors formed ties or funded the same candidate, based on whether or not they came from the same industry, had similar total contributions, and had similar percent breakdowns of their funds donated to either party. The binary dependent variable is if ties exist in the form of an adjacency matrix, which, as stated above, represents whether any two actors supported the same candidate in any given Assembly or Senate race. We made stacked adjacency matrices for the independent variables (continuous variables: PerDem difference, PerRep difference, absolute difference in total contributions + binary variable if same group) for network regression model across all six datasets to ensure we have all actors who belong to our groups. To test if having the same group matters in forming ties and if groups had political affiliations, we included these combinations: **Health** and **Labor** (for Democratic ties), **General Business** and **Agriculture** (for Republican ties), and **Finance and Real Estate** (for Democratic and Republican ties). **Finance and Real Estate** was placed to test the party affiliation as a metric of comparison as the “neutral” industry.

Our purpose in including all these attributes is to better understand how different aspects of campaign funding including the tension between larger and smaller donors along with those that fund multiple candidates versus only one impact how ties are formed in campaign contributor networks. Also, we want to expand on our theory that certain organizations or groups have expectations or needs that are met by either party’s ideals and goals based on socioeconomic factors associated with certain careers, as well as, most importantly, income levels and status. For example, a union may want to donate to the Democratic Party so that it can raise money for candidates that support Democratic policies on workers' rights. Thus, an increase in ties between popular Democratic donors in public health and labor groups would support our hypothesis that those groups are more targeted and aligned with the Democratic Party. Likewise, we also want to address whether donors of a certain financial status are more likely to form ties amongst themselves essentially leading to a higher level of subgroups within each party's donor network as addressed in the result of our community detection algorithm. For example, big businesses may donate to Republicans, the party of deregulation, so that they can elect candidates that want businesses to pay less money in taxes.

Discussion of Results

Network Visualizations[1]



[1] In our graphs, we will be referring to the California State Assembly as the "House," because it has the same position in the California legislature as the US House.

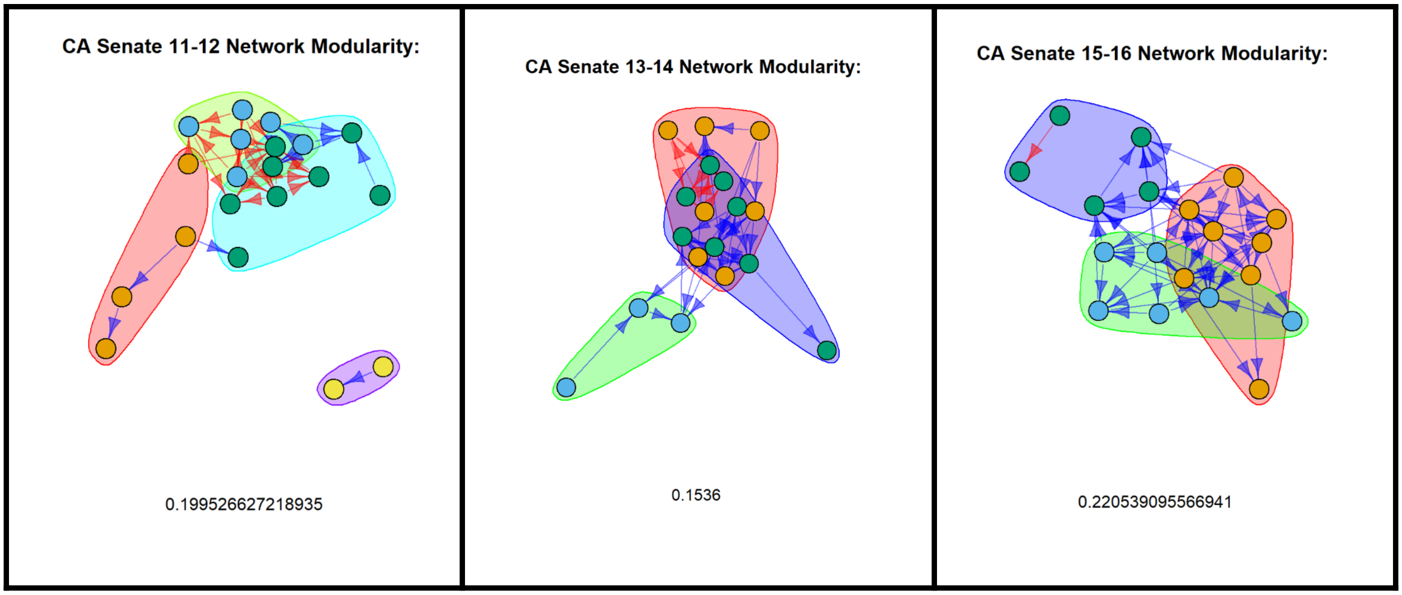


Figure 1. Top fifty California State Assembly and Senate donor transaction networks (2011-2016), which display the most influential actors involved in campaign funding. The differently-colored nodes and node groupings represent different communities of donors. Blue ties represent both donors contributing to a Democratic candidate, while red indicates both actors funding a Republican candidate.

Community Detection Algorithm and Modularity Results

CA House 11-12		CA House 13-14		CA House 15-16	
	Modularity: 0.19		Modularity: 0.23		Modularity: 0.33
Community	**Donors**	**Community**	**Donors**	**Community**	**Donors**
Blue	3 Republicans	Blue	4 Republicans	Blue	5 Republicans
Green	7 Democrats	Green	5 Democrats	Green	6 Democrats
Orange	3 Democrats	Orange	5 Democrats	Orange	4 Democrats
NA	NA	Yellow	4 Democrats	NA	NA
	13 Total Donors		18 Total Donors		15 Total Donors

Figure 2. The modularity results of the community detection algorithms for the California State Assembly donor networks, 2011-2016, split up by party.

CA Senate 11-12		CA Senate 13-14		CA Senate 15-16	
	Modularity: 0.20		Modularity: 0.15		Modularity: 0.22
Community	Donors	Community	Donors	Community	Donors
Blue	6 Republicans	Blue	3 Republicans	Blue	6 Republicans
Green	8 Democrats	Green	8 Democrats	Green	5 Democrats
Orange	4 Democrats	Orange	7 Democrats	Orange	8 Democrats
Yellow	2 Democrats	NA	NA	NA	NA
	20 Total Donors		18 Total Donors		19 Total Donors

Figure 3. The modularity results of the community detection algorithms for the California State Senate donor networks, 2011-2016, split up by party.

Our calculations determined how the top fifty donor transactions representative of the most influential financial contributors to California State Assembly and Senate campaigns were grouped, and detected any patterns in the partisan donor networks. We wanted to determine the level of polarization per election cycle among the highest donors, to see if they exhibited a tendency to only form ties within their own party group. We identified two Assembly donor networks: the Democratic network, made of two or three closely connected communities, and the Republican network, made of one community with members that became more connected over time. The networks became more polarized from 2011 to 2016 because Democratic donors became more connected to other Democratic donors, while both parties' nodes became less connected and formed fewer ties with each other's nodes. The Republican network grew by one donor each cycle as well. In 2011-2012, there were fewer ties formed between both networks; the two parts of the Democratic network were not as connected to each other and there were only three directed ties in the Republican one. By 2015-2016, the Democratic network had more ties between its two subsections, while the Republican network's nodes had more ties between its own members. The network modularity increased every electoral cycle for the California State Assembly, indicating a growing level of polarization and willingness of the partisan networks to only form ties with each other. The Assembly network had many repeating donors. As California is a majority-Democratic state, there is some factor that leads to subgroups being formed within the larger contributor circles, even with party donor networks.

The networks of donors to California State Senate campaigns also became more polarized between 2011 and 2016. In 2011-2012, there were three closely connected bipartisan communities, while there was a smaller network that consisted of two Democratic donors. There were many Republican donor ties and fewer Democratic ones. In 2013-2014, while there were still bipartisan ties in the two most closely connected networks, there were significantly fewer; there were more Democratic donor ties than in 2011-2012. There were two bipartisan communities. 2015-2016 was the most polarized year. The number of Democratic donor ties significantly increased to the point that almost all the ties in that network were between Democratic donors. There was only one tie between Republican donors, which were separate from the other nodes and part of the only bipartisan community. This is because there were only two Republican donors in the top fifty donor transactions in 2015-2016. The Senate's network had more unique donors than the Assembly's. For both the Assembly and Senate data, most of the consistent donors from one election cycle to the next were party committees. There were not as many unique non-party donors, so the party networks for the State Senate were not that diverse as those for the State Assembly.

The network modularity score remained somewhat consistent in the California State Senate races for the top fifty donor contributions from 2011-2016. It is important to note, however, that the donor networks were less polarized in terms of party affiliation, as communities were not so much based on Democratic versus Republican inclinations, but rather another factor, especially from 2011-14. The Republican influence in the most important donor circles in terms of financial contributions dropped significantly in the 2015-16 race, which also indicates the extremely polarized environment during that time period, especially due to the upcoming presidential election, in comparison to previous years. The Republican Senate donor network in 2015-2016 reflects the network of the Assembly.

Descriptive Statistics

The following tables will show the top five highest proportions of donor pairings, separated by general group of donors, in each year from 2011 to 2016. **Labor** groups consistently formed ties to others in the Democratic donor coalition, and **Business** groups did so for the Republican coalition; the top tie partners of **Labor** and **Business** changed throughout the election cycles. It is important to understand the proportions of tie pairings because the data can be used to analyze the motivations of campaign donors. The Democratic donor network is more diverse than the Republican one, because it is not dominated by one donor pairing. The differences between each of the top five proportions in the Republican donor network are larger than those in the Democratic donor network.

CA House 11-12

Democrat Pairings	D
Labor-Labor	0.13
Finance-Health	0.12
Health-Labor	0.11
Finance-Labor	0.10
Finance-Business	0.10

CA House 13-14

Democrat Pairings	D
Health-Labor	0.12
Finance-Health	0.11
Labor-Labor	0.11
Finance-Labor	0.10
Finance-Business	0.09

CA House 15-16

Democrat Pairings	D
Health-Labor	0.13
Finance-Health	0.11
Finance-Labor	0.10
Labor-Labor	0.10
Business-Health	0.09

Figure 4. The top five most frequent pairings for the Democratic Party for California State Assembly, 2011-16[2]

CA House 11-12		CA House 13-14		CA House 15-16	
Republican Pairings	R	Republican Pairings	R	Republican Pairings	R
Finance-Business	0.16	Business-Agriculture	0.16	Finance-Business	0.19
Finance-Agriculture	0.14	Finance-Business	0.14	Business-Agriculture	0.14
Business-Agriculture	0.12	Finance-Agriculture	0.11	Finance-Agriculture	0.12
Agriculture-Agriculture	0.11	Agriculture-Agricultur	0.09	Finance-Finance	0.12
Finance-Health	0.10	Finance-Health	0.09	Finance-Health	0.09

Figure 5. The top five most frequent pairings for the Republican Party for California State Assembly, 2011-16

In 2011-2012, the highest proportion of donor ties to Democratic candidates for the Assembly was **Labor-Labor**. For donors to Republicans, the pairing that had the highest proportion of ties was **Finance-Business**. All five major groups showed up in the 2011-2012 election pairing data, and will do so in successive election cycles. The highest proportion of ties between donors to Democratic candidates in 2013-2014 was **Health-Labor**. For donors to Republicans, the pairing with the highest proportion of ties that year was **Business-Agriculture**. The proportion of **Health-Labor** donor ties increased by 0.01 between 2011-2012 and 2013-2014, and the proportion of **Labor-Labor** ties decreased by 0.02. The proportion of **Business-Agriculture** ties increased by 0.04 between 2011-2012 and 2013-2014, while the proportion of **Finance-Business** ties decreased by 0.02. The highest proportion of Democratic donor ties in 2015-2016 was **Health-Labor**, the same one as 2013-2014. The proportion of **Health-Labor** ties increased by 0.01. **Business-Health** became a prominent donor pair in 2015-2016 because pharmaceutical companies were a major donor in 2016. For Republican

[2] The Finance and Real Estate groups in our data are listed as "Finance" in the graphs and discussion.

donors, the highest proportion was the **Finance-Business** pair, the highest proportion in our Assembly data. The proportions of ties made by **Finance-Business** groups increased by 0.05 between 2013-2014 and 2015-2016. **Agriculture** groups decreased in prominence in 2015-2016 because ties made between them and other groups took up two, as compared to three, of the places on the top five donors list.

Overall, **Health and Labor** groups form the majority of the more loyal Democratic donor base, though **Labor** donors are more likely to share a tie with one another while two **Health** groups are less likely to do so. **Labor** groups consistently are a top supporter for all the years we looked at. **Finance** groups that donate to Democratic campaigns also are tied to **Labor** and **Health** groups that do so, instead of to other **Finance** groups. On the other hand, **General Business, Finance, and Agriculture** groups form the majority of the Republican donor support with various pairings that are more frequent some years, such as the earlier prominence of **Agriculture** groups compared to the later dominance of **Finance** groups**. Business** groups remained a consistent top supporter across all the years.

CA Senate 11-12		CA Senate 13-14		CA Senate 15-16	
Democrat Pairings	D	Democrat Pairings	D	Democrat Pairings	D
Labor-Labor	0.16	Health-Labor	0.15	Health-Labor	0.12
Health-Labor	0.14	Finance-Health	0.14	Finance-Health	0.11
Finance-Labor	0.14	Finance-Labor	0.11	Finance-Labor	0.10
Business-Labor	0.11	Labor-Labor	0.10	Business-Health	0.10
Finance-Health	0.09	Health-Health	0.10	Business-Labor	0.09

Figure 6. The top five most frequent pairings for the Democratic Party for California Senate, 2011-16

CA Senate 11-12 Republican Pairings	R	CA Senate 13-14 Republican Pairings	R	CA Senate 15-16 Republican Pairings	R
Finance-Business	0.18	Business-Agriculture	0.18	Finance-Business	0.33
Finance-Health	0.15	Finance-Agriculture	0.18	Finance-Finance	0.21
Finance-Finance	0.13	Finance-Business	0.16	Business-Business	0.14
Finance-Agriculture	0.12	Agriculture-Agricultur	0.12	Finance-Health	0.09
Business-Health	0.10	Finance-Finance	0.08	Business-Health	0.09

Figure 7. The top five most frequent pairings for the Republican Party for California Senate, 2011-16

In 2011-2012, the highest proportion of donor ties to Democratic campaigns to California's Senate candidates was **Labor-Labor**. For groups that donated to Republicans, the highest proportion of ties was between the **Finance-General Business** pair, which made up a larger proportion of ties than **Labor-Labor** did. The highest proportion of Democratic donor ties in 2013-2014 was **Health-Labor** (which was larger than the previous year's value). The proportion of **Labor-Labor** ties dropped by 0.04. For Republican donors, the highest proportion was the **General Business-Agriculture** pair, which was not on the list of the top five donors in 2011-2012. The proportion of **Finance-Business** ties dropped by 0.02. The highest proportion of Democratic donor ties in 2015-2016 was **Health-Labor**, the same as the previous election cycle, though the proportions were relatively smaller. For Republican donors, the highest proportion was between the **Finance-General Business** (the highest values out of all the years for the proportion of ties) with a notable zero **Labor-Labor** and **Health-Labor** ties in total and no mention of **Agriculture** donor groups.

Overall, the Senate donor category per each party trends similarly to the results from the Assembly. As in the Assembly data, the most prominent Democratic donors are from the **Health** and **Labor** industries, while the most prominent Republican ones are from the **Business** and

Finance industries. The Senate and Assembly donor networks differ because **Agriculture** is noted to have less prominence in the 2015-16 race, while both **Finance** and **General Business** dominate the majority of fundings for that race with little to no presence of any **Health** or **Labor** Republican donor groups. Also, the highest percentages for the Senate donor pairings are higher than the top percentages for the Assembly donor ones.

Network Regression Results

The tables below represent the results when we isolated the groups, along with the previously-mentioned independent and dependent variables. As such, we found that when two donors are of the same industry, they are much more likely to have a connection or a tie. As part of our research process, we initially used both an ERGM and netlogit model, in which our only independent variables were whether two donors were of the same group and the absolute difference in total contributions made by both donors. Our ERGM contained a high level of degeneracy as our predictive attributes had an infinite coefficient. Likewise, the netlogit model also output infinite coefficients for the attribute testing whether two donors were of the same group, as that variable was almost always significant in how the model was able to correctly predict whether a tie was present amongst two donors. Thus, we realized that neither an ERGM nor a netlogit model could actually present definitive results, due to the high level of degeneracy present in both, unlike our network regression model. Also, at this point, we did not add **Finance and Real Estate** as a group that could be considered in our filtered data; however, we found that adding that industry as an option in our data and model reduced our same group estimate in the network regression model.

Network Regression Models to Determine the Presence of Ties between Two Donors

Estimates	CA House 11-12	CA House 13-14	CA House 15-16
Intercept	0.04	0.06	0.06
Same Group	0.48	**0.50**	0.46
Difference in Contributions	0.00	0.00	0.00
Difference in PerDem (%)	0.01	0.02	0.02
Difference in PerRep (%)	0.01	NA	NA

Figure 8. Network Regression Model Estimates for California State Assembly, 2011-16. The bolded value represents the highest estimate for the same group attribute found amongst the model results for the State Assembly and Senate data.

Estimates	CA Senate 11-12	CA Senate 13-14	CA Senate 15-16
Intercept	0.08	0.10	**0.14**
Same Group	0.45	0.45	0.46
Difference in Contributions	0.00	0.00	0.00
Difference in PerDem (%)	0.01	0.01	0.02
Difference in PerRep (%)	NA	NA	NA

Figure 9. Network Regression Model Estimates for California State Senate 2011-16. The bolded value represents the highest intercept estimate found amongst the model results for the California State Assembly and Senate data, which implies that, regardless of the attributes used in the model, there was a higher level of ties present amongst the 2015-16 California State Senate donor networks. This is because more donors might have wanted to form ties with each other in the polarizing 2015-2016 election cycle.

Looking at the summary statistics or specifically the attribute specific estimates, for the majority of the electoral years in both the State Assembly and Senate in all the years specified, there was a 45-50% higher likelihood of two donors funding the same candidates, assuming that two donors were from the same group. Out of all of our independent variables, the same group variable proved to be the only statistically significant factor in how ties between donors form. For the majority of the other attributes, it is important to note that many of these explanations are unique to the political and economic composition of California.

Regarding the influence of party affiliation, California is such a majority Democratic state that the groups that were more likely to donate to Republicans were not reflected enough in our isolated data. As such, when looking at the difference in the percentage a donor contributes to either party candidates, it is important to note that the majority of the top fifty donor transactions were in the Health and Labor industries as well as in political party groups from our community detection algorithm and description statistic results above. There is no Republican majority industry, because there are only a few Republican donors amongst the top contributors for the California State Assembly and Senate elections. Because the industries isolated in our model other than Finance and Real Estate are so coded and demonstrative of strong party affiliation, the difference between PerDem and PerRep funds for any ties has a minimal impact on ties forming, considering how most donors are very partisan in nature and they perhaps donate to multiple candidates within the same party. Very rarely is there a 50% contribution for each partisan; essentially, California State Assembly and Senate races have rather polarized donor bases. Also, as mentioned earlier, we chose California as our case study because it is a very influential actor in state politics, especially in Democratic states, and very wealthy, but it also has a substantial wealth gap. The difference in contributions is not as significant when forming ties, because it is possible that many small donors attach themselves to larger ones that hold more influence. Michael Malbin found that there are differences in the causes that smaller and larger donors support, which are aligned with their social and economic interests (Malbin 388). Small and large donors donate to candidates who are on different points on the ideological spectrum (Malbin 396-397). The majority of the top donors come from party affiliated groups or other political organizations, though many of the top donor base industries, such as Health and Labor, show up in the top fifty campaign contributions.

For our network regression model, when we set a condition that PerDem or PerRep >= 50% vs. removing it, we found little to no difference in estimates compared to adding Finance, a more balanced group type. Our second hypothesis is correct because party affiliations already run so deep among our predicted group pairings and party association. These donors from those chosen groups already donate almost all money to their party of choice; the difference in total contribution and loyalty to either party is insignificant, compared to donors coming from the same group. In our previous models, we found a high level of degeneracy and infinite coefficients for the same groups attribute in our ERGM model and similar results in our netlogit one, which always predicted a tie and had a 97% chance of predicting when there was no tie. After seeing the results of all three models, though we felt only our network regression model was fit to use as evidence because of the higher estimate within a reasonable range, we concluded that predicting ties in our donor network based on donors coming from the same industry is very accurate.

Donor bases reflect how party policies and plans do take into account the needs of those funding campaigns. Groups are so eager to donate to the party they are associated with for ideological or other motivations; this is the main factor in forming ties because the other attributes are already given. Mapping donor behaviors and recognizing why Democratic policies address concerns of **Health** and **Labor** organizations vs. Republicans with **Agriculture**, **Finance** and **Real Estate**, and **General Businesses** have become increasingly important. As the political atmosphere becomes more polarized and less bipartisan laws pass, largely due to who is more likely to support which groups, the parties' demands likewise also grow further and further apart, contributing more to the future plans of either party. This corroborates the previous literature on small donor behavior in that they cling to larger, more influential ones.

Conclusion

We found that polarization has increased in the networks of donors to California State Assembly and Senate campaigns from 2011 to 2016, proving our first hypothesis that it would increase. The increases in polarization were larger in the Senate's networks than in the Assembly's, but the effects were noteworthy for both chambers. Polarization was represented in our Assembly data through an increase in the ties between the Democratic sub-communities and the Republican nodes. It was represented in our Senate data through an increase in Democratic ties, especially those between the Democratic subnetworks, and a decrease in bipartisan communities. We found that **Health** and **Labor** groups were the most common donors to Democratic candidates, and that **Business** and **Finance** groups were consistently a top donor to Republican candidates. We found that **Business-Health** was a prominent donor pair in 2015-2016, so those donations might have had an impact on the election of California State Assembly and Senate candidates who supported drug pricing reform. The importance of the **Agriculture** group for both chambers of the California legislature decreased over time, while it was consistently a Republican donor. In addition, we found that two donors from the same industry group have a higher chance of donating to the same candidate than others from different groups did. Our second hypothesis about which groups would donate to which political parties is proven correct.

Our descriptive statistics have shown that **Health** and **Labor** were very Democratic-coded industries, because there was a high proportion of ties present with donors from these industries donating over 50% of their contributions to Democratic candidates. They have also proven that **Business** and **Agriculture** were very Republican-coded industries, for the same reason. These industries, which are already partisan, show results that the majority of donors will donate to others in their group, leading to more intraparty collaboration. Cross-industry ties (e.g. ties between **Health** and **Labor** groups) between donors backing the same candidate exist because of party affiliation, not because of status or financial level. This is also connected to the results of the community detection algorithm, in which donor networks become more polarized every year based on party affiliation.

Overall, this paper adds a new dimension to the current research on campaign finance and polarization. We have shown that past connections between political parties and groups of donors still exist in the 2010s, and found more evidence of polarization in campaign donor networks that we applied to California. In the future, we would like to conduct a similar study on a state where donor networks are more bipartisan to see if the networks are different. We may also like to compare the party networks of states that represent both ends of the red-blue binary and the industries we have looked at in this paper (e.g. a state with a strong agricultural industry or a large number of people in unions). We may find that the networks are not as polarized in swing or less dominant-party states, because the donors are likely to donate to both parties.

Appendix

CA House 11-12

Democrat Pairings	D	Republican Pairings	R
Labor-Labor	0.13	Finance-Business	0.16
Finance-Health	0.12	Finance-Agriculture	0.14
Health-Labor	0.11	Business-Agriculture	0.12
Finance-Labor	0.10	Agriculture-Agriculture	0.11
Finance-Business	0.10	Finance-Health	0.10

Figure 10. The top five most frequent pairings per party for California State Assembly 2011-12

CA House 13-14

Democrat Pairings	D	Republican Pairings	R
Health-Labor	0.12	Business-Agriculture	0.16
Finance-Health	0.11	Finance-Business	0.14
Labor-Labor	0.11	Finance-Agriculture	0.11
Finance-Labor	0.10	Agriculture-Agriculture	0.09
Finance-Business	0.09	Finance-Health	0.09

Figure 11. The top five most frequent pairing per party for California State Assembly 2013-14

CA House 15-16

Democrat Pairings	D	Republican Pairings	R
Health-Labor	0.13	Finance-Business	0.19
Finance-Health	0.11	Business-Agriculture	0.14
Finance-Labor	0.10	Finance-Agriculture	0.12
Labor-Labor	0.10	Finance-Finance	0.12
Business-Health	0.09	Finance-Health	0.09

Figure 12. The top five most frequent pairing per party for California State Assembly 2015-16

CA Senate 11-12

Democrat Pairings	D	Republican Pairings	R
Labor-Labor	0.16	Finance-Business	0.18
Health-Labor	0.14	Finance-Health	0.15
Finance-Labor	0.14	Finance-Finance	0.13
Business-Labor	0.11	Finance-Agriculture	0.12
Finance-Health	0.09	Business-Health	0.10

Figure 13. The top five most frequent pairings per party for California Senate 2011-12

CA Senate 13-14

Democrat Pairings	D	Republican Pairings	R
Health-Labor	0.15	Business-Agriculture	0.18
Finance-Health	0.14	Finance-Agriculture	0.18
Finance-Labor	0.11	Finance-Business	0.16
Labor-Labor	0.10	Agriculture-Agriculture	0.12
Health-Health	0.10	Finance-Finance	0.08

Figure 14. The top five most frequent pairings per party for California Senate 2013-14

CA Senate 15-16

Democrat Pairings	D	Republican Pairings	R
Health-Labor	0.12	Finance-Business	0.33
Finance-Health	0.11	Finance-Finance	0.21
Finance-Labor	0.10	Business-Business	0.14
Business-Health	0.10	Finance-Health	0.09
Business-Labor	0.09	Business-Health	0.09

Figure 15. The top five most frequent pairings per party for California Senate 2015-16

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