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Primary Elections, Endorsements, and Campaign Funding

Data Overview

These datasets were provided by course staff to aid our analysis:

1) Demographic, electoral, and endorsement data for Senate, House, and governor candidates in the 2022 primary elections via Primary Project [link]
2) 2022 Senate Campaign Financing Data via the Federal Election Commission of the United States of America [link]
3) 2022 House of Representatives Campaign Financing Data via the Federal Election Commission of the United States of America [link]

We also used an additional outside dataset to supplement our research:

1) Database on Ideology, Money in Politics, and Elections (DIME) via Stanford University Social Science Data Collection [link]

The DIME dataset contains information on candidates' ideological stances, which we used as a confounder in our model. It also includes the funding data found in the FEC datasets, which we ultimately used in our final analysis.

All of these datasets are censuses as they contain information on the entire population of candidates who ran for congressional positions in the 2022 midterm elections. Candidates running in elections in Louisiana were left out of the Primary Project's dataset on endorsements for unknown reasons.

One major concern in our dataset is that of convenience sampling. In a population as large as every candidate running for any congressional position in the 2022 primary elections, it is easy to miss out on lesser-known candidates who may not have a lot of data on them. This was evident as the size of our datasets mismatched, and not all candidates who were represented in the Stanford University DIME dataset were represented in the endorsements dataset. Since our second research question uses the DIME dataset, we were only able to include candidates who were present in all of our datasets, potentially leaving out candidates with less campaign funds and/or few to no endorsements.

Some important potential confounding features that we did not have in our data were the candidate's age, religious affiliation, professional experience, and education level. Our group attempted to find data on these variables, but a dataset containing this information for all congressional candidates across America does not exist.

Our dataset contained some missing values for runoff outcomes and within the endorsement columns. There were only a handful of candidates who had unknown runoff outcomes, so we dropped those entries. For candidates with null values under a specific endorsement, we went under the presumption that null meant the candidate was not endorsed by the organization. This assumption was verified as we could not find any evidence of an endorsement on the internet for such situations.

We conducted extensive cleaning between our datasets. The biggest challenge was merging the datasets, as our primary identifier, candidate name, had mismatching formats. To fix this, we used fuzzy matching, which assigns similarity scores for candidate names in different datasets. Once we implemented the matching and set a threshold that yielded a good amount of matches, we verified the matches by making sure the similar features between datasets, such as ‘Party’ and ‘State’, were the same. This process allowed us to match 2016 unique candidates between our Stanford DIME dataset and our Primary Project dataset on demographic and endorsement data. Some candidates may have been dropped if they were not present in both datasets, or if the formatting of their name between the two datasets was so dissimilar that they did not meet the threshold. However, due to our validation method, we were able to set the threshold relatively low, so almost all candidates with matches were retained.

Our data preprocessing included binarizing our outcome column, dummy encoding categorical variables, and scaling numerical variables.

Prior Work

Ferguson, Jorgensen & Chen

In their study “How Money Drives US Congressional Elections” (Ferguson, T., Jorgensen, P., & Chen, J. (2016), the authors use a spatial Bayesian latent instrumental variable model to analyze whether money influences election outcomes. This study seeks to answer a similar question to our second research question, which is to prove a causal relationship between campaign funding and election outcomes. However, this study observed general elections rather than primary elections. Their initial approach is similar to ours; they regress the difference in Democratic and Republican vote share on the difference in campaign spending. However, proving causality is trickier due to the dilemma of reverse causality. It is hard to find valid, observed instrumental variables to use in this case, so they decided to use the spatial, Bayesian latent instrumental variables to consider spatial correlations between districts. They use candidate popularity as their unobserved instrumental variable and use Bayesian inference to estimate the posterior distribution. This new model finds a slightly reduced causal effect of money on outcomes, but the effect is still significant. By using a linear model, we might overestimate the causal effect of funding on primary election outcomes because it does not consider reverse causality.

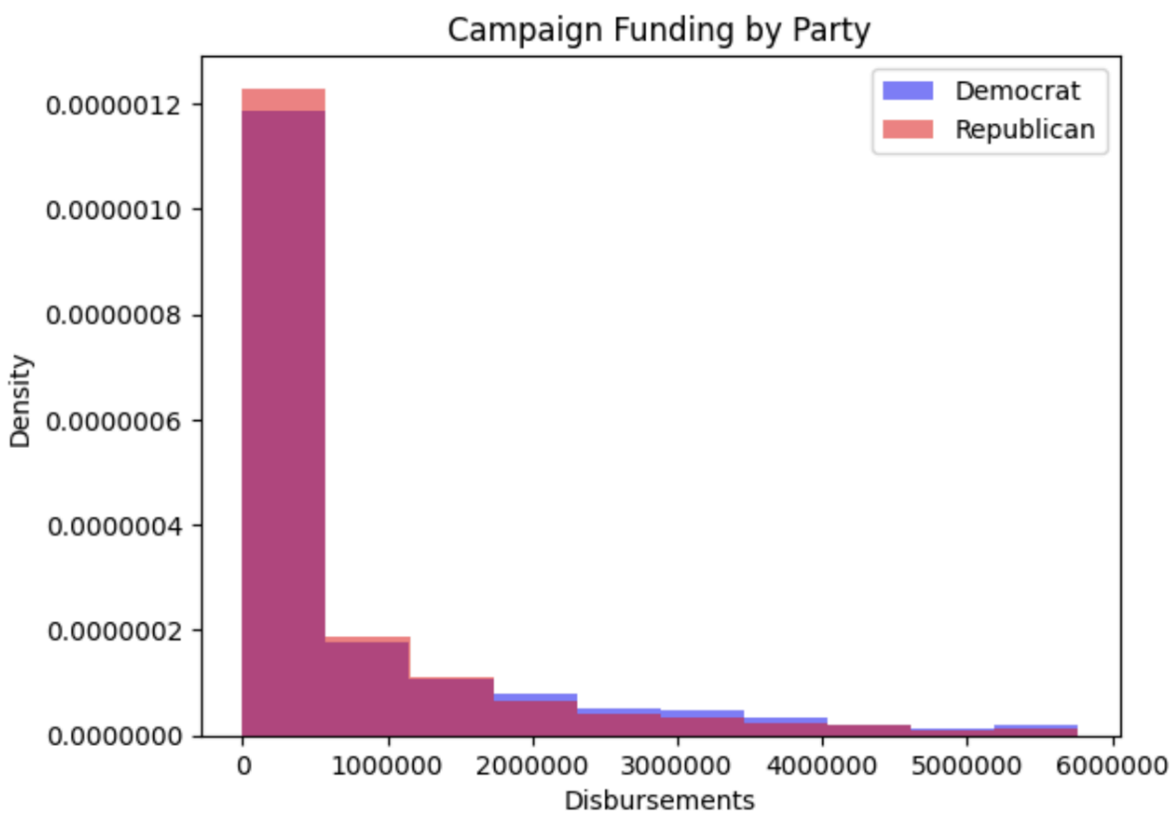
Boudreau

In another 2016 paper titled "The Persuasion Effects of Political Endorsements" by Cheryl Boudreau, the author provides both theoretical and empirical justification for how endorsements by political organizations influence elections. The paper acknowledges that endorsements can serve as a proxy for information to uninformed voters who lack detailed knowledge on political issues, and that endorsements by well-established or elite groups can have a significant impact on voter decisions. The paper also provides an overview of empirical evidence for the persuasion effects of political endorsements, indicating that endorsements can help voters make decisions that better align with their preferences, but impacts vary significantly depending on the endorser's credibility.

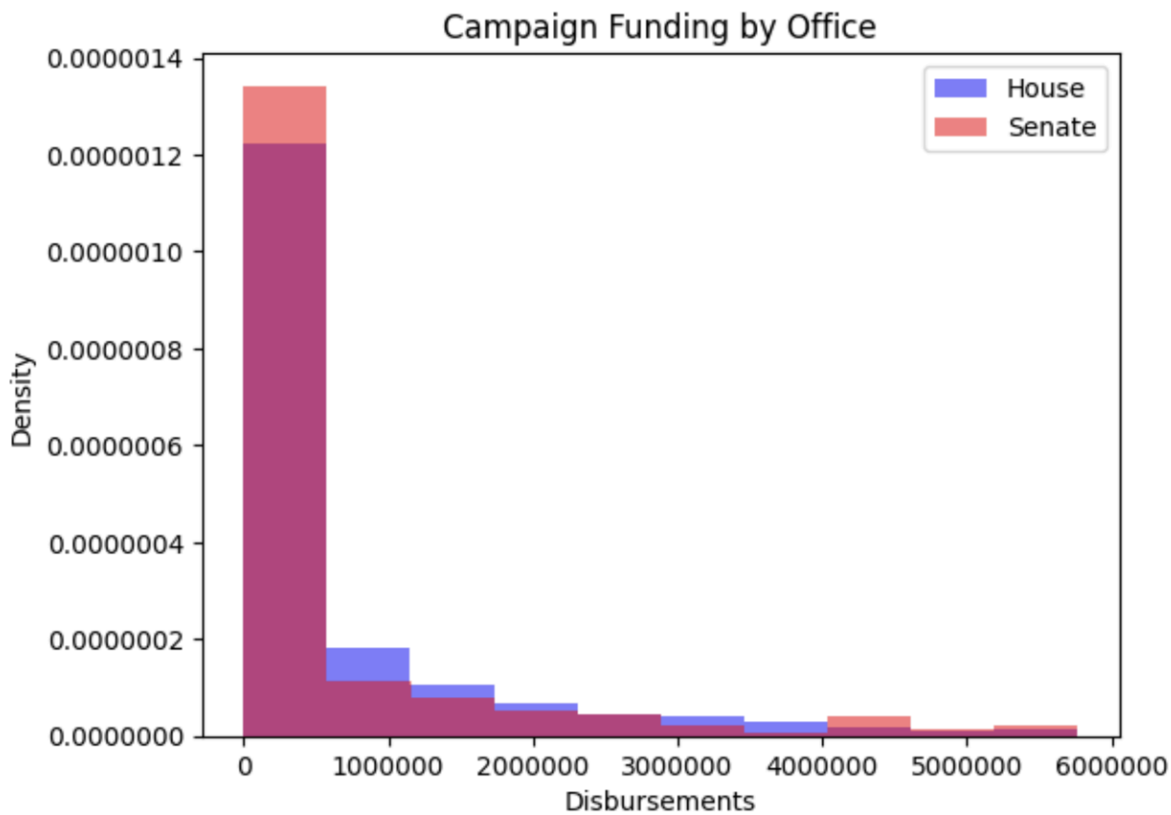
Exploratory Data Analysis

Campaign Funding

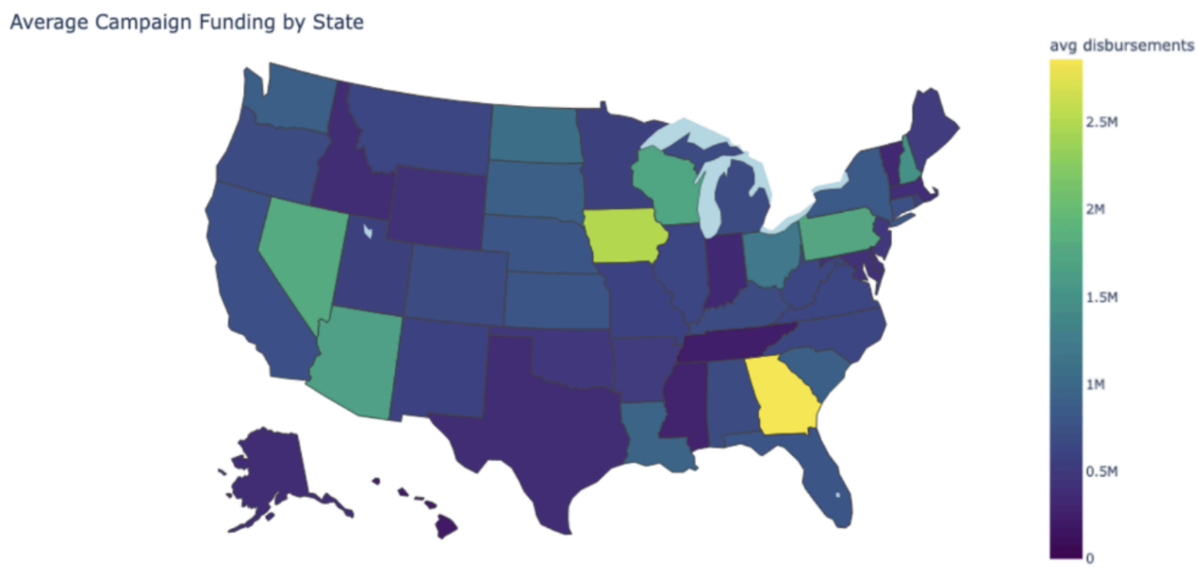
Based on our graphs, Democrats tend to have slightly higher-funded campaigns than



Republicans. This means that the party could be a confounding variable.



Senate campaign funding is more varied when compared to House campaigns, which see a lower spread in their distribution. A potential hypothesis for this is that Senate seats are deemed more important than House seats due to the fact that there are fewer of them, and races in contentious states can attract the attention of donors across the nation, causing extreme outliers in our campaign funding dataset.

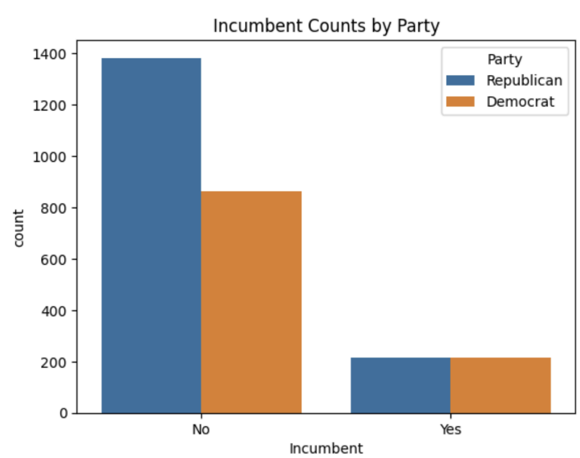


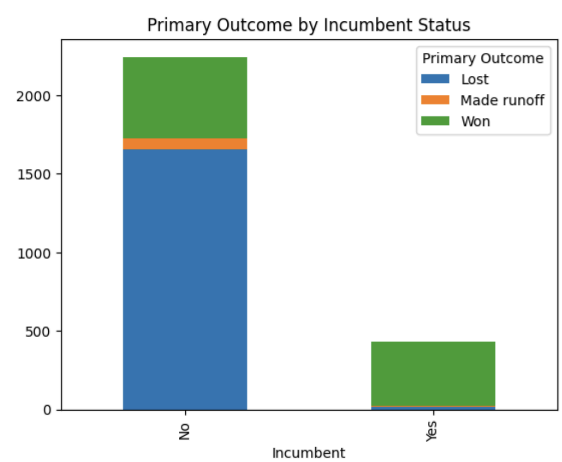
Traditional swing states have higher campaign funding, on average. This suggests that a candidate's state is a confounding variable.

Wins Above Replacement (WAR)

WAR is a metric used to measure how well candidates performed in an election compared to how they "should have" performed based on a number of different factors. We pulled this variable from the Split Ticket WAR Database. However, after performing EDA on the dataset, we learned that there was difficulty merging the WAR dataset with the Primary Project dataset. Therefore, we decided to use binary election results as our outcome variable instead of WAR.

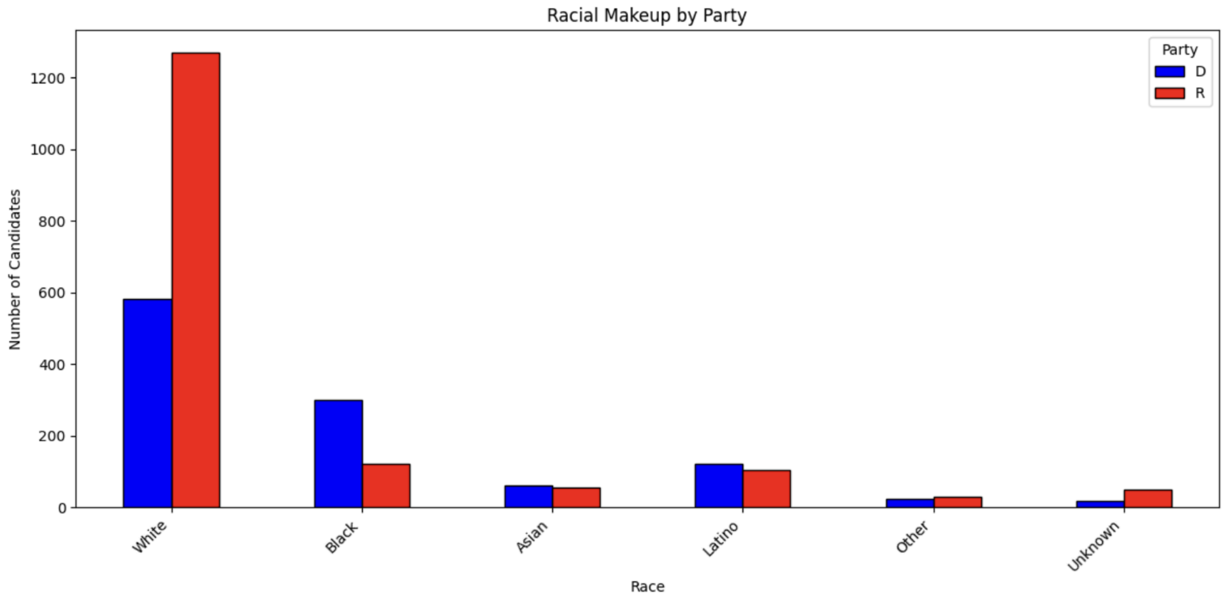
Incumbency





There are a similar number of incumbent candidates in the democratic and republican parties, but there are 521 more non-incumbent candidates in the republican party. Candidates are much more likely to lose if they are not incumbents. This means that incumbency may be another confounding variable in our study.

Race



There may be a correlation between race and party, with Republicans having notably more white candidates. This could contribute to collinearity in our model.

First Research Question

- **Question:** How are different political endorsements associated with the success of candidates in the 2022 primaries?
- **Regressor variable:** A binary treatment variable for each endorser, either 1 or 0, indicating whether a candidate was endorsed by the given endorser or not.
  - In the original dataset, the endorsement variable can take the values “yes”, meaning the candidate was endorsed, “N/A”, meaning the endorser did not weigh in on the candidate, or “no”, meaning the endorser opposed the candidate. For the purposes of this study, “yes” will mean they’re an endorsed candidate (T=1), and “N/A” and “no” mean they’re an unendorsed candidate (T=0). This does raise a limitation in our study, since we are not directly acknowledging how opposition from endorsers is associated with the election outcome.
  - Confounders were also included in the regression model as regressor variables, and they are discussed below.
- **Outcome variable:** Categorical election variable, which takes the values “Yes”, “No”, or “Run-off”. We processed this outcome variable to be a binary variable indicating a win or a loss by converting “Run-off” to the results of the run-off election. This presents a

limitation in our study due to the potential of endorsement status changing between the initial election and the run-off election.

Methodology

In order to answer the question of how political endorsements from different endorsers are associated with the election outcome, we will use multiple hypothesis testing. It makes sense to use multiple hypothesis testing as opposed to one hypothesis test because there are a number of different possible endorsements a candidate can receive, each of which could have a different association with the election outcome. Our null hypothesis states that, for a given endorser, the proportion of endorsed candidates that won is equal to the proportion of unendorsed candidates that won. Our alternative hypothesis states that, for a given endorser, the proportion of endorsed candidates that won is not equal to the proportion of unendorsed candidates that won. For example, if we are looking at the Maggie's List endorsement, the null hypothesis would be that the proportion of candidates endorsed by Maggie's List who won is equal to the proportion of candidates not endorsed by Maggie's List who won. Moreover, the alternative hypothesis would be that the proportion of candidates endorsed by Maggie's List who won is not equal to the proportion of candidates not endorsed by Maggie's List who won. The statistical powers for all 15 of the hypothesis tests run, which range from 0.51 to 0.63, can be found in the tables in our results section.

To test these hypotheses, we will be running a logistic regression with an input variable for each possible endorsement, which will output a beta coefficient and a p-value for each possible endorsement. Based on a significant level of 0.05, we will either reject the null hypothesis if the p-value is less than 0.05, or fail to reject the null hypothesis otherwise. Therefore, we will be rejecting or failing to reject the null hypothesis based on the probability of getting the observed difference in proportions between the treatment and control groups if the null hypothesis is true. We will be looking at the association, as opposed to any causal effect, because the data is not randomized, and there is a wide range of potential confounding variables that make it difficult to make causal claims about the data.

Next, to correct for the multiple hypothesis tests, we will use Benjamin-Hochberg (B-H) procedure and Bonferroni Correction. We will implement the B-H procedure to identify which political endorsements have statistically significant differences between the endorsed candidates and unendorsed candidates using an adjusted threshold based on the observed p-values. B-H procedure is a way to control the false discovery rate (FDR) by sorting p-values produced in a regression and indexing them, and then finding the largest p-value that is less than your desired FDR threshold. The desired FDR threshold is determined by taking the desired FDR, dividing it by the number of p-values, and multiplying it by the index value of a given p-value. Finally, we use the largest p-value that is less than the desired FDR threshold as the new significance level threshold to determine whether to reject or fail to reject the null hypothesis. By controlling for

FDR, we are ensuring that the expected proportion of discoveries that were wrong in our particular decisions does not exceed a certain value. Here are the steps of the B-H procedure:

1. Sort p-values (indexed by k, starting at 1 for the smallest p-value and going up to m, the largest p-value)
2. Draw the line $y(k) = \frac{\alpha}{m}k$
3. Find the largest p-value that's under the line
4. Use that p-value as the threshold

In addition to using the B-H procedure and controlling for FDR, we will also run the Bonferroni Correction procedure, which controls the family-wise error rate (FWER). The family-wise error rate is the probability of any false positives across all of our hypothesis tests, and therefore is a more conservative correction method than the B-H procedure. Bonferroni Correction works by using a p-value threshold of the desired FWER divided by the number of p-values (m). We then reject the null hypothesis for all p-values that are less than the threshold value, and fail to reject the null hypothesis for all other p-values. The Bonferroni Correction method is very conservative, meaning that it will fail to reject the null hypothesis in more cases than any other method used in this study.

The big difference between the B-H procedure and the Bonferroni Correction is the error rate that they each control for. B-H controls for FDR, the expected proportion of discoveries that were wrong in our particular decisions, whereas Bonferroni Correction controls for FWER, the probability of any false positives across all tests. This means that FWER is a more conservative estimate since it looks at avoiding false positives at all costs, as opposed to FDR, which looks at the number of false positives in proportion to the number of tests. Therefore, B-H is a more dynamic correction method that allows for more false positives as the number of tests run increases. The results section provides an in-depth comparison of the number of discoveries that each correction method makes.

Data Limitations and Approaches

Candidates with multiple endorsements

By running a multivariate logistic regression with a regressor variable for each possible endorsement a candidate could receive, we are taking into account all other endorsements when looking at the coefficient and p-value produced by one endorsement variable.

Run-off elections

Some elections do not have a binary outcome and instead go into a run-off election. We do not have enough data to account for the potential changes in endorsements during a run-off election, so we will be assuming that endorsement status does not change in the event of a run-off election.

Confounders

By running two separate regressions, one on the democrat dataset and one on the republican dataset, we are accounting for political party as a confounding variable.

In our logistic regression for each political party dataset, we included the following available variables as confounders:

- Incumbent status
- State
- Gender
- Race

We attempted to include the election district as a confounding variable, but ran into issues of multicollinearity and singularity. Therefore, it was determined that the regression results would be stronger without using the district as a confounding variable.

Data Cleaning

In order to prepare the candidate datasets for regression analysis and hypothesis testing, the following steps were taken:

- Created a "Final Outcome" column, containing a binary indicator for whether the candidate won or lost the primary based on the outcome of the election or the run-off election
- Removed any candidates with missing data in crucial fields (e.g., election outcome missing)
- Converted "N/A" entries in endorsement columns to boolean False entries to make endorsements all binary columns (as our treatment or control classification)
- One-hot encoded all categorical variables into binary columns

Results

Republican Candidates

Endorser	coefficient	p-value	Std. Error	Naive Reject ($p < 0.05$)	Bonferroni Reject	BH corrected p-value	BH Reject	TP	FP	TN	FN	Power (TPR)
Trump	3.5369	1.26E-17	0.4138	TRUE	TRUE	8.85E-17	TRUE	282	40	1067	203	0.5814
E-PAC	3.1208	8.3E-07	0.6333	TRUE	TRUE	2.91E-06	TRUE	261	39	1068	224	0.5381
Maggie's List	2.1909	2.72E-06	0.467	TRUE	TRUE	6.3E-06	TRUE	261	55	1052	224	0.5381
Club for Growth	3.2958	3.6E-06	0.7113	TRUE	TRUE	6.3E-06	TRUE	260	36	1071	225	0.5361
Renew America	-5.8172	4.62E-06	1.2697	TRUE	TRUE	6.46E-06	TRUE	249	30	1077	236	0.5134

Winning for Women	2.1828	0.0002	0.5951	TRUE	TRUE	0.0003	TRUE	257	53	1054	228	0.5299
VIEW PAC	1.2948	0.0019	0.4167	TRUE	TRUE	0.0019	TRUE	252	35	1072	233	0.5196

Democratic Candidates

Endorser	coefficient	p-value	Std. Error	Naive Reject ($p<0.05$)	Bonferroni Reject	BH-corrected p-value	BH Reject	TP	FP	TN	FN	Power (TPR)
EMILY's List	2.2583	1.9E-05	0.4788	TRUE	TRUE	1.9E-05	TRUE	294	53	541	177	0.6242
Sanders	1.2426	0.0452	0.6203	TRUE	FALSE	0.1806	FALSE	299	68	526	172	0.6348
Indivisible	0.9686	0.0869	0.5658	FALSE	FALSE	0.2318	FALSE	299	68	526	172	0.6348
Our Revolution	0.702	0.1883	0.5336	FALSE	FALSE	0.3765	FALSE	300	71	523	171	0.6369
PCCC	-0.6746	0.285	0.631	FALSE	FALSE	0.4561	FALSE	300	67	527	171	0.6369
AOC	0.546	0.4983	0.8061	FALSE	FALSE	0.6643	FALSE	299	69	525	172	0.6348
Justice Dems	0.4731	0.5965	0.8934	FALSE	FALSE	0.6816	FALSE	299	68	526	172	0.6348
Sunrise	0.158534	0.846	0.8163	FALSE	FALSE	0.846	FALSE	298	68	526	173	0.6327

Table 1 shows the results of the hypothesis tests on endorsements of republican candidates. For republican endorsements under the naive hypothesis tests, we reject the null hypothesis for all possible endorsers, meaning that the probability of seeing the observed election results is less than 5% if the null hypothesis is true for all possible endorsements of republican candidates in our study. Even after applying the Bonferroni Correction and the B-H correction, all seven of the hypothesis tests still reject the null hypothesis. This means that we reject the null hypothesis even under the most conservative correction, which indicates a strong association between endorsements and election success.

Table 2 shows the results of the hypothesis tests on endorsements of Democratic candidates. For democrat endorsements under the naive hypothesis tests, we only reject the null hypothesis for Emily's List and Sanders endorsements, and we fail to reject the null hypothesis for Invisible, Our Revolution, PCCC, AOC, Justice Dems, and Sunrise endorsements. This means that we can only say that the probability of seeing the observed election results is less than 5% if the null hypothesis is true for Emily's List and Sanders endorsed candidates, but other observed results of endorsements are more than 5% likely under the null hypothesis. After applying the Bonferroni Correction and B-H procedure, we can only reject the null hypothesis for Emily's List-endorsed candidates, whereas we now fail to reject the null hypothesis for all other endorsements of Democratic candidates. This means that, in general, Democratic candidate endorsements do not have a strong association with election success.

As mentioned in the methods section above, the Bonferroni Correction method and B-H procedures are two separate correction methods that differ in the error rate they control for and how conservative their results are. Bonferroni Correction is a more conservative method that controls for FWER, the probability of any false positives across all hypothesis tests. B-H procedure is a less conservative method that controls for FDR, the expected proportion of discoveries that were wrong in our particular decisions. Bonferroni Correction is more conservative because it penalizes any false positives across all hypothesis tests, whereas B-H allows for higher p-values as the number of tests increases.

Discussion

After applying the Bonferroni Correction method to the republican candidates' regression results, no hypothesis testing results changed. This is because the regression results for all of the republican candidate endorsers yielded very small p-values, indicating a low probability of seeing the observed data if the null hypothesis were true. On the other hand, after applying the Bonferroni Correction method to the Democratic candidates' regression results, the hypothesis test for Sanders' endorsement changes to fail to reject the null hypothesis. All other democrat results remain the same. This is likely due to the fact that the p-value for the Sanders endorsement regression results in 0.0452, which is very close to the threshold significance level of 0.05. After applying the correction method, the threshold value drops well below 0.0452, and we fail to reject the null for Sanders endorsements.

Similarly, after applying the B-H procedure to the republican candidates' regression results, no hypothesis testing results changed. This makes sense and complements the Bonferroni Correction results, because B-H is less conservative than Bonferroni and therefore it will reject at least as many, if not more, hypothesis tests. Moreover, after applying the B-H procedure to the Democratic candidates' results, the only change is seen in the Sanders endorsement hypothesis test again. Even with the relatively less conservative method of B-H, we still see Sanders' endorsement results change due to how close its p-value is to the naive threshold.

Based on the results from the republican candidate results, it should be considered highly influential on election results for republican candidates to get endorsements from any possible endorsement party included in the study. Even after applying correction methods, we reject the null hypothesis for all endorsements of republicans, meaning that it is highly unlikely that endorsements are not changing the election results of candidates. However, since our alternative hypothesis is that the proportion of wins differs, not necessarily increases, we cannot say whether these results indicate whether a republican candidate will have more success with an endorsement. In order to determine how each endorsement changes the success of a candidate, the beta coefficient values must be assessed. The coefficients show that the Renew America endorsement actually decreases the election win proportion for endorsed candidates, and all other endorsements increase the election win proportion for endorsed candidates.

Based on the results from the Democratic candidate results, there is no clear influence of political endorsements at a significance level of 0.05, except for candidates endorsed by Emily's List. For all endorsements other than Emily's List, endorsed candidates may or may not differ in their election win proportion. For Emily's List-endorsed candidates, we still reject the null hypothesis even after applying correction methods, and the beta coefficient is positive, so we can expect an increase in election win proportion for candidates endorsed by Emily's List.

The main limitation of this multiple hypothesis testing is that we may not have included all possible confounding variables. There are a number of different demographic variables, region-specific variables (e.g., election district), and funding-related variables that we did not have access to or have issues of singularity or multicollinearity with. However, our results avoided p-hacking because we included all possible political endorsements and did not drop outlier candidates from the tests.

If we had access to more data, specifically the confounding variables, these results would call for a causal inference test. Considering that we reject the null hypothesis for all republican endorsements, a causal inference test may give a better idea of how exactly endorsements influence republican candidates. However, the democrat endorsement results were relatively insignificant, so further testing may not reveal much about democrat endorsements.

Similar to our results, the research paper titled "Manipulation through political endorsements" published by Mehmet Ekmekci in 2009, also found that political endorsements can sway election results in favor of the endorsed candidate. This study considered a non-binary election with a third, less prominent party, so its results are far more complex than our results. However, this paper does, in summary, complement our results.

Second Research Question

- **Question:** What is the causal relationship between campaign funding and primary election outcomes?

Methodology

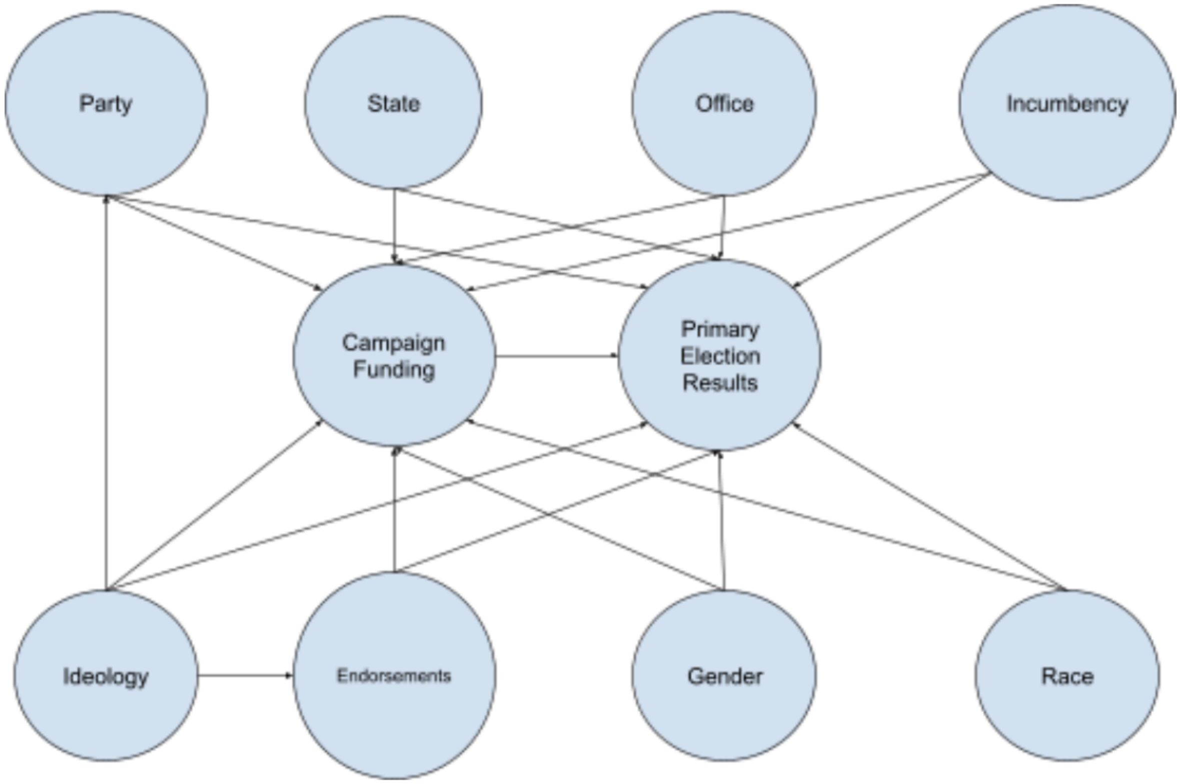
For this causal inference study, we are examining the relationship between the treatment variable of campaign funding and the outcome variable of primary election results. Campaign funding describes the total disbursements made by a candidate on their campaign during an election cycle, and the primary result describes whether the candidate won or lost their primary election. For confounders, we decided to use variables representing state, party, office, endorsements, gender, race, ideology, and incumbency. All of the variables were binarized, besides ideology, which is a continuous numerical metric developed by the Stanford DIME Database to measure candidates' ideology on a scale from liberal to conservative. Below are the justifications for each of these variables as confounders, or why they affect both the treatment and outcome:

- **State:** Certain states are more competitive than others, affecting a candidate's ability to win their primary election. States with wealthier populations might also have better connections to donors with more money, affecting campaign funding.
- **Party:** Parties have different patterns of voting, which affects election outcomes, and also different access to donor networks and funding.
- **Office:** Winning a Senate primary and winning a House primary may have different levels of difficulty, affecting a candidate's success. Senate candidates may receive more funding than House candidates (or vice versa).
- **Endorsements:** Candidates endorsed by certain political organizations may have a better chance at winning their primary election, and donors may be more likely to allocate funding towards candidates with high endorsements.
- **Gender:** Due to potential biases among voters, women may have a harder time winning primaries than men. In addition, women face disparities in access to political funding (Sudulich et al., 2024).
- **Race:** Similar to gender, voters may have biased preferences towards white candidates, and minorities have historically faced structural barriers to accessing campaign funding (Page, 2024).
- **Ideology:** Ideological alignment is an important factor for both voter selections and donor decisions for doling out funding.
- **Incumbency:** Incumbents face many advantages in elections, both in receiving more funding and having more popularity among voters (Campbell, 1983; Fouirnaies & Hall, 2014).

We believe that these variables encompass all of the possible measurable confounders, and thus, the unconfoundedness assumption holds for this study.

Causal DAG

Below is a directed acyclic graph outlining the relationships between variables considered in our study.



To adjust for confounders in our analysis, we used outcome regression to estimate the conditional relationship between our treatment and outcome, given all the confounders. Because our treatment variable is continuous and our outcome variable is binary, we modeled this problem using logistic regression. With this setup, the coefficient for the campaign funding variable in our regression model was thus used as our estimate for the causal effect on the primary election outcome.

Results

Feature Importance based on Regression Model

Feature	Coefficient	Odds Ratio	P-Value	Statistical Significance
Trump	3.753	42.643	2.63492112761706E-08	Significant
Party Committee	3.722	41.357	0.000543536044827537	Significant
Incumbent_Yes	3.085	21.877	5.99584612595799E-19	Significant
Campaign Funding	**1.605**	**4.978**	**2.61342816573512E-07**	**Significant**
State_Massachusetts	1.124	3.078	0.228648811312296	Not Significant
Sanders	1.096	2.994	0.249241373830397	Not Significant

State_South Carolina	1.094	2.985	0.181248660864239	Not Significant
State_Connecticut	0.936	2.549	0.317738059326534	Not Significant
State_Indiana	0.927	2.527	0.180097754037665	Not Significant
E-PAC	0.904	2.469	0.235684788536713	Not Significant
Club for Growth	0.894	2.445	0.200304051292121	Not Significant
State_Tennessee	0.846	2.33	0.265552969794331	Not Significant
State_Minnesota	0.839	2.314	0.309625263561068	Not Significant
Our Revolution	0.807	2.241	0.275506925100185	Not Significant
Race_Unknown	0.762	2.144	0.394640902814419	Not Significant
EMILY'S List	0.738	2.091	0.164199102437319	Not Significant
State_Kansas	0.723	2.062	0.429236483328668	Not Significant
State_Arkansas	0.723	2.06	0.534591963563732	Not Significant
Maggie's List	0.665	1.945	0.302752920596702	Not Significant
State_Idaho	0.659	1.933	0.582658286821638	Not Significant
State_Kentucky	0.625	1.869	0.407965930122952	Not Significant
State_Utah	0.602	1.825	0.625746200372833	Not Significant
Race_White	0.548	1.73	0.14012166320715	Not Significant
State_Colorado	0.487	1.627	0.492799422017194	Not Significant
State_North Dakota	0.487	1.627	0.723385337376696	Not Significant
Indivisible	0.452	1.572	0.54187756786694	Not Significant
State_New York	0.348	1.416	0.570308506721408	Not Significant
Ideology Score	0.346	1.414	0.1665831657836	Not Significant
State_South Dakota	0.341	1.406	0.86975410599677	Not Significant
Race_Native American	0.32	1.377	0.733406977365701	Not Significant
State_Washington	0.319	1.376	0.631938184640878	Not Significant
Race_Pacific Islander	0.31	1.363	0.89535969447471	Not Significant
State_Delaware	0.291	1.338	0.884929849755522	Not Significant
Justice Dems	0.272	1.313	0.85526817494141	Not Significant
Race_Latino	0.271	1.312	0.52492678580255	Not Significant
Race_Black	0.258	1.295	0.515111217452536	Not Significant
State_New Mexico	0.25	1.285	0.809472408385348	Not Significant
State_Vermont	0.249	1.283	0.79567102890287	Not Significant
State_Mississippi	0.229	1.258	0.807644760032555	Not Significant
State_Maine	0.222	1.249	0.879125809305286	Not Significant
State_Rhode Island	0.203	1.225	0.823015302830552	Not Significant
State_Alaska	0.188	1.207	0.890961233537961	Not Significant
State_Iowa	0.121	1.129	0.89362271164587	Not Significant

State_West Virginia	0.073	1.076	0.962574540182911	Not Significant
State_California	0.069	1.071	0.9036690641913	Not Significant
AOC	0.056	1.058	0.973466914174261	Not Significant
State_Wisconsin	0.052	1.053	0.94342672455339	Not Significant
Winning for Women	-0.05	0.951	0.958869197633482	Not Significant
State_Nebraska	-0.076	0.926	0.946145469040717	Not Significant
Sunrise	-0.105	0.9	0.932691258365229	Not Significant
State_Hawaii	-0.119	0.887	0.894313621110251	Not Significant
State_Maryland	-0.181	0.834	0.786262944748805	Not Significant
State_New Jersey	-0.181	0.834	0.788060974656126	Not Significant
State_Wyoming	-0.183	0.833	0.888059827655002	Not Significant
Gender_Male	-0.199	0.819	0.209346695860214	Not Significant
State_Missouri	-0.317	0.728	0.614529045228478	Not Significant
State_Ohio	-0.327	0.721	0.60468513387029	Not Significant
State_Pennsylvania	-0.459	0.632	0.474979962789451	Not Significant
State_North Carolina	-0.486	0.615	0.423822292649174	Not Significant
State_Oregon	-0.512	0.599	0.448011332455308	Not Significant
State_New Hampshire	-0.577	0.562	0.48682516632354	Not Significant
State_Michigan	-0.582	0.559	0.370831055214057	Not Significant
Office_Senator (unexpired term)	-0.588	0.555	0.44081454377799	Not Significant
State_Virginia	-0.638	0.528	0.332911468277389	Not Significant
State_Texas	-0.703	0.495	0.223541104073406	Not Significant
State_Florida	-0.763	0.466	0.183622464374957	Not Significant
State_Oklahoma	-0.773	0.462	0.285581324490353	Not Significant
State_Arizona	-0.797	0.451	0.26293900288781	Not Significant
State_Montana	-0.817	0.442	0.36547452883728	Not Significant
Race_Middle Eastern	-1.061	0.346	0.274568074932	Not Significant
State_Illinois	-1.205	0.3	0.0501659867523153	Not Significant
Party_R	-1.263	0.283	0.0128606734824444	Significant
State_Georgia	-1.306	0.271	0.042964548972832	Significant
PCCC	-1.309	0.27	0.0832407052260843	Not Significant
VIEW PAC	-1.401	0.246	0.0569795311032829	Not Significant
State_Nevada	-1.431	0.239	0.0763980807820286	Not Significant
Renew America	-1.563	0.21	0.2497531222803	Not Significant
Office_Senator	-1.622	0.198	3.67689852888281E-08	Significant
Incumbent Challenger_Yes	-4.318	0.013	1.53231507291267E-19	Significant

This table shows the coefficients on each feature of our logistic regression model and the respective odds ratio, as well as the statistical significance of each estimate. The odds ratio describes how much each feature increases a candidate's odds of winning their primary election, according to the model. For example, if the value of a binary feature was 3.5, this implies that a candidate having that feature multiplies their odds of winning by 3.5. Similarly, if the odds ratio is negative, a candidate having that feature decreases their odds. For continuous variables such as campaign funding and ideology score, the features were scaled such that the coefficient describes how the odds of winning would increase or decrease for a standard deviation change in the predictor. The p-value for each feature describes whether there is statistically significant evidence that the given feature has an impact on the election outcome. We use a threshold of 0.05 to determine statistical significance.

The coefficient of Campaign Funding in the model was 1.605, and the resulting odds ratio was 4.978. The standard deviation of Campaign Funding before scaling is approximately 825,000. This means that for each $825,000 increase in campaign funding, the candidate's odds of winning their primary increase by nearly 5 times. Our model found that this was statistically significant, so it is highly probable that campaign funding has a true effect on election outcome, and this estimate is not due to random noise in our data. In order for this to be a causal effect, we must assume unconfoundedness, meaning that there are no other variables besides state, party, office, endorsements, gender, race, ideology, and incumbency that would impact both the amount of funding received and the outcome of primary elections.

Although the model suggests a causal link between campaign funding and election outcome, our model found several other features that were stronger predictors of primary election outcome. Being endorsed by either President Trump or the candidate's respective Party Committee multiplies the odds of winning by around 40, and holding incumbent status multiplies the odds of winning by just over 20. Additionally, challenging an incumbent significantly decreases a candidate's odds of winning. In total, our model found eight features that have a significant causal impact on the election outcome, assuming unconfoundedness.

Discussion

One limitation of our study is the lack of inclusion of a direct variable representing candidate quality. Candidate quality is an important confounder that may impact both campaign funding and the primary election outcome. While certain variables we used, such as ideology, incumbency, and endorsements, can be considered proxies for candidate quality, there is no publicly available data assessing a quantifiable measure of candidate quality. Furthermore, data on other proxies for candidate quality, like education and experience, were not available for use in this study. Other intangible characteristics of political candidates may also act as confounders and undermine the necessary assumptions we made for causal inference.

Given this limitation, we are still confident that the association between campaign funding and primary election outcome is causal. Campaign funding allows candidates to increase their success in a number of ways, including targeted advertisements for voters and the capacity for hiring qualified campaign staff. This finding is supported by a myriad of past literature (Ferguson et al., 2016; Koerth, 2018; Schuster, 2020). Existing research, both empirical and theoretical, finds a causal link between campaign funding and election results; however, the extent to which it does varies across studies. For example, some studies find that funding has a much stronger impact on new candidates, compared to incumbents. One possible alternative explanation for the correlation between campaign funding and election outcome is that candidates who are already primed to be successful receive more donations, raising the question of whether there may be a degree of reverse causality.

Conclusion

Our first research question sought to examine the correlation between various political endorsements and the success of the endorsed candidate. Through the use of multiple hypothesis testing and Bonferroni and Benjamini-Hochberg correction methods, we found that the effectiveness of endorsements varies, and there are significant differences between the effectiveness of endorsements for Republican and Democratic candidates. For Democratic candidates, we were only able to find statistically significant correlations between endorsements from Bernie Sanders and EMILY’s List. In comparison, every single endorsement we observed for Republicans had a statistically significant correlation with a candidate's success. What we can take away from this is that among Democrats, endorsements from Bernie Sanders and EMILY’s List may help improve a candidate’s chance of success, while on the Republican side, an endorsement from any of the organizations in our study may help a candidate. One limitation of this study is that our multiple hypothesis testing does not consider confounders and thus can not prove a causal relationship between endorsements and candidate success. One very obvious potential confounder could be the candidate's popularity before being endorsed. Perhaps an organization only endorses candidates that it believes have a high chance of winning their primary. This would lead to a strong relationship between the endorsement and candidate success, but not necessarily a causal one. A future study could run causal inference on our statistically significant endorsements to prove a causal relationship between the endorsement and a candidate's success.

Some domain knowledge we would like to seek out is how these organizations choose which candidates to endorse. Perhaps some organizations strategically pick candidates to help them win in a close race. Other organizations may pick purely based on which candidate most aligns with their political values. This could give us a better insight into the true value of these endorsements and which organizations could just be picking candidates that are destined to win their primary regardless.

Our findings are fairly robust. However, there are modeling choices that could have impacted our findings. One of these choices was to run separate logistic regressions on each endorsement. By separating our regression models, we are not considering the correlation between endorsements and could potentially be overestimating the individual impact of endorsements that are highly correlated. Our findings are likely generalizable due to the size and diversity of candidates in our dataset. Voters are also likely to stay consistent with their beliefs between election cycles, leading to equal weighting of an endorsement's value regardless of who the candidate is or what election cycle they are voting in.

For our second research question, we studied the causal relationship between campaign funding and primary outcomes. We found that campaign funding has a significant causal effect on primary election success. We considered many confounders in our study, but due to the complex nature of voter decisions, it was impossible to consider every possible confounder for every case. This limited our study, but we believe that we accounted for many of the major confounders that generally have a causal relationship with campaign funding and primary outcomes. For this reason, it is reasonable to say that the causal relationship observed is not due to outside confounders.

A piece of domain knowledge that could have helped in this study is to consider how campaign funds are allocated, in other words, how individual contributors decide who to donate to. This could highlight whether we need to consider reverse causality in our study. For example, if a candidate is perceived as nonviable, people may be less likely to donate money to them, meaning that the predicted outcome has a causal effect on how much funds they raise, not the other way around. This means our study could be overestimating the causal effect of funds on primary outcomes. Our model is moderately robust. The modeling decision to treat funding as a continuous linear variable might misrepresent the log-odds of primary success if campaign funding suffers from diminishing returns. This might bias our results by overstating the impact of funding for campaigns with lots of funding and understating the impact of campaigns with very little funding. The user should reason with this by understanding that the average marginal effect is an estimate and may not generalize perfectly for all campaigns.

Our study could be helpful to political candidates as they can use it to build an understanding of how endorsements and funding impact their chances of success and strategize with these considerations in mind. This raises ethical considerations as a political candidate’s messaging should be consistent with their beliefs and how they will act as a politician, not bent towards the values of a specific organization or donor base.

For our first research question, a further study that could refute our claim could examine a larger number of political endorsements to see how many endorsements are valuable or not. Since all of our endorsements for republican candidates had a high correlation with success, it would be interesting to see where the cutoff is in terms of notoriety for an endorsement's impact.

For our second research question, a further study could investigate the impact of specific political donations. For example, examining how early, independent grassroots donations impact a campaign's trajectory compared to large donations from political action committees that typically come later in the cycle.

Our recommendation would be to address the influence of funding on political elections by limiting the amount of money campaigns are allowed to spend. This objective is possible and has been attempted before. In 2023, H.J.Res.78 was introduced to the House floor to allow states to regulate the amount of money campaigns raise and spend. However, it is unlikely that a bill like this would be passed, as it would need to be voted on by future congressional incumbent candidates, the same people it would likely negatively impact. An action like this would severely change our political landscape, as it would provide more equitable opportunities to smaller campaigns that are not able to raise as much funding. Additionally, it would change the way that sitting politicians act. Rather than voting with values aligned to their political donors, they could vote with stronger consideration for their constituents, as the risk of losing donations is not as crippling when spending is limited. This recommendation aligns with the belief that political decisions should not be made with monetary incentives or potential endorsements in mind, but rather the well-being of the country and its people.

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