Patterns in Congressional Campaign Financing in Recent Decades

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Abstract

We researched the relationships and trends found between total receipts and various candidate and campaign characteristics from a data set of congressional campaign candidates between 1979 and 2014. Due to correlation involved with candidates' repeated campaign runs, we were unable to effectively use a more traditional regression model. Initially, we considered both mixed effects and marginal models, but after researching these two modelling methods we settled on utilizing a marginal model for our final model. Key variables of interest included the number of givers to the campaign, the percentage of votes achieved in the general election, incumbency or whether the candidate achieved greater than 50% of the general election votes, the decade the candidate ran in, whether the candidate's ideology was moderate or extreme, and whether the candidate made it to the general election. Of these variables, all but the last one were included in our final and most optimal model. Our final model allowed us to specify important patterns found in campaign financing, such as the clear positive impact of receiving funding from a larger pool of donors and the boost in funds for moderate candidates vs. their competitors with more extreme ideologies.

1. Introduction

Fundraising is a key component to any candidate's campaign, as raising sufficient funds can have a large impact on their chance of winning. Researching and understanding the relationships between candidates' attributes and their total funds raised can potentially help determine effective strategies for political fundraising. It can also illuminate existing inequalities between candidates with different demographics. To explore this issue, we set out to model the nonzero funds raised by a sample of the congressional candidates in the Standford's DIME dataset, which includes data on candidates from 1979 to 2014 (Bonica, n.d.). The data set and variables of interest will be discussed in later sections of this paper.

In our initial exploration of the data, we considered related studies of congressional campaign fundraising. Zachary Albert specifically studied the same data set as ours in conjunction with additional data, and he found, in particular, that over time the amounts of funds raised and the number of individual donors increased (Albert 2017). This is rather interesting, as Albert claims it is a result of technological advancements and the media's strong influence. Lawrence Shepard suggests a list of three primary indicators for higher campaign contributions: voter predilection, candidate incumbency, and candidate primary performance (Shepard 1977). Michael Barber also focuses on the effects of incumbency and ideology on contributions (Barber 2016). Another group of researchers highlight a substantial gender gap that they found in the funds raised by state legislators' campaigns between 1990 and 2010 when district characteristics are held constant (Barber et al. 2016). Several of these sources turned out to be very promising leads for our research. We found the number of donors, time, and incumbency to be particularly useful in our models, and ideology and primary performance were informative as well. However, we had such few women in our data set that we were unable to derive meaningful relationships between gender and total fundraising. These patterns are explored further in the sections below.

In the following section of this paper, Section 2, we start by outlining our methods. In this section, we describe the data set, the variables of interest and how they were measured, our statistical methods, and our model selection process, including the criteria used for model evaluation. In Section 3, we detail our results. We start by analyzing the results of our predictor-selection process. Next, we use our final set of predictors to compare between correlation structures and determine which fits our purposes the best. Finally, in Section 4, we summarize our conclusions and wrap up our discussion.

2. Methods

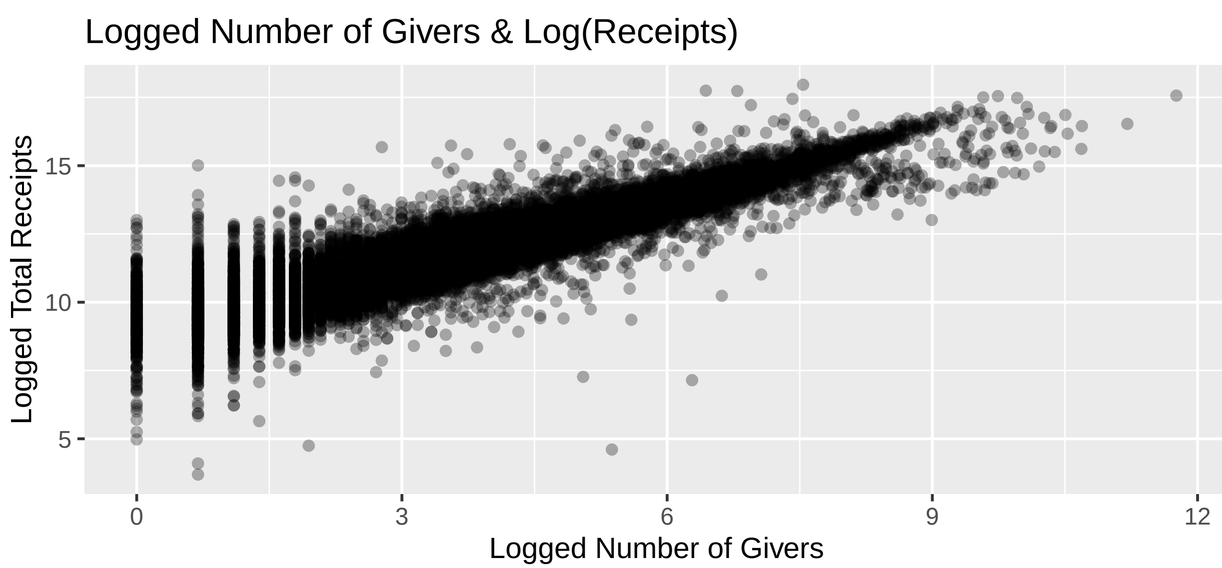
First, we will describe the data and our methods. Our research focused on applying marginal models in order to model congressional candidates' total campaign funding receipts.

2.1 The Data Set

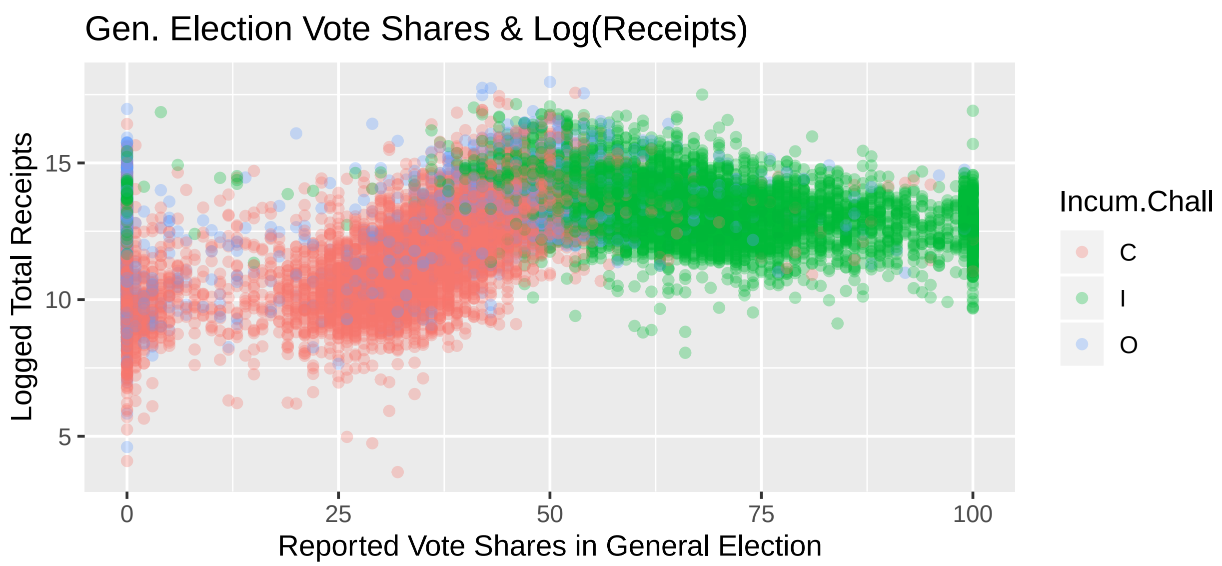
In order to study the campaign finance and ideology that arises within American politics, we used Stanford's Database on Ideology, Money in Politics, and Elections (DIME). The database contains over 130 million entries regarding political congressional campaign contributions spanning a period from 1979 to 2014 and was created as a part of an ongoing project on Ideology in the Political Marketplace (Bonica, n.d.). However, for the purpose of our work, we only used a sample of the data. To be specific, we focused on only approximately 18,000 entries and 22 different variables. It is important to mention that we only modeled non-zero funds, and individual candidates may have multiple instances in the data for the different times they ran for office.

2.2 Variables of Interest

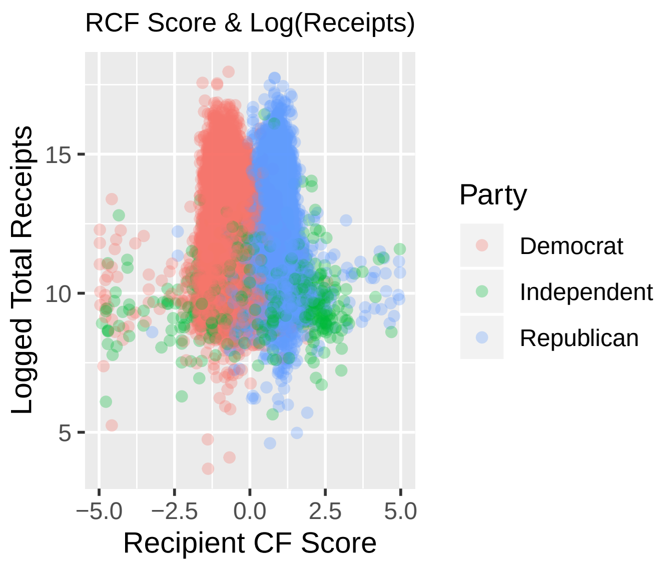
With that being said, the main goal of our work was to understand what characteristics and features of a candidate affect campaign financing. Therefore, our main variable of interest was total.receipts. The DIME codebook defines total.receipts as "the total dollars raised by a candidate during an election cycle" (Bonica, n.d.). However, after visualizing total dollars we noticed that the variable was extremely right-skewed, so in order to find more fair and stronger overall relationships we logged this variable. Additional variables of interests included: num.givers, gen.elect.pct, recipient.cf.score, Decade, and ran.general. Of these variables, num.givers had to also be transformed to be on a log scale because it was highly skewed. After performing this transformation, we observed the very strong linear relationship between logged number of givers and logged total receipts shown in the plot below.

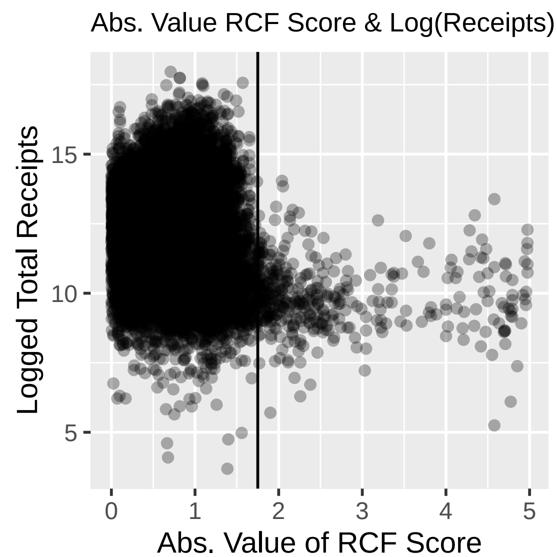


Along with logging these two variables, we had to do some additional variable manipulation to be able to accurately capture other relationships within our data. To elaborate, an interesting pattern, often known as the "broken stick problem," emerged within our variables. Originally, inspired by our research and explorative plots, we chose to include an interaction between general election percentage and incumbency/challenger/open race status in our model. The exploratory plot that inspired this is shown below. It shows that incumbents tended to have slightly lower total receipts as they achieved higher general election percentages, while open race candidates and challengers tended to achieve significantly higher total receipts as their general election percentages rose. However, when we realized that incumbency appeared to be a proxy for a general election percentage of 50 or greater, we realized that this was indeed an instance of the "broken stick problem." This allowed us to simplify this interaction term by switching incumbency/challenger/open race status for whether the candidate's general election percentage was greater than 50. This transformed variable was a simpler way to express essentially the same pattern we originally expressed by utilizing an interaction between general election percentage and incumbent/challenger/open status.



Another transformation proved to be helpful with recipient.cf.score. This was a quantitative variable, but we chose to transform it into a categorical variable. This is because when visualized we saw that the more extreme politicians were not getting as much funding, compared to those closer to the "middle" of the scale. Hence why it was more valuable to transform the variable to be two categorical levels instead: moderate and extreme. This variable is plotted below, both before and after the transformation. The vertical bar in the righthand plot represents our cutoff for moderate vs. extreme candidates.





In addition to these observed patterns, we also found key patterns with Decade and ran.general. In general, total receipts appeared to rise over time, and including the categorical variable for decade proved to be a simple and effective method to incorporate this trend in our model. Furthermore, our research also prompted us to consider success in the primary as a potential factor for higher raised funds, and success in the primary is captured by the variable for whether a candidate participated in the general election.

2.3 Statistical Methods and Model Selection Process

In regards to modeling our variables, as a result of the possible correlation within our data set we were unable to use a basic regression approach as the correlation for repeated candidates violated the independence assumption made by traditional linear regression procedures (Hubbard et al. 2010). Thus, we had to use either a marginal model or a mixed-effects model for our statistical analysis. However, to determine the best approach to analyze our data we had to consider the assumptions of each method and how they affect the inferences and outcomes.

With that being said, a random-effects model, better known as a mixed-effects model, uses maximum likelihood or restricted maximum likelihood estimation to create estimates (Laird, Ware, and others 1982). Since mixed-effects models use maximum likelihood estimations, one would be able to use AIC and BIC to compare model results. The inference for the estimates of the various coefficients, on the other hand, is derived from just the restricted maximum likelihood estimation, so the accuracy of those predictions relies on the correct specification of the underlying mean and error distribution models (Hubbard et al. 2010). This brings us to some of the mixed-effect model's limitations. Mixed-effects models require the mean model, random effects, and distributional assumptions about random effects and errors to be correct to allow for accurate interpretations of coefficients. Many of these limitations arose when we applied mixed-effects models to our DIME data. To elaborate, one of the major issues was that some politicians only ran once which meant that estimating the correct slopes for our model was made essentially impossible; we were completely unable to utilize random slopes due to this issue and had to solely rely on random intercepts.

Marginal models, which were created by Liang and Zeger, on the other hand, do not require distribution assumptions (Liang and Zeger 1986). This is because estimations only depends on specifying a few aspects of the observed distribution. They also involve fewer assumptions because they do not require an understanding of how individuals within the data set are correlated and utilize a population average. A major advantage of marginal models is the fact that we are still able to obtain robust inference even if the correlation structure is misspecified (Hubbard et al. 2010). However, the better the correlation struture, the closer we are to the truth, thus giving more efficient estimates of β, but unfortunately, the correlation structure will never be fully correct. In addition, marginal models provide more informative outputs. The details in the output include robust and standard errors as well as p-values. As a result of the more detailed output, we can compare two models with differing correlation structures. Thus, since a marginal model incorporates fewer assumptions, and have better tools to verify the assumptions that are made, we felt more inclined to favor a marginal model over a mixed-effects model.

Since we used a marginal model for our analysis, we will only be highlighing the model selection process for marginal models. With that being said, for our analysis we used the geeM R package, as it is omptimized for large data. One of the advantages of the geeM package is that it provides us with nice interpretable output and utilizes an anova method which assists with model comparison (Heggeseth 2019). The syntax is rather similar to a basic regression model, however, the geem function requires us to also specifiy the vector that identifies the clusters, the link function, and the correlation structure (Heggeseth 2019).

In regards to choosing the correct predictors, the X's, we did some initial background research and then created a couple of initial visualization to better understand the relationships among the predictors. This initial research is detailed in the previous subsection. To summarize, much of the research and the visualizations created pointed to decade, gen.elect.pct, and num.givers as being strong predictors for the total dollars raised by a candidate. Other variables were considered as well: recipient.cf.score, which captures a candidate's ideology, and ran.general. As a result, we fit several different models using subsets of the initially found predictors, including interesting interactions, and looked at the Robust SE for the variables in each of our models. The Robust SE are valid for making inferences, as the robust standard errors are valid even if the initial correlation structure is wrong. Therefore, we started off using an ar-1 correlation structure, as that structure is known to be the most complex and would serve well in helping us choose our predictors.

Once we chose our X's, we carried out further investigation regarding the correlation structure. To determine the accuracy of different correlation structures we compared the resulting Robust SE and model standard errors (Model SE). Specifically, we searched for where the two had the smallest differences between them, as smaller differences indicate that our correlation structure is closer to the truth.

Along with standard errors, geem also provides us with wald statistics and associated p-values for testing an initial hypothesis. In our case, our null hypothesis was that our slope coefficient equals zero, $H_0 : \beta_k = 0$, and our alternative hypothesis is that it does not equal zero, $H_A : \beta_k \neq 0$. It is important to note that we used a 0.05 significance threshold, meaning that if a coefficient's p-value was greater than 0.05, then we did not have enough evidence to reject the null. In this case, the variable is not contributing to the model and it can be removed. However, if the p-value is below the cut-off threshold, then we have enough evidence to reject the null, allowing us to confidently accept the alternative hypothesis that the predictor is contributing to the model. In addition, we isolated groups of coefficients for our categorical and interaction terms in order to determine their overall significance. Lastly, since our model had a quantitative outcome, we can see the resulting residuals and whether or not they have a pattern. Ideally, we hope to see little to no pattern between our predictions and residuals, meaning we want to make sure that our residuals are smaller, centered around 0, and are spread evenly. If our residual plot follows a pattern then we would have to assume that our model is either over or undepredicting our response in certain cases, therefore, further refinements to the model would be needed.

3. Results

Now that we have discussed our methods, we move on to analyze and discuss the results of our research.

3.1 Choosing Appropriate Marginal Model Predictors

In our analysis, we considered five sets of predictors of increasing complexity. Our smallest model included only the logged number of givers and an interaction between general election percentage and the identity matrix multiplied by a matrix of whether general election percentage exceeded 50%. Our next two models added Decaded and our transformed variable, the categorical of moderate vs. extreme cf-scores, respectively. Our fourth model combined all of these predictors into a single model. Finally, our fifth model included a categorical for whether the candidate ran in the general election, which indicates success in the primary. As a starting point, we utilized an AR(1) correlation structure, but we further discuss the choice of correlation structures later in this section.

3.1.1 Hypothesis Testing for Fixed Coefficients (One at a Time and Many at a Time)

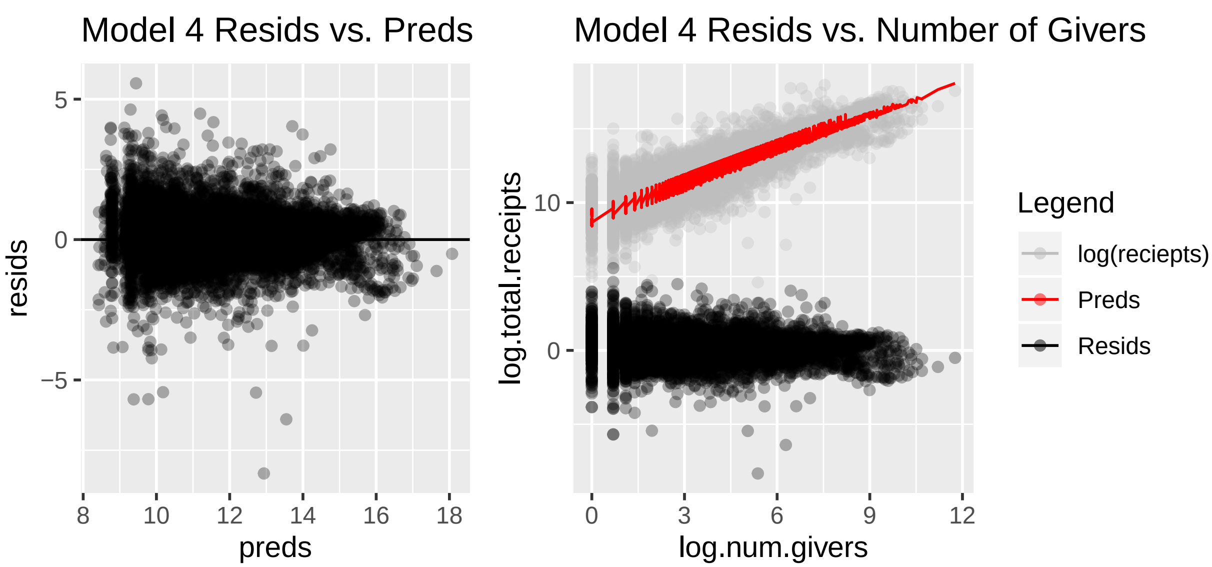
After performing our hypothesis tests for fixed coefficients, analyzing the coefficients one at a time, we found that all of our variables were significant, with a threshold of alpha = 0.05, for all of the models, even the largest model. These results, specifically having all significant p-values, differed from our initial analyses, when we had used more complex predictors, which was before we carried out the variable transformations described in our methods section above. The results for our largest model are summarized in the table below. So far, it appears that all considered predictors make significant contributions to the model.

Our next step was a comparison of the nested models, particularly the nested models that add either interactions or categorical variables with more than two categories, whose overall significance cannot be as effectively analyzed by observing individual p-values. Our results from this comparative analysis reaffirmed that even our largest model contained all significant variables. This conclusion was less than surprising, given that nearly all of our p-values were zero in the previous step, and we had no p-values above our significance threshold for any individual variables.

	Estimates	Model.SE	Robust.SE	Wald	p
(Intercept)	8.546	0.63	0.02	398.00	0.00
gen.elect.pct	0.003	0.00	0.00	6.66	0.00
I(gen.elect.pct > 50)TRUE	0.532	0.05	0.04	14.45	0.00
log.num.givers	0.778	0.00	0.00	160.50	0.00
Decade90s	-0.450	0.01	0.01	-31.42	0.00
Decade00s	-0.488	0.02	0.02	-28.21	0.00
Decade10s	-0.653	0.02	0.02	-26.24	0.00
rec.cf.cutExtreme	-0.166	0.04	0.05	-3.21	0.00
ran.general	0.695	0.63	0.01	56.57	0.00
gen.elect.pct:I(gen.elect.pct > 50)TRUE	-0.006	0.00	0.00	-9.88	0.00

Table 1: Model 5 Summary Table

3.1.2 Resiudals and Other Diagnostics



We then analyzed various residual plots for each of our models. Specifically, we plotted our residuals vs. our models' predictions and each of our quantitative variables, logged number of givers and general election percent. The residuals vs. the predictions and the residuals vs. the logged number of givers are both shown above. We found that each of these models performed very similarly for each of these residual plots. Each was consistently centered around zero, although there were certain imperfect yet explainable variations in shape. For example, our residual plots show the spread of the residuals becoming thinner as we reach higher values of predictions and logged number of givers. This makes sense, however, because we see fewer candidates achieve these higher prediction and logged number of givers values. Also, for the plot of the residuals vs. the general election percentages, we saw a strange thin patch around 12%. It appears, however, that this general election percentage was also rare in our data set, as shown by the plotted actual observed values of total receipts. Overall, our two largest models displayed ever so slightly better residual plots. These largest two models also appeared to have identical residual and prediction plots, suggesting the addition of the categorical variable for whether the candidate ran in the general election might not add very much to the model, despite its p-value.

Lastly, we also observed a drastically large difference between the robust standard error and model standard error values for the categorical variable of whether the candidate ran in the general election. This difference occurred regardless of the correlation structure chosen, suggesting that the addition of this variable may not be the best choice.

3.1.3 Predictor-Analysis Results

From these analyses, we chose our second largest set of predictors to be included in our final marginal model: an interaction between general election percentage and the identity matrix multiplied by the conditional of the general election percentage being above 50%, logged number of givers, decade, and our categorically coded summary of the recipient cf-score as moderate or extreme.

3.2 Choosing a Correlation Structure

After analyzing and choosing our set of predictors, our X's, we moved on to compare different correlation structures. After fitting various models with geem(), we found that the AR(1) correlation structure resulted in the smallest differences between the model standard errors and robust standard errors. However, we also observed that even the model with the independent correlation structure performed similarly to the model with the AR(1) correlation structure, suggesting that the structure may be AR(1), but it still may also be close to independence. The fact that the observed estimated correlation parameters for all of our models were quite low also further backs up this claim. A table summarizing our final model can be seen below.

	Estimates	Model.SE	Robust.SE	Wald	p
(Intercept)	9.240	0.01	0.02	479.20	0.00
gen.elect.pct	0.003	0.00	0.00	6.67	0.00
I(gen.elect.pct > 50)TRUE	0.532	0.05	0.04	14.46	0.00
log.num.givers	0.778	0.00	0.00	160.60	0.00
Decade90s	-0.450	0.01	0.01	-31.42	0.00
Decade00s	-0.488	0.02	0.02	-28.21	0.00
Decade10s	-0.653	0.02	0.02	-26.24	0.00
rec.cf.cutExtreme	-0.166	0.04	0.05	-3.21	0.00
gen.elect.pct:I(gen.elect.pct > 50)TRUE	-0.006	0.00	0.00	-9.89	0.00

Table 2: Final Model Summary Table

Interpreting the coefficients of our final model helps us observe and characterize key patterns that affect a candidate's overall campaign fundraising. For candidates with a general election percentage at or below 50, every additional general election percentage point, on average, results in 0.003 additional logged receipts. For a candidate who received a higher general election percentage point, however, every additional election percentage point results in approximately 0.006 fewer additional logged receipts than for candidates with 50 or lower general election percentage values, or a decrease of about 0.003. Despite this decrease in funding per additional general election percentage points observed for these very successful candidates, they do achieve higher logged receipts in general, with an additional intercept of 0.532 logged receipts. For all candidates, a one-unit increase in logged number of givers results in a 0.778 increase in total logged receipts. The decade in which the candidate ran also affects logged receipts, with each successive decade resulting in a higher cut in total logged funds: -0.450 for the 90s, -0.488 for the 00's, and -0.653 for the 10s. Although total receipts rose over time, we suspect this reversed relationship with decade results from a Simpson's paradox. Perhaps accounting for the number of givers, which has drastically increased over time, reverses the trend of receipts raising over time. Finally, "extreme"-ideology candidates typically receive 0.166 fewer logged total receipts than their more moderate counterparts. Besides these patterns, we found that an AR(1) correlation structure was the best fitting correlation structure to account for repeated candidates over time, but we also found that this correlation structure did not perform much better than an independent correlation structure. Therefore, different runs of the same candidate may actually be close to independent from each other. Alternatively, it is possible that there were not enough instances of repeated candidates in our data for the correlation structure to become more significant.

4. Conclusion

Even though marginal models essentially give us some room for error, they do still carry a few limitations. First of all, marginal models rely heavily on choosing the "right" predictors. If the predictors are misspecified, then the resulting average mean estimates may be biased (Liang and Zeger 1986). However, since we have a more limited number of model selection tools, the chance for error in predictor selection is also somewhat greater. For example, marginal models do not allow us to define or use BIC or AIC, which are important model selection tools that are used to assess a model's fit. Another limitation of marginal models is that they rely on an assumption that the sample size approaches infinity. In practice, having a large data set is typically seen as sufficient, but this assumption is a limitation nevertheless. Despite these limitations, we preferred marginal models to mixed effects models due to the larger number of limitations and concerns that mixed effects models raise, which are discussed in detail in our methods section.

Therefore, we stand by the general findings of our marginal model, from which we can learn some interesting trends. In conclusion, we found a model including an interaction between general election percentage and the identity matrix multiplied by the conditional of the general election percentage being above 50%, logged number of givers, decade, and our categorically coded summary of the recipient cf-score as moderate or extreme to be our best attempt at modelling a congressional candidate's total raised receipts. Candidates who have more givers and are more moderate have a leg up on their competitors with regards to fundraising. Furthermore, candidates who have tougher campaigns ahead of them, or more specifically, candidates who achieve 50% or fewer of the general election votes, appear to rely very heavily on receipts in order to achieve higher percentages of the votes in the general election. Candidates who win beyond 50% of the general election votes appear to be less reliant on funds to achieve additional votes, but also tend to receive high funding anyways and also are often incumbents. Finally, when controlling for these other factors, the effects of time on total receipts actually reverses. We also were unfortunately unable to observe the effects of gender on campaign funding due to the low percentage of women in our campaign data. Overall, we hope that these findings can help to improve understanding of the factors that impact campaign fundraising and to spur further research into remaining questions about this subject.

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