Undergraduate Seminar Paper

Forecasting the 2020 US Presidential Elections: A State-Level Forecast

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Abstract

The 2016 US presidential election was both a success and a failure for the forecasting community (Graefe et al. 2017). Thus it seems particularly important to obtain accurate forecasts in the upcoming 2020 election in order to counteract the propagated *Polling crisis*. However, the 2020 election itself faces difficult but interesting conditions. How much will the ongoing Covid-19 crisis and the consequences of the Black Lives Matter movement affect the election? In order to predict the winner of the 2020 US presidential election, we model the possible outcomes of the Electoral College using a structural regression model on the state level. Our model, partially based on the thoughts of Jerôme & Jerôme-Speziari (2016), predicts a 7% probability for the incumbent parties candidate to win the Electoral College. Since the model predicts an especially close race for the electors of eight states, the election is still far from being decided.

Contents

1 Introduction

Is Joe Biden able to win the White House back after just one term for Donald Trump and the Republicans? Coming from the last US presidential election in 2016, we know that this was all but a usual one. To political scientists, political professionals and pundits, almost every step of the 2016 election campaign was some sort of surprise (Gelman & Azari 2017). Coming closer to 2020 it doesn´t seem at all like a regular election again as the USA was not spared by the global corona pandemic. Tremendous death rates and a heavily risen unemployment rate (NYT 2020) are just some hints pointing to a severe crisis that hit the country. Nationwide protests for racial justice further lead to a polarised starting point for the upcoming election campaign.

Within this period, former Vice-President Joe Biden took over the lead in the Democratic primaries and is now also leading most of the polls against current president Donald Trump nationwide. In fact, both parties seem to have already come to regard the 2020 race as one of the most important within the post-war decades. For the Grand Old Party (GOP), it is furthermore the opportunity to prove that 2016 wasn't a coincidence (CNN 2019).

The 2020 election is a special one for social scientists and forecasters, too. After the 2016 US presidential election was seen as both a success and a failure for the forecasting community (Graefe et al. 2017), the 2020 election now offers the opportunity for "reconciliation" by testing improved and adapted models. It will be interesting to see whether the forecasting community has learned from its mistakes, or whether the 2016 polling crisis will experience a revival.

Besides relying on polling data there, are also other possibilities, for example structural modeling approaches, to forecast elections. However, they share the general intuition behind forecasting to predict events before they actually take place (Lewis-Beck 2005). In this paper we present our own contribution to the field of structural model based 2020 U.S. presidential election forecasting. We begin by briefly elaborating the United States presidential election process and reviewing previous forecasting methods. This leads us to the justification of our model choice, including a detailed explanation of the fundamental thoughts going into it, its variables and its actual functioning. After that we present the results of our forecast and outline surrounding uncertainty. To conclude, we end up with a brief summary and a prospect into the near future.

2 Exploring the US Presidential Elections

The US presidential elections take place every four years. In contrast to parliamentary systems, the American president is not elected from among the members of parliament but indirectly by the citizens. From this derives a constitutionally secured strong position, which, for instance forbids the parliament to remove him from office (except the *Impeachment Procedure*).

Registered voters give their vote for members of the so-called Electoral College which then cast direct votes, known as electoral votes, for the president and vice president. The candidate who receives an absolute majority of electoral votes (at least 270 out of 538) is then elected to office. If no candidate receives an absolute majority of votes (what, until now never happened), it is up to the House of Representatives to decide which candidate will become the next President of the United States (Korte 2008).

Today, 48 US states and the federal district (District of D.C.) use a relative majority voting system, often referred to as *winner-takes-all* system. Here, the candidate who receives the most votes gets all the votes assigned to the state, while the other candidates are left empty-handed. Beside this, there still exists a second system that designates one electorate for each constituency of the House of Representatives and two others statewide. In exceptional cases, this leads to a distribution of electors within a federal state (e.g. Maine split its electoral votes in 2016 into three for Clinton and one for Trump), although this can usually be neglected.

As a consequence of the *winner-takes-all* system, many states regularly lean to a single party and avoid a competitive election campaign. Such states are generally known as *safe states*. Simultaneously, there exist so-called *swing states*, where one experience a balanced probability to win the electorates by either the Democratic or Republican candidate (Beachler et al. 2015). The election analytic website *FiveThirtyEight* currently identifies the states of Colorado, Florida, Iowa, Michigan, Minnesota, Nevada, New Hampshire, North Carolina, Ohio, Pennsylvania, Virginia and Wisconsin as *swing states*, since they have regularly experienced close contests over the last few campaigns. Following the *FiveThirtyEight* classification, there should be 156 electoral votes in the 2020 presidential election, which refer to such *swing states* (Silver 2016), leading to a wide range of possible Electoral College compositions.

3 State of the Art

3.1 A Brief History of Election Forecasting

Election forecasting is a relatively recent phenomenon. Since the 30s and 40s, polling companies such as Gallup attempted first forecasts of the US presidential elections. National fame reached the 1936 election where Gallup successfully predicted a Roosevelt victory against Alfred Landon, a prediction which stood in direct contradiction to the formerly popular "The Literary Digest". Although the success was modest at first, more and more pollsters joined by the 50s and extended their forecasts to other elections and other countries (Lewis-Beck 2005).
In the 70s and 80s, economists and political scientists discovered the forecast field and extended it by introducing a second key approach besides pure polling, namely structural modelling. Here, researchers rather rely on variable-based regression models that are believed to predict the electoral outcome better than polls (Sigelman 1979, Lewis-Beck & Rice 1984). Within the same time period, the establishment of political stock markets, for instance the the Iowa Electronic Market (IEM), took place. Here, real-money futures markets (where contract payoffs will be determined by the election outcomes) were used as election outcome predictors (Arrow et al. 2008).
Within the past few years, the development of several new forecasting methods, such as polling aggregation, synthetic models and especially the usage of social media data (Huberty 2015) went ahead. This was in part due to new technical possibilities, but also represents an overdue reaction to declining poll responses (Skibba 2016).

3.2 Considering the 2016 Presidential Election

The victory of Donald Trump in the 2016 Presidential Election surprised pollsters and political analysts as well as reporters, experts and members of the Trump campaign (Jacobs & House 2016). This shock was rooted above all in the overwhelming majority of forecasts and polls that predicted a victory for Hillary Clinton. After election day, we

knew better. Although Clinton won the popular vote[1], Trump was still able to win the decisive states and thus achieved a majority in Electoral College. This was exceptional and only happened three times before (1876, 1888 and 2000).
The highly divergent US presidential forecasts led Pollsters and Forecasters into a serious crisis and led to an intensive evaluation of the various presidential election forecasts of 2016 (Kennedy et al. 2018).
Concerning the popular vote share predictions, the accuracy of former known models was impressive, independent of the used forecast method. The most common structural models e.g. achieved very accurate predictions ranging from 0.1% (Lewis-Beck & Tien 2016) to 3.6% (Norpoth 2016) deviation of the actual popular vote share and Kennedy et al. (2018) showed that the final national polls in 2016 were more accurate than 2012 national polls and similar to the 2008 national polls. So why is there a talk about failure?
Although the popular vote share could be predicted almost perfectly, the composition of the Electoral College, which is, after all, what really matters, was mostly predicted incorrectly. Jerôme & Jerôme-Speziari (2016) e.g. stated, that "notwithstanding unforeseen shocks, Hillary Clinton's chances of victory seem to be solid in terms of Electoral Votes" and HuffPost ranked the probability of a Clinton victory at 98.2% (Jackson 2016).
A major problem in the 2016 election seemed to be the accuracy of state-level polls. Campbell et al. (2017) and Graefe et al. (2017) both emphasized this fact in their forecast, pointing out that state-level polls in 2016 were historically bad in comparison with the past four elections. Turning to possible systematic errors in structural models of 2016, Jerôme & Jerôme examined their own forecast (Jerôme & Jerôme-Speziari 2016) within the Recap of Campbell et al. (2017). Except for the extremely narrowly predicted election outcomes in Florida and Pennsylvania, they found no rational reason why Trump was elected in states like Michigan, Ohio, or Wisconsin, even though all model indicators pointed to Clinton's success. It will be interesting to see whether the 2016 election can be considered as a one-off occurrence with regard to these deviation. In any case, the 2020 election will help us to shed light on this issue. Besides the above mentioned limitations, the evaluation of the 2016 presidential election can still be well summarized by the following quote from Lewis-Beck & Tien in Campbell et al. (2017): "Forecasting the 2016 US presidential election, the polls stumbled while the models stood tall". Partly driven by the lessons of the 2016 election, we also use a structural model in our own forecast which will be explained in more detail below.

[1] the total number or percentage of votes cast for a candidate by voters in the 50 states and Washington, D.C

4 Methodology

4.1 Fundamental Model Thoughts

Already Lewis-Beck & Tien (2001) pointed out that forecasting requires satisfying theory and should be therefore more than just curve fitting. In our work, we are taking the thoughts of political economy forecasting models, which model the electoral outcome of the incumbents presidents party as a function of political and economic performance as base. Following Jerôme & Jerôme-Speziari (2016), we develop a state-level structural model, using pooled time series data.

Previous research provides evidence that economic and political conditions (represented in our independent variables), influence the choice of the voters at the election. Lewis-Beck & Paldam (2000) for instance wrote that it is theoretically clear that the economy is connected to the voter by the *Responsibility Hypothesis*, meaning that the voters hold the government responsible for economic occurrences. Other research emphasizes that the evaluation of the presidential performance not only based on economic but also on political conditions, has impact onto citizens´ decision behavior (Fiorina 1978). Following the theory, our model - like other political economy models - looks at the election as a referendum on how well the president in charge has handled economic and non-economic issues (Lewis-Beck & Tien 2016). Ceteris paribus, the better the current president performs on these two dimensions, the better will the party holding the white house perform in the next presidential election.

Sticking to a pure structural model on the state-level entails several advantages. Klarner (2012) for instance emphasized that a strength of structural models compared with for example forecasting methods based on expert judgments or prediction markets is that they also give more insight into the reasons an election turned out the way it did. Furthermore, using this approach enables us to address the actual target of interest (the Electoral College) without being forced to rely on state-level polls (for the above mentioned reasons). Our believe to have a greater chance of success when sticking to a pure structural model is supported by the highly unfamiliar, difficult and unstable economic and political situation. The volatility that would be introduced by incorporating e.g. opinion polls makes it, according to us, necessary to rely on a picture purely created by the fundamentals of vote. We use a pooled time series voting model to improve our prediction accuracy at the national level respectively for the Electoral College, by making use of data from the state-level (Jerôme & Jerôme-Speziari 2016). Looking at the states and not only the national-level additionally raises the number of observations in the dataset and therefore the degrees of freedom of the model which should also improve his performance (Jerôme & Jerôme-Speziari 2012). This increase of cases by the use of pooled time-series data can further help to avoid or lower issues that arise when election forecasts are build on only limited numbers of cases which were also identified by Cuzán & Bundrick (2009).

4.2 Building the Model

According to Lewis-Beck (2005), a consensus on the ultimately best macroeconomic variable to predict election outcomes does not exist. Nevertheless unemployment rates, GDP growth and inflation rates (Lewis-Beck & Paldam 2000) are considered the best possible macroeconomic indicators. Due to its dynamic and direct impact onto citizen's life's (with regard to the ongoing Covid-19 crisis) as well as its availability on the state-level we choose to rely on the change in unemployment rate as our economic variable. In particular we add the change in state-level unemployment rates between June of the election year and its value of the preceding year as independent variable to our model.

To operationalize the overall political performance of incumbents, we use the latest measurement of the Gallup President's approval rating in June of the election year. If the electorate evaluates the work done by the incumbent president positively, this variable has a more positive value and vice versa.

For both variables we rely on measurements from June, some month in advance of the actual election. The reasons are mainly of practical origin, making it possible to publish our forecast with some lead time until the election. Without lead time, when a forecast is made just a few days before the election, it risks being trivial because the gain though the prediction is rather small (Lewis-Beck 2005). Expanded lead time is also supported by survey data of the American National Election Studies (ANES) which report that almost two-thirds of voters had made their vote decision for presidential election before Labor Day, the traditional kick off of the general election campaigns (Brox & Giammo 2009).

Since we expect indirect and direct effects of ideology and partisanship on the decision-making of the voter, we address this subject by including the Cook Partisan Voting Index (CPVI). The CPVI is based on the election results of the previous two US presidential elections. Its index value is obtained for each state by taking the mean of both election years differences between the Democratic national election result and the respective results within each state. We further multiply its value with "1" if the incumbent president is from the Democratic Party and with "-1" if he is from the Republicans.

As final independent variable we incorporate a dummy variable, to account for the potential effect of already being in office since four years, with the value "1" if the incumbent president is rerunning for office and "0" otherwise. We also interact this with the presidential approval variable, because we expect its effect to be different for a rerunning president than just for a running candidate from the incumbent president's party.

As our dependent variable we use the two-party vote share of the incumbent party's candidate in the respective state. Therefore the prediction made by our forecast is the vote share of the Democrats when the president at the time of the election is a Democrat and vice versa.

Because the state-level unemployment rate is only available since the 1980 election, our estimations incorporate ten elections in 51 jurisdictions. This leads to a dataset substantially wider spatially, but shorter temporally, than those used by a lot of other forecasting models (Berry & Bickers 2012).

To sum up, our specified linear regression model can be described by the following equation:

$$\begin{aligned} Incumbent2PV = \beta_0 + \beta_1 Gallup + \beta_2 Rerunning + \beta_3 Unemployment \\ + \beta_4 Gallup * Rerunning + \beta_5 CookPVI * IncumbentParty + u \end{aligned}$$

Subsequently, we use OLS estimation on all 510 pooled observations (51 states and 10 elections) to receive our equation coefficients. We then insert the values of the independent variables of the 2020 election year for each state separately to receive the predicted incumbent parties vote share for every state (51 predictions in total). Furthermore, we compute the standard error of the prediction (the square root of the variance of the prediction error). With this value and assuming the incumbent parties vote share is normal distributed, we can quantify for each state the probability that the incumbent parties candidate will win. These estimates allow us to apply a bootstrapping procedure, where the Electoral College outcome gets re-sampled 10000 times based on the probabilities that either the Democratic or the Republican candidate will win the College votes in a given state. Following this procedure we can display a distribution of possible Electoral Collage outcomes and calculate the overall probability that the incumbent parties' candidate will win the majority in the College.

4.3 Limitations

Following the thoughts of Lewis-Beck (2005) we belief that eventually the statistical modelling approaches (since built on vote theories), will perform better than e.g. vote intention surveys, vote expectation surveys and political stock markets. Nevertheless, they are not spared of limitations. Maybe one of the biggest limitations of structural modelling lay in the actual uncertainty of its predictions. Lauderdale & Linzer (2015) showed that it is not rare that published forecasts go wrong in accounting for the full range of uncertainty in specification and estimation in their used models. This can lead to an overstated degree of confidence in the predicted outcome of the election. We try to take this into account by looking at the total combined uncertainty in the coefficient estimates and model residuals when presenting the uncertainty of our prediction. But still there is uncertainty within the model specification procedure. This is hard to quantify but at least important to mention. What should also not be neglected are the possible influences of national-level vote swings on state-level election outcomes and the correlation of election results in each state. The state-level prediction errors will be correlated over time within each state and additionally across states by election (Lauderdale & Linzer 2015). Although somehow obvious but noteworthy to mention is that the measures of independent variables used in this and other forecasting models contain sampling and other measurement errors which may be refined and improved years and decades after the election (Campbell 2008).

5 Results

5.1 Model Evaluation

Before passing over to our 2020 U.S. presidential election predictions, we look at our model and it´s performance in earlier elections. The independent variables coefficient´s values and some further information (coefficient´s significance, R^2 of the model or F statistic) are shown in Table 1. All independent variables are separately and combined at least significant at the 0.01 level. The value of R^2 is 0.848, indicating a good fit of our model to the data.

Table 1: Linear Regression Results

	Dependent variable:
	Incumbent Two-Party Vote Share
Gallup President Approval Rating	0.119***
	(0.032)
Rerunning	-13.146***
	(2.137)
Unemployment Rate Change	-0.946***
	(0.239)
Gallup President Approval Rating * Rerunning	0.333***
	(0.047)
Cook Partisan Voting Index * Incumbent Party	1.009***
	(0.021)
Constant	43.968***
	(1.475)
Observations	510
R^2	0.848
Adjusted R^2	0.847
Residual Std. Error	4.362 (df = 504)
F Statistic	563.543*** (df = 5; 504)
Note:	*p<0.1; **p<0.05; ***p<0.01

Still we want to prevent our model from overfitting, which arises when the number of variables is large relative to the sample size. Here again our risen size of the sample helps to work against this. The trouble with an model that overfits the data is that it tends to be inaccurate in predicting future cases, because it is so over-particular about handling the past ones included in the dataset (Silver 2011). The relationship between the out-of-sample predictions and the observed state-level vote shares of the incumbent party is shown in Figure 1. From the year 1980 until 2016 the root mean squared error (RMSR; the sample standard deviation of the forecast errors (without any degrees of freedom adjustment) (Wooldridge 2012)) was on average across all states 6.725 and the mean absolute error (MAE; the average of the absolute forecast errors (Wooldridge 2012)) has an value of 4.817. Therefore the predicted vote shares of our state-level model are off by 4.817 percentage points from the observed vote shares on average. Since this relates to the separate predictions for the states, the value is higher than for comparable nationwide forecasts. However combining the state predictions to forecast the Electoral College should lower the errors on average, because the state-level errors will partially cancel each other out. Still the errors in each year will not balance out completely, this occurs partly due to the earlier mentioned positive correlations of election results between the states.

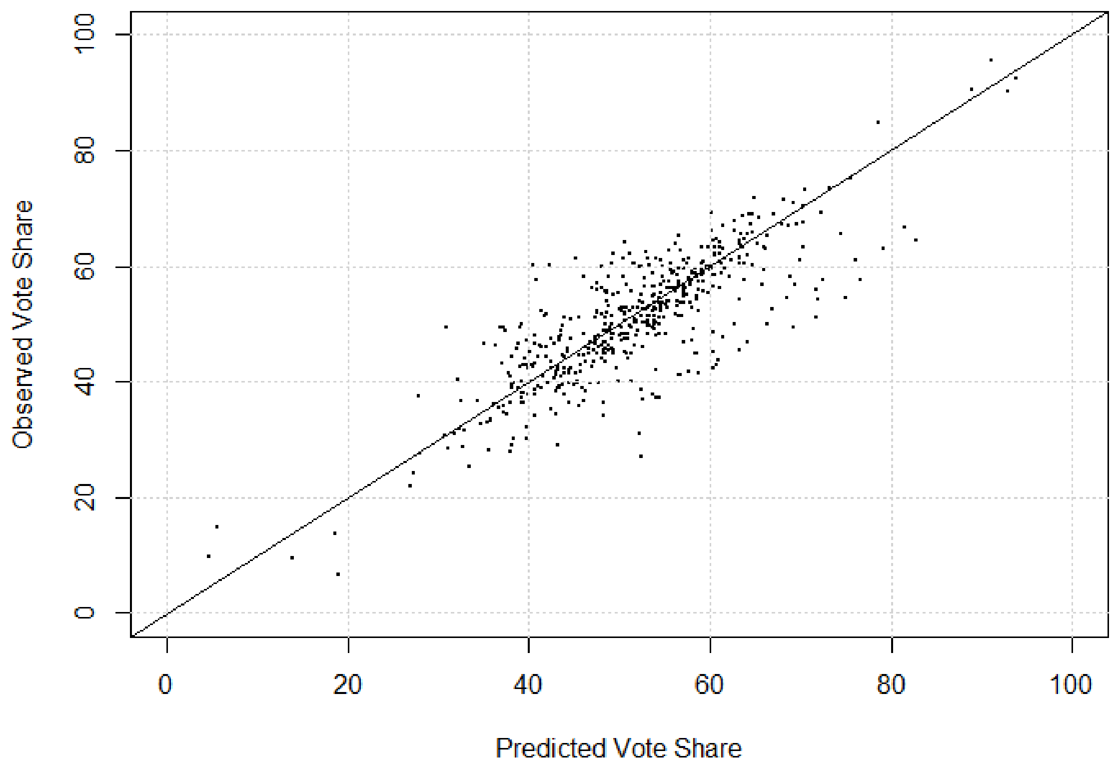

Figure 1: Out-of-Sample Predictions of State-Level Vote Shares (1980-2016)

5.2 Model Predictions

To achieve our final forecast of the incumbent parties probability to hold the White House, we first use our linear regression model to predict the incumbent party's two-party vote share in each state separately. Therefore we include the respective values of the independent variables in this election year. The point predictions of the state-level incumbent two-party vote share and their respective standard errors of the prediction are given in Table 2 and Table 3, which can be found in the Appendix. Predicted vote shares over 50% indicate states with a higher chance for the Republicans to win and under 50% indicate a higher chance for the Democrats. This way of looking at the results is shown in Figure 2, where these chances are represented by the respective colors of the states.

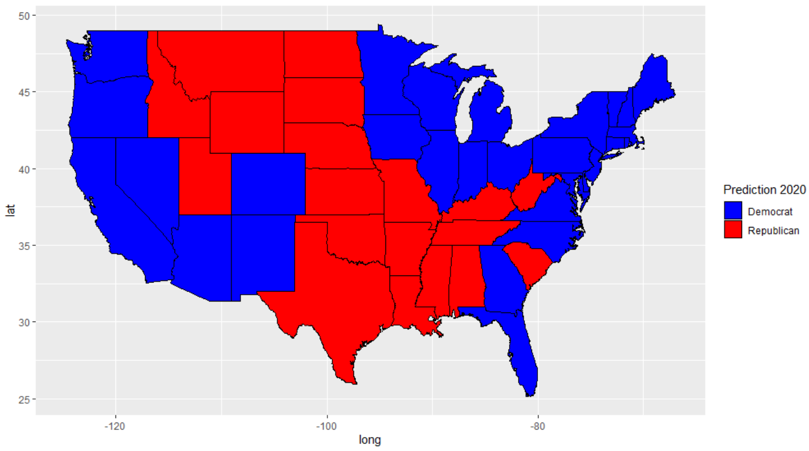

Figure 2: State Predictions 2020

In Figure 3 we further display all the swing states according to our predictions - here shown by the purple color of the respective states.

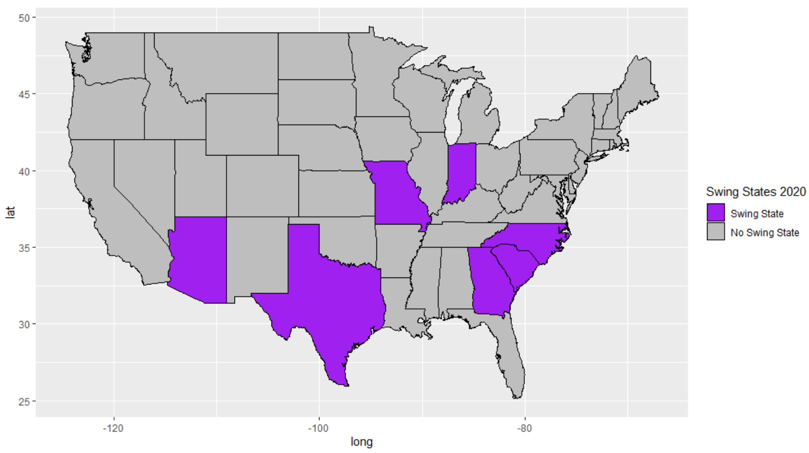

Figure 3: Swing State Predictions 2020

After our definition, states fall into the swing state category if the probability for the favoured party to win, based on the vote share point prediction for the state and the standard error of the prediction, is 80% or lower. Following this, eight states fall into this category: Alaska, Arizona, Georgia, Indiana, Missouri, North Carolina, South Carolina and Texas.
Employing the bootstrapping procedure in our last step to receive the probability that Donald Trump, the candidate of the incumbent party will win the 2020 US presidential election is illustrated by the following density plot (Figure 4).

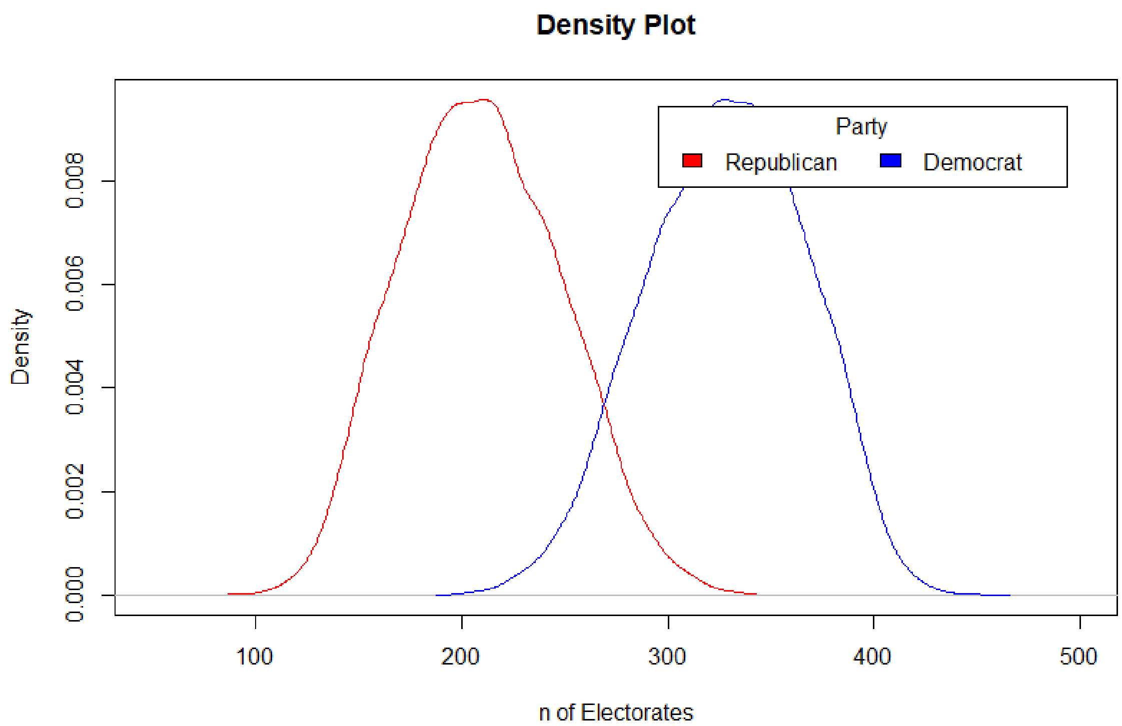

Figure 4: Simulated Electoral College Outcomes

As can be seen in Figure 4, there are a lot more possible cases in which the Democratic candidate obtains the majority in the Electoral Collage (at least 270 electoral votes), than the Republican. The probability for the incumbent parties candidate to win the Electoral College and therefore the presidential election, based on this simulated results, is 7%. Consequently our forecast predicts a win for Donald Trump win in 7 out of 100 elections and a victory for Joe Biden in the remaining 93 out of 100 cases.

5.3 Taking Responsibility for Uncertainty

We intentionally chose this way of presenting the results in probabilistic terms and not solely as e.g. a point prediction of the electoral votes or the plurality vote, because it does a better job in representing the inherent uncertainty of our forecast. Besides the uncertainty accounted for in our model, it is worth to mention, that their is notably more uncertainty surrounding the outcome of the election and therefore also our forecast. As stated before, there could be an influence of the correlation of election outcomes between the states. For instance, if an candidate outperforms one of our state-level predictions it could be expected that he will be likely to also do so in others. Furthermore, the economic situation is not set in stone and although the unemployment rate is in double-digits in a lot of stats by June it could also lower until election day. But the fact that (especially in this election under the influence of the Corona Virus) many voters will cast their ballot per mail way in advance of election day, diminishes the incorporated uncertainty of changing economic conditions.

6 Conclusion

This paper is taking the thoughts of political economy models and forecasts the electoral outcome of the incumbent presidents´ party as a function of political and economic performance. Unlike many other forecasts, we aim to exceed a single popular vote share prediction and instead try to conduct a state-level based forecast for the election deciding Electoral College.
Our forecasting model for the 2020 US presidential election points to a relatively clear election win for the Democratic challenger Joe Biden, giving him a 93% probability to obtain the majority of seats in the Electoral College. Regarding the uncertainty of predicting the right candidate to win, we identify eight states, among them four Biden-favoured states (ARI, GA, IND, NC) with a winning probability less than 80%, still giving Trump a chance to win. Nevertheless, increased unemployment and low approval ratings strongly suggest that a challengers success in the upcoming elections is on the cards. Whether this prediction is accurate, or whether Donald Trump and the GOP will surprise again and cause another crisis for Pollsters and Forecasters, will be known after November 3.

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Appendix

State-Level Prediction Tables

Table 2: State-Level Predictions

State	Vote Share	Standard Error of Prediction
Alabama	58.03	4.50
Alaska	51.62	4.58
Arizona	47.83	4.52
Arkansas	58.65	4.49
California	25.12	5.01
Colorado	39.35	4.71
Connecticut	35.48	4.59
Delaware	33.35	4.80
District of Columbia	1.89	4.50
Florida	42.94	4.64
Georgia	49.03	4.46
Hawaii	19.69	4.99
Idaho	64.35	4.43
Illinois	30.75	4.97
Indiana	49.92	4.71
Iowa	45.23	4.54
Kansas	56.62	4.48
Kentucky	63.20	4.39
Louisiana	54.48	4.50
Maine	41.20	4.44
Maryland	31.32	4.48
Massachusetts	22.22	5.53
Michigan	37.08	4.99
Minnesota	42.05	4.52
Mississippi	53.86	4.43

Table 3: State-Level Predictions

State	Vote Share	Standard Error of Prediction
Missouri	52.49	4.49
Montana	55.22	4.44
Nebraska	59.75	4.41
Nevada	36.50	5.07
New Hampshire	41.70	4.61
New Jersey	28.60	5.35
New Mexico	41.23	4.43
New York	23.63	5.11
North Carolina	47.74	4.43
North Dakota	59.94	4.52
Ohio	44.43	4.63
Oklahoma	64.75	4.44
Oregon	35.91	4.70
Pennsylvania	39.96	4.80
Rhode Island	29.78	4.81
South Carolina	50.52	4.55
South Dakota	58.59	4.46
Tennessee	55.80	4.59
Texas	51.26	4.50
Utah	65.69	4.43
Vermont	25.97	4.64
Virginia	42.13	4.51
Washington	35.89	4.54
West Virginia	62.16	4.57
Wisconsin	43.10	4.51
Wyoming	69.43	4.49