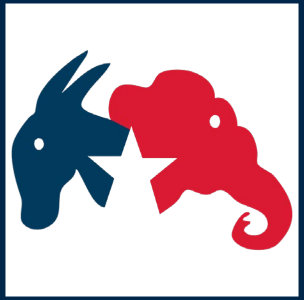

PEORIA Presidential Prediction Project: Battleground States

September 7, 2020

GW GSPM

Our Research Mission

We seek to learn how Twitter data, which measures the pulse of public conversations about campaign politics, can improve predictions of election outcomes.

We have constructed a model that forecasts the battleground state results for the 2020 presidential election based on current information.

We will update the calculations on a biweekly basis between August 10th and the November election.

Our Forecast Model

- The forecast model predicts incumbent (Trump) vote share in these twelve battleground states
  - AZ, CO, FL, GA, IA, MI, NC, NV, OH, PA, TX, WI
- The remaining 38 states and D.C. are scored as party base states to yield an electoral total.
  - For example, MA is part of the Democratic base, while WY is part of the Republican base

Variables

Our battleground state model relies on the variables:

- State-level polling, aggregated by state weekly (using polling available on RCP and FiveThirtyEight)
- State's partisan lean (using Gallup's state-level party affiliation)
- State-level negative candidate Twitter mentions (share of mentions interacted with negative sentiment)
- State-level change in unemployment since January of the election year (using US Bureau of Labor Statistics)
- National net candidate favorability (using RCP)

*For further details, see slide 26

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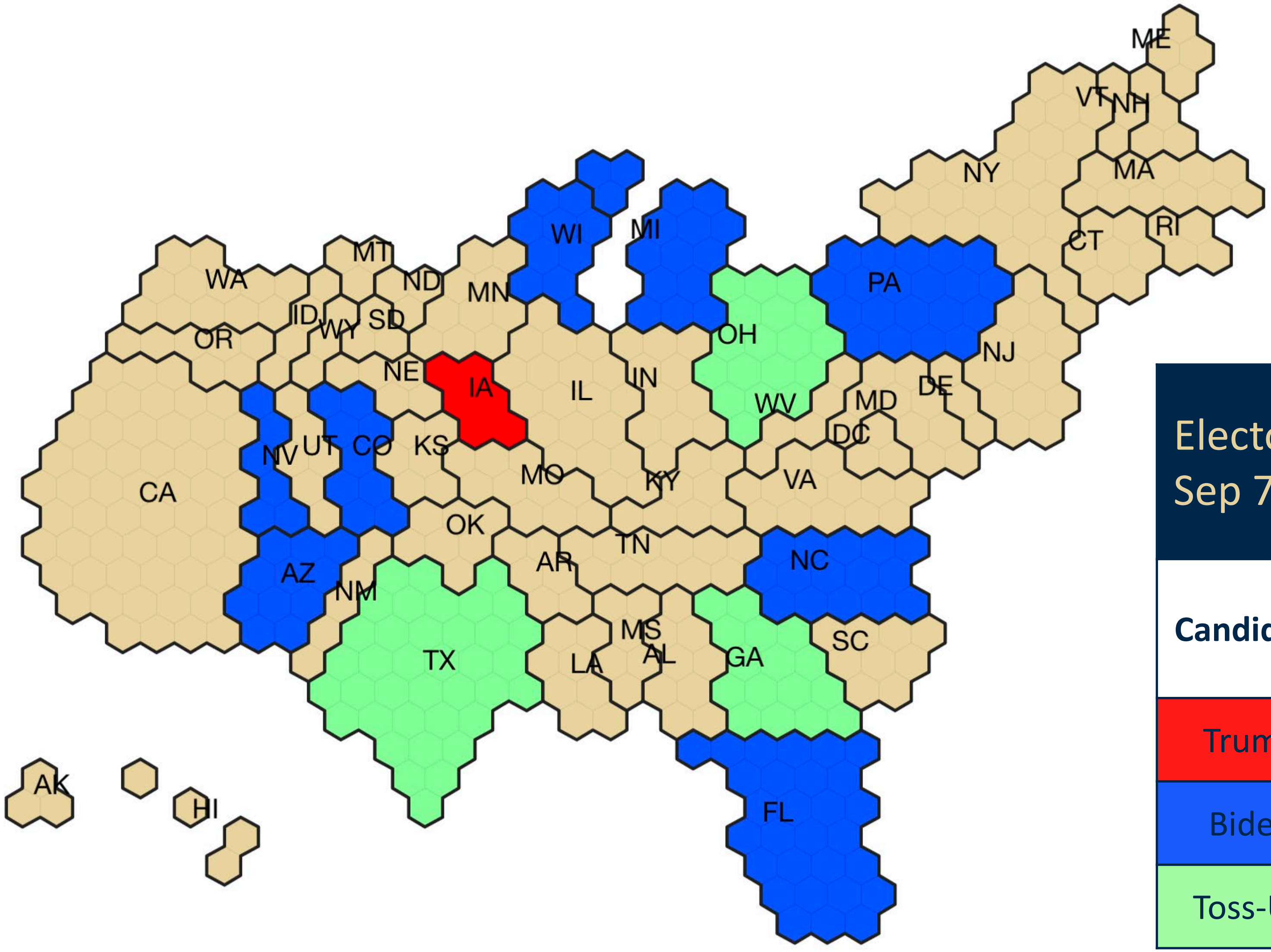

Electoral Vote Forecast
Sep 7, 2020 Model

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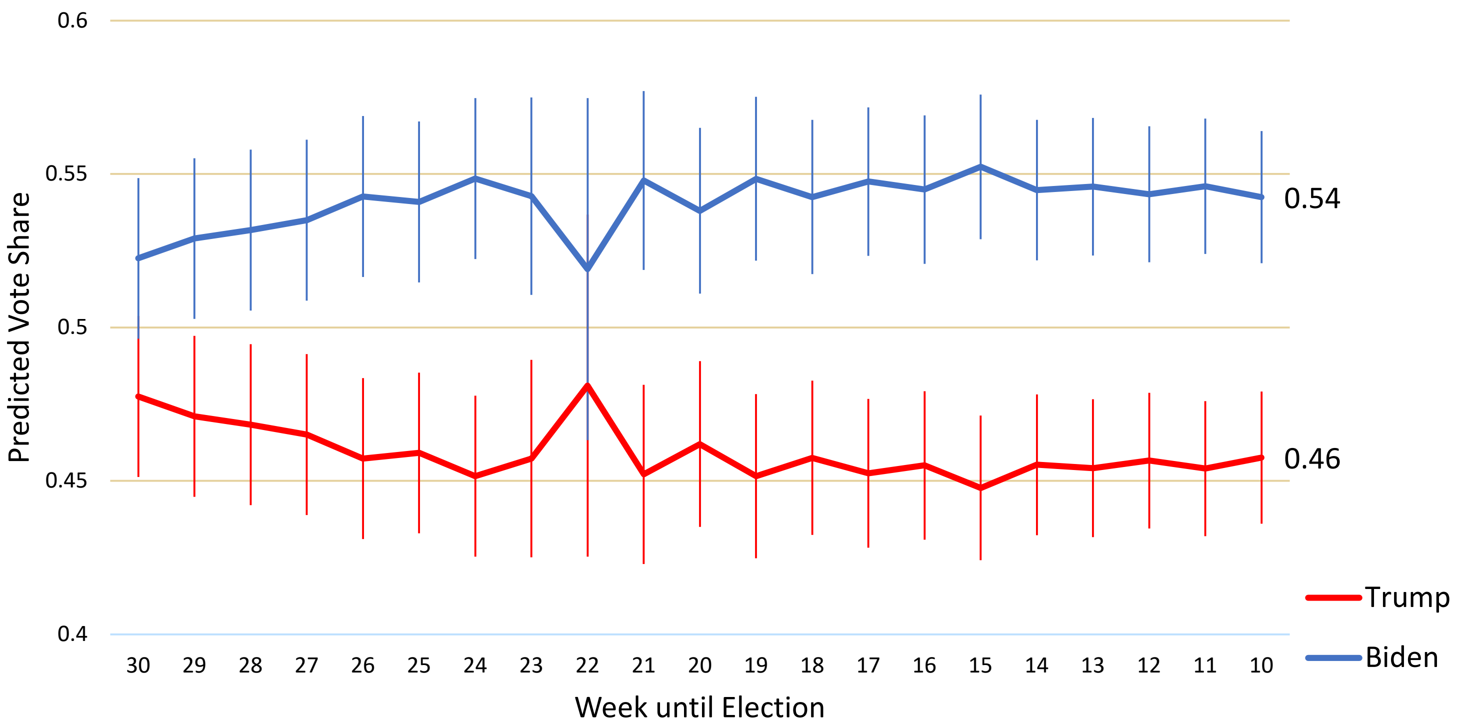
Candidate	Base	Model Estimate	Total
Trump	126	6	132
Biden	218	116	334
Toss-Up	0	72	72

National Vote



Trump's chance of winning popular vote: 2%

(1M simulations)

Likely popular vote: 43.5 – 47.8%

(80% prediction intervals)

Trump's Predicted State Vote Share* Relative to his National Vote Share: September 7, 2020 Model

Incumbent (Trump) National Vote Share	AZ	CO	FL	GA	IA	MI	NC	NV	OH	PA	TX	WI
45	47	43	47	49	51	45	49	47	49	47	50	47
46	48	44	48	50	52	46	50	48	50	48	51	48
47	49	45	49	51	53	47	51	49	51	49	52	49
48	50	46	50	52	54	48	52	50	52	50	53	50
49	51	47	51	53	55	49	53	52	53	52	54	51
50	52	48	52	54	56	50	54	52	54	52	55	52
51	53	49	53	55	57	51	55	53	55	53	56	53

*Vote share calculated as the two-party vote

In 2016, Trump won 48.9% of the two-party vote share

In 2018, Republicans in the House won 45.6% of the two-party vote share

Model Changes Over Time

Electoral Vote Forecast Aug 10, 2020 Model			
Candidate	**Base**	**Model Estimate**	**Total**
Trump	126	6	132
Biden	218	116	334
Toss-Up	0	72	72

Electoral Vote Forecast Aug 24, 2020 Model			
Candidate	**Base**	**Model Estimate**	**Total**
Trump	126	6	132
Biden	218	101	319
Toss-Up	0	87	87

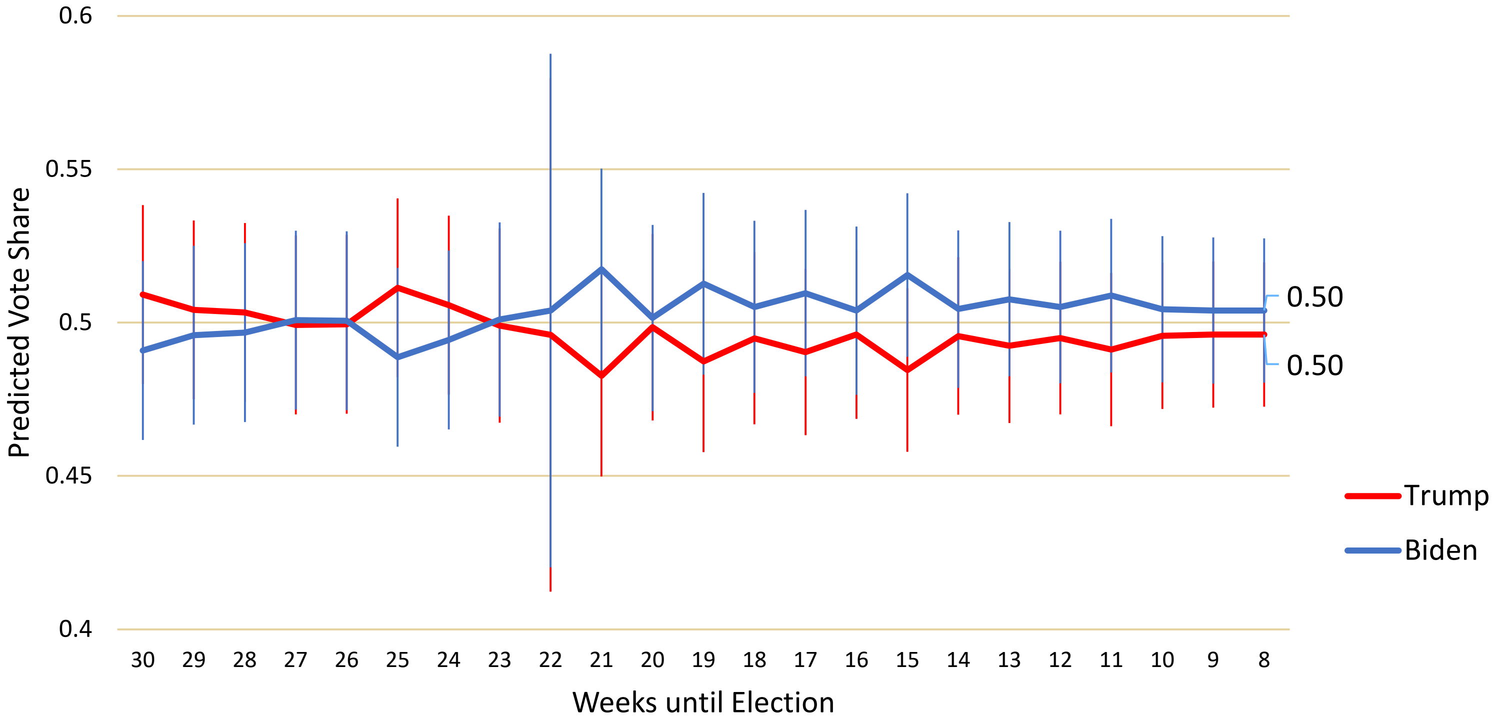
Electoral Vote Forecast Sep 7, 2020 Model			
Candidate	**Base**	**Model Estimate**	**Total**
Trump	126	6	132
Biden	218	116	334
Toss-Up	0	72	72

The model estimates generally have not changed, apart from North Carolina's shifts from Biden base (Aug 10) to Toss-Up (Aug 24), back to Biden base (Sep 7).

Toss-Up States

Presented in order of most to least competitive.

Ohio



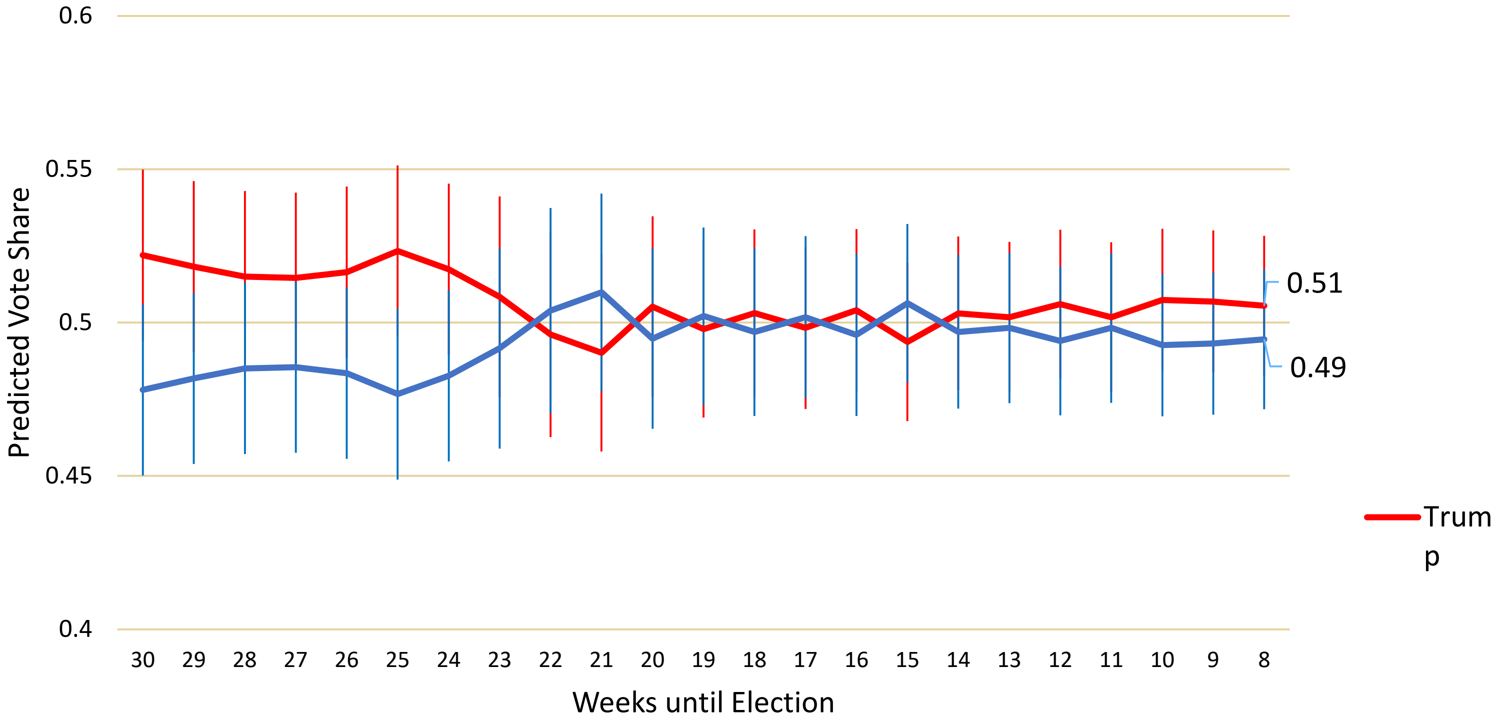
Trump's chance of winning: 46%

(1M simulations)

Likely popular vote: 47.3 – 52.0%

(80% prediction intervals)

Texas



Trump’s chance of winning: 57%

(1M simulations)

Likely popular vote: 48.3 – 52.8%

(80% prediction intervals)

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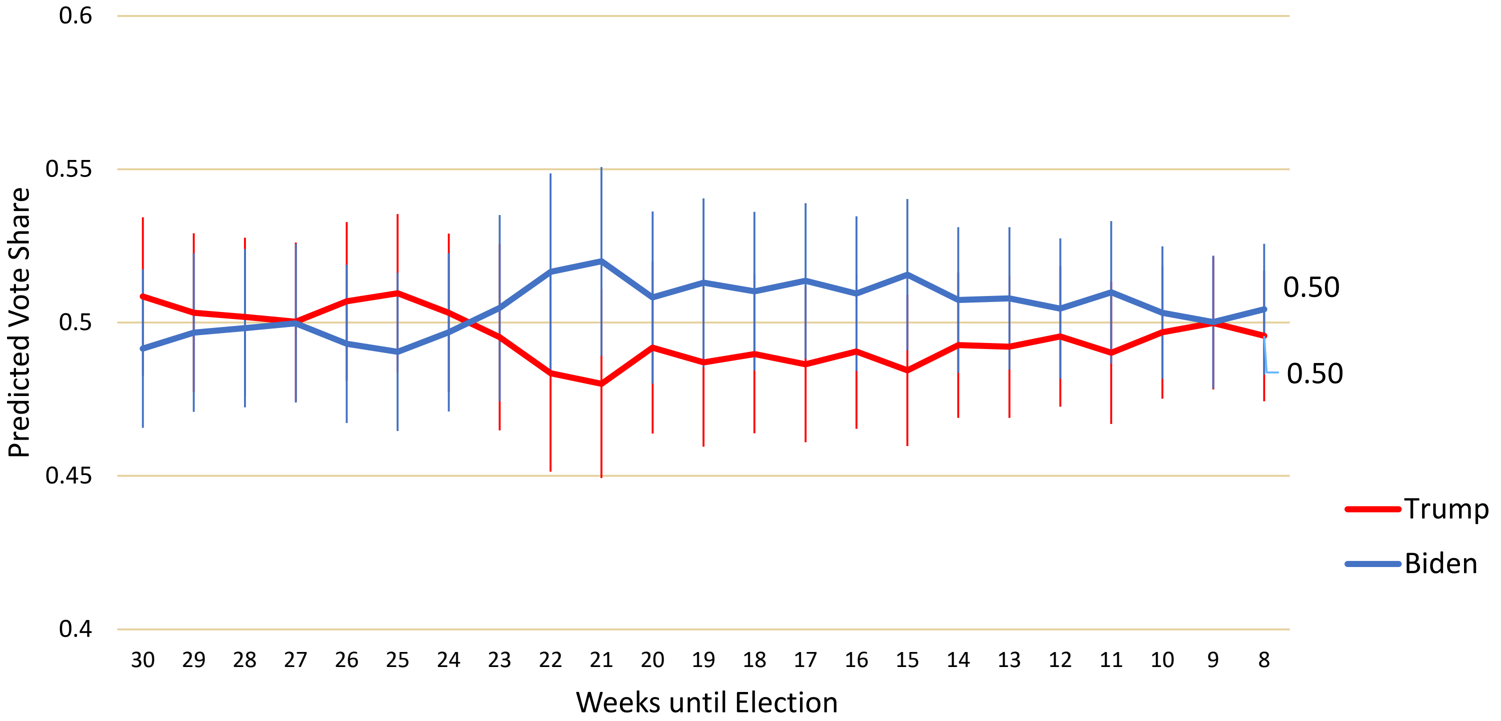
Georgia



Trump’s chance of winning: 42%

(1M simulations)

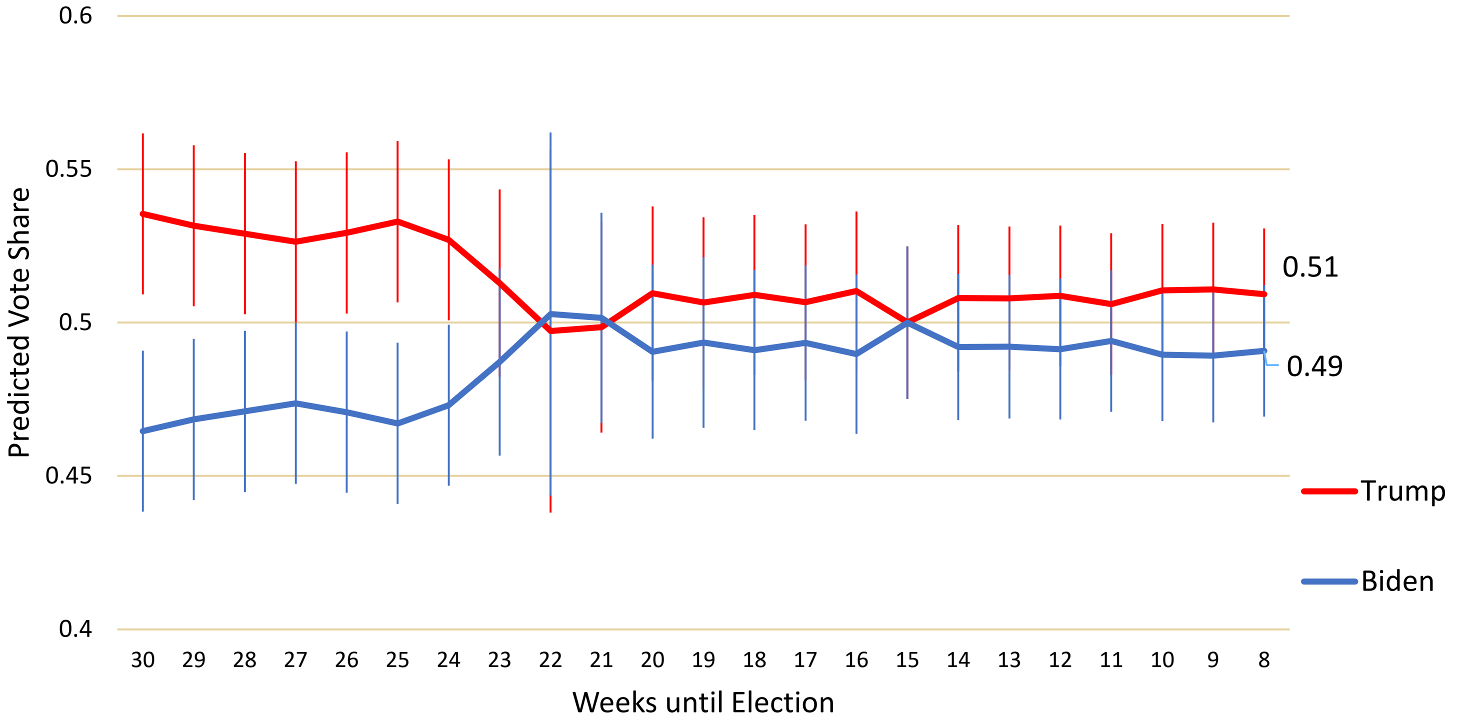
Likely popular vote: 47.4 – 51.7%

(80% prediction intervals)

States Likely to Go to Incumbent

Presented in order of most to least competitive.

Iowa



Trump's chance of winning: 65%

(1M simulations)

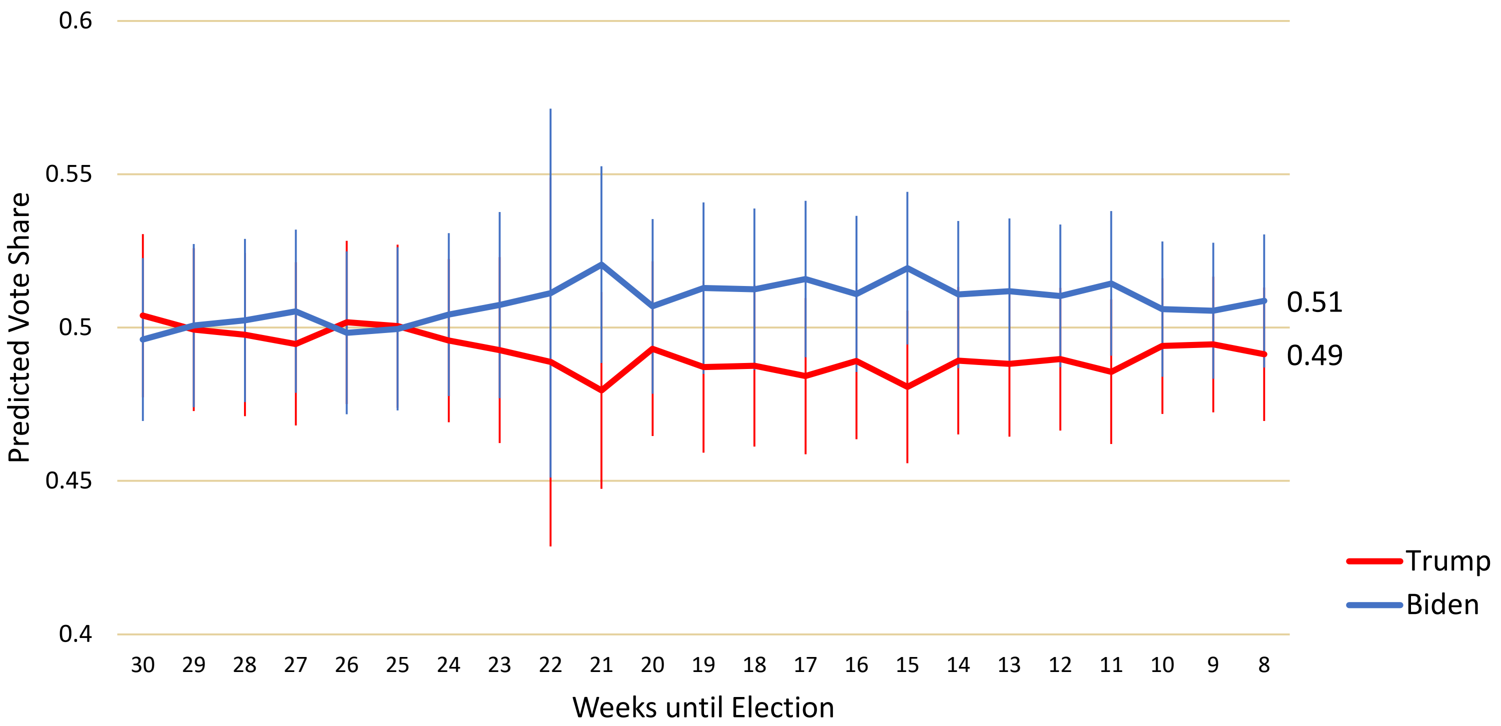
Likely popular vote: 48.8 – 53.1%

(80% prediction intervals)

States Likely to Go to Challenger

Presented in order of most to least competitive.

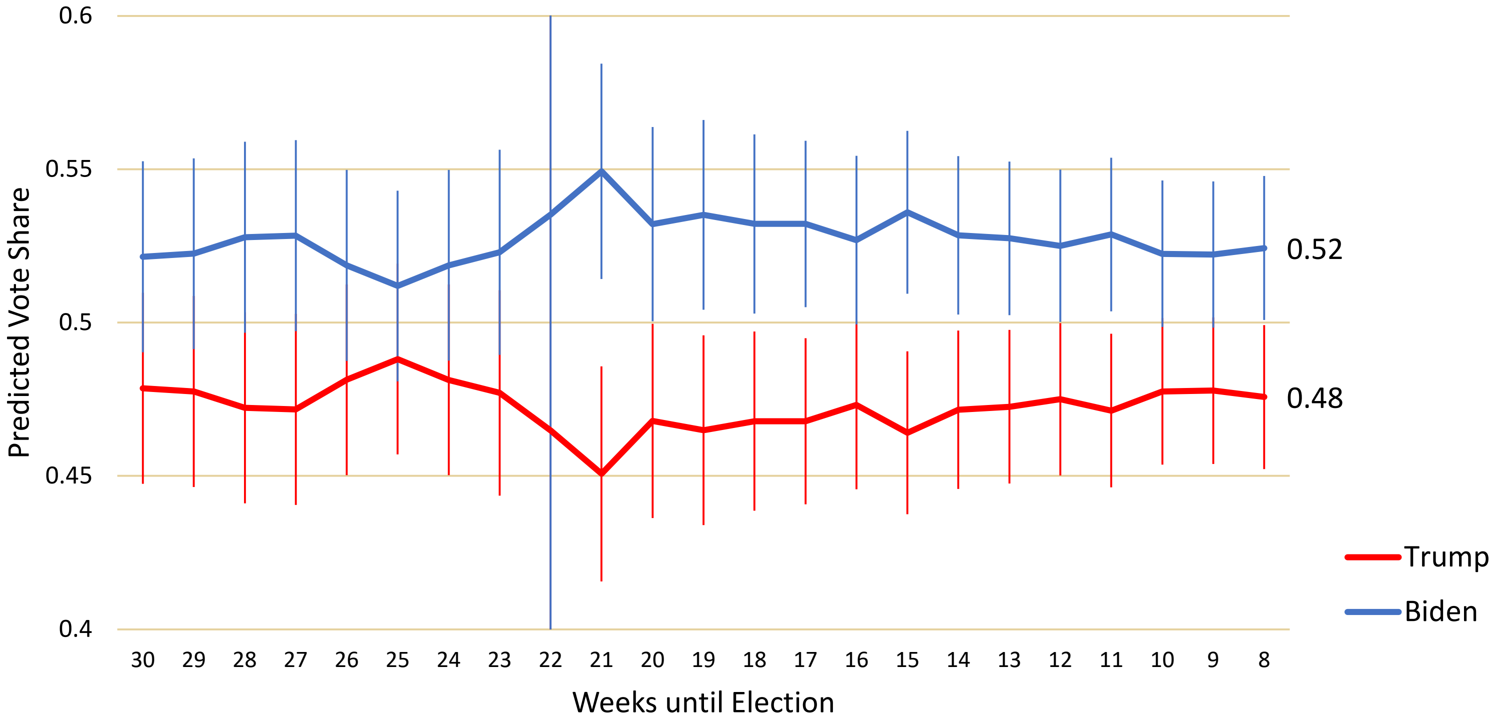
North Carolina



Trump's chance of winning: 37%
(1M simulations)

Likely popular vote: 47.0 – 51.3%
(80% prediction intervals)

Nevada



Trump's chance of winning: 25%

(1M simulations)

Likely popular vote: 45.2 – 49.9%

(80% prediction intervals)

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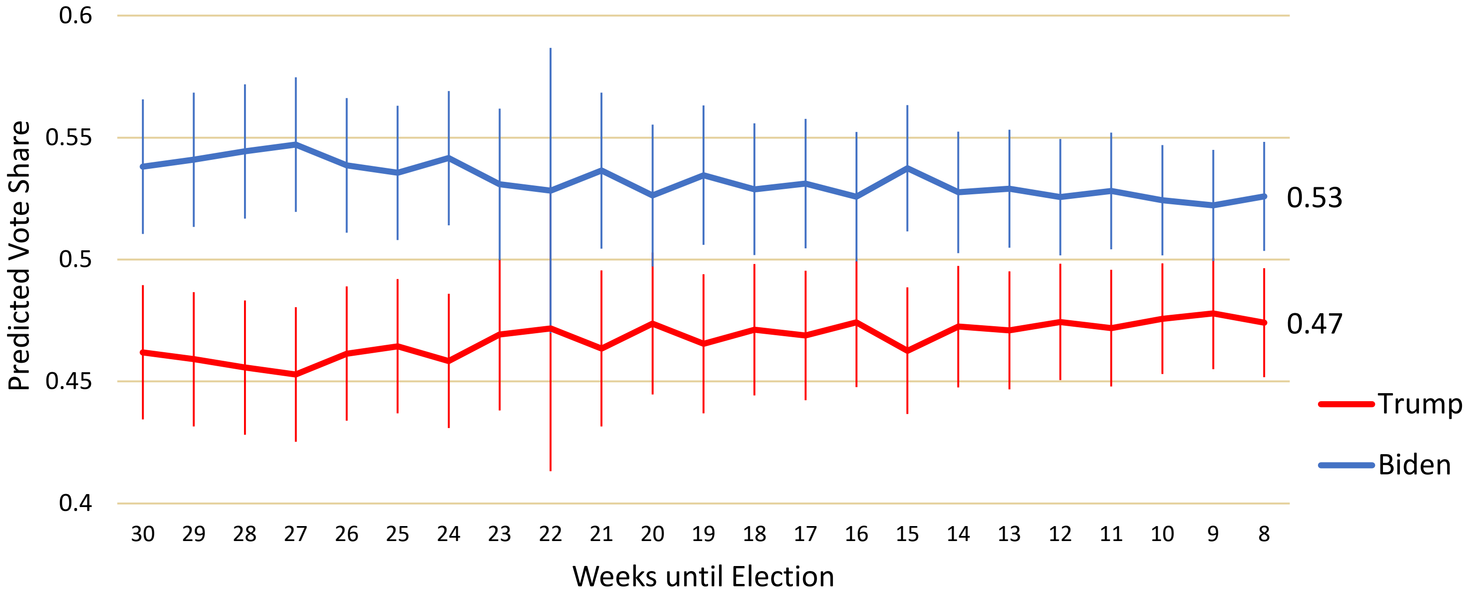
Arizona



Trump’s chance of winning: 19%

(1M simulations)

Likely popular vote: 45.2 – 49.6%

(80% prediction intervals)

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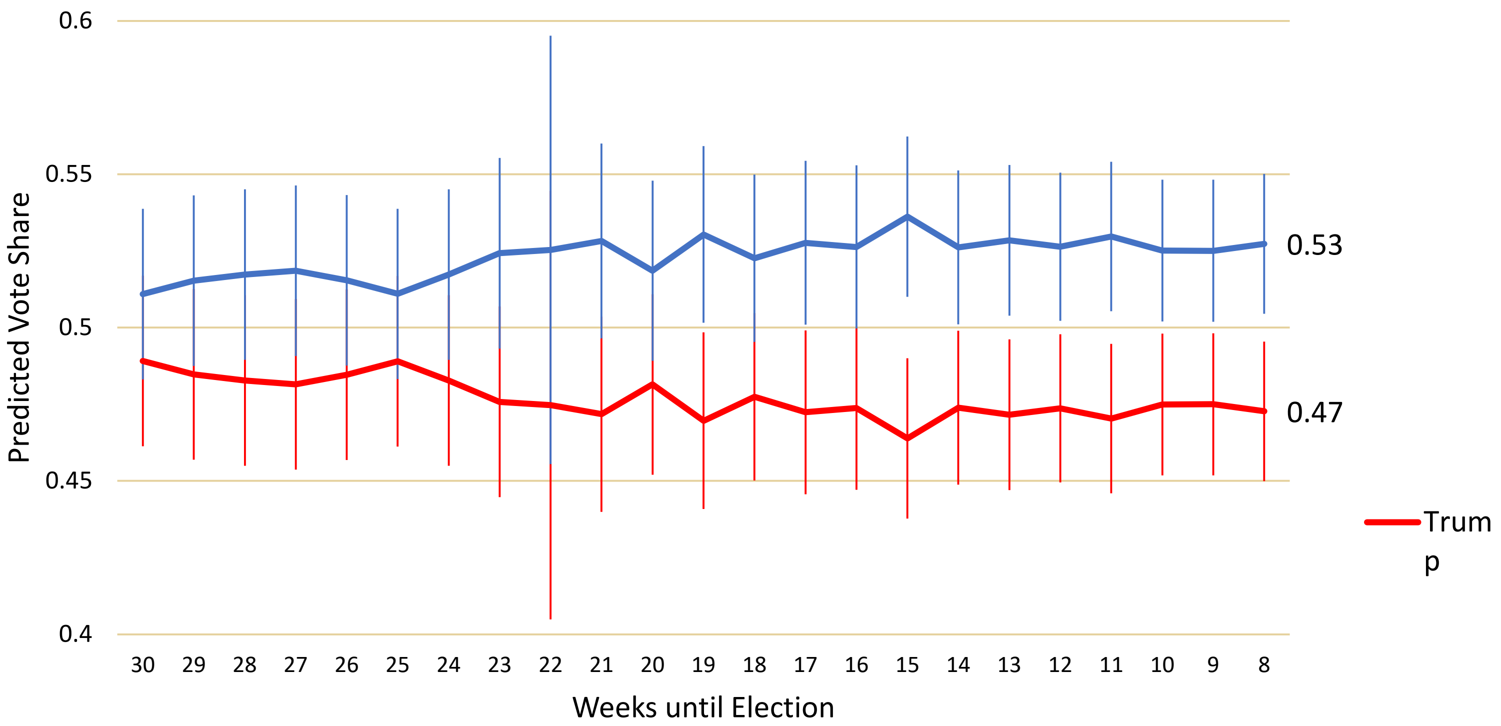
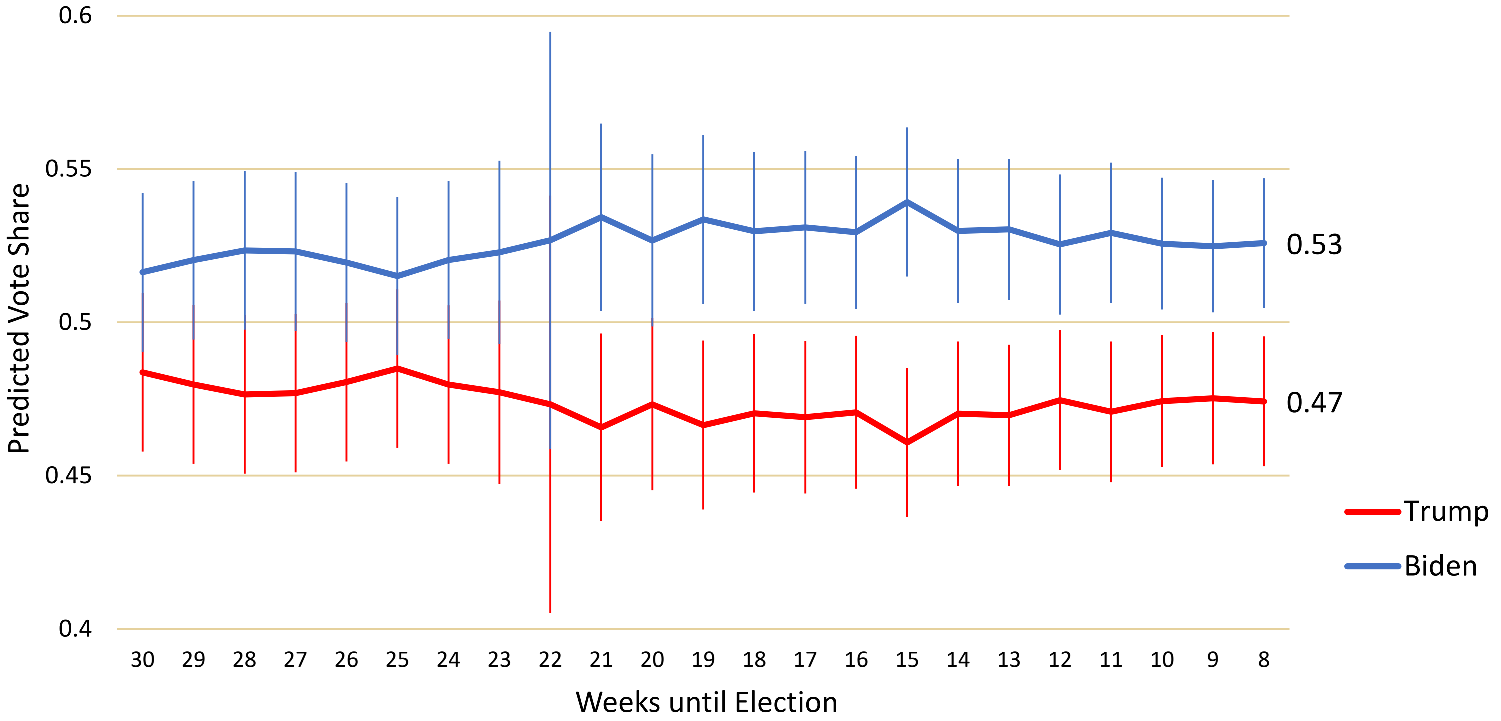
Pennsylvania



Trump's chance of winning: 19%
(1M simulations)

Likely popular vote: 45.0 – 49.5%
(80% prediction intervals)

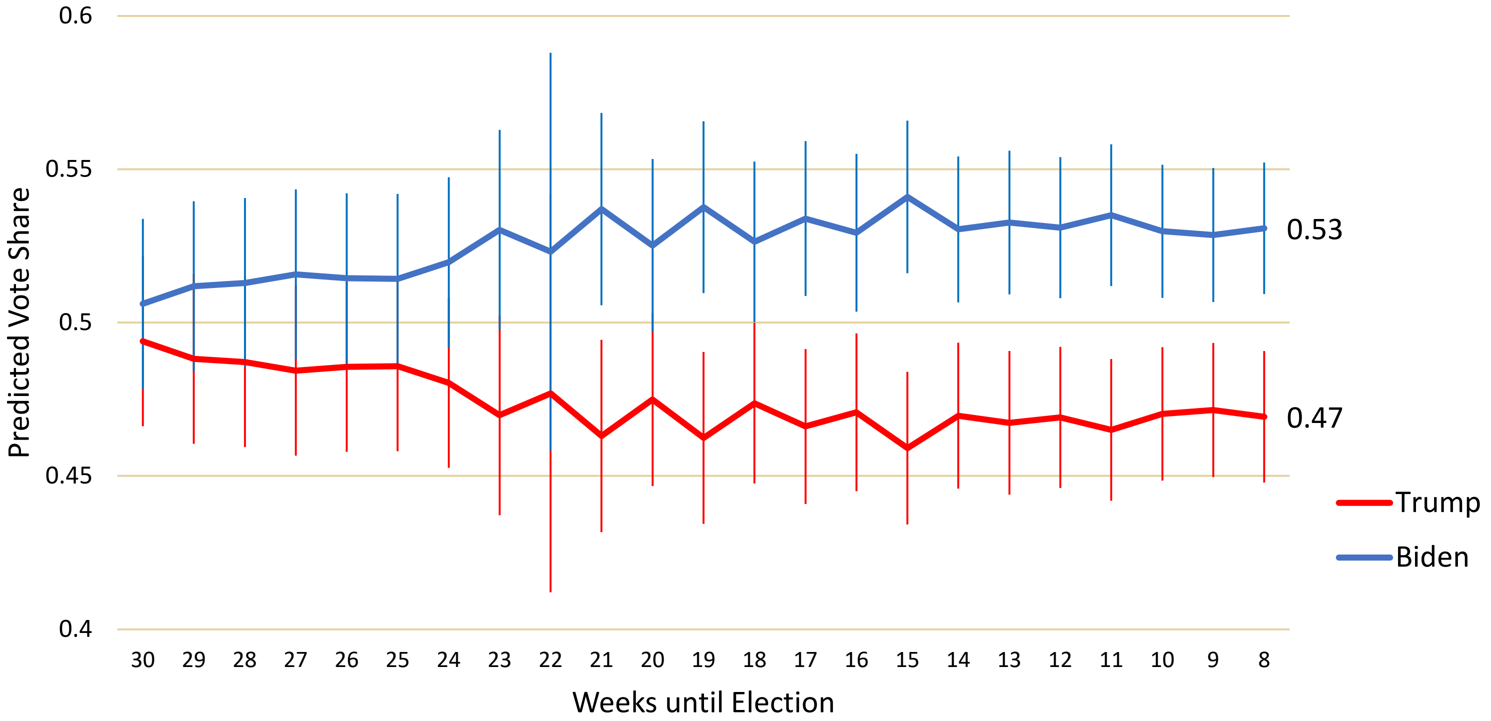
Florida



Trump’s chance of winning: 17%
(1M simulations)

Likely popular vote: 45.3 – 49.5%
(80% prediction intervals)

Wisconsin



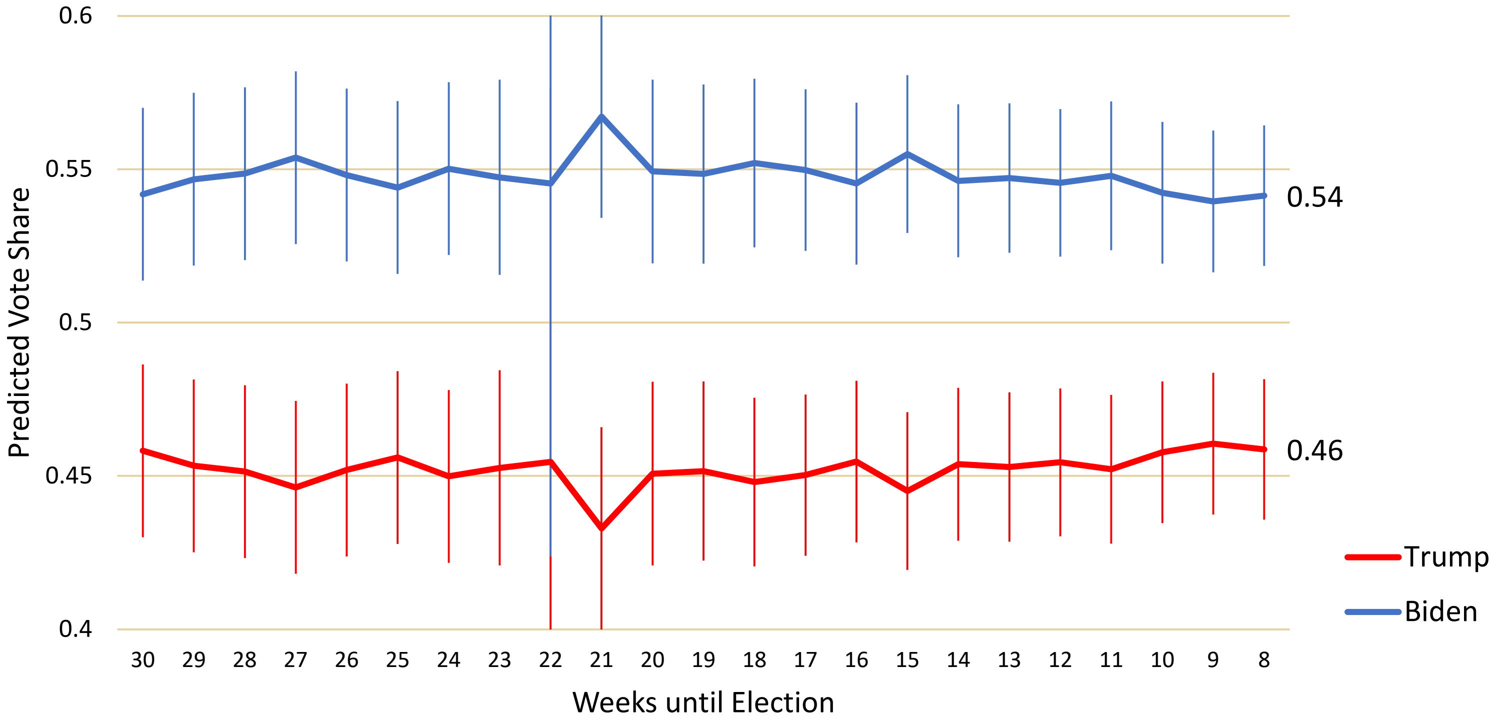
Trump’s chance of winning: 11%

(1M simulations)

Likely popular vote: 44.8 – 49.1%

(80% prediction intervals)

Michigan



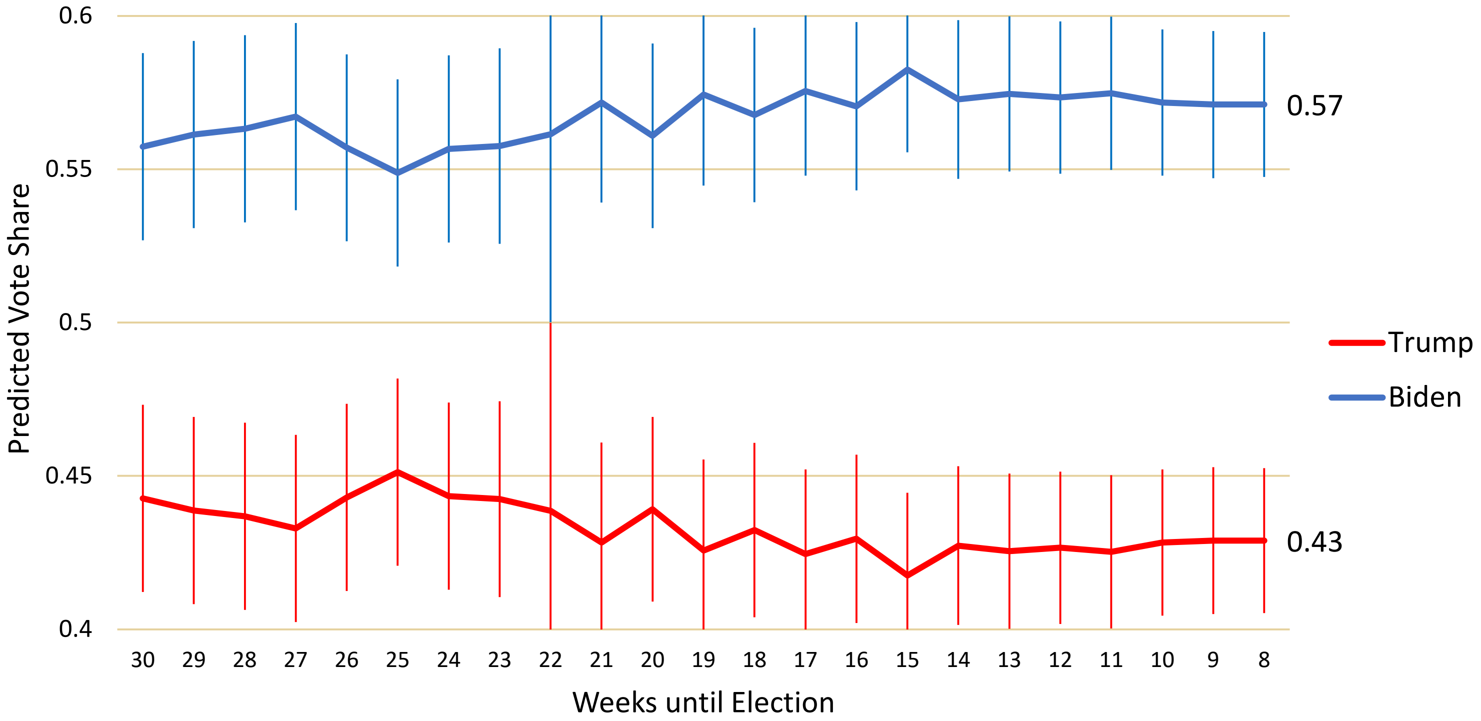
Trump's chance of winning: 10%

(1M simulations)

Likely popular vote: 43.6 – 48.2%

(80% prediction intervals)

Colorado



Trump's chance of winning: 3%

(1M simulations)

Likely popular vote: 40.5 – 45.3%

(80% prediction intervals)

Equation Information: 2020

Note: This is only with current data and will be updated throughout the project until election day.

Table 1

Abbreviated summary of the mixed model with autoregressive regressive correlation 2020

Term	Estimate	SE	Statistic
(intercept)	0.501**	0.008	60.286
Week	-0.000	0.000	-0.459
Negative * Mentions	0.156	0.125	1.250
State lean	0.351*	0.145	2.422
Favorability Difference	0.060*	0.027	2.174
Unemployment since Jan	-0.000	0.000	-0.922
AR(1)	0.376	NA	NA
AR(2)	-0.032	NA	NA
AR(3)	-0.049	NA	NA
AR(4)	0.011	NA	NA
rnd state sd_(Intercept)	0.019	NA	NA
rnd state residual	0.015	NA	NA

$^{*}p < .05$. $^{**}p < .01$.

Table 2

Per state random effects 2020

State	(intercept)
AZ	-0.018
CO	-0.029
FL	-0.005
GA	0.020
IA	0.026
MI	-0.003
NV	0.019
NC	0.005
OH	-0.001
PA	0.012
TX	0.011
WI	-0.014

Equation Information: 2016

Table 3

Abbreviated summary of the mixed model with autoregressive regressive correlation 2016

Term	Estimate	SE	Statistic
(intercept)	0.525**	0.010	54.422
Week	-0.010**	0.000	-3.869
Negative * Mentions	0.080	0.253	0.315
State lean	0.816**	0.216	3.777
Favorability Difference	0.061*	0.024	2.562
Unemployment since Jan	-0.049*	0.019	-2.520
AR(1)	0.362	NA	NA
AR(2)	0.079	NA	NA
AR(3)	0.031	NA	NA
AR(4)	0.059	NA	NA
rnd state sd__(Intercept)	0.019	NA	NA
rnd state residual	0.023	NA	NA

*$p < .05$. **$p < .01$.

Table 4

Per state random effects 2016

State	(intercept)
AZ	-0.012
CO	0.030
FL	-0.013
GA	-0.019
IA	0.016
MI	0.004
NV	-0.004
NC	-0.018
OH	-0.010
PA	0.001
TX	-0.001
WI	0.025

Equation Information: 2012

Table 5

Abbreviated table summarizing the mixed model with autoregressive regressive correlation 2012

Term	Estimate	SE	Statistic
(intercept)	0.517**	0.008	62.760
Week	-0.000*	0.000	-1.998
Negative * Mentions	-0.199	0.155	-1.282
State lean	0.603**	0.136	4.430
Favorability Difference	-0.016	0.014	-1.137
Unemployment since Jan	0.015	0.012	1.226
AR(1)	0.388	NA	NA
AR(2)	0.084	NA	NA
AR(3)	-0.065	NA	NA
AR(4)	-0.085	NA	NA
sd__(Intercept)	0.018	NA	NA
Residual	0.019	NA	NA

*$p < .05$. **$p < .01$.

Table 6

Per state random effects 2012

State	(intercept)
AZ	0.004
CO	0.029
FL	-0.004
GA	-0.031
IA	-0.009
MI	-0.014
NV	0.023
NC	-0.011
OH	-0.010
PA	0.006
TX	-0.007
WI	0.002

Thanks

- Bhaskar V. Karambelkar and Fivethirtyeight for the map code and public information, see https://rpubs.com/bhaskarvk/electoral-Map-2016
- Brandwatch for availability of Twitter data and net sentiment analysis
- RCP and FiveThirtyEight for their polling data
- Gallup for their state lean polling

For additional questions or media inquiries, please contact Danny Parra (dparra@email.gwu.edu)

Appendix A: Explanation of Models

What Our Models Do
Our models predict the final vote share for the Presidential elections weekly.

How We Predict Vote Share
In order to predict each candidate's vote share in the battleground states, we input the latest variable data (see below) into the mixed effect regression model with an autoregressive correlation of past polls to generate an estimate as well as an upper- and lower-bound for the predicted performance of each candidate in each state. Then we created a normal distribution around the estimation with the model's error to create a probability distribution. This distribution was drawn from 1 million times to create probabilities of the candidate winning the state (specifically, greater than 50%). The state-level polling share was used as a dependent variable with each state allowed a unique slope. The model was tested using 2012 and 2016 data. The following were then used for fixed effects:

Fourth order autoregressive model of weekly state polling averages : Weekly trial-heat state-level polling averages are entered into an autoregressive model. The last four weeks are used in the model to account for possible outliers in the trial-heat polls. Polls are often aggregated to predict vote share on a state-level (Linzer, 2013; Kennedy, Wojcik, & Lazer, 2017; The Economist, FiveThirtyEight). Since 2008, more battleground state trial polls have been conducted, allowing for better accuracy (Linzer, 2013). Our measure creates a two-party vote share form the polls. For weeks without polls, this variable was not adjusted, such that it represents the last week polled. The polling data was obtained from RCP and FiveThirtyEight's state-level polling websites (for example, for Arizona: https://www.realclearpolitics.com/epolls/2020/president/az/arizona_trump_vs_biden-6807.html and https://projects.fivethirtyeight.com/polls/president-general/arizona/)

State lean: A measurement using the year prior's Gallup results. Specifically, we took the Gallup's question reporting on whether citizens of that state consider themselves Democrat, Republican, or Independent. The incumbent's party percentage of identification or those who lean towards the party minus the challenger's party percentage was used in our model. For 2012's data, see: https://news.gallup.com/poll/152438/states-move-gop-2011.aspx

Interaction of mentions on Twitter and change in negative Tweets: A qualitative analysis was completed in net sentiment provided by Brandwatch. While negative Tweets indicated opposition to the candidate (on average 83%), positive Tweets did not indicate support of the candidate (on average 26%). Thus, only negative Tweets were examined. Using net sentiment was found to improve prediction of swing states (Heredia, Prusa, & Khoshgoftaar, 2018). We are specifically interested in how the change in negative Tweets influence polling vote share. This interaction involved multiplying the share of Tweets about the incumbent multiplied by the change in percent negative share of the Tweets. Although not significant in the overall model, the measure improved the prediction of the 2016 election. Additionally, the interaction term was significant in a regression model with only Twitter information. Because it has been hypothesized that Trump has changed the way candidates interact with voters (Valentino, King, & Hill, 2017), we are specifically interested if this measure again improves the model performance.

State-level unemployment change since January: Economic factors influence vote share (Abramowitz, 1988; Fair, 1978; Linzer, 2013). To measure state-level economic data, state unemployment was utilized (provided by the US Bureau of Labor Statistics). Because economic data is comparative, the change in unemployment since January of election year was used in the model.

Favorability: The polling favorability question represents character of the candidates (Cohen, 2004). This was added to our model to capture the positive and negative polling opinions on each candidate. Because Twitter data only captured negative, it was important to represent positive evaluations of the candidates. Additionally, favorability and Twitter information was compared (see next slide). Additionally, Favorability gives us a global measure across the country, while Twitter data is examined, specifically in the state. Although state-level favorability would have been preferred, the polling demonstrated inconsistency with asking this question on the state level.

Appendix B: Exploration of Twitter

- Favorability and Twitter: Are we measuring the same concept?
  - For a fair comparison of the negative sentiment compared to the favorability measure, we calculated correlations between the unfavorable rating share (unfavorable rating of incumbent divided by the unfavorable rating of both candidates) and the global negative Twitter share of the candidates.
    - Across years: $r = -0.0006$, $p = 0.9856$
    - 2012: $r = 0.1901$, $p < 0.001$
    - 2016: $r = -0.0265$, $p = 0.6157$
    - 2020 (currently): $r = -0.4184$, $p < 0.001$
  - Incumbent's percentage of unfavorable versus their negative Tweet percentage (negative Tweets divided by total Tweets about the incumbent) were compared
    - Across years: $r = 0.4283$, $p < 0.001$
    - 2012: $r = 0.0186$, $p = 0.7252$
    - 2016: $r = -0.1243$, $p = 0.0183$
    - 2020 (currently): $r = -0.0023$, $p = 0.9751$
    - The t-test indicates that the variables are not equal (2012: $t(359) = -121.72$, $p < 0.001$; 2016: $t(359) = -171.00$, $p < 0.001$).
  - Challenger's percentage of unfavorable versus their negative Tweet percentage were compared
    - Across years: $r = -0.6844$, $p < 0.001$
    - 2012: $r = 0.2607$, $p < 0.001$
    - 2016: $r = -0.2779$, $p < 0.001$
    - 2020 (currently): $r = -0.1678$, $p = 0.0243$
    - The t-test indicates that the variables are not equal (2012: $t(359) = -47.339$, $p < 0.001$; 2016: $t(359) = -161.85$, $p < 0.001$).
  - Thus, there is evidence the variables are not the same concept

Appendix B1: Additional Twitter Exploration

- Overall, the regression predicting next week's poll share with only Twitter data is significant ($F(3,920) = 15.23$, $p < 0.001$), with a significant interaction term between mentions and change in negative sentiment ($\beta = 0.3354$, $p = 0.0373$)
- Twitter mentions are negatively correlated with the state lean (2012: $r = -0.24$, $p < 0.001$; 2016: $r = -0.06$, ns)
- Twitter mentions and favorability are not significantly correlated (2012: $r = 0.06$, ns; 2016: 0.05, ns)