Forecasting U.S. elections using compartmental models

SIAM Applications of Dynamical Systems: May 2019

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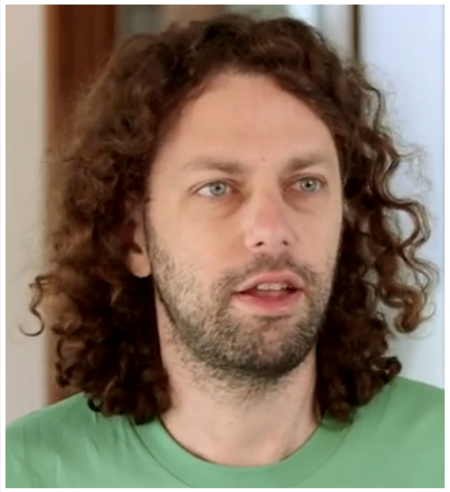

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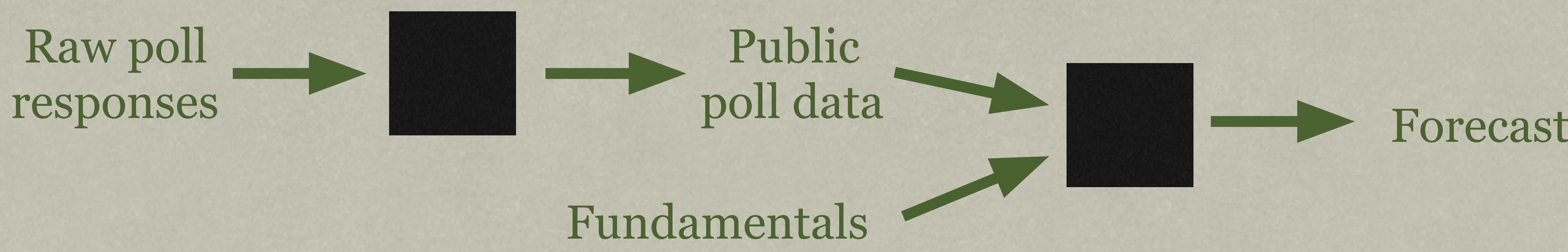
Motivation & background

	NYT	538	HuffPost	PW	PEC	DK	Cook	Roth.[1]	Sabato
Win presidency	85% Dem.	71% Dem.	98% Dem.	89% Dem.	>99% Dem.	92% Dem.	Lean Dem.	Lean Dem.	Lean Dem.



Different results based on the same Florida poll:

Pollster	Clinton	Trump	Margin
Charles Franklin Marquette Law	42%	39%	Clinton +3%
Corbett-Davies, Gelman, Rothschild Stanford University/Columbia University/Microsoft Research	40%	41%	Trump +1%
Omero, Green, Rosenblatt Penn Schoen Berland Research	42%	38%	Clinton +4%

Goal: Better understand the election forecasting process

{Tables from The Upshot, NY Times}

Motivation & background

	NYT	538	HuffPost	PW	PEC	DK	Cook	Roth.[1]	Sabato
Win presidency	85% Dem.	71% Dem.	98% Dem.	89% Dem.	>99% Dem.	92% Dem.	Lean Dem.	Lean Dem.	Lean Dem.

Elections are contested at the state level, but errors are correlated

Demographic/regional error:

- Due to polls being off in states with similar demographics
- 538 accounts for this by randomly varying the vote among groups with common features

	Ala.	Calif.	Fla.	Minn.	N.C.	N.M.	R.I.	Wis.
Alabama		.60	.61	.53	.72	.54	.41	.55
California	.60		.73	.67	.69	.80	.61	.68
Florida	.61	.73		.67	.75	.70	.63	.76
Minnesota	.53	.67	.67		.68	.58	.64	.84
N. Carolina	.72	.69	.75	.68		.60	.53	.67
New Mexico	.54	.80	.70	.58	.60		.54	.64
Rhode Island	.41	.61	.63	.64	.53	.54		.69
Wisconsin	.55	.68	.76	.84	.67	.64	.69	

Goal: Account for directed relationships between states

{A user's guide to FiveThirtyEight's 2016 general election forecast; Right table from FiveThirtyEight; Top table from Upshot, NY Times}

Example related previous work

Example statistical or economic approaches to forecasting:

Klarner (2008)	Fundamentals- & polls-based
Hummel, Rothschild (2014)	Fundamentals-based
Abramowitz (2016)	Fundamentals-based
Alexander, Ellingson (2019)	Polls-based Bayesian model (2016)

Example dynamical systems approaches to election dynamics:

Fernàndez-Gracia, Suchecki, et al. (2014)	voter model (results data)
Galam (2017)	local majority rule model
Braha, de Aguiar (2017)	voter model (results data)

NYT Sabato Cook HuffPost 538

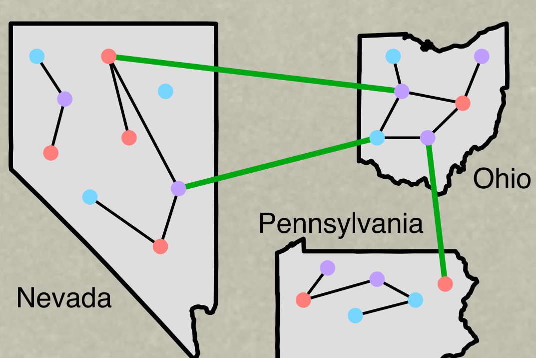
Goals & outline

Goals:

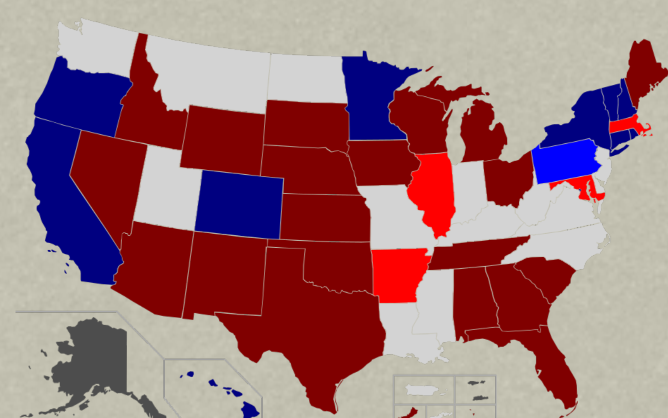
- Develop a model that accounts for directed interactions between states
- Shed light on the forecasting process & raise questions
- Help suggest improved ways of polling and forecasting elections

Outline:

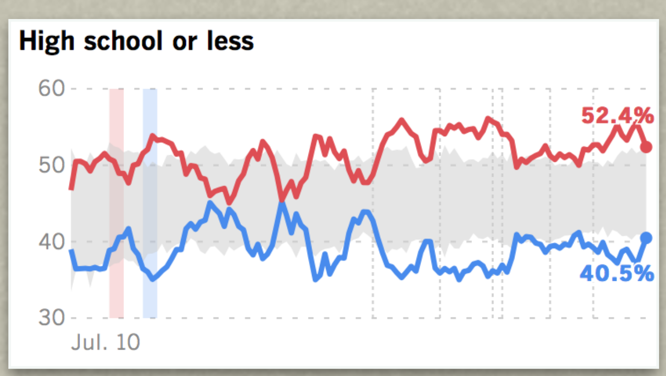
Model



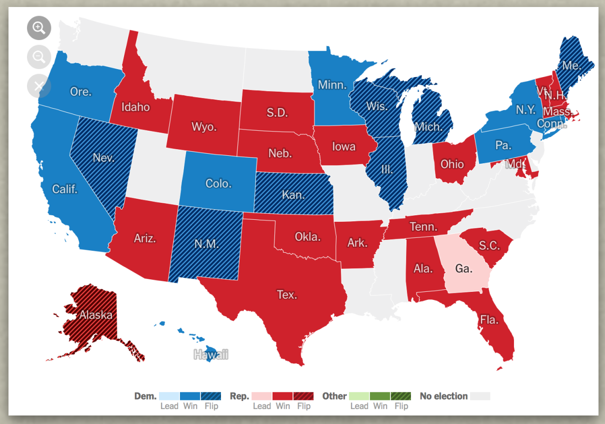
2012-2016



Uncertainty



2018

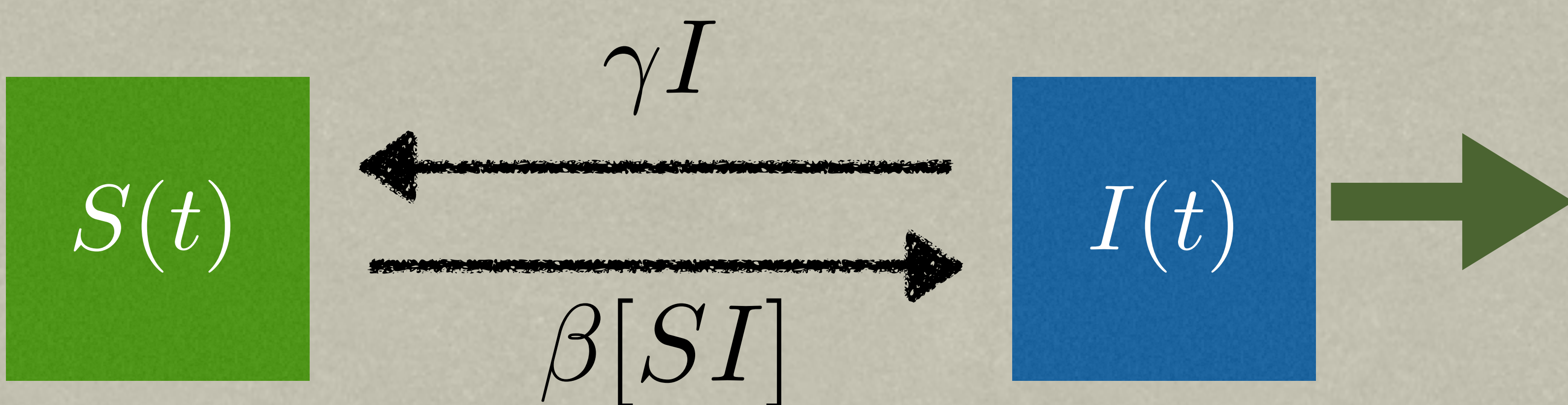


Approach: Compartmental models of infection fit to polling data

{US images from Wikipedia; Graph from LA Times}

Modeling approach

SIS model:



Assuming uniform mixing:

$$\frac{dS}{dt} = \gamma I - \frac{\beta}{N} S I$$

$$\frac{dI}{dt} = -\gamma I + \frac{\beta}{N} S I$$

Our approach: Reframe the SIS compartmental model for elections

- ➡ 2 contagions = Democrat & Republican voting inclinations
- ➡ Susceptible = Undecided voters
- ➡ Parameters fit to polling data for each election year

Our model

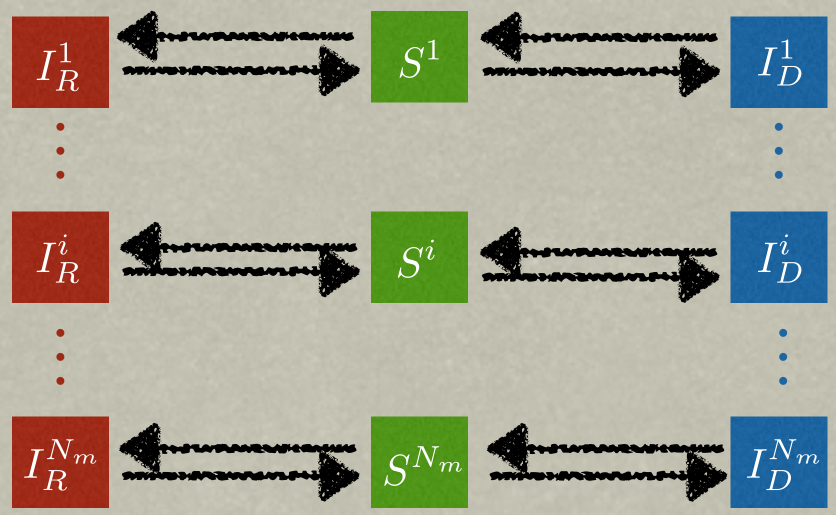
$S^i =$ expected fraction of undecided (or non) voters in module i

$I_R^i =$ expected fraction of Republican voters in module i

$I_D^i = 1 - S^i - I_R^i =$ expected fraction of Democrat voters in module i

$N = 249,485,228 =$ total number of voting-age individuals in the US

$N^i =$ number of voting-age individuals in each module



Dem.

$$\frac{dI_D^i}{dt}(t) = \underbrace{-\gamma_D^i I_D^i}_{\text{Dem. loss}} + \underbrace{\sum_{j=1}^{M} \beta_D^{ij} \frac{N^j}{N} S^i I_D^j}_{\text{Dem. infection}}$$

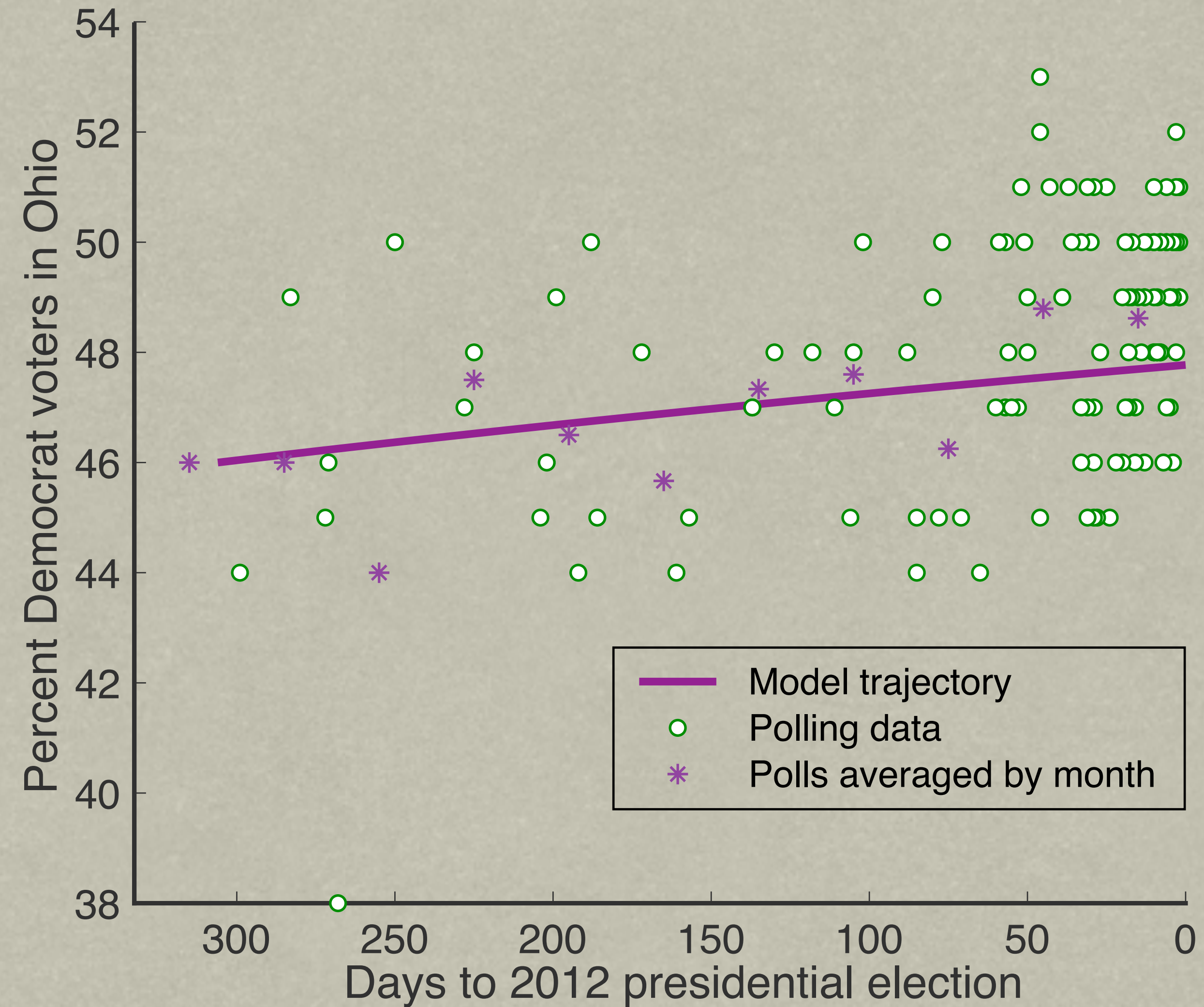
Rep.

$$\frac{dI_R^i}{dt}(t) = \underbrace{-\gamma_R^i I_R^i}_{\text{Rep. loss}} + \underbrace{\sum_{j=1}^{M} \beta_R^{ij} \frac{N^j}{N} S^i I_R^j}_{\text{Rep. infection}}$$

Undec.

$$\frac{dS^i}{dt}(t) = \gamma_D^i I_D^i + \gamma_R^i I_R^i - \sum_{j=1}^{M} \beta_D^{ij} \frac{N^j}{N} S^i I_D^j - \sum_{j=1}^{M} \beta_R^{ij} \frac{N^j}{N} S^i I_R^j$$

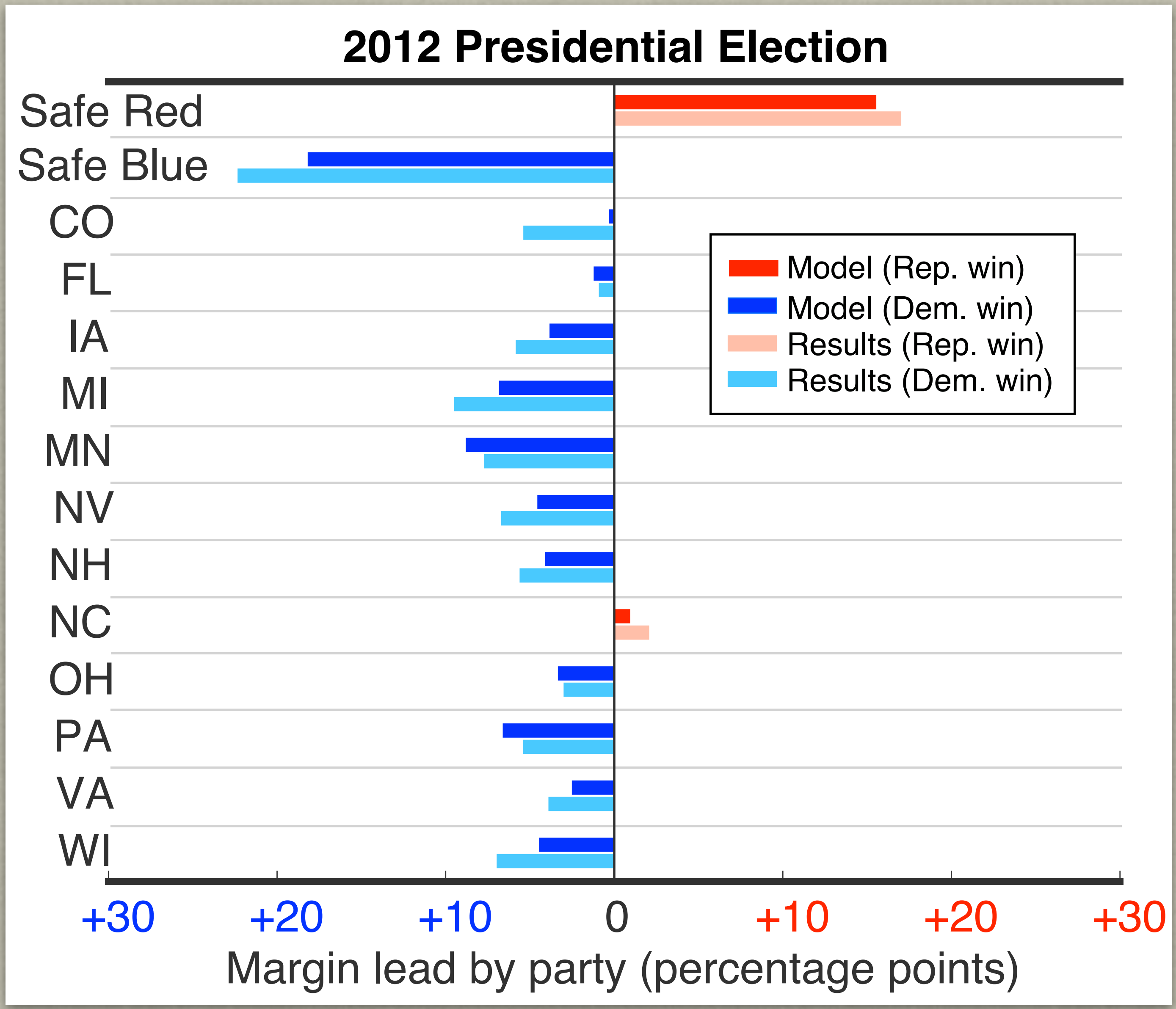
Incorporating public polling data

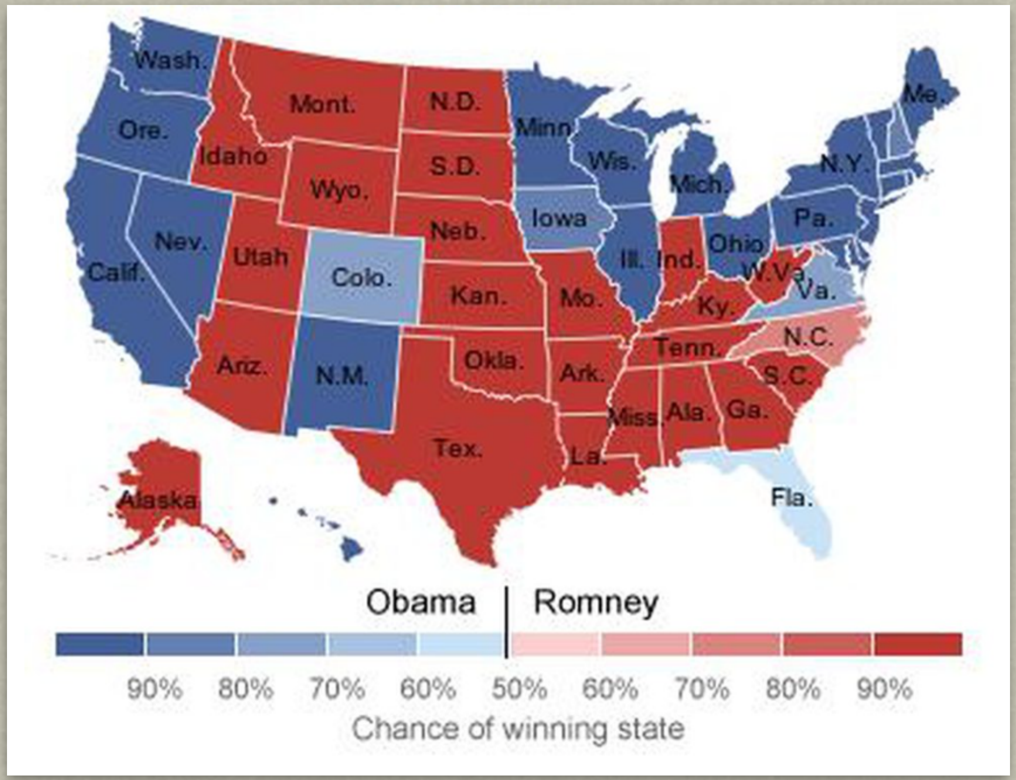


- Parameters are fit to polls in the year leading up to an election
- Polls are averaged by month
- No adjustments to polls of likely voters, registered voters, or all adults
- No adjustments for poll accuracy, recency, or partisanship
- No adjustments for convention bounce, third parties, or undecided voters

Forecasting the 2012 presidential race

- Actual results: Romney 206, Obama 332
- Accuracy: 100%
- Model agrees with 538





{538}

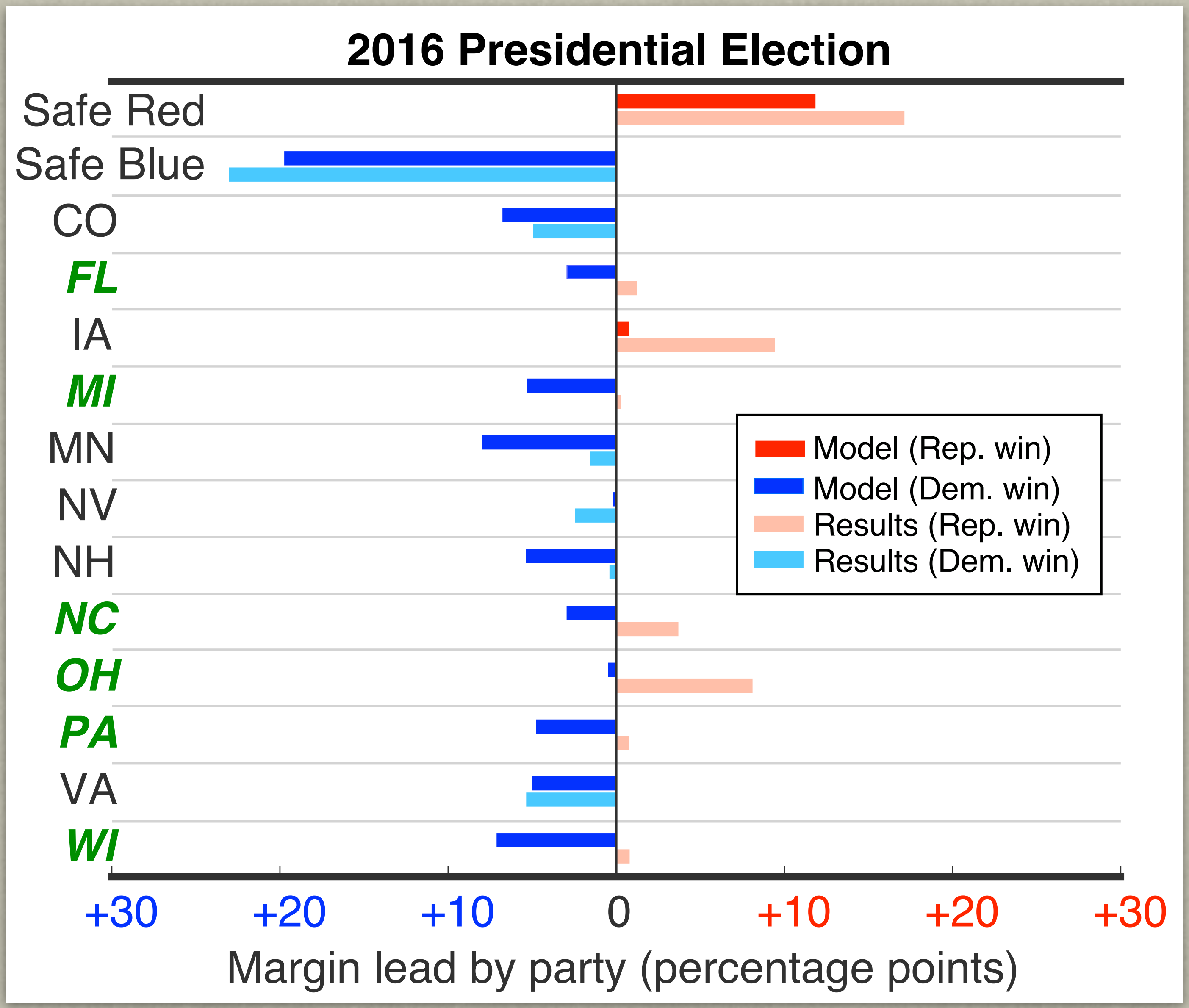
Most influential states:

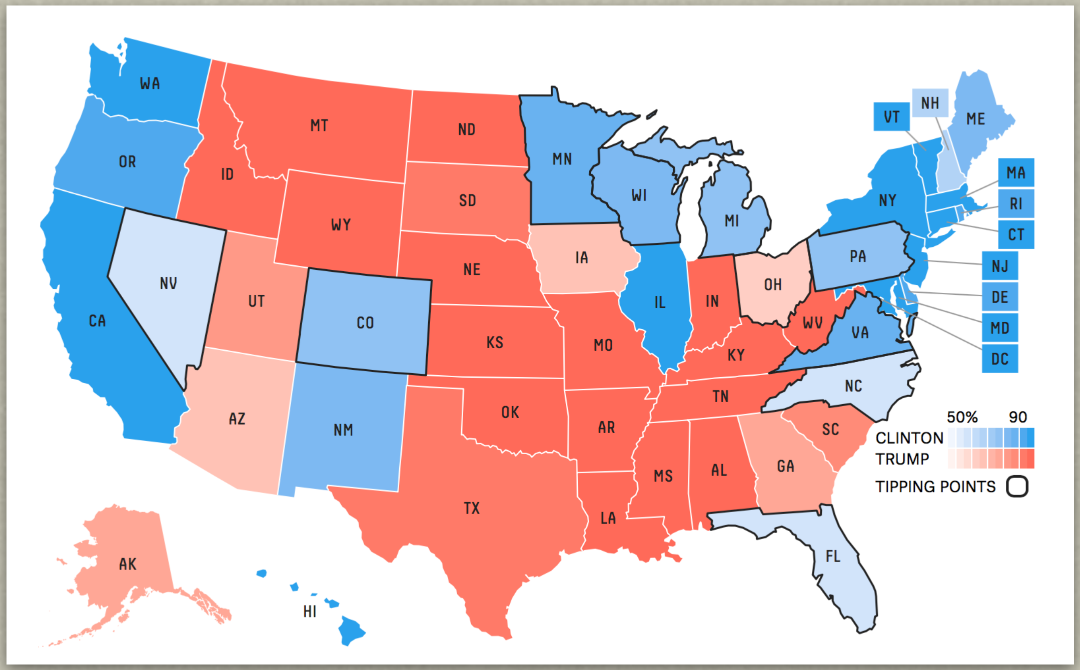
- Florida
- Pennsylvania
- Ohio

$$\sum_{j=1}^{14} \boxed{\beta_R^{ij}} \frac{N^j}{N} S^i I_R^j$$

{US image from https://www.forbes.com/sites/quora/2012/11/07/how-accurate-were-nate-silvers-predictions-for-the-2012-presidential-election/#65aca396fe3c}

Forecasting the 2016 presidential race





{538}

- Model forecast agrees with 538 with the exception of OH
- FL, MI, NC, OH, PA, and WI are predicted incorrectly
- CO, IA, MN, NV, NH, and VA are predicted correctly

Accuracy in past elections

Election	FiveThirtyEight.com	Our model	Sabato
2016 President	90.2%	88.2%	90.2%
2016 Senate	90.9%	87.9%	93.9%
2016 Governor	NA	91.7%	83.3%
2012 President	100%	100%	96.1%
2012 Senate	NA	90.3%	93.5%
2012 Governor	NA	88.9%	77.8%

Our simple compartmental model approach often agrees with popular forecasters and gives similar accuracy

Accounting for uncertainty

Dem. $$dI_D^i(t) = \left(\underbrace{-\gamma_D^i I_D^i}_{\text{Dem. turnover}} + \sum_{j=1}^{M} \underbrace{\beta_D^{ij} \frac{N^j}{N} S^i I_D^j}_{\text{Dem. influence from state } j \text{ to state } i} \right) dt + \underbrace{\sigma dW_D^i(t)}_{\text{uncertainty}}$$

Rep. $$dI_R^i(t) = \left(-\gamma_R^i I_R^i + \sum_{j=1}^{M} \beta_R^{ij} \frac{N^j}{N} S^i I_R^j \right) dt + \sigma dW_R^i(t)$$

Undec. $$dS^i(t) = \left(\gamma_D^I I_D^i + \gamma_R^i I_R^i - \sum_{j=1}^{M} \beta_D^{ij} \frac{N^j}{N} S^i I_D^j \right) - \left(\sum_{j=1}^{M} \beta_R^{ij} \frac{N^j}{N} S^i I_R^j \right) dt + \sigma dW_S^i(t)$$

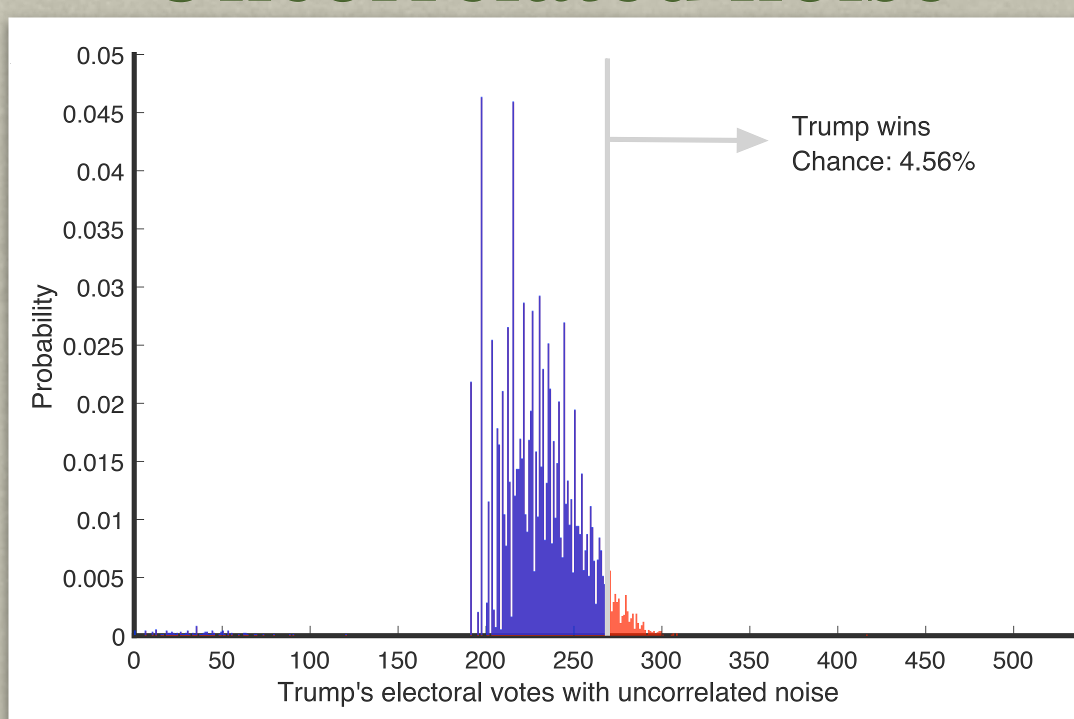
538

71% Dem.

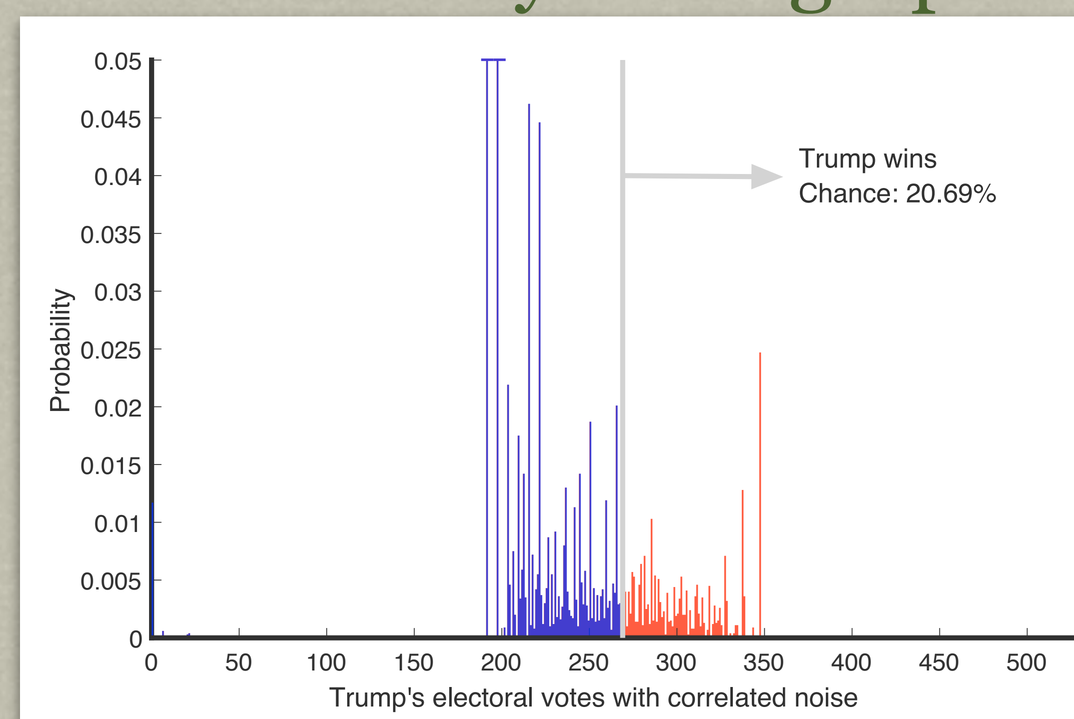
HuffPost

98% Dem.

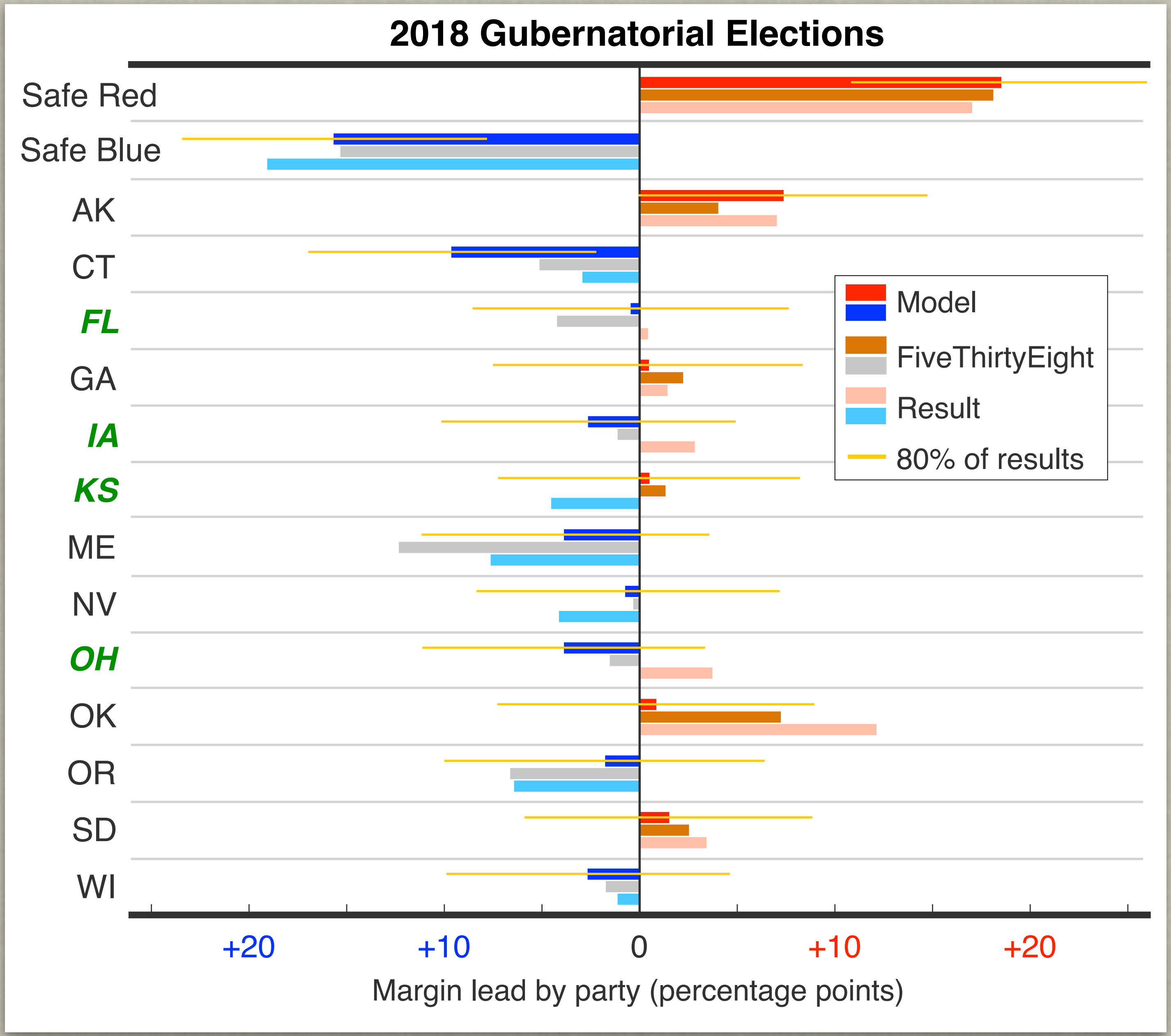
Uncorrelated noise



Correlated by demographic



Forecasting the 2018 governor races



- Model forecast on Nov. 3 compared to final 538 forecast on Nov. 6
- We miss the same states as 538

Forecaster	Gov. margin error	Gov. # states missed	Gov. log-loss error
Our model	4.1 pts.	4 missed	0.590
FiveThirtyEight.com	3.1 pts.	4 missed	0.548
Sabato	NA	1 missed, 1 not called	0.585
Cook	NA	12 not called	0.670
Inside Elections	NA	2 missed, 2 not called	0.619
RealClearPolitics.com	NA	12 not called	0.647

Forecasting the 2018 Senate races

	Model 7 Oct.	Sabato 11 Oct.	IE 12 Oct.	538 30 Oct.	IE 1 Nov.	**Model** 3 Nov.	Sabato 5 Nov.	538 6 Nov.
Arizona	69.7%			64.5%	Tilt	66.4%		61.4%
Florida	67.0%			70.6%	Tilt	59.1%		70.4%
Indiana	81.4%			67.2%		76.1%		71.8%
Minnesota*	97.1%			89.7%		95.7%		92.4%
Missouri	62.9%			60.1%	Tilt	57.8%		56.9%
Montana	76.6%		Tilt		Tilt	83.3%		76.0%
Nevada	59.6%			59.2%	Tilt	52.3%		57.0%
New Jersey	79.8%			89.9%		77.6%		94.6%
North Dakota	85.0%		Tilt	73.6%		89.0%		73.2%
Ohio	99.8%			95.7%		99.2%		96.7%
Tennessee	69.6%			76.3%		55.7%		80.4%
Texas	87.3%			80.6%		86.7%		78.8%
West Virginia	93.6%		Tilt	89.4%	Tilt	93.5%		87.9%
Wisconsin	94.3%			98%		95.8%		97.7%

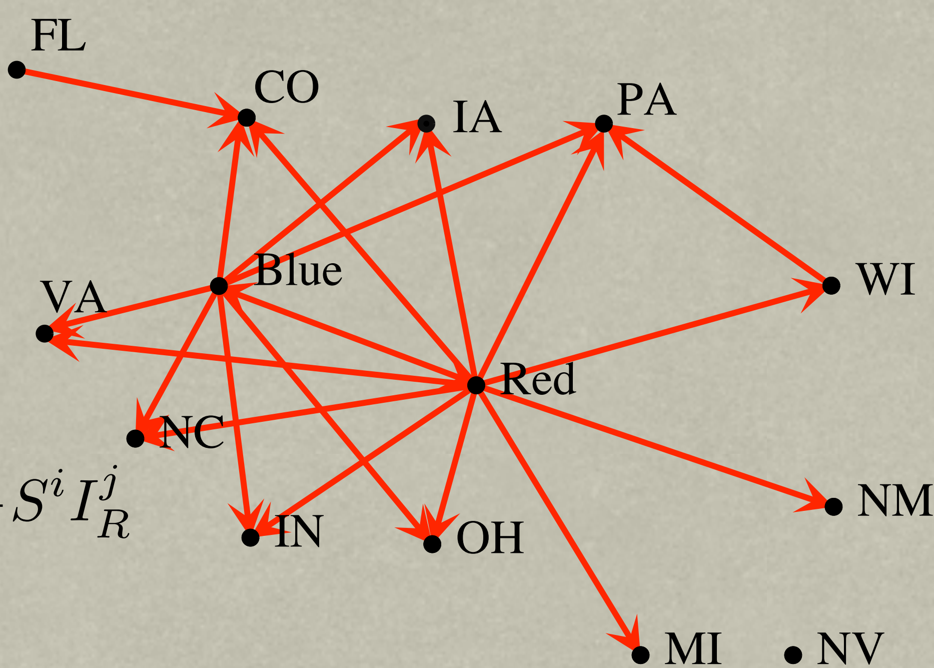
- Solid Rep. (≧ 95%)
- Likely Rep. (≧ 75%)
- Lean Rep. (≧ 60%)
- Toss-Up (< 60%)
- Lean Dem. (≧ 60%)
- Likely Dem. (≧ 75%)
- Solid Dem. (≧ 95%)

Forecaster	Sen. margin error	Sen. # states missed	Sen. log-loss error
Our model	4.6 pts.	3 missed	0.400
FiveThirtyEight.com	3.7 pts.	3 missed	0.410
Sabato	NA	1 missed	0.379
Cook	NA	9 not called	0.553
Inside Elections	NA	1 missed, 1 not called	0.415
RealClearPolitics.com	NA	8 not called	0.071

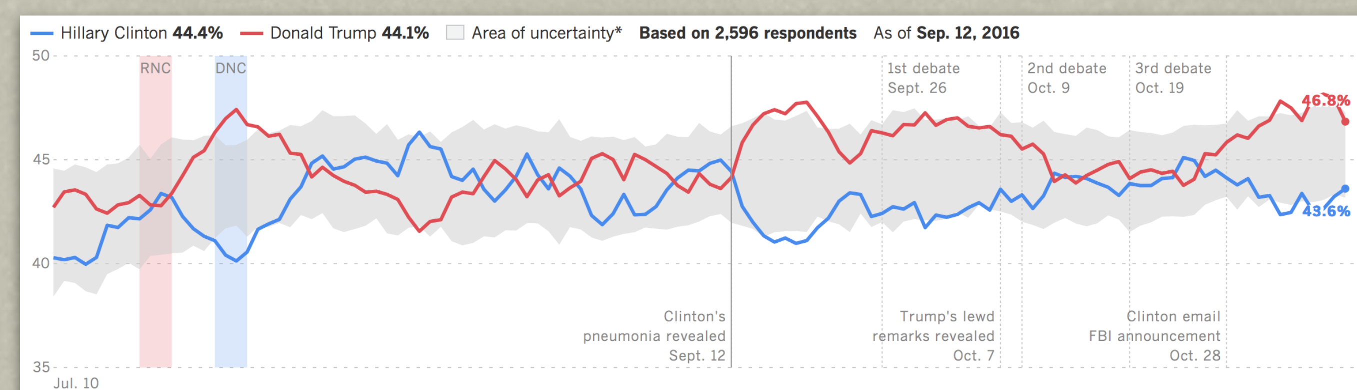
Thanks for listening!

Outlook:

- Which states are most influential?
- How do state relationships change in time?
- How do other choices for correlated noise impact forecasts?
- How do external forces impact voting dynamics?



$$\sum_{j=1}^{14} \boxed{\beta_R^{ij}} \frac{N^j}{N} S^i I_R^j$$



{LA Times}

Support: This work was supported by the MBI & NSF under DMS-1440386.

{A V—, DF Linder, MA Porter, GA Rempala, Submitted. arXiv 1811.01831}

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Dynamics of Democracy

Influence of media on opinion dynamics in social networks
Heather Brooks & Mason Porter

“Very fine people on both sides” of Twitter: Analyzing the network structure of the online conversation about #Charlottesville
Joseph Tien

The effect of the convergence parameter in the Deffuant model of opinion dynamics
Susan Fennell

A network model of immigration: enclave formation vs. cultural integration
Maria D’Orsogna, Tom Chao, & Yao-li Chuang

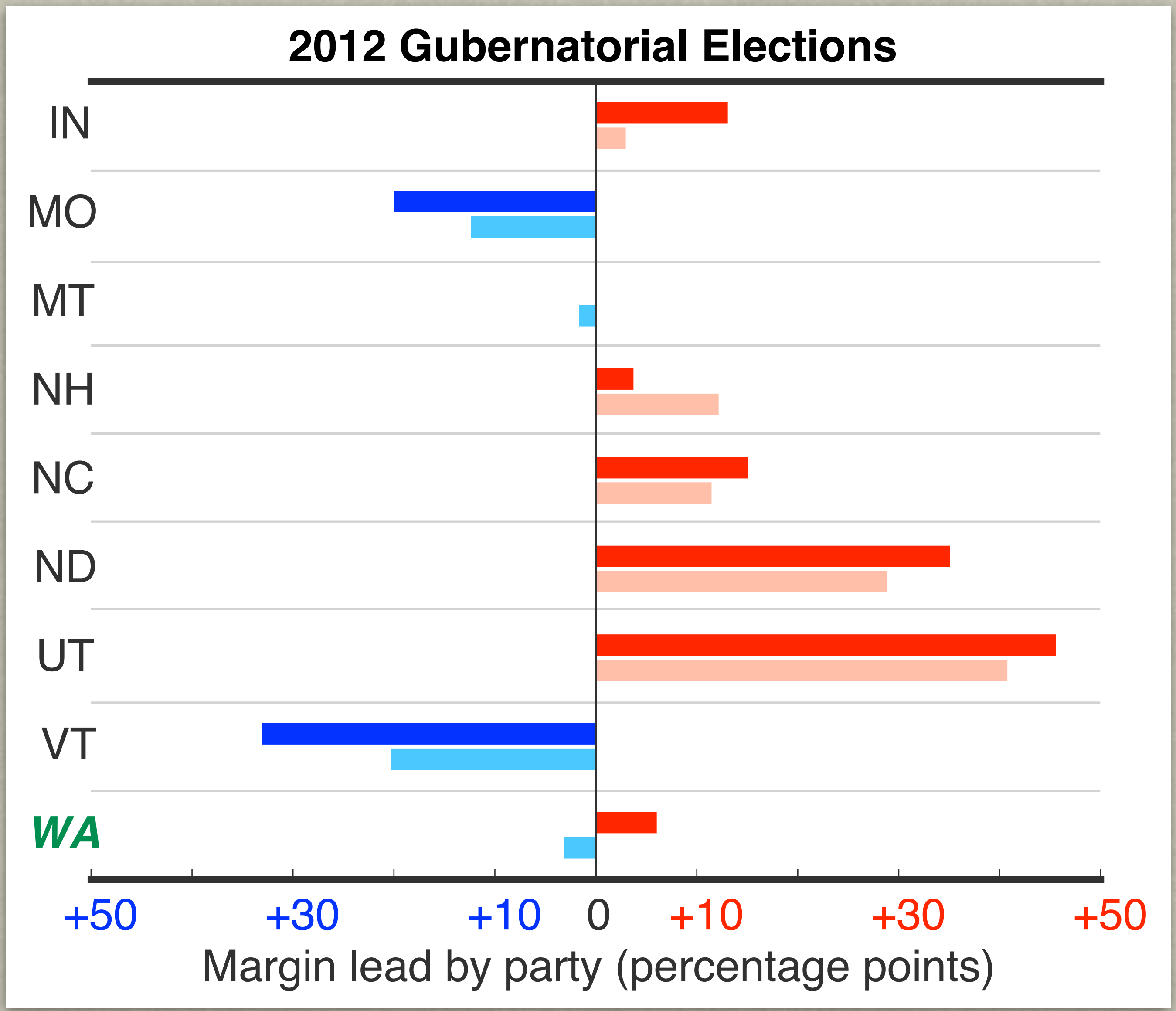
Interdisciplinary inclusive communities of undergraduates doing social-justice inspired research
Carlos Castillo-Chavez

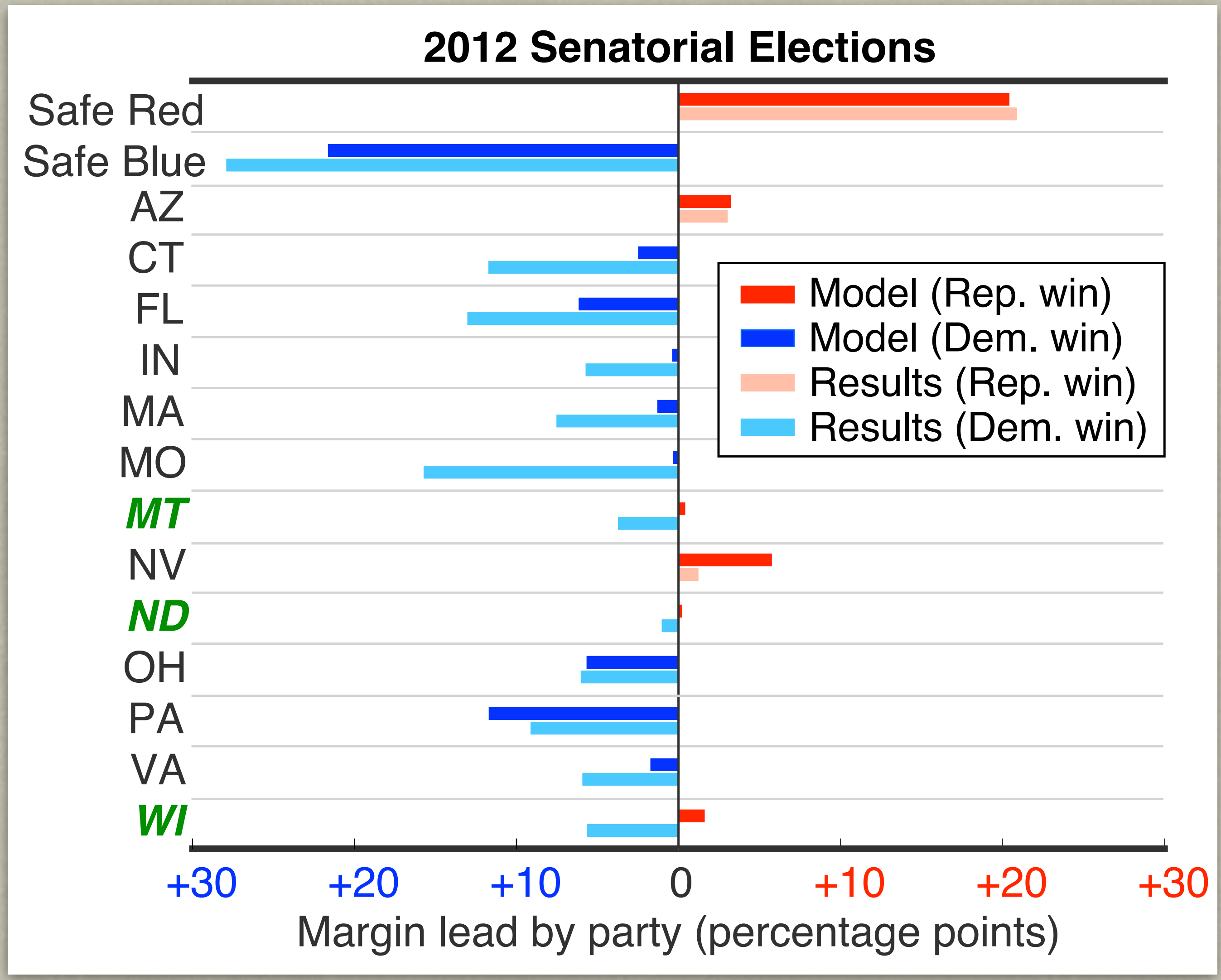
Quantifying gerrymandering using random dynamics
Jonathan Mattingly & Gregory Herschlag

A topological approach to detecting neighborhood segregation
Michelle Feng

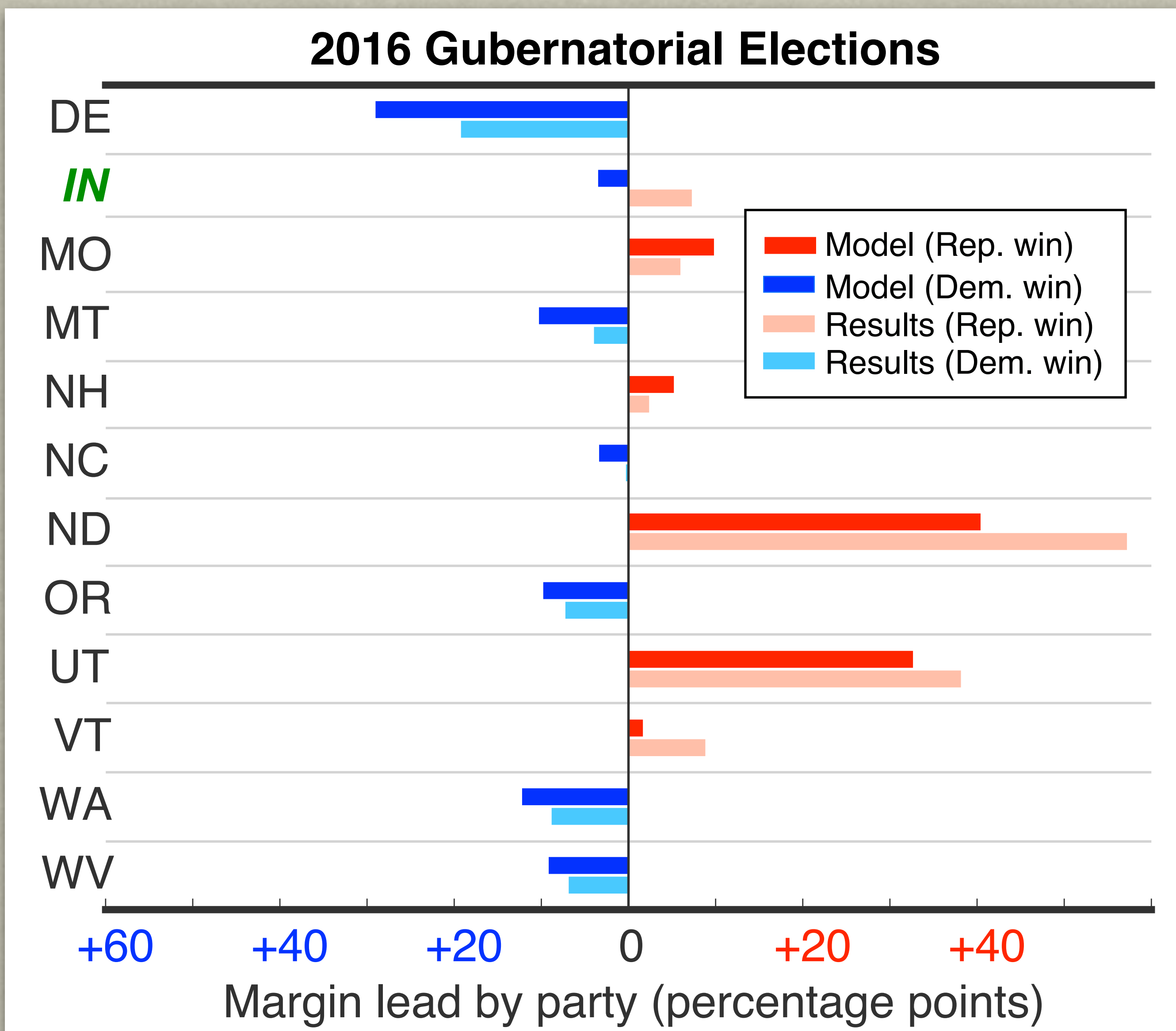
Forecasting U.S. elections using compartmental models
Alexandria Volkening, Daniel Linder, Mason Porter, & Grzegorz Rempala

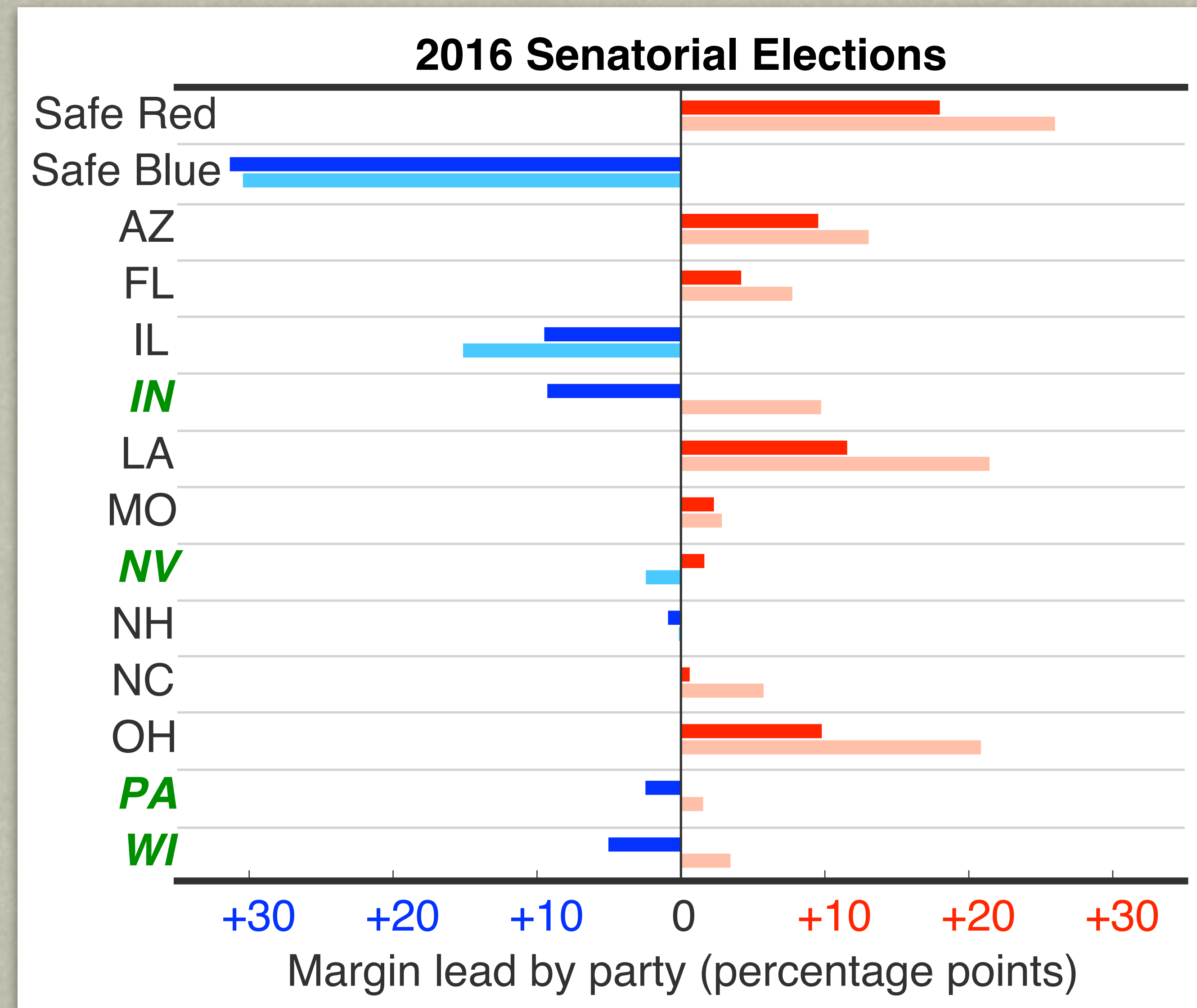
Forecasting the 2012 governor & senate races





Forecasting the 2016 senate & governor races





Assessing the 2018 forecasts

Forecaster	Gov. margin error	Gov. # states missed	Gov. log-loss error
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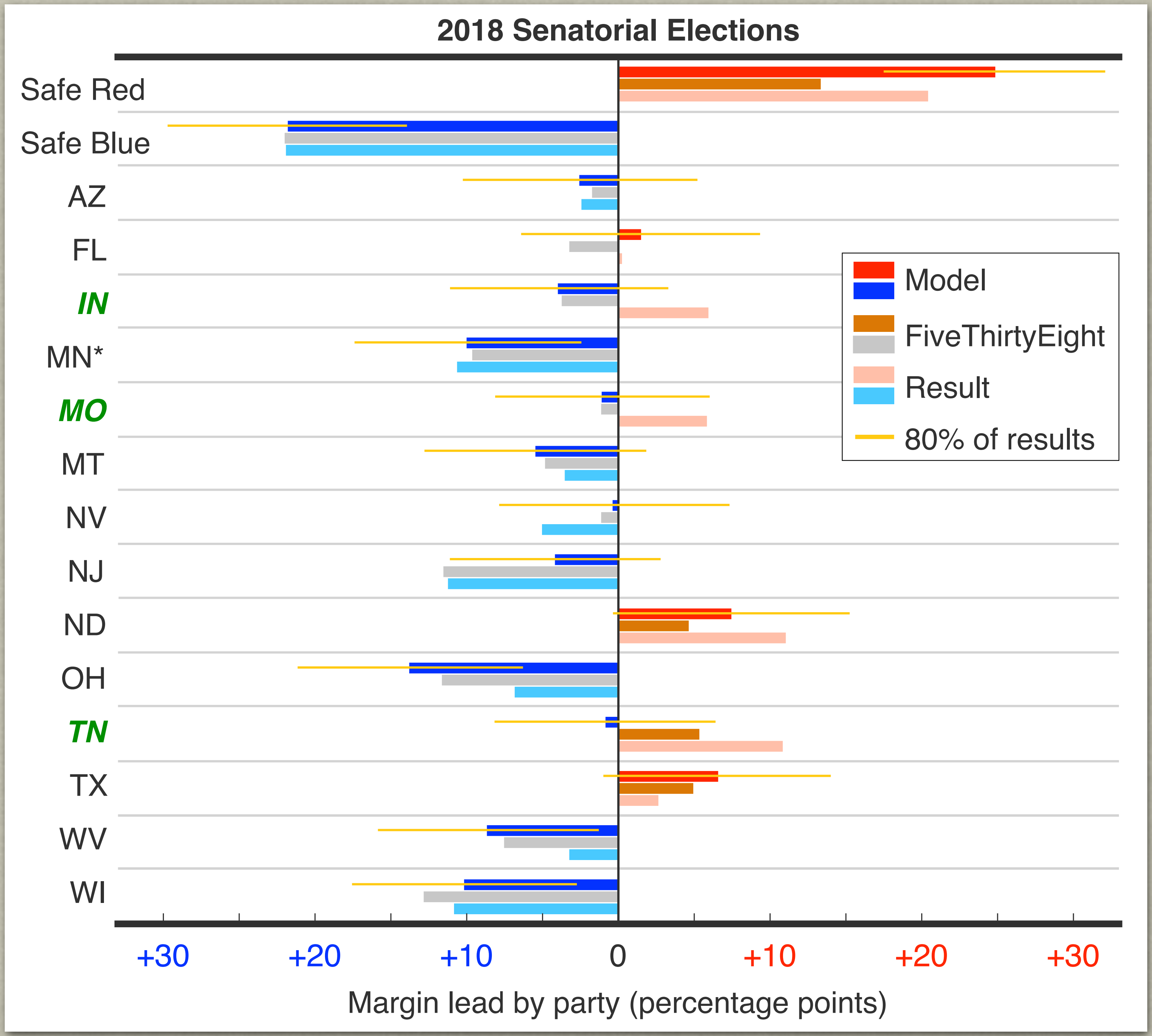
- Log-loss error is a measure that rewards strong correct forecasts and penalizes strong incorrect forecasts:

$$\text{log loss} = -\frac{1}{M}\sum_{j=1}^{M}\left(y_i \log p_i + (1-y_i)\log(1-p_i)\right)$$

Forecasting the 2018 Senate races



- Model forecast compared to 538 forecast
- We agree by color except for FL and TN

Forecasting the 2018 governor races

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Alaska		Tilt	89.9%	70.2%			68.9%
Connecticut			95.5%	78.6%			79.0%
Florida		Tilt	52.6%	75.7%			77.2%
Georgia		Tilt	53.0%	59.2%			67.8%
Iowa		Tilt	67.2%	52.1%			57.3%
Kansas			53.3%	58.2%			57.2%
Maine		Tilt	74.6%	94.4%			94.7%
Nevada		Tilt	54.9%	55.0%			51.5%
Ohio			75.3%	55.2%			59.5%
Oklahoma			55.9%	86.2%			85.7%
Oregon		Tilt	61.1%	81.4%			82.3%
South Dakota		Tilt	60.2%	83.1%			63.1%
Wisconsin			68.3%	60.6%			59.7%

- Solid Rep. (≧ 95%)
- Likely Rep. (≧ 75%)
- Lean Rep. (≧ 60%)
- Toss-Up (< 60%)
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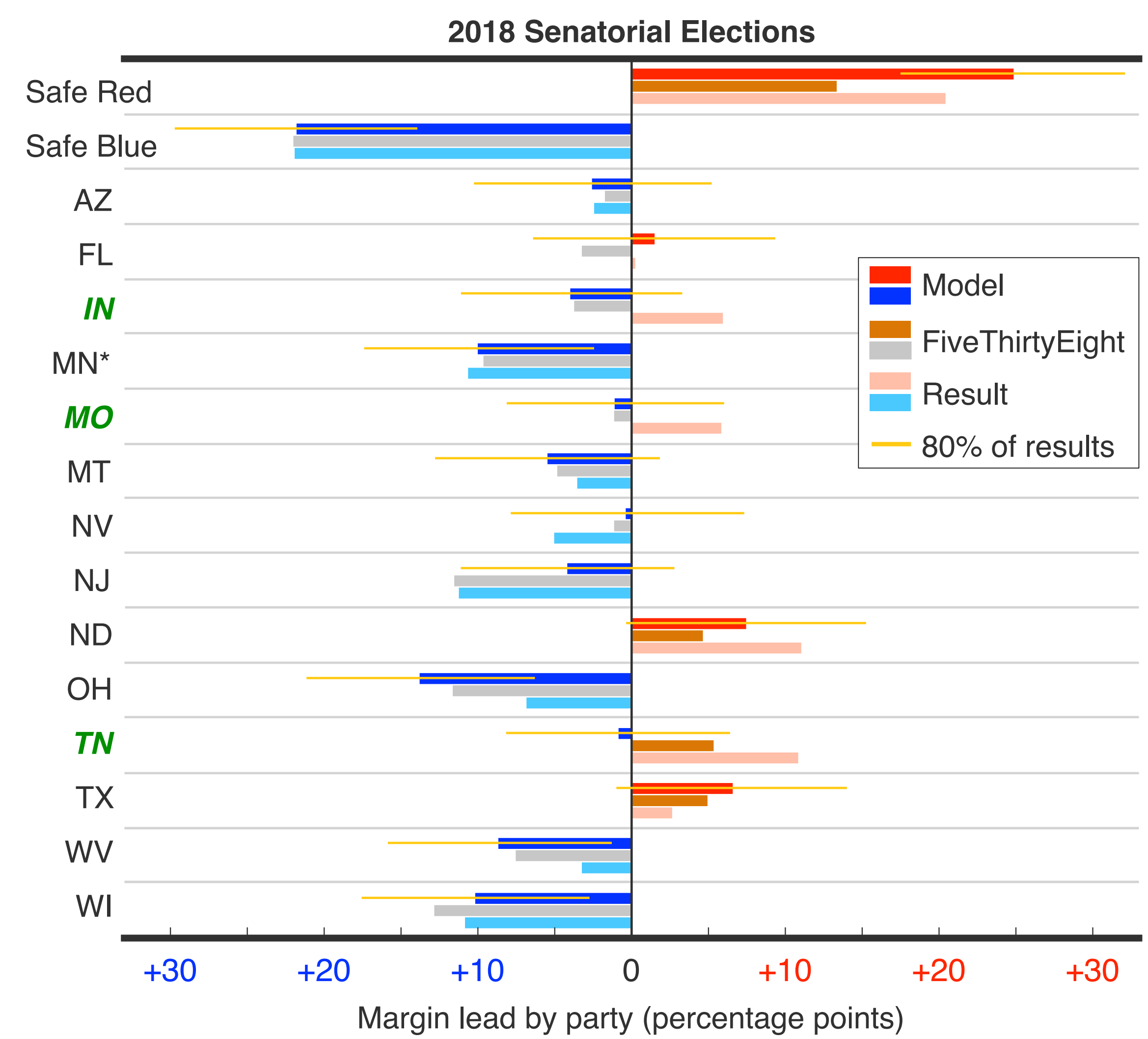
Forecasting the 2018 senate races



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North Dakota	85.0%		Tilt	73.6%		89.0%		73.2%
Ohio	99.8%			95.7%		99.2%		96.7%
Tennessee	69.6%			76.3%		55.7%		80.4%
Texas	87.3%			80.6%		86.7%		78.8%
West Virginia	93.6%		Tilt	89.4%	Tilt	93.5%		87.9%
Wisconsin	94.3%			98%		95.8%		97.7%

Solid Rep. (≥95%)
Likely Rep. (≥75%)
Lean Rep. (≥60%)
Toss-Up (<60%)
Lean Dem. (≥60%)
Likely Dem. (≥75%)
Solid Dem. (≥95%)

- We differ from 538 in our forecasts of Florida and Tennessee

Forecasting the 2018 governor races

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Kansas			53.3%	58.2%			57.2%
Maine		Tilt	74.6%	94.4%			94.7%
Nevada		Tilt	54.9%	55.0%			51.5%
Ohio			75.3%	55.2%			59.5%
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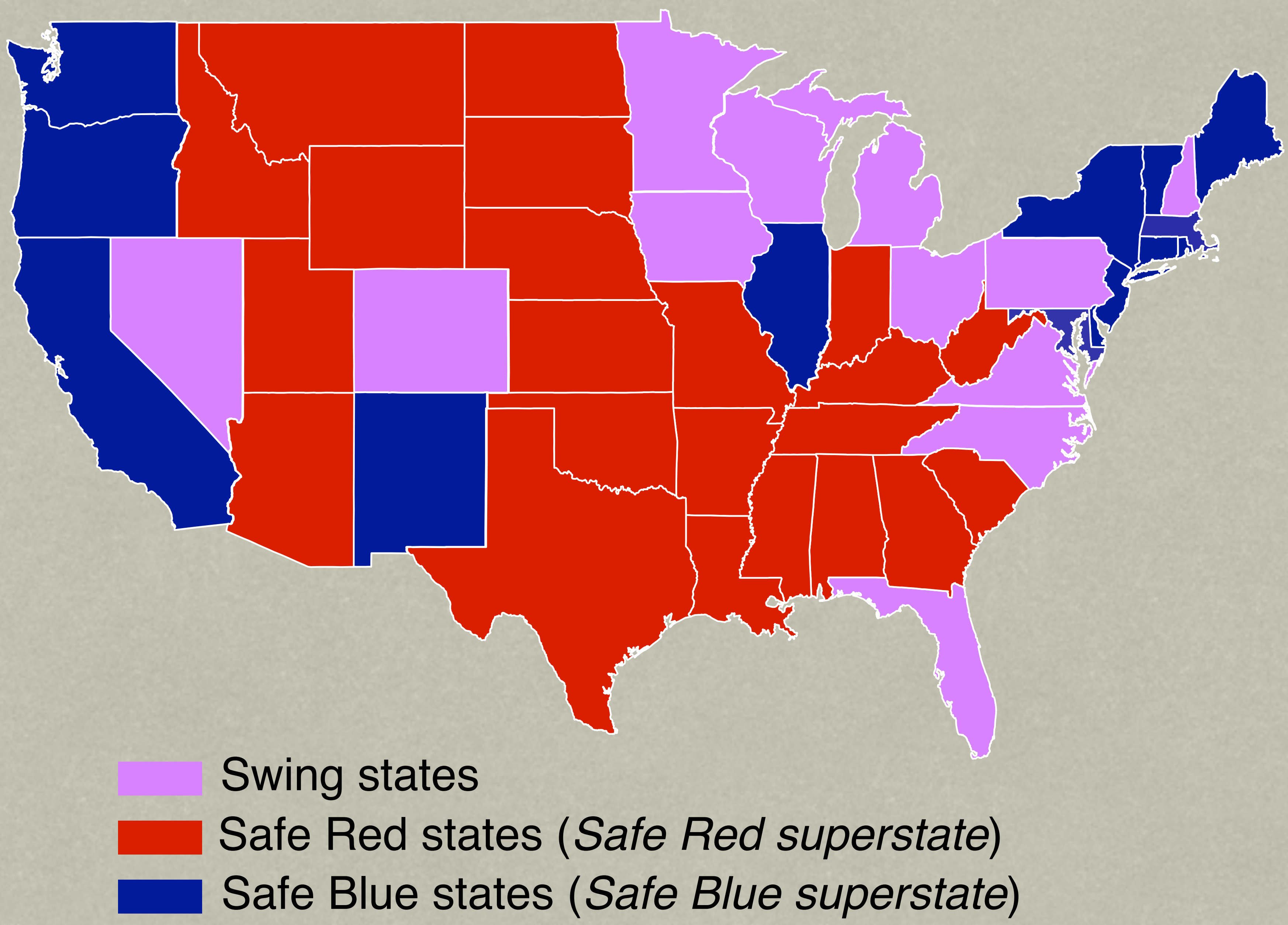
- Lean Dem. (≧ 60%)
- Likely Dem. (≧ 75%)
- Solid Dem. (≧ 95%)

- Model accuracy: 88.9% (FL, IA, KS, OH wrong)
- 538 (Nov. 4) accuracy: 86.1% (FL, IA, KS, NV, OH wrong)
- 538 (Nov. 6) accuracy: 88.9% (FL, IA, KS, OH wrong)
- Sabato accuracy: 91.7% (FL, IA, OH wrong)

Approach: Superstates

Combine safe states into red and blue superstates



1. Safe Red
2. Safe Blue
3. Colorado
4. Florida
5. Iowa
6. Michigan
7. Minnesota
8. Nevada
9. North Carolina
10. New Hampshire
11. Ohio
12. Pennsylvania
13. Virginia
14. Wisconsin

Background: 538

	NYT	538	HuffPost	PW	PEC	DK	Cook	Roth.[1]	Sabato
Win presidency	85% Dem.	71% Dem.	98% Dem.	89% Dem.	>99% Dem.	92% Dem.	Lean Dem.	Lean Dem.	Lean Dem.

1. Collect polls
- Polls weighted by sample size, recency, and 538 pollster rating

2. Adjust polls
- Adjustments made to account for third parties, convention bounce, house effects, poll sample (e.g. likely voters or registered voters), etc.

3. Combine polls with other data
- Polling data combined with demographic and regional regressions, home-state advantage, etc.

4. Simulate election and account for uncertainty
- National, demographic/regional error, state-specific error accounted for

{A user's guide to FiveThirtyEight's 2016 general election forecast; Table from Upshot, NY Times}

Background: HuffPost

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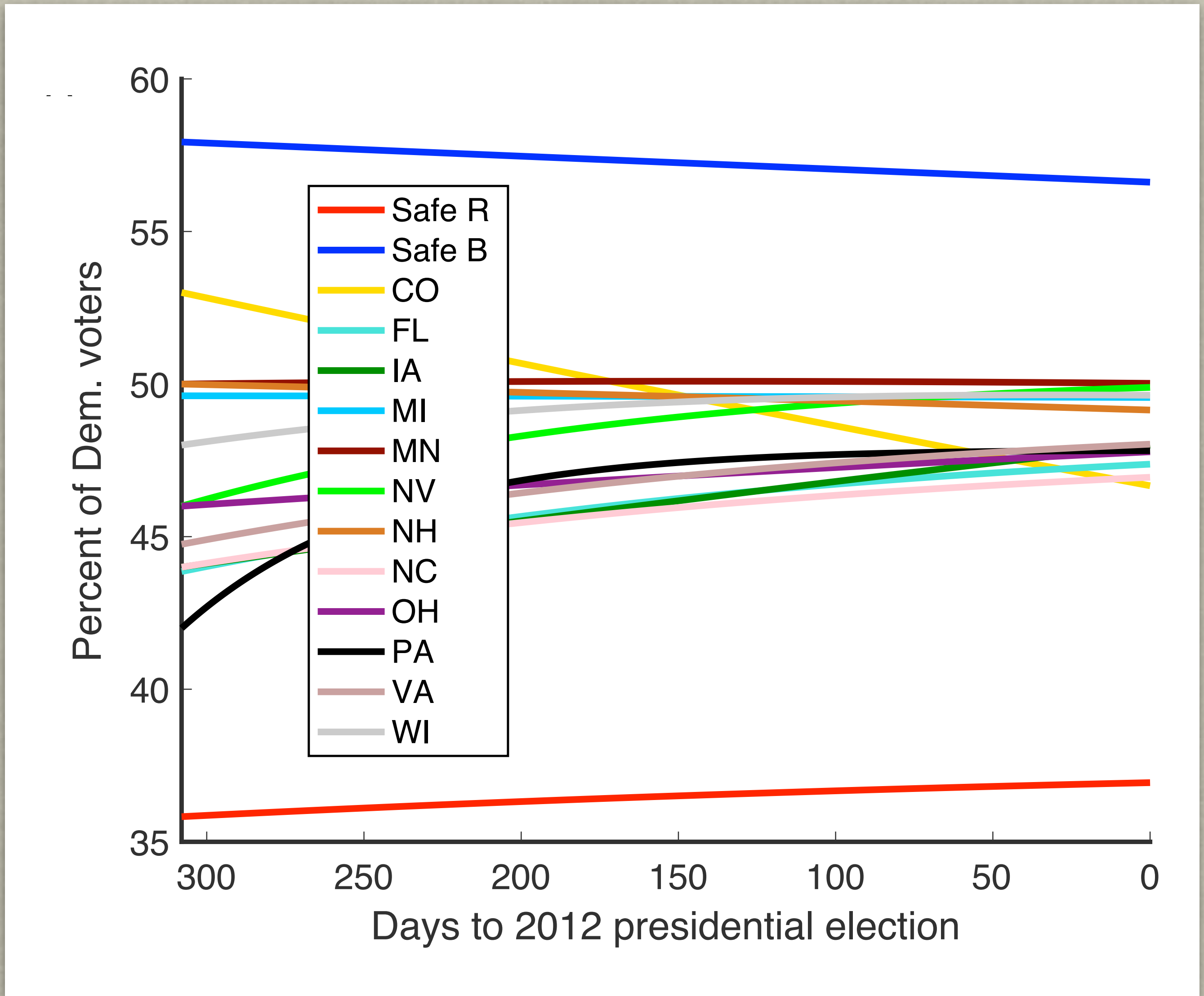
1. Average polls by state
- Bayesian Kalman filter model used to average polls
- Recent polls more heavily weighted
- Historical data used for priors

2. Forecast chance of winning by state
- Model simulated until Nov. 8 assuming voter intentions continue along current trajectories
- Undecideds incorporated into margin of error

3. Simulate Electoral College outcome
- Undecideds at the national level incorporated into margin of error
- Monte Carlo within each state, but random numbers are correlated based on state-state correlations of results from past elections

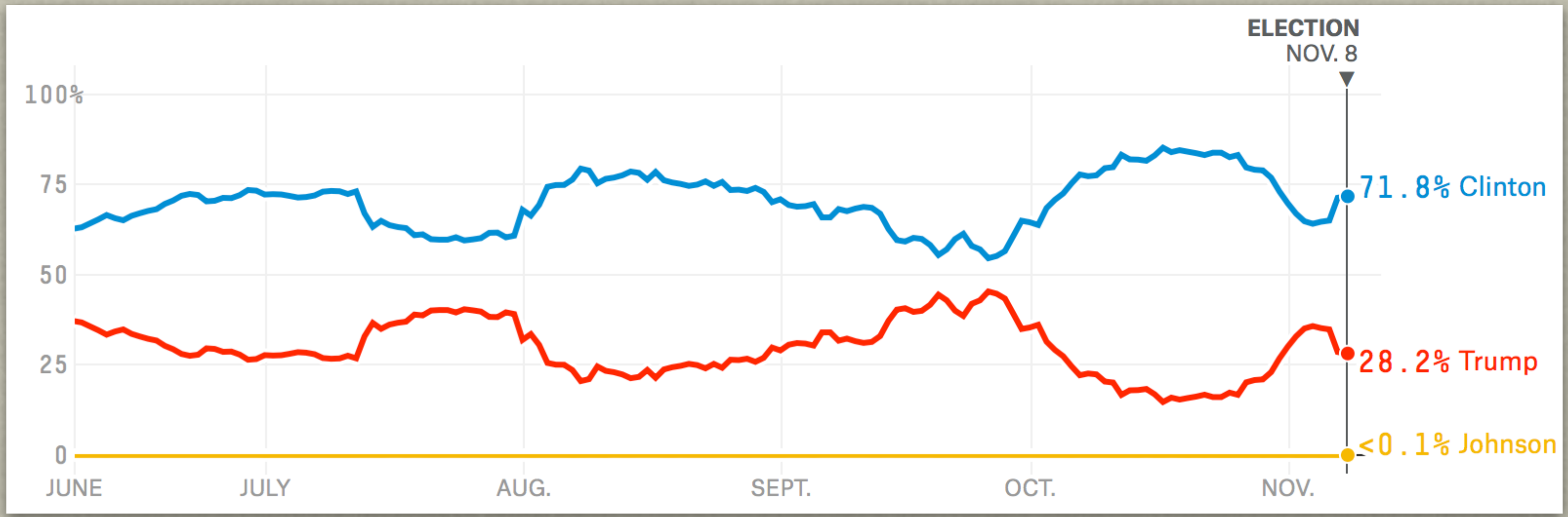
{How we're forecasting the presidential election, HuffPost; Table from Upshot, NY Times}

1. Example model dynamics



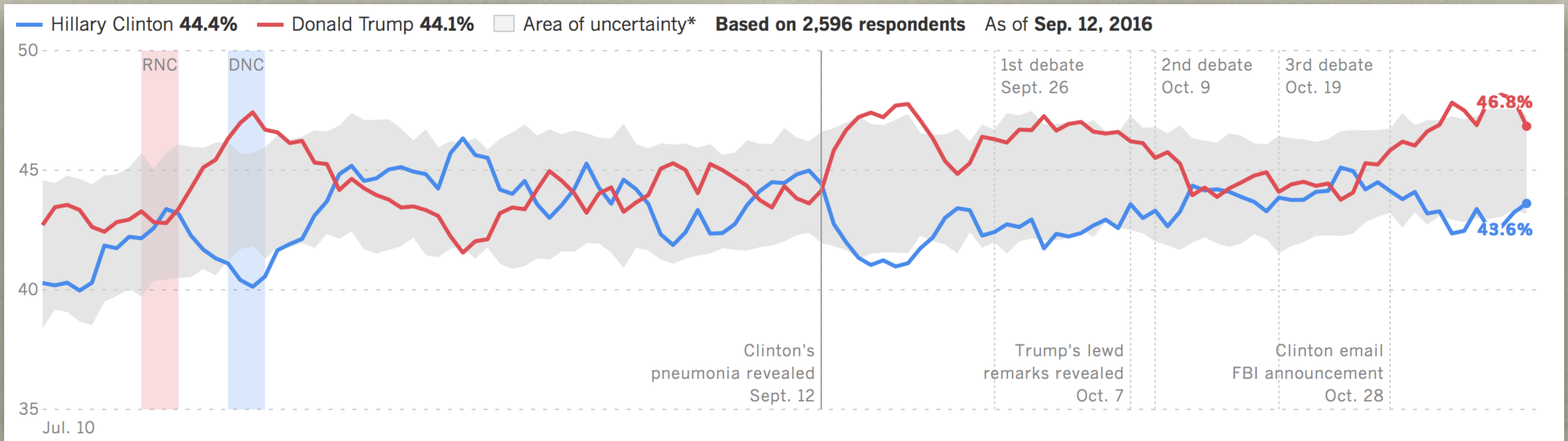
Model forecasts are based on data up until (not including) election day

Averaging polling data within each month removes finer scale features



{FiveThirtyEight}

2016: Identifying likely voters



{LA Times: Where the presidential race stands today}

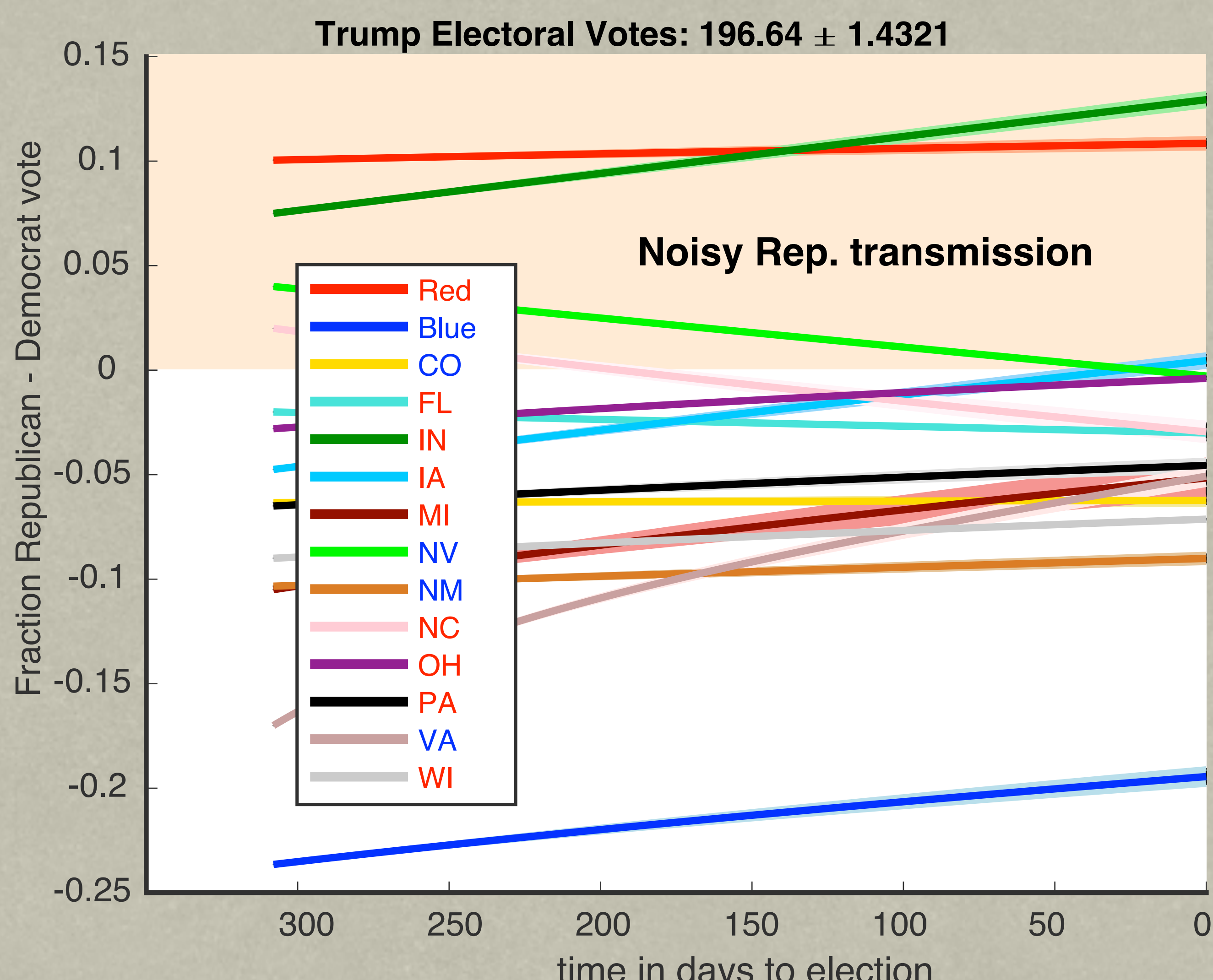
- LA Times predicted a Trump win
- Their polls do not ignore “unlikely” voters
- In other polls, likely voters are defined heavily by voter history
- Some demographics who did not vote in 2012 favored Trump

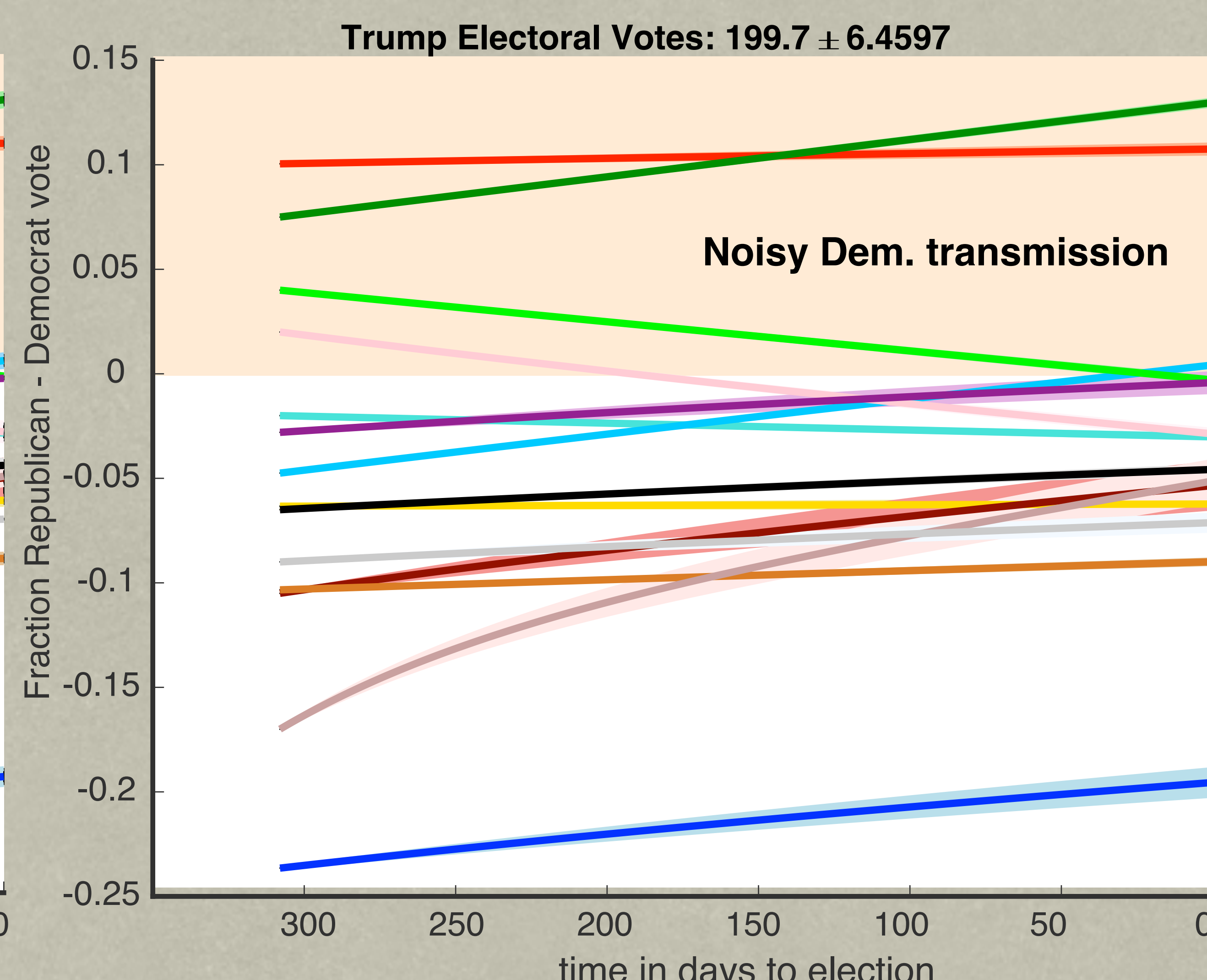
3. Impact of noise in transmission parameters

$$\frac{dS^i}{dt} = \gamma_R^i I_R^i + \gamma_D^i I_D^i - \sum_{j=1}^{14} \boxed{\beta_R^{ij}} \frac{N^j}{N} S^i I_R^j - \sum_{j=1}^{14} \boxed{\beta_D^{ij}} \frac{N^j}{N} S^i I_D^j$$

$$\frac{dI_R^i}{dt} = -\gamma_R^i I_R^i + \sum_{j=1}^{14} \beta_R^{ij} \frac{N^j}{N} S^i I_R^j$$

- Model suggests a robust Republican voter bloc
- Election results were sensitive to noise in Dem. transmission



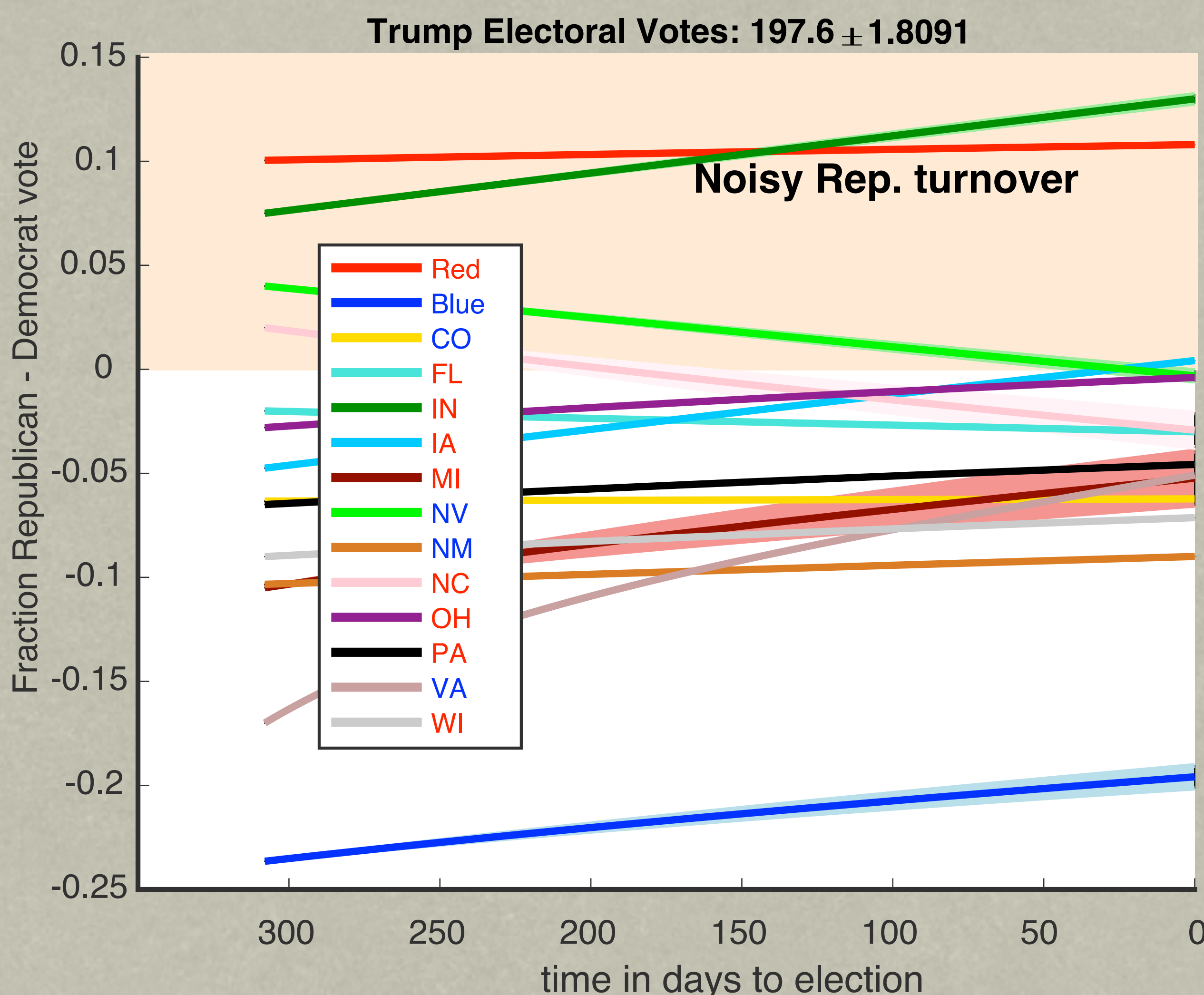


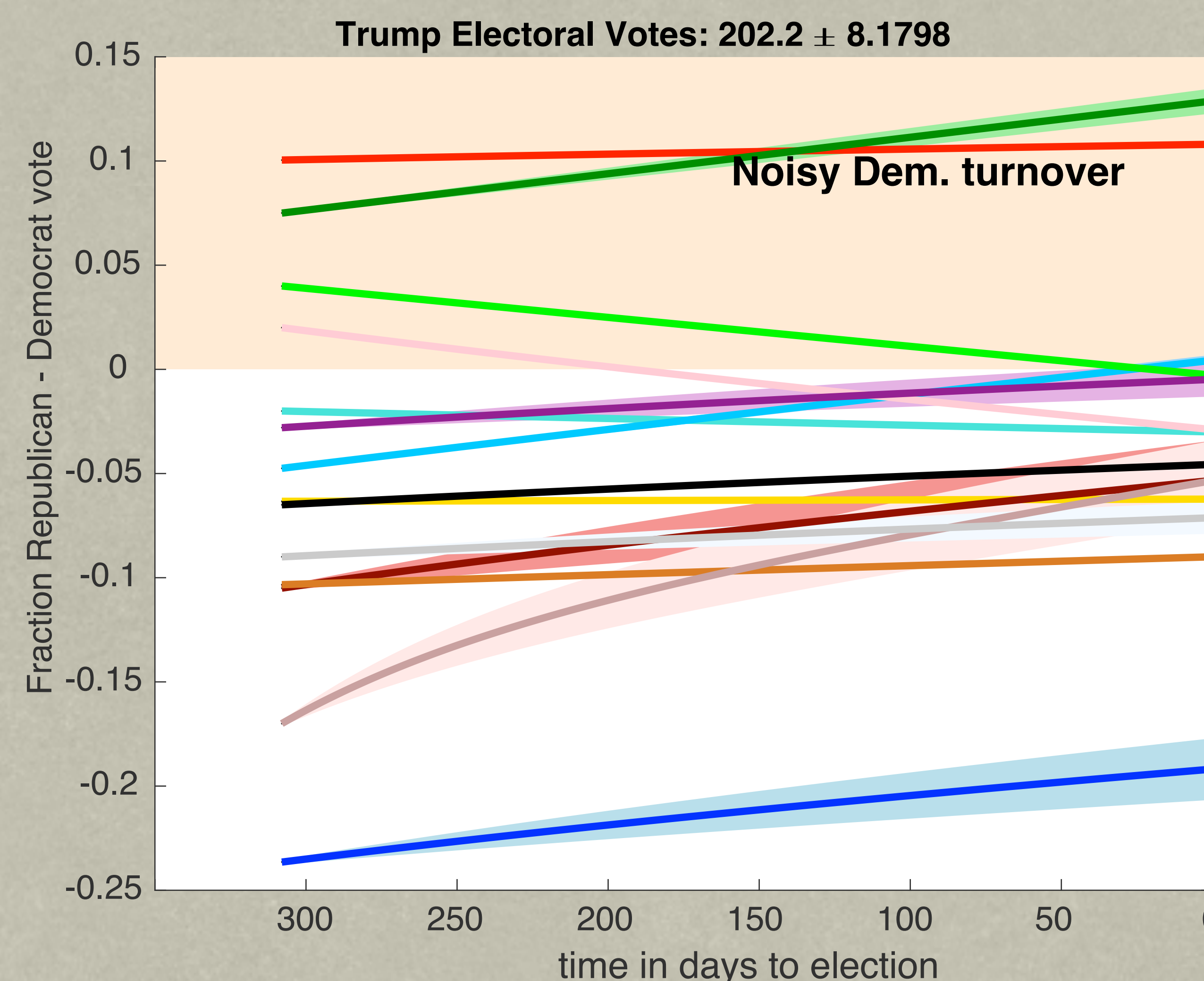
3. Impact of noise in turnover parameters

$$\frac{dS^i}{dt} = \boxed{\gamma_R^i} I_R^i + \boxed{\gamma_D^i} I_D^i - \sum_{j=1}^{14} \beta_R^{ij} \frac{N^j}{N} S^i I_R^j - \sum_{j=1}^{14} \beta_D^{ij} \frac{N^j}{N} S^i I_D^j$$

$$\frac{dI_R^i}{dt} = -\gamma_R^i I_R^i + \sum_{j=1}^{14} \beta_R^{ij} \frac{N^j}{N} S^i I_R^j$$

- Election results are more sensitive to fluctuations in Dem. turnover than Rep. turnover





Comparison of 2012 & 2016 (presidential)

2016

States with most influential Rep.:

1. FL
2. PA
3. VA
4. OH
5. MI

States with most influential Dem.:

1. FL
2. PA
3. NC
4. OH
5. MN

2012

States with most influential Rep.:

1. FL
2. PA
3. OH
4. NC
5. MN

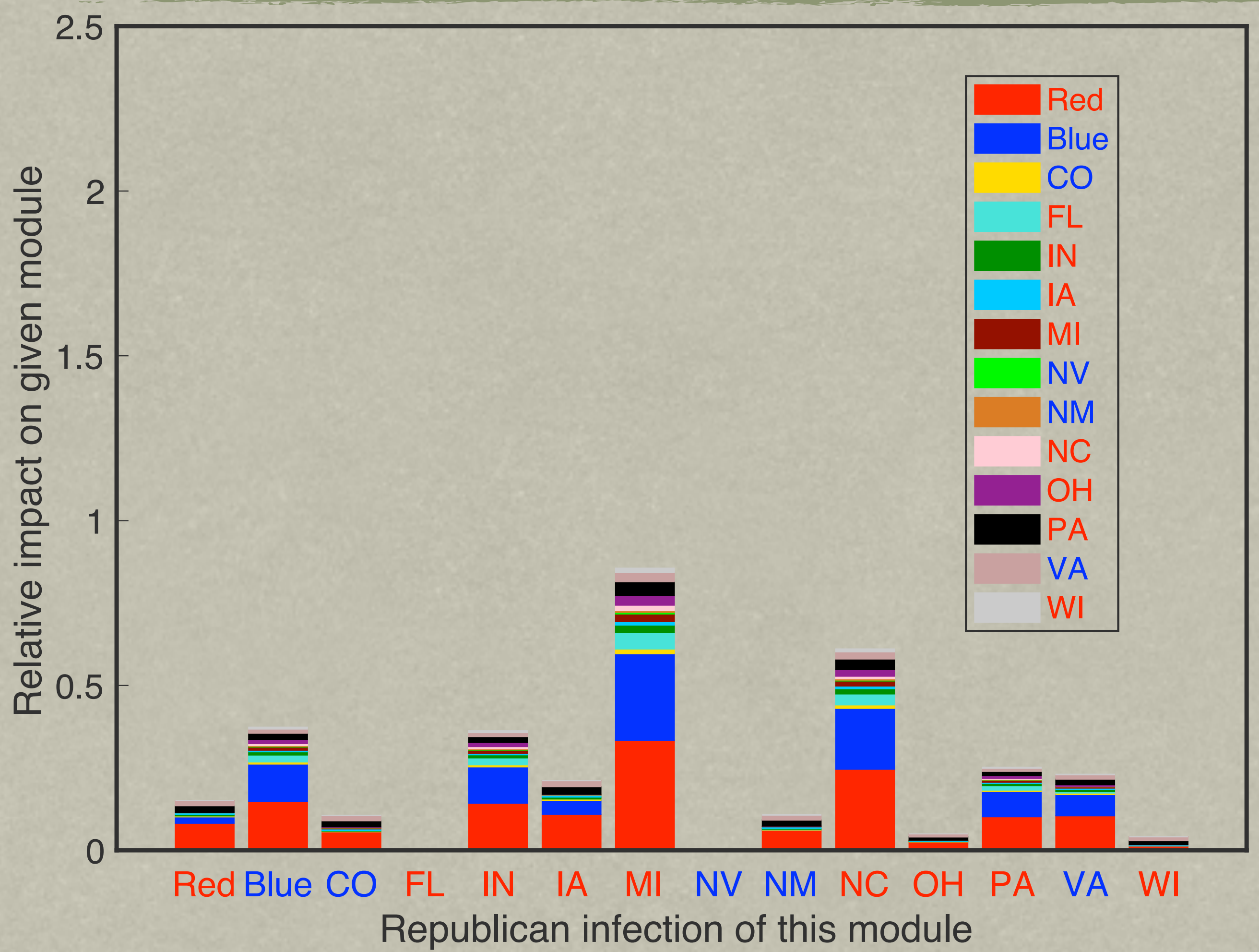
States with most influential Dem.:

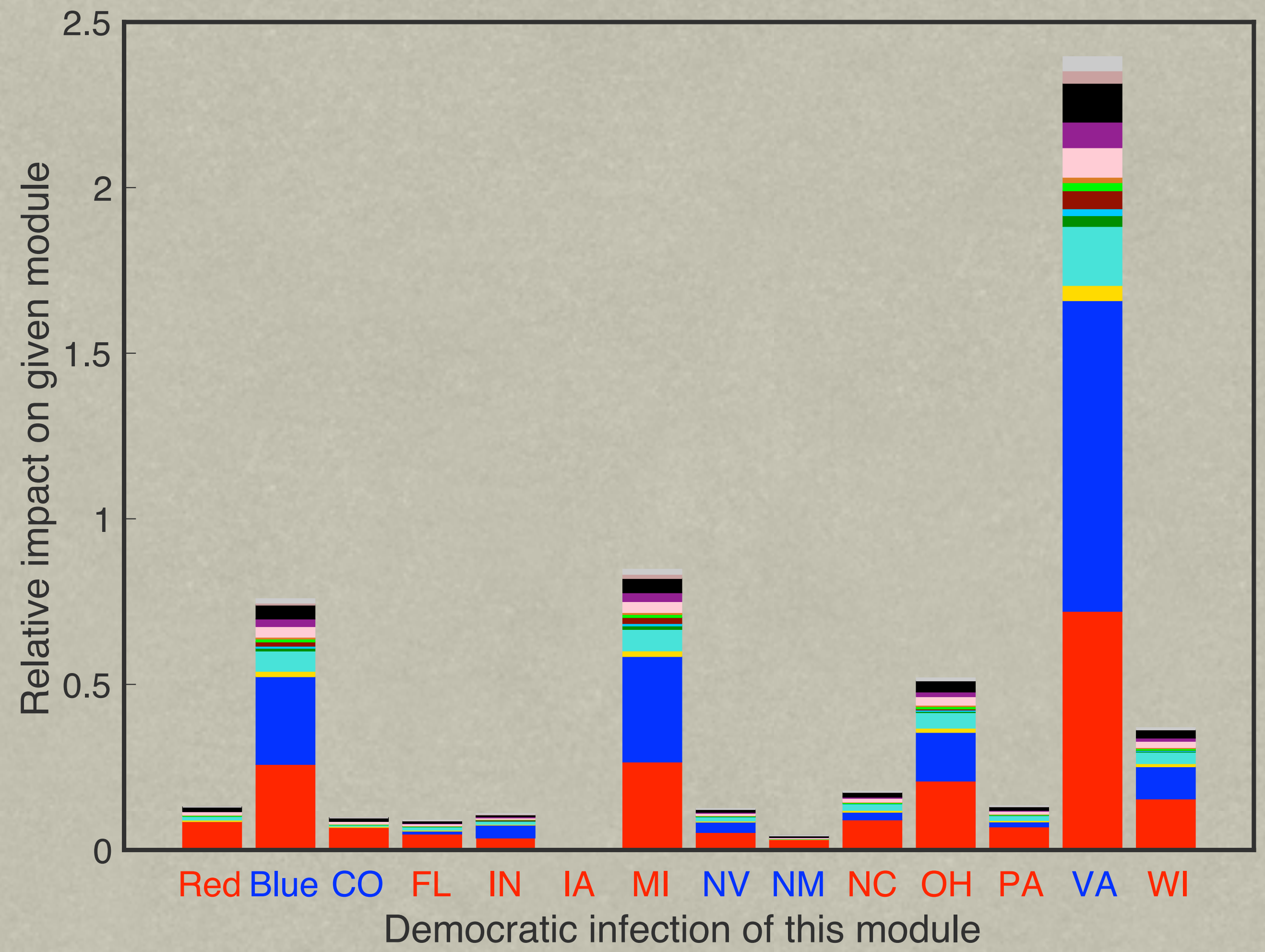
1. FL
2. PA
3. OH
4. MN
5. VA

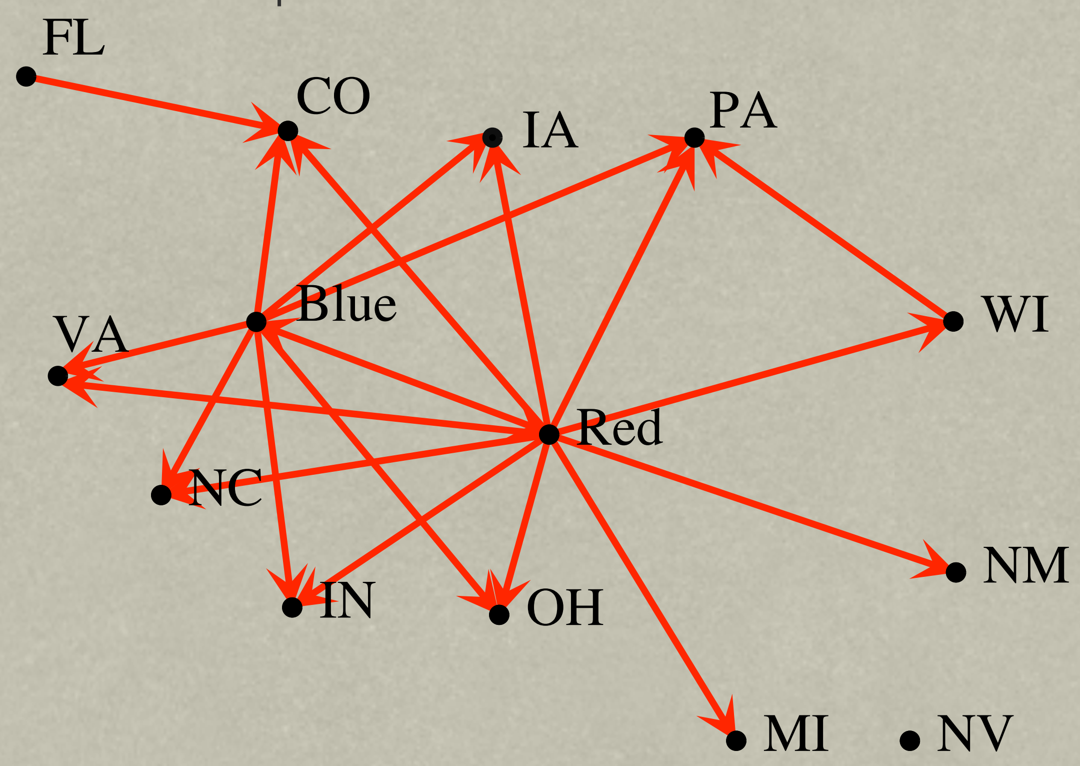
*Note we do not consider the Red and Blue modules

Outlook: transmission parameters

$$\sum_{j=1}^{14} \boxed{\beta_R^{ij}} \frac{N^j}{N} S^i I_R^j$$

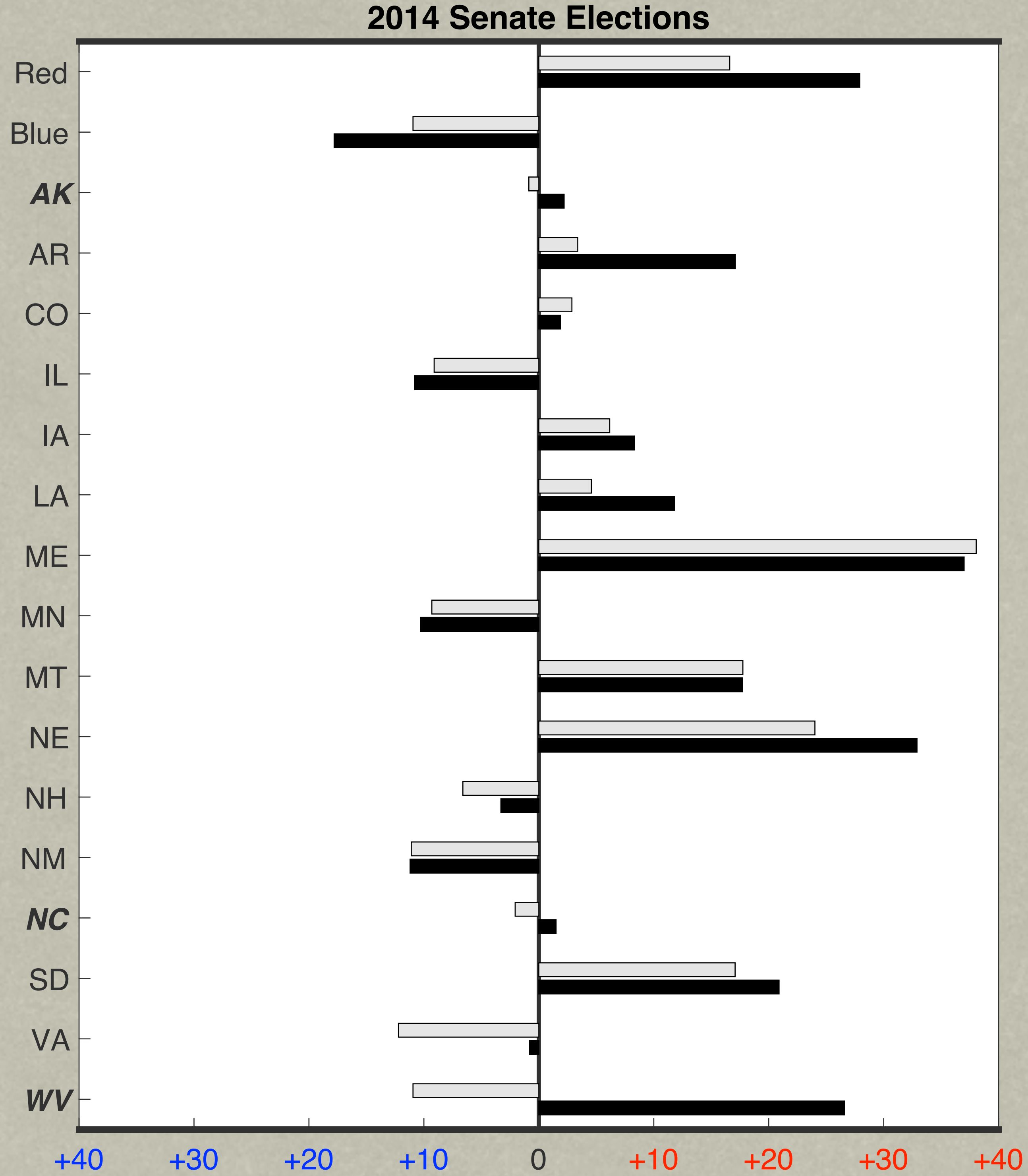




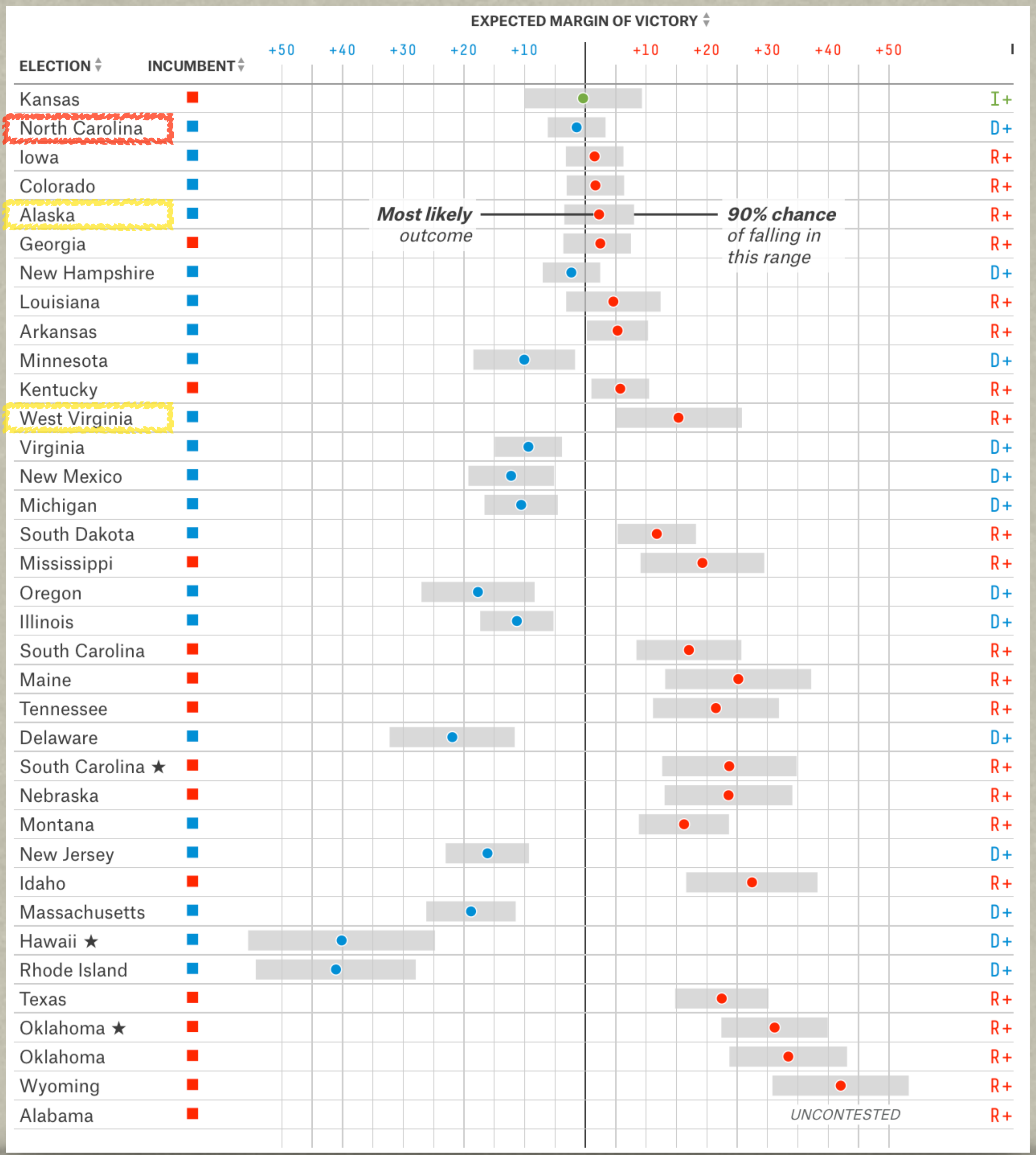


Most influential swing states in 2016 and 2012: FL & PA

2. Forecasting the 2014 senate races



538's Forecast

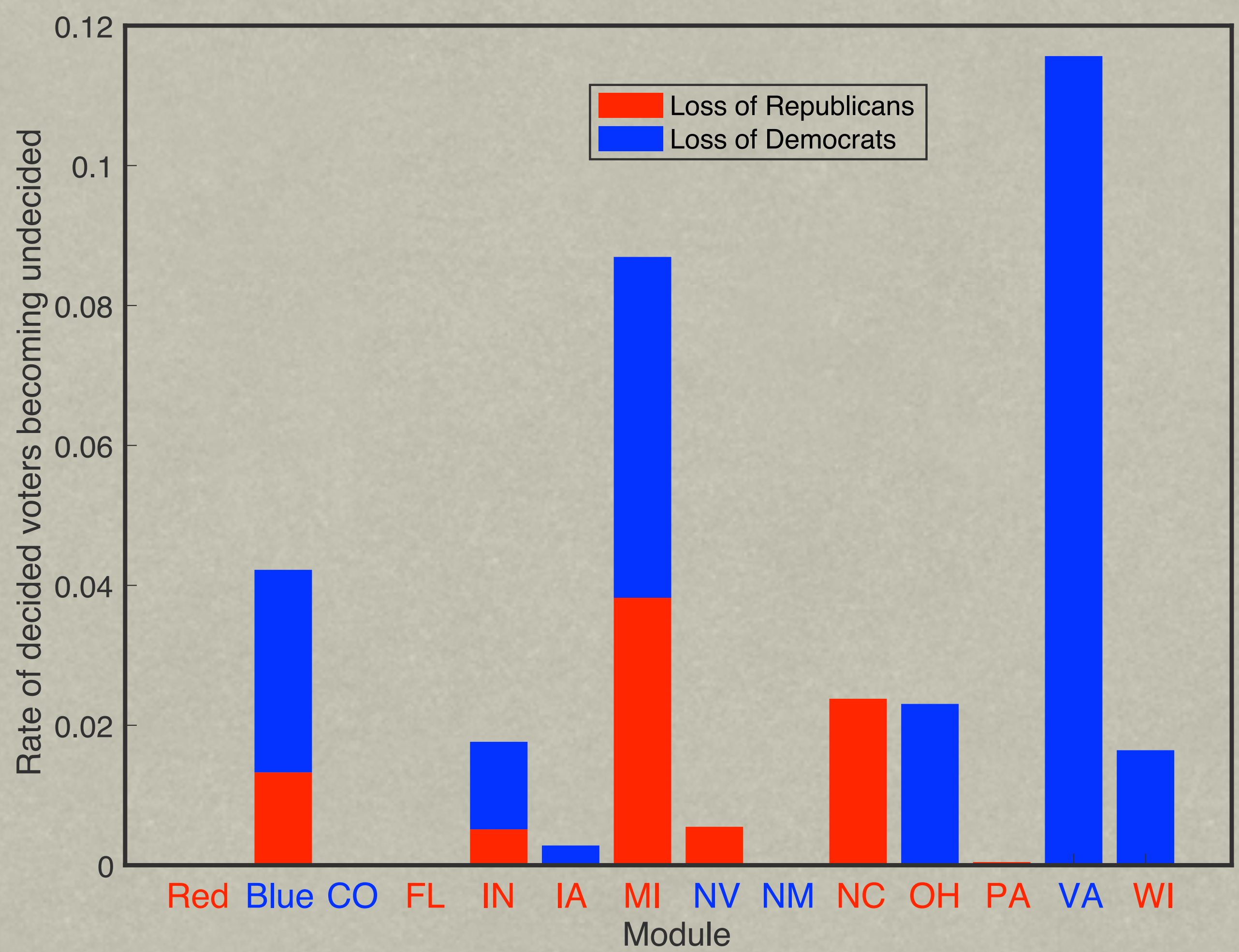


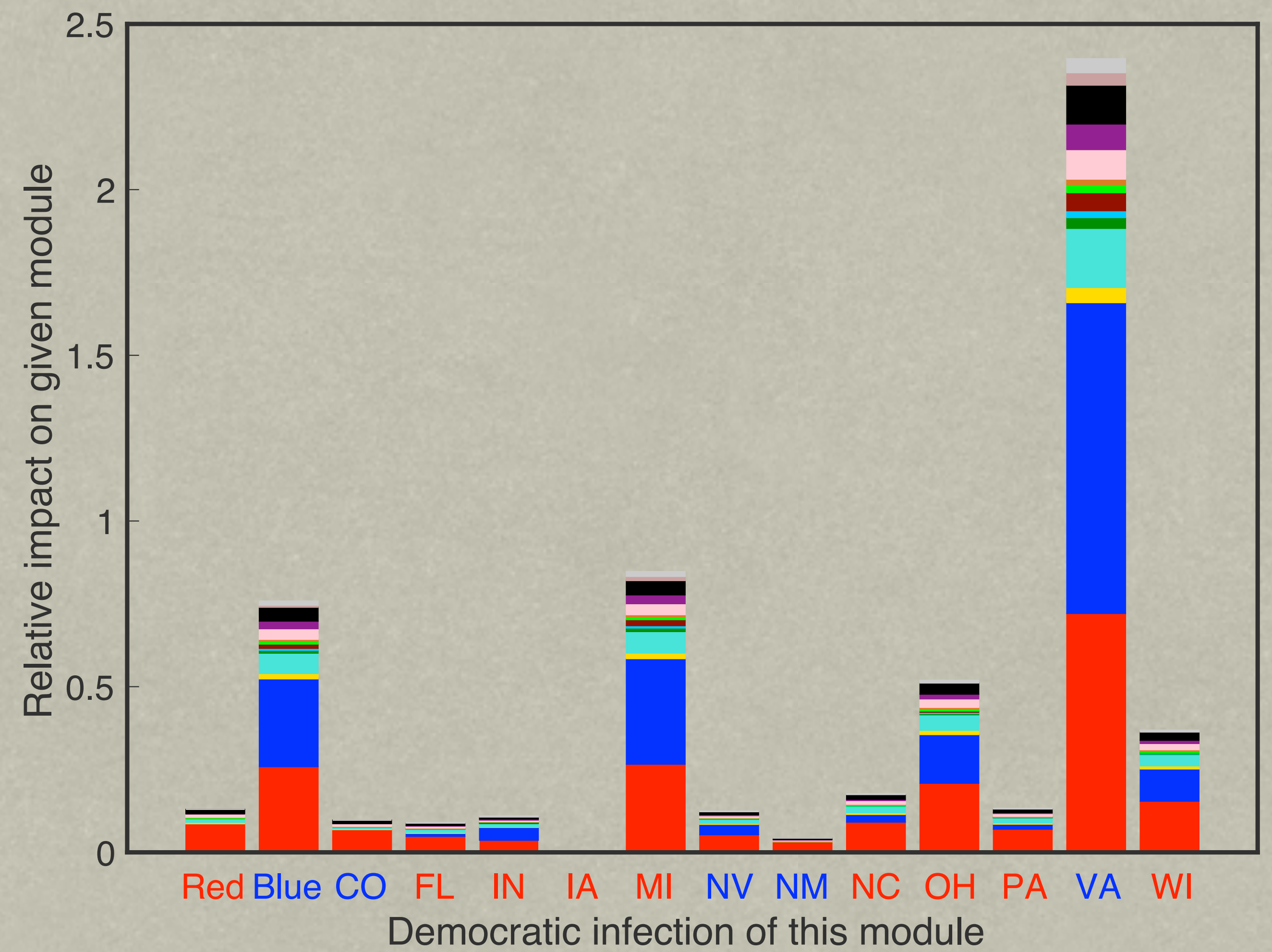
{538 Image from https://fivethirtyeight.com/interactives/senate-forecast/}

2016 voter turnover parameters

$$\frac{dS^i}{dt} = \boxed{\gamma_R^i I_R^i + \gamma_D^i I_D^i} - \sum_{j=1}^{14} \beta_R^{ij} \frac{N^j}{N} S^i I_R^j - \sum_{j=1}^{14} \beta_D^{ij} \frac{N^j}{N} S^i I_D^j$$

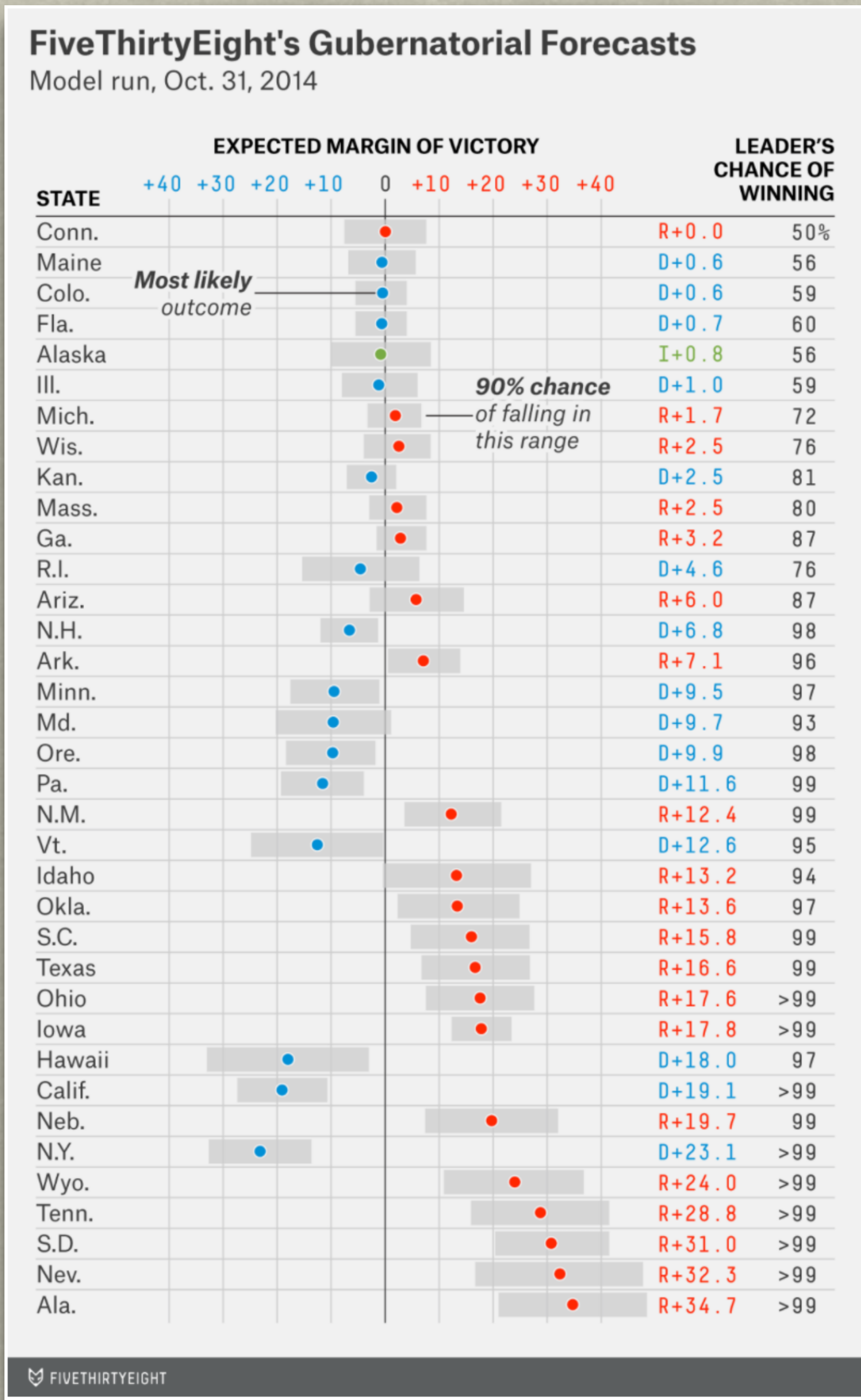
$$\frac{dI_R^i}{dt} = -\gamma_R^i I_R^i + \sum_{j=1}^{14} \beta_R^{ij} \frac{N^j}{N} S^i I_R^j$$





- High infection rates are associated with high voter turnover

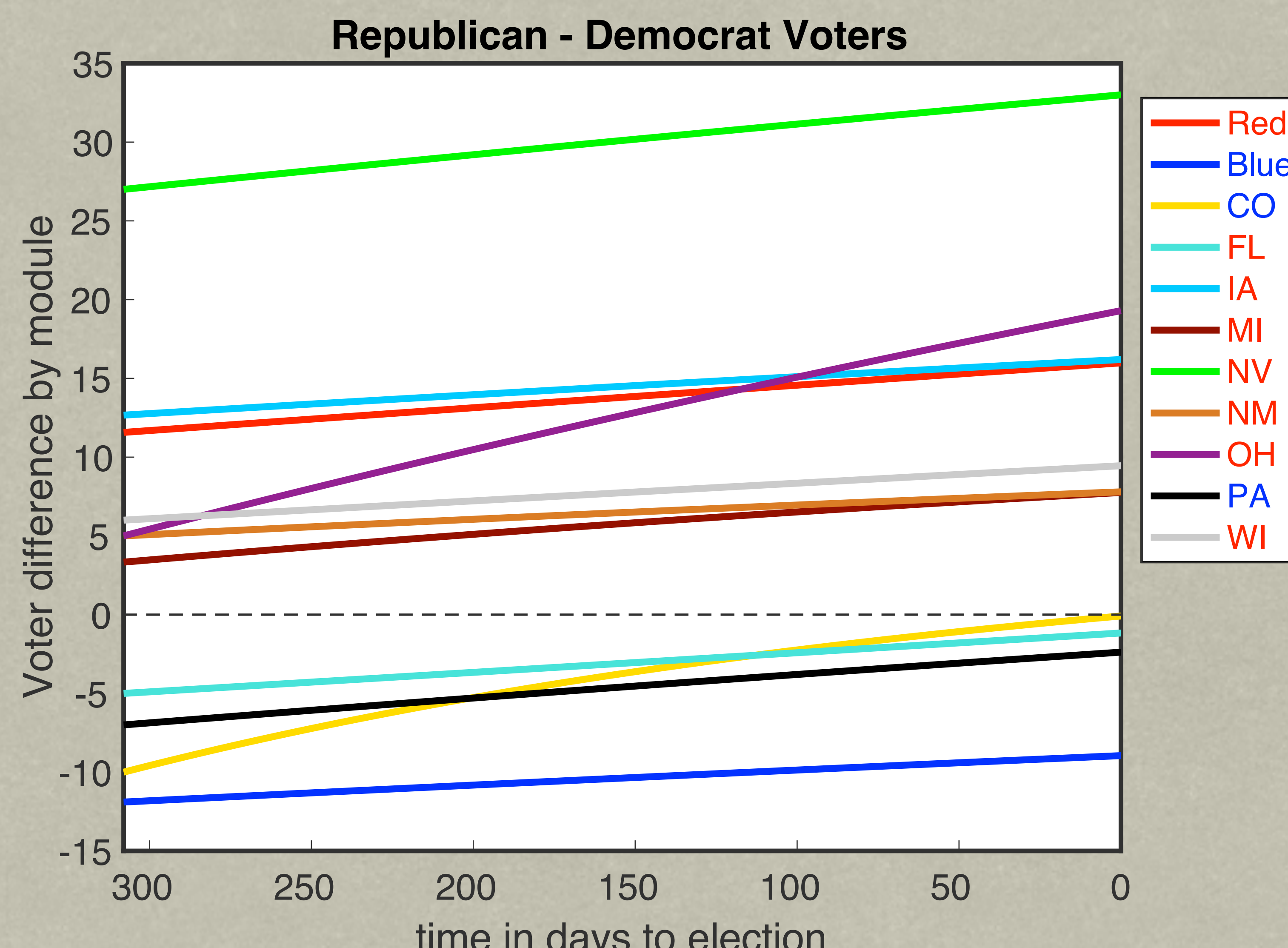
Forecasting the 2014 gubernatorial races



FiveThirtyEight's Gubernatorial Forecasts
Model run, Oct. 31, 2014

STATE	EXPECTED MARGIN OF VICTORY	LEADER'S CHANCE OF WINNING
Conn.	R+0.0	50%
Maine	D+0.6	56
Colo.	D+0.6	59
Fla.	D+0.7	60
Alaska	I+0.8	56
Ill.	D+1.0	59
Mich.	R+1.7	72
Wis.	R+2.5	76
Kan.	D+2.5	81
Mass.	R+2.5	80
Ga.	R+3.2	87
R.I.	D+4.6	76
Ariz.	R+6.0	87
N.H.	D+6.8	98
Ark.	R+7.1	96
Minn.	D+9.5	97
Md.	D+9.7	93
Ore.	D+9.9	98
Pa.	D+11.6	99
N.M.	R+12.4	99
Vt.	D+12.6	95
Idaho	R+13.2	94
Okla.	R+13.6	97
S.C.	R+15.8	99
Texas	R+16.6	99
Ohio	R+17.6	>99
Iowa	R+17.8	>99
Hawaii	D+18.0	97
Calif.	D+19.1	>99
Neb.	R+19.7	99
N.Y.	D+23.1	>99
Wyo.	R+24.0	>99
Tenn.	R+28.8	>99
S.D.	R+31.0	>99
Nev.	R+32.3	>99
Ala.	R+34.7	>99

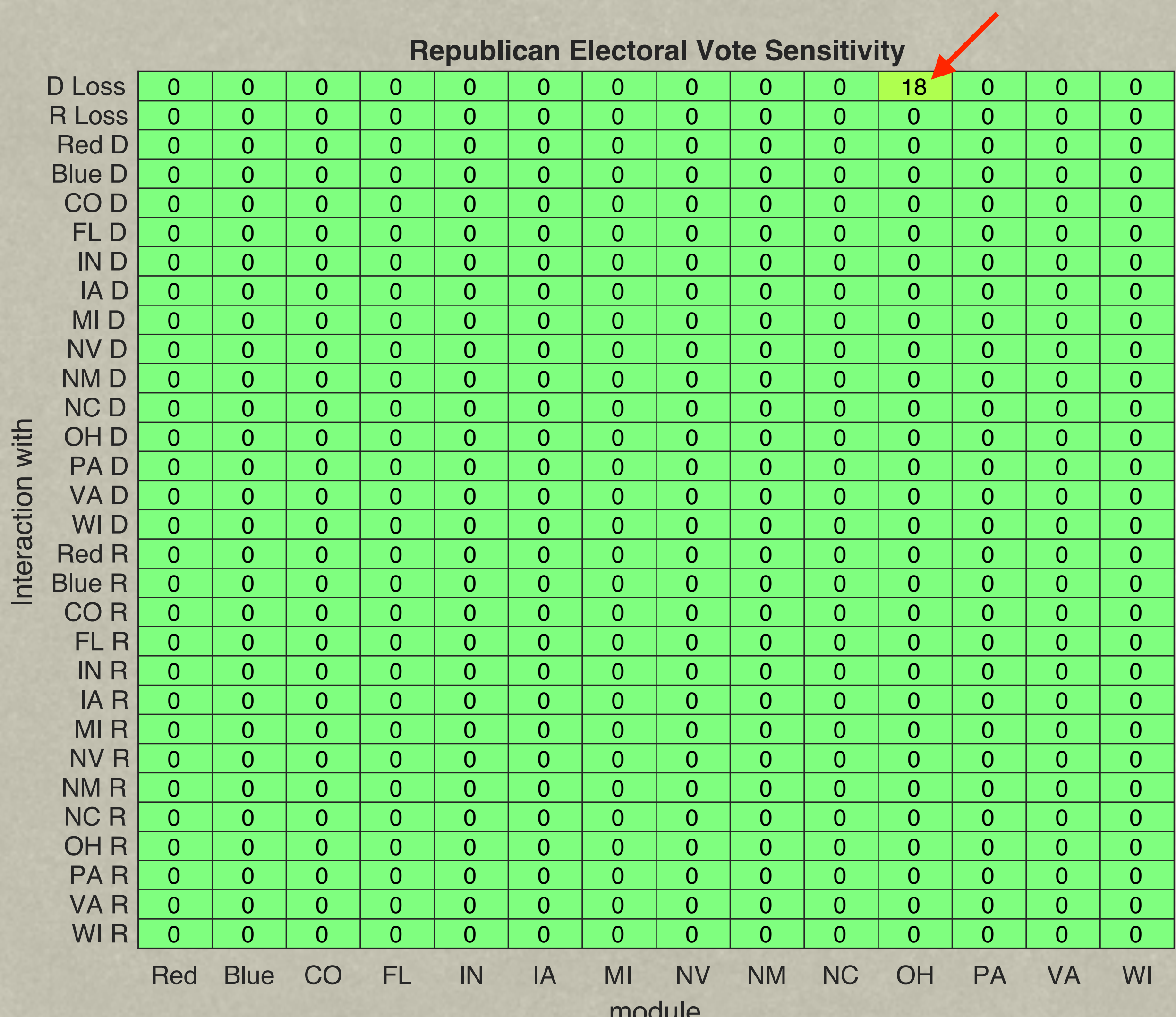
- Our predictions agree with 538
- Both models fail at FL, the closest race



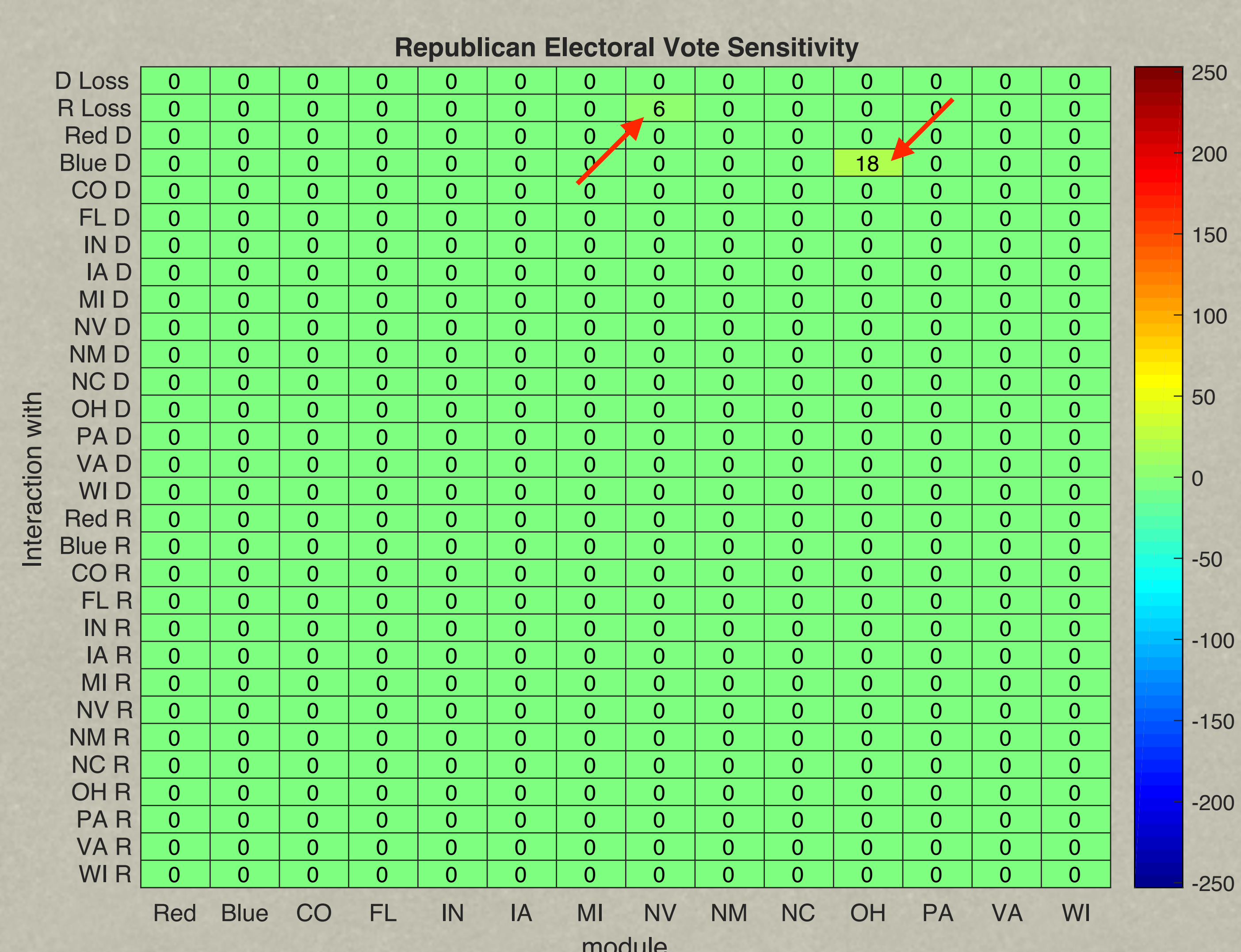
{Table from 538}

2016: Example sensitivity analysis

- Noise favors Trump
- Increased Dem. turnover leads OH to vote Rep.
- Reduced interaction between Blue Democrats and OH leads OH to vote Rep.
- Increased Rep. turnover leads NV to vote Rep.



10% increase on each nonzero parameter



15% decrease on each nonzero parameter