Post-election Analysis of Presidential Election/Poll Data: Liars Continued to Lie But What Have Changed?

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Outline

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- However, like many other prediction models, the 538 model also incorrectly predicted the 2016 USPE outcome.
- To the best of our knowledge, there have been no academic studies using data science tools to jointly analyze the 2016 and 2020 elections.

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- On the other hand, there have been informally published academic studies on the 2016 election (e.g., https://science.nu/community/the-great-society-reagans-revolution-and-generations-of-presidential-voting/)
- There have also been statistical analysis of election data concerning political elections elsewhere in the world (e.g., Brisco and Migliorati 2020).
- However, due to the unique natures of the USPE, namely, the EC system, and the special candidate, such results and models from other studies are less likely to be applicable to our problems of interest.

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- Number of EC votes then add up over the 50 states to yield the total of EC votes, for each candidate, and whoever receives 270 or more of the EC votes wins the presidency.
- Due to this special feature of the EC, it makes sense to think of a state-based prediction problem.

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- The term "small area" typically refers to a population for which reliable statistics of interest cannot be produced due to certain limitations of the available data
- Examples of domains include a geographical region (e.g., a state, county or municipality), a demographic group (e.g., a specific age×sex×race group), a demographic group within a geographic region, and so on.
- A basic strategy in SAE is called "borrowing strength". Basically, it says that one can do better than the small number of domain-wide observation by borrowing strength, or information, from other domains and/or sources.

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- Have these behaviors been changed since 2016, given that the Republican candidate was the sitting President during the 2020 election?
- If not, have the 2020 pollsters figured out some way to correct the infamous "lies" to the surveys?

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- That is, $y_{ijkt} = \log(p_{ijkt}/\pi_{ikt}) = \log(p_{ijkt}) - \log(\pi_{ikt})$, where i for state, j for pollster, k for party, t for year.
- Thus, $y_{ijkt} < 0$ (> 0) means that the poll under-projects (over-projects) the election result.

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- An alternative model is fitted, which assumes univariate and independent random effects at the state-candidate level.
- However, the independent assumption seems unreasonable.

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- 1. A simple model

$$y_{ia} = \beta_0 + \beta_1 I_{\text{can},ia} + \beta_2 I_{\text{year},ia} + \beta_3 I_{\text{can},ia} I_{\text{year},ia} + z_{ia} v_i + e_{ia}, \qquad (1)$$

$i = 1, \ldots, 51,\ a = 1, \ldots, n_i.$

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$i = 1, \ldots, 51$, $a = 1, \ldots, n_i$.

- 2. State-time level random effect

$$y_{itb} = \beta_0 + \beta_1 I_{\text{can},itb} + \beta_2 I_{\text{year},itb} + \beta_3 I_{\text{can},itb} I_{\text{year},itb} + z_{itb} v_{it} + e_{itb}, \tag{2}$$

$i = 1, \ldots, 51$, $b = 1, \ldots, n_{it}$.

- 3. Random effects at state and pollster levels

$$\begin{aligned} y_{ipc} &= \beta_0 + \beta_1 I_{\mathrm{can},ipc} + \beta_2 I_{\mathrm{year},ipc} + \beta_3 I_{\mathrm{can},ipc} I_{\mathrm{year},ipc} + z_{ipc} v_i \\ &\quad + u_p + e_{ipc}, \end{aligned} \tag{3}$$

$i = 1, \dots, 51$, $p \in S_i$, where S_i is a subset of $\{1, \dots, 175\}$ and 175 is the total number of pollsters, and $c = 1, 2, 3, 4$ denotes the combination of indexes for the two parties and two years.

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- 4. Random effects at state-time and pollster levels

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y_{itpd} \;=\;& \beta_0 + \beta_1 I_{\mathrm{can},itpd} + \beta_2 I_{\mathrm{year},itpd} + \beta_3 I_{\mathrm{can},itpd} I_{\mathrm{year},itpd} + z_{itpd} v_{it} \\
& + u_p + e_{itpd},
\end{aligned} \tag{4}
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$i = 1, \ldots, 51$, $p \in S_i$.

- Estimation results: Model (1)

Parameter	Estimate	Standard Error	t-statistic	Group
β_0	-0.055	0.009	-5.903	Fixed
β_1	-0.081	0.020	-4.030	Fixed
β_2	0.072	0.006	12.057	Fixed
β_3	-0.018	0.009	-2.151	Fixed
σ_{d}	0.059	0.007	8.997	State
σ_{r}	0.082	0.009	9.427	State
ρ	-0.891	0.050	-17.704	State
τ	0.082	0.001	65.628	Residual

- Estimation results: Model (2)

Parameter	Estimate	Standard Error	t-statistic	Group
β_0	-0.060	0.009	-6.550	Fixed
β_1	-0.076	0.020	-3.865	Fixed
β_2	0.084	0.013	6.404	Fixed
β_3	-0.034	0.028	-1.186	Fixed
σ_{d}	0.056	0.006	10.036	Year:State
σ_{r}	0.079	0.007	11.731	Year:State
ρ	-0.890	0.043	-20.534	Year:State
τ	0.080	0.001	54.298	Residual

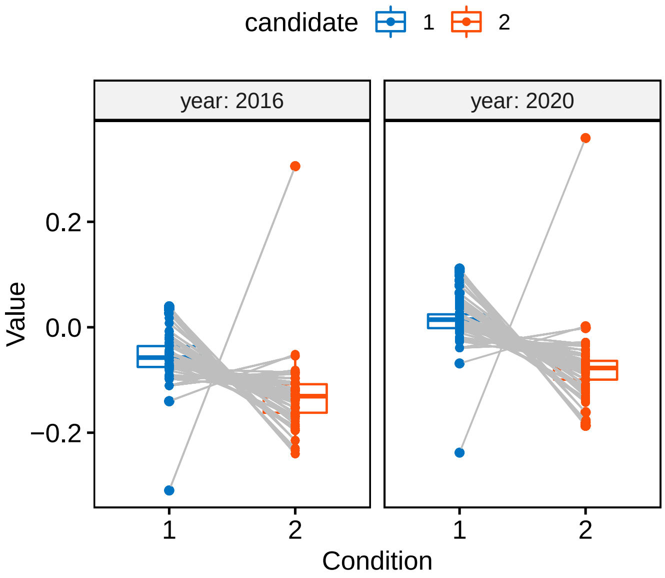
- Estimation results: Model (3)

Parameter	Estimate	Standard Error	t-statistic	Group
β_0	-0.049	0.010	-5.029	Fixed
β_1	-0.081	0.021	-3.905	Fixed
β_2	0.054	0.006	9.680	Fixed
β_3	-0.018	0.0071	-2.577	Fixed
σ	0.031	0.003	9.492	Pollster
$\sigma_{\rm d}$	0.060	0.007	8.469	State
$\sigma_{\rm r}$	0.093	0.010	9.227	State
ρ	-0.733	0.082	-8.895	State
τ	0.069	0.001	52.380	Residual

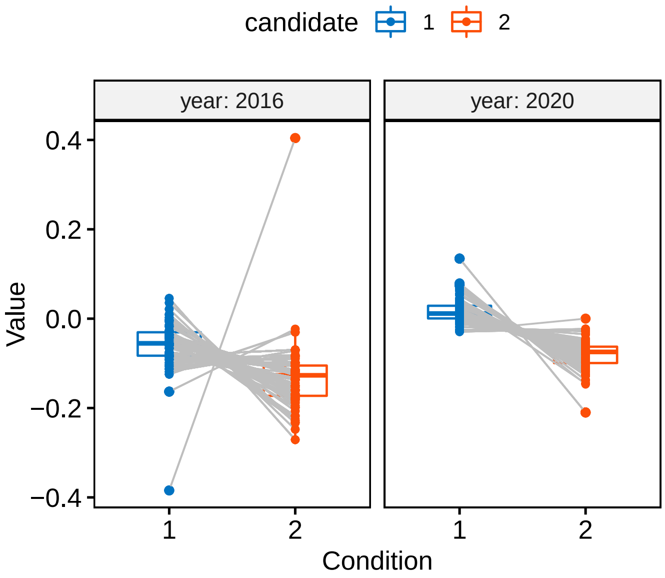
- Estimation results: Model (4)

Parameter	Estimate	Standard Error	t-statistic	Group
β_0	-0.055	0.010	-5.739	Fixed
β_1	-0.073	0.021	-3.573	Fixed
β_2	0.066	0.013	5.034	Fixed
β_3	-0.038	0.029	-1.302	Fixed
σ	0.032	0.003	9.935	Pollster
σ_{d}	0.058	0.006	10.358	Year:State
σ_{r}	0.091	0.007	12.659	Year:State
ρ	-0.798	0.054	-14.697	Year:State
τ	0.066	0.001	52.613	Residual

- Small area means: Model (1)



- Small area means: Model (2)



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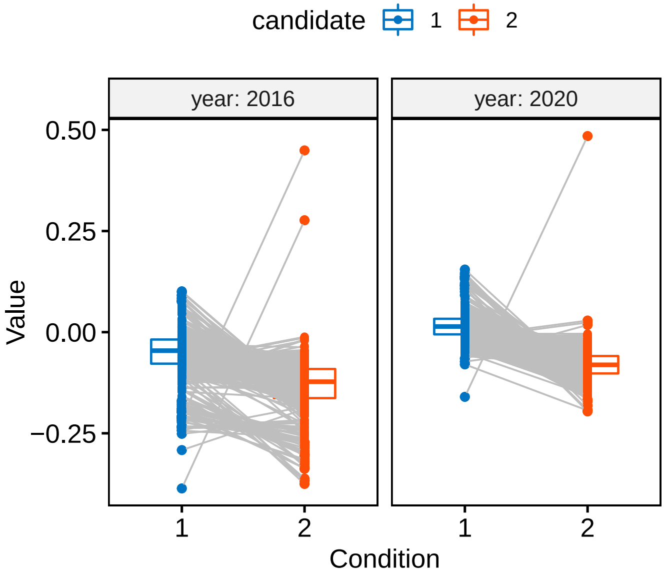
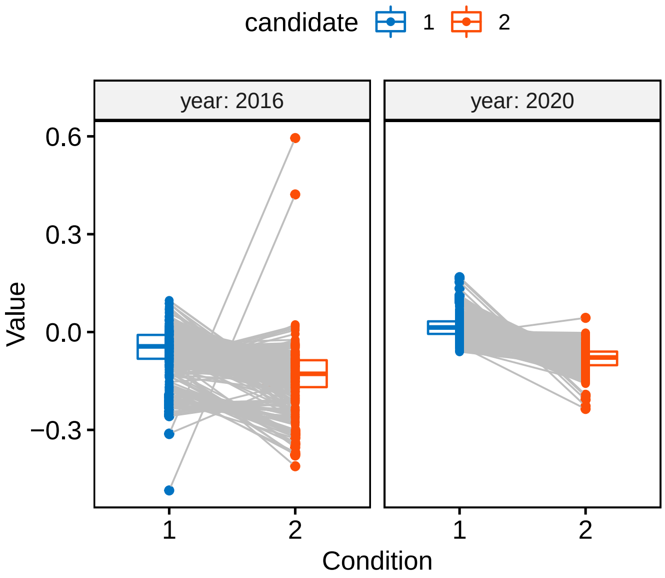


- Small area means: Model (4)



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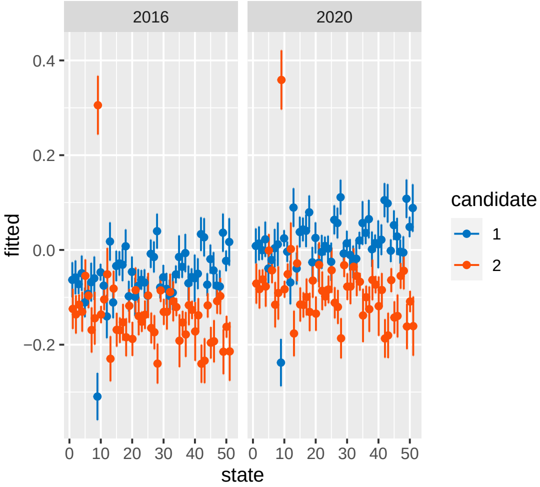

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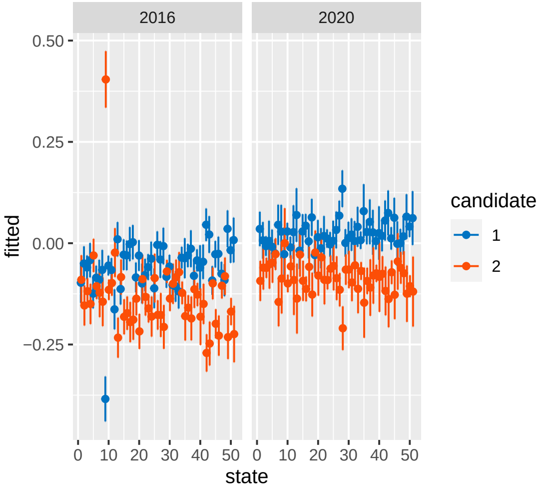

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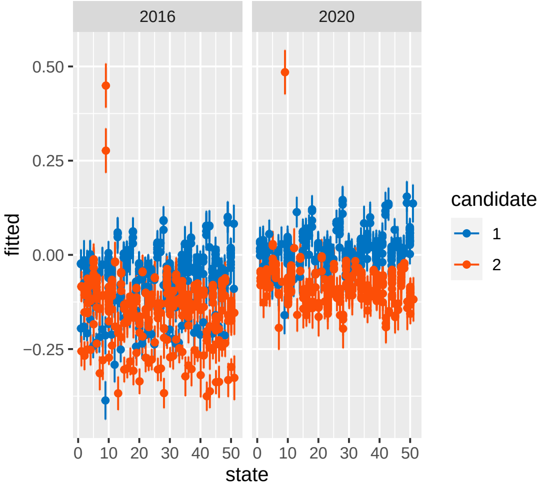

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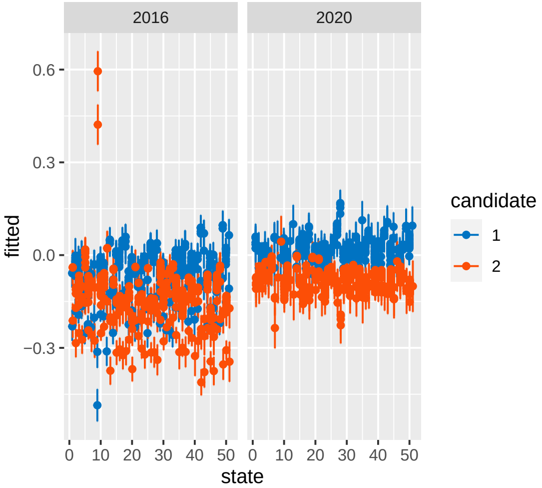

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- Practically, the elections, 2016 and 2020, are not at equal, or even similar, positions in terms of predicting one from the other, even if both predictions were possible.
- Reasons in terms of lesson-learning, or transfer learning.
- This lesson-learning prediction is simply our SAE method, now used to make prediction about the outcomes of another election involving the same Republican candidate.

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- Because the data only involve one election year, Models (2) and (4) do not apply.
- Models 1 and 3 also need to be modified by dropping the year indicator and its interaction with the candidate indicator. The modified models are

$$\text{Model I}: \quad y_{ia} = \beta_0 + \beta_1 I_{\text{can},ia} + z_{ia} v_i + e_{ia},$$
$$\text{Model III}: \quad y_{ipc} = \beta_0 + \beta_1 I_{\text{can},ipc} + z_{ipc} v_i + u_p + e_{ipc}.$$

- First consider Model I. As noted, the small area means, $\theta_{ia} = \beta_0 + \beta_1 I_{\text{can},ia} + z_{ia} v_i$, do not depend on the pollster; therefore, they can be denoted by $\theta_{ik} = \beta_0 + \beta_1 1_{(k=2)} + v_i$, $i = 1, \ldots, 51$, $k = 1, 2$.

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- By fitting Model I with one year's data, we obtain the EBLUP,

$$\hat{\theta}_{ik} = \hat{\beta}_0 + \hat{\beta}_1 1_{(k=2)} + \hat{v}_i, \tag{5}$$

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  $i = 1, \dots, 51$, $k = 1, 2$.
- Then, for another year's election, we have, also under Model I,

$$\log(p^*_{ijk}) - \log(\pi^*_{ik}) \quad = \quad \theta^*_{ik} + e^*_{ijk}, \tag{6}$$

  where p^*_{ijk} is the poll result for state i, pollster j and candidate k, which is available for all i, j, k.

- We then average both sides of (6) over $j \in J_i$, where J_i is the subset of pollsters who ran the polls in state i, to get

$$\overline{\log(p^*_{i\cdot k})} - \log(\pi^*_{ik}) \quad = \quad \theta^*_{ik} + \bar{e}^*_{i\cdot k}, \tag{7}$$

where $\overline{\log(p^*_{i\cdot k})} = |J_i|^{-1} \sum_{j \in J_i} \log(p^*_{ijk})$, $\bar{e}^*_{i\cdot k} = |J_i|^{-1} \sum_{j \in J_i} e^*_{ijk}$, and $|J_i|$ denotes the cardinality of J_i.

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- If we replace the right side of (7) by the $\hat{\theta}_{ik}$ in (5), we obtain $\log(\pi^*_{ik}) \approx \overline{\log(p^*_{i\cdot k})} - \hat{\theta}_{ik}$, or, equivalently,

$$\pi^*_{ik} \approx \hat{\pi}^*_{ik} \equiv \exp\left\{\overline{\log(p^*_{i\cdot k})} - \hat{\theta}_{ik}\right\}, \quad i = 1, \dots, 51, \;\; k = 1, 2. \tag{8}$$

- Question: If (8) a better predictor than the "poll of polls", that is,

$$\bar{p}^*_{i\cdot k} = \frac{1}{|J_i|}\sum_{j\in J_i} p^*_{ijk}, \quad i = 1,\dots,51, \quad k = 1,2? \tag{9}$$

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- Comparison results: Model I

Training	Predicting	State	Actual	SAE	PoP	EC Votes
2016	2020	Arizona	D	R	D	11
		Florida	R	D	D	29
		Nebraska	R	R	D	5
		North Carolina	R	R	D	15
		National	D (306/232)	D (324/214)	D (355/183)	
2020	2016	Florida	R	R	D	29
		Michigan	R	D	D	16
		Nevada	D	R	D	6
		North Carolina	R	R	D	15
		Pennsylvania	R	R	D	20
		Wisconsin	R	D	D	10
		National	R (232/306)	R (252/286)	D (322/216)	

- Comparison results: Model III

Training	Predicting	State	Actual	SAE	PoP	EC Votes
2016	2020	Arizona	D	R	D	11
		Florida	R	D	D	29
		Nebraska	R	R	D	5
		North Carolina	R	R	D	15
		National	D (306/232)	D (324/214)	D (355/183)	
	2016	Florida	R	R	D	29
		Michigan	R	R	D	16
		Nevada	D	R	D	6
		North Carolina	R	R	D	15
		Pennsylvania	R	R	D	20
		Wisconsin	R	R	D	10
		National	R (232/306)	R (226/312)	D (322/216)	

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- As noted, compared to 2016, 2020 is a "small lesson" to learn.

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- Imagine what one could do if a "big lesson" were learned, such as 2016.
- Clearly, the same lesson should be, could be, and have been learned, one way or the other.