EXPERT REPORT OF SEAN P. TRENDE, Ph.D.

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1 Expert Qualifications

1.1 Career

I serve as Senior Elections Analyst for Real Clear Politics. I joined Real Clear Politics in January of 2009 and assumed a fulltime position in March of 2010. Real Clear Politics is a company of approximately 50 employees, with its main offices in Washington D.C. It produces one of the most heavily trafficked political websites in the world, which serves as a one-stop shop for political analysis from all sides of the political spectrum and is recognized as a pioneer in the field of poll aggregation. Real Clear Politics produces original content, including both data analysis and traditional reporting.

My main responsibilities with Real Clear Politics consist of tracking, analyzing, and writing about elections. I collaborate in rating the competitiveness of Presidential, Senate, House, and gubernatorial races. As a part of carrying out these responsibilities, I have studied and written extensively about demographic trends in the country, exit poll data at the state and federal level, public opinion polling, and voter turnout and voting behavior. In particular, understanding the way that districts are drawn and how geography and demographics interact is crucial to predicting United States House of Representatives races, so much of my time is dedicated to that task.

I am currently a Visiting Scholar at the American Enterprise Institute, where my publications focus on the demographic and coalitional aspects of American Politics.

I am also a Lecturer at The Ohio State University. My courseload is detailed below.

1.2 Publications and Speaking Engagements

I am the author of the 2012 book The Lost Majority: Why the Future of Government is up For Grabs and Who Will Take It. In this book, I explore realignment theory. It argues that realignments are a poor concept that should be abandoned. As part of this analysis, I conducted a thorough analysis of demographic and political trends beginning in the 1920s and continuing through modern times, noting the fluidity and fragility of the coalitions built by the major political parties and their candidates.

I also co-authored the 2014 Almanac of American Politics. The Almanac is considered the foundational text for understanding congressional districts and the representatives of those districts, as well as the dynamics in play behind the elections. My focus was researching the history of and writing descriptions for many of the 2012 districts, including tracing the history of how and why they were drawn the way that they were drawn. Because the 2014 Almanac covers the 2012 elections, analyzing how redistricting was done was crucial to my work. I have also authored a chapter in Dr. Larry Sabato's post-election compendium after every election dating back to 2012.

I have spoken on these subjects before audiences from across the political spectrum, including at the Heritage Foundation, the American Enterprise Institute, the CATO Institute, the Bipartisan Policy Center, and the Brookings Institution. In 2012, I was invited to Brussels to speak about American elections to the European External Action Service, which is the European Union's diplomatic corps. I was selected by the United States Embassy in Sweden to discuss the 2016 elections to a series of audiences there and was selected by the United States Embassy in Spain to fulfill a similar mission in 2018. I was invited to present by the United States Embassy in Italy, but was unable to do so because of my teaching schedule.

1.3 Education

I received my Ph.D. in political science at The Ohio State University in 2023. I passed comprehensive examinations in both Methodology and American Politics. The first chapter of my dissertation involves voting patterns on the Supreme Court from 1900 to 1945; the second chapter involves the application of integrated nested LaPlace approximations to enable the incorporation of spatial statistical analysis in the study of United States elections. The third chapter of the dissertation involves the use of communities of interest in redistricting simulations. In pursuit of this degree, I also earned a Master's Degree in Applied Statistics. My coursework for my Ph.D. and M.A.S. included, among other things, classes on G.I.S. systems, spatial statistics, issues in contemporary redistricting, machine learning, non-parametric hypothesis tests and probability theory. I also earned a B.A. from Yale University in history and political science in 1995, a Juris Doctor from Duke University in 2001, and a Master's Degree in political science from Duke University in 2001.

In the winter of 2018, I taught American Politics and the Mass Media at Ohio Wesleyan University. I taught Introduction to American Politics at The Ohio State University for three semesters from Fall of 2018 to Fall of 2019, and again in Fall of 2021. In the Springs of 2020, 2021, 2022 and 2023, I taught Political Participation and Voting Behavior at The Ohio State University. This course spent several weeks covering all facets of redistricting: how maps are drawn, debates over what constitutes a fair map, measures of redistricting quality, and similar topics. It also covers the Voting Rights Act and racial gerrymandering claims. I also taught survey methodology in Fall of 2022 and Spring of 2024.

1.4 Prior Engagements as an Expert

A full copy of all cases in which I have testified or been deposed is included on my C.V., attached as Exhibit 1. In 2021, I served as one of two special masters appointed by the Supreme Court of Virginia to redraw the districts that will elect the Commonwealth's representatives to the House of Delegates, state Senate, and U.S. Congress in the following decade. The Supreme Court of Virginia accepted those maps, which were praised by observers from across the political spectrum. [1]

In 2019, I was appointed as the court's expert by the Supreme Court of Belize. In that case I was asked to identify international standards of democracy as they relate

[1] *See, e.g.*, *New Voting Maps, and a New Day, for Virginia*, The Washington Post (Jan. 2, 2022), available at `https://www.washingtonpost.com/opinions/2022/01/02/virginia-redistricting-voting-maps-gerrymander`; Henry Olsen, *Maryland Shows How to do Redistricting Wrong. Virginia Shows How to Do it Right*, The Washington Post (Dec. 9, 2021), available at `https://www.washingtonpost.com/opinions/2021/12/09/maryland-virginia-redistricting`; Richard Pildes, *Has VA Created a New Model for a Reasonably Non-Partisan Redistricting Process*, Election Law Blog (Dec. 9, 2021), available at `https://electionlawblog.org/?p=126216`.

to malapportionment claims, to determine whether Belize's electoral divisions (similar to our congressional districts) conformed with those standards, and to draw alternative maps that would remedy any existing malapportionment.

I served as a Voting Rights Act expert to counsel for the Arizona Independent Redistricting Commission in 2021 and 2022.

2 Scope of Engagement and Conclusions

I was retained by Snell & Wilmer, counsel for Pinal County, to evaluate the claims raised by Pinal County Supervisor Kevin Cavanaugh in his "Report of Obvious Errors in the 2024 Primary Election" (the "Report") as well as the accompanying "Analysis of Anomalies in Primary Returns" (the "Analysis" and excel spreadsheets showing his underlying calculations. Having thoroughly reviewed these documents, using standards and approaches typical of the social sciences, I conclude that Supervisor Cavanaugh's calculations are unsupported by the data. I am being compensated at a rate of $500/hr, which is my standard consulting rate. My remuneration is in no way dependent upon the conclusions that I reach.

3 My Independent Analysis of the Data Finds No Sign of Fraud in the Election Returns

As a preliminary matter, I conducted my own analysis into the July 2024 Republican Party Primary elections. My analysis did not reveal any signs of fraud.

People are very bad at inventing random numbers, or at creating numbers that follow particular distributions. Thus, fraudulent elections frequently show oddities in the distribution of reported digits. Political science research into the prevalence of fraud has focused on the distribution of leading, second, and final digits of numbers.[2] *See, e.g.*, Cantu, Francisco & Sebastian M. Saiegh, "Fraudulent Democracy? An Analysis of

[2] "Leading Digit" means the first digit in a number. I.e., 6 is the leading digit for the number 6,897. The final digit is the "ones" column. That is a 7 in the number 6,897.

Argentina's Infamous Decade Using Supervised Machine Learning." 19 *Political Analysis* 409 (2011); Pericchi, Luis Raul & David Torres, "Quick Anomaly Detection by the Newcomb Benford Law, with Applications to Electoral Processes Data from the USA, Puerto Rico and Venezuela", 26 *Statistical Science* 502 (2011); Beber, Bernd & Alexandra Scacco. "What the Numbers Say: A Digit-Based Test for Election Fraud", 20 *Political Analysis* 211 (2012).

The idea is that leading digits should follow some sort of logarithmic distribution, where the most common value is 1, followed by 2, followed by 3, and so forth. This makes sense: When counting ballots in a precinct, it is to get to 900 ballots than to 200 ballots, and more difficult to get to 8000 ballots than 1000.[3]. Here, I analyze the various ballot drops where any ballots were counted. The final digits, on the other hand, should follow a roughly uniform distribution, much like the dice rolls described below, with a slight dropoff toward higher numbers. We can't perform an exact statistical test here, because unfortunately we don't know the exact distribution of ballot drops in Pinal County. We do, however, know what the distributions should look like.

When we look at the ballot drops in Pinal County, we see the appropriate distributions. More importantly, we see similar distributions for both the Republican primary and the Democratic primary. For the final digits, the distribution does, indeed, appear to be uniform.[4]

[3]For an intuitive approach: Every precinct with at least 8,000 votes had to pass 2,000 votes, but precincts with 2,000 votes do not have to pass 8,000 votes

[4]A chi-square test comparing observed versus expected 0-9 in the trailing digit in the Republican primary against a presumed uniform distribution has a p-value of 0.618, suggesting no statistically meaningful difference from a uniform distribution. A chi-square test comparing observed versus expected 0-9 in the trailing digit in the Democratic primary has a p-value of 0.21, suggesting no statistically meaningful difference from a uniform distribution.

Figure 1: Distribution of leading digits, Pinal County 2024 Republican primary

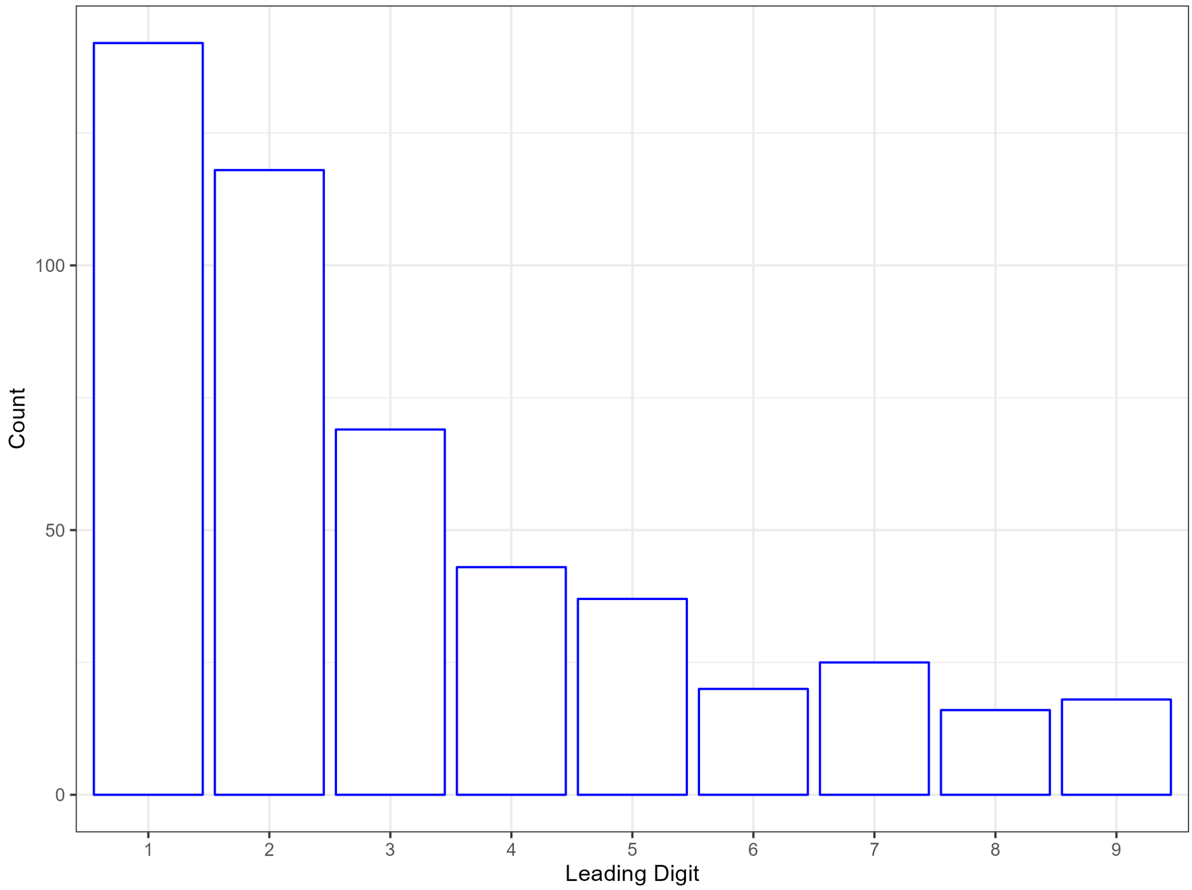


Figure 2: Distribution of leading digits, Pinal County 2024 Democratic primary

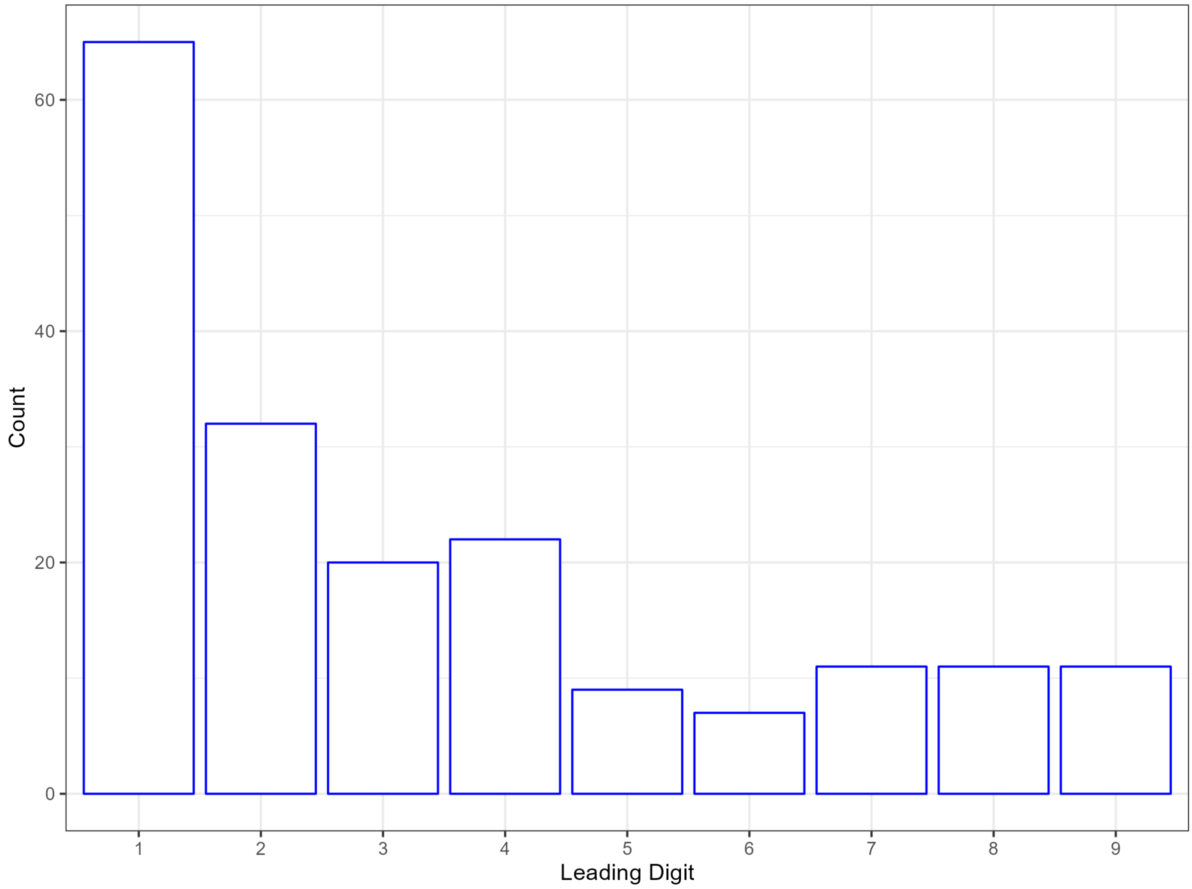


Figure 3: Distribution of final digits, Pinal County 2024 Republican primary

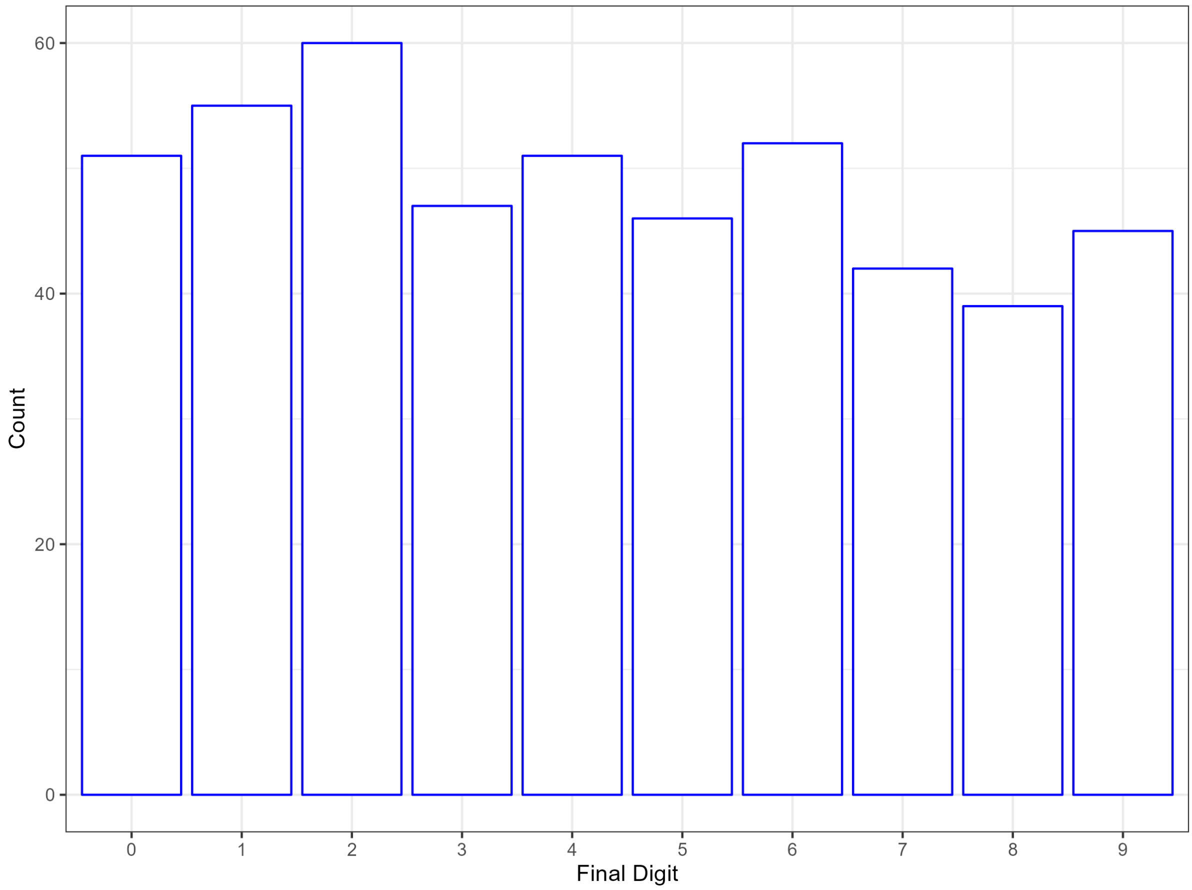
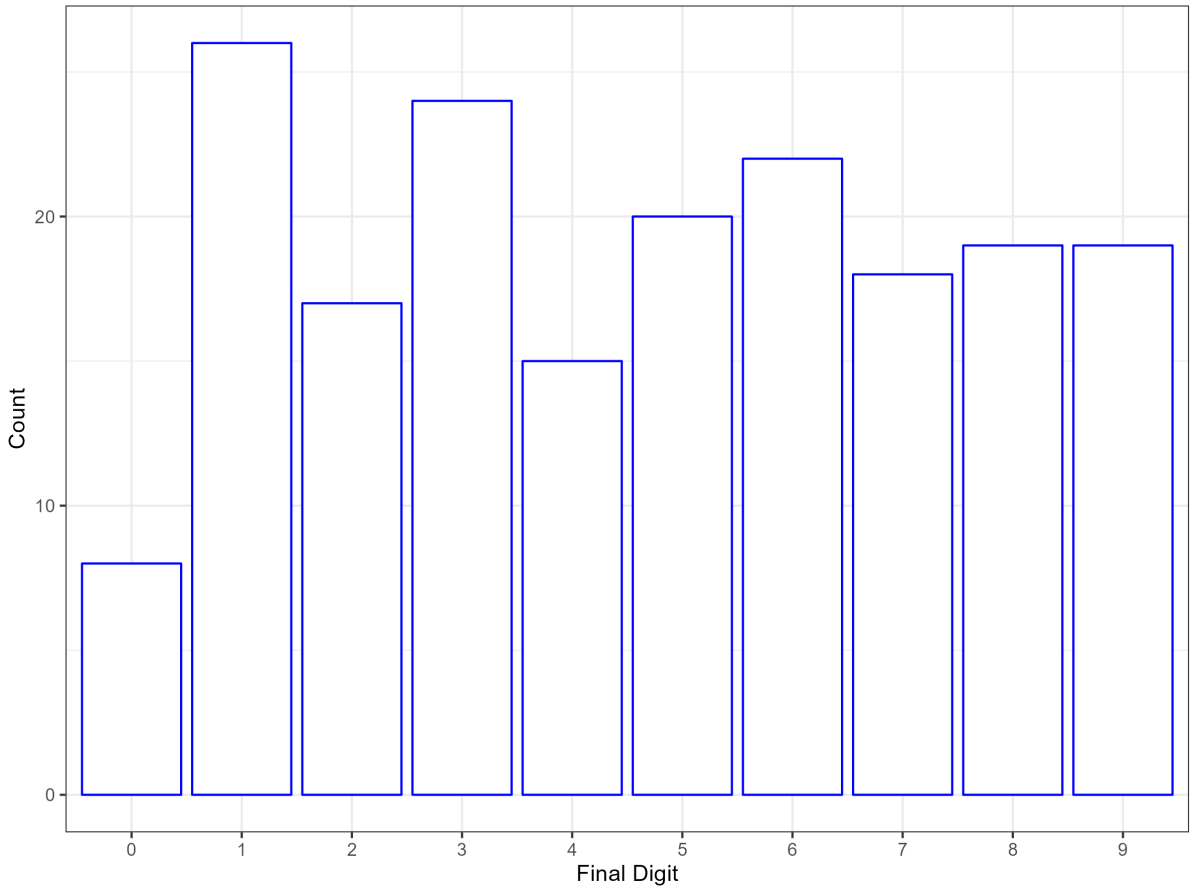


Figure 4: Distribution of final digits, Pinal County 2024 Democratic primary



4 Supervisor Cavanaugh's Analysis Is Not Statistically Sound and Lacks Important Data

In addition to the fact that there is nothing facially suspect about the elections results in Pinal County, there are several problems with Supervisor Cavanaugh's methodology in his Report and Analysis which render those documents unpersuasive.

4.1 Understanding Supervisor Cavanaugh's approach

While Supervisor Cavanaugh does include a section in the Analysis entitled "Methodology for PERCENTAGE OF DIFFERENCE AND CANDIDATE TOTAL PER RACE," it is uncertain what test he actually employs to determine whether or not an election is anomalous or not. My understanding is as follows:

- Supervisor Cavanaugh's dataset consists of election results from the 2016, 2020 and 2024 Republican primary elections;
- Supervisor Cavanaugh compares the candidates' vote shares among the early vote totals with their vote shares from Election Day vote totals and takes the difference;
- Supervisor Cavanaugh takes the absolute value of these differences. That is to say, a candidate whose early vote share runs 3 points ahead of his Election Day vote share is treated the same as a candidate whose early vote share runs 3 points behind his Election Day vote share;
- Supervisor Cavanaugh then creates a histogram of differences. To my understanding, Supervisor Cavanaugh conducts a visual inspection of the resulting histogram and concludes that the results from 2020 and 2016 followed a Normal (aka a "Gaussian" distribution),[5] while those from 2024 did not. This forms the basis for claiming an anomalous outcome.
- Other evidence is largely anecdotal, which provides useful explication of Supervisor Cavanaugh's overall approach, but does not allow us to draw conclusions.

4.2 Errors in Supervisor Cavanaugh's Methodology

Based on my review, there are several methodological errors in the Report and Analysis. The following is simply a collection of exemplars; I have not included every error throughout Supervisor Cavanaugh's materials. But, these issues are persuasive enough to render the Report and Analysis unsound from a professional perspective.

[5] A Normal distribution does, indeed, have a bell shape. But not all bell curves are Gaussian or Normal. A Normal distribution follows a specific type of bell curve, where roughly 68% of the data are within 1 standard deviation of the mean, roughly 95% of the data are within two standard deviations of the mean, and roughly 99% of the data fall within three standard deviations of the mean.

4.2.1 Supervisor Cavanaugh's Analysis Contains Several Basic Calculation Errors and Lacks Entire Datasets

At the outset, Supervisor Cavanaugh's calculations contain multiple calculation errors, which, in my view, render his analysis suspect and unreliable. Supervisor Cavanaugh's section entitled "Analysis of Anomalies in Primary Returns" opens with an example of the Supervisor District election for 2016 and 2020. It appears as follows. Please note that the highlighting is Supervisor Cavanaugh's, not my own. Instead, I focus on the "Total Votes" column here.

Figure 5: First example from Supervisor Cavanaugh's "Analysis of Anomalies in Primary Returns"

2016 Pinal				
BOS DIST 2 - 2016				
	EARLY	**POLL**	**PROVISIONAL**	**Total Votes**
WAYNE BACHMANN	435	149	24	608
TISHA CASTILLO	482	244	37	763
CHERYL CHASE	786	243	21	1050
MIKE GOODMAN	796	398	76	1270
MANUEL VEGA	**55**	**17**	**6**	**78**
WRITE-IN	**10**	**1**	**1**	**3769**
TOTAL	**2564**	**1052**	**165**	**7538**
WAYNE BACHMANN	17%	14%		**Diff**
TISHA CASTILLO	19%	23%		**4.40%**
CHERYL CHASE	31%	23%		**7.56%**
MIKE GOODMAN	31%	38%		**6.79%**
MANUEL VEGA	2%	2%		**0.53%**
WRITE-IN	0%	0%		

(a) Image taken from Supervisor Cavanaugh's report

The problem with this is that in the "Total Votes" column, for "write-in" votes, 3,769 votes are listed. It would be highly unusual for 3,769 write-in votes to be cast in an election where no other candidate received more than 1,270 votes, and indeed, this is an error. 3,769 is the sum of 608, 763, 1050, 1270, and 78, which are the five cells immediately above. It appears that Supervisor Cavanaugh accidentally cut-and-pasted the "sum" formula from the "Total" row into this cell. This, then, has the effect of doubling the number of votes cast in the race.

Or consider the next example, from the 2020 supervisor race from Pinal County. Once again, the highlighting is from Supervisor Cavanaugh's report. Instead, the reader should focus on the "Early" column, expressed as percentages at the bottom:

Figure 6: Second example from Supervisor Cavanaugh's "Analysis of Anomalies in Primary Returns"

2020 Pinal					
BOS DIST 2 - 2020					
		EARLY	**POLL**	**PROVISIONAL**	**Total Votes**
MIKE GOODMAN		4810	1242	35	6087
CHUCK GRAY		3666	754	10	4430
					0
Write In		13	7	0	20
		8489	**2003**	**45**	**10537**
					Diff
MIKE GOODMAN		45.65%	62.35%		**16.70%**
CHUCK GRAY		34.79%	37.30%		**2.51%**
	0	0.00%	0.00%		**0.00%**
Write In		0.12%	0.73%		**0.61%**

(a) Image taken from Supervisor Cavanaugh's report

The problem here is that the percentages of early vote do not add up to 100%, as 45.65% + 34.79% = 80.44%. But percentages have to add up to 100%, and someone has to win a majority of the early vote. While it is not entirely clear what happened, the correct percentages are 56.67% of the early vote for Mr. Goodman and 43.19% of the early vote for Mr. Gray. This, in turn, changes the differences reported to 5.35% and 5.54%, respectively. That is a substantially different result than Supervisor Cavanaugh highlights.

Finally, Supervisor Cavanaugh did not include all vote totals in his analysis. I observed this because, having observed the above errors, I obtained the results from all nine ballot deliveries from the county through counsel. My understanding is that ballot deliveries 1, 5, 6, 7, and 8 consist of early voting results, while numbers 2, 3, and 4 consist of Election Day. Ballot delivery 9 consists of provisional and late early results. I then totaled them up using the computer programming language "R." In my experience, an automated approach through a software package such as R minimizes the opportunity for user error that is present in Excel.

The third example that Supervisor Cavanaugh cites is an example of how excluding the final ballot deliveries can alter his results in meaningful ways. He points to the 2024 County Assessor election as the first example of an "anomalous" election result:

Figure 7: Third example from Supervisor Cavanaugh's "Analysis of Anomalies in Primary Returns"

COUNTY ASSESSOR	2024			
PINAL COUNTY 2024				
	EARLY	**POLL**	**PROVISIONAL**	**Total Votes**
STORM COX	7423	2930	0	10353
DOUG WOLF	19145	7551	0	26696
			0	0
Write In	29	55	0	84
	26597	**10536**	**0**	**37133**
				Diff
STORM COX	27.91%	27.81%		**0.10%**
DOUG WOLF	71.98%	71.67%		**0.31%**
0	0.00%	0.00%		**0.00%**
Write In	0.08%	0.15%		**0.07%**

(a) Image taken from Supervisor Cavanaugh's report

Mr. Wolf did, indeed, receive 7,551 Election Day votes. But his early vote total was 19,145 only after the first early ballot drop. After the final votes were tabulated, his total had swelled to 24,623. Mr. Cox appears to have fared better in these later drops, as well. A corrected table follows:

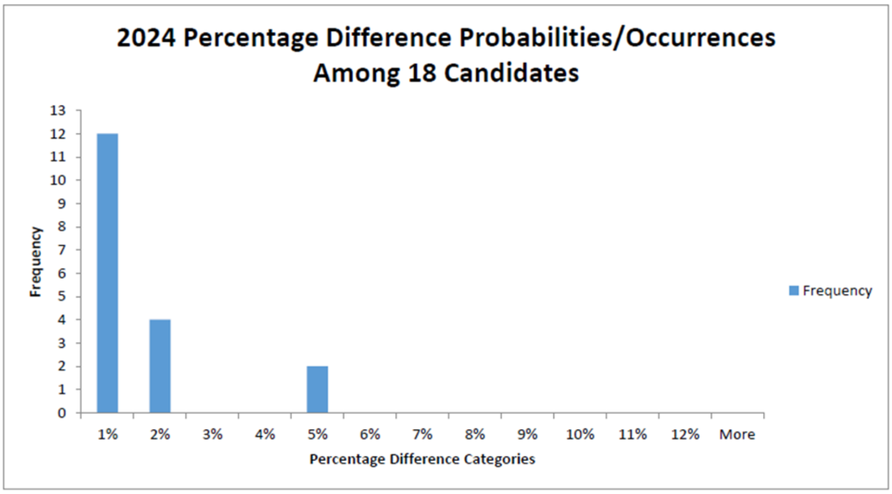
Figure 8: Corrected vote totals for Storm Cox and Douglas Wolf

Candidate	Early Vote Total	Election Day Total	Early Vote Share	Election Day Share	Difference
COX, DECEMBER 'STORM'	10,095	2,930	29.01%	27.88%	1.14%
WOLF, DOUGLAS	24,623	7,551	70.77%	71.85%	1.08%
Total:	34,794	10,510	100.00%	100.00%	0.00%
—	—	—	—	—	—

Mr. Wolf's share of the early vote drops to 70.8%, while Mr. Cox's increases to 29%. Thus, the true differential should be 1.08% for Mr. Wolf and 1.14% for Mr. Cox. While this may still qualify as a "small" difference for Supervisor Cavanaugh's purposes, the actual differential for Mr. Cox is 11.4 times as large as Supervisor Cavanaugh reports, while the actual differential for Mr. Wolf is 3.5 times as large as Supervisor Cavanaugh reports.

These errors are meaningful and would alter Supervisor Cavanaugh's summary histograms had they been corrected. For example, consider the histogram that Supervisor Cavanaugh provides in his conclusion and upon which his ultimate conclusions are based:

Figure 9: Supervisor Cavanaugh's histogram of 2024 vote differential



(a) Image taken from Supervisor Cavanaugh's report

Because of the difference described above for Messers. Cox and Wolf, there should instead be 10 candidates with differences of less than 1%, and 6 candidates with differences of between 1% and 2%. That is assuming everything else is calculated correctly.

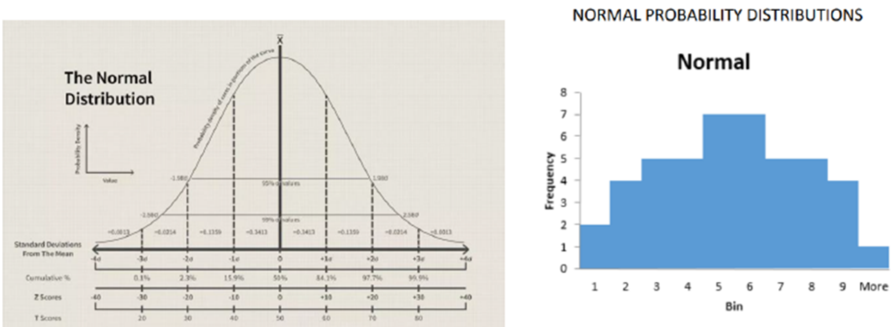
As I said, these are not the only errors that I identified. I report corrected totals further below, but the errors are common enough to undermine confidence in the overall conclusions.

4.2.2 Supervisor Cavanaugh Seemingly Misunderstands the Importance and Meaning of the Normal Distribution.

As explained below, Pinal County's July 2024 Republican Primary results actually do follow a "Normal" distribution. But, even if they did not, there would not be anything suspect about that because there are many different distributions beyond "Normal" bell-curves.

Supervisor Cavanaugh's methodology section begins with an explication of the Normal distribution, which he correctly identifies as taking on a bell shape.

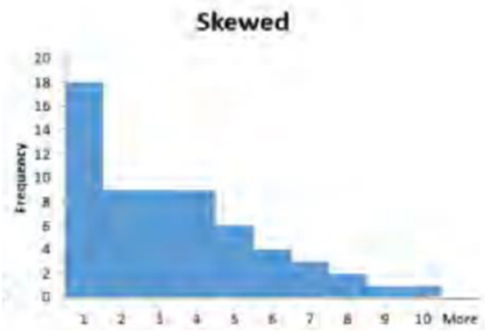
Figure 10: Supervisor Cavanaugh Desription of Normal Distribution



(a) Image taken from Supervisor Cavanaugh's report

First, we should note that while Normal distributions are, in fact, bell curves, not all bell curves are normally distributed. Instead, the Normal distribution follows a specific relationship between the average (mean) and the spread (standard deviation) of

Figure 11: Right-Skewed distribution



(a) Image taken from Supervisor Cavanaugh's report

the data. This is what the lines in the chart on the left mean. *E.g.,* George Casella and Roger L. Berger, *Statistical Inference* 102 (2002) (describing properties of a Normal distribution).

Supervisor Cavanaugh then refers throughout his report to "normal errors."[6] He states that "these are ideal distributions that don't occur in real life, but the curve should look more like these than this," with "this" apparently referring to the following skewed distribution.

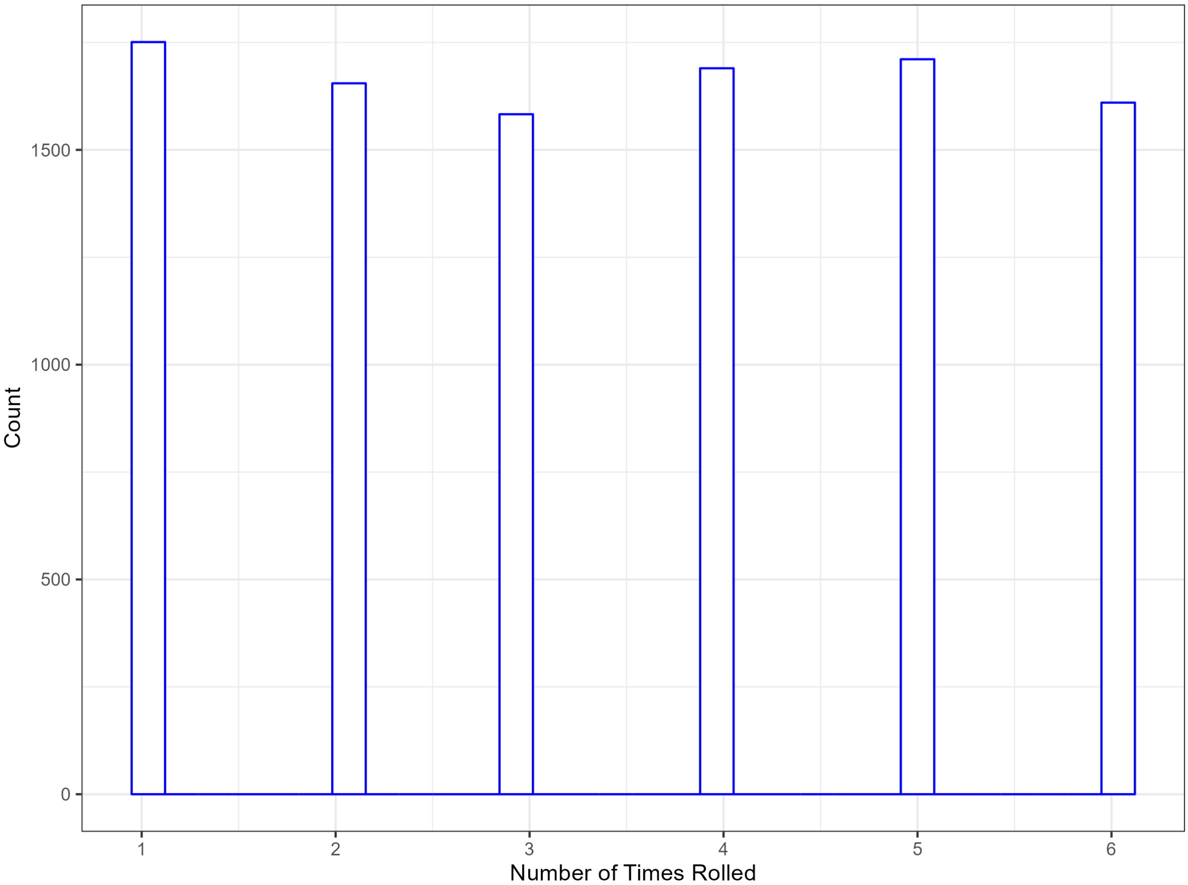
This reflects a common misunderstanding. The "Normal" distribution is a term of art that is often used to describe what is formally called a "Gaussian" distribution, named after the mathematician who is credited with having described its properties. I will refer to this distribution here with capitalization, to clarify that I am talking about the formal distribution.

The Normal Distribution, however, should not be conflated with "normal" or typical. There are, in fact, multiple ways that randomness can manifest that are normal but not Normal. In fact, some of these random distributions take on the skewed distribution style that Supervisor Cavanaugh disclaims.

[6]Supervisor Cavanaugh's reference to "normal errors" perhaps refers to the results of a regression analysis, which *assumes* independent, identically distributed Normal errors as a foundation for that type of analysis. But errors do not have to be Normal, and in any event, whether the data here are based on errors is a conclusion to be tested and therefore not a valid assumption.

For example, consider coin flipping a coin. The results from flipping a coin will obviously not reflect a bell curve, since a coin can only take on a value of heads or tails.[7] Coin flips, which are obviously random, follow what is known as a "binomial" distribution, with a probability parameter of 0.5. E.g. Larry Wasserman, *All of Statistics: A Concise Course in Statistical Inference* §2.3 (2004) Or consider rolling a single die. We can simulate a dice roll 10,000 easily in R, and plot the results. *Id.* at § 2.3.

Figure 12: Results of 10,000 simulated dice rolls.



As you can see, it is obviously not Normal. Yet no one disputes dice rolls are not random. Dice rolls follow what is called a Uniform distribution, discussed in passing

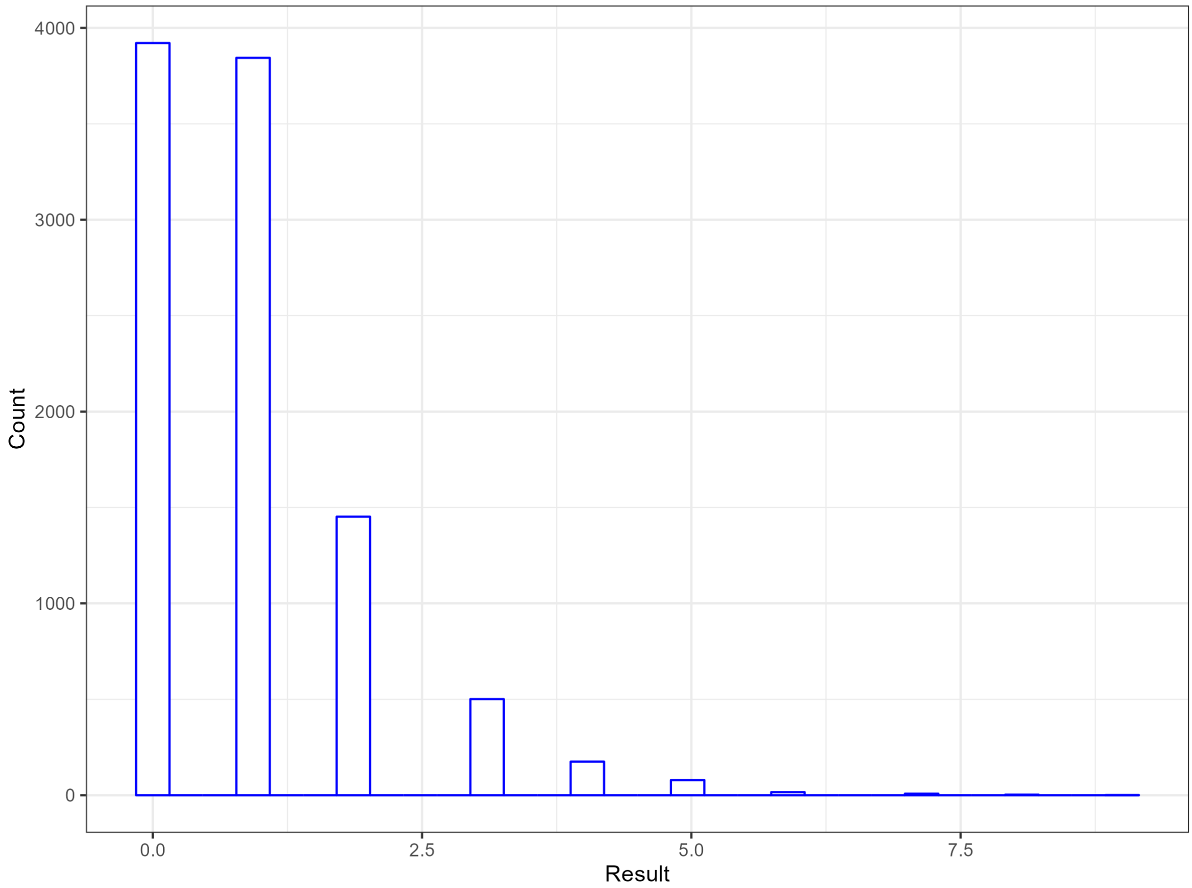
[7]If you graph the averages of repeated coin tosses, they will be Normally distributed, which is part of why the Normal distribution is so important in statistics; repeated sample means will, in fact, tend to be Normal.

above, as every outcome in the sample space (here, 1, 2, 3, 4, 5 or 6) is equally likely to occur.

Having demonstrated that "not Normal" is not the same as "not normal," what about the skewed distribution that Supervisor Cavanaugh describes? There are, indeed, random events that are skewed. Earthquake aftershocks are random; we do not know exactly when they will occur after the initial earthquake. At the same time, we can say with confidence that they are more likely to occur shortly after the earthquake than, say, two days after the earthquake. We also know, by definition, that they cannot occur *before* the earthquake.

Earthquakes instead follow what is known as an "exponential" distribution. See, e.g., Matteo Taroni and Michele Matteo Cosimo Carafa, "Earthquake Size Distributions are Slightly Different in Compression vs. Extension," 4 *Communications Earth and Environment* 398 (2023).

Figure 13: Example of Exponential Distribution with rate parameter = 1



Likewise, things such as insurance claims, cancer rates, and rainfall are what is known as beta distributed. This is also typically skewed. Two examples follow:

Figure 14: Example of Beta Distribution with parameters of 1 and 2

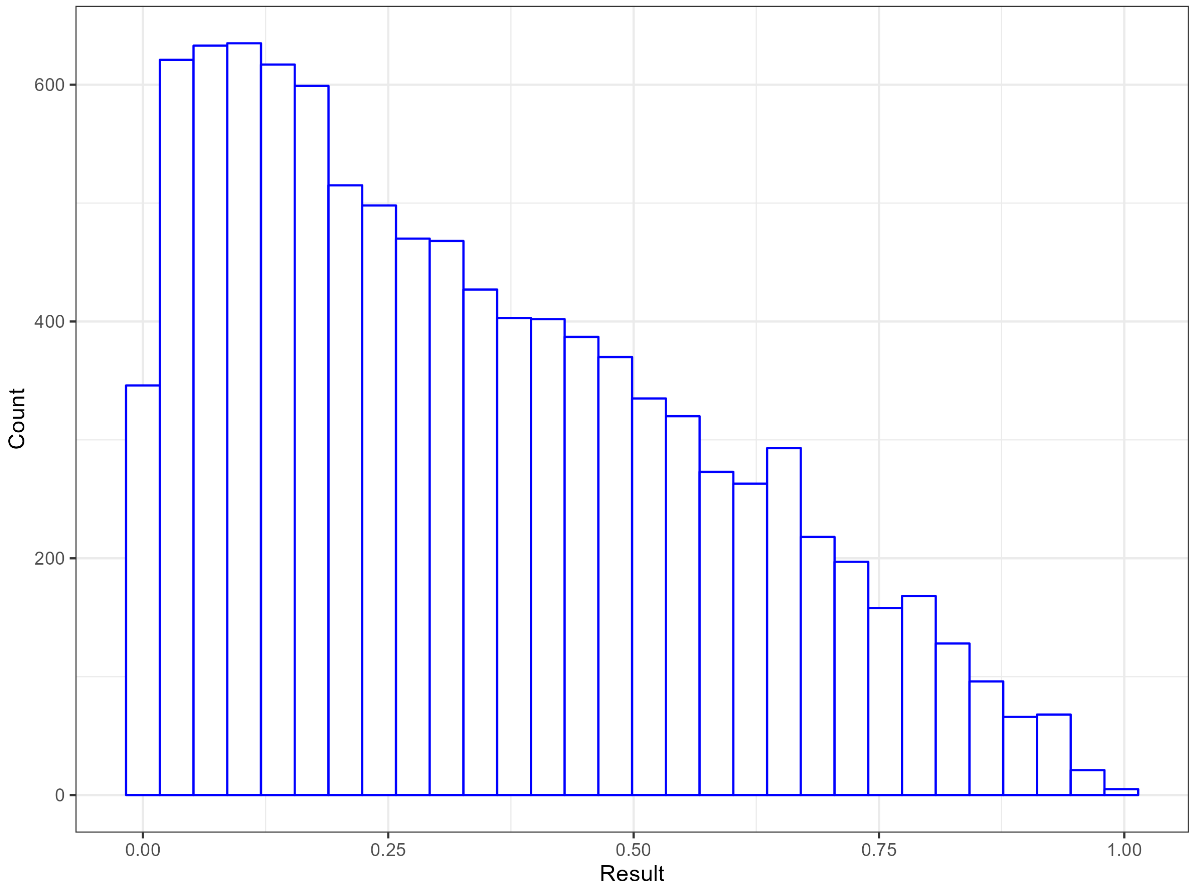
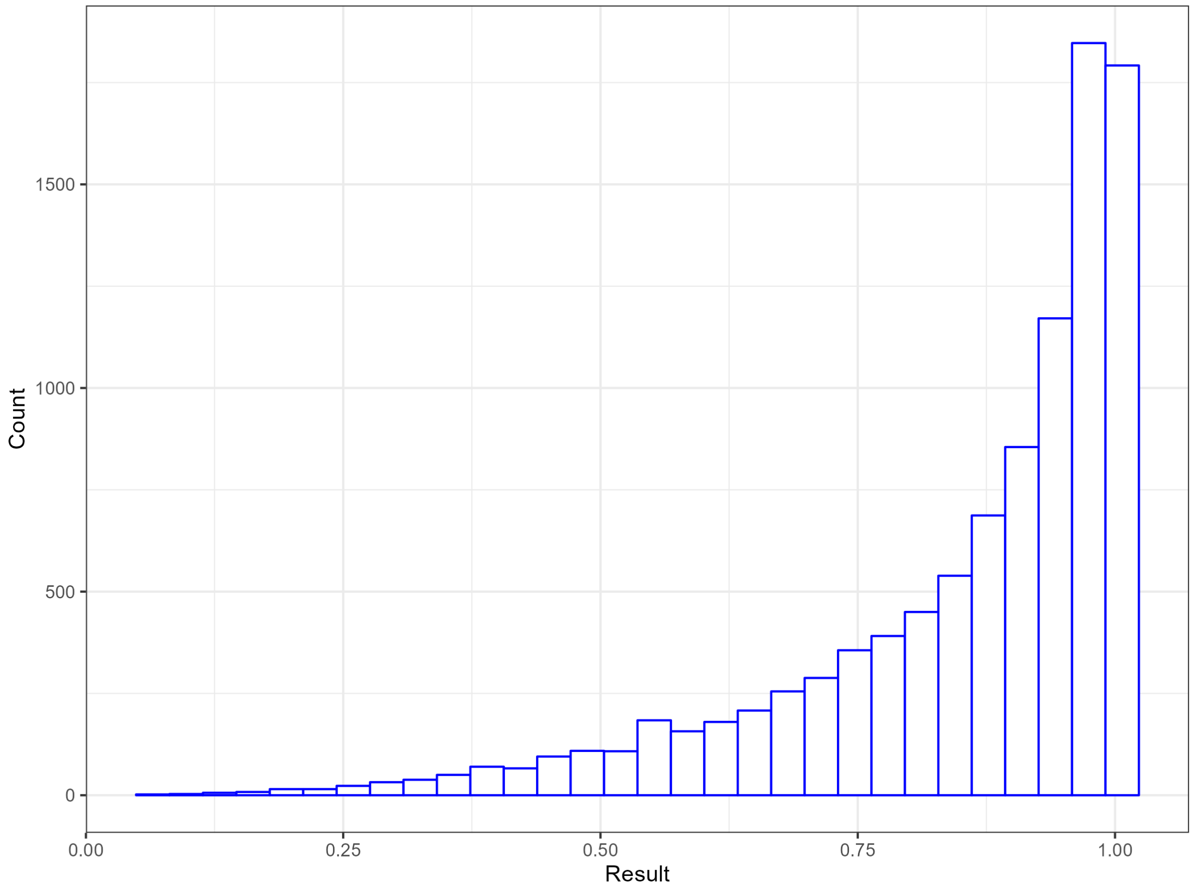


Figure 15: Example of Beta Distribution with parameters of 3 and 0.5



In short, Supervisor Cavanaugh seems to conflate Normal with "normal" and "not Normal" with "abnormal." But the fact that the differences between early vote shares and Election Day vote shares are not Normally distributed does not mean anything is amiss. There are ways for errors to be randomly distributed that do not necessarily follow a Normal distribution. In fact, there are ways to do so that are skewed in a way that resemble Supervisor Cavanaugh's calculations. The fact that the differences are not Normal does not mean that they are anomalous.

4.2.3 The 2024 Republican Primary Results in Pinal County, Properly Calculated Do Form a Bell Curve.

All of this is academic, however, as the 2024 data do, properly calculated, form a bell curve. In fact, Supervisor Cavanaugh sets up his analysis in such a way that the data cannot be Normal. Part of the definition of a Normal distribution is that it runs from negative infinity to infinity. Wasserman § 2.4. That is to say, the "inputs" have to be able to take on any value, positive or negative.

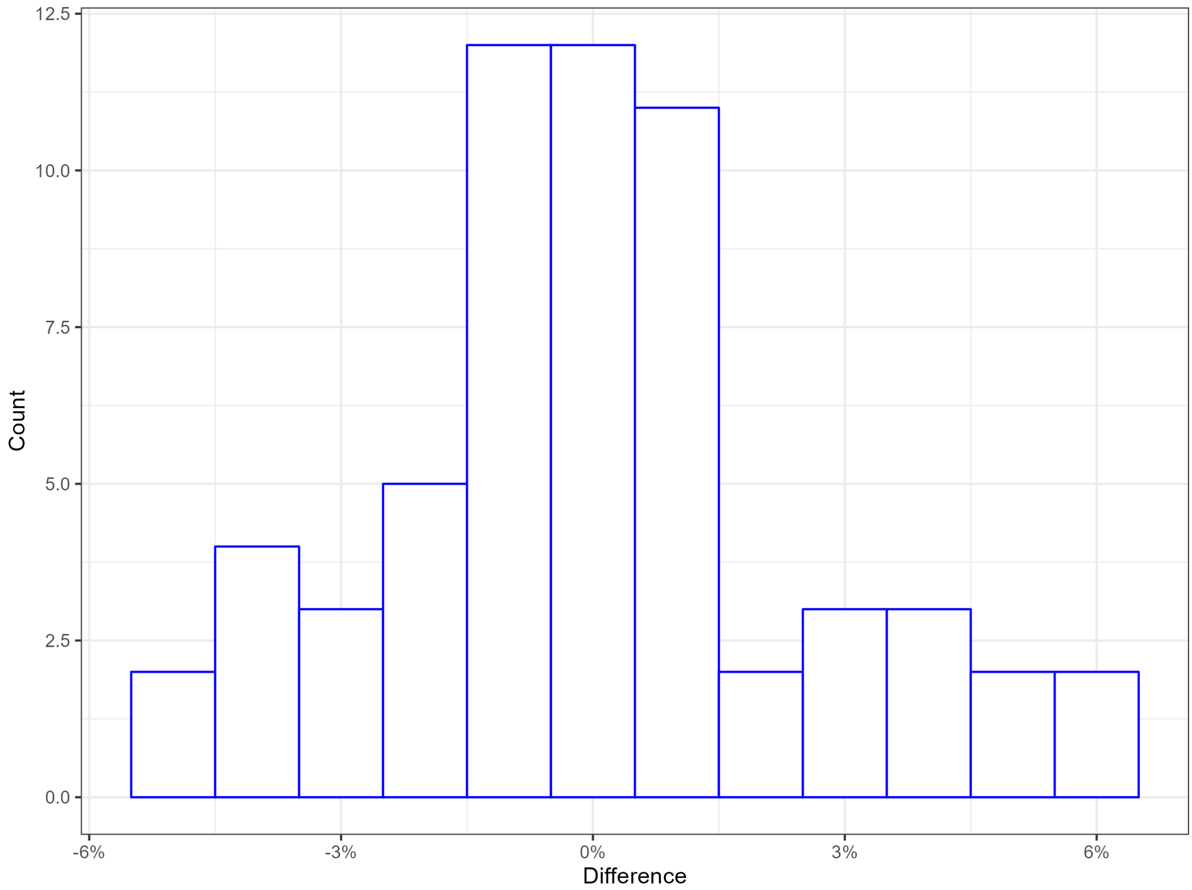
As discussed above, Supervisor Cavanaugh takes the absolute value of the difference between early and Election Day vote share. In other words, the same result is returned whether a candidate runs two points ahead of his Election Day vote share in early voting, or two points behind his Election Day vote share. But by definition, this cannot be Normal.[8]

This becomes more of a problem when the average deviation becomes very small. It becomes increasingly difficult for a left "tail" of the bell curve to exist, because absolute values can't fall below zero. This setup increases the odds of producing a skewed distribution.

Instead, I reran Supervisor Cavanaugh's analysis using all Republican races conducted in the Pinal County primary, using the simple difference as the relevant metric, and using all nine drops instead of Supervisor Cavanaugh's truncated sample to calculate early and Election Day vote shares. When I do so, the results plot out like this:

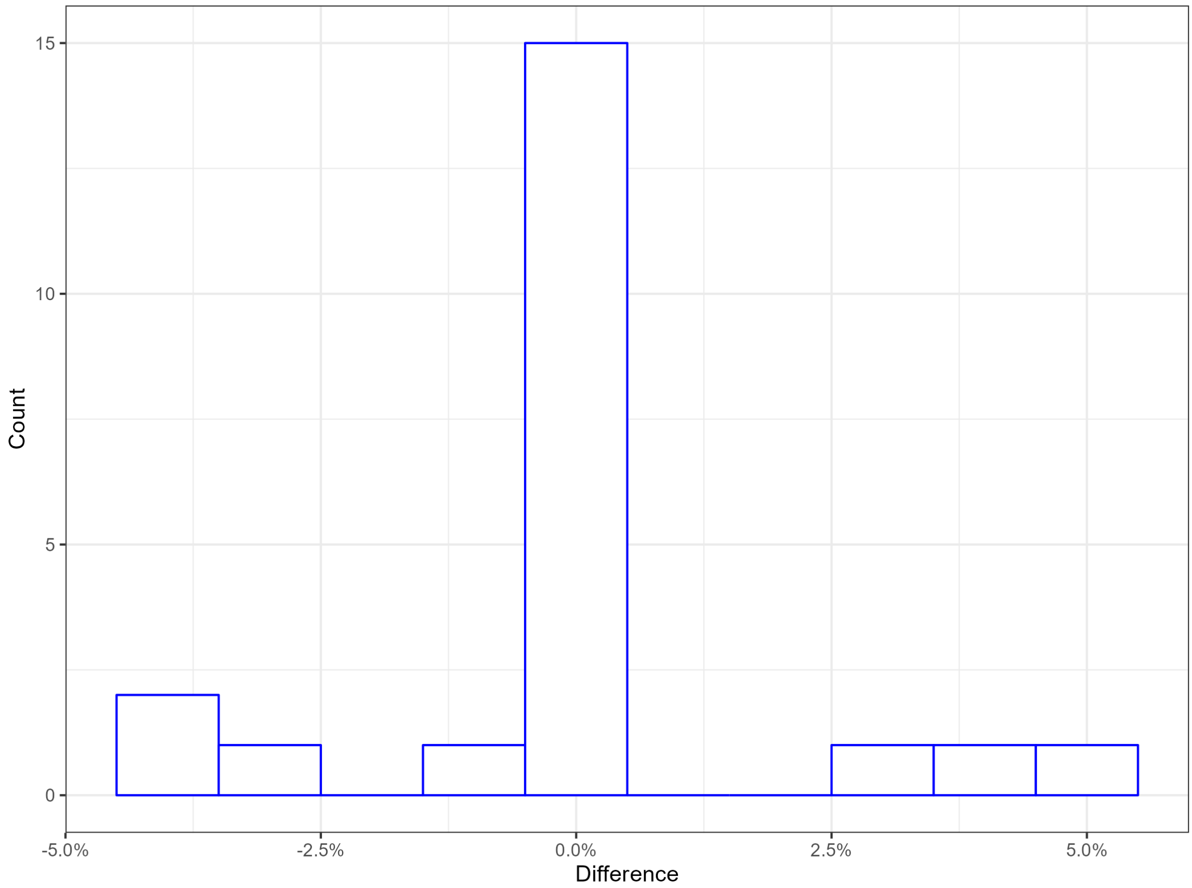
[8]Normal outputs also cannot be count data (e.g., the number of candidates having less than a 1% difference), as count data can only take on the value of whole numbers, and not fractions (e.g., it cannot be the case here that there are 1.4532 candidates with less than a 1% difference between their early vote share and Election Day vote share).

Figure 16: Histogram of Deviations, Pinal County 2024 Republican Primary



As you can see, when we allow the data to traverse the range required of a Normal distribution, the data look Normal. The same is true of the Democratic primary, although fewer candidates means that the distribution is not as filled out:

Figure 17: Histogram of Deviations, Pinal County 2024 Democratic Primary



4.2.4 Cavanaugh Lacks Sufficient Data To Draw His Conclusions.

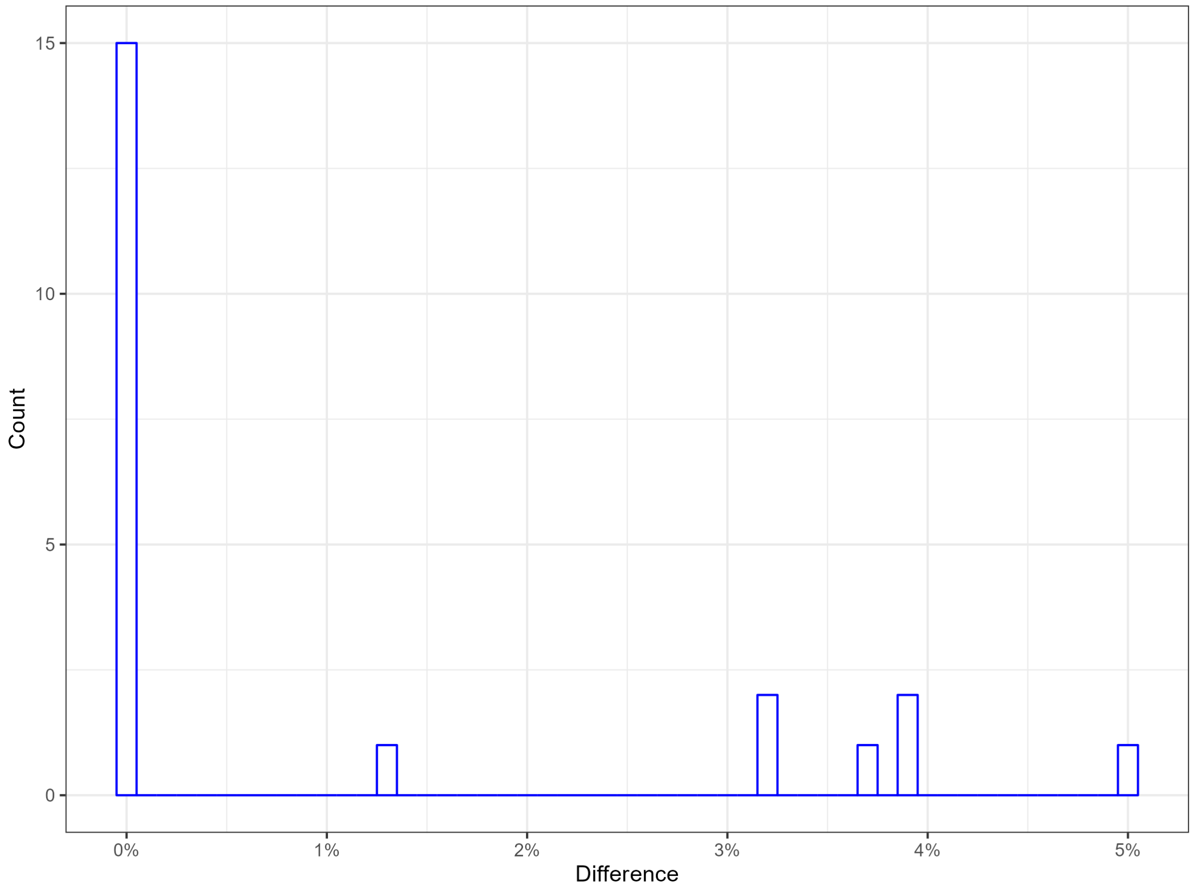
The final problem with Cavanaugh's analysis is that he claims the difference between in person and early votes in certain years are "normal" and other years are "abnormal." But this begs the question: even assuming arguendo that there are differences in the distributions between the outcome in 2016, 2020 and 2024, which should we use as the baseline?

We lack a sufficient basis to draw conclusions. The problem is that the data we have are grouped by year. That is, the various election results from 2016 all occur in 2016, and collectively form the basis for a single observation. Likewise, the various election results from 2020 all collectively form the basis for a single observation. Put in social science terms, the data are clustered. E.g., Robert S. Erikson Lorraine C. Minnite, "Modeling Problems in the Voter Identification – Voter Turnout Debate," 8 *Election Law Journal* 85 (2009).

This creates a small "n" problem, with "n" representing the number of observations we have. The problem can create statistical problems, but it can also cause analytical problems that confound our conclusions. Even if Supervisor Cavanaugh were to demonstrate that the distributions in 2016, 2020 and 2024 are statistically different, he lacks the data to show that 2020 or 2016 are the proper baseline. In short, perhaps those years are the anomalies.

In fact, we have reason to believe that they might be. After all, 2020 in particular was an odd year for selection of mail voting versus in person voting, given the COVID-19 pandemic. Moreover, in 2016 and 2020 Donald Trump urged Republicans to avoid voting early or by mail. This cycle, the strategies may have been different. It would not even require this degree of sophistication to explain these results. If the Election Day population began to look more like the Early voting population, we would see the effect Supervisor Cavanaugh describes. Indeed, if we look at the distribution of votes in the Democratic primary, using the "absolute difference" that Supervisor Cavanaugh describes, we see the same distribution that we see in the Republican primary:

Figure 18: Histogram of Absolute Deviations, Pinal County 2024 Democratic Primary



5 Conclusion

In short, the data simply do not support the contention that something was amiss in the Republican primary. The data do not show telltale signs of vote manipulation. Properly interpreted and calculated, the data resemble the Normal distribution that Supervisor Cavanaugh desires. And the Democratic primary shows similar distributions to those found in the Republican primary. The simplest explanation is that in this election, Election Day voters were similar to early voters, and it showed up in the results.

I declare under penalty of perjury under the laws of the State of Ohio that the foregoing is true and correct to the best of my knowledge and belief. Executed on 8 October, 2024 in Delaware, Ohio.

Sean Trende

Sean P. Trende

6 Exhibit 1 – Sean Trende C.V.

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EDUCATION

Ph.D., The Ohio State University, Political Science, 2023. Dissertation titled *Application of Spatial Analysis to Contemporary Problems in Political Science*, September 2023.

M.A.S. (Master of Applied Statistics), The Ohio State University, 2019.

J.D., Duke University School of Law, *cum laude*, 2001; Duke Law Journal, Research Editor.

M.A., Duke University, *cum laude*, Political Science, 2001. Thesis titled *The Making of an Ideological Court: Application of Non-parametric Scaling Techniques to Explain Supreme Court Voting Patterns from 1900-1941*, June 2001.

B.A., Yale University, with distinction, History and Political Science, 1995.

PROFESSIONAL EXPERIENCE

Law Clerk, Hon. Deanell R. Tacha, U.S. Court of Appeals for the Tenth Circuit, 2001-02.

Associate, Kirkland & Ellis, LLP, Washington, DC, 2002-05.

Associate, Hunton & Williams, LLP, Richmond, Virginia, 2005-09.

Associate, David, Kamp & Frank, P.C., Newport News, Virginia, 2009-10.

Senior Elections Analyst, RealClearPolitics, 2010-present.

Columnist, Center for Politics Crystal Ball, 2014-17.

Visiting Scholar, American Enterprise Institute, 2018-present.

BOOKS AND BOOK CHAPTERS

Larry J. Sabato, ed., *The Red Ripple*, Ch. 15 (2023).

Larry J. Sabato, ed., *A Return to Normalcy?: The 2020 Election that (Almost) Broke America* Ch. 13 (2021).

Larry J. Sabato, ed., *The Blue Wave*, Ch. 14 (2019).

Larry J. Sabato, ed., *Trumped: The 2016 Election that Broke all the Rules* (2017).

Larry J. Sabato, ed., *The Surge:2014's Big GOP Win and What It Means for the Next Presidential Election*, Ch. 12 (2015).

Larry J. Sabato, ed., *Barack Obama and the New America*, Ch. 12 (2013).

Barone, Kraushaar, McCutcheon & Trende, *The Almanac of American Politics* 2014 (2013).

The Lost Majority: Why the Future of Government is up for Grabs – And Who Will Take It (2012).

PREVIOUS EXPERT TESTIMONY AND/OR DEPOSITIONS

Dickson v. Rucho, No. 11-CVS-16896 (N.C. Super. Ct., Wake County) (racial gerrymandering).

Covington v. North Carolina, No. 1:15-CV-00399 (M.D.N.C.) (racial gerrymandering).

NAACP v. McCrory, No. 1:13CV658 (M.D.N.C.) (early voting).

NAACP v. Husted, No. 2:14-cv-404 (S.D. Ohio) (early voting).

Ohio Democratic Party v. Husted, Case 15-cv-01802 (S.D. Ohio) (early voting).

Lee v. Virginia Bd. of Elections, No. 3:15-cv-357 (E.D. Va.) (early voting).

Feldman v. Arizona, No. CV-16-1065-PHX-DLR (D. Ariz.) (absentee voting).

A. Philip Randolph Institute v. Smith, No. 1:18-cv-00357-TSB (S.D. Ohio) (political gerrymandering).

Whitford v. Nichol, No. 15-cv-421-bbc (W.D. Wisc.) (political gerrymandering).

Common Cause v. Rucho, No. 1:16-CV-1026-WO-JEP (M.D.N.C.) (political gerrymandering).

Mecinas v. Hobbs, No. CV-19-05547-PHX-DJH (D. Ariz.) (ballot order effect).

Fair Fight Action v. Raffensperger, No. 1:18-cv-05391-SCJ (N.D. Ga.) (statistical analysis).

Pascua Yaqui Tribe v. Rodriguez, No. 4:20-CV-00432-TUC-JAS (D. Ariz.) (early voting).

Ohio Organizing Collaborative, et al v. Ohio Redistricting Commission, et al, No. 2021-1210 (Ohio) (political gerrymandering).

NCLCV v. Hall, No. 21-CVS-15426 (N.C. Sup. Ct.) (political gerrymandering).

Szeliga v. Lamone, Case No. C-02-CV-21-001816 (Md. Cir. Ct.) (political gerrymandering).

Montana Democratic Party v. Jacobsen, DV-56-2021-451 (Mont. Dist. Ct.) (early voting; ballot collection).

Carter v. Chapman, No. 464 M.D. 2021 (Pa.) (map drawing; amicus).

NAACP v. McMaster, No. 3:21-cv-03302 (D.S.C.) (racial gerrymandering).

Graham v. Adams, No. 22-CI-00047 (Ky. Cir. Ct.) (political gerrymandering).

Harkenrider v. Hochul, No. E2022-0116CV (N.Y. Sup. Ct.) (political gerrymandering).

LULAC v. Abbott, Case No. 3:21-cv-00259 (W.D. Tex.) (racial/political gerrymandering/VRA).

Moore et al., v. Lee, et al., (Tenn. 20th Dist.) (state constitutional compliance).

Agee et al. v. Benson, et al., (W.D. Mich.) (racial gerrymandering/VRA).

Faatz, et al. v. Ashcroft, et al., (Cir. Ct. Mo.) (state constitutional compliance).

Coca, et al. v. City of Dodge City, et al., Case No. 6:22-cv-01274-EFM-RES (D. Kan.) (VRA).

Milligan v. Allen, Case No. 2:21-cv-01530-AMM (N.D. Ala.) (VRA).

Nairne v. Ardoin, NO. 22-178-SDD-SDJ (M.D. La.) (VRA).

Robinson v. Ardoin, NO. 22-211-SDD-SDJ (M.D. La.) (VRA).

Republican Party v. Oliver, No. D-506-CV-2022-00041 (N.M. Cir. Ct. (Lea County)) (political gerrymandering).

Palmer v. Hobbs, Case No. 3:22-CV-5035-RSL (W.D. Wash) (VRA; remedial phase only).

Clarke v. Evers, No. 2023AP001399-OA (Wisc.) (Political gerrymandering; remedial phase only).

Stone v. Allen, No. 2:21-cv-1531-AMM (N.D. Ala.) (VRA).

Milligan v. Allen, No. 2:21-cv-01530-AMM (S.D. Ala.) (VRA).

Pierce v. NC State Board of Elections, Case No. 4:23-cv-193 (E.D.N.C.) VRA.

COURT APPOINTMENTS

Appointed as Voting Rights Act expert by Arizona Independent Redistricting Commission (2020)

Appointed Special Master by the Supreme Court of Virginia to redraw maps for the Virginia House of Delegates, the Senate of Virginia, and for Virginia's delegation to the United States Congress for the 2022 election cycle.

Appointed redistricting expert by the Supreme Court of Belize in Smith v. Perrera, No.

55 of 2019 (one-person-one-vote).

INTERNATIONAL PRESENTATIONS AND EXPERIENCE

Panel Discussion, European External Action Service, Brussels, Belgium, Likely Outcomes of 2012 American Elections.

Selected by U.S. Embassies in Sweden, Spain, and Italy to discuss 2016 and 2018 elections to think tanks and universities in area (declined Italy due to teaching responsibilities).

Selected by EEAS to discuss 2018 elections in private session with European Ambassadors.

TEACHING

American Democracy and Mass Media, Ohio Wesleyan University, Spring 2018.

Introduction to American Politics, The Ohio State University, Autumns 2018, 2019, 2020, Spring 2018.

Political Participation and Voting Behavior, Springs 2020, 2021, 2022, 2023.

Survey Methodology, Fall 2022, Spring 2024.

PUBLICATIONS

James G. Gimpel, Andrew Reeves, & Sean Trende, "Reconsidering Bellwether Locations in U.S. Presidential Elections," Pres. Stud. Q. (2022) (forthcoming, available online at http://doi.org/10.1111/psq.12793).

REAL CLEAR POLITICS COLUMNS

Full archives available at `http://www.realclearpolitics.com/authors/sean_trende/`