Exh. 27 – Declaration of Eric Quinnell

Declaration of Eric Quinnell

1. My name is Dr. Eric Quinnell. I am over 18 years of age, and I am competent to testify in this action. All of the facts stated herein are true and based on my personal knowledge. All scientific conclusions herein are made to a reasonable degree of scientific certainty in my fields of expertise.

2. I received a Bachelor of Science Degree in Engineering in May of 2004, a Master of Science in Circuit Design in May of 2006, and a Doctorate in Computer Arithmetic in May of 2007, all from The University of Texas at Austin.

3. I have extensive professional experience as an engineer designing and leading teams engaged in various aspects of circuit architecture and processing. In this capacity, I frequently engage in complex and sophisticated predictive mathematical modeling and statistical analysis. I am required to prepare reports and analysis on the same for presentations to executives and other decision makers. I make this declaration in my personal capacity.

Executive Summary

4. I was asked to analyze the results of the 2020 General Election in Fulton County, Georgia to determine if there were any statistical anomalies in voting, and if so, to perform a predictive modeling analysis to analyze those anomalies.

5. When compared to the 2016 General Election Democrat to Republican voting ratio, the voting distribution gains for 2020 are well outside the 2016 ratio of a multiple of 2.52. Specifically, for every one additional voter for President Donald J. Trump ("Trump") over the full total from the 2016 General Election in Fulton County, former Vice-President Joseph R. Biden ("Biden") gained 4.2 additional voters over the full total from 2016 in Fulton County.

6. The Biden distribution kurtosis or "4th moment" shows a value classifying it as "platykurtic", which indicates as compared to the standard normal, the distribution lacks a "tail". This fact is irregular as we often expect our data to be close to a normal distribution. Significant deviations from the normalized distribution can indicate an event that is statistically unlikely. With the number of data points we have, it is reasonable to expect normal-like behavior.

7. At a county or district level of analysis, statistical anomalies appear in even greater ratios. For example, CountyJC, which was a majority Republican county in the 2106 General Election, showed Biden gained 4.6 new voters to every 1 new Trump voter. Biden also achieved >100% of all additional new votes above 2016 General Election total vote sum in some of CountyJC's districts—meaning Biden not only captured all votes in the district above the total from 2016, but took extra votes lost by the Libertarian column. In one specific district, Biden's new voter gains exceed 150% of the total new registrations over 2016 registrations in the same district.

8. Such local mathematical anomalies are not seen in all counties of Fulton County, but rather only a select few.[1]

9. I constructed a mathematical model that subtracted out local statistical anomalies and renormalized them according to their 2016 ratios, all while keeping pace with the additional turnout for Trump as a control. This allowed me to quantize a predicted number of anomalous votes per county, which are listed at the end of the Declaration. In all, I identified some 32,347 votes as statistically anomalous.

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1 Fulton is split into "counties" with each county having a letter/number prefix and letter/number suffix, representing what is classically considered elsewhere a "precinct". Several precincts share prefixes as a super-group. Hereafter, I shall refer to the super-groups with common letter/number prefixes as "counties" and their sub-divisions unique by letter/number suffix as "districts".

Data Set Selection

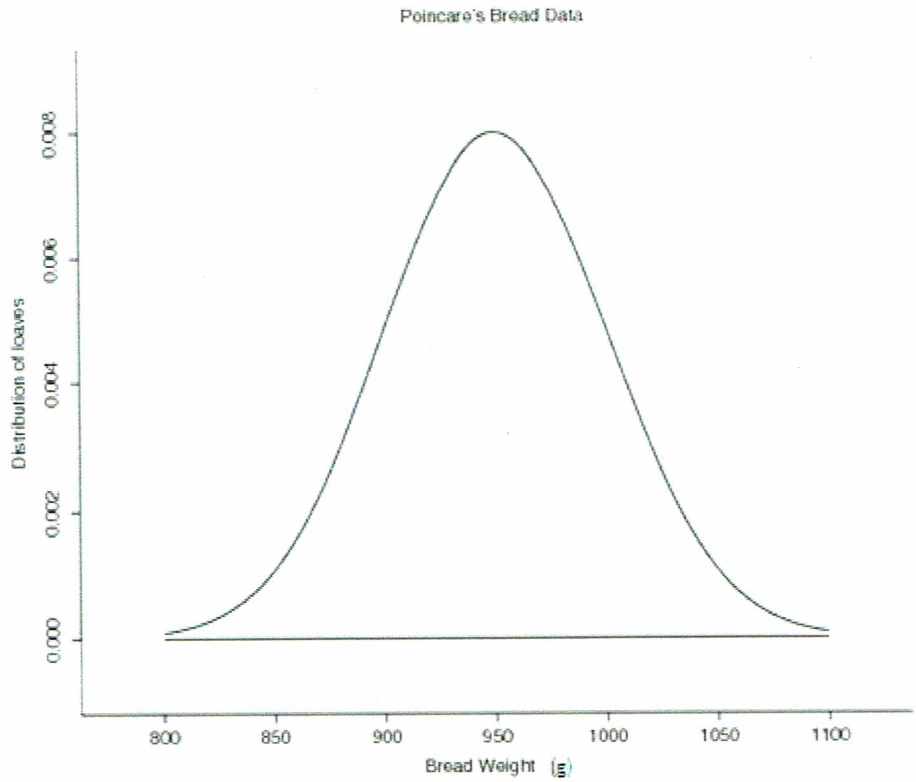
10. I retrieved publicly available data from the https://data.fultoncountyga.gov/Elections/Election-Results-General-Election-November-8-2016/eiwi-wrhe website containing the official Fulton County 2016 General Election Results. I also retrieved the publicly available unofficial Fulton County 2020 General Election Results from https://results.enr.clarityelections.com/GA/Fulton/105430/web.264614/#/detail/1 website as of November 11, 2020.

Basic Methodology

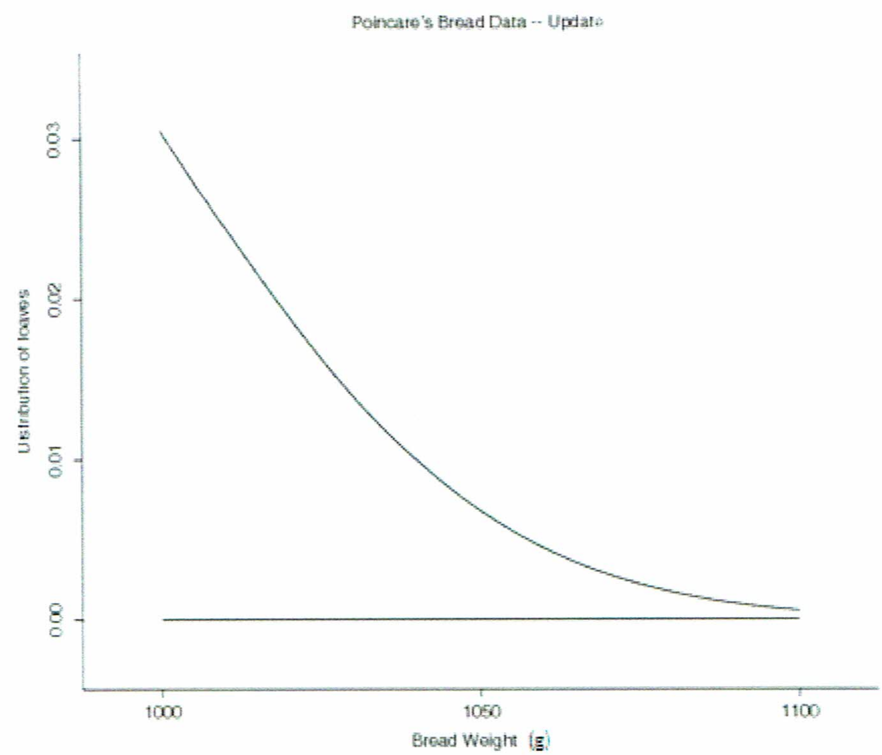
11. The anecdote of the 19th century French mathematician Henri Poincaré and a bread baker under his employ illustrate how one can use statistical inference to detect when agents are adjusting the data of the events under consideration. In particular, even if we only see part of behavior, we can often infer the rest.

12. Henri wished for a bakery he owned in Paris to produce bread that averaged 1kg in weight and provided capital accordingly to his baker. Every morning, the baker would bring bread to Henri, who, being a mathematician, would weigh the bread and record the weight in a log. After a year, Henri sued the baker for making bread consistently lighter than 1kg.

13. Henri's accusation was backed by the normal distribution of data (more commonly known as the "bell curve" or sometimes "Gaussian") of natural variation across a year of different bread. Henri said that the average (or "mean") of the weight of the bread was centered around 950g, and only weighing 1kg at a lower frequency. This means primitively that the weight of the bread he received was under the specified 1kg more than half the time.



14. The baker admitted his scheme, paid a fine, and was given a second chance to start being honest while working for Henri's bakery. The following year, the pattern repeated—the baker would bring bread to Henri, who would chart the weight. At the end of the year, Henri fired the baker for his continued scheme by showing him the plot of his newly logged bread-weight data.



15. The baker, caught again, asked how Henri managed to root out the scheme with this new graph, as it clearly says the bread was always at least 1kg. What Henri noticed is that when he plotted the frequencies of weights of the loaves, he did not see a distribution, but instead just a tail. This plot is indicative of the baker throwing away all data points less than 1kg. Henri told the baker that he inferred he didn't change his behavior, but merely always brought him the heaviest piece of bread in the day's batch.

16. Henri's correct observation of the statistical anomaly in this particular anecdote is an abuse of the "tail of the curve". In natural phenomena, nearly all repeated behaviors in nature have a universal variance—or a bell curve, albeit of different variants of shapes. History continues to show examples of such observable mathematical anomalies to the tail of a variance curve.

17. Most recently the 2008 sub-prime mortgage risk management featured an "abuse of the tail" when risk management bankers stuffed sub-prime risk into the tail of that very curve—allowing for immediate positive returns. However, when one stacks the tail over

and over with bad risk, eventually the tail becomes the center of the curve (called "platykurtic") and the bad risk finally materializes.

18. In addition to the mean[2] and the standard deviation[3], one can look at other statistics to get a sense of the shape of the distribution. The next two are the skewness[4] and the kurtosis[5]. These statistics are normalized by dividing by the standard deviation, so they are all of a comparable scale; the standard normal has a skewness of 0 and a kurtosis of 3. As we often expect our data to be close to a normal distribution, significant deviations from these values can indicate an event that is statistically anomalous.

Mathematical Signature of Differential Vote Gain Anomaly

19. To set a baseline of the variability of Atlanta's vote pattern changes from the 2016 General Election, I plot the natural distribution of gain/lost votes per specific district in a histogram plot for both Trump in Figure 1 and Biden in Figure 2 vote gains vs the 2016 General Election in the same areas:

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[2] "Mean" is the average value of a dataset.
[3] "Standard Deviation" is the scale of fluctuations about the mean.
[4] "Skew" or the "3rd moment" is the expected value of the cube of the fluctuations about the mean divided by the standard deviation. This tells us which side of the distribution has more mass.
[5] "Kurtosis" or the "4th moment" is the expected value of the fourth power of the fluctuations about the mean divided by the standard deviation, which informs us on how much of the tail is outside the main distribution.

	Trump Distribution
MEAN	59.70
STDEV	169.05
3-sigma	507.16
Skew	0.82
Kurtosis	20.10

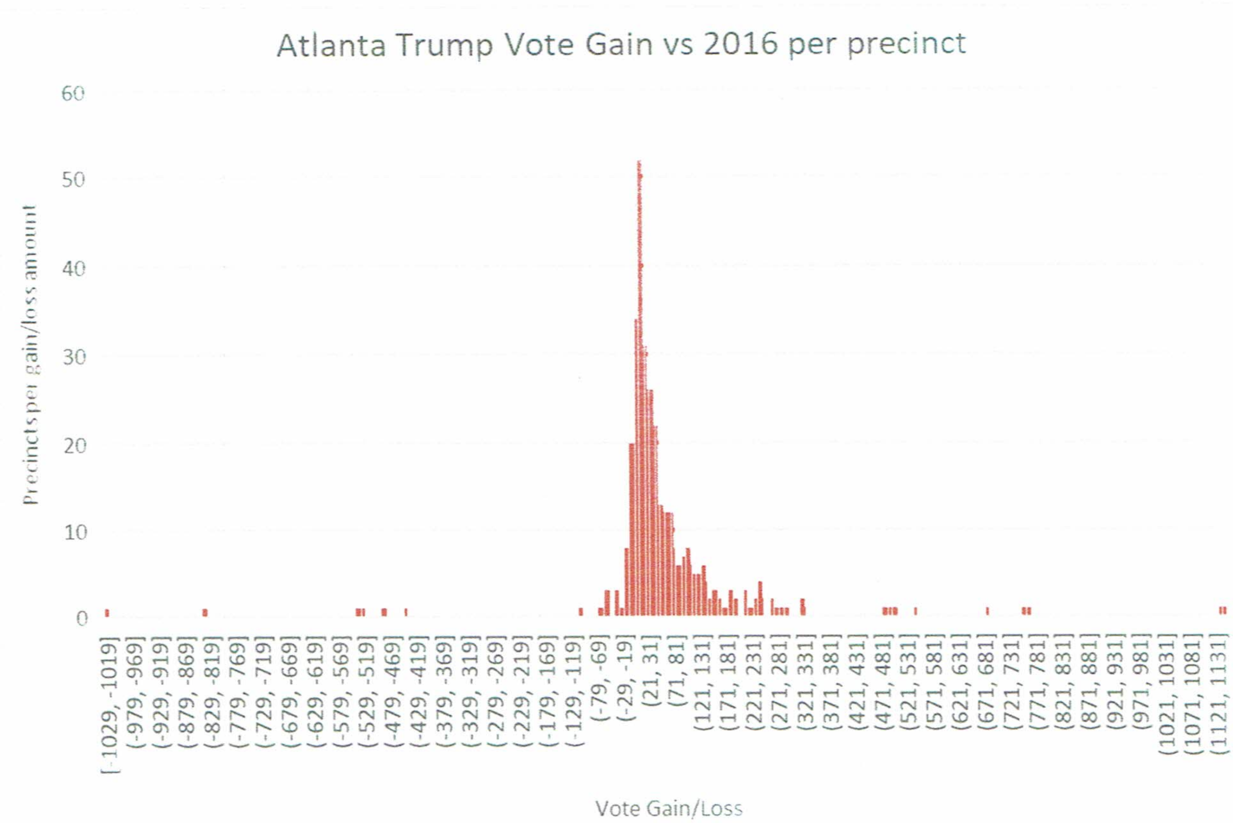

Figure 1. Trump Vote Gain Distribution

	Biden Distribution
MEAN	250.89
STDEV	340.59
3-sigma	1021.77
Skew	0.92
Kurtosis	**2.74**

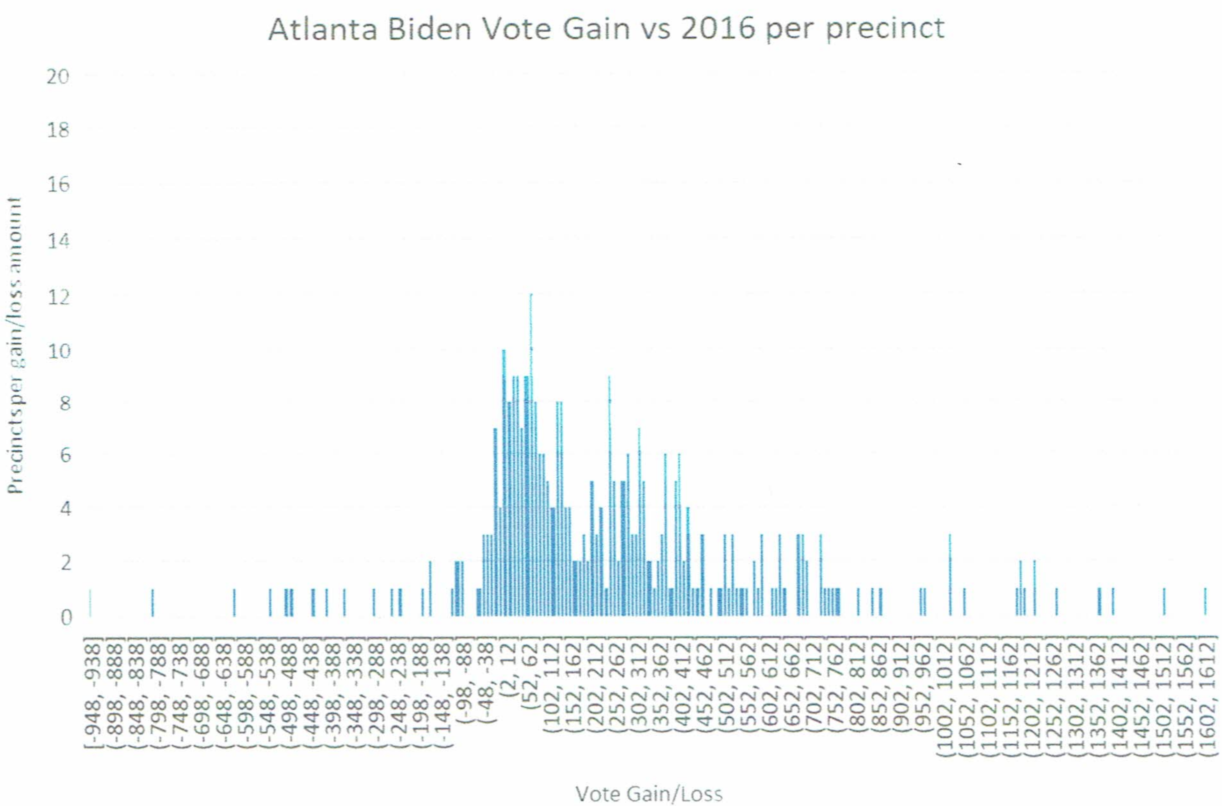

Figure 2. Biden Vote Gain Distribution

20. The "tail of the curve" in Biden's vote gain visually seems most unusual. To quantify, what's even more surprising are the values of the kurtosis of the distribution.

21. The kurtosis, or the measure of how much of the distribution is considered "the tail" is the real oddity here. Any numbers less than 3 in kurtosis make it platykurtic, with 3 being the kurtosis of a standard normal distribution as a baseline.

22. A distribution that is platykurtic roughly states that the tail of the distribution is not a tail, but rather part of the mean itself. To pull from the same example already cited, the 2008 mortgage collapse occurred when the sub-prime risk became platykurtic—meaning the high-risk sub-prime mortgages became the main risk curve and the bad bets were finally part of the mean.

23. Further, by calculating the gain in votes for both Trump and Biden over the respective 2016 total from the same districts, the Democratic/Republican ratio (D/R ratio or DEM/GOP ratio) of added votes gained for Biden over Trump was a high 4.2x.

	Gained Votes Avg. per District
Trump	59.7
Biden	250.89
Diff	191.19
2020 DEM/GOP New Vote Gain Ratio	4.2
%	81D / 19R
2016 DEM/GOP Ratio	2.52
%	69D / 27R

24. While this gain is quite anomalous, especially considering the historical voting ratio of the city—technically both the abnormal tail of Biden's curve and gained ratio fall under the standard deviation of the 200,000 new registered voters presumed from the new Georgia "motor-voter" law. Registrations from this law netted an average of 652 new registrations with a standard deviation of 699 new registrations vs 2016. In context, this mean and standard deviation infers that some counties lost voters, while others more than doubled their mean.

25. At the Fulton County level, the new influx of overwhelmingly Democratic new votes technically fits registration deviations. However, in select counties, when the new vote distribution is broken down into per county and per district changes, the ratios appear well outside the normal.

26. What's truly anomalous is that the ratios well outside the normal occurred commonly in districts roughly 50D/50R, or even in districts from the 2016 General Election which were leaning Republican. Some districts in this county show that Biden picked up over >100% of the new votes in excess to 2016 General Election totals—despite the fact that Trump also picked up votes in most of the same districts. Note yet another oddity in JC13B, where votes in excess of 2016 exceeds the registrations in excess of 2016.

** means redistricted

2016 Results							2020 Gain/Loss in Votes over 2016					
County	Trump	Clinton	Votes	Ratio Dem/Rep	Turnout	Dem % of Voters	Trump Gain	Biden Gain	New Votes	Gain Dem/Rep	New Vote % of Additional Registrations over 2016	Dem % of New Voters
JC01**	1322	1870	3312	1.41	78.3%	44.2%	251	1032	1194	4.1	72.9%	86.4%
JC02	697	722	1454	1.04	79.2%	39.3%	200	584	766	2.9	65.8%	76.2%
JC03A	199	196	412	0.98	87.1%	41.4%	-1	87	74	-87	61.2%	117.6%
JC03B	373	549	960	1.47	78.4%	44.9%	72	228	283	3.2	72.2%	80.6%
JC04**	1455	1501	3116	1.03	80.3%	38.7%	56	766	704	13.7	79.7%	108.8%
JC05	651	736	1468	1.13	78.8%	39.5%	49	318	315	6.5	64.8%	101.0%
JC06	1025	713	1793	0.70	76.3%	30.3%	-58	381	291	-6.6	59.4%	130.9%
JC07	1207	1390	2704	1.15	78.1%	40.1%	196	755	882	3.9	73.1%	85.6%
JC08	964	872	1946	0.90	81.3%	36.4%	49	395	362	8.1	67.5%	109.1%
JC09	806	1059	1954	1.31	78.1%	42.3%	141	367	450	2.6	60.2%	81.6%
JC10	619	800	1488	1.29	77.5%	41.6%	106	446	510	4.2	70.8%	87.5%
JC11	1224	897	2198	0.73	78.7%	32.1%	140	417	513	3.0	73.0%	81.3%
JC12	1177	579	1797	0.49	81.8%	26.4%	151	328	464	2.2	73.1%	70.7%
JC13A	1011	449	1521	0.44	80.1%	23.7%	56	319	327	5.7	78.0%	97.6%
JC13B	153	38	200	0.25	77.2%	14.7%	3	38	35	12.7	152.2%	108.6%
JC14	1000	708	1768	0.71	80.5%	32.2%	40	334	335	8.4	81.5%	99.7%
JC15	202	294	525	1.46	77.7%	43.5%	64	136	181	2.1	64.0%	75.1%
JC16	907	802	1811	0.88	82.5%	36.5%	69	306	300	4.4	58.6%	102.0%
JC18	1100	791	1991	0.72	81.1%	32.2%	51	355	340	7.0	84.6%	104.4%
JC19	1239	1251	2633	1.01	81.7%	38.8%	123	543	582	4.4	61.1%	93.3%

TOTAL	Trump	Clinton	Votes	2016 Dem/Rep	Turnout	Dem % of Voters	Trump Gain	Biden Gain	New Votes	Gain Dem/Rep	New Vote % of Additional Registrations over 2016	Dem % of New Voters
JC	17331	16217	35051	0.9	79.6%	49.4%	1758	8135	8908	4.6	70.0%	91.3%
		2016 D/R JC		~48D / 52 R				2020 D/R JC Gain		~82D / 18R		

Predictive Model to Identify Mathematically Anomalous Vote Totals

27. I constructed a reverse engineered predictive model to try and identify where such anomalies existed at a district level by using the 2016 General Election D/R total ratio per district and comparing

them to the same ratio in the same district in 2020. The Trump 2020 General Election vote gains are used as a control for the increase in turnout (generally) in Georgia as applied to both campaigns. The model is not presuming a standard normal distribution, but rather one with a mean that increases according to the 2016 General Election D/R ratio within a reasonable variance. The model is also constrained to attempt a result with a positive kurtosis above 3 (or with "excess kurtosis").

28. To achieve this, I did not create a distribution model from scratch. Rather, I began with the actual Biden 2020 General Election vote distribution and corrected anomalies from the original, district by district, until the distribution targets were achieved.

29. The predictive mathematical model creates a Biden vote gain distribution seen in Figure 3. The predictive vote gain distribution lacks a visually unusual tail. The model's mean is equal to the multiple of D/R ratios seen in the 2016 General Election and brings the Biden new vote skew to a 2x multiple of mass in the curve over Trump's skew. Finally, and likely most importantly, the prediction pulls the kurtosis back outside a platykurtic distribution.

	Predicted Biden Distribution
MEAN	150.63
STDEV	274.30
3-sigma	822.90
Skew	1.67
Kurtosis	6.03

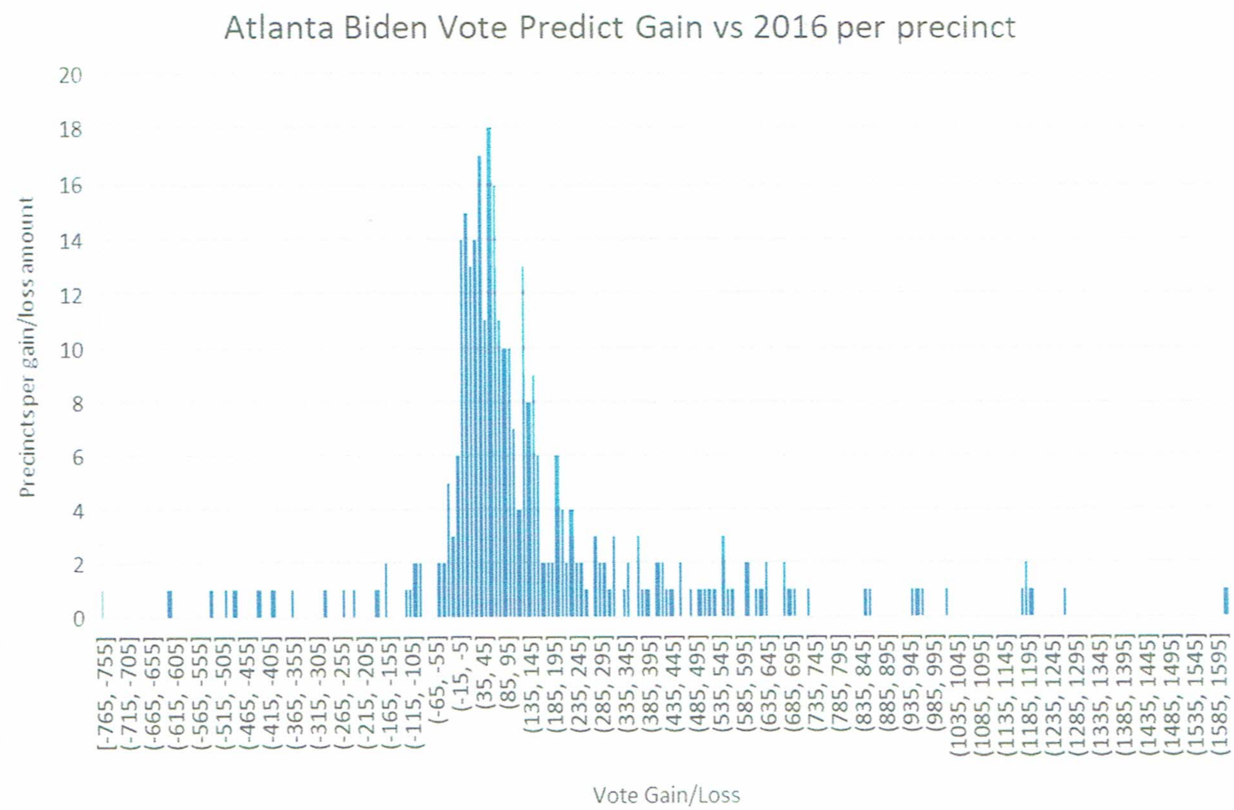

Figure 3. Biden Distribution Predicted Correction

30. The difference between the raw 2020 General Election data and the reverse-engineered predictive model follows.

The 2020 General Election raw data results are below:

2020	**Register**	**Voted**	**Biden**	**Trump**	**D/R**
Total	799612	520760	377586	136946	2.76
Turnout - underinflated b/c motor-votor	65.13%	share	72.51%	26.30%	

The predicted model, holding turnout and 2016 General Election ratios consistent and correlated to the Trump baseline in the 2020 General Election, are below:

Predicted 2020	Registered	Voted	Biden	Trump	D/R	Biden Vote Diff
Total	799612	488576	345402	136946	2.52	32347
Turnout	61.10%	Share	70.70%	28.00%	2016 ratio	

The difference between the 2020 General Election raw data and the predicted correction show exceedingly large vote block gains to only specific counties.

31. An observation of the actual election results in select counties identifies several thousands of anomalous votes distributed within their districts. The picture in Figure 4 communicates the necessary effect to reconstruct the actual election data from the predicted model.

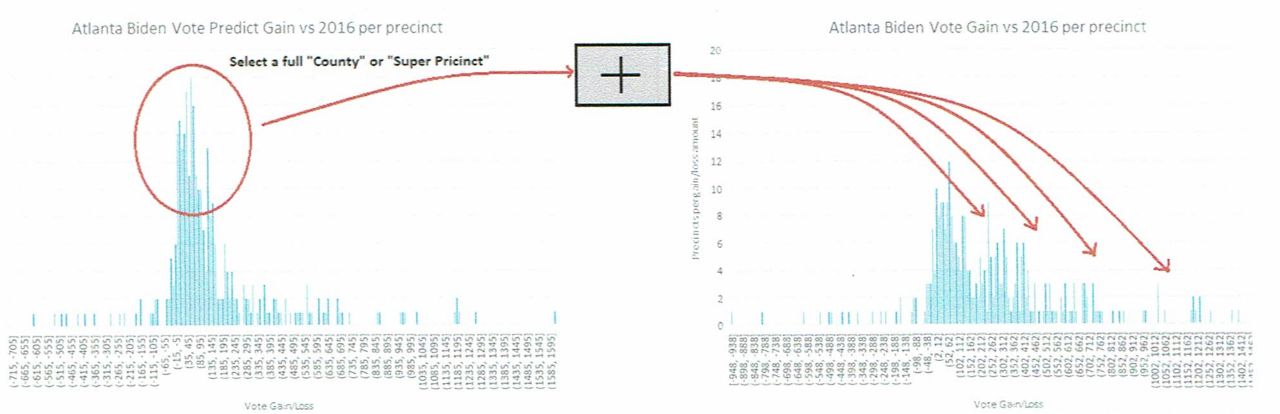

Figure 4. Reconstructing actual election data from predicted model

Full Predictive List of Biden Vote Gains Outside the Predicted Distribution in Fulton County

32. While some counties hold their 2016 ratio gains well within the historical variance and match the model perfectly, other counties or super districts stand out. Specifically, 139 districts of ~320 districts have a sum of ~32,347 votes exceeding the predicted model. These votes are statistically anomalous.

County Totals

County	**Total Biden Votes Above Prediction**
County RW	6135
County JC	5822
County SS	4388
County 07	3239
County 08	2713
County ML	1704
County 06	1576
County AP	1142
County 09	1295
County 02	1139
County SC	541
County HP	269
County PA	258
County 03	182
County 01	169
County UC	148
County CP	139
County 04	81
County 05	67
County CH	34
County 12	7

33. As an example, a particular county well exceeding the model looks like this:

*** means redistricted from 2016*

County	**District**	**Total Biden Votes above Prediction**
County RW	**TOTAL**	**6135**
	RW01	526
	RW02	443
	RW03	401
	RW04	32
	RW05	190
	RW06	386
	RW07A	59
	RW07B	0
	RW08	270
	RW09**	591
	RW10	248
	RW11A	242
	RW12**	749
	RW13	487
	RW16	162
	RW17	224
	RW19	171
	RW20	245
	RW21	310
	RW22A	401

34. The entire list, sorted by total votes exceeding expected per district, is as follows. The ** indicates some form of re-districting versus 2016, which lowers the confidence of prediction in that specific district slightly due to unknown specifics of the partition.

**** means redistricted from 2016**

District	Total Biden Votes above Prediction
07A	881
*FA01***	813
*06D***	792
*RW12***	749
*JC04***	708
*JC01***	677
AP09A	621
SC211	600
*RW09***	591
JC07	529
RW01	526
07C	509
RW13	487
*SC07***	466
08J	458
07D	446
RW02	443
09M	425
JC19	419
RW03	401
RW22A	401
08B	400
RW06	386
JC02	377
ML05	373
SS11A	369
JC08	351
*ML01***	339
09F	336
02L2	332
*02A***	323
*ML03***	319
07F	318
JC18	318
JC11	314

RW21	310
JC10	309
ML06B	306
JC14	306
SS09B	305
SS17	304
CP011	302
JC13A	294
SS12	294
AP01C	285
SS29A	282
06J	278
RW08	270
HP01	269
ML04	263
JC05	263
PA01	258
08L	256
JC12	254
08A	251
RW10	248
08P	245
JC16	245
RW20	245
08G	244
RW11A	242
SS08D	240
07M	237
07J	233
09G	232
08F1	225
RW17	224
SS06	220
02E	217
*SC05***	216
07H	208
SS09A	201
SS03	200
SS31	199
08N2	194

SS08A	192
RW05	190
CP012	186
JC09	182
SS07A	181
SS05	177
09A	174
RW19	171
RW16	162
02B	161
07B	153
UC031	148
SS19A	147
08E	145
SS11B	142
06F	142
SS07B	139
AP07A	136
08C	133
SS02A	130
01B	130
09H	129
07E	127
07N	127
*SS2***	125
JC03B	122
JC06	116
03M	114
02W	106
ML06A	104
08N1	102
SS15A	102
CP02	98
06I	97
SS08C	82
04I	81
06B	80
SS15B	77
06L1	73
06Q	69

03P1A	67
05J	65
AP10	61
08K	60
RW07A	59
SC04	58
SS11D	57
SS08B	56
SC08F	56
SS16	54
SS02B	52
06E	44
CP05B	40
01D	39
AP03	38
JC13B	37
CH05	34
RW04	32
SS11C	32
SS18B	21
12G	7
SS18A	6
05D	3
SS07C	3
JC03A	1

I declare under the penalty of perjury that the foregoing is true and correct.

November 19, 2020

Eric Quinnell, Ph.D.