December 5, 2020

***Pearson v. Kemp,* Case No. 1:20-cv-4809-TCB**

United States District Court for Northern District of Georgia

Expert Report of Jonathan Rodden, PhD

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I. INTRODUCTION AND SUMMARY

On Saturday, November 28, 2020 I received declarations from Dr. Eric Quinnell, Dr. Shiva Ayyadurai, and Mr. James Ramsland, Jr. Each of these declarations makes rather strong claims to have demonstrated "anomalies" or "irregularities" in the results of the presidential election in Georgia on November 3, 2020. I have been asked by Counsel to assess the validity of their claims. Unfortunately, these reports do not meet basic standards for scientific inquiry. For the most part, they are not based on discernable logical arguments. Without any citations to relevant scientific literature about statistics or elections, the authors identify common and easily explained patterns in the 2020 election results, and without explanation, assert that they are somehow "anomalous." Each of these reports lacks even a basic level of clarity or transparency about research methods that would be expected in a scientific communication. As detailed below, each of these reports is based on puzzling but serious mistakes and misunderstandings about how to analyze election data.

Dr. Quinnell's report amounts to an odd claim that there is something "anomalous" about the fact that Joseph Biden achieved sizable increases in votes over Hillary Clinton's totals in the fast-growing suburban precincts of Fulton County. Dr. Ayyadurai's report amounts to a claim that there is something "anomalous" about the fact that in a set of suburban counties that he chose to study, Biden made gains in relatively white, Republican-leaning precincts. He does not explain why split-ticket voting or deviations from strict ethnic voting are indicative of fraud. Finally, Mr. Ramsland's report identifies a cross-state correlation between voting equipment and election outcomes, but the fact that Democratic and Republican regions of the country have adopted different types of voting equipment cannot possibly be taken as evidence of fraud.

II. QUALIFICATIONS

I am currently a tenured Professor of Political Science at Stanford University and the founder and director of the Stanford Spatial Social Science Lab ("the Lab")—a center for research and teaching with a focus on the analysis of geo-spatial data in the social sciences. In my affiliation with the Lab, I am engaged in a variety of research projects involving large, fine-grained geo-spatial data sets including ballots and election results at the level of polling places, individual records of registered voters, census data, and survey responses. I am also a senior fellow at the Stanford Institute for Economic Policy Research and the Hoover Institution. Prior to my employment at Stanford, I was the Ford Professor of Political Science at the Massachusetts Institute of Technology. I received my Ph.D. from Yale University and my B.A. from the University of Michigan, Ann Arbor, both in political science. A copy of my current C.V. is included as an Appendix to this report.

In my current academic work, I conduct research on the relationship between the patterns of political representation, geographic location of demographic and partisan groups, and the drawing of electoral districts. I have published papers using statistical methods to assess political geography, balloting, and representation in a variety of academic journals including *Statistics and Public Policy*, *Proceedings of the National Academy of Science*, *American Economic Review Papers and Proceedings*, the *Journal of Economic Perspectives*, the *Virginia Law Review*, the *American Journal of Political Science*, the *British Journal of Political Science*, the *Annual Review of Political Science*, and the *Journal of Politics*. One of these papers was recently selected by the American Political Science Association as the winner of the Michael Wallerstein Award for the best paper on political economy published in the last year, and another received an award from the American Political Science Association section on social networks.

I have recently written a series of papers, along with my co-authors, using automated redistricting algorithms to assess partisan gerrymandering. This work has been published in the *Quarterly Journal of Political Science*, *Election Law Journal*, and *Political Analysis*, and it has been featured in more popular publications like the *Wall Street Journal*, the *New York Times*, and *Boston Review*. I have recently completed a book, published by *Basic Books* in June of 2019, on the relationship between political districts, the residential geography of social groups, and their political representation in the United States and other countries that use winner-take-all electoral districts. The book was reviewed in the *New York Times*, *New York Review of Books*, *Wall Street Journal*, *The Economist*, and *The Atlantic*, among others.

I have expertise in the use of large data sets and geographic information systems (GIS), and conduct research and teaching in the area of applied statistics related to elections. My PhD students frequently take academic and private sector jobs as statisticians and data scientists. I frequently work with geo-coded voter files and other large administrative data sets, including in recent paper published in the *Annals of Internal Medicine* and *The New England Journal of Medicine.* I have developed a national data set of geo-coded precinct-level election results that has been used extensively in policy-oriented research related to redistricting and representation.[1]

I have been accepted and testified as an expert witness in six recent election law cases: *Romo v. Detzner*, No. 2012-CA-000412 (Fla. Cir. Ct. 2012); *Missouri State Conference of the NAACP* v. *Ferguson-Florissant School District*, No. 4:2014-CV-02077 (E.D. Mo. 2014); *Lee v. Virginia State Board of Elections*, No. 3:15-CV-00357 (E.D. Va. 2015); *Democratic National Committee et al. v. Hobbs et al.*, No. 16-1065-PHX-DLR (D. Ariz. 2016); *Bethune-Hill v. Virginia State Board of*

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[1] The dataset can be downloaded at http://projects.iq.harvard.edu/eda/home.

Elections, No. 3:14-cv-00852-REP-AWA-BMK (E.D. Va. 2014); and *Jacobson et al. v. Lee*, No. 4:18-cv-00262 (N.D. Fla. 2018). I also worked with a coalition of academics to file amicus briefs in the Supreme Court in *Gill v. Whitford*, No. 16-1161, and *Rucho v. Common Cause*, No. 18-422. Much of the testimony in these cases had to do with geography, voting, ballots, and election administration. I am being compensated at the rate of $500/hour for my work in this case. My compensation is not dependent upon my conclusions in any way.

III. DATA SOURCES

I have collected county-level data on presidential elections for each year from 1988 to 2020 from the Georgia Secretary of State. I have also collected 2016 precinct-level data on Georgia from the Metric Geometry and Gerrymandering Group at Tufts University. I obtained digitized 2020 Georgia precinct boundary files from the Voting and Election Science Team at the University of Florida and Wichita State University. I also obtained geo-spatial boundaries from the county GIS departments of DeKalb, Chatham, and Fulton Counties. I obtained precinct-level data on race among registered voters from the Georgia Secretary of State, as well as 2020 and 2016 precinct-level election results. I created a national county-level dataset on election results using information assembled from county election administrators by the New York Times and Associated Press, along with demographic data from the 2014-2018 American Community Survey (ACS), as well as the September 2020 county-level unemployment rate from the Bureau of Labor Statistics, and as described in detail below, data on voting technologies used in each U.S. jurisdiction collected by Verified Voting. I have also collected yearly county-level population estimates for Georgia from the U.S. Census Department.

IV. QUINNELL REPORT

At the heart of Dr. Quinnell's analysis is a claim that, in my 25 years of election data analysis, I have never heard before. He claims that if one has a set of results from an election, the distribution of votes for candidates should approximate a normal, bell-shaped statistical distribution, and any departure from a normal distribution is unnatural and somehow suspicious: "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" (paragraph 18). Specifically, Dr. Quinnell claims that if votes for one of the candidates has a long tail—that is to say, he or she has a concentration of support in a small number of districts where the vote share is much greater than the average district—this is "anomalous" and indicative of fraud. He then goes on to analyze a highly flawed precinct-level data set from Fulton County, about which he makes a set of puzzling claims.

First, Dr. Quinnell's basic claims about the distribution of election data across geographic units are nonsensical and should be rejected out of hand. Second, his data analysis is fatally flawed and essentially meaningless. The skewed distribution of

Biden vote gains pointed out in his report is merely a reflection of Biden's success in rapidly-growing suburban areas.

The Geographic Distribution of Election Results

Dr. Quinnell begins with a tangential anecdote about Henri Poincaré's baker, who was caught dropping a set of values from a data set that fell below a certain threshold. In that case, the left side of the distribution—all of the low values—had been simply discarded. He also mentions the sub-prime mortgage crisis, but the relevance to his report is unclear. Neither of these anecdotes provides even the slightest intuition for his claim that election results from a set of geographic units should display a normal distribution, or why departures from the normal distribution are indicative of fraud.

He cites no academic literature. Nor does he attempt to articulate a theory of vote distributions and fraud. The reader is left to imagine how such a theory might work. If a nefarious election administrator or computer programmer were able to take votes from candidate B and give them to candidate A in some county, it is not clear why this action would affect the distribution of votes across precincts. The entire distribution would simply shift in the direction of candidate A. Perhaps Dr. Quinnell wishes to imply that such nefarious actors are only able to operate in a small minority of precincts. Perhaps this is why he believes it is suspicious if candidate A experiences a cross-precinct distribution with a long right tail—that is to say, a distribution in which candidate A performs especially well in a set of precincts, without a corresponding set of precincts where candidate B does exceptionally well.

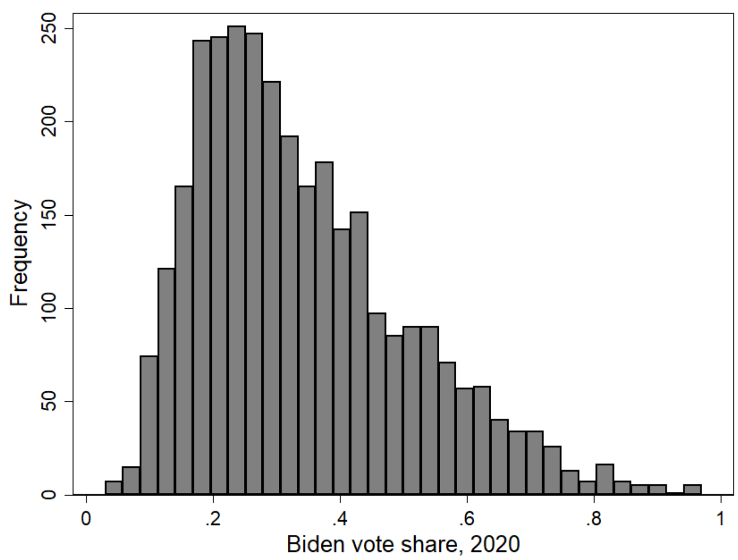
However, there are many far more plausible explanations for non-normal distributions of votes across precincts, counties, or districts. There is nothing even slightly unusual about skewed distributions of votes, vote shares, or changes over time in votes or vote shares, across geographic units. A very large literature dating back to the earliest mathematical analyses of elections has explained, and demonstrated using high-quality data analysis, that these distributions are very frequently non-normal. In their classic 1979 book, Graham Gudgin and Peter Taylor argue that if the partisan divide in a country with two political parties is correlated with some social characteristic (for instance race or social class) that is not uniformly distributed in space but is rather concentrated in certain districts, the distribution of vote shares will be skewed. They presented evidence that because working-class voters were concentrated in neighborhoods near factories, the distribution of support across electoral districts for Labor parties in Britain and Australia was highly skewed for much of the 20th century.[2] More recently, I have demonstrated that support for the Democratic Party in the United States typically has a pronounced right skew

[2] See Graham Gudgin and Peter Taylor, 1979, *Seats, Votes, and the Spatial Organisation of Elections*. London: Pion. For a literature review, see Jonathan Rodden, 2010, "The Geographic Distribution of Political Preferences." *Annual Review of Political Science* 13,55.

across districts, counties, and often precincts.[3] The fact that the Labour Party consistently wins by extremely large margins in urban districts in London, or that the Democrats win by extremely large margins in urban Atlanta or Austin, has nothing to do with fraud.

In Figure 1 below, I provide a histogram of Joe Biden's vote share across counties in 2020. Like the precinct-level histograms from Fulton County in Dr. Quinnell's report, the distribution is clearly right-skewed, but it is very difficult to imagine what this might have to do with fraud.

Figure 1: Distribution of Biden Vote Share Across U.S. Counties, 2020



[3] Jonathan Rodden. 2019. *Why Cities Lose: The Deep Roots of the Urban-Rural Divide*. New York: Basic Books.

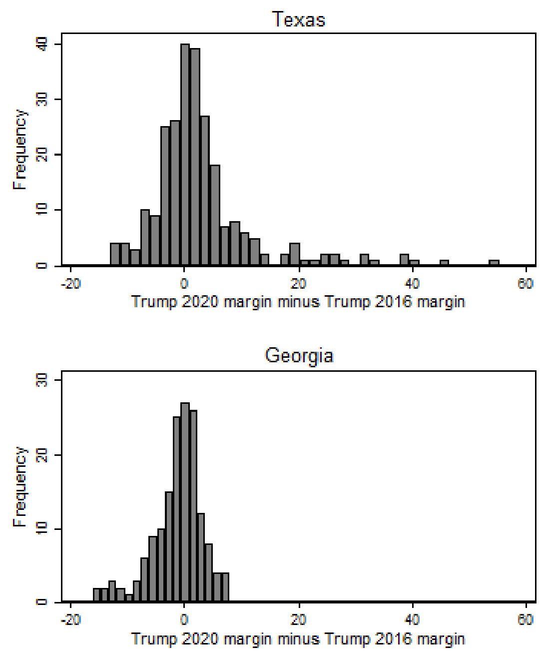
In short, there is no natural law suggesting that election results across geographic units should be normally distributed around the mean, especially if those units are asymmetric in their size. To the contrary, when relevant social groups are clustered in space, it is more typical to see a skewed distribution.

Dr. Qinnell's underlying theory of fraud, however, apparently relates to the *change* in vote share. Perhaps he means to argue that the distribution of the *change from one election to the next* in votes or vote shares across geographic units should always have a normal distribution. But this argument would make no more sense than an argument about voting levels. Members of politically relevant groups—for instance young people, racial minorities, or college graduates—are typically not uniformly or randomly distributed across geographic units, especially in the United States. If an incumbent candidate pursues policies and rhetoric that attract or repel a geographically clustered group, we can expect to see a non-normal distribution of changes in vote shares.

For instance, it appears that Donald Trump's appeals in the 2020 election resonated with Cuban and Venezuelan Americans in South Florida, and with *Tejano* voters in Texas. As a result, Trump experienced surprisingly large increases in vote shares in counties where those groups made up a large share of the population. This translated into a right-skewed distribution of *changes* in the Republican vote share from 2016 to 2020. We can see this in the top panel of Figure 2, which focuses on

Texas. I take the 2020 Trump margin of victory (or loss) in each county and subtract the 2016 margin so that higher numbers mean Trump *improved* his vote share over 2016, while lower numbers mean that he *lost* support relative to 2016.

Figure 2: County Histograms of Increase in Trump Margin, 2016-2020



In Texas, the distribution of Trump's gains across counties has a pronounced right skew—just as in Dr. Quinnell's graphs. On the left side of the graph, there are a large number of suburban counties in which Trump lost support, but some counties in the tail of the distribution experienced rather extraordinary *increases* in Republican vote share. Yet, according to Dr. Quinnell's rule, we must conclude that some nefarious actor committed fraud on behalf of President Trump in Texas. This is simply not a credible argument. The counties in the tail of the distribution are majority-Hispanic counties along the border. A far more likely story is that President Trump experienced a non-fraudulent increase in support among this population of Hispanic voters.

The next panel in Figure 2 repeats this histogram for the counties of Georgia. In Georgia, there is a slight left skew, indicating that there are a handful of counties where Biden's gains were a bit further from the average county than in the rural counties on the right side of the histogram, where Trump was gaining. Note that the left side of the distribution in Georgia looks similar to that in Texas. As in Texas, there are some suburban counties, like Cobb, Forsyth, and Henry, where the Democratic margin increased substantially. Just as it makes little sense to blame the very long right tail of the Texas distribution on fraud, it makes little sense to blame the modest left tail of the Georgia distribution on fraud.

A much better explanation is that Georgia is similar to almost every other state in the country, in that Biden made especially large gains relative to Clinton in diverse, educated, and growing suburbs. Prior to 2020, many of these suburban counties had Republican majorities. This fact is relevant for conspiracy theories about nefarious actors, since in many of these counties in Georgia and around the country, election administrators were appointed by Republicans. It is difficult to comprehend why Republican election administrators would participate in a plot to help the Democratic presidential candidate.

In other words, just as with Republicans in Texas—where the story has to do with a shift among Hispanic voters—in Georgia there is an obvious reason why the distribution of changes in votes for the Democratic presidential candidate would be skewed relative to those of the Republican candidate. In Georgia, as in many other states, population growth is an important part of the story. Perhaps the most striking feature of the Georgia counties where Biden made the largest gains relative to Clinton is that they have been experiencing high population growth, above all due to in-migration from other places.

Figure 3: Population Change and Change in Democratic Vote Share, Georgia Counties

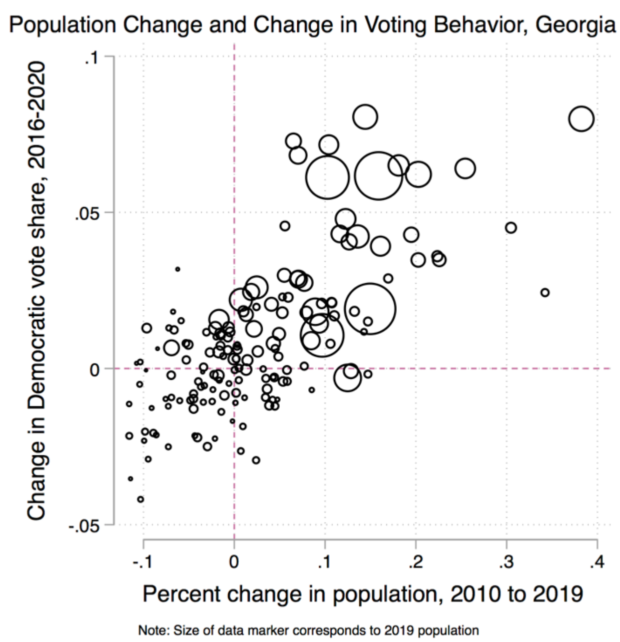


Figure 3 uses population estimates from the census department to calculate county-level population change over the last decade on the horizontal axis. On the vertical axis, it displays the change in county-level Democratic vote share from 2016 to 2020, so that higher numbers correspond to higher Democratic vote share in 2020 than in 2016. The size of the data marker corresponds to the size of the county in 2019. We can see that throughout the state, Trump's support increased primarily in small, rural counties where the population has been declining over the last decade (the lower left-hand part of the graph). Relative to Clinton, Biden's support increased the most in counties where the population grew the most (the upper right-hand part of the graph). In fact, this is true in almost every U.S. state, and this trend was already quite strong prior to 2020.[4] Thus, there is nothing anomalous or nefarious about the fact that Biden added far more votes than Trump in the rapidly-growing suburban counties of Georgia.

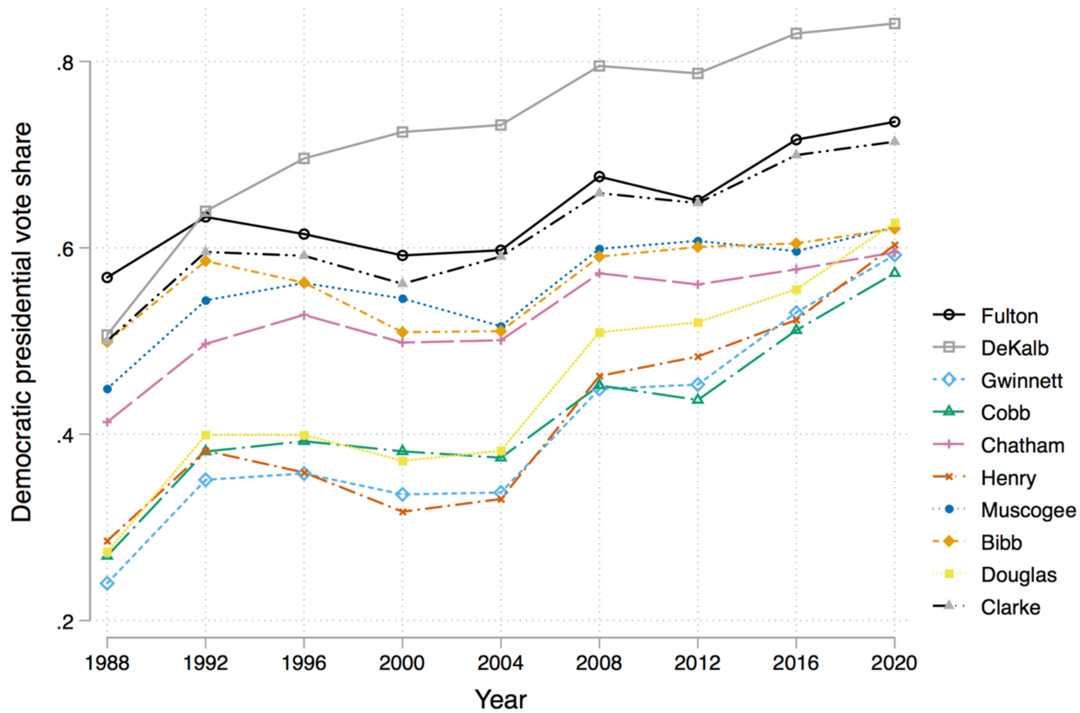
Precinct-level analysis of Fulton County

Perhaps for good reason, Dr. Quinnell did not test his "departure from normality" theory on county-level data. For reasons he does not explain, he examined only precinct-level data from Fulton County. His choice of Fulton County for a case study is rather odd. He seems to want to argue that the shift toward the Democrats in Fulton County was suspiciously high and anomalous. In order to examine whether this claim is plausible, Figure 4 displays the evolution of the Democratic vote share over time in Fulton County and several other Georgia counties. While Fulton County is indeed one of the most Democratic counties in the

[4] Rodden, *Why Cities Lose*, op cit, chapter 9.

state, there is no way to interpret the Fulton County time series as displaying a deviation from trend in 2020. In fact, the increase in Democratic vote share over the previous election was far lower in 2020 than in 2016. As described above, the Democratic vote share has been growing far more rapidly in suburban counties surrounding Fulton County, like Cobb, Douglas, Henry, and Gwinnett.

Figure 4: Democratic Presidential Vote, 1988 to 2020, Selected Georgia Counties

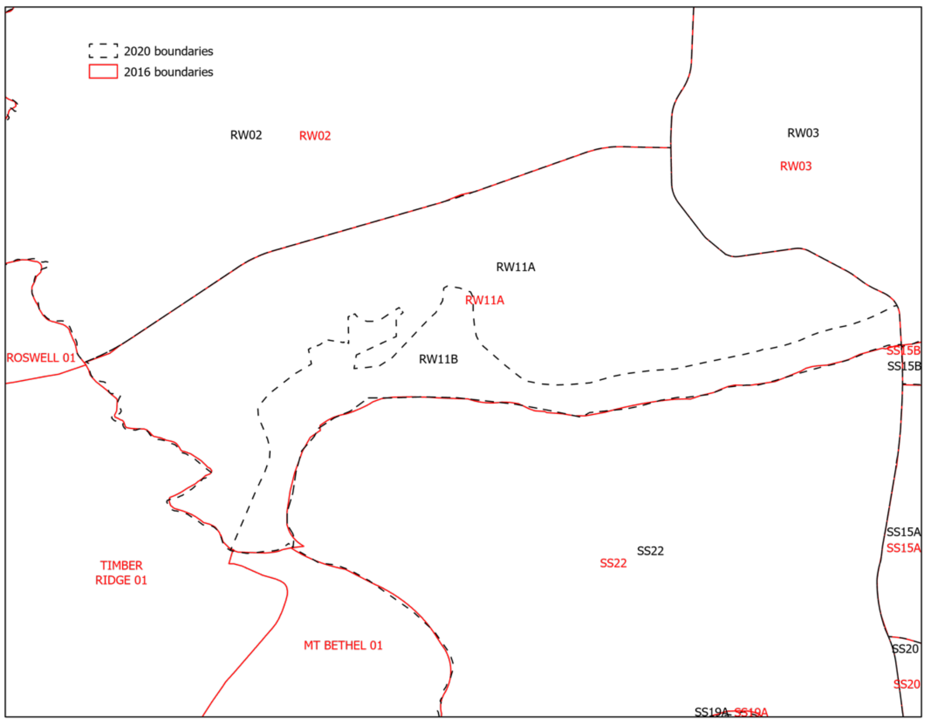


Even though there is little evidence that Fulton County's overall results are anomalous in any sense, let us examine Dr. Quinnell's claims about the distribution of votes across Fulton County's precincts. Dr. Quinnell's analysis focuses on the distribution of *changes* in raw vote totals for the two parties from 2016 to 2020 across precincts in Fulton County. Evidently, Dr. Quinnell downloaded precinct-level results from 2016 and 2020 and attempted to merge the two datasets together based on their precinct identifiers. Unfortunately, constructing a meaningful time-series precinct-level data set is not so simple. County-level election administrators frequently combine or split precincts or change their boundaries. Sometimes only two or three precincts in an area are affected; other times, officials re-precinct a wide swath of territory. In order to draw inferences about changes in votes over time *within* precincts, one must be absolutely certain that the boundaries are identical in the two time periods. This was most certainly not the case in Fulton County between 2016 and 2020. In November of 2016, votes were recorded in 342 precincts in Fulton County, whereas in November of 2020, votes were recorded in 384 precincts—an increase of 42 precincts. This is a problem for Dr. Quinnell's analysis because he is comparing votes cast in two different systems of precincts. In many cases, precincts with the same name in 2016 and 2020 are quite different in the two years, especially in suburban areas.

I have obtained digital boundary files for the precincts used in 2016 and 2020. Using geo-spatial software, I mapped the two boundary systems, and inspected each of the 384 precincts used in 2020 to ascertain which precincts used the same boundaries in 2016 and again in 2020. I discovered that only 260 of the precincts used the same boundaries in both years. It is not clear what Dr. Quinnell has done with the other 124 precincts. Some of them are completely new precincts that have been carved out since 2016, such that there was no precinct by the same name in 2016. For many others, I discovered a mix of splits, combinations, and swaths of geography where the boundaries have been completely redrawn. It is often the case that a precinct still exists with the same name, but it has different boundaries and includes a different set of voters. For each of these precincts, it is completely meaningless to subtract the precinct-level vote total of one of the candidates in 2016 from the total in 2020 for the precinct with the same name. Many of the precincts that experienced boundary changes were in the rapidly-growing, suburban sections of South Fulton County, such as Chatahoochee Hills and Fairburn, where new real estate developments are bringing significant change to the built environment each year.

It seems that Dr. Quinnell was at least somewhat aware of this problem, because in his report, he placed asterisks by the precincts that he claims were redistricted. He does not explain, however, how he ascertained which precincts were redistricted. And something went wrong, because Dr. Quinnell's list is far from complete. For instance, just to take one example, in the table on page 15, he does not place an asterisk next to precinct RW11A (in Roswell). In Figure 5, I provide a map of the boundaries of precincts in that part of Fulton County in 2016, in solid red, and in 2020, with a dashed black line. We can see that the old precinct RW11A was subdivided into RW11A and RW11B. A comparison of vote totals in the old and new versions of RW11A based on a simple name merge would not be meaningful.

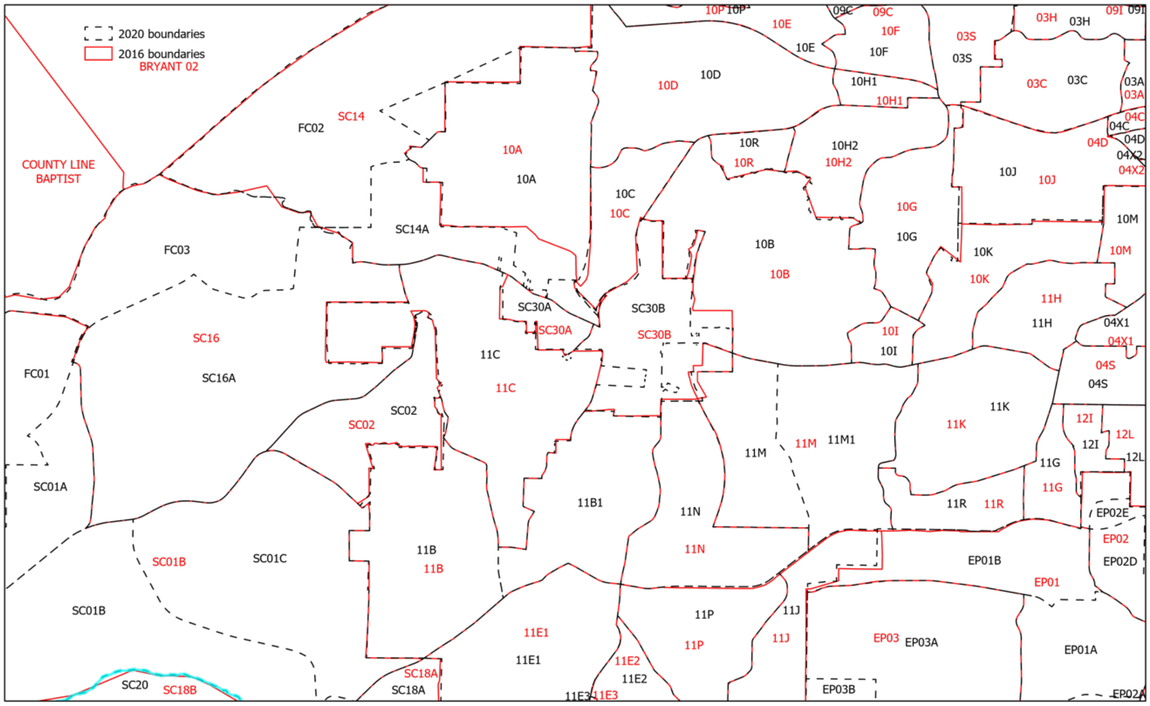
Figure 5
Selected Precinct Boundaries in Fulton County, Georgia



In fact, in much of Fulton County, the problem of matching precincts is far more complex than simple splits like RW11A and RW11B. For instance, consider the case of precinct SC30B, in the middle of Figure 6. The old boundary is in red. The new boundaries (marked with black dashes) carve out parts of SC30B and place fragments in 11C, 11M, and 10B. Meaningful over-time comparisons cannot be made in any of these precincts. Note that there are similar issues throughout Figure 6. For instance, fragments of the old SC14 have been placed in 10A, FC02, and

SC14A. Similar examples, where the red and dashed block lines are not directly on top of one another, can be found throughout Fulton County.

Figure 6
Selected Precinct Boundaries in Fulton County, Georgia

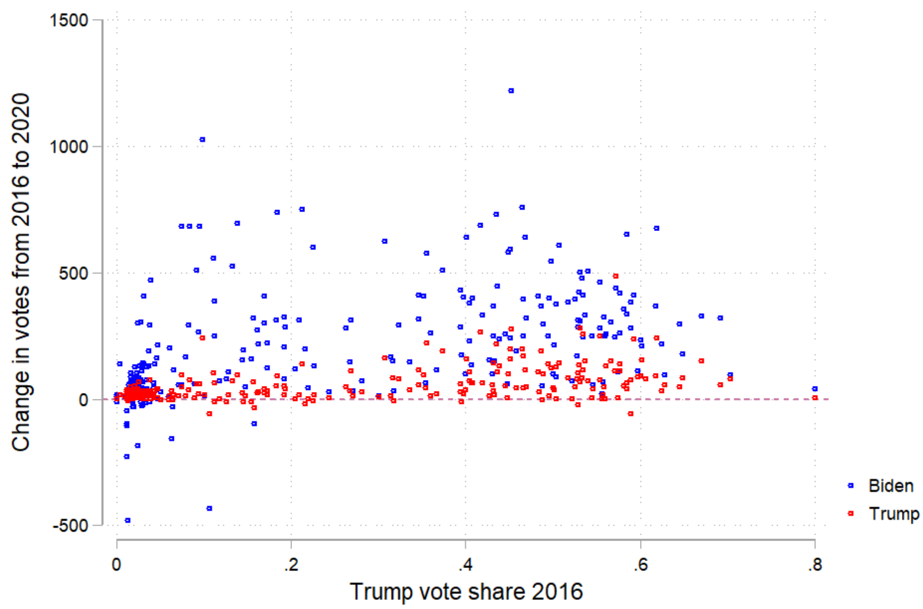


Perhaps in anticipation of this type of critique, Dr. Quinnell conducted some analysis in which he aggregated the data to the level of units he refers to as "counties." If I understand correctly, he aggregates 2016 and 2020 votes by clusters of precincts according to the first two letters of the precinct name (10, 11, EP, SC, FC, and so forth). Those beginning with numbers are based in the city of Atlanta. The others correspond loosely to names of other cities of Fulton County, e.g. EP = East Point, CP = College Park, and so on. This clustering, however, does not solve the problem at all because these units are not stable over time. That is to say, precinct splits, combinations, and complete redraws frequently cross over from one of these clusters to another, as demonstrated in Figure 6. This problem is especially severe in suburban parts of Southern Fulton County.

In sum, I am skeptical that any inferences can be drawn from Dr. Quinell's data set at all—even the observations without asterisks. Fulton County's precinct structure has experienced far too much change for his data set to be useful. He wishes to characterize certain precinct-level vote changes as "anomalous," even though many of his so-called anomalies are likely completely meaningless because they compare different geographic units, and hence different voters, over time.

Let us examine the 260 precincts, for which I have verified that the precinct geography is common over time, and examine whether there is evidence of something odd about the data in these precincts for which valid over-time comparisons *can* be made. As explained above, Dr. Quinnell's main concern is that there are a number of precincts with very large increases in Democratic votes relative to the increases in Republican votes. Indeed, in my data set, which includes most of central and Northern Fulton County, there are 28 precincts in which Biden's total number of votes exceeded Clinton's by more than 500, and there is not a single precinct where Donald Trump's vote total increased by more than 500 votes since 2016.

Figure 7: Trump 2016 Vote Share and Increases in Votes for Both Candidates in 2020, Fulton County Precincts



What is going on with these precincts where votes for Biden increased by a great deal and votes for Trump did not? First of all, these precincts are not the extremely Democratic precincts of the Atlanta urban core. Figure 7 presents a scatter plot, where Donald Trump's 2016 vote share is displayed on the horizontal axis. On the vertical axis is, for each precinct, a red dot for the increase in raw votes for Trump vis-à-vis 2016, and blue dot for the increase in votes for Biden over Clinton's votes in 2016. It shows that there is not a strong relationship between precinct partisanship and the relative increase in Biden votes. If anything, Biden's gains were somewhat larger in more Republican precincts—a pattern that was also noted by Dr. Ayyadurai (see below).

Figure 8: Increase in Registered Voters and Increases in Votes for Both Candidates in 2020, Fulton County Precincts

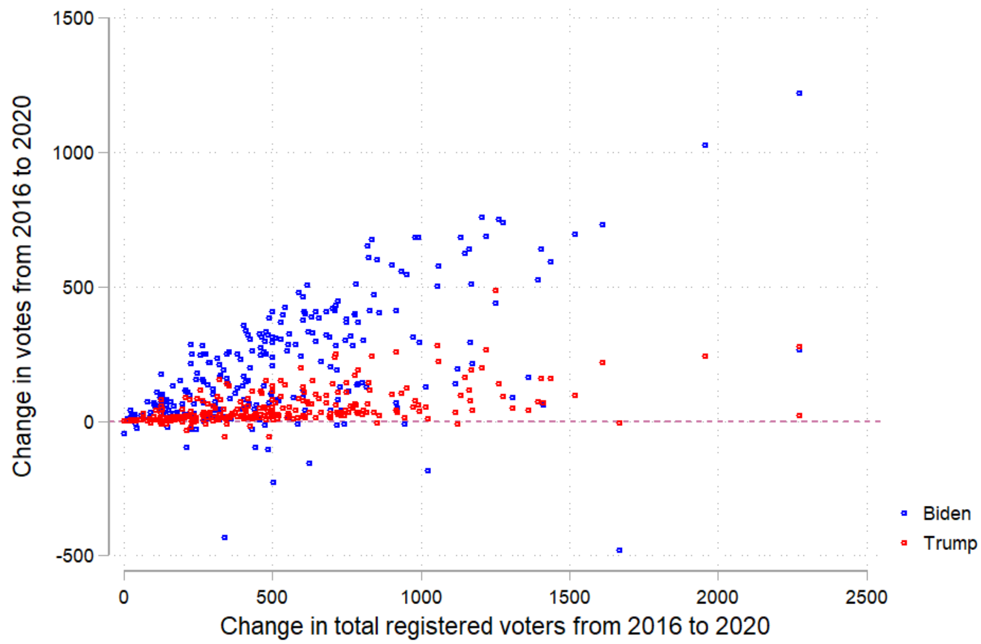


Figure 8 resolves any mystery about the precincts that experienced large asymmetric increases in Democratic votes in Fulton County. It once again plots the raw vote changes for the candidates on the vertical axis, but on the horizontal axis it plots the increase in the number of registered voters from 2016 to 2020. On the left side of the graph are precincts that did not experience much population gain over the last four years. Many of these are in the urban core of Atlanta. As we move to the right on the graph, we move into rapidly-growing precincts in more suburban parts of Fulton County, where new housing developments, and in some cases entirely new neighborhoods, have been built since 2016. In other words, the precinct-level results in Fulton County are entirely consistent with the county-level relationship discussed above, and indeed with the relationship that has been seen in metro areas around the country: Biden's gains were modest in the stagnant urban core and largest in the most rapidly-growing suburban areas. There is nothing anomalous about Fulton County and nothing that would indicate fraud. Just as Trump's large gains in certain Hispanic neighborhoods do not indicate fraud, Biden's large gains in growing suburban neighborhoods do not indicate fraud.

V. AYYADURAI REPORT

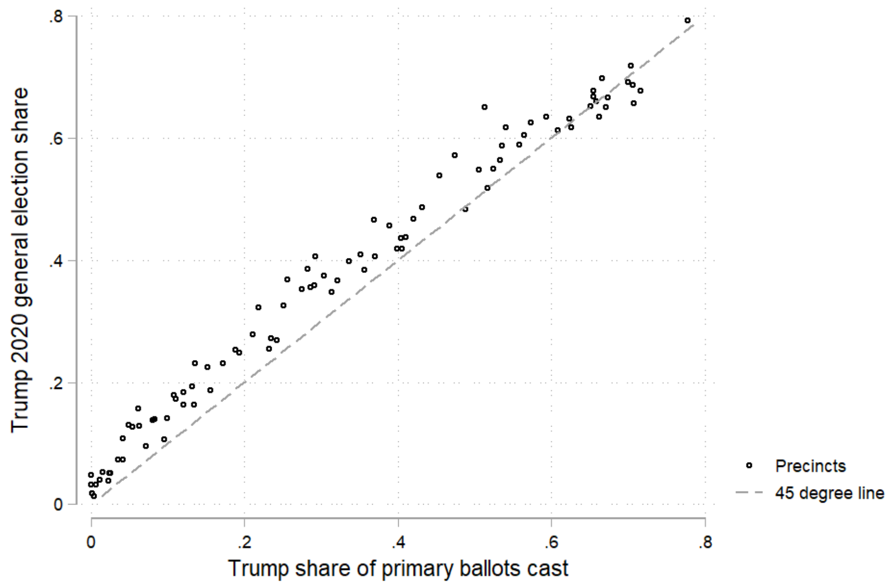
Dr. Ayyadurai claims to have discovered "massive anomalies in Republican voting patterns and ethnic distribution of votes." First, he uses data from several counties to establish a pattern that he repeatedly calls "High Republican, But Low Trump." He provides no indications about his data sources and does not explain how he measures his variables. Yet he appears to claim, in essence, that split-ticket voting among white Republicans is evidence of fraud. His claims about race and ethnicity are, frankly, inscrutable, and thus difficult to evaluate with data analysis. Nevertheless, I have assembled precinct-level data in order to search for any possible anomalies that might be linked with the most reasonable possible interpretations of what Dr. Ayyadurai appears to be claiming.

Let us begin, as does Dr. Ayyadurai, in Chatham County—home to Savannah. On page four of his report, Dr. Ayyadurai presents a graph that purports to show that "as the percentage of Republicans in precincts increases, President Trump gets fewer votes." He does not explain why this is problematic or what these graphs even mean.

If one takes some quantity of interest and then subtracts some number from it, it is quite likely to be negatively correlated with that number. He also does not explain how he determines "the percentage of Republicans in precincts." Partisanship is not an immutable characteristic, and in Georgia, one does not register with election administrators as a member of one party or the other. When participating in primaries, voters can request the ballot of any party they choose. Perhaps Dr. Ayyadurai has obtained precinct-level results of the most recent primary and determined that "the percentage of Republicans in a precinct" is simply the number of Republican ballots cast as a share of all ballots cast in the primary.

This would be a very poor measure of precinct-level partisanship, however, because relatively few voters participate in primaries, and their participation is likely to be driven by the competitiveness of the races for each party. For instance, President Trump was not being challenged in the June primary, while there was a competitive Democratic primary. In any case, in an effort to reverse engineer Dr. Ayyadurai's analysis, I have calculated the share of ballots cast for President Trump in the 2020 primary as a share of all ballots cast in either party's presidential primary. In Figure 9, I plot Trump's share of all primary ballots cast—my best guess of Ayyadurai's measure of Republican partisanship—on the horizontal axis, and Trump's share of the vote in the 2020 general election on the vertical axis. I also include a 45-degree line, so that any observation above the line indicates that Trump over-performed in the general election vis-à-vis the primary.

Figure 9: Trump Share of 2020 Total Primary Ballots Cast and Trump Share of 2020 General Election Vote, Precincts, Chatham County



Given that there was considerable excitement about the primary among Democrats, and there was only a single uncontested candidate for the Republicans, it is not surprising that most of the dots are above the line. It appears that there was a participation gap in favor of Democrats in the primary, but this gap faded by election day. Only in the very Republican precincts were the observations clustered around the 45-degree line or slightly below.

Let us now transform this graph into the one presented by Dr. Ayyadurai. We can measure Trump's over-performance in the general election relative to the primary by subtracting the primary vote share from the election-day vote share. We can then plot that quantity on the vertical axis, and the primary vote share—presumably Ayyadurai's measure of "the share of Republicans in a precinct"—on the horizontal axis.

Figure 10: Reverse Engineering of Ayyadurai Plot

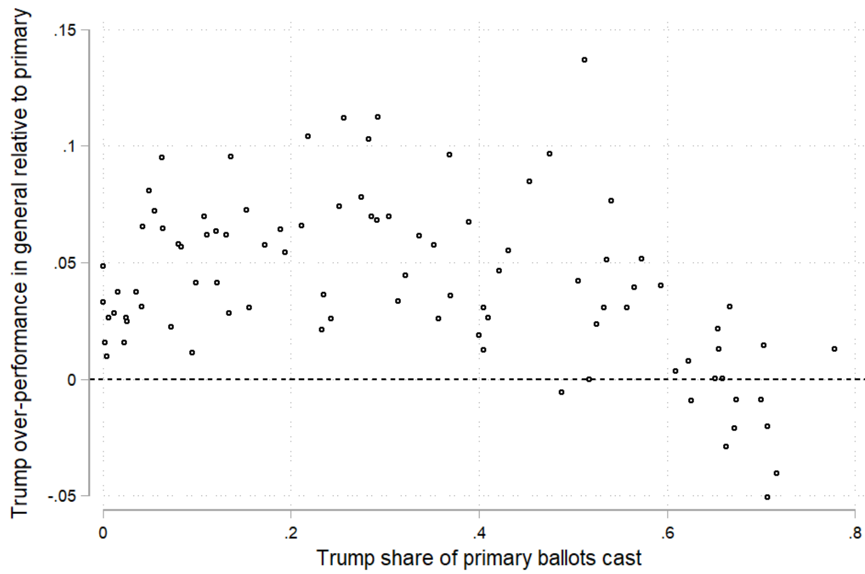


Figure 10 looks very similar to Dr. Ayyadurai's plot (page 5). Due to the relatively weak primary turnout among Republicans relative to Democrats, it is not at all surprising that Trump received a higher vote share in the General Election than in the primary in most precincts. It is also not surprising that this effect would fade in precincts with relatively few Democrats. What is surprising is that this could possibly be viewed as somehow indicative of fraud.

Figure 11: Down-Ballot Republican Vote Share and Trump Vote Share, 2020 General Election, Precincts of Chatham County

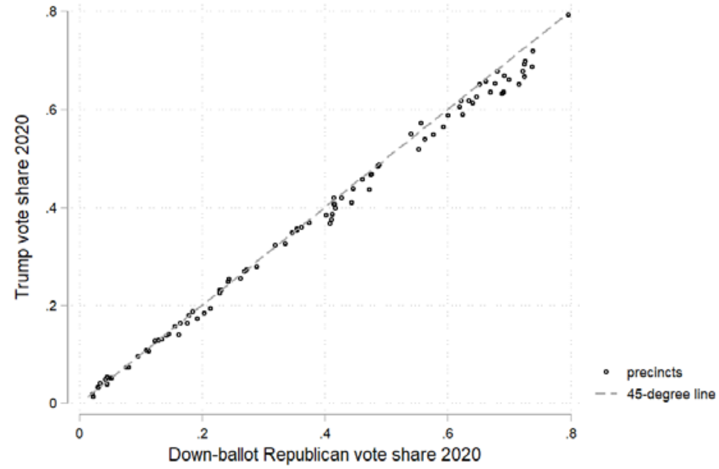
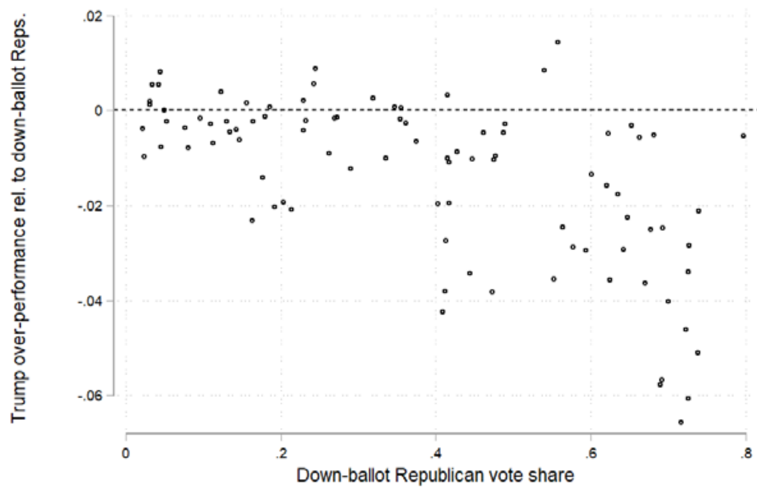


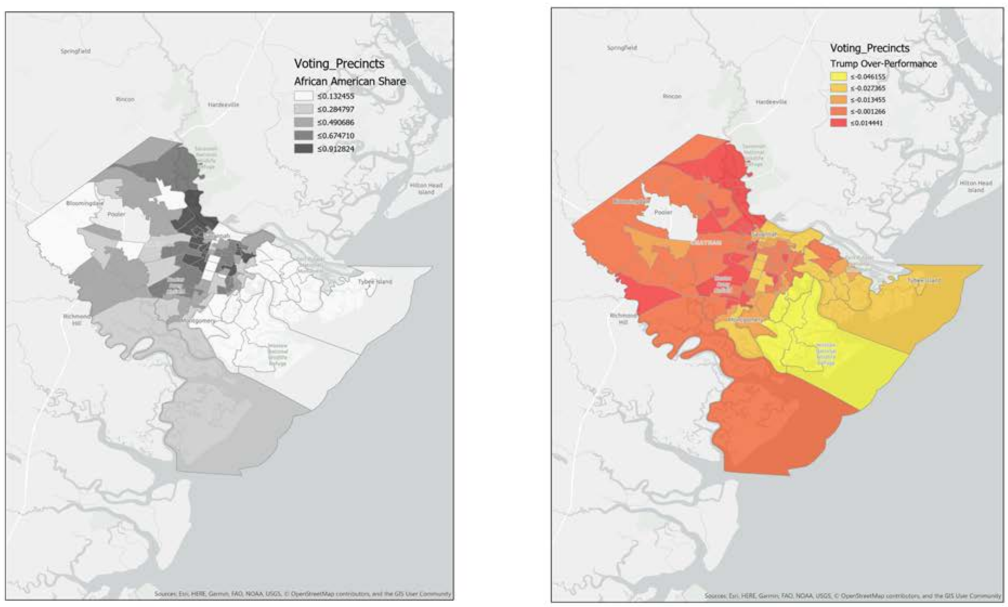
Figure 12: Trump Over-Performance Relative to Down-Ballot Republicans, 2020 General Election, Precincts of Chatham County



Let us take another approach to the measurement of precinct-level partisanship by looking at other races that occurred on the same ballot on November 3, 2020. In addition to the first round of the Senate election, there were two relatively low-profile races for the Georgia Public Services Commission. One might argue that such races are more likely to be based on underlying partisan attachments rather than personalities. I have added up the Republican vote share in these down-ballot races and plot this against the Trump vote share in Figure 11, again including a 45-degree line. And in Figure 12, I present the data using Dr. Ayyadurai's approach.

In Figure 11, we see that in the majority-Democratic precincts on the left, down-ballot vote shares and presidential vote shares are almost exactly the same. However, as we move to the right—into more Republican precincts—we see that Trump begins to under-perform relative to the down-ballot Republicans. And in Figure 12, we see once again the pattern that Dr. Ayyadurai refers to as "high Republican but low Trump." Trump under-performed relative to other Republican candidates throughout Chatham County, but that under-performance was most pronounced in the most Republican districts—many of which are overwhelmingly white, educated, and high-income. Figure 13 helps us visualize this. I have obtained geographic boundary files of Chatham county's 2020 precincts and combined them with data on race and election results. On the left is a map of race, and on the right is a map of split ticket voting expressed as Trump's over-performance relative to down-ballot Republicans. The darkest orange color captures the precincts where Trump very slightly over-performed relative to down-ballot Republicans. Many of these are precincts with relatively large African-American populations. As the colors get lighter and move toward yellow, Trump *under*-performs relative to down-ballot Republicans by larger amounts. We can see that his greatest under-performance was in white, traditionally Republican neighborhoods, many of which are relatively educated and affluent.

Figure 13: Race and Split-Ticket Voting in Chatham County, GA, November 2020



Dr. Ayyadurai's phrase—"high Republican but low Trump"—describes something we saw not only in Savannah but in metro areas around Georgia and the United States: white metro-area voters who typically vote for Republican candidates continued to do so in down-ballot races, but a number of them voted for the Democratic candidate in the presidential race. It is quite unclear what this pattern of split-ticket voting could possibly have to do with election fraud.

In addition to his curious claims about partisanship, Dr. Ayyadurai also makes some statements about race that are difficult to comprehend. He presents graphs that he says are "cumulative vote totals." He does not explain what he means by this or what is happening as one moves from left to right on these graphs. It is unclear whether they are supposed to represent an array of precincts, arranged from small to large or from Republican to Democratic, vote counts as they unfold over time on election night, or something else. He then introduces a line on the graph that he says "plots the number of votes for President Trump based on the same ethnic demographic distribution to match the pattern of actual votes reported by the Secretary of State" (p.7). I simply have no idea what this means. Perhaps he has estimated some sort of model using precinct-level data, where he tries to predict vote shares from precinct-level racial data. He does not tell the reader what he has done with racial data, what assumptions he has made, or why race is even relevant for his analysis. Without any corresponding analysis or data, he then makes a truly incomprehensible claim: "the only way to explain the results, reported by the Secretary of State, is if President Trump did not receive one single Black vote" (p. 8). Because this claim is not supported by any data or even a description of the logic that gave rise to it, I am not sure how to evaluate it. Dr. Ayyadurai seems to have made some unusual assumptions about how ethnic identity should, in his view, translate into votes in Georgia. The ballot is secret, and individual-level data on race and voting are unavailable. It is possible to conduct ecological inference analysis using precinct-level data in order to estimate the voting behavior of racial groups, but Dr. Ayyadurai makes no mention of having conducted this type of analysis, and even if he had, it is simply not possible to use aggregate data to make a claim like the one about Trump "not receiving a single black vote." One cannot draw any such conclusion from the data at hand.

In the remainder of his report, Dr. Ayyadurai repeats the same analysis for several additional counties. For each of the counties, Dr. Ayyadurai merely points out that Donald Trump under-performed in relatively white, Republican suburban areas. At no point does he explain what President Trump's difficulties in suburban Georgia have to do with election fraud.

Finally, Dr. Ayyadurai makes an additional claim. On page 26, he claims to find "unequivocal evidence of an algorithm that has been put in place such that when a precinct nears approximately ten-percent ("10%") in White voters, a linearly increasing percentage of total votes is transferred from President Trump to Mr. Biden." Dr. Ayyadurai does not provide any evidence of any such phenomenon. Once again, it is quite difficult to piece together the logic behind this claim, or to make sense of the data that Dr. Ayyadurai believes might support it. His analysis appears to involve some estimate of "the difference between Mr. Biden's votes as reported by the Secretary of State of Georgia and what he should have received based on the ethnic distribution of DeKalb County" (p. 27). Dr. Ayyadurai does not help the reader by explaining what Biden "should have received." Evidently, he believes that Biden should have received only votes from African Americans, and zero votes from whites, such that any Biden vote share above 60 percent, for instance, in a 60 percent white precinct is viewed as somehow anomalous or excessive. For reasons that are unclear, he seems to then claim that it is especially suspicious if Biden's over-performance relative to an "ethnic headcount" model is larger in whiter precincts. This view of voting as a simple ethnic headcount in a diverse suburban environment like DeKalb County is unusual to say the least. Moreover, it is unclear why a strong performance for Biden in majority-white suburban precincts would constitute evidence of fraud.

Once again, it is helpful to visualize the data in question. From the Secretary of State, I have obtained precinct-level racial data along with 2020 election results for Fulton County. In Figure 14, I plot whites as a share of registered voters on the horizontal axis, and Biden's vote share on the vertical axis. There is a negative relationship between whites as a share of registered voters and Biden's vote share, but DeKalb County elections cannot be characterized as an ethnic headcount. Note that in DeKalb County, even the precincts that are over 80 percent white are still, on average, strongly Democratic. And in the upper right-hand section of the graph, there are a large number of overwhelmingly white precincts where Biden received a very large share of votes. It is not possible to identify anything resembling a mechanical, machine-like increase in Democratic vote share as one moves from left to right in Figure 14. Rather, there is a cloud of majority-white districts where Biden performs especially well.

Figure 14: Whites as Share of Registered Voters and November 2020 Biden Vote Share, Precincts of DeKalb County, GA

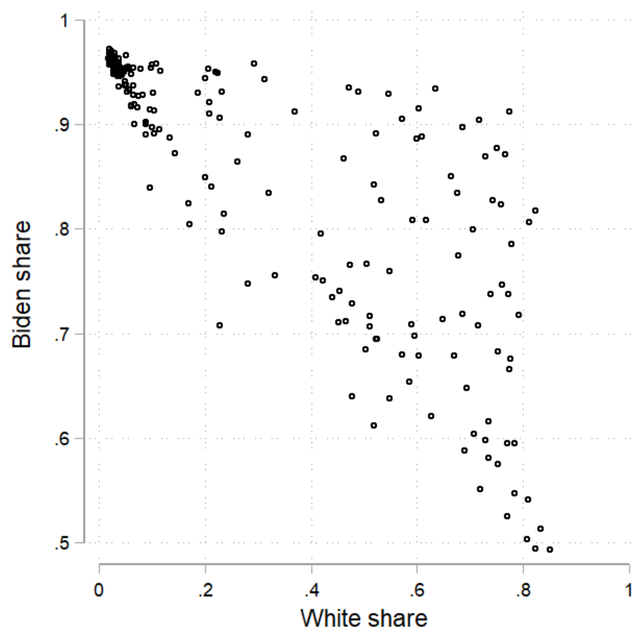
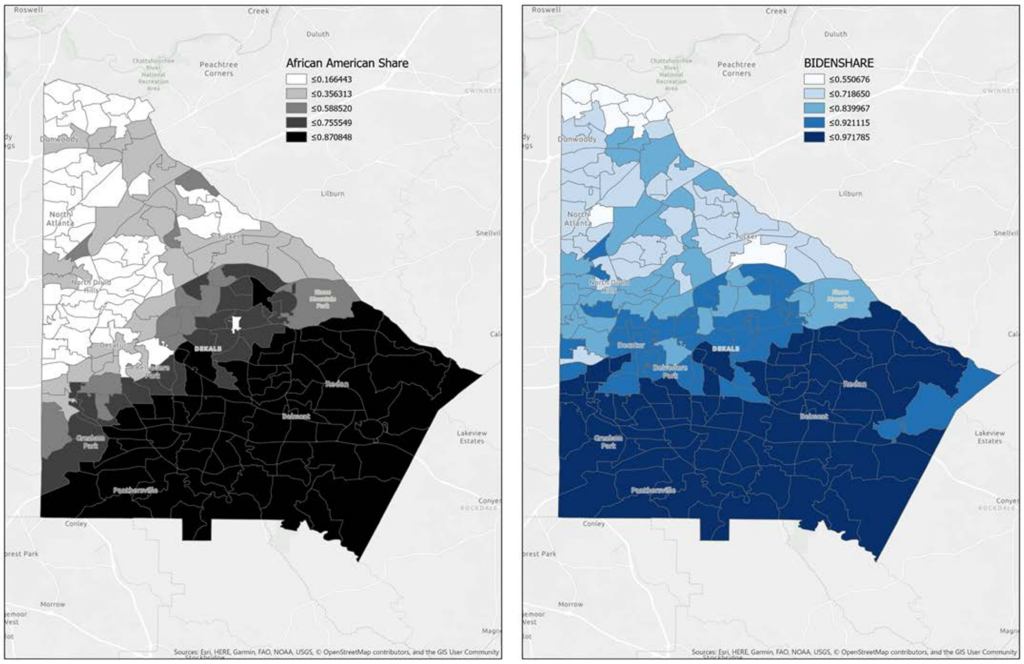


Figure 15: Map of Race and November 2020 Biden Vote Share, Precincts of DeKalb County, GA



It is also useful to visualize DeKalb County election results on a map. For instance, many of the white precincts with relatively high Biden vote shares are contiguous neighbors on the West side of the county, closer to Atlanta. There is nothing about the data displayed in Figures 14 or 15 that would seem to indicate any kind of fraud. Support for Democrats among suburban whites in racially heterogeneous areas is common around the United States and does not constitute evidence of fraud.

VI. RAMSLAND REPORT

Mr. Ramsland presents empirical analysis that demonstrates, in his telling, that Joseph Biden receive higher vote shares in counties that use voting machines made by the manufacturers Dominion and Hart, and that Biden "overperforms" in a larger share of counties using those machines than in counties using other machines. Mr. Ramsland makes vague allusions to rogue foreign actors, and concludes with the statement that the use of certain voting machines "affected 2020 election results" (page 11), indicating that he believes he has uncovered a *causal* relationship, whereby certain types of machines are responsible for boosting the Democratic vote share. Mr. Ramsland's research design is flawed in several crucial respects. First, he relies on idiosyncratic, non-standard statistical techniques that are not suited for the analysis he wishes to accomplish, and more importantly, he relies on a correlation that is driven primarily by cross-state variation and makes no effort to address a serious causal inference problem.

To demonstrate these problems and conduct a more appropriate analysis, I have created my own dataset of county-level votes from 2008 to 2020, merged with county demographic data from the 2014-2018 American Community Survey (ACS),[5] September 2020 county-level unemployment rate from the Bureau of Labor

[5] Demographic variables from the ACS include: the age distribution, sex distribution, percent Black, percent Latino, the percent of renters, median household income, percent of the county with a college degree, and percent under the poverty line.

Statistics, and data on voting technologies used in each jurisdiction collected by Verified Voting.[6] Verified Voting is a "non-partisan organization focused exclusively on the critical role technology plays in election administration" that has developed "the most comprehensive publicly-accessible database of voting systems used around the country."[7] I accessed a dataset showing the various voting systems that were in place for each jurisdiction in 2012, 2016, and 2020.

Mr. Ramsland's report says he uses data from the Election Assistance Commission (EAC). I have been unable to locate a dataset from the EAC that contains data on voting systems used across the country in 2020. The most recent data available from the EAC is from 2018.[8] Its 2020 survey of election administrators—which appears to be the source of the data on voting systems—has yet to be released. As the complaint notes, Georgia had not adopted Dominion voting equipment in 2018.

Mr. Ramsland describes a two-step procedure that is not a standard method of data analysis. Instead of generating predictions using a model that does not include data on voting systems, a more appropriate analysis should include both voting-

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[6] In preparing this this data set and conducting the analysis set forth in this section of the report, I received assitance from William Marble—a advanced PhD candidate in political science at Stanford University. Mr. Marble has worked with me in a similar capacity in the past and it is standard to utilize such assistants in my field of expertise.

[7] https://verifiedvoting.org/about/

[8] https://www.eac.gov/research-and-data/datasets-codebooks-and-surveys

systems data as well as demographic data in one unified model.[9] I conduct such an analysis below. Additionally, Mr. Ramsland makes some incorrect statements when describing his analysis. The report states that "[i]n normal circumstances any candidate should perform above expectations roughly 50% of the time and under-perform roughly 50% of the time" (par. 11). This statement is incorrect. In fact, the statistical procedure used in Mr. Ramsland's report guarantees that the average difference between the actual vote share and the predicted vote share is 0. It does not guarantee, however, that the proportion of observations in which the vote share is over- or under-predicted is roughly 50%.[10]

Though Mr. Ramsland's two-step procedure is not especially useful, let us take very seriously his claim that the introduction of certain types of voting technology, via some unspecified form of fraud, actually has a causal impact on vote shares. In other words, we would like to answer the following question: if there are two counties that are otherwise identical in every respect, including their initial type of voting technology, and one switches from some other voting technology to Dominion and the other stays the same, does the switching county exhibit a change in voting behavior relative to the "control" county that stayed the same? In the ideal

[9] Additionally, Mr. Ramsland's report is light on methodological details. For example, it does not describe which Census variables are included in his model.

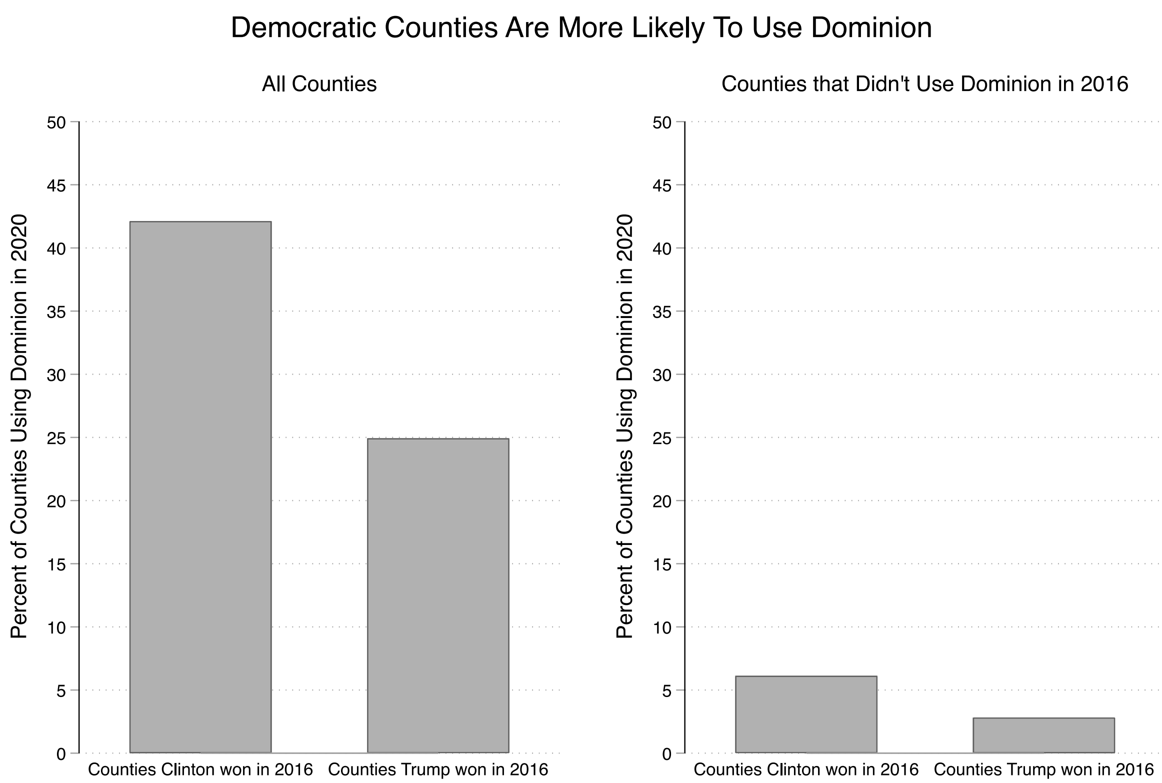
[10] This is a well-known result. Technically, linear regression finds a set of coefficients so that the sum of squared deviations between the predicted and actual values is minimized, along with the constraint that the average deviation is 0. This procedure can produce results where there are many small positive deviations, offset by a few large negative deviations (or vice versa).

world, we would conduct an experiment, much like a drug trial, randomly assigning some counties but not others to either the "treatment condition"—the use of Dominion software—or the control condition—the maintenance of the existing system. By randomizing a sufficiently large number of counties to the treatment and control condition, a researcher would be able to anticipate that there are no systematic differences between the treatment and control counties. Above all, we would hope that this randomization would achieve a balance between the two groups, such that prior Democratic or Republican voting would be similar in the two groups, as would other correlates of voting behavior, such as income, race, and education. We would then be able to isolate any possible impact of voting equipment.

Unfortunately, this type of experiment is unavailable to us. Counties and states have adopted voting technology in a way that is far from random. Counties that adopted Dominion systems between 2016 and 2020 are quite different from those that did not. Counties that switched to Dominion systems between 2016 and 2020 have larger shares of female residents, Latino residents, college-educated residents, and have lower median incomes. All of these variables are correlated with political attitudes. Moreover, they are likely correlated with *unobservable* variables that also correlate with political attitudes and partisanship.

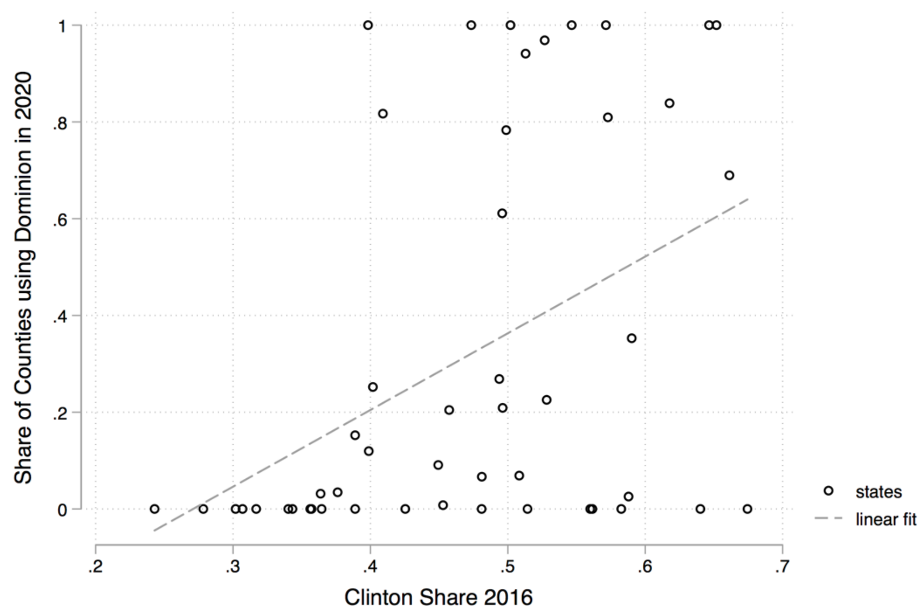
Even worse, it is clearly the case that Democratic counties have been more likely to adopt Dominion machines than Republican counties. This is demonstrated in Figure 16. The left-hand panel considers all counties in the country and shows that counties won by Clinton in 2016 were far more likely than counties won by Trump to make use of Dominion technology in 2020. The right-hand panel focuses on counties that were not yet using Dominion technology in 2016 and shows that counties won by Clinton were significantly more likely than counties won by Trump to adopt Dominion technology.

Figure 16: Voting Technology Use in 2020 by County Partisanship



Seven states have adopted Dominion technology across all of their counties, and 20 states have not adopted Dominion technology in any of their counties. The former counties are predominately Democratic, and the latter lean Republican. This can be seen in Figure 17, which plots Hillary Clinton's 2016 statewide vote share on the horizontal axis and the share of counties using Dominion software in 2020 on the vertical axis. It shows that Dominion software was mostly prominently in use in 2020 in states that were already relatively Democratic in 2016.

Figure 17: Clinton 2016 Vote Share and 2020 Voting Technology



By now it should be clear why Mr. Ramsland's empirical analysis suffers from a vexing causal inference problem. If extremely Democratic counties in states like New England adopted a certain software in the past, and one examined a contemporary correlation between voting behavior and the use of that technology, that correlation could not plausibly be interpreted as evidence that the technology *caused* the voting outcomes, even if one attempted to control for potential observable confounders like race and income. It is simply not plausible that Connecticut is more Democratic than Wyoming because of its voting technology.

State Fixed Effects Model

Mr. Ramsland sweeps these complexities under the rug. Unfortunately, there is no easy solution to this causal inference problem. At a minimum, we can try to draw inferences from *within* the states where there is variation across counties in voting technology, attempting to control for observable county-level confounders. This can be achieved by estimating a model with "fixed effects" for states. Inclusion of state-level fixed effects allows us to control for a variety of common factors within states that cause there to be a correlation in counties' outcomes within the same state. This does not "solve" the causal inference problem, but at least it allows for more valid comparisons. For this reason, inclusion of fixed effects is standard practice in social science research for this type of study.[11]

I estimate a county-level model in which the dependent variable is the 2020 Democratic vote share and the main independent variable of interest is a binary

[11] For example, see Angrist, J., and Pischke, S., *Mostly Harmless Econometrics*. 2009. Princeton, NJ: Princeton University Press.

variable indicating whether the state used Dominion technology in 2020. The model includes a set of demographic control variables, past election results, and state-level fixed effects. The full results are presented in Appendix Table A1. The coefficient capturing the impact of the use of Dominion technology is statistically indistinguishable from zero. The same is true for the use of Hart technology.

Placebo Test Using Bordering Counties

In sum, when we rely on comparisons of counties within states, there is no evidence that election technology has an impact on vote shares. Mr. Ramsland provides no regression output or details about his analysis, but he seems to have estimated some sort of regression model. He makes no mention of having included fixed effects. As one can see in Figure 17 above, it is clear that a naïve empirical model without fixed effects for states would generate the illusion of a relationship between voting technology and election outcomes simply because Democratic states have been somewhat more likely to purchase Dominion equipment.

A good way to observe this phenomenon is to conduct a "placebo" test in which we examine Biden's vote share in counties that *did not* use Dominion systems but border a county that *did* use Dominion. If there is an impact of voting software on election outcomes via fraud, it should certainly not be detected in counties that border the Dominion counties but use some other election technology system. If we see that those counties have elevated Democratic vote shares mimicking the supposed “effect” of Dominion software—what is known as a “placebo” effect—we should be very skeptical about claims that use of the software is associated with increased Democratic voting. Rather, we would understand that the correlation reported by Mr. Ramsland is driven by some features of the types of regions where Dominion software has been adopted—not the software itself.

The result of this analysis is shown in Appendix Table A2. It shows results of a linear regression of Biden vote share on an indicator variable for whether a county borders a Dominion (or Hart) county. This regression is estimated among counties that used neither Dominion nor Hart systems, and it includes a set of demographic control variables. It shows that Biden received a higher vote share, about .86 of a percentage point, in counties that border a Dominion county than in those that do not. It would be implausible to claim that voting technology in bordering counties has a causal impact on Biden’s vote share. A more plausible interpretation is that there are some common features of politics in the regions that have adopted the software, and the research design that Mr. Ramsland appears to have used in his report is likely to turn up spurious results.

Placebo Test Using Prior Election Results

A research strategy designed to estimate the effect of one variable on another variable can be evaluated by its tendency to detect an effect when an effect *does* exist, and its tendency *not* to detect an effect when an effect *does not* exist. When a research design detects an effect where none exists, we say it returns a *false positive*. Designs with a high false positive rate are not very informative: an effect could be detected by the research design due to the existence of a real effect, or it could be a false positive.

We can make a further evaluation of the propensity of the research design that Ramsland appears to have used in his report to return false positives by seeing whether it detects that *future* events have an "effect" on *past* outcomes. Of course, this is logically impossible—we know that events happening in the future cannot affect past outcomes. Thus, any effect detected on past outcomes is necessarily a false positive.

In Appendix Table A3, I replicate the basic research design that I believe was used in the Ramsland report. It uses linear regression models, without state fixed effects, to predict Democratic vote share as a function of whether a county used Dominion voting technology in 2020, along with county-level demographic and economic control variables. Except, instead of predicting *2020* vote share, I predict *2012* and *2016* vote share. I exclude counties that used Dominion systems at the time of the election being analyzed.

The results indicate that in 2012, in counties that did not use Dominion in 2012 but did use them in 2020, Barack Obama received about 5 to 7 percentage point higher vote share, compared to counties that did not use Dominion machines in either 2012 or 2020. The next column shows a similar pattern for 2016. Future use of Dominion predicts higher Clinton vote share in 2016, even in counties that did not use Dominion in 2016.

These results are false positives: there is no logical way that future use of Dominion voting machines could have affected past outcomes. Instead, these results are due to the fact that counties that used Dominion voting systems in 2020 are politically different than counties that did not, even after controlling for demographic and economic variables. This test shows that the research design used in the Ramsland report is ill-equipped to detect differences in vote shares that are *caused* by use of particular voting systems. As such, the statistical analysis in the Ramsland report provides no evidence of fraud due to use of Dominion or Hart voting machines.

Ranked Choice Voting

Mr. Ramsland also makes a confusing claim that election results may have been altered in Michigan because voting machines were set to perform ranked choice voting, which Mr. Ramsland refers to as a "feature enhancement." From this discussion, it seems likely that Mr. Ramsland is not familiar with ranked choice voting. It involves a different type of ballot, in which voters rank their preferences among candidates. This type of ballot was not used in Michigan. Even if all of the ballots in Michigan were somehow counted or processed using ranked choice voting, but using ballots that only allowed voters to select one candidate, the result would be the same. Ranked choice voting is a system where in the first round of counting, if one candidate has a majority, the process is over, and no votes are redistributed. If there were multiple candidates and voters' choices were ranked, there would then be a second round, where the lowest-ranked candidate would be dropped, and those voters who ranked that candidate first would then have their second-choice votes tallied. Clearly, nothing of the sort happened in Georgia. Jo Jorgensen, the Libertarian candidate, was credited with 62,138 votes in Georgia. Significant votes were also recorded throughout the state for additional parties as well as write-in candidates.

Mr. Ramsland also seems to believe that ranked choice voting would somehow produce non-integer vote totals. This is simply not the cases. Ranked-choice voting is no more capable of producing non-integer vote totals than is the winner-take-all plurality system. I have examined precinct-level vote totals from county election officials around Georgia and have seen no non-integer vote totals. It appears that Mr. Ramsland may have been thrown off by election-night reporting by

Edison Research that contained Biden and Trump vote totals that were not always whole numbers. One obvious possibility is that when sharing data on election night, workers at Edison Research multiplied total votes cast by vote shares that had been rounded when producing a field for total vote numbers in their data feed.

VII. Conclusion

None of these authors offers a specific theory about how they believe fraud was actually carried out. They veer between insinuations that foreign actors changed votes via malicious software, to more traditional efforts to blame nefarious election administrators in specific counties or precincts. Dr. Quinnell does not specify whether he believes that some unspecified fraud took place among administrators in particular suburban Fulton County precincts, or that a malicious actor at the county level or beyond somehow selected these suburban precincts to manipulate. For reasons that are unclear, Dr. Ayyadurai seems to suggest that malicious coders decided to add Democratic votes to precisely the white, suburban, traditionally Republican precincts in Georgia that have been trending away from the Republican Party in the Trump era. Mr. Ramsland seems to have a broader conspiracy in mind, where malicious coders are subverting the will of voters in every state, including extremely Democratic states of the Northeast.

The visions of fraud and conspiracy that motivate these reports are difficult to pin down and seem to conflict with one another. The data presented in these reports have nothing to do with fraud, and the authors do not even attempt to link their so-called "anomalies" to theories about how fraud might be carried out. Though these reports offer some insight into the production process for conspiracy theories, they provide no evidence whatsoever of anomalies or irregularities in Georgia's 2020 general election results.

Appendix

Table A1: Fixed Effects Model, County-Level Democratic Vote Share in 2020

	Dem vote share, 2020
Dominion 2020	0.031
	(0.25)
Hart 2020	-0.014
	(0.08)
female	-0.003
	(0.18)
Black	0.022
	(2.57)*
Latino	-0.078
	(9.43)**
College	0.086
	(7.31)**
Age 25-34	0.014
	(0.52)
Age 35-44	0.074
	(2.56)*
Age 45-54	-0.028
	(0.85)
Age 55-64	0.123
	(4.16)**
Age 65 and over	-0.030
	(1.63)
Median income	-0.016
	(1.79)
Poverty rate	-0.003
	(0.16)
Unemployment rate	-0.140
	(3.73)**
Renter share	-0.011
	(0.88)
Share urban	0.019
	(7.81)**
Log population density	0.240
	(3.54)**
Dem. vote share 2016	1.047
	(51.38)**
Dem. vote share 2012	-0.093
	(3.76)**
Dem. vote share 2008	-0.026
	(1.43)
Constant	0.465
	(0.26)
R^2	0.99

N	3,110

* $p<0.05$; ** $p<0.01$

Table A2: Border Placebo Analysis

	Dem vote share, 2020
Dominion 2020	0.855*
	(1.96)
Hart 2020	-3.860
	(6.97)**
female	0.067
	(0.60)
Black	0.389
	(16.44)**
Latino	0.148
	(5.00)**
College	0.746
	(13.81)**
Age 25-34	-0.238
	(1.53)
Age 35-44	-0.504
	(3.03)**
Age 45-54	0.060
	(0.33)
Age 55-64	0.738
	(3.70)**
Age 65 and over	-0.231
	(2.43)*
Median income	0.156
	(3.05)**
Poverty rate	0.564
	(5.58)**
Unemployment rate	0.901
	(6.10)**
Renter share	0.274
	(4.56)**
Share urban	0.014
	(1.04)
Log population density	1.812
	(7.04)**
Constant	-25.082
	(2.43)*
R^2	0.68
N	1,846

* p<0.05; ** p<0.01

Table A3: Previous Election Placebo Analysis

	2012 Dem vote share	2016 Dem vote share
2020 Dominion	5.605	3.310
	(1.241)**	(1.358)*
female	0.400	0.198
	(0.131)**	(0.113)
Black	0.352	0.466
	(0.024)**	(0.021)**
Latino	0.143	0.258
	(0.034)**	(0.031)**
College	0.331	0.660
	(0.061)**	(0.054)**
Age 25-34	-0.411	-0.254
	(0.177)*	(0.153)
Age 35-44	-0.799	-0.576
	(0.194)**	(0.168)**
Age 45-54	0.272	0.269
	(0.225)	(0.198)
Age 55-64	0.842	0.850
	(0.235)**	(0.206)**
Age 65 and over	-0.117	-0.033
	(0.120)	(0.100)
Median income	0.152	0.150
	(0.061)*	(0.050)**
Poverty rate	0.656	0.671
	(0.108)**	(0.098)**
Renter share	0.325	0.337
	(0.077)**	(0.068)**
Share urban	0.008	0.006
	(0.016)	(0.013)
Log population density	2.444	2.387
	(0.276)**	(0.246)**
Constant	-29.495	-41.937
	(12.358)*	(10.381)**
R^2	0.39	0.61
N	1,946	2,097

* p<0.05; ** p<0.01

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Publications

Books

Why Cities Lose: The Deep Roots of the Urban-Rural Divide. Basic Books, 2019.

Decentralized Governance and Accountability: Academic Research and the Future of Donor Programming. Co-edited with Erik Wibbels, Cambridge University Press, 2019.

Hamilton's Paradox: The Promise and Peril of Fiscal Federalism, Cambridge University Press, 2006. Winner, Gregory Luebbert Award for Best Book in Comparative Politics, 2007.

Fiscal Decentralization and the Challenge of Hard Budget Constraints, MIT Press, 2003. Co-edited with Gunnar Eskeland and Jennie Litvack.

Peer Reviewed Journal Articles

Partisan Dislocation: A Precinct-Level Measure of Representation and Gerrymandering, 2020, *Political Analysis* forthcoming (with Daryl DeFord Nick Eubank).

Who is my Neighbor? The Spatial Efficiency of Partisanship, 2020, *Statistics and Public Policy* (with Nick Eubank).

Handgun Ownership and Suicide in California, 2020, *New England Journal of Medicine* 382:2220-2229 (with David M. Studdert, Yifan Zhang, Sonja A. Swanson, Lea Prince, Erin E. Holsinger, Matthew J. Spittal, Garen J. Wintemute, and Matthew Miller).

Viral Voting: Social Networks and Political Participation, 2020, *Quarterly Journal of Political Science* (with Nick Eubank, Guy Grossman, and Melina Platas).

It Takes a Village: Peer Effects and Externalities in Technology Adoption, 2020, *American Journal of Political Science* (with Romain Ferrali, Guy Grossman, and Melina Platas). Winner, 2020 Best Conference Paper Award, American Political Science Association Network Section.

Assembly of the LongSHOT Cohort: Public Record Linkage on a Grand Scale, 2019, *Injury Prevention* (with Yifan Zhang, Erin Holsinger, Lea Prince, Sonja Swanson, Matthew Miller, Garen Wintemute, and David Studdert).

Crowdsourcing Accountability: ICT for Service Delivery, 2018, *World Development* 112: 74-87 (with Guy Grossman and Melina Platas).

Geography, Uncertainty, and Polarization, 2018, *Political Science Research and Methods* doi:10.1017/psrm.2018.12 (with Nolan McCarty, Boris Shor, Chris Tausanovitch, and Chris Warshaw).

Handgun Acquisitions in California after Two Mass Shootings, 2017, *Annals of Internal Medicine* 166(10):698-706. (with David Studdert, Yifan Zhang, Rob Hyndman, and Garen Wintemute).

Cutting Through the Thicket: Redistricting Simulations and the Detection of Partisan Gerrymanders, 2015, *Election Law Journal* 14,4:1-15 (with Jowei Chen).

The Achilles Heel of Plurality Systems: Geography and Representation in Multi-Party Democracies, 2015, *American Journal of Political Science* 59,4: 789-805 (with Ernesto Calvo). Winner, Michael Wallerstein Award for best paper in political economy, American Political Science Association.

Why has U.S. Policy Uncertainty Risen Since 1960?, 2014, *American Economic Review: Papers and Proceedings* May 2014 (with Nicholas Bloom, Brandice Canes-Wrone, Scott Baker, and Steven Davis).

Unintentional Gerrymandering: Political Geography and Electoral Bias in Legislatures, 2013, *Quarterly Journal of Political Science* 8: 239-269 (with Jowei Chen).

How Should We Measure District-Level Public Opinion on Individual Issues?, 2012, *Journal of Politics* 74, 1: 203-219 (with Chris Warshaw).

Representation and Redistribution in Federations, 2011, *Proceedings of the National Academy of Sciences* 108, 21:8601-8604 (with Tiberiu Dragu).

Dual Accountability and the Nationalization of Party Competition: Evidence from Four Federatons, 2011, *Party Politics* 17, 5: 629-653 (with Erik Wibbels).

The Geographic Distribution of Political Preferences, 2010, *Annual Review of Political Science* 13: 297–340.

Fiscal Decentralization and the Business Cycle: An Empirical Study of Seven Federations, 2009, *Economics and Politics* 22,1: 37–67 (with Erik Wibbels).

Getting into the Game: Legislative Bargaining, Distributive Politics, and EU Enlargement, 2009, *Public Finance and Management* 9, 4 (with Deniz Aksoy).

The Strength of Issues: Using Multiple Measures to Gauge Preference Stability, Ideological Constraint, and Issue Voting, 2008. *American Political Science Review* 102, 2: 215–232 (with Stephen Ansolabehere and James Snyder).

Does Religion Distract the Poor? Income and Issue Voting Around the World, 2008, *Comparative Political Studies* 41, 4: 437–476 (with Ana Lorena De La O).

Purple America, 2006, *Journal of Economic Perspectives* 20,2 (Spring): 97–118 (with Stephen Ansolabehere and James Snyder).

Economic Geography and Economic Voting: Evidence from the U.S. States, 2006, *British Journal of Political Science* 36, 3: 527–47 (with Michael Ebeid).

Distributive Politics in a Federation: Electoral Strategies, Legislative Bargaining, and Government Coalitions, 2004, *Dados* 47, 3 (with Marta Arretche, in Portuguese).

Comparative Federalism and Decentralization: On Meaning and Measurement, 2004, *Comparative Politics* 36, 4: 481-500. (Portuguese version, 2005, in *Revista de Sociologia e Politica* 25).

Reviving Leviathan: Fiscal Federalism and the Growth of Government, 2003, *International Organization* 57 (Fall), 695–729.

Beyond the Fiction of Federalism: Macroeconomic Management in Multi-tiered Systems, 2003, *World Politics* 54, 4 (July): 494–531 (with Erik Wibbels).

The Dilemma of Fiscal Federalism: Grants and Fiscal Performance around the World, 2002, *American Journal of Political Science* 46(3): 670–687.

Strength in Numbers: Representation and Redistribution in the European Union, 2002, *European Union Politics* 3, 2: 151–175.

Does Federalism Preserve Markets? *Virginia Law Review* 83, 7 (with Susan Rose-Ackerman). Spanish version, 1999, in *Quorum* 68.

Working Papers

Federalism and Inter-regional Redistribution, Working Paper 2009/3, Institut d'Economia de Barcelona.

Representation and Regional Redistribution in Federations, Working Paper 2010/16, Institut d'Economia de Barcelona (with Tiberiu Dragu).

Chapters in Books

Political Geography and Representation: A Case Study of Districting in Pennsylvania (with Thomas Weighill), forthcoming 2021.

Decentralized Rule and Revenue, 2019, in Jonathan Rodden and Erik Wibbels, eds., *Decentralized Governance and Accountability*, Cambridge University Press.

Geography and Gridlock in the United States, 2014, in Nathaniel Persily, ed. *Solutions to Political Polarization in America*, Cambridge University Press.

Can Market Discipline Survive in the U.S. Federation?, 2013, in Daniel Nadler and Paul Peterson, eds, *The Global Debt Crisis: Haunting U.S. and European Federalism*, Brookings Press.

Market Discipline and U.S. Federalism, 2012, in Peter Conti-Brown and David A. Skeel, Jr., eds, *When States Go Broke: The Origins, Context, and Solutions for the American States in Fiscal Crisis*, Cambridge University Press.

Federalism and Inter-Regional Redistribution, 2010, in Nuria Bosch, Marta Espasa, and Albert Sole Olle, eds., *The Political Economy of Inter-Regional Fiscal Flows*, Edward Elgar.

Back to the Future: Endogenous Institutions and Comparative Politics, 2009, in Mark Lichbach and Alan Zuckerman, eds., *Comparative Politics: Rationality, Culture, and Structure* (Second Edition), Cambridge University Press.

The Political Economy of Federalism, 2006, in Barry Weingast and Donald Wittman, eds., *Oxford Handbook of Political Economy*, Oxford University Press.

Fiscal Discipline in Federations: Germany and the EMU, 2006, in Peter Wierts, Servaas Deroose, Elena Flores and Alessandro Turrini, eds., *Fiscal Policy Surveillance in Europe*, Palgrave MacMillan.

The Political Economy of Pro-cyclical Decentralised Finance (with Erik Wibbels), 2006, in Peter Wierts, Servaas Deroose, Elena Flores and Alessandro Turrini, eds., *Fiscal Policy Surveillance in Europe*, Palgrave MacMillan.

Globalization and Fiscal Decentralization, (with Geoffrey Garrett), 2003, in Miles Kahler and David Lake, eds., *Governance in a Global Economy: Political Authority in Transition*, Princeton University Press: 87-109. (Updated version, 2007, in David Cameron, Gustav Ranis, and Annalisa Zinn, eds., *Globalization and Self-Determination: Is the Nation-State under Siege?* Routledge.)

Introduction and Overview (Chapter 1), 2003, in Rodden et al., *Fiscal Decentralization and the Challenge of Hard Budget Constraints* (see above).

Soft Budget Constraints and German Federalism (Chapter 5), 2003, in Rodden, et al, *Fiscal Decentralization and the Challenge of Hard Budget Constraints* (see above).

Federalism and Bailouts in Brazil (Chapter 7), 2003, in Rodden, et al., *Fiscal Decentralization and the Challenge of Hard Budget Constraints* (see above).

Lessons and Conclusions (Chapter 13), 2003, in Rodden, et al., *Fiscal Decentralization and the Challenge of Hard Budget Constraints* (see above).

Online Interactive Visualization

Stanford Election Atlas, 2012 (collaboration with Stephen Ansolabehere at Harvard and Jim Herries at ESRI)

Other Publications

How America's Urban-Rural Divide has Shaped the Pandemic, 2020, *Foreign Affairs*, April 20, 2020.

An Evolutionary Path for the European Monetary Fund? A Comparative Perspective, 2017, Briefing paper for the Economic and Financial Affairs Committee of the European Parliament.

Representation and Regional Redistribution in Federations: A Research Report, 2009, in *World Report on Fiscal Federalism*, Institut d'Economia de Barcelona.

On the Migration of Fiscal Sovereignty, 2004, *PS: Political Science and Politics* July, 2004: 427–431.

Decentralization and the Challenge of Hard Budget Constraints, *PREM Note* 41, Poverty Reduction and Economic Management Unit, World Bank, Washington, D.C. (July).

Decentralization and Hard Budget Constraints, *APSA-CP* (Newsletter of the Organized Section in Comparative Politics, American Political Science Association) 11:1 (with Jennie Litvack).

Book Review of *The Government of Money* by Peter Johnson, *Comparative Political Studies 32,7: 897-900.*

Fellowships and Honors

Fund for a Safer Future, Longitudinal Study of Handgun Ownership and Transfer (LongSHOT), GA004696, 2017-2018.

Stanford Institute for Innovation in Developing Economies, Innovation and Entrepreneurship research grant, 2015.

Michael Wallerstein Award for best paper in political economy, American Political Science Association, 2016.

Common Cause Gerrymandering Standard Writing Competition, 2015.

General support grant from the Hewlett Foundation for Spatial Social Science Lab, 2014.

Fellow, Institute for Research in the Social Sciences, Stanford University, 2012.

Sloan Foundation, grant for assembly of geo-referenced precinct-level electoral data set (with Stephen Ansolabehere and James Snyder), 2009-2011.

Hoagland Award Fund for Innovations in Undergraduate Teaching, Stanford University, 2009.

W. Glenn Campbell and Rita Ricardo-Campbell National Fellow, Hoover Institution, Stanford University, beginning Fall 2010.

Research Grant on Fiscal Federalism, Institut d'Economia de Barcelona, 2009.

Fellow, Institute for Research in the Social Sciences, Stanford University, 2008.

United Postal Service Foundation grant for study of the spatial distribution of income in cities, 2008.

Gregory Luebbert Award for Best Book in Comparative Politics, 2007.

Fellow, Center for Advanced Study in the Behavioral Sciences, 2006-2007.

National Science Foundation grant for assembly of cross-national provincial-level dataset on elections, public finance, and government composition, 2003-2004 (with Erik Wibbels).

MIT Dean's Fund and School of Humanities, Arts, and Social Sciences Research Funds.

Funding from DAAD (German Academic Exchange Service), MIT, and Harvard EU Center to organize the conference, "European Fiscal Federalism in Comparative Perspective," held at Harvard University, November 4, 2000.

Canadian Studies Fellowship (Canadian Federal Government), 1996-1997.

Prize Teaching Fellowship, Yale University, 1998-1999.

Fulbright Grant, University of Leipzig, Germany, 1993-1994.

Michigan Association of Governing Boards Award, one of two top graduating students at the University of Michigan, 1993.

W. J. Bryan Prize, top graduating senior in political science department at the University of Michigan, 1993.

Other Professional Activities

International Advisory Committee, Center for Metropolitan Studies, Sao Paulo, Brazil, 2006–2010.

Selection committee, Mancur Olson Prize awarded by the American Political Science Association Political Economy Section for the best dissertation in the field of political economy.

Selection committee, Gregory Luebbert Best Book Award.

Selection committee, William Anderson Prize, awarded by the American Political Science Association for the best dissertation in the field of federalism and intergovernmental relations.

Courses

Undergraduate

Politics, Economics, and Democracy

Introduction to Comparative Politics

Introduction to Political Science

Political Science Scope and Methods

Institutional Economics

Spatial Approaches to Social Science

Graduate

Political Economy of Institutions

Federalism and Fiscal Decentralization

Politics and Geography

Consulting

2017. Economic and Financial Affairs Committee of the European Parliament.

2016. Briefing paper for the World Bank on fiscal federalism in Brazil.

2013-2018: Principal Investigator, SMS for Better Governance (a collaborative project involving USAID, Social Impact, and UNICEF in Arua, Uganda).

2019: Written expert testimony in *McLemore, Holmes, Robinson, and Woullard v. Hosemann*, United States District Court, Mississippi.

2019: Expert witness in *Nancy Corola Jacobson v. Detzner*, United States District Court, Florida.

2018: Written expert testimony in *League of Women Voters of Florida v. Detzner* No. 4:18-cv-002510, United States District Court, Florida.

2018: Written expert testimony in *College Democrats of the University of Michigan, et al. v. Johnson, et al.*, United States District Court for the Eastern District of Michigan.

2017: Expert witness in *Bethune-Hill v. Virginia Board of Elections*, No. 3:14-CV-00852, United States District Court for the Eastern District of Virginia.

2017: Expert witness in *Arizona Democratic Party, et al. v. Reagan, et al.*, No. 2:16-CV-01065, United States District Court for Arizona.

2016: Expert witness in *Lee v. Virginia Board of Elections*, 3:15-cv-357, United States District Court for the Eastern District of Virginia, Richmond Division.

2016: Expert witness in *Missouri NAACP v. Ferguson-Florissant School District*, United States District Court for the Eastern District of Missouri, Eastern Division.

2014-2015: Written expert testimony in *League of Women Voters of Florida et al. v. Detzner, et al.*, 2012-CA-002842 in Florida Circuit Court, Leon County (Florida Senate redistricting case).

2013-2014: Expert witness in *Romo v Detzner*, 2012-CA-000412 in Florida Curcuit Court, Leon County (Florida Congressional redistricting case).

2011-2014: Consultation with investment groups and hedge funds on European debt crisis.

2011-2014: Lead Outcome Expert, Democracy and Governance, USAID and Social Impact.

2010: USAID, Review of USAID analysis of decentralization in Africa.

2006–2009: World Bank, Independent Evaluations Group. Undertook evaluations of World Bank decentralization and safety net programs.

2008–2011: International Monetary Fund Institute. Designed and taught course on fiscal federalism.

1998–2003: World Bank, Poverty Reduction and Economic Management Unit. Consultant for *World Development Report*, lecturer for training courses, participant in working group for assembly of decentralization data, director of multi-country study of fiscal discipline in decentralized countries, collaborator on review of subnational adjustment lending.

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