Comment on "A Simple Test for the Extent of Voter Fraud with Absentee Ballots in the 2020 Presidential Election"*

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January 4, 2021

Abstract

In a recent paper,[1] John Lott Jr. claims to find evidence of anti-Trump fraud in the absentee counting procedure in Fulton County, Georgia, and Allegheny County, Pennsylvania. Using Lott's own data, we show that his claims are utterly baseless. Lott uses an unusual estimation strategy that suffers from a subtle but fundamental flaw: his conclusions about fraud in Fulton and Allegheny counties are entirely dependent on the completely arbitrary order in which pairs of precincts in *other* counties are entered in the dataset. When we rerun Lott's analysis using an alternative but equally justifiable coding rule, the evidence for anti-Trump fraud in these two counties entirely disappears. When we replace Lott's unusual specification with a more standard estimation strategy, we find absolutely no evidence of fraud. In short, Lott's (2020) analysis provides no evidence of anything distinctive or suspicious about the absentee ballot results in either Fulton County or Allegheny County.

*We thank John Lott for sharing his data on the same day we made the request.

[1]John Lott Jr., "A Simple Test for the Extent of Voter Fraud with Absentee Ballots in the 2020 Presidential Election". https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3756988.

1 Introduction

We reexamine the evidence for voter fraud presented in "A Simple Test for the Extent of Voter Fraud with Absentee Ballots in the 2020 Presidential Election" (hereafter Lott (2020)). Lott (2020) claims that a comparison of adjacent election precincts in Georgia and Pennsylvania supports the Trump campaign's allegations that the 2020 presidential election was "stolen" through fraud. In Lott (2020)'s abstract, he estimates that fraud in Fulton County contributed 11,350 votes to Biden (over 80% of Joe Biden's lead in Georgia) and fraud in Allegheny County contributed about 55,270 votes to Biden's victory in Pennsylvania (around 2/3 of Biden's lead in Pennsylvania). If true, these claims would cast serious doubts on the integrity of the 2020 election. The paper has already received wide attention.[2]

In this comment, we show that Lott's claims are entirely baseless: his analysis produces absolutely no evidence of fraud in either Fulton County or Allegheny County. Perhaps in recognition of the high stakes surrounding claims of electoral fraud in the 2020 presidential election, Lott shared his data with us, making it possible to re-analyze his claims. Our reanalysis of the data shows that Lott's evidence for fraud depends completely on an entirely arbitrary decision about how counties are entered in the dataset: the conclusion is reversed when an alternative and equally justified data entry rule is used. When we replace Lott's unusual specification with a more standard approach that does not depend on arbitrary coding rules, we find absolutely no evidence for fraud in either Fulton County or Allegheny County.

In short, even if we accept Lott's premise that differences in Trump's share of the absentee vote between adjacent precincts can be used to detect fraud (which is itself debatable), and even if we use Lott's own data to conduct this assessment, we find no evidence of fraud whatsoever in the allegedly problematic counties.

2 Lott's (2020) Results Depend Entirely on an Arbitrary Coding Rule

Lott (2020) seeks to estimate the effect of the absentee ballot counting procedure in counties where fraud has been alleged by Trump and other Republicans: Fulton County, GA, and Allegheny County, PA. Lott (2020)'s approach assumes that Trump's share of the absentee vote in a precinct is related to Trump's share of the *in-person* vote in the precinct and voter demographics. Lott (2020) recognizes, however, that a difference in Trump's share of the absentee vote across neighboring counties, even controlling for Trump's share of the in-person vote and demographics, is not necessarily evidence of fraud. There may be other factors that

[2]Peter Navarro, the outgoing Assistant to the President and Director of the Office of Trade and Manufacturing Policy, promoted the paper in a tweet on December 29 (https://twitter.com/RealPNavarro/status/1343979253659004928). The next day, Donald Trump also tweeted about the study (https://twitter.com/realDonaldTrump/status/1344173684983017473).

vary across counties that could produce such differences.

To eliminate some of these alternative explanations for differences in Trump's absentee support between "suspect" counties and neighboring counties, Lott (2020) focuses on precincts that lie along county borders. Specifically, he forms pairs of precincts that lie along a boundary separating a suspect county (i.e. one where Republicans have alleged that fraud took place) and an adjacent county where Trump won a majority of the vote and no fraud allegations have been made.[3] Lott (2020) also forms pairs of precincts that lie along the boundary between two of these Republican counties, which serve as a kind of control group for the other pairs. Lott (2020) then conducts his analysis using within-pair *differences* in each variable: he regresses the difference in Trump's share of the absentee vote between the two precincts on the difference in Trump's share of the in-person vote between the two precincts and an indicator for whether the pair contains a precinct in a suspect county.[4] That is, his basic regression equation is

$$\left(\text{Absentee}_i - \text{Absentee}_j\right) = \beta_0 + \beta_1 \left(\text{InPerson}_i - \text{InPerson}_j\right) + \delta \text{SuspectCounty}_i + u_{ij},$$

where Absentee_i is Trump's share of the absentee vote in precinct i, Person_i is Trump's share of the in-person vote in precinct i, SuspectCounty_i indicates whether precinct i is located in a "suspect" county, and i and j are adjacent precincts that Lott assigns to a pair. Thus β_0 measures the within-pair difference in Trump's share of the absentee vote among pairs that don't involve a suspect county (adjusting for the within-pair difference in Trump's in-person share), and the key coefficient is δ, which compares the adjusted difference in Trump's share of the absentee vote within pairs involving the suspect county against the corresponding adjusted difference within pairs not involving the suspect county. The underlying logic seems to be that fraud is the likely explanation if there is a bigger drop in Trump's share of the absentee vote when we cross from, for example, Coweta County to Fulton County than when we cross from Coweta County to Carroll County, two Republican counties where no fraud has been alleged.

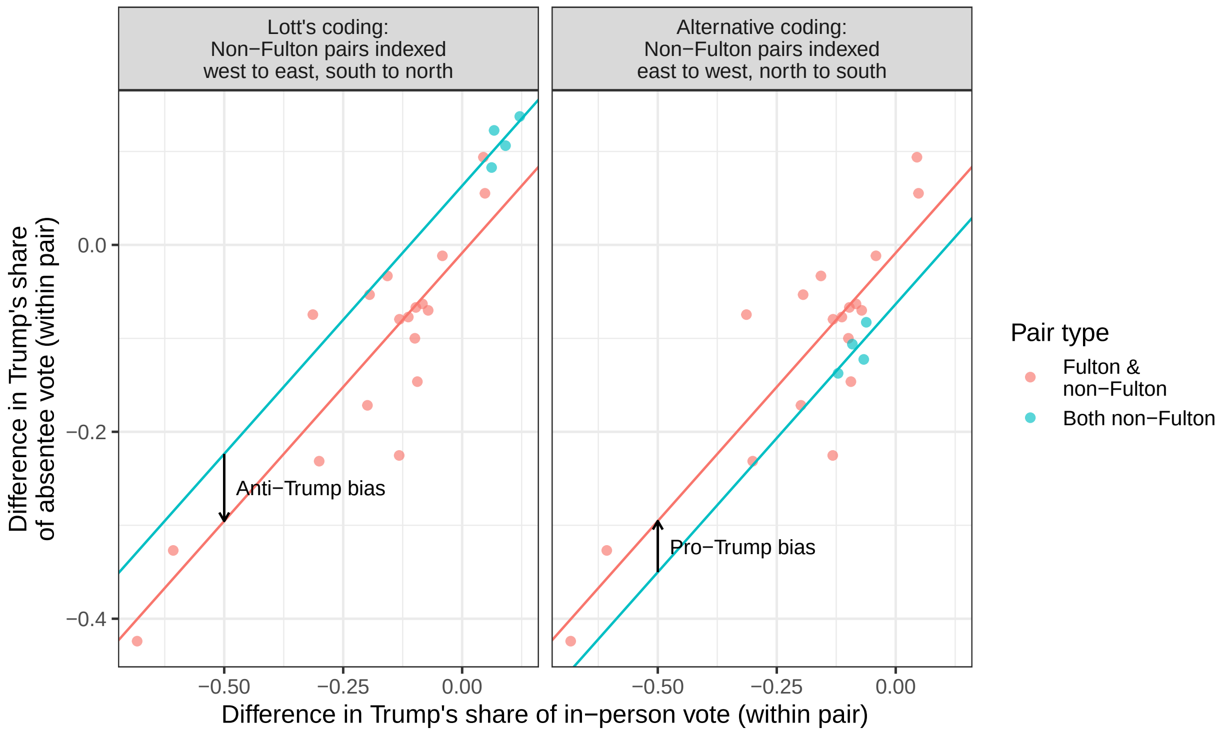
Even if we stipulate that focusing on adjacent precincts successfully addresses all relevant confounding variables,[5] Lott (2020)'s design suffers from a fatal flaw. As noted, Lott (2020)'s design measures a difference in two differences: is the drop in Trump's share of the absentee vote larger when we cross the Fulton County border into Republican counties than when we cross the border of one Republican county into another Republican county? The problem arises in measuring the second difference: there is no clear rule for determining the order of the difference. For example, should we record the change in Trump's absentee vote share as we move from Carroll to Coweta, or as we move from Coweta to Carroll? Neither

[3]By ruling out comparisons between precincts in "suspect" counties and surrounding Democratic-leaning counties, Lott severely restricts his sample size and likely excludes the most similar comparisons.

[4]In some specifications he also includes differences in various race-and-gender groups between the two precincts.

[5]This is doubtful. For example, Trump won just 9.6% of the in-person vote in a precinct in Fulton County (FA01B) that is adjacent to a precinct in Coweta County where Trump won 78% of the in-person vote (Fischer Road). It seems unlikely that precincts that differ so markedly in voting outcomes would be similar in e.g. voters' propensity to vote in person vs. absentee conditional on their vote choice.

Figure 1: Evidence for fraud in Fulton County, GA, is reversed if arbitrary coding rule is reversed



county is "suspect", so either approach could be justified. Lott (2020, footnote 13) chooses one rule (subtracting east from west and north from south) but the opposite rule or indeed any rule would be equally justified. This arbitrariness is a symptom of the underlying lack of compelling logic behind this aspect of the design: there is no clear reason to benchmark the difference in voting patterns across the key county boundary against the corresponding difference across another boundary.[6]

As it turns out, Lott (2020)'s evidence for fraud in Fulton County, GA, and Allegheny County, PA, relies entirely on this arbitrary coding rule: if a different but equally valid rule is used we reach the opposite conclusion from Lott (2020). Figure 1 illustrates the point for Fulton County. In both panels, each red dot corresponds to a pair of precincts lying on opposite sides of the Fulton County boundary; each blue dot corresponds to a pair of precincts lying on opposite sides of the boundary between two nearby Republican counties. The vertical axis shows the difference in Trump's share of the absentee vote within the precinct pair; the horizontal axis shows the difference in Trump's share of the in-person vote within the precinct pair.

The left panel of Figure 1 shows the analysis using Lott (2020)'s coding: for pairs in-

[6] One could imagine a better design that compared the *magnitude* (i.e. absolute value) of differences across suspect boundaries and other boundaries. In this case the ordering of precinct pairs would not matter. This is not Lott's design.

cluding a Fulton County precinct, the Trump share for the non-Fulton County precinct is subtracted from the Trump share for the Fulton County precinct; for pairs not including a Fulton County precinct, Lott (2020) uses the arbitrary rule noted above. This coding results in what Lott interprets as evidence for anti-Trump bias in Fulton County. Conditional on the difference in Trump's in-person vote share within a precinct pair, the difference in Trump's absentee vote share is lower in precinct pairs involving Fulton County than in other precinct pairs.

In the right panel of Figure 1 we show that the conclusion is reversed when we reverse Lott's arbitrary coding rule: instead of subtracting east from west and north from south in computing differences for non-Fulton precinct pairs, we subtract west from east and south from north. The scatterplot looks identical to the left panel except that the four blue dots (representing non-Fulton precinct pairs) are reflected through the origin. This small change reverses the conclusion, however: by Lott (2020)'s logic we now have evidence of pro-Trump bias in Fulton County.

Table 3 (Appendix) reports coefficient estimates and standard errors for both sets of analysis depicted in Figure 1. The evidence of pro-Trump fraud with the alternative coding rule has a similar absolute t-statistic ($t = 1.67$) as Lott's evidence of anti-Trump fraud with the original coding rule ($t = 1.89$).

The Pennsylvania results also depend on Lott's arbitrary coding rule, as we show in the same manner in Figure 2 and Table 4 (Appendix). Lott (2020) concludes from his analysis that anti-Trump fraud took place in Allegheny County, but if we apply a different but equally valid coding rule we find (by the same logic) stronger evidence for *pro-Trump* fraud in Allegheny County: the positive coefficient we obtain with the alternative coding rule is both larger in magnitude and more significant than the negative coefficient Lott reports.

We can further highlight the dependence of Lott's results on arbitrary coding decisions by exploring the universe of possible fraud estimates that Lott could have reported with equally justified alternative coding rules. In Figure 3 we show that, among the possible rules that could be used, any alternative rule would have produced weaker apparent evidence for anti-Trump fraud in Fulton County and almost any rule would have produced weaker evidence for anti-Trump fraud in Allegheny County.[7] In the Fulton County analysis, there are four non-Fulton precinct pairs and thus $2^4 = 16$ possible rules for computing differences within non-Fulton pairs. The left panel of Figure 3 shows the histogram of the key coefficient across these sixteen possible rules, with a vertical line highlighting the estimate for the rule Lott used. Among the sixteen possible rules, Lott's rule produces the strongest apparent evidence of anti-Trump fraud; six possible rules produce apparent evidence of pro-Trump fraud. In the Pennsylvania analysis we have seventeen non-implicated precinct pairs, allowing for over 130,000 possible coding rules. The right panel of Figure 3 shows the distribution of estimates

[7] In personal communication Lott said the ordering of precincts followed a rule in a prior AER paper. We believe that is Bronars and Lott (1998).

Figure 2: Evidence for fraud in Allegheny County, PA, is reversed if arbitrary coding rule is reversed

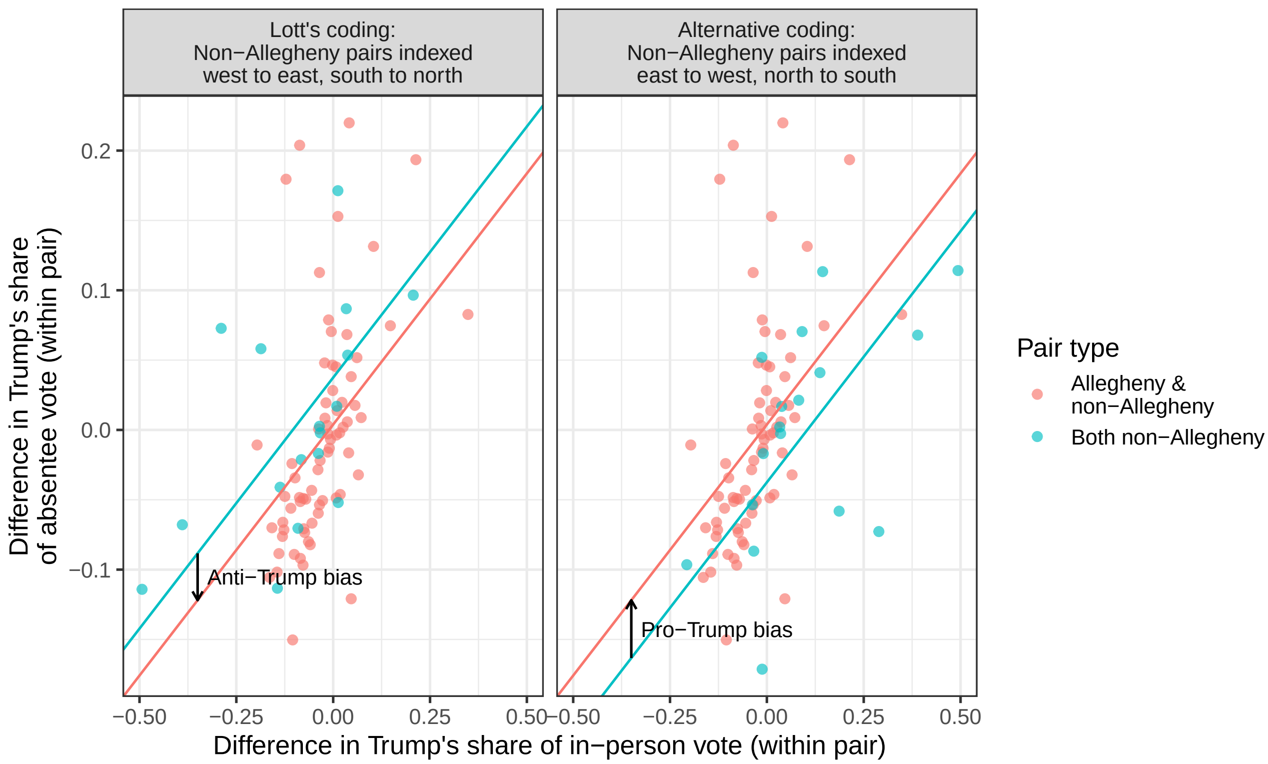
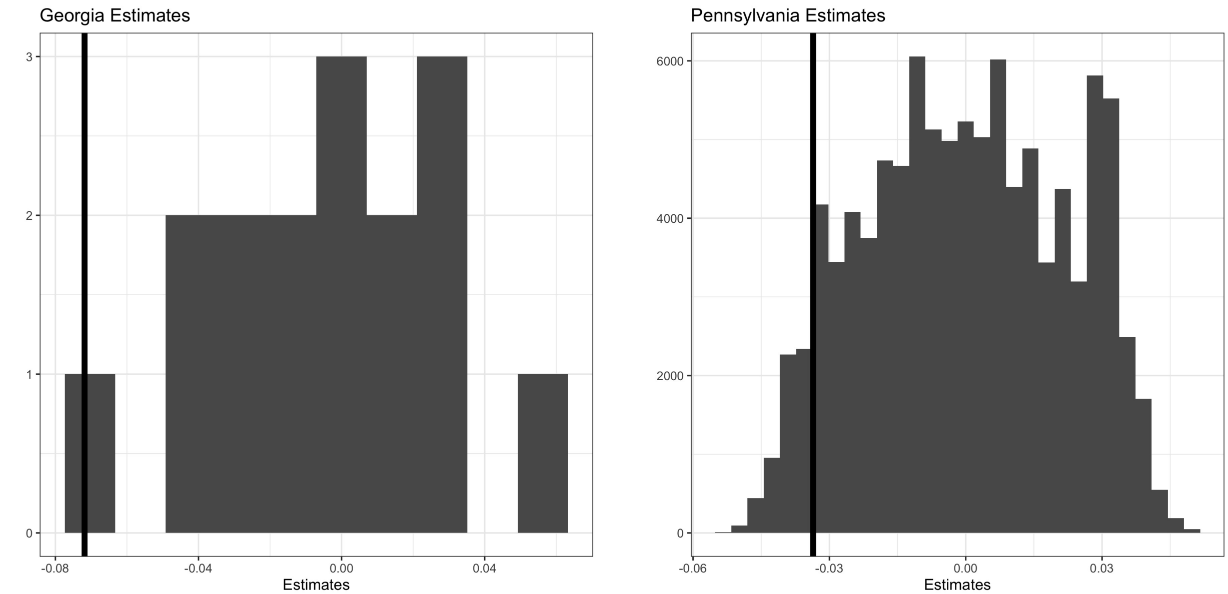


Figure 3: Evidence for fraud in Georgia and Pennsylvania depends on arbitrary coding rules; Lott's estimates are outliers in the distribution of estimates



for a random sample (with replacement) of 100,000 of these rules,[8] with the actual estimate again shown with a vertical line. The distribution is centered around zero, with roughly as many rules producing apparent evidence of pro-Trump and anti-Trump fraud; Lott's rule again happens to produce among the strongest apparent evidence of anti-Trump fraud.

Although the issue we highlight was not obvious to us on first reading Lott's study, it is an example of a known problem that crops up in research studying pairs of observations, or "dyads." When there is a clear distinction between members of dyads, such as aggressor/victim or source/destination, it can be sensible to address unobserved differences across dyads by studying within-dyad differences as Lott does. When no such distinction exists for some or all dyads (as in Lott's case), it becomes arbitrary how to define within-dyad differences. In such cases, "there is no consistent, non-arbitrary way to order the two members" of a dyad (Olsen and Kenny, 2006) and, as pointed out in Wheeler, Updegraff and Umaña-Taylor (2018), dyads whose members cannot logically be classified in a meaningful way "cannot be easily analyzed with the difference approach", i.e. the approach that Lott (2020) uses.

[8]To explore the space of changes to the difference order, we first sample the number of difference orders to change from a Uniform(1, 16). Once this number is obtained, we then randomly sample the specific units that will have the difference order changed. This explores the space, but does not provide a sampling distribution that gives an equal probability to each rearrangement, because our sampling method is biased towards either too few or too many rearrangements.

3 A More Standard Estimation Strategy Produces No Evidence of Fraud

Although Lott's specification problematically depends on arbitrary coding decisions, Lott's basic strategy of examining differences in voting patterns across a county boundary has some merit. Such differences in voting patterns could of course be explained by differences in voter behavior rather than fraud (particularly because county boundaries determine school districts and other policy outcomes, and some precincts along county boundaries are rather large geographically), but focusing on precincts along the county border does seem likely to reduce the role of these differences.[9]

To more effectively achieve Lott's objective of comparing voting patterns across county boundaries, we reanalyze Lott's data using a more standard specification that does not suffer from the problems highlighted in the previous section. Rather than using within-pair differences as Lott does, we employ a simple fixed effects model. The regression equation can be written as

$$\text{Absentee}_i = \beta_1 \text{InPerson}_i + \delta \text{SuspectCounty}_i + \sum_{k=1}^{K} \alpha_k I(\text{pair}_i = k) + \epsilon_{i,j} \qquad (1)$$

where Absentee_i and InPerson_i denote Trump's share of the absentee and in-person vote (respectively) in precinct i, SuspectCounty_i indicates whether precinct i is located in a "suspect" county (Fulton or Allegheny, depending on the state being analyzed), and each precinct is identified with one of K precinct pairs indexed by k, with α_k indicating the fixed effect for pair k. The regression thus asks whether Fulton or Allegheny county precincts have lower absentee support for Trump than would be expected controlling for their in-person support for Trump and any factors (observable or unobservable) that are common to paired precincts. Precinct pairs that do not involve a suspect county contribute to estimating the coefficient β_1 but do not otherwise contribute to the estimation of the key coefficient δ. Crucially, no arbitrary coding decisions are necessary.

We report the results of these analyses for Georgia in Table 1 below. In column 1 we simply regress Trump's share of the absentee vote on Trump's share of the in-person vote and a dummy for Fulton County; in column 2 we add precinct-pair fixed effects as in equation 1, essentially allowing the intercept to vary across Lott's precinct pairs; in column 3 we instead use county-pair fixed effects, with one intercept for Fulton-Coweta pairs, another for Carroll-Coweta pairs, etc. None of these specifications shows a substantively or statistically significant difference between Trump's share of the absentee vote in Fulton County precincts and other precincts.

Table 2 shows the same analysis for Pennsylvania in the same manner. Again, none of the specifications shows a substantively or statistically significant difference between Trump's

[9] Even if we could find a difference in voting patterns between county A and county B that is so suspicious as to suggest fraud, we may not know which county conducted the fraud.

Table 1: A Fixed Effects Specification Shows Nothing Suspicious in Fulton County, GA

	Dependent variable:		
	Trump Share Absentee		
	(1)	(2)	(3)
Trump Share, In-Person	0.760	0.606	0.654
	(0.049)	(0.077)	(0.056)
Fulton County	0.019	−0.003	0.006
	(0.019)	(0.020)	(0.018)
Observations	44	44	44
Precinct-Pair Fixed Effects		✓	
County-Pair Fixed Effects			✓

share of the absentee vote in Allegheny County precincts and other precincts.

In short, when we reanalyze Lott (2020)'s data with a more sensible fixed effects specification, we find no evidence of differences in voting patterns between precincts in Fulton County or Allegheny County and adjacent precincts in Republican-leaning counties. If such differences existed they would hardly be convincing evidence of fraud. But we find no such differences, undermining the basis for Lott (2020)'s claims.[10]

4 Conclusion

Lott (2020) claims to provide statistical evidence for voter fraud in Georgia and Pennsylvania in the 2020 election. We reanalyze Lott (2020)'s data to show that this claim is false. Lott (2020)'s results are reversed if we alter an entirely arbitrary coding rule, and we find no evidence of differences in voting behavior across county boundaries using a more standard and appropriate estimation technique. Thus even if we accepted the questionable premise that differences in voting behavior across county boundaries provide proof of fraud, we find no evidence of fraud in Fulton County or Allegheny County using Lott (2020)'s own data.

Like other claims of fraud following the 2020 election, Lott (2020)'s assertions have the potential to undermine belief in the integrity of American elections. Unlike most of these other claims, Lott's analysis has the appearance of careful social scientific research and cannot easily be dismissed as obviously illogical or mere hearsay. We emphasize that despite

[10] In the Appendix we also replicate and extend Lott's analysis of provisional ballots in Pennsylvania. As with his analysis of absentee voting, his conclusions about provisional ballots depend on the arbitrary coding of non-Allegheny precinct pairs (Figures 4 and 5) and fixed effects estimation shows no difference in Biden's share of the provisional vote in Allegheny precincts and other precincts (Tables 5 and 6).

Table 2: A Fixed Effects Specification Shows Nothing Suspicious in Allegheny County, PA

	Dependent variable:		
	Trump Share, Absentee		
	(1)	(2)	(3)
Trump Share, In-Person	0.511	0.307	0.442
	(0.042)	(0.066)	(0.048)
Allegheny County	0.003	0.003	0.006
	(0.008)	(0.009)	(0.009)
Observations	174	174	174
Precinct-Pair Fixed Effects		✓	
County-Pair Fixed Effects			✓

its incorrect conclusions, Lott (2020) has attractive aspects: focusing on border precincts is a reasonable way to address possible differences between counties, and to carry out that analysis one must painstakingly collect data from various county and municipality websites. Indeed, it is because Lott (2020) shares many characteristics with rigorous social scientific research that we considered it especially important to investigate these claims more deeply.

Observers concerned about the integrity of the 2020 election can be reassured that Lott (2020)'s claims of election fraud in Georgia and Pennsylvania have no basis in fact. We hope that our analysis helps undo some of the damage that has already been done by these and other unfounded claims of election fraud.

References

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Appendix

Table 3: Lott's Conclusions Are Reversed if the Arbitrary Ordering of Precinct Differences is Reversed (Georgia)

	Dependent variable:	
	Difference, Trump Absentee (Lott (2020), Table 2)	
	(1)	(2)
Difference, Trump In-Person Vote	0.574	0.574
	(0.073)	(0.073)
Fulton County	−0.072	0.055
	(0.038)	(0.033)
Observations	22	22
Reverse Coding		✓

Table 4: Lott's Conclusions Are Reversed if the Arbitrary Ordering of Precinct Differences is Reversed (Pennsylvania)

	Dependent variable:	
	Difference, Trump Absentee (Lott (2020), Table 5)	
	(1)	(2)
Difference, Trump In-Person Vote	0.359	0.359
	(0.069)	(0.069)
Allegheny County	−0.034	0.041
	(0.019)	(0.020)
Observations	87	87
Reverse Coding		✓

Table 5: Pennsylvania Provisional Ballot Results

	Dependent variable:			
	Difference, Trump Provisional (Lott (2020), Table 6)	Trump Provisional Vote		
	(1)	(2)	(3)	(4)
Difference, Trump In-Person Vote	1.038			
	(0.558)			
Trump, In-Person Vote		0.729	1.055	0.690
		(0.222)	(0.552)	(0.257)
Allegheny County	−0.125	−0.004	−0.036	−0.047
	(0.141)	(0.036)	(0.044)	(0.048)
Observations	34	120	120	120
Precinct-Pair Fixed Effects			✓	
County-Pair Fixed Effects				✓

Table 6: Pennsylvania Provisional Ballot Results, Total Ballots

	Dependent variable:			
	Difference, Biden Share of Votes From Provisional Ballots (Lott (2020), Table 7a)	Biden Share of Votes From Provisional Ballots		
	(1)	(2)	(3)	(4)
Difference, Share of Trump Vote from Provisional Ballots	0.364			
	(0.105)			
Share of Trump Vote from Provisional Ballots		0.371	0.385	0.342
		(0.078)	(0.103)	(0.082)
Allegheny County	0.010	0.007	0.007	0.007
	(0.004)	(0.002)	(0.002)	(0.002)
Observations	87	174	174	174
Precinct-Pair Fixed Effects			✓	
County-Pair Fixed Effects				✓

Figure 4: Distribution of Estimates for Alternative Precinct Differencing Orders, Pennsylvania Provisional Ballots

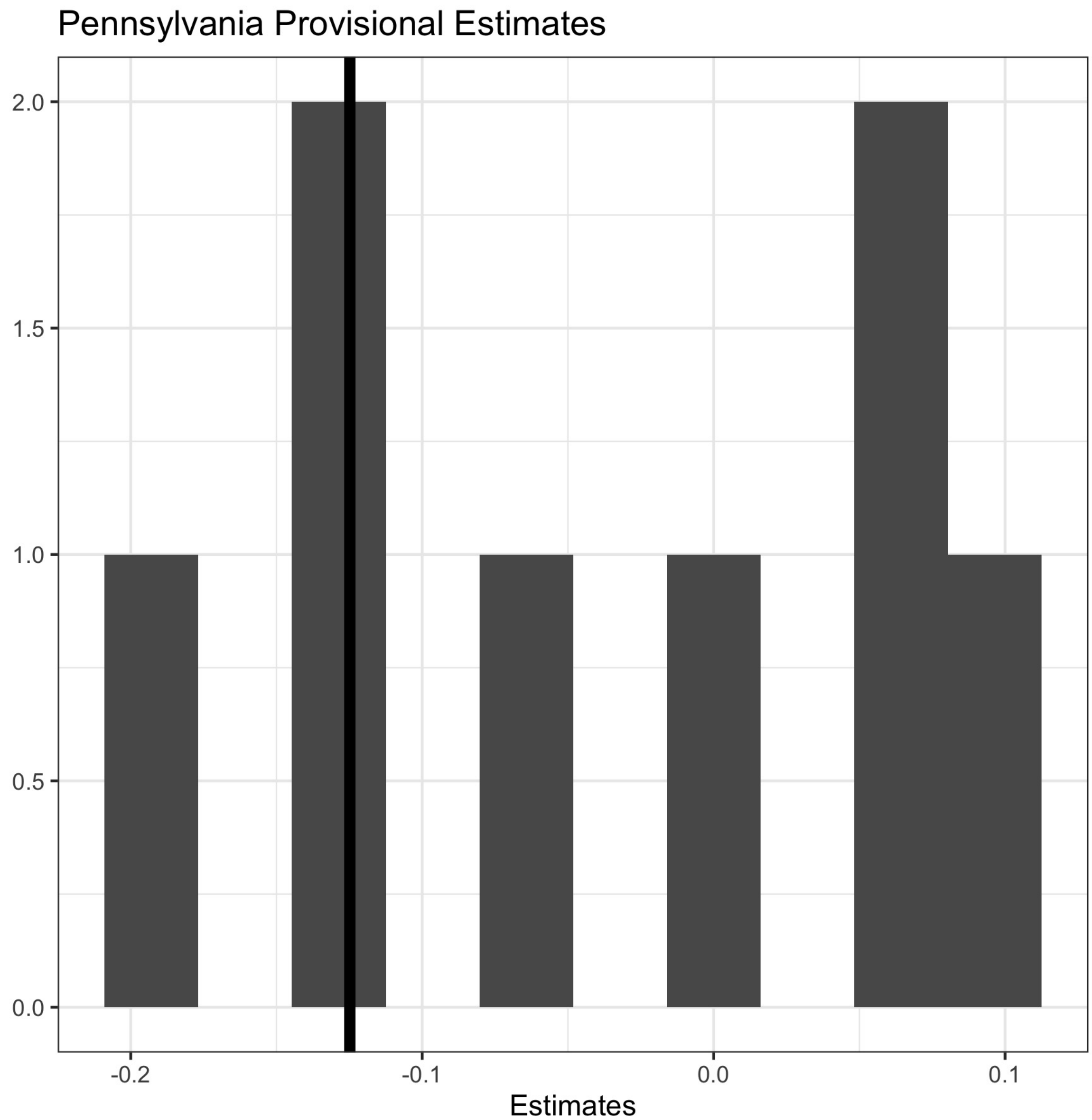

Figure 5: Distribution of Estimates for Alternative Precinct Differencing Orders, Share of Biden Ballots from Pennsylvania Provisional Ballots