

Comment on “Voter Identification Laws and the Suppression of Minority Votes”*

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Abstract

Widespread concern that voter identification laws suppress turnout among racial and ethnic minorities has made empirical evaluations of these laws crucial. But problems with administrative records and survey data impede such evaluations. We replicate and extend Hajnal, Lajevardi and Nielson (2017), which reports that voter ID laws decrease turnout among minorities, using validated turnout data from five national surveys conducted between 2006 and 2014. We show that the results of the paper are a product of data inaccuracies; the presented evidence does not support the stated conclusion; and alternative model specifications produce highly variable results. When errors are corrected, one can recover positive, negative, or null estimates of the effect of voter ID laws on turnout, precluding firm conclusions. We highlight more general problems with available data for research on election administration and we identify more appropriate data sources for research on state voting laws’ effects.

*Supplementary material for this article is available in the appendix. Replication files are available in the JOP Data Archive on Dataverse <http://thedata.harvard.edu/dvn/dv/jop>.

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Requiring individuals to show photo identification in order to vote has the potential to curtail voting rights and tilt election outcomes by suppressing voter turnout. But isolating the effect of voter ID laws on turnout from other causes has proved challenging (Highton 2017). States that implement voter ID laws are different from those that do not implement the laws. Even within states, the effect of the laws is hard to isolate because 85 to 95 percent of the national voting-eligible population possesses valid photo identification,¹ so those with ID dominate over-time comparisons of state-level turnout. Surveys can help researchers study the turnout decisions of those most at-risk of being affected by voter ID, but survey-based analyses of voter ID laws have their own challenges. Common national surveys are typically unrepresentative of state voting populations, and may be insufficiently powered to study the subgroups believed to be more affected by voter ID laws (Stoker and Bowers 2002). And low-SES citizens, who are most affected by voter ID laws, are less likely to be registered to vote and respond to surveys (Jackman and Spahn 2017), introducing selection bias.

The problems of using survey data to assess the effect of voter ID laws are evident in a recent article on this subject, Hajnal, Lajevardi and Nielson (2017) (HLN hereafter). HLN assesses voter ID using individual-level validated turnout data from five online Cooperative Congressional Election Studies (CCES) surveys, 2006-2014. HLN concludes that strict voter ID laws cause a large turnout decline among minorities, including among Latinos, who “are 10 [percentage points] less likely to turn out in general elections in states with strict ID laws than in states without strict ID regulations, all else equal” (368).² HLN implies that voter ID laws represent a major impediment to voting with a disparate racial impact.

In this article, we report analyses demonstrating that the conclusions reported by HLN are unsupported. HLN use survey data to approximate state-level turnout rates, a technique

¹See “Issues Related to State Voter Identification Laws.” 2014. GAO-14-634, U.S. Government Accountability Office; Ansolabehere and Hersh (2016).

²HLN also examine the relationship between voter ID laws and Democratic and Republican turnout rates. Here, we focus on minority turnout because of its relevance under the Voting Rights Act.

we show to be fraught with measurement error due to survey nonresponse bias and variation in vote validation procedures across states and over time. HLN’s CCES-based turnout measures, combined with a coding decision about respondents who could not be matched to voter files, produce turnout estimates that differ substantially from official ones.

Using a placebo test that models turnout in years prior to the enactment of voter ID laws, we show that the core analysis in HLN, a series of cross-sectional regressions, does not adequately account for unobserved baseline differences between states with and without these laws. In a supplementary analysis, HLN include a difference-in-differences (DID) model to estimate within-state changes in turnout, a better technique for removing omitted variable bias. This additional analysis asks too much of the CCES data, which is designed to produce nationally representative samples each election year, not samples representative over time within states. In fact, changes in CCES turnout data over time within states bear little relationship to actual turnout changes within states. After addressing errors of specification and interpretation in the DID model, we find that no consistent relationship between voter ID laws and turnout can be established using the HLN CCES data.

Use of National Surveys for State Research

The CCES is widely used in analysis of individual-level voting behavior. The CCES seems like a promising resource for the study of voter ID laws because it includes self-reported racial and ethnic identifiers, variables absent from most voter files. But the CCES data are poorly suited to estimate state-level turnout for several reasons. First, even large nationally representative surveys have few respondents from smaller states, let alone minority groups from within these states.³ Unless a survey is oversampling citizens from small states and minority populations, many state-level turnout estimates, particularly for minorities, will be extremely noisy. Second, Jackman and Spahn (2017) find that many markers of

³For example, 493 of the 56,635 respondents on the 2014 CCES were from Kansas, only 17 and 24 of whom are black and Hispanic, respectively.

socioeconomic status positively associate with an individual being absent both from voter registrations rolls and consumer databases. The kind of person who lacks an ID is unlikely to be accurately represented in the opt-in online CCES study.

Third, over-time comparisons of validated voters in the CCES are problematic because the criteria used to link survey respondents to registration records have changed over time and vary across states. Table A.1 shows that the percentage of respondents who fail to match to the voter registration database increased from about 10 percent in 2010 to 30 percent in 2014. The change in the number of unmatched Hispanics is even starker, increasing from 15 to 42 percent over the same time period. The inconsistency in the CCES vote validation process is relevant to the analysis of voter ID because it generates time-correlated measurement error in turnout estimates.

These features of the CCES data, as well as several coding decisions in HLN, make HLN’s turnout measures poor proxies for actual turnout. To demonstrate this, Figure 1 reports a cross-sectional analysis comparing “implied” turnout rates in HLN—the rates estimated for each state-year when using HLN’s coding decisions—to actual state-level turnout rates as reported by official sources. While this figure measures overall statewide turnout, note that the problems we identify here likely would be magnified if we were able to compare actual and estimated turnout by racial group. We cannot do so because few states report turnout by race.

Figure 1 (panel 1) shows that HLN’s estimates of state-year turnout often deviate substantially from the truth. If the CCES state-level turnout data were accurate, we should expect only small deviations from the 45-degree line. In most state-years, the HLN data overstate the share of the voters by about 25 percentage points, while in 15 states, HLN’s rates are about 10 points below actual turnout.⁴ Many cases in which turnout is severely

⁴In the appendix, Table A.2 and Table A.3 report turnout rates by state-year in general and primary elections, respectively.

underestimated are from jurisdictions that were not properly validated. Many jurisdictions were not validated with turnout in the 2006 CCES. Virginia was not validated until 2012.⁵ Respondents who claimed to have voted in such jurisdictions were coded as not matching to the database, and hence dropped, while those who claim not to have voted remained in the sample. As a consequence, HLN’s analysis assumes a turnout rate of close to zero percent. Given the limitations of the vote validation, we contend that neither 2006 data anywhere, nor Virginia’s records from 2008, should be included in any over-time analysis.⁶

As the upper-right panel shows, once the 2006 data and Virginia 2008 data are excluded, HLN almost always substantially overestimate turnout in a state-year. One potential reason for this overestimation is because HLN drop observations that fail to match to the voter registration database. This contrasts with Ansolabehere and Hersh’s (2012) recommendation that unmatched respondents be coded as non-voters. Being unregistered is the most likely reason why a respondent would fail to match. The bottom left panel of Figure 1 shows that when respondents who fail to match to the voter database are treated as non-voters rather than dropped, CCES estimates of turnout more closely match actual turnout. One way to assess the improvement is to compare the R^2 when CCES estimates of state-level turnout are regressed on actual turnout. We find that the R^2 increases from 0.36 to 0.58 when we code the unmatched as non-voters.⁷ The R^2 further increases to 0.69 when we weight observations by the inverse of the sampling variance of CCES turnout in the state, suggesting that small sample sizes limit the ability of the CCES to estimate turnout in smaller states.⁸

The CCES data might be salvageable here if errors were consistent within each state.

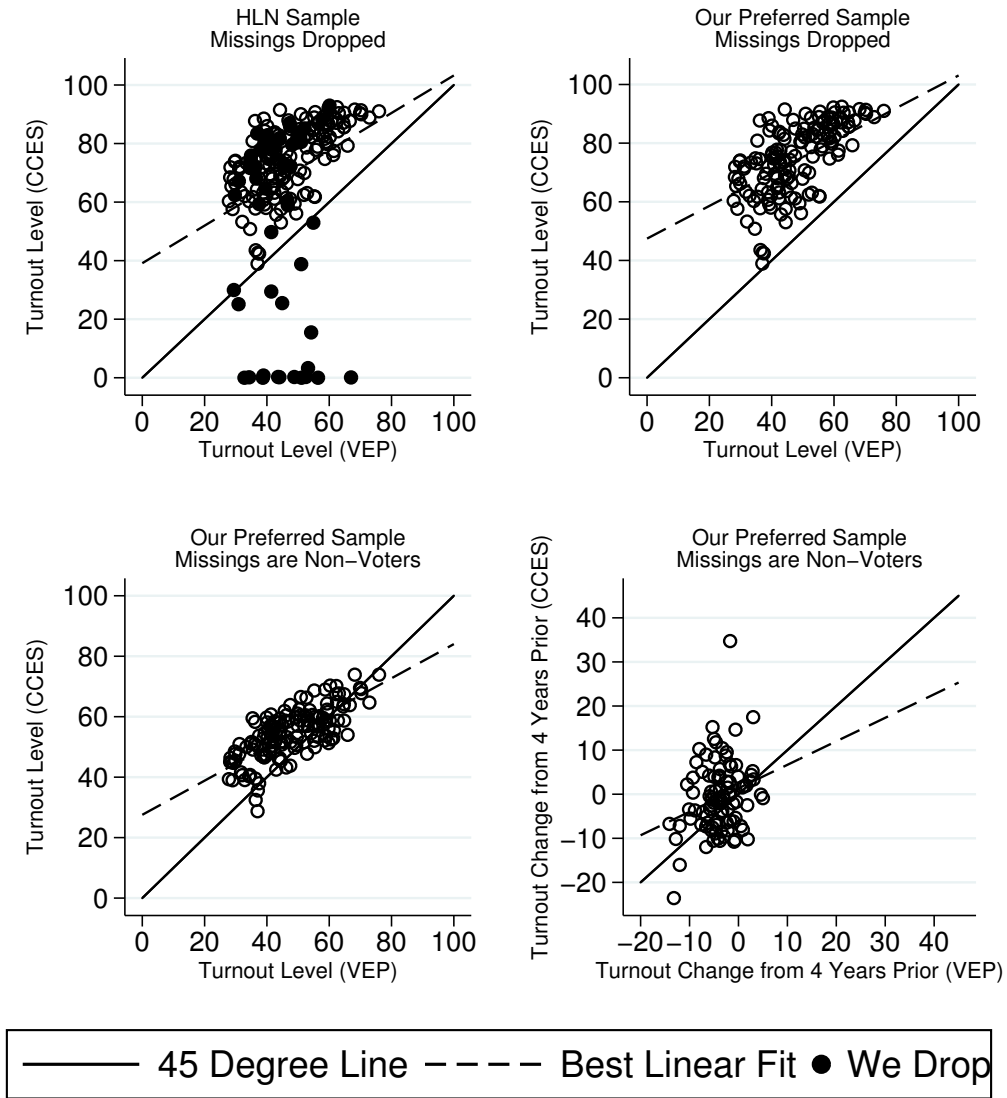
⁵Due to a state policy in Virginia that was in effect through 2010, CCES vendors did not have access to vote history in that state. HLN correctly code Virginia’s turnout as missing in 2010, but code nearly all Virginia CCES respondents as non-voters in 2008.

⁶We also exclude primary election data from Louisiana and Virginia for all years based on inconsistencies highlighted in Table A.3.

⁷In addition, the mean-squared error declines from 9.0 to 5.8.

⁸In addition, the mean-squared error declines from 5.8 to 4.9.

Figure 1: Measurement Error in HLN's State-Level Turnout Estimates



Note: HLN turnout percentage is calculated to be consistent with how turnout is coded in HLN Table 1, meaning that we apply sample weights, drop respondents who self-classify as being unregistered, and drop respondents who do not match to a voter file record. Actual turnout percentage is calculated by dividing the number of ballots cast for the highest office on the ballot in a state-year by the estimated voting-eligible population (VEP), as provided by the United States Election Project.

Unfortunately, as the bottom right panel of Figure 1 shows, within-state changes in turnout as measured in the CCES have little relationship to within-state changes in turnout according to official records. The R^2 is less than 0.15 when we regress the change in CCES turnout between elections on the actual change in turnout between elections, (dropping bad data, coding unmatched as missing, and weighting by the inverse of the sampling variance).⁹ This means the overwhelming share of the within-state variation in turnout in the CCES is noise.

No definitive source exists on turnout by race by state and year; however, Figure A.2 in the Appendix shows weak relationships between the racial gaps estimated in the CCES and the Current Population Survey (CPS), a common resource in the study of race and turnout. For Hispanics, there is an insignificant negative relationship between the racial gap in the CCES and CPS in a state-year. In contrast, there is a positive association between the difference in white and black turnout in the CPS and the CCES. These findings are consistent with the claim that the sample issues in the CCES are magnified when looking at racial heterogeneity in turnout within a state.

While the CCES is an important resource for individual-level turnout research (e.g., Fraga 2016) it is problematic when repurposed to make state-level inferences or inferences about small groups (Stoker and Bowers 2002). The data are particularly problematic when the analysis requires the use of state fixed-effects to reduce concerns of omitted variable bias, because the small sample within states makes within-state comparison noisy. The survey data and coding decisions used in HLN inject substantial error into state-level estimates of voter turnout. While this error can be reduced with alternative coding decisions, a substantial amount of error is unavoidable with these data.

Estimating Voter ID Laws' Effects on Turnout

⁹Figure A.1 separates the within state change between the presidential elections in 2008 and 2012 and the midterm elections in 2010 and 2014, and shows there is a stronger relationship between CCES estimates and actual turnout change for the later than the former.

Imperfect data do not preclude a useful study, and social scientists often rightly choose to analyze such data rather than surrender an inquiry altogether. In light of this, we now replicate and extend the analysis in HLN. We highlight and attempt to correct specification and interpretation errors in HLN. Our goal is to assess whether improving the estimation procedures can yield meaningful and reliable estimates of voter ID laws' effect. We find no clear evidence about the effects of voter ID laws.

Cross-sectional comparisons. A central concern in the study of voter ID laws' impact is omitted variable bias: states that did and did not adopt voter ID laws systematically differ on unobservable dimensions that also affect turnout. To address the systematic differences, HLN presents a series of cross-sectional regressions that include a host of variables meant to account for confounding factors. In these regressions, an indicator variable for existence of a strict ID law in a state in each year is interacted with the respondent race/ethnicity. The main weakness of this approach is clearly acknowledged in HLN: the causal effect of voter ID laws is identified only if all relevant confounders are assumed included in the models.

We report results of a placebo test meant to assess the plausibility of this assumption by applying the HLN cross-sectional regression models to turnout in the period before ID laws were enacted. Table A.4 in our appendix presents estimates from this placebo test using nearly the same specification that HLN report in their Table 1, Column 1.¹⁰ The interpretation of the coefficient on the voter ID treatment variable is voter ID laws' effect before their adoption in states *that had not yet implemented strict voter ID laws* relative to states *which never implemented such a law*, after adjusting for the same individual-level and

¹⁰There are two main differences. First, we do not include states that previously implemented strict voter ID. Second, our treatment variable is an indicator for whether the state will implement a strict voter ID law by 2014. We also omit 2006 data due to the data problems cited above, and 2014 data because, after applying the above restrictions, no states that implemented a voter ID law by 2014 remain in the sample. By defining the treatment this way we necessarily drop the authors' indicator variable for a state being in the first year of its voter ID law.

state-level variables used in HLN. The results presented in Table A.4 suggest that voter ID laws “caused” turnout to be lower at baseline in states where they had yet to be adopted. The failure of the placebo test implies that HLN’s cross-sectional regressions fail to account for baseline differences across states.

Within-state analyses If cross-state comparisons are vulnerable to unobserved confounders, perhaps a within-state analysis could yield more accurate estimates of a causal effect. That’s why HLN report a supplementary model (HLN Appendix Table A9) with state and year fixed effects (i.e., a difference-in-differences (DID) estimator) meant to address this issue.¹¹ The main text of HLN notes that this is “among the most rigorous ways to examine panel data,” and that the results of this fixed-effects analysis tell “essentially the same story as our other analysis... Racial and ethnic minorities...are especially hurt by strict voter identification laws,” (p.375).

This description is inaccurate. The estimates reported in HLN Table A9 imply that voter ID laws *increased* turnout across all racial and ethnic groups, though the increase was less pronounced for Hispanics than for whites.¹² As Table A.5 in our appendix shows, this fixed-

¹¹In an email exchange Hajnal, Lajevardi and Nielson asserted that the model in the appendix is mistakenly missing three key covariates: Republican control of the state house, state senate, and governor’s office. The authors provided additional replication code in support of this claim. This new replication code differs from the original code and model in several respects. First, we replicated the original coefficients and standard errors in Table A9 using a linear regression with unclustered standard errors and without using weights. The new code uses a logit regression, survey weights, and clusters the standard errors at the state level. While including Republican control of political office adjusts the coefficients, this is the result of the included covariates removing Virginia from the analysis. Even if we stipulate to this design, we still find that the reported effect estimates are sensitive to the model specification, coding decisions, and research design.

¹²In contrast to the other models in the paper, we replicated the results in Table A9 using OLS regression, no survey weights, and without clustering the standard errors in order to replicate the published results. HLN provided replication code for their appendix, but the estimated model from that code does not produce the estimates reported in Table A9.

effects model estimates that the laws increased turnout among white, African American, Latino, Asian American and mixed race voters by 10.9, 10.4, 6.5, 12.5 and 8.3 percentage points in general elections, respectively. The laws’ positive turnout effects for Latinos are only *relatively* lower compared to the large positive effects estimated for the other groups. Compared to most turnout effects reported in prior work, these effects are also implausibly large (Citrin, Green and Levy 2014).

In addition to Table A9, HLN Figure 4 presents estimates from simple bivariate difference-in-differences models, comparing changes in turnout (2010 to 2014) in just three of the states that implemented strict ID laws between these years to the changes in turnout in the other states. HLN reports that voter ID laws increase the turnout *gap* between whites and other groups without demonstrating that voter ID laws generally suppress turnout.¹³ Our replication produces no consistent evidence of suppressed turnout. Figure A.3 in our appendix shows that the large white-minority gaps reported in HLN Figure 4 are driven by increased white turnout in Mississippi, North Dakota, and Texas, not by a drop in minority turnout.

Importantly, the difference between a law that suppresses turnout for minorities versus one that increases turnout for minorities but does so less than for whites is very important for voting rights claims, since claims under Section 2 of the VRA are focused on laws resulting in the “denial or abridgement of the right...to vote on account of race or color.”

Improved analysis, inconclusive results. HLN contains additional data processing and modeling errors which we attempt to correct in order to determine whether an improved analysis leads to more robust results. Without explanation, HLN includes in their DID model an indicator of whether a state had a strict voter ID law *and* a separate indicator

¹³Note: In replicating these results, we recovered different effects than those reported in Figure 4 and accompanying text. In an email exchange, the authors stated they had miscalculated the effects for Asian Americans and those with mixed race backgrounds.

of whether the state was in its first year with this strict ID law. With this second variable included, the correct interpretation of their estimates is not the effect of ID laws on turnout, but the effect after the first year of implementation. In this model, the interactions with racial groups are harder to interpret since they are not also interacted with the “first year” indicator.¹⁴ There are also a number of inconsistencies in model specifications.¹⁵¹⁶¹⁷¹⁸

Figure 2 presents the treatment effect estimates implied by the data and fixed-effects model in HLN Table A9, as well as alternative estimates after we address the modeling

¹⁴The first year indicator contains some coding errors. Table A.2 shows that HLN code “First year of strict law” in Arizona occurring in 2014, even though it is coded in their data as having a strict ID law since 2006. HLN also never code “First year of strict law” in Virginia, even though Virginia implemented a strict ID law in 2011, according to the HLN data. Research provides no clear suggestions on the direction of a “new law effect.” When a law is first implemented, people must adjust to the law and obtain IDs, additionally depressing turnout, but such laws also often induce a counter mobilization that can be strongest in the first years after passage Valentino and Neuner (2016).

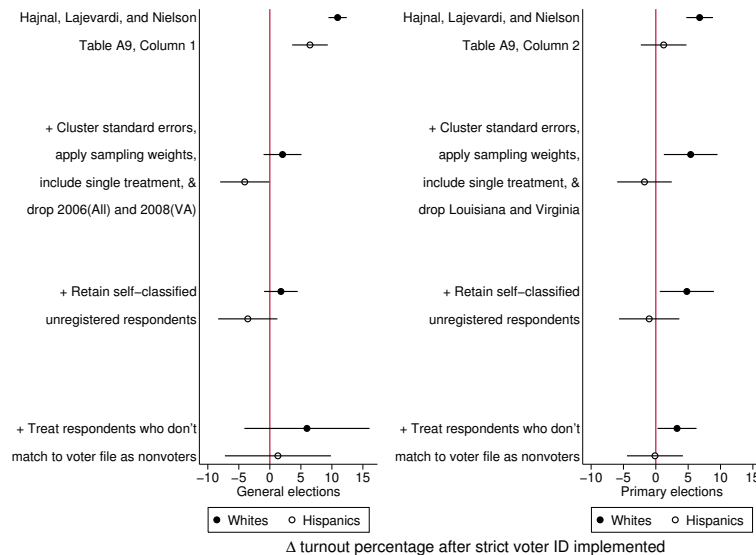
¹⁵For example, HLN reports standard errors clustered at the state level in the main analysis, but not in the appendix analysis. Standard errors need to be clustered by state because all respondents in a state are affected by the same voter ID law, and failing to cluster would likely exaggerate the statistical precision of subsequent estimates. Many state-level attributes affect the turnout calculus of all individuals in a given state. And in any given election year, the turnout decisions of individuals in a state may respond similarly to time variant phenomena.

¹⁶Based on our replications, it also appears that sampling weights were only used in Table 1, but not Figure 4 or Table A9. For the analyses reported in Table 1 and Table A9, but not Figure 4, HLN exclude about 8% of respondents based on their self-reported registration status. Because the decision of whether to register could also be affected by a strict voter ID law, it seems more appropriate to keep these respondents in the sample.

¹⁷HLN code six states as implementing voter ID between 2010 and 2014 when constructing Table 1 and Table A9, but then only consider three of them when performing the analysis that appears in Figure 4.

¹⁸An additional concern is that in HLN’s models of primary election turnout control for competitiveness using a measure of general election competitiveness rather than primary competitiveness. If the model is meant to mirror the general election model, it should include a control for primary competitiveness, which is important given the dynamics of presidential primaries over this period.

Figure 2: Sensitivity of Estimates from Models with State Fixed Effects to Alternative Specifications



Note: Bars represent 95% confidence intervals. Models are cumulative (e.g., we are also retaining self-classified unregistered respondents in model in which we treat respondents who do not match to voter file as nonvoters). See Table A.6 (left) and Table A.7 (right) in our appendix for more details on the models used to produce these estimates.

and specification concerns. For clarity and brevity, we focus on effects among white and Hispanic voters only.¹⁹ The effect for whites is positive, but only statistically significant in primaries. The effect for Latinos is sometimes positive, sometimes negative, and generally not significant. Our 95% confidence intervals are generally 8 to 10 percentage points wide, consistent with the previous observation that models of this sort are underpowered to adjudicate between plausible effect sizes of voter ID policy (Erikson and Minnite 2009).²⁰

We find similar patterns when we examine the robustness of the results presented in

¹⁹Results for all racial groups are presented in Table A.6 (general elections) and Table A.7 (primary elections) in our appendix.

²⁰In addition, these confidence intervals do not account for uncertainty in model specification and multiple testing. We maintain HLN's statistical model for comparability.

HLN’s Figure 4.²¹ In no specification do we find that primary or general turnout significantly declined between 2010 and 2014 among Hispanics or Blacks in states that implemented a strict voter ID law in the interim, and in many the point estimate is positive. Several specifications suggest that white turnout increased, particularly in primary elections. But we suspect that this is largely due to the data errors we identified, as actual returns indicate that overall turnout declined in these states relative to the rest of the country.²²

Implications for Future Research

Our analysis shows that national surveys are ill-suited for estimating the effect of state elections laws on voter turnout. While augmented national survey data have useful applications, they have limited use in this context. The CCES survey used in HLN is not representative of hard-to-reach populations (such as people lacking photo IDs), and many of the discrepancies we identify are due to substantial year-to-year differences in measurement and record linkage. These data errors are sufficiently pervasive—across states and over time—that standard techniques cannot recover plausible effect estimates.

Our results may explain why the published results in HLN deviate substantially from other published findings of a treatment effect of zero, or close to it (Citrin, Green and Levy 2014; Highton 2017). The cross-sectional regressions that comprise the central analysis in the study fail to adequately correct for omitted variable bias. The difference-in-differences model yields results that, if taken as true, would actually *refute* the claim that voter ID laws suppress turnout. Finally, our attempts to address measurement and specification issues still fail to produce the robust results required to support public policy recommendations. Using

²¹See Figure A.5, Table A.9, and Table A.10 for more details.

²²In our appendix, Figure A.4 and Table A.8 present our tests of the robustness of the pooled cross-sectional results presented in HLN’s Table 1. We find that the negative association between a strict photo ID law and minority turnout attenuates but remains as these errors are corrected. While this replication is consistent with HLN’s initial findings, we do not find it credible since our previous analysis shows the vulnerability of the pooled cross-sectional to omitted variable bias.

these data and this research design, we can draw no firm conclusions about the turnout effects of strict voter ID laws.

Problems specific to the CCES have been discussed here, but similar problems are sure to appear in the context of any survey constructed to be representative at the national level. One key implication of our work is that distributors of survey data should provide additional guidance to researchers. The CCES does not presently offer users clear enough guidelines for how to use features like validated vote history, including how to deal with over-time variation in the vote-validation procedures and in data quality. Given the existing evidence, researchers should turn to data that allow more precision than surveys offer. Such measures could include voter databases linked to records of ID holders (Ansolabehere and Hersh 2016), or custom-sampling surveys of individuals affected by voter ID laws. While strategies like these may require more financial investments and partnerships with governments, the stakes are high enough to warrant additional investment.

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