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Enrico Cantoni
Vincent Pons

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ABSTRACT

U.S. states increasingly require identification to vote – an ostensive attempt to deter fraud that prompts complaints of selective disenfranchisement. Using a difference-in-differences design on a 1.3-billion-observations panel, we find the laws have no negative effect on registration or turnout, overall or for any group defined by race, gender, age, or party affiliation. These results hold through a large number of specifications and cannot be attributed to mobilization against the laws, measured by campaign contributions and self-reported political engagement. ID requirements have no effect on fraud either – actual or perceived. Overall, our results suggest that efforts to reform voter ID laws may not have much impact on elections.

Enrico Cantoni
University of Bologna
Department of Economics
Piazza Scaravilli 2, Bologna
Italy
enrico.cantoni@unibo.it

Vincent Pons
Harvard Business School
Morgan Hall 289
Soldiers Field
Boston, MA 02163
and NBER
vpons@hbs.edu

1 Introduction

A tension exists in democracies between safeguarding the integrity of the vote and ensuring broad participation. Electoral fraud – which takes the form of stuffing ballot boxes, buying or intimidating voters, or impersonating citizens who are deceased, absentee, or no longer in residence – was prevalent in the early decades of Western democracies (e.g., Garrigou, 1992) and is still widespread in developing democracies today (e.g., Collier and Vicente, 2012). Combating such fraud is critical to building citizen confidence in election results and consolidating democratic regimes (Diamond, 1999; Berman et al., 2014). However, rules pursuing those objectives can also weaken democracy if they keep eligible citizens away from the polling booth. Compounding the matter, legislators have an incentive to push for restrictions if citizens enfranchised by flexible rules will likely vote against them – or oppose restrictions if that will widen their base.

This paper presents empirical evidence on the consequences of strict ID laws in the context of the United States, where the debate on control versus enfranchisement is particularly heated. Between 2006 and 2016, 11 states, mostly with Republican majorities, adopted strict voter identification measures (Hicks et al., 2015).[1] These laws require voters to present an accepted form of identification document before voting. Voters who fail to do so can cast a provisional ballot but their vote will be rejected unless they present proper ID within the next few days. Other states either do not request identification or allow voters without ID to sign an affidavit and cast a regular ballot.

The effects of these measures on overall participation are ex-ante ambiguous: while strict ID laws create additional costs for people without ID, those who want to vote can acquire it before the election, and it is unclear what share of non-ID-holders would vote otherwise. Moreover, other citizens may become more likely to vote if the laws enhance their confidence in the fairness of the election, similarly to the participation boost of improving beliefs about ballot secrecy (Gerber et al., 2013b).

Using a nationwide individual-level panel dataset 2008–2016 and a difference-in-differences (DD) design, we find that strict ID laws have no significant negative effect on registration or turnout, overall or for any subgroup defined by age, gender, race, or party affiliation. Most importantly, they do not decrease the participation of ethnic minorities relative to whites. The laws' overall effects remain close to zero and non-significant whether the election is a midterm or presidential election, and whether the laws are the more restrictive type that stipulate photo IDs. Voters in treated states did have different turnout levels prior to the laws, but they did not show different participation *trends* than others, lending support for our identification strategy.

[1] These states are Arizona, Georgia, Indiana, Kansas, Mississippi, North Dakota, Ohio, Tennessee, Texas, Virginia, and Wisconsin. Texas is the only state which experienced a reversal: its strict ID law, adopted in 2014, was struck down by a federal court in 2016.

These results contrast with the large participation effects of other dimensions of election administration: voter registration laws (Rosenstone and Wolfinger, 1978; Braconnier et al., 2017), convenience voting (Gerber et al., 2013a; Hodler et al., 2015; Kaplan and Yuan, 2018), voting technology (Fujiwara, 2015), and distance to the polling station (Cantoni, 2018). It could be that our null findings reflect two mutually opposing forces: the laws' negative effect on participation versus a mobilization of voters against a threat to their right to vote (Citrin et al., 2014; Biggers and Smith, 2018). However, we do not find evidence of such backlash. Strict ID laws had no significant negative effect on any of our measures of mobilization: people's self-reported having been contacted by a campaign or having donated to a candidate, put up a campaign sign, or volunteered for a campaign, measured using the Cooperative Congressional Election Study surveys; or campaign contributions, measured using administrative records from Bonica (2015).

Our findings complement existing studies comparing turnout in states with and without voter ID laws which have found either no effect (e.g., Mycoff et al., 2009; Erikson and Minnite, 2009; Highton, 2017) or negative effects (e.g., Alvarez et al., 2011; Government Accountability Office, 2014; Hajnal et al., 2017).[2] We improve on this literature in three critical ways. First, existing estimates rely on state-level turnout aggregates, which make estimating heterogeneous effects by voter characteristics difficult, or on national surveys, which have limited representativeness and accuracy. Their samples can fail to reflect state voting populations; voters' likelihood to respond can differ across groups; and their turnout data are based on self-reports (which are untrustworthy) (Silver et al., 1986; Ansolabehere and Hersh, 2012) or use validation procedures which vary across states and over time (Grimmer et al., 2018). By contrast, we use administrative records of individual registration and turnout. Our data, collected by the political data vendor Catalist, cover the vast majority of U.S. voting-age individuals, 2008–2016, resulting in a total of more than 1.3 billion observations. Second, prior research has examined the effects of ID laws using the participation of registered citizens as sole outcome, neglecting possible effects on voter registration (citizens who expect not to be able to vote may not register in the first place), and possibly underestimating the laws' effects on turnout (if citizens deterred from registering have a low propensity to vote). By contrast, Catalist data include unregistered voters, allowing us to measure effects on both registration and turnout. Finally, previous papers have used unconvincing or untestable identification assumptions, such as cross-sectional regressions or DD regressions with only two cross-sections. We use the full length of our panel to test the validity of the parallel-trends assumption underlying our design; we demonstrate the robustness of our estimates to alternative specifications including

[2] Other studies use surveys or administrative records to directly count people prevented from voting due to lack of valid identification, and find small numbers (e.g., Ansolabehere, 2009; Henninger et al., 2018). However, administrative counts of people who go to the polls and cannot vote for lack of ID exclude voters deterred from even trying. Estimates based on survey responses might similarly be biased downwards, if non-voters underreport lacking a valid ID as the reason for choosing not to vote, or upwards, if those without an ID overreport their desire to vote.

state and voter controls, linear state time trends (or state-by-year fixed effects, for heterogeneous effects), and voter fixed effects; and we show that our results hold when restricting our sample to adjacent counties in neighboring states.

Furthermore, we give evidence on both sides of the debate: while most existing research has focused on the effects of strict ID laws on participation, we also measure their effects on voter fraud – the laws' ostensive target. Research has shown that interventions such as deploying observers (Ichino and Schündeln, 2012) or informing voters (Vicente, 2014) can successfully reduce fraud in contexts where it is prevalent. Even if fraud is much more limited in the United States, the extensive attention paid to existing cases could make any reduction consequential. We use two datasets listing cases of voter fraud: one by the Heritage Foundation, a conservative think tank, and another one by News21, a more liberal initiative. We find no significant effect in either dataset. Irrespective of any effect on fraud, the very existence of stricter controls at polling places could be perceived as an improvement in election administration and increase voter confidence (Norris, 2004; Atkeson and Saunders, 2007). Stewart et al. (2016) uses the Survey of the Performance of American Elections to show that perceived occurrence of different types of fraud is similar in states with and without strict ID laws. Our DD estimates use the same survey to show no significant impact on this outcome. In addition, we use the American National Election Studies surveys to measure the laws' impact on citizens' belief that elections were fair. Again, we find no significant effect.

Our finding that voter ID laws have null effects is particularly salient in the United States, given the country's history of balancing the threat of fraud against the promise of enfranchisement. Well into the 19th century, political parties took advantage of the lack of control over the identity of people coming to vote. They hired large groups of "repeaters," who walked from one polling place to another and voted over and over again (Converse, 1972). After 1890, many states addressed widespread fraud by requiring citizens to prove their identity and eligibility and sign a register before voting. Registration laws reduced voter impersonation, as voters' signatures could be verified on Election Day, and the registers were frequently purged of nonresidents and the deceased. However, they also created an additional burden for eligible voters, which has prevented many from participating in elections ever since (Nickerson, 2015). Conversely, voting by mail, early voting, and other forms of convenience voting, which have become more widespread since the turn of the century, facilitate participation (e.g., Gerber et al., 2013a) but are more susceptible to fraud than in-person voting on Election Day (Gronke et al., 2008).

Over the last decade, strict ID laws have become one of the country's most polarizing issues (Hasen, 2012): they are supported by a large majority of the overall population, but with a growing gap between Republicans and Democrats (Stewart et al., 2016). Advocates and opponents of these laws disagree both on their benefits and costs.

On benefits, advocates insist that electoral fraud still exists today – about one third of Americans believe it is widespread (Kobach, 2011; Richman et al., 2014). They argue that strict ID laws are required to deter voter impersonation, double-voting, and non-citizen voting, and to boost public confidence in the integrity of elections (von Spakovsky, 2012). Opponents argue that voter fraud, extremely rare, results from individual cases of initiative or error rather than a coordinated effort (Minnite, 2010; Cottrell et al., 2018). On costs, advocates of strict laws argue that they impose only a minor ordeal on voters, as proof of identification is also required for other activities, like cashing a check. They point to the fact that most other Western democracies also require voters to show identification (Commission on Federal Election Reform, 2005). Opponents observe that, unlike other countries, the United States does not require its citizens to hold a national ID card, (Schaffer and Wang, 2009), and as a result 5 to 19 percent of eligible voters (depending on the state) lack any accepted form of identification (Government Accountability Office, 2014; Ansolabehere and Hersh, 2017). They see these laws as a deliberate and politically motivated attempt to disenfranchise minorities, akin to the poll taxes, literacy tests, and other Jim Crow legislation prevalent before the 1965 Voting Rights Act (Rocha and Matsubayashi, 2014). Blacks and Hispanics, who favor the Democratic Party, are (together with the young, the elderly, and poorer and less educated voters) less likely to hold an ID, and the laws are enforced more stringently against them (Atkeson et al., 2014; White et al., 2015).

Our results suggest that efforts both to safeguard electoral integrity and enfranchise more voters may be better served through other reforms.

The remainder of the paper is organized as follows. Section 2 provides more information on Catalist's voter-level panel data and the other datasets we use. Section 3 presents the empirical specifications and results. Section 4 concludes.

2 Data

2.1 Catalist Voter-Level Panel Data

We measure voter turnout and registration using a novel individual-level panel dataset collected by Catalist, a U.S. company that provides data and data-related services to progressive organizations and has a long history of collaborating with academics (e.g., Hersh and Nall, 2016; Nickerson and Rogers, 2014). The panel covers the vast majority of the U.S. voting-eligible population in the 2008, 2010, 2012, 2014, and 2016 general elections, resulting in a total of about 1.3 billion observations.

For each voter-election, the data report state and county of residence, registration status, voter turnout, and partisan affiliation (in the 30 states with partisan registration). The data also contain age, race, and gender. These demographic characteristics are available for nearly all voters and have been shown to be very reliable (Fraga, 2016).

Catalist's data on registered voters primarily come from voter registration and turnout records from all states. In addition, about 55 million unregistered voters are covered thanks to three different data sources. First, Catalist keeps track of voters present in past voter files and absent from the most recent one. Second, it identifies unregistered voters using information from data aggregation firms (so-called "commercial data") and customer files of retailers and direct marketing companies. Finally, unregistered voters include individuals who moved to a state without registering, according to commercial data or USPS National Change of Address data (NCOALink®).

Despite Catalist's efforts and multiple data sources, coverage of the unregistered population is likely incomplete: Jackman and Spahn (2018) estimate that at least 11 percent of the adult citizenry – and a disproportionate share of minority voters – do not appear in commercial voter lists like Catalist's. This generates the following risk. Suppose some voters only register absent strict ID laws. We will observe all these marginal registrants in states without ID requirements – as the data cover the universe of the registered population – but might only observe a subset of them in states with ID requirements – as they would not register in these states and coverage of the unregistered population is incomplete. Under this scenario, our estimated registration effects would be biased upward as we would underestimate the share of unregistered voters in state-years with strict ID laws. Reassuringly, Table A14 shows that the probability of voters appearing in or disappearing from the Catalist data is (conditionally) orthogonal to the presence of strict ID laws. Specifications controlling for voter fixed effects further assuage this concern since they estimate the effect out of individuals who faced a strict ID law for some but not all years. These individuals are present in our sample before the implementation of the law, reducing the risk of sample selection bias.

Another potential issue is that some unregistered individuals in Catalist data may be ineligible to vote. Yet, it seems implausible that the implementation of strict ID laws correlates systematically with the presence of ineligible voters in the data. In addition, Tables 1 and A13 show that our results hold when we restrict attention to registered voters, all of whom should be voting-eligible individuals.

Further details on the Catalist panel data are given in Appendix A.1.

2.2 Data on Mobilization and Campaign Contributions

Measures of campaign contact and voter engagement come from the 2008—2016 post-electoral Cooperative Congressional Election Study (CCES) surveys. We use questions on whether the interviewee was contacted by a campaign, donated to a candidate or campaign (and how much she contributed), attended a political meeting, posted a campaign sign, or volunteered for a campaign.[3] We also construct a summary index of voter activity, defined to be the equally weighted average of the z-scores of its components.

[3] For all survey data we use, exact questions are detailed in Appendix A.2.

Information on state-level campaign contributions is from Bonica (2015)'s Database on Ideology, Money in Politics, and Elections (DIME), version 2.2. The data contain all political contributions recorded by the Federal Elections Commission, 2004–2014. We compute the total dollar-value contributed by residents of each state in each election cycle, normalize it by the state population in that election year, and take the log, to reduce the impact of outlier states like New York.

2.3 Voter Fraud

Measuring voter fraud represents a challenge, as federal and state agencies vary in the extent they collect and share information on it (Government Accountability Office, 2014).

We found two datasets covering reported cases of voter fraud. The first is by News21, an investigative project funded by the Carnegie Corporation and the John S. and James L. Knight Foundation. For the project, 24 students from 11 U.S. universities submitted more than 2,000 public-records requests and combed through nearly 5,000 court documents, official records, and media reports about voter fraud. The result is a collection of 2,068 cases of suspected voter fraud reported from 2000 through 2012. The database is admittedly incomplete, as the research team received partial or no responses from several states, and even replying jurisdictions may have failed to include some cases.[4] The second dataset, by the Heritage Foundation, includes 1,177 proven cases. Again, the Foundation's website indicates that this database is non-exhaustive.[5]

We define two outcomes separately in either dataset: the number of fraud cases documented in each state-year per 100,000 residents, and the number of cases potentially preventable by strict identification requirements.[6] We restrict attention to cases of fraud reported in or after 2004, the last election year before the implementation of the country's first strict ID law.

In both datasets, the summaries are typically insufficient to reconstruct the election year the alleged fraud took place. We thus take the reported years as given. We assign records with odd years (i.e., years in which no general election took place) to the previous year's treatment status and covariates.

Despite their limitations, these two datasets allow us to propose the first estimates of the effect of strict ID laws on voter fraud.

[4]Further details on News21 are available here: `https://votingrights.news21.com/article/election-fraud-explainer/` Accessed: November 12, 2018.

[5]See `https://www.heritage.org/voterfraud`. Accessed: November 12, 2018.

[6]We classify voter impersonation, duplicate voting, false registrations, and ineligible voting as preventable frauds. Other categories are buying votes, altering the vote counts, fraudulent use or application of absentee ballots, illegal assistance at the polls, and intimidation.

2.4 Surveys on Perceived Election Integrity

To assess if strict identification laws alter the perceived integrity of the electoral process, we use the 2004, 2012, and 2016 waves of the American National Election Studies (ANES) survey and the 2008–2016 waves of the Survey of the Performance of American Elections (SPAE). From the ANES, we construct a dummy identifying respondents who think the past election was very fair or fair. From the SPAE, we construct separate dummy outcomes for whether the respondent believes the following frauds happen commonly or occasionally: pretending to be another voter, casting multiple votes, non-citizens casting a ballot, casting an absentee ballot intended for another person, officials changing the vote counts, stealing or tampering with ballots. As with voter activity, we construct a standardized index of perceived election integrity based on the individual voter-fraud outcomes.

2.5 Calendars of Voter ID Laws, Election Laws, and State Party Control

We use the National Conference of State Legislatures (NCSL) to identify the type of ID law enforced in each state-year. Following recent literature (e.g., Hajnal et al., 2017), our main treatment is the presence of strict ID laws. Appendix Tables A2–A5 show that all results are substantively identical using strict-photo ID laws as treatment.

We also use the NCSL, together with data from Biggers and Hanmer (2015), to construct the following state-level covariates. We build state-by-year indicators for the availability of no-excuse absentee voting, early voting, all-mail voting, and Election-Day registration. Partisan control of the state legislature is identified by three dummies indicating whether the state legislature was controlled by Republicans, Democrats, or its control was split among the two main parties.[7] Similarly, the party affiliation of the governor can take three possible values, Democratic, Republican, and independent.[8]

3 Results

3.1 Impact on turnout

We first estimate the average impact of strict ID laws on all voters with DD specifications of the following form:

$$Y_{ist} = \beta ID_{st} + X_{ist}'\gamma + \alpha_s + \delta_t + \mu_{ist}, \tag{1}$$

[7] We include Nebraska's non-partisan state legislature in the final category.

[8] We include the District of Columbia in the final category.

where Y_{ist} is a dummy equal to 1 if individual i in state s voted in election year t, ID_{st} is a dummy for whether the state used a strict ID law in that year, X_{ist} is a vector of individual and state controls, α_s are state fixed effects, and δ_t election year fixed effects. Since the treatment varies at the state-year level, we follow Bertrand et al. (2004) and conservatively cluster standard errors by state.[9]

The coefficient of interest, β, measures the difference in average participation between states with and without strict ID laws (henceforth, treated and control states), conditional on controls. This represents the causal impact of the laws under the assumption that treated and control states were on parallel trends, so that year-to-year turnout changes in control states correspond to the counterfactual evolution in treated states, had they not implemented the law.

The results from Equation (1) are presented in Table 1. Panel A restricts the sample to registered citizens, following the existing literature. Using a specification with state and election-year fixed effects but without any other control, we obtain an effect close to null (-0.7 percentage points) and not statistically significant (column 1). Angrist and Pischke (2015) suggest that credible DD estimates should be robust to the inclusion or omission of covariates and linear state time trends. Accordingly, we test the robustness of our result to three additional specifications. The first includes individual controls (age, gender, race, race by year fixed effects, and race by state fixed effects) and state controls (partisan control of the state legislature, governor's party, and other election administration rules affecting turnout: no-excuse absentee voting, early voting, same-day registration, and all-mail voting). The second also adds state time trends, to allow treated and control states to be on differential linear trajectories, thus relaxing our identification assumption. The third includes voter fixed effects and hence estimates the impact out of individuals who faced a strict ID law for some but not all years because they experienced a change in their state's law (or because they moved between treated and control states).[10] Corresponding estimates are unaffected by the possibility that strict ID laws changed people's likelihood to appear in the Catalist sample, which is otherwise a possible source of bias as discussed in Section 2.1. We find no significant effect in any of these alternative specifications (columns 2 through 4).

Effects on the turnout of registered citizens miss possible effects on registration: while strict ID laws do not change registration requirements, citizens who expect not to be able to vote might decide not to register in the first place, and citizens who stop voting are more likely to be purged from voter rolls. In addition, restricting the sample to registered voters might lead us to underesti-

[9] Appendix Tables A6–A9 show that the state-clustered asymptotic p-values of Tables 1–4's coefficients are very close to their wild cluster bootstrap counterparts (Esarey and Menger, 2017).

[10] Due to the large sample size, the number of included covariates, and the architecture of Stata's fixed-effects routines, it is computationally very costly to estimate state-clustered standard errors in voter fixed-effects specifications. Thus, standard errors for these specifications come from bivariate regressions of residualized outcomes on residualized treatments with state-clustered standard errors. They do not account for the degrees of freedom lost by partialling out the covariates and voter fixed effects, and are therefore underestimated. This works *against* finding the null result which we obtain under this and other specifications.

mate the laws' true effects on turnout if they decrease registration of citizens with lower propensity to vote than the average registrant. In other words, the estimated null effect on registered voters' turnout could reflect two negative effects: decreased registration (leading to increased turnout of registered citizens, if those deterred from registering have low propensity to vote) and decreased turnout of voters whose registration is unaffected. In Panel B, we thus include both registered and unregistered individuals in the sample and consider two outcomes: unconditional turnout (equal to 1 if the individual is registered and votes, and 0 otherwise), in columns 1–4, and registration, in columns 5–8. The effects of strict ID laws on both outcomes are close to 0: point estimates vary between -0.4 and 0.5 percentage points and are not statistically significant in any specification. In the remaining analysis on turnout, we use unconditional turnout on the full sample as our outcome, unless specified otherwise.[11]

In Appendix Tables A10 and A15, we test the robustness of the null result to two additional strategies. First, following Dube et al. (2010), we compare voters in contiguous county-pairs that straddle a state border. Focusing on voters living in adjacent counties across state borders (and controlling for county-pair-by-year fixed effects) further enhances the causal credibility of our estimates.[12] Second, instead of using individual-level registration and turnout data, we use McDonald's aggregate state-level estimates, which are widely considered as the most reliable. Both strategies confirm the null result.

Finally, to corroborate the validity of the parallel-trend assumption, we plot estimates of β_τ's from the following leads-and-lags regression:

$$Y_{ist} = \sum_{\tau} \beta_\tau ID^{\tau}_{st} + X'_{ist}\gamma + \alpha_s + \delta_t + \mu_{ist}, \tag{2}$$

where ID^{τ}_{st} is a dummy equal to 1 if election year t occurs τ elections after state s first implemented its strict ID law. τ ranges between -4 and +2. The β_τ's measure the difference in participation between treated and control states before ($\tau < 0$) or after ($\tau \geq 0$) the first implementation of the law, conditional on controls. All coefficients are normalized relative to the last pre-treatment election ($\tau = -1$).

Figure 1, Panel A, shows that turnout does not change differentially in treated states *after* the first implementation of the law, consistent with the estimates in Table 1. Corroborating our identification strategy, we also find no evidence of differential trends *before* implementation: though strict ID laws are not randomly assigned to states (Table A1 shows slightly lower turnout level in treated states), their implementation does not correlate with differential pre-trends in turnout.

[11] In Appendix Table A13, we show robustness of our race-heterogeneity results to using turnout of the registered as outcome.

[12] As in the specification controlling for voter fixed effects, we partial out county-pair-by-year fixed effects and voter and state controls from the outcome and treatment, and run bivariate regressions of the residualized outcome on the residualized treatment. Again, this leads us to underestimate the standard errors.

3.2 Heterogeneity analysis

The null effects of strict ID laws on overall registration and turnout could potentially mask negative effects on minorities (who are less likely to possess an accepted ID) and positive effects on whites (e.g., if the laws increase their trust in the electoral system), or differences along other dimensions. To assess treatment impact heterogeneity, we estimate regressions of the following form:

$$Y_{ist} = ID_{st} \times Z'_{ist}\lambda + Z'_{ist}\eta + X'_{ist}\gamma + \alpha_s + \delta_t + \mu_{ist}, \tag{3}$$

where Z_{ist} is the vector of characteristics along which we allow for heterogeneity in the treatment effects.

Table 2 reports the results for the main dimension of heterogeneity: race. We use the same specifications as in Table 1, with one difference: in column 3, we control for state-by-year fixed effects instead of state time trends, thereby using a triple-difference framework akin to Cascio and Washington (2014). The inclusion of state-by-year fixed effects allows us to account for a larger set of possible confounders. It precludes estimating the overall effect of the laws, which varies at this level, but not differential effects by race.

As shown in Panel A, in all specifications the point estimates are close to 0 for whites and positive but statistically non-significant for non-whites. We cannot reject the null of identical effects on both groups. In Panel B, we allow the effects to differ by detailed race. Surprisingly, we find a large and positive effect on Hispanics, significant at the 1- or 5-percent level. The sign and magnitude of this effect are robust across specifications. The estimated difference relative to whites is 3.4 to 4.6 percentage points, depending on the specification, and significant at the 1-percent level. The next subsection discusses one possible mechanism underlying this effect. Instead, we do not find any significant direct or differential effect of the laws on blacks. The effect on other races is not statistically significant but it is significantly larger (more positive) than on whites in the specification controlling for voter fixed effects. The bottom line is that strict ID laws did not decrease the participation of any race group. The validity of this result relies on the assumption that turnout trends were parallel between treated and control states for each race, which is supported by the lack of differential pre-trends in race-specific event studies plotted in Figure 1, Panels 2–5.

Appendix Table A11 explores treatment impact heterogeneity along other individual characteristics. We find that the laws did not significantly affect the participation of any group of voters defined by age, gender, or partisan affiliation.[13]

Finally, we test whether specific components of the laws or contextual factors are associated

[13] Party affiliation is only available for one of the treated states. Corresponding estimates should thus be interpreted with caution.

with larger effects. Strict ID laws requiring photo identification (like a driver's license) could affect participation more negatively than those also allowing non-photo IDs (like a utility bill). However, we do not find support for this hypothesis (Appendix Tables A2 through A5). The effects of strict ID laws could also vary over time: they could be largest immediately following implementation, if people are confused by the new rules, or escalate later, if the laws become more stringently enforced. Alternatively, the effects might vary with election type: they might be larger in presidential elections, if these attract more voters unlikely to have an ID (Burden, 2018), or in midterms, if these elections' lower salience makes the administrative cost of acquiring an ID more prohibitive. However, we find no evidence of differential effects along any of these dimensions (Table A12).

3.3 Mobilization against the laws

The null average effect of strict ID laws on participation and the positive effect on Hispanics could result from the combination of a direct negative effect of the new requirements imposed by the laws, on one hand, and mobilization against them, on the other. Voters belonging to groups least likely to have an ID might perceive these laws as an attempt to deprive them of their rights, and mobilize (Valentino and Neuner, 2017). Biggers and Smith (2018) report large effects on turnout of being threatened to be purged from voter rolls, particularly for Hispanics, and explain it based on psychological reactance theory (Brehm, 1966). According to this theory, a threat to a right (here, the right to vote) can enhance its perceived value and lead individuals to take steps to protect it even if they rarely used it previously. We do not have data on feelings associated with strict ID laws, but can estimate their effects on forms of political engagement beyond voting: the likelihood to donate to a candidate, put up a campaign sign, or volunteer for a campaign, reported in the CCES surveys. We aggregate these responses into a standardized index, and measure campaign contributions by state and election year using Bonica (2015)'s data. In addition, parties and candidates who fear they might lose votes as a result of the laws might mobilize their supporters around this issue (Citrin et al., 2014). While we do not measure the extent to which electoral campaigns specifically refer to the laws or provide assistance to obtain acceptable ID, people's self-reported likelihood to be contacted by a campaign, in the CCES data, is a good proxy for campaign intensity.

We find no significant impact of the laws on any of these outcomes, in any specification (see Table 3). We cannot fully reject the possibility that mobilization against the laws alleviated direct negative effects – that would require evidence on additional outcomes such as people's feelings – yet we do not find any sign of it in available data.

3.4 Voter fraud and perception of fraud

Finally, we explore the effects of strict ID laws on voter fraud and beliefs on election integrity. Studies of crime face a well-known challenge: increases in crime statistics can reflect changes in both the number of committed and reported crimes, and many treatments can have both direct and reporting effects (e.g., Bhuller et al., 2013; Draca et al., 2018). Similarly, strict ID laws might affect both the actual number of fraud cases and the likelihood that they get detected and reported. Other limitations inherent to the data available to us and discussed in Section 2 compound this issue. With these caveats in mind, we report the effects on the extent of fraud in Table 4. We consider both the total number of cases (columns 1–2 and 5–6) and the subset of cases belonging to categories more directly addressed by strict ID requirements (columns 3–4 and 7–8), as described in Section 2.3. The total number of cases reported in both the News21 and Heritage Foundation datasets is very low, corroborating existing studies (Minnite, 2010; Cottrell et al., 2018): 0.08 and 0.02 cases per year per 100,000 residents, respectively. About one third (0.03) and one half (0.01) of these cases were directly addressed by the laws. We do not find any significant effect of the laws on either outcome in either dataset.

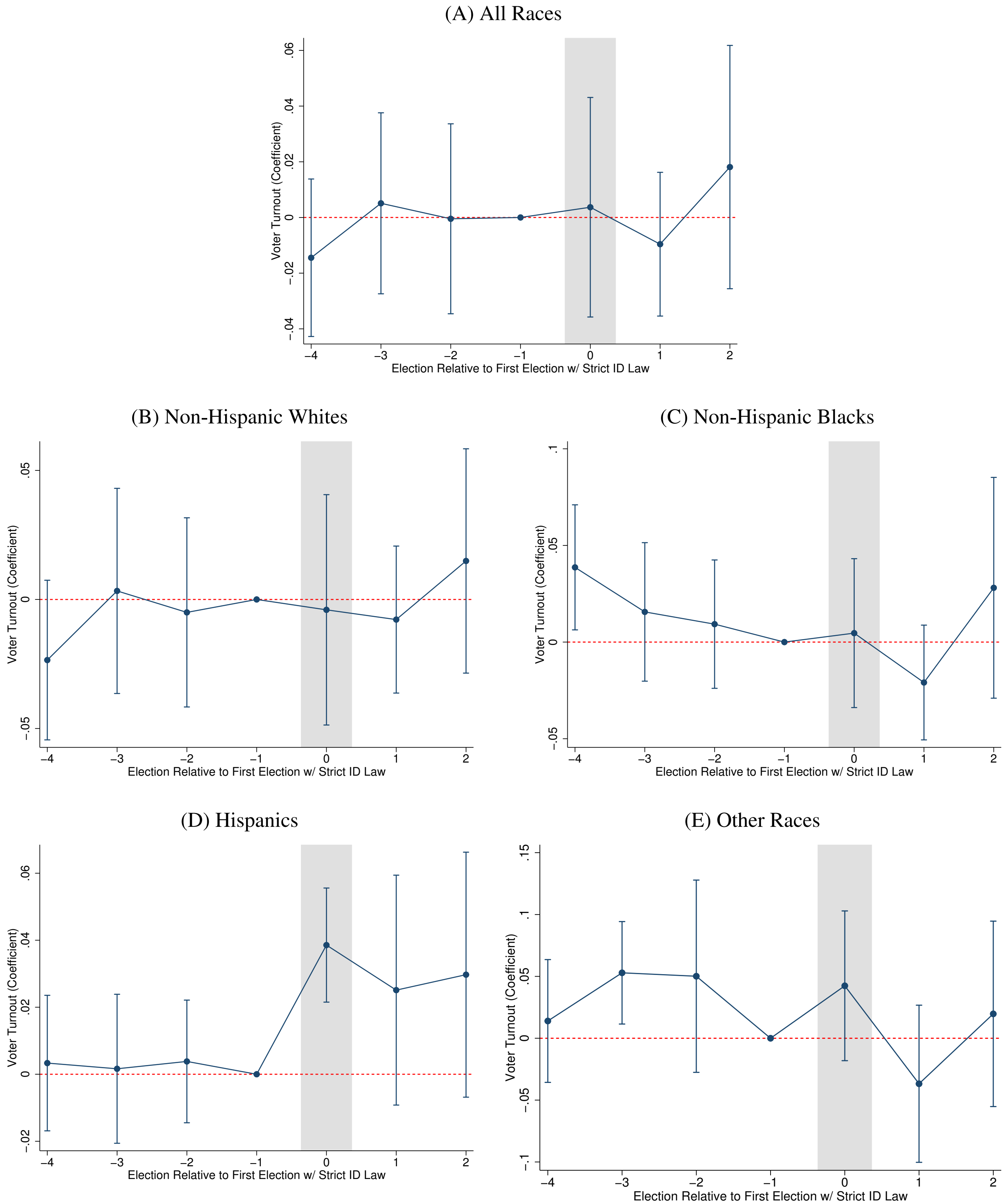
The lack of effect on detected fraud does not preclude effects on voters' beliefs on election integrity. However, using SPAE data, we find the laws had no significant effect on the perceived occurrence of voter impersonation, multiple voting, and non-citizen voting (columns 11–16). The effect on an index aggregating these outcomes (along with the other outcomes reported in Appendix Table A17) is small (-0.01) and non-significant (columns 9–10). Similarly, the laws did not significantly affect citizens' belief that the election was fair, recorded in the ANES (columns 17–18).

4 Conclusion

For all the heated debates around strict voter ID laws, our analysis of their effects obtains mostly null results. First, the fears that strict ID requirements would disenfranchise disadvantaged populations have not materialized. Second, contrary to the argument used by the Supreme Court in the 2008 case *Crawford v. Marion County* to uphold the constitutionality of one of the early strict ID laws, we find no significant impact on fraud or public confidence in election integrity. This result weakens the case for adopting such laws in the first place.

Because states adopted strict ID laws only 2 to 12 years ago, our results should be interpreted with caution: we find negative participation effects neither in the first election after the adoption of the laws nor in following ones, but cannot rule out that such effects will arise in the future. Enforcement of the laws already varies across locations and could very well become more stringent over time, especially if polarization on the issue increases. So we do not see our results as the last word on this matter – quite the opposite, we hope that they will provide guidance on the types of data and empirical strategies others can use to analyze the longer-run effects of the laws in a few years. For now, outdated voting technology and other limitations in the administration of U.S. elections decrease faith in them (Alvarez et al., 2012), but strict ID laws are unlikely to change that. At the same time, low and unequal participation represent real threats to democracy – but these may be more effectively addressed by reducing other barriers to voting, such as voter registration costs (Braconnier et al., 2017) or long travel and waiting time in areas with low polling station density (Cantoni, 2018).

Figure 1: Event-Study Graphs of the Turnout Effect of Strict ID Laws



Notes: Each panel plots event-study estimates and 95-percent confidence intervals from a separate regression (in the form of equation [2]) run on all registered and unregistered voters of a given race. The sample includes treated and control states. To avoid picking up variation from 2016 Texas (which, unlike 2014 Texas, did not enforce a strict law), we define $ID^{\tau=1}_{TX,2016} = 0$.

Table 1: Turnout and Registration Effects of Strict ID Laws

	Outcome:							
	1(Voted)				1(Registered)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A. Only Registered Voters							
1(Strict ID Law)	-.007	-.003	.003	-.005	-	-	-	-
	(.012)	(.011)	(.023)	(.014)				
	Panel B. Registered and Unregistered Voters							
1(Strict ID Law)	-.003	.003	.004	-.001	-.004	.005	-.002	.004
	(.013)	(.011)	(.016)	(.012)	(.011)	(.011)	(.006)	(.009)
Year FEs	✓	✓	✓	✓	✓	✓	✓	✓
State FEs	✓	✓	✓	✓	✓	✓	✓	✓
State & Voter Controls		✓	✓	✓		✓	✓	✓
State Linear Trends			✓				✓	
Voter FEs				✓				✓

Notes: Each cell reports estimates from a separate regression run on the Catalist data. The sample for Panels A and B consists of, respectively, registered voters and both registered and unregistered voters. The sample size in the two panels is 914,872,375 and 1,320,258,968, respectively. State controls are dummies for the availability of no-excuse absentee voting, early in-person voting, all-mail voting, and Election-Day registration, along with indicators for the partisan composition of the state legislature and the governor's party as of Election Day. Voter controls are gender, dummies for the voter's age ventile (defined in the full panel data and including an additional dummy for voters with missing age information), and dummies for whether the voter is black, Hispanic, or of other non-white, non-Hispanic (or unknown) race, along with interactions of these race dummies with states and years. For computational reasons, voter FEs specifications rely on Frisch-Waugh-Lovell theorem. From both the treatment and the outcome, we first partial out voter FEs and the full set of controls used in columns 2 and 6. We then run a simple bivariate regression of the residualized outcome on the residualized treatment. Standard errors clustered at the state level in parentheses.

Table 2: Turnout Effects of Strict ID Laws by Race

	Outcome: 1(Voted)			
	(1)	(2)	(3)	(4)
	Panel A. Whites vs. Non-Whites			
1(Strict ID Law)×White	-.004	-.001		-.006
	(.013)	(.012)		(.014)
1(Strict ID Law)×non-White	.010	.012		.013
	(.015)	(.010)		(.011)
$\beta^{nonwhite} - \beta^{white}$	.013	.012	.009	.019
	(.011)	(.012)	(.011)	(.012)
	Panel B. By Detailed Race			
1(Strict ID Law)×White	-.004	-.001		-.006
	(.013)	(.012)		(.014)
1(Strict ID Law)×Hispanic	.038	.038		.040
	(.015)	(.007)		(.009)
1(Strict ID Law)×Black	-.011	-.006		-.007
	(.013)	(.011)		(.011)
1(Strict ID Law)×Other Race	.007	.003		.011
	(.023)	(.016)		(.013)
$\beta^{hispanic} - \beta^{white}$	.042	.039	.034	.046
	(.012)	(.012)	(.008)	(.013)
$\beta^{black} - \beta^{white}$	-.007	-.005	-.003	-.001
	(.008)	(.007)	(.006)	(.007)
$\beta^{other} - \beta^{white}$	.011	.004	-.007	.017
	(.015)	(.011)	(.011)	(.007)
Race-by-Year FEs	✓	✓	✓	✓
Race-by-State FEs	✓	✓	✓	✓
State & Voter Controls		✓	✓	✓
State-by-Year FEs			✓	
Voter FEs				✓

Notes: The sample (N = 1,320,258,968) consists of both registered and unregistered voters. See notes to Table 1 for details on the controls. Standard errors clustered at the state level in parentheses.

Table 3: Effects of Strict ID Laws on CCES Campaign Contact, Voter Activity, and DIME Campaign Donations

	Was Contacted by Campaign		Index of Voter Activity		Contributions ln($1k/100k residents)	
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A. Average Effect			
1(Strict ID Law)	.014	.011	.001	-.004	.039	.057
	(.019)	(.017)	(.015)	(.014)	(.123)	(.114)
			Panel B. By Detailed Race			
1(Strict ID Law)×White	.009	.004	-.001	-.008		
	(.019)	(.017)	(.015)	(.014)		
1(Strict ID Law)×Hispanic	.022	.018	.008	.001		
	(.020)	(.016)	(.020)	(.019)		
1(Strict ID Law)×Black	.027	.029	.008	.014		
	(.024)	(.023)	(.018)	(.016)		
1(Strict ID Law)×Other Race	.054	.045	.029	.015		
	(.025)	(.022)	(.029)	(.027)		
$\beta^{hispanic} - \beta^{white}$	.014	.013	.009	.009		
	(.019)	(.015)	(.019)	(.014)		
$\beta^{black} - \beta^{white}$	.018	.025	.009	.023		
	(.016)	(.015)	(.012)	(.010)		
$\beta^{other} - \beta^{white}$	.046	.041	.030	.023		
	(.021)	(.020)	(.028)	(.025)		
Year & State FEs	✓	✓	✓	✓	✓	✓
State & Voter Controls		✓		✓		✓
Mean dep. Var.	.640	.640	.000	.000	14.55	14.55
N	221,926	221,926	256,896	256,896	306	306

Notes: The voter-level outcome for columns 1-2 is a dummy for whether a CCES survey respondent reported being contacted by a campaign in the last general election. The outcome for columns 3-4 is a summary index (i.e., sum of z-scores of individual components) of voter engagement defined on the CCES data and described in the text. The outcome for columns 5-6 is the log of political donations to candidates and parties by state-year per 100k residents, 2004-2014. For a description of state controls, see the notes to Table 1. Voter controls in columns 1-4 are education, gender, income, and race. Standard errors clustered at the state level in parentheses.

Table 4: Effects of Strict ID Laws on Reported and Perceived Frequency of Voter Fraud

	News21 Frauds/100k Residents		News21 Preventable Frauds/100k Residents		Heritage Frauds/100k Residents		Heritage Preventable Frauds/100k Residents			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)		
1(Strict ID Law)	.045	.025	.015	.004	-.0003	-.005	.004	.001		
	(.106)	(.101)	(.044)	(.046)	(.0089)	(.011)	(.010)	(.012)		
Year & State FEs	✓	✓	✓	✓	✓	✓	✓	✓		
State & Voter Controls		✓		✓		✓		✓		
Mean dep. Var.	.078	.078	.033	.033	.020	.020	.013	.013		
N	459	459	459	459	663	663	663	663		
	SPAE Perceived Fraud Index		SPAE Voter Impersonation		SPAE Multiple Voting		SPAE Non-Citizen Voting		ANES Fair Election	
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
1(Strict ID Law)	-.006	-.001	-.003	.00003	-.009	-.015	-.026	-.029	.010	.022
	(.029)	(.028)	(.016)	(.01514)	(.023)	(.022)	(.022)	(.022)	(.044)	(.037)
Year & State FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
State & Voter Controls		✓		✓		✓		✓		✓
Mean dep. Var.	.000	.000	.210	.210	.209	.209	.275	.275	.698	.698
N	42,600	42,385	42,488	42,277	30,534	30,424	30,533	30,423	11,397	11,397

Notes: Regressions in columns 1-4 are at the state-year level and their sample includes both even (i.e., general election) and odd years. The News21 and Heritage data cover, respectively, the 2004-2012 and 2004-2016 years. Preventable frauds include voter impersonation, duplicate voting, false registration, and ineligible voting. The outcome for columns 9-10, described in the text, is constructed by normalizing and aggregating SPAE responses used as outcomes in columns 11-16 and in Appendix Table A9. The outcomes for columns 11-16 are dummies for whether SPAE survey respondents perceive different types of fraud as happening frequently or occasionally. Standard errors clustered at the state level in parentheses.

References

Alvarez, R. Michael, Delia Bailey, and Jonathan N. Katz, "An empirical Bayes approach to estimating ordinal treatment effects," *Political Analysis*, 2011, *19* (1), 20–31.

_ **, Jonathan N. Katz, Charles III Stewart, Ronald L. Rivest, Stephen Ansolabehere, and Thad E. Hall**, "Voting: What Has Changed, What Hasn't, & What Needs Improvement," Technical Report, Caltech/MIT Voting Technology Project 2012.

Angrist, Joshua D. and Jörn-Steffen Pischke, *Mastering 'Metrics: The Path from Cause to Effect*, Princeton University Press, 2015.

Ansolabehere, Stephen, "Effects of Identification Requirements on Voting: Evidence from the Experiences of Voters on Election Day," *PS: Political Science & Politics*, 2009, *42* (01), 127–130.

_ **and Eitan D. Hersh**, "The Measure of American Elections," in Barry C. Burden and Charles III Stewart, eds., *Voter Registration: The Process and Quality of Lists*, Cambridge: Cambridge University Press, 2014, chapter 3, pp. 61–90.

_ **and** _ , "ADGN: An Algorithm for Record Linkage Using Address, Date of Birth, Gender and Name," *Statistics and Public Policy*, 2017, *4* (1), 1–10.

_ **and Eitan Hersh**, "Validation: What big data reveal about survey misreporting and the real electorate," *Political Analysis*, 2012, *20* (4), 437–459.

Atkeson, Lonna Rae and Kyle L. Saunders, "The Effect of Election Administration on Voter Confidence: A Local Matter?," *PS - Political Science and Politics*, 2007, *40* (4), 655–660.

_ **, Yann P. Kerevel, R. Michael Alvarez, and Thad E. Hall**, "Who Asks for Voter Identification? Explaining Poll-Worker Discretion," *Journal of Politics*, 2014, *76* (4), 944–957.

Berman, Eli, Michael Callen, Clark Gibson, and James Long, "Election Fairness and Government Legitimacy in Afghanistan," *NBER Working Paper 19949*, 2014.

Bertrand, Marianne, Esther Duflo, and Sendhil Mullainathan, "How Much Should We Trust Differences-in-Differences Estimates?," *The Quarterly Journal of Economics*, 2004, *119* (1), 249–275.

Bhuller, Manudeep, Tarjei Havnes, Edwin Leuven, and Magne Mogstad, "Broadband Internet : Broadband Internet : An Information Superhighway to Sex Crime?," *Review of Economic Studies*, 2013, *80* (4), 1237–1266.

Biggers, Daniel R. and Daniel A. Smith, "Does threatening their franchise make registered voters more likely to participate? Evidence from an aborted voter purge," *British Journal of Political Science*, 2018, pp. 1–22.

_ **and Michael J. Hanmer**, "Who Makes Voting Convenient? Explaining the Adoption of Early and No-Excuse Absentee Voting in the American States," *State Politics and Policy Quarterly*, 2015, *15* (2), 192–210.

Bonica, Adam, "Database on Ideology, Money in Politics, and Elections (DIME)," 2015.

Braconnier, Celine, Jean-Yves Dormagen, and Vincent Pons, "Voter Registration Costs and Disenfranchisement: Experimental Evidence from France," *American Political Science Review*, 2017, *111* (3), 584–604.

Brehm, Jack W., *A theory of psychological reactance*, New York: Academic Press, 1966.

Burden, Barry C, "Disagreement over ID Requirements and Minority Voter Turnout," *The Journal of Politics*, 2018, *80* (3), 1060–1063.

Cantoni, Enrico, "A Precinct Too Far: Turnout and Voting Costs," *American Economic Journal: Applied Economics*, 2018, *Forthcomin.*

Cascio, Elizabeth U. and Ebonya L. Washington, "Valuing the Vote: The Redistribution of Voting Rights and State Funds Following the Voting Rights Act of 1965," *The Quarterly Journal of Economics*, 2014, *129* (1), 379–433.

Citrin, Jack, Donald P. Green, and Morris Levy, "The Effects of Voter ID Notification on Voter Turnout: Results from a Large-Scale Field Experiment," *Election Law Journal: Rules, Politics, and Policy*, 2014, *13* (2), 228–242.

Collier, Paul and Pedro C. Vicente, "Violence, bribery, and fraud: The political economy of elections in Sub-Saharan Africa," *Public Choice*, 2012, *153* (1-2), 117–147.

Commission on Federal Election Reform, "Building Confidence in U.S. Elections," Technical Report 2005.

Converse, Philip E, "Change in the American Electorate," in "The human meaning of social change," New York: Russell Sage, 1972, pp. 263–337.

Cottrell, David, Michael C. Herron, and Sean J. Westwood, "An exploration of Donald Trump's allegations of massive voter fraud in the 2016 General Election," *Electoral Studies*, 2018, *51*, 123–142.

Diamond, Larry, *Developing Democracy*, Baltimore: Johns Hopkins University Press, 1999.

Draca, Mirko, Theodore Koutmeridis, and Stephen Machin, "The Changing Returns to Crime: Do Criminals Respond to Prices?," *Review of Economic Studies*, 2018.

Dube, Arindrajit, T. William Lester, and Michael Reich, "Minimum Wage Effects Across State Borders: Estimates Using Contiguous Counties," *The Review of Economics and Statistics*, 2010, *92* (4), 945–964.

Erikson, Robert S. and Lorraine C. Minnite, "Modeling Problems in the Voter Identification Voter Turnout Debate," *Election Law Journal*, 2009, *8* (2), 85–101.

Esarey, Justin and Andrew Menger, "Practical and Effective Approaches to Dealing with Clustered Data," *Political Science Research and Methods*, 2017.

Fraga, Bernard L., "Candidates or Districts? Reevaluating the Role of Race in Voter Turnout," *American Journal of Political Science*, 2016, *60* (1), 97–122.

Fujiwara, Thomas, "Voting Technology, Political Responsiveness, and Infant Health: Evidence From Brazil," *Econometrica*, 2015, *83* (2), 423–464.

Garrigou, Alain, *Le Vote et la vertu, comment les Français sont devenus électeurs*, Paris: Presses de Sciences Po, 1992.

Gerber, Alan S., Gregory A. Huber, and Seth J. Hill, "Identifying the Effect of All-Mail Elections on Turnout: Staggered Reform in the Evergreen State," *Political Science Research and Methods*, 2013, *1* (1), 91–116.

_ , _ , David Doherty, Conor M. Dowling, and Seth J. Hill, "Do Perceptions of Ballot Secrecy Influence Turnout? Results from a Field Experiment," *American Journal of Political Science*, 2013, *57* (3), 537–551.

Government Accountability Office, "Issues related to state voter identification laws," Technical Report 2014.

Grimmer, Justin, Eitan Hersh, Marc Meredith, Jonathan Mummolo, and Clayton Nall, "Obstacles to Estimating Voter ID Laws' Effect on Turnout," *Journal of Politics*, 2018, *80* (3), 1045–1051.

Gronke, Paul, Eva Galanes-Rosenbaum, Peter A. Miller, and Daniel Toffey, "Convenience Voting," *Annual Review of Political Science*, 2008, *11* (1), 437–455.

Hajnal, Zoltan, Nazita Lajevardi, and Lindsay Nielson, "Voter Identification Laws and the Suppression of Minority Votes," *The Journal of Politics*, 2017, *79* (2), 363–379.

Hasen, Richard, *The Voting Wars*, New Haven: Yale University Press, 2012.

Henninger, Phoebe, Marc Meredith, and Michael Morse, "Who Votes Without Identification? Using Affidavits from Michigan to Learn About the Potential Impact of Strict Photo Voter Identification Laws," *Working Paper*, 2018, pp. 1–34.

Hersh, Eitan D. and Clayton Nall, "The Primacy of Race in the Geography of Income-Based Voting: New Evidence from Public Voting Records," *American Journal of Political Science*, 2016, *60* (2), 289–303.

Hicks, William D., Seth C. McKee, Mitchell D. Sellers, and Daniel A. Smith, "A Principle or a Strategy? Voter Identification Laws and Partisan Competition in the American States," *Political Research Quarterly*, 2015, *68* (1), 18–33.

Highton, Benjamin, "Voter Identification Laws and Turnout in the United States," *Annual Review of Political Science*, 2017, *20* (1), 149–167.

Hodler, Roland, Simon Luechinger, and Alois Stutzer, "The Effects of Voting Costs on the Democratic Process and Public Finances," *American Economic Journal: Economic Policy*, 2015, *7* (1), 141–171.

Ichino, Nahomi and Matthias Schündeln, "Deterring or Displacing Electoral Irregularities? Spillover Effects of Observers in a Randomized Field Experiment in Ghana," *Journal of Politics*, 2012, *74* (1), 292–307.

Jackman, Simon and Bradley Spahn, "Politically Invisible in America," *Working Paper*, 2018.

Kaplan, Ethan and Haishan Yuan, "Early Voting Laws, Voter Turnout, and Partisan Vote Composition: Evidence from Ohio," *Working Paper*, 2018.

Kobach, Kris W., "The Case for Voter ID," may 2011.

Minnite, Lorraine, *The Myth of Voter Fraud*, Ithaca: Cornell University Press, 2010.

Mycoff, Jason D., Michael W. Wagner, and David C. Wilson, "The Empirical Effects of Voter-ID Laws: Present or Absent?," *PS: Political Science & Politics*, 2009, *42* (01), 121–126.

Nickerson, David and Todd Rogers, "Political Campaigns and Big Data," *Journal of Economic Perspectives*, 2014, *28* (2), 51–74.

Nickerson, David W., "Do Voter Registration Drives Increase Participation? For Whom and When?," *Journal of Politics*, 2015, *77* (1), 88–101.

Norris, Pippa, *Electoral Engineering. Voting rules and Political Behavior*, Cambridge University Press, 2004.

Richman, Jesse T., Gulshan A. Chattha, and David C. Earnest, "Do non-citizens vote in U.S. elections?," *Electoral Studies*, 2014, *36*, 149–157.

Rocha, Rene R. and Tetsuya Matsubayashi, "The Politics of Race and Voter ID Laws in the States: The Return of Jim Crow?," *Political Research Quarterly*, 2014, *67* (3), 666–679.

Rosenstone, Steven J. and Raymond E. Wolfinger, "The Effect of Registration Laws on Voter Turnout," *American Political Science Review*, 1978, *72* (1), 22–45.

Schaffer, Frederic Charles and Tova Andrea Wang, "Is Everyone Else Doing It: Indiana's Voter Identification Law in International Perspective," *Harvard Law and Policy Review*, 2009, *3* (2), 398–412.

Silver, Brian D., Barbara A. Anderson, and Paul R. Abramson, "Who Overreports Voting?," *American Political Science Review*, 1986, *80* (2), 613–624.

Stewart, Charles, Stephen Ansolabehere, and Nathaniel Persily, "Revisiting Public Opinion on Voter Identification and Voter Fraud in an Era of Increasing Partisan Polarization," *Stanford Law Review*, 2016, *68* (6), 1455–1489.

Valentino, Nicholas A. and Fabian G. Neuner, "Why the Sky Didn't Fall: Mobilizing Anger in Reaction to Voter ID Laws," *Political Psychology*, 2017, *38* (2), 331–350.

Vicente, Pedro C., "Is Vote Buying Effective? Evidence from a Field Experiment in West Africa," *Economic Journal*, 2014, *124* (574), 356–387.

von Spakovsky, Hans A., "Protecting the Integrity of the Election Process," *Election Law Journal: Rules, Politics, and Policy*, 2012, *11* (1), 90–96.

White, Ariel R., Noah L. Nathan, and Julie K. Faller, "What Do I Need to Vote? Bureaucratic Discretion and Discrimination by Local Election Officials," *American Political Science Review*, 2015, *109* (1), 129–142.

A Online Appendix

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A.1 Additional Details on the Catalist Data

Over time, Catalist continually updates its database to incorporate new state voter files as well as commercial data refreshes, and it identifies deceased voters based on the Social Security Death Master File (SSDMF) datasets. Catalist also identifies people changing addresses based on NCOA records and by systematically comparing voter lists and commercial records of different states. Catalist gives each person a unique ID, invariant across years and files. Data matching procedures are run to ascertain potential matches across files. For example, if a voter registered with the first name "Tom," but commercial records include an individual called "Thomas" with the same address and sociodemographic characteristics, Catalist will recognize that it is the same individual and reconcile the two sources of information (Ansolabehere and Hersh, 2014).

The information Catalist shares with its clients usually stems from a cross-sectional "live file," containing the present-day address and information and the full voter turnout history of every individual who ever appeared in its database. Since 2008, however, Catalist has also been saving "historical files": snapshots of its live file as of the date of each biennial nationwide election.[14]

We received five historical files, corresponding to the 2008, 2010, 2012, 2014, and 2016 nationwide elections, and matched them with the current live file. The live file constitutes our source of longitudinal information on voter turnout and the historical files our source of longitudinal information on voters' residence.

For each election, the historical files we received from Catalist report voters' state and county of residence at that time, a flag for whether the voter was deceased,[15] registration status,[16] partisan affiliation (for voters registered in the 30 states with partisan registration), an indicator for permanent absentee status, and a flag for "best state."[17] From the Catalist live file, we received the following variables: full turnout history, the state where the voter cast her ballot in each general election in our sample, if any, age, race, source of race information, and gender.

[14]Since it takes two to five months after Election Day for election administrators to process and give Catalist individual-level voter turnout information, historical files are copies of the live file as of two to five months after the corresponding Election Day. For instance, the 2008 historical file was saved between January and March 2009.

[15]Voters are flagged as deceased when they appear in the SSDMF or are reported as deceased in commercial records.

[16]Voter registration features five possible values: A, I, D, M, or U. "A" and "I" denote voters appearing on a state registration file with "active" or "inactive" registration status, respectively. "D" flags "dropped" individuals who appeared on past state voter files, but not in the most recent one. "M" indicates "moved, unregistered" voters who, according to NCOA or commercial data, moved into the state, but did not re-register in that state. "U" are voters whose status is "unregistered": they do not appear on current or past voter files but are known to reside in the state.

[17]When a voter is observed moving across states, Catalist creates a new record, and updates the original record (e.g., recoding the voter's registration status from "active" to "dropped") instead of erasing it. Consequently, the Catalist database is uniquely identified by voter ID *and* state. After using voter ID and state to match the historical files with the live file, we use the "best-state" flag to deduplicate on voter ID. Specifically, we deduplicate the matched historical files using the following lexicographic rules: we privilege the record corresponding to the state where a voter voted, if any; then records flagged as "best state"; then we use voter registration, privileging voter registration statuses in this order: "A", "M", "U", "I", and "D"; then we privilege the record with the oldest registration date; finally, among residual duplicates, we keep a reproducibly random record.

Table A1: Summary Statistics

	Control States		Treated States		All States	
	Catalist	Census	Catalist	Census	Catalist	Census
	(1)	(2)	(3)	(4)	(5)	(6)
Female	.526	.504	.528	.503	.527	.504
White	.744	.669	.738	.670	.742	.670
Black	.115	.109	.135	.136	.120	.116
Hispanic	.049	.081	.032	.047	.044	.072
Other race	.092	.141	.095	.146	.093	.142
Age:						
Missing values	.106	-	.123	-	.110	-
Mean	47.8	37.7	47.3	36.2	47.7	37.3
Std. dev.	18.5	-	18.1	-	18.3	-
Voted	.440	-	.414	-	.433	-
Registered	.694	-	.691	-	.693	-
Party registration:						
Living in a party registration state	.730	-	.103	-	.558	-
…and registered as Democrat	.216	-	.021	-	.162	-
…and registered as Republican	.150	-	.027	-	.116	-
…and registered as unaffiliated	.122	-	.019	-	.093	-
…and registered for a third party	.018	-	.005	-	.014	-
Median household income	-	57,693	-	53,156	-	56,453
Share high-school graduates	-	.87	-	.86	-	.87
N	958,638,060	40	361,620,908	11	1,320,258,968	51

Notes: Treated states are defined as states that enforced a strict ID law in the sample years (2008-2016). Race shares for the population 18 or older, age, and the proportion of females in columns 2, 4, and 6 come from the 2010 decennial census (respectively, questions P11, QTP1, and QTP1). Information on median household income and the share of high-school graduates is from the 2016 5-year ACS (questions B19013 and B15003, respectively).

A.2 Details on ANES, SPAE, and CCES Survey Outcomes

The survey questions used to construct the SPAE-based outcomes are as follows:

- Voter impersonation: q38 (SPAE 2008), q29c (2012), Q37C (2014), Q37C (2016).
- Multiple voting: q29a (2012), Q37A (2014), Q37A (2016).
- Non-citizen voting: q29d (2012), Q37D (2014), Q37D (2016).
- Absentee ballot fraud: q29e (2012), Q37E (2014), Q37E (2016).
- Officials changing vote tallies: q29f (2012), Q37F (2014), Q37F (2016).
- Votes stealing: q37 (2008), q29b (2012), Q37B (2014), Q37B (2016).

The SPAE survey was not administered in 2010. There were also no questions on multiple voting, non-citizen voting, absentee ballot fraud, and officials changing vote counts in 2008.

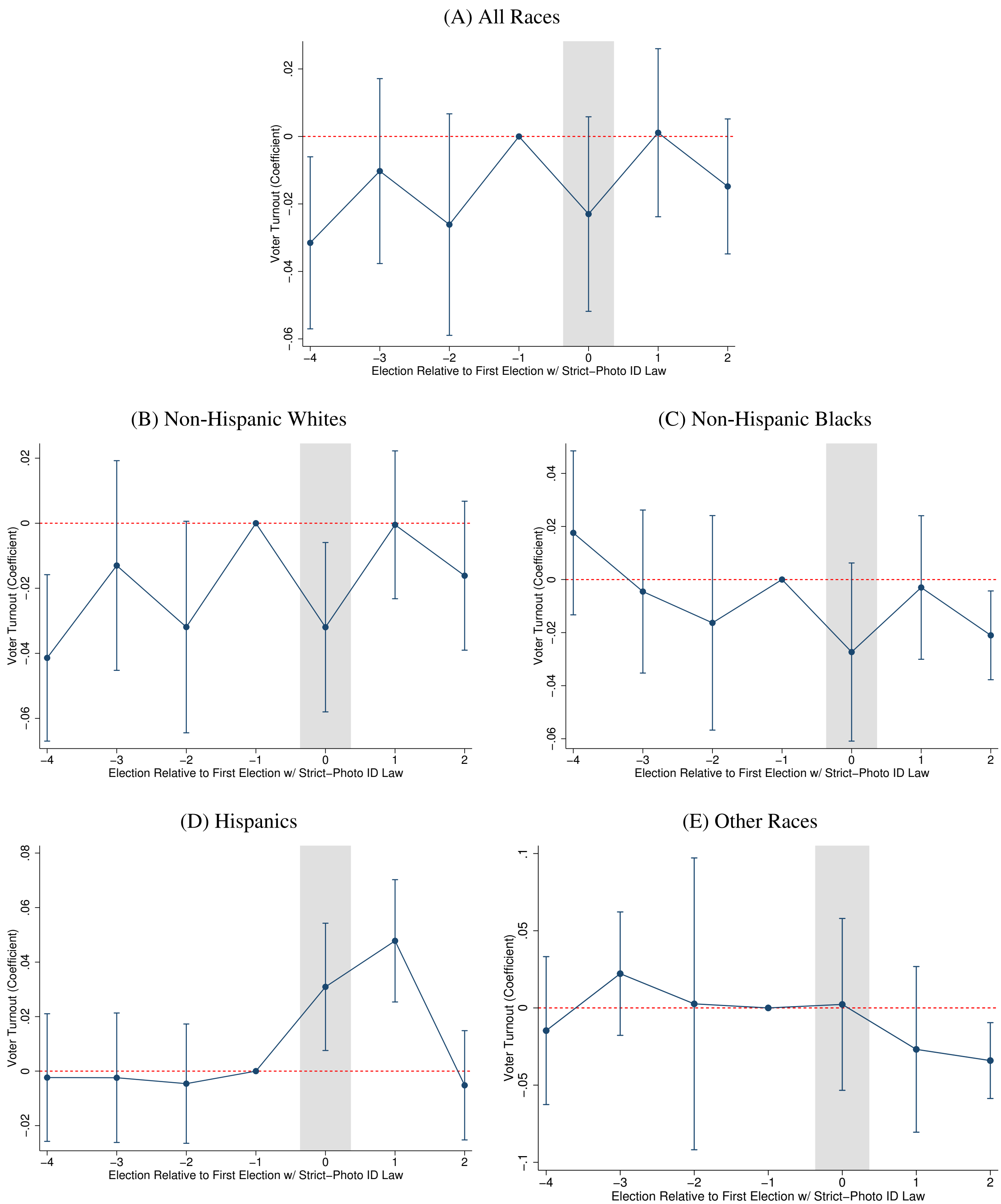
For the ANES-based outcome on whether the past election was fair, we use the following post-election survey waves and questions: V045042 (2004), electintpo_countfair (2012), V162219 (2016). The question wording changed slightly across years. In 2004, the question was generically whether the 2004 presidential election was fair. In 2012 and 2016, voters were asked whether votes were counted fairly.

CCES dummy outcomes are based on the following years and survey questions (omitted years correspond to years in which the relevant survey question was not asked):

- Voter was contacted by a campaign: v4065 (2006), CC425a (2010), CC425a (2012), CC425a (2014), CC16_425a (2016).
- Donated to a candidate or campaign: v4062 (2006), CC415_6 (2008),CC417a_4 (2010), CC417a_4 (2012), CC417a_4 (2014), CC16_417a_4 (2016).
- Amount donated (equal to 0 for people who answered no to the "Donated to a candidate or campaign" question): CC416b (2008), CC417c (2010), CC417c (2012), CC417c (2014), CC16_417c (2016).
- Attended a local political meeting: CC415_1 (2008), CC417a_1 (2010), CC417a_1 (2012), CC417a_1 (2014), CC16_417a_1 (2016).
- Posted a campaign sign: CC415_3 (2008), CC417a_2 (2010), CC417a_2 (2012), CC417a_2 (2014), CC16_417a_2 (2016).
- Volunteered for a campaign: CC415_4 (2008), CC417a_3 (2010), CC417a_3 (2012), CC417a_3 (2014), CC16_417a_3 (2016).

A.3 Effects of Strict-Photo ID Laws

Figure A1: Event-Study Graphs of the Turnout Effect of Strict-Photo ID Laws



Notes: The figure replicates Figure 1 using strict-photo (instead of strict) ID laws as treatment.

Table A2: Turnout and Registration Effects of Strict-Photo ID Laws

	Outcome:							
	1(Voted)				1(Registered)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A. Only Registered Voters							
1(Strict-Photo ID Law)	-.014	-.011	-.017	-.016	-	-	-	-
	(.011)	(.010)	(.019)	(.012)				
	Panel B. Registered and Unregistered Voters							
1(Strict-Photo ID Law)	-.011	-.005	-.013	-.008	-.014	.001	-.007	.001
	(.009)	(.007)	(.014)	(.009)	(.011)	(.010)	(.006)	(.008)
Year FEs	✓	✓	✓	✓	✓	✓	✓	✓
State FEs	✓	✓	✓	✓	✓	✓	✓	✓
State & Voter Controls		✓	✓	✓		✓	✓	✓
State Linear Trends			✓				✓	
Voter FEs				✓				✓

Notes: This table replicates Table 1 using strict-photo (instead of strict) ID laws as treatment. Standard errors clustered at the state level in parentheses.

Table A3: Turnout Effects of Strict-Photo ID Laws by Race

	Outcome: 1(Voted)			
	(1)	(2)	(3)	(4)
	Panel A. Whites vs. Non-Whites			
1(Strict-Photo ID Law)×White	-.011	-.009		-.014
	(.009)	(.007)		(.009)
1(Strict-Photo ID Law)×non-White	.003	.005		.006
	(.014)	(.011)		(.012)
$\beta^{nonwhite} - \beta^{white}$	.014	.014	.009	.020
	(.012)	(.012)	(.011)	(.012)
	Panel B. By Detailed Race			
1(Strict-Photo ID Law)×White	-.011	-.009		-.014
	(.009)	(.007)		(.009)
1(Strict-Photo ID Law)×Hispanic	.035	.035		.037
	(.014)	(.008)		(.010)
1(Strict-Photo ID Law)×Black	-.019	-.014		-.015
	(.010)	(.008)		(.008)
1(Strict-Photo ID Law)×Other Race	-.003	-.007		-.001
	(.016)	(.010)		(.007)
$\beta^{hispanic} - \beta^{white}$	.046	.044	.034	.050
	(.011)	(.009)	(.008)	(.011)
$\beta^{black} - \beta^{white}$	-.008	-.005	-.003	-.002
	(.008)	(.007)	(.006)	(.007)
$\beta^{other} - \beta^{white}$	.008	.002	-.008	.013
	(.012)	(.010)	(.010)	(.007)
Race-by-Year FEs	✓	✓	✓	✓
Race-by-State FEs	✓	✓	✓	✓
State & Voter Controls		✓	✓	✓
State-by-Year FEs			✓	
Voter FEs				✓

Notes: This table replicates Table 2 using strict-photo (instead of strict) ID laws as treatment. Standard errors clustered at the state level in parentheses.

Table A4: Effects of Strict-Photo ID Laws on CCES Campaign Contact, Voter Activity, and DIME Campaign Donations

	Was Contacted by Campaign		Index of Voter Activity		Contributions ln($1k/100k residents)	
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A. Average Effect			
1(Strict-Photo ID Law)	-.001	-.005	-.005	-.009	.023	.043
	(.018)	(.017)	(.016)	(.015)	(.142)	(.128)
			Panel B. By Detailed Race			
1(Strict-Photo ID Law)×White	-.004	-.010	-.006	-.013		
	(.020)	(.019)	(.017)	(.016)		
1(Strict-Photo ID Law)×Hispanic	-.007	-.009	.001	-.002		
	(.014)	(.013)	(.017)	(.017)		
1(Strict-Photo ID Law)×Black	.002	.004	-.002	.011		
	(.017)	(.016)	(.019)	(.017)		
1(Strict-Photo ID Law)×Other Race	.048	.040	.017	.004		
	(.031)	(.030)	(.035)	(.034)		
$\beta^{hispanic} - \beta^{white}$	-.003	.001	.007	.011		
	(.022)	(.016)	(.023)	(.016)		
$\beta^{black} - \beta^{white}$	.006	.014	.004	.024		
	(.016)	(.015)	(.011)	(.012)		
$\beta^{other} - \beta^{white}$	.052	.050	.023	.017		
	(.026)	(.026)	(.034)	(.032)		
Year & State FEs	✓	✓	✓	✓	✓	✓
State & Voter Controls		✓		✓		✓
Mean dep. Var.	.640	.640	.000	.000	14.55	14.55
N	221,926	221,926	256,896	256,896	306	306

Notes: This table replicates Table 3 using strict-photo (instead of strict) ID laws as treatment. Standard errors clustered at the state level in parentheses.

Table A5: Effects of Strict-Photo ID Laws on Reported and Perceived Frequency of Voter Fraud

	News21 Frauds/100k Residents		News21 Preventable Frauds/100k Residents		Heritage Frauds/100k Residents		Heritage Preventable Frauds/100k Residents	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
1(Strict-Photo ID Law)	.067	.047	.025	.014	-.005	-.012	.002	-.004
	(.166)	(.156)	(.068)	(.070)	(.010)	(.012)	(.013)	(.015)
Year & State FEs	✓	✓	✓	✓	✓	✓	✓	✓
State & Voter Controls		✓		✓		✓		✓
Mean dep. Var.	.078	.078	.033	.033	.020	.020	.013	.013
N	459	459	459	459	663	663	663	663

	SPAE Perceived Fraud Index		SPAE Voter Impersonation		SPAE Multiple Voting		SPAE Non-Citizen Voting		ANES Fair Election	
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
1(Strict-Photo ID Law)	.003	.008	-.005	-.004	-.004	-.004	-.025	-.029	.022	.032
	(.033)	(.032)	(.018)	(.016)	(.024)	(.025)	(.022)	(.023)	(.046)	(.039)
Year & State FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
State & Voter Controls		✓		✓		✓		✓		✓
Mean dep. Var.	.000	.000	.210	.210	.209	.209	.275	.275	.698	.698
N	42,600	42,385	42,488	42,277	30,534	30,424	30,533	30,423	11,397	11,397

Notes: This table replicates Table 4 using strict-photo (instead of strict) ID laws as treatment. Standard errors clustered at the state level in parentheses.

A.4 Wild Bootstrap P-Values

Table A6: Turnout and Registration Effects of Strict ID Laws: Asymptotic vs. Wild Bootstrap P-Values

	Outcome:							
	1(Voted)				1(Registered)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A. Only Registered Voters							
1(Strict ID Law)	-.007	-.003	.003	-.005	-	-	-	-
	[.554]	[.807]	[.907]	[.722]				
	{.620}	{.825}	{.935}	{.797}				
	Panel B. Registered and Unregistered Voters							
1(Strict ID Law)	-.003	.003	.004	-.001	-.004	.005	-.002	.004
	[.797]	[.793]	[.817]	[.956]	[.709]	[.657]	[.797]	[.699]
	{.810}	{.813}	{.844}	{.957}	{.753}	{.697}	{.849}	{.717}
Year FEs	✓	✓	✓	✓	✓	✓	✓	✓
State FEs	✓	✓	✓	✓	✓	✓	✓	✓
State & Voter Controls		✓	✓	✓		✓	✓	✓
State Linear Trends			✓				✓	
Voter FEs				✓				✓

Notes: This table reports the same point estimates as Table 1. State-clustered asymptotic p-values are reported in brackets. Wild bootstrap state-clustered p-values are reported in braces. Bootstrap p-values are based on Webb weights and 999 repetitions, where this number was chosen following Davidson and MacKinnon (2000) to ensure that the significance level times the sum of the number of bootstraps and one is an integer. To account for the possibility of having too few treated clusters, we follow MacKinnon and Webb (2018) and assign bootstrap weights at a finer level (i.e., by counties) than the level of clustering of the standard errors (i.e., by states). Bootstrap p-values are computed using Stata *boottest* routine (Roodman et al., 2018).

Table A7: Turnout Effects of Strict ID Laws by Race: Asymptotic vs. Wild Bootstrap P-Values

	Outcome: 1(Voted)			
	(1)	(2)	(3)	(4)
	Panel A. Whites vs. Non-Whites			
1(Strict ID Law)×White	-.004	-.001		-.006
	[.770]	[.963]		[.668]
	{.785}	{.965}		{.746}
1(Strict ID Law)×non-White	.010	.012		.013
	[.517]	[.265]		[.229]
	{.536}	{.282}		{.275}
$\beta^{nonwhite}$ - β^{white}	.013	.012	.009	.019
	[.241]	[.301]	[.399]	[.113]
	{.260}	{.349}	{.528}	{.205}
	Panel B. By Detailed Race			
1(Strict ID Law)×White	-.004	-.001		-.006
	[.770]	[.965]		[.669]
	{.785}	{.966}		{.748}
1(Strict ID Law)×Hispanic	.038	.038		.040
	[.015]	[.000]		[.000]
	{.026}	{.002}		{.005}
1(Strict ID Law)×Black	-.011	-.006		-.007
	[.398]	[.589]		[.549]
	{.414}	{.585}		{.594}
1(Strict ID Law)×Other Race	.007	.003		.011
	[.748]	[.833]		[.408]
	{.792}	{.841}		{.538}
$\beta^{hispanic}$ - β^{white}	.042	.039	.034	.046
	[.001]	[.002]	[.000]	[.001]
	{.009}	{.023}	{.047}	{.037}
β^{black} - β^{white}	-.007	-.005	-.003	-.001
	[.384]	[.448]	[.583]	[.908]
	{.414}	{.486}	{.624}	{.932}
β^{other} - β^{white}	.011	.004	-.007	.017
	[.444]	[.716]	[.526]	[.016]
	{.499}	{.731}	{.634}	{.039}
Race-by-Year FEs	✓	✓	✓	✓
Race-by-State FEs	✓	✓	✓	✓
State & Voter Controls		✓	✓	✓
State-by-Year FEs			✓	
Voter FEs				✓

Notes: This table reports the same point estimates as Table 2. State-clustered asymptotic p-values are reported in brackets. Wild bootstrap state-clustered p-values are reported in braces. See notes to Table A6 for details on the bootstrap procedure.

Table A8: Effects of Strict ID Laws on CCES Campaign Contact, Voter Activity, and DIME Campaign Donations: Asymptotic vs. Wild Bootstrap P-Values

	Was Contacted by Campaign		Index of Voter Activity		Contributions ln($1k/100k residents)	
	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A. Average Effect			
1(Strict ID Law)	.014	.011	.001	-.004	.039	.057
	[.451]	[.538]	[.947]	[.798]	[.751]	[.617]
	{.486}	{.580}	{.932}	{.838}	{.761}	{.596}
			Panel B. By Detailed Race			
1(Strict ID Law)×White	.009	.004	-.001	-.008		
	[.641]	[.798]	[.929]	[.565]		
	{.673}	{.800}	{.931}	{.686}		
1(Strict ID Law)×Hispanic	.022	.018	.008	.001		
	[.262]	[.268]	[.695]	[.967]		
	{.278}	{.302}	{.689}	{.965}		
1(Strict ID Law)×Black	.027	.029	.008	.014		
	[.266]	[.215]	[.660]	[.375]		
	{.351}	{.309}	{.699}	{.478}		
1(Strict ID Law)×Other Race	.054	.045	.029	.015		
	[.038]	[.041]	[.328]	[.578]		
	{.074}	{.079}	{.412}	{.658}		
$\beta^{hispanic}$ - β^{white}	.014	.013	.009	.009		
	[.476]	[.363]	[.626]	[.517]		
	{.512}	{.379}	{.646}	{.591}		
β^{black} - β^{white}	.018	.025	.009	.023		
	[.261]	[.100]	[.432]	[.033]		
	{.318}	{.146}	{.449}	{.080}		
β^{other} - β^{white}	.046	.041	.030	.023		
	[.036]	[.042]	[.290]	[.353]		
	{.060}	{.068}	{.358}	{.415}		
Year & State FEs	✓	✓	✓	✓	✓	✓
State & Voter Controls		✓		✓		✓
Mean dep. Var.	.640	.640	.000	.000	14.548	14.548
N	221,926	221,926	256,896	256,896	306	306

Notes: This table reports the same point estimates as Table 3. State-clustered asymptotic p-values are reported in brackets. Wild bootstrap state-clustered p-values are reported in braces. See notes to Table A6 for details on the bootstrap procedure.

Table A9: Effects of Strict ID Laws on Reported and Perceived Frequency of Voter Fraud: Asymptotic vs. Wild Bootstrap P-Values

	News21 Frauds/100k Residents		News21 Preventable Frauds/100k Residents		Heritage Frauds/100k Residents		Heritage Preventable Frauds/100k Residents			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)		
1(Strict ID Law)	.045	.025	.015	.004	-.0003	-.005	.004	.001		
	[.673]	[.803]	[.738]	[.938]	[.971]	[.655]	[.674]	[.908]		
	{.589}	{.709}	{.626}	{.908}	{.970}	{.692}	{.716}	{.915}		
Year and State FEs	✓	✓	✓	✓	✓	✓	✓	✓		
State Controls		✓		✓		✓		✓		
Mean dep. Var.	.078	.078	.033	.033	.020	.020	.013	.013		
N	459	459	459	459	663	663	663	663		
	SPAE Perceived Fraud Index		SPAE Voter Impersonation		SPAE Multiple Voting		SPAE Non-Citizen Voting		ANES Fair Election	
	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
1(Strict ID Law)	-.006	-.001	-.003	.00003	-.009	-.015	-.026	-.029	.010	.022
	[.822]	[.977]	[.869]	[.999]	[.694]	[.522]	[.247]	[.187]	[.823]	[.559]
	{.840}	{.977}	{.885}	{.999}	{.725}	{.562}	{.389}	{.390}	{.857}	{.750}
Year & State FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
State & Voter Controls		✓		✓		✓		✓		✓
Mean dep. Var.	.000	.000	.210	.210	.209	.209	.275	.275	.698	.698
N	42,600	42,385	42,488	42,277	30,534	30,424	30,533	30,423	11,397	11,397

Notes: This table reports the same point estimates as Table 4. State-clustered asymptotic p-values are reported in brackets. Wild bootstrap state-clustered p-values are reported in braces. See notes to Table A6 for details on the bootstrap procedure.

A.5 Additional Results

Table A10: Turnout Effect of Strict ID Laws – Adjacent County-Pair Estimates

	Outcome: 1(Voted)				
	All Races	Whites	Blacks	Hispanics	Other
	(1)	(2)	(3)	(4)	(5)
1(Strict ID Law)	.013	.014	.003	.032	-.001
	(.014)	(.013)	(.014)	(.010)	(.026)
Year FEs	✓	✓	✓	✓	✓
State FEs	✓	✓	✓	✓	✓
State & Voter Controls	✓	✓	✓	✓	✓
County-Pair-by-Year FEs	✓	✓	✓	✓	✓

Notes: The table reports estimates from specifications run on registered and unregistered voters living in adjacent counties across state borders based on Dube et al. (2010)'s strategy. The sample size is: 1,007,904,125 (column 1), 767,932,850 (column 2), 131,256,215 (column 3), 70,735,208 (column 4), and 37,979,852. Standard errors are two-way clustered by states and border segments.

Table A11: Turnout Effects of Strict ID Laws by Gender, Age, and Partisanship

	Outcome: 1(Voted)			
	(1)	(2)	(3)	(4)
	Panel A. By Gender			
1(Strict ID Law)×Male	-.002	.003	.004	.001
	(.012)	(.011)	(.015)	(.012)
1(Strict ID Law)×Female	-.005	.002	.003	-.002
	(.013)	(.011)	(.016)	(.012)
	Panel B. By Age			
1(Strict ID Law)×1(age < 35)	.012	.012	.014	.021
	(.017)	(.017)	(.019)	(.015)
1(Strict ID Law)×1(35 <= age < 60)	.001	.002	.004	.001
	(.014)	(.013)	(.019)	(.013)
1(Strict ID Law)×1(60 <= age)	-.004	-.003	-.0001	-.005
	(.012)	(.012)	(.0180)	(.012)
	Panel C. By Party			
1(Strict ID Law)×Republican	-.0003	.010	.028	.020
	(.0121)	(.007)	(.011)	(.008)
1(Strict ID Law)×Democrat	.012	.020	.037	.022
	(.014)	(.008)	(.012)	(.008)
1(Strict ID Law)×Other	-.001	.009	.026	.016
	(.009)	(.006)	(.011)	(.006)
Year FEs	✓	✓	✓	✓
State FEs	✓	✓	✓	✓
State & Voter Controls		✓	✓	✓
State Linear Trends			✓	
Voter FEs				✓

Notes: The table reports estimated heterogeneous effects by gender, age, and party affiliation. All samples include both registered and unregistered voters. Samples for Panels A and B exclude voters with missing gender and age, respectively. The sample in Panel C is restricted to the 30 states that record voters' partisan affiliation. Every regression includes year- and state-specific fixed effects for the interacting characteristic (e.g., female in Panel A). Standard errors clustered at the state level in parentheses.

Table A12: Turnout Effects of Strict ID Laws by Election Timing

	Outcome: 1(Voted)			
	(1)	(2)	(3)	(4)
	Panel A. Presidential vs. Midterm			
1(Strict Law)×Presidential	.004	.012	.015	.003
	(.015)	(.013)	(.019)	(.015)
1(Strict Law)×Midterm	-.010	-.006	-.002	-.014
	(.012)	(.010)	(.015)	(.011)
	Panel B. First Election vs. Following Ones			
1(Strict Law)×Following Elections	-.005	.002	-.008	-.005
	(.012)	(.009)	(.028)	(.009)
1(Strict Law)×First Election	-.003	.003	.003	-.006
	(.014)	(.012)	(.015)	(.014)
Year FEs	✓	✓	✓	✓
State FEs	✓	✓	✓	✓
State & Voter Controls		✓	✓	✓
State Linear Trends			✓	
Voter FEs				✓

Notes: The sample includes registered and unregistered voters. Panel A explores heterogeneous effects in presidential vs. midterm elections, while Panel B compares effects in the election that immediately follows the laws' implementation and in following elections. Standard errors clustered at the state level in parentheses.

Table A13: Turnout Effects of Strict ID Laws by Race – Registered Voters Only

	Outcome: 1(Voted)			
	(1)	(2)	(3)	(4)
	Panel A. Whites vs. Non-Whites			
1(Strict ID Law)×White	-.009	-.009		-.018
	(.012)	(.012)		(.017)
1(Strict ID Law)×non-White	.015	.015		.006
	(.019)	(.016)		(.013)
$\beta^{nonwhite} - \beta^{white}$	.025	.023	.014	.025
	(.019)	(.018)	(.015)	(.016)
	Panel B. By Detailed Race			
1(Strict ID Law)×White	-.009	-.009		-.018
	(.012)	(.012)		(.017)
1(Strict ID Law)×Hispanic	.069	.068		.048
	(.023)	(.016)		(.013)
1(Strict ID Law)×Black	-.015	-.014		-.020
	(.012)	(.012)		(.013)
1(Strict ID Law)×Other Race	-.002	-.008		.000
	(.025)	(.023)		(.017)
$\beta^{hispanic} - \beta^{white}$	.079	.076	.059	.066
	(.021)	(.019)	(.011)	(.020)
$\beta^{black} - \beta^{white}$	-.006	-.005	-.004	-.002
	(.009)	(.009)	(.007)	(.010)
$\beta^{other} - \beta^{white}$	.007	.001	-.019	.019
	(.023)	(.022)	(.023)	(.010)
Race-by-Year FEs	✓	✓	✓	✓
Race-by-State FEs	✓	✓	✓	✓
State & Voter Controls		✓	✓	✓
State-by-Year FEs			✓	
Voter FEs				✓

Notes: The table replicates Table 2 restricting the sample to registered voters. N = 914,872,375. Standard errors clustered at the state level in parentheses.

Table A14: Effects of Strict ID Laws on Probability of Appearing in and Disappearing from the Catalist Data

	(1)	(2)	(3)	(4)
	Panel A. Appearing in the Sample			
1(Strict ID Law)	.004	.004	.037	.014
	(.016)	(.018)	(.006)	(.010)
Mean dep. Var.	.096	.096	.096	.096
	Panel B. Disappearing from the Sample			
1(Strict ID Law)	.001	-.001	-.002	-.002
	(.007)	(.004)	(.004)	(.003)
Mean dep. Var.	.060	.060	.060	.060
Year FEs	✓	✓	✓	✓
State FEs	✓	✓	✓	✓
State & Voter Controls		✓	✓	✓
State Linear Trends			✓	
Voter FEs				✓

Notes: The outcome for Panel A is a dummy indicating the first election in which a voter (previously not in the Catalist data) appears in the data. The outcome for Panel B is a dummy indicating the last election before a voter disappears from the data. The samples for panels A and B exclude, respectively, the 2008 and 2016 elections. N in the two panels is 1,072,159,471 and 1,030,517,120, respectively.

Table A15: Turnout Effect of Strict ID Laws – Michael McDonald’s State Turnout Figures

	Outcome: Ballots/VEP				Outcome: Ballots/VAP			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Panel A. 2008-2016 Elections				
1(Strict ID Law)	-.008	-.009	.004	.017	-.008	-.009	.0002	.006
	(.012)	(.015)	(.015)	(.022)	(.013)	(.016)	(.0146)	(.024)
N	255	255	255	255	255	255	255	255
				Panel B. 2004-2016 Elections				
1(Strict ID Law)	.001	.0004	.003	.018	.002	.001	.002	.014
	(.011)	(.0117)	(.012)	(.012)	(.011)	(.012)	(.012)	(.014)
N	357	357	357	357	357	357	357	357
Year FEs	✓	✓	✓	✓	✓	✓	✓	✓
State FEs	✓	✓	✓	✓	✓	✓	✓	✓
State-Year Controls		✓	✓	✓		✓	✓	✓
VAP Weights			✓	✓			✓	✓
State Linear Trends				✓				✓

Notes: The table reports estimated turnout effects based on Michael McDonald's state turnout data. Panels A and B include, respectively, election years 2008-2016 (i.e., matching the Catalist years) and 2004-2016 (2004 is the last year before Arizona and Ohio became the first states in the country to implement a strict ID law). VEP and VAP stand for Voting-Eligible and Voting-Age Population, respectively. Standard errors clustered at the state level in parentheses.

Table A16: Effects of Strict ID Laws on CCES Voter Activities

	Donated to a Candidate or Campaign		Amount Donated		Attended Political Meetings		Posted a Campaign Sign		Volunteered for a Campaign	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A. Average Effect										
1(Strict Law)	.009	.004	.3	-3.3	-.004	-.007	-.005	-.007	.006	.003
	(.008)	(.008)	(24.5)	(23.8)	(.005)	(.005)	(.015)	(.015)	(.008)	(.008)
Panel B. By Detailed Race										
1(Strict ID Law)×White	.007	.0004	-.4	-3.4	-.006	-.008	-.006	-.008	.004	.001
	(.008)	(.0083)	(26.2)	(25.6)	(.005)	(.005)	(.015)	(.015)	(.008)	(.008)
1(Strict ID Law)×Hispanic	.019	.009	-34.3	-50.6	-.002	-.011	.006	-.002	.017	.010
	(.020)	(.013)	(24.2)	(20.6)	(.010)	(.009)	(.017)	(.019)	(.010)	(.009)
1(Strict ID Law)×Black	.019	.020	26.7	22.6	-.003	-.006	.002	-.002	.012	.008
	(.010)	(.012)	(52.6)	(52.1)	(.008)	(.007)	(.015)	(.014)	(.009)	(.009)
1(Strict ID Law)×Other Race	.025	.013	17.5	10.9	.014	.009	-.007	-.012	.016	.012
	(.022)	(.018)	(86.8)	(87.1)	(.013)	(.012)	(.023)	(.022)	(.011)	(.011)
$\beta^{hispanic} - \beta^{white}$	.012	.009	-33.8	-47.1	.004	-.003	.013	.007	.013	.009
	(.021)	(.013)	(28.8)	(23.5)	(.009)	(.007)	(.013)	(.014)	(.008)	(.006)
$\beta^{black} - \beta^{white}$	.012	.019	27.2	26.0	.003	.002	.008	.007	.008	.006
	(.009)	(.010)	(38.4)	(38.9)	(.007)	(.006)	(.006)	(.006)	(.006)	(.005)
$\beta^{other} - \beta^{white}$	.018	.012	18.0	14.3	.020	.017	-.001	-.003	.012	.010
	(.021)	(.017)	(90.6)	(90.6)	(.013)	(.011)	(.016)	(.015)	(.009)	(.009)
Year & State FEs	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
State & Voter Controls		✓		✓		✓		✓		✓
Mean dep. Var.	.278	.278	122.5	122.5	.149	.149	.217	.217	.087	.087
N	250,688	250,688	220,475	220,475	220,475	220,475	220,475	220,475	220,475	220,475

Notes: The table reports estimated effects on the CCES campaign engagement variables used to construct Table 3's summary index of voter activity and not already reported as outcomes in that table. Standard errors clustered at the state level in parentheses.

Table A17: Effects of Strict ID Laws on Non-Preventable Frauds

	People Cast Other Voters' Absentee Ballots		Officials Change Vote Counts		People Steal/Tamper with Ballots	
	(1)	(2)	(3)	(4)	(5)	(6)
1(Strict ID Law)	.002	-.004	.005	.004	-.002	.003
	(.022)	(.021)	(.011)	(.011)	(.014)	(.014)
Year & State FEs	✓	✓	✓	✓	✓	✓
State & Voter Controls		✓		✓		✓
Mean dep. Var.	.261	.261	.190	.190	.188	.189
N	30,535	30,424	30,539	30,429	42,518	42,307

Notes: The table reports estimated effects on the SPAE measures of perceived electoral integrity used to construct Table 4's summary index and not already reported as outcomes in that table. Standard errors clustered at the state level in parentheses.