Online Appendix

Online Appendix for "The Durable Differential Deterrent Effects of Strict Photo Identification Laws."

Intended for online publication only.

Contents

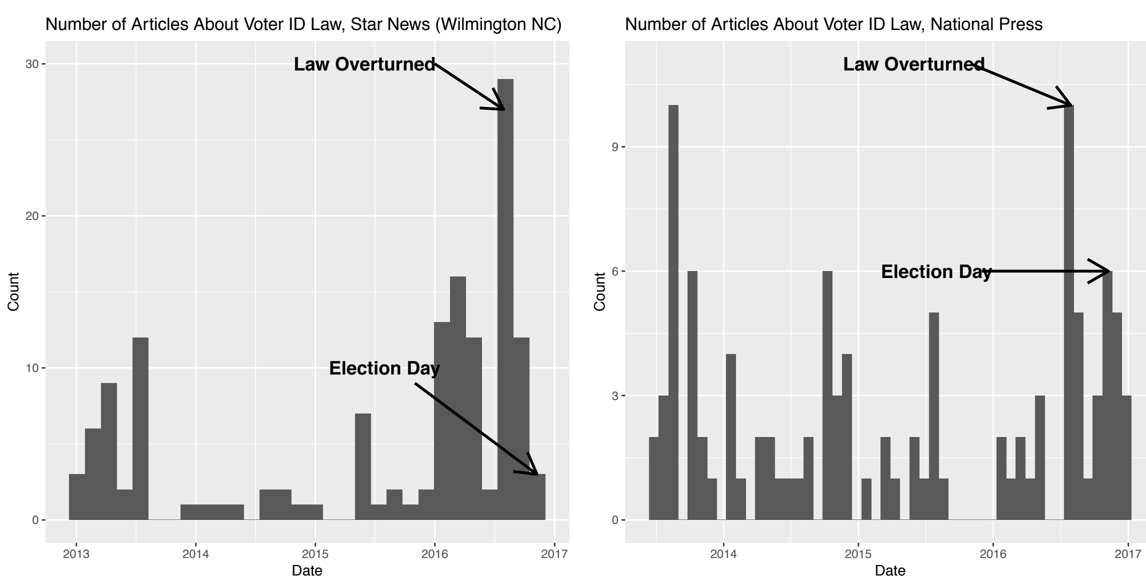
A.1 News Coverage of the Voter Identification Law

In order to provide a baseline assessment of how the North Carolina voter identification law was covered, we engage in a simple analysis of newspaper coverage. To do this, we use two different kinds of news sources. To approximate coverage in North Carolina, we use the relatively small paper: The Star News, in Wilmington. And to approximate what national coverage looks like, we used The New York Times, Washington Post, and USA Today. Using the papers we first searched for all stories that contained the words "campaign" and "North Carolina".

From this set of stories we did a simple regular expression search for instances of "voter id". This will capture a variety of uses of the word. Obviously, this might include stories other than those about the requirements for voting or the controversy surrounding the law, but a reading of the stories suggests that this captures stories that cover the North Carolina law.

Figure A.1 counts the number of stories covered in the Star News (left-histogram) and the national papers (right-histogram). We have labeled the date of the appellate court ruling and the date of the election. This shows that a large share of the coverage comes right as the appellate court decision was made, three months before the election. And subsequently there was little coverage in the local paper, even as election day approached. The national papers covered voter identification more, but those stories tended to not focus on the specific requirements in North Carolina.

Figure A.1 – News Coverage of North Carolina Voter ID Law



Together, Figure A.1 suggests that voters without identification would not find easily accessible information about the changing requirements for voting. Voters could seek the information out, but it does not appear that the information would happened to be discovered by voters not explicitly looking for the information.

A.2 Measuring Who Holds Identification

To measure who lacks a state-issued ID, we combine administrative data from North Carolina voter files – which includes information on a voter's address, age, race, and turnout history in every primary and general election from 2008 to 2016 – with individual-level administrative data on who possesses a state-issued ID.[25] We use the unique identifier the NCSBE generated to identify voters without identification, which we use to merge to the voter file to measure an individual's lack of ID.

Several features of the matching process suggest the measurement error in this matching is likely to be small. The main source of measurement error comes from matching voters to DMV records. There could be either false positives, where two records are linked but correspond to different individuals, or false negatives, where individuals are not linked but are present in both datasets. Individuals are nearly always unique within characteristics available in the voter file (Ansolabehere and Hersh 2017), which makes the risk of false positives extremely low when merging across these types of administrative data. We have reason to believe the rate of false positives is extremely low in our case: in North Carolina the voter registration records and DMV ID records both contain driver's license or state ID numbers, as well as the last 4 digits of the social security number, date of birth, first name, last name, and full address.[26] The NCSBE used exact matching on first and last name, as well as either driver's license number or last four digits of social security number, in the vast majority of its matches, making the risk of false positives low. False negatives would come from missingness or typographical errors in variables used for matching, but we again have reason to believe the false negative rate is low. Over 80% of voter file registrants report their DMV-issued ID number, and individuals report the last 4 digits of their social security number on both the voter registration form and DMV-issued ID forms. Overall, given the quantity and quality of identifying information in both the voter file and the DMV ID records, we suspect that the measurement error in our treatment variable is likely to be small.

Even if the matching process had no merge error, people who possess ID might lack access to it on Election Day (Henninger, Meredith, and Morse 2018). For example, voters could show up to the polls but have lost or forgotten their photo ID. In that case, we would underestimate the number of individuals without photo ID. To the extent that this happens on Election Day, it would attenuate our estimates of the effect of the voter ID law among those without ID because individuals in our control group (coded as having ID) would be deterred. It is also possible that some individuals without state-issued ID could still have photo ID required to vote, such as a US passport or valid military ID. In that case, voters with acceptable ID would be coded as treated, leading us to over-estimate the number of voters who actually lack acceptable photo ID. We can measure this indirectly because the North Carolina State Board of Elections sent a mailer to each voter that did not match to state ID records. For registrants on the state's no match list, about 8.6% responded to the

[25] All of this information is publicly available and provided by the North Carolina State Board of Elections (NCSBE).

[26] The NCSBE implemented the same matching criteria as described in this report: `https://canons.sog.unc.edu/wp-content/uploads/2013/12/St-Bd-voter-ID-report.pdf`

NCSBE mailer claiming they had photo ID.[27] This would also attenuate an estimate of the differential effect of law among those who actually lack ID. For these reasons, we interpret our treatment effect as the differential deterrent effect of the voter ID law among those who the state identified as possibly lacking ID, relative to those who have a state ID.

[27] https://www.ncmd.uscourts.gov/sites/ncmd/files/opinions/13cv658moo_0.pdf.

A.3 Provisional Ballots Cast for Lack of ID in North Carolina

In the 2016 primary election, 1,169 provisional ballots were ultimately not counted with the reason listed being that adequate ID was not provided by the voter. For the 2010, 2012, and 2014 primary elections, these counts were 7, 134, and 3, respectively. There are a few possible reasons for non-zero values when the law was not in effect. First, the reason for the provisional ballot could be misreported. Second, by federal statute voters who register by mail and have not yet voted in an election in the state have pending eligibility and are required to provide "current and valid photo identification" or "a current utility bill, bank statement, government check, paycheck, or other government document that shows the name and address of the voter." (`https://uscode.house.gov/view.xhtml?path=&req=%28title%3A52+section%3A21083+edition%3Aprelim%29&f=&fq=&num=0&hl=false&edition=prelim`). Third, poll workers – who exercise considerable discretion – might inappropriately ask voters to present ID in these elections. For example, over one-third of New Mexico poll workers indicated they had asked voters that approached without ID to present photo identification during the 2008 general election, contrary to New Mexico election law (Atkeson et al. 2014).

A.4 Reasons for Provisional Ballots

In this section, we show the share of provisional ballots cast by reason for each election. Figure A.2 shows provisional ballot reasons for primary elections on the left and general elections on the right. The y-axis represents the share of provisional ballots cast in the election for each type of reason. As discussed in the main text, the vast majority of rejected provisional ballots are because the voter was not registered, and this is true for every election in our study. Other reasons for provisional ballots include voting at the incorrect precinct, voting the wrong party's ballot in the primary, or having been previously removed from the voter file, among others.

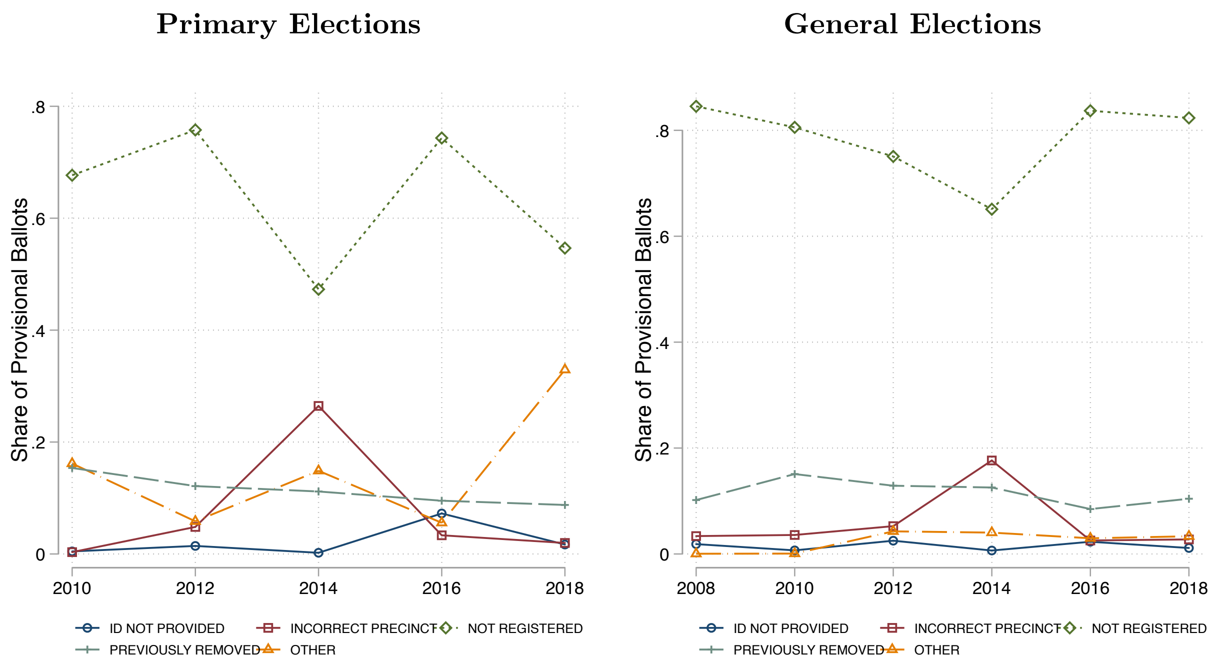


Figure A.2 – Reasons for Provisional Ballots The left panel plots the share of provisional ballots cast for different reasons in primary elections. The right plots the same series for general elections. The blue line indicates the share of provisional ballots cast because the voter lacked proper ID. The only election for which the ID law was in effect was the 2016 primary, where about 10% of provisional ballots were cast for lack of ID.

A.5 Turnout by ID Holding Status, Controlling for Birth Year and Race

In this section, we plot the mean turnout rate in each primary and general election from 2008 to 2016 separately for those who have and do not have ID, including race by birth year fixed effects. Even within race and birth year, those who do not have photo ID (in red) have slightly different turnout trends in the pre-treatment period (2008-2014) than those who have ID (in blue).

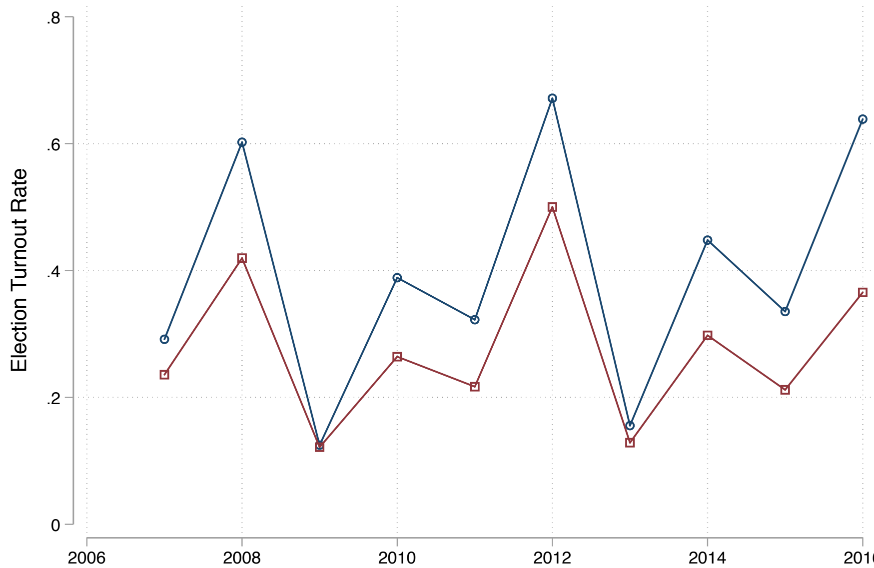


Figure A.3 – Turnout by ID Holding Status, Controlling for Birth Year and Race. Mean election turnout for primary and general elections from 2008 through 2016 are plotted separately for those who do not match to a DMV-issued ID record (in red squares) and for those who do match to a photo ID (in blue circles). We residualize on race by birth year fixed effects, so the figure shows that trends in turnout among these two groups are different in the pre-treatment periods (2008-2014) even after controlling for race and birth year.

A.6 Evaluating the Parallel Trends Assumption

Our estimation of the deterrent effect of the voter ID law on turnout among those without ID, in Tables 2 and 3, relies on the parallel trends assumption being satisfied. In column 1 of these tables, where we simply include individual fixed effects and year fixed effects, it must be the case that individuals who lacked ID would have followed the same turnout trends in 2016 as those who had ID. There are reasons to be skeptical of this assumption, given that there are large differences between the types of people who have photo ID and those who do not. For that reason, in columns 2 through 7 of Tables 2 and 3 we adjust the estimation in a variety of ways to make the parallel trends assumption increasingly plausible. We describe these alternative specifications in more detail in the main body of the paper, but in this section we try to assess whether the parallel trends assumption might be satisfied under each of our specifications.

Table A.1 – Evidence of Pre-Trending: Effect of Voter ID Law Lead on Primary Election Turnout Among Those Without ID, Individual Level, 2008–2016.

	Voted in Primary (0-1)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
No DMV Match * Year = 2016	-0.071	-0.067	-0.048	-0.042			
	(0.001)	(0.001)	(0.001)	(0.001)			
No DMV Match * Year = 2014	0.026	0.023	0.023	0.023	-0.003	-0.003	-0.004
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
N	33,136,560	33,136,560	33,089,505	33,089,485	26,509,248	26,509,248	26,471,604
# Voters	6,627,312	6,627,312	6,617,901	6,617,897	6,627,312	6,627,312	6,617,901
Individual FEs	Y	Y	Y	Y	N	N	N
Year FEs	Yes	N	N	N	Y	Y	Y
Race by Year FEs	N	Y	N	N	N	N	N
Age by Year FEs	N	N	Y	N	N	N	N
Race by Age by Year FEs	N	N	N	Y	N	N	N
Exact Match on Turnout	N	N	N	N	Y	Y	Y
Exact Match on Race	N	N	N	N	N	Y	Y
Exact Match on Age Bin	N	N	N	N	N	N	Y

Robust standard errors clustered by individual in parentheses. Main effect for No DMV Match is absorbed by fixed effects. Exact matching on turnout matches units based on all primary and general elections from 2008-2012. For exact matching on age, we construct a separate age bin for each group of voters who were under 18 for a given set of elections, so the cohort of voters who became newly eligible to participate in 2010, 2012, and 2014 each have their own age bin. For voters who were eligible for all elections since 2008, we construct age deciles.

To do so, in Table A.1 we mirror the columns in Table 2 but include a lead of the treatment variable to check for evidence of pre-trending. We find that the coefficients on the leads are small, and the coefficients on the main effects in columns 1-4 remain similar to those in Table 2. This adds to the plausibility of the parallel trends assumption, at least for primary election turnout.

In columns 5-7, because we use exact matching on pre-treatment turnout, we have to adjust the estimation slightly to check for pre-trending. We implement exact matching on 2008-2012 primary and general election turnout, and then we estimate the effect of the voter ID law among those without ID in 2014, which is before the voter ID law went into effect. We see substantively small, but negative, effects on these coefficients, suggesting that turnout among those without ID declined slightly prior to the law being implemented, even after matching exactly on turnout history, race, and age decile. One possible explanation for this is that the North Carolina voter ID law was passed in 2013 but to be implemented starting in 2016. If individuals without ID were confused about when the law went into effect, they could have been deterred from voting even prior to the law being implemented.

Table A.2 – Evidence of Pre-Trending: Effect of Voter ID Law Lead on General Election Turnout Among Those Without ID, Individual Level, 2008–2016.

	Voted in General (0-1)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
No DMV Match * Year = 2016	-0.117	-0.120	-0.105	-0.099			
	(0.001)	(0.001)	(0.001)	(0.001)			
No DMV Match * Year = 2014	0.008	0.009	0.006	0.009	-0.011	-0.010	-0.009
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
N	33,136,560	33,136,560	33,089,505	33,089,485	26,509,248	6,627,312	26,509,248
# Voters	6,627,312	6,627,312	6,617,901	6,617,897	6,627,312	26,509,248	6,627,312
Individual FEs	Y	Y	Y	Y	N	N	N
Year FEs	Y	N	N	N	Y	Y	Y
Race by Year FEs	N	Y	N	N	N	N	N
Age by Year FEs	N	N	Y	N	N	N	N
Race by Age by Year FEs	N	N	N	Y	N	N	N
Exact Match on Turnout	N	N	N	N	Y	Y	Y
Exact Match on Race	N	N	N	N	N	Y	Y
Exact Match on Age Bin	N	N	N	N	N	N	Y

Robust standard errors clustered by individual in parentheses. Main effect for No DMV Match is absorbed by fixed effects. Exact matching on turnout matches units based on all primary and general elections from the 2008 primary through the 2014 primary. For exact matching on age, we construct a separate age bin for each group of voters who were under 18 for a given set of elections, so the cohort of voters who became newly eligible to participate in 2010, 2012, and 2014 each have their own age bin. For voters who were eligible for all elections since 2008, we construct age deciles.

Next, in Table A.2 we do the same checks for pre-trending using general election turnout as the outcome. Here, the results are similar: using our exact matching approach in columns 5-7, those who did not match to a DMV record saw a small decline in turnout in 2014, before the voter ID law went into effect. Again, this is consistent with the idea that if individuals were confused about the timing of the law's implementation, the deterrent effects of the voter ID law on those without ID could manifest prior to the law going into effect.

A.7 Effect of ID Law for Those Registered Pre-2008

In this section, we estimate the deterrent effect of the ID law, but we limit the sample to those registered before 2008, the start of our panel. In the main results in Table 2, the sample is all registrants as of the 2014 general election, which is the voter file the North Carolina State Board of Elections used to match voters to DMV records. This means that in our main analyses, we face one small measurement issue: for voters who registered sometime between 2008 and 2014, we cannot be sure of their true turnout history. Imagine a voter who newly registers in 2012, for example. We code this as not having voted in all elections prior to their registration. It could be, however, that the voter moved in from out of state and had indeed been voting in another state. In that case, we would incorrectly be coding this voter as not having voted in elections prior to 2012, when in fact they had been.

To circumvent this potential source of measurement error, in Table A.3 we estimate the deterrent effect of the ID law in the 2016 primary, but we limit the sample only to those who were registered to vote in North Carolina prior to 2008. This means that we can be sure that there is no measurement error in the voter's turnout history. The tradeoff we make here, however, is that our sample in Table A.3 includes only long-time registrants. We might expect that the effect of the ID law on turnout among those without ID will be different for long-time registrants compared to the full sample we study in the main analyses.

We show the results for the 2016 primary in Table A.3, and the columns mirror those in Table 2 in the main text. In our most preferred specification (column 7), the ID law leads to a decrease in 2016 primary turnout of about 0.5 percentage points among those without ID relative to those with ID. This effect is slightly smaller in magnitude than the one we estimate in 2, which suggests that the effect of the ID law is much smaller among long-time registrants.

Table A.3 – Effect of Voter ID Law on Primary Election Turnout Among Those Without ID, Individual Level, 2008–2016, Including Only Those Registered Pre-2008.

	Voted in Primary (0-1)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
No DMV Match * Year = 2016	-0.091	-0.086	-0.044	-0.039	-0.010	-0.009	-0.005
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
N	19,836,570	19,836,570	19,790,245	19,790,190	19,836,570	19,836,570	19,836,570
# Voters	3,967,314	3,967,314	3,958,049	3,958,038	3,967,314	3,967,314	3,967,314
Individual FEs	Y	Y	Y	Y	N	N	N
Year FEs	Y	N	N	N	Y	Y	Y
Race by Year FEs	N	Y	N	N	N	N	N
Age by Year FEs	N	N	Y	N	N	N	N
Race by Age by Year FEs	N	N	N	Y	N	N	N
Exact Match on Turnout	N	N	N	N	Y	Y	Y
Exact Match on Race	N	N	N	N	N	Y	Y
Exact Match on Age Bin	N	N	N	N	N	N	Y

Robust standard errors clustered by individual in parentheses. Main effects for No DMV Match and 2016 are absorbed by fixed effects. Exact matching on turnout matches units based on all primary and general elections from 2008-2014. For exact matching on age, we construct a separate age bin for each group of voters who were under 18 for a given set of elections, so the cohort of voters who became newly eligible to participate in 2010, 2012, 2014, and 2016 each have their own age bin. For voters who were eligible for all elections since 2008, we construct age deciles.

We observe the same pattern in for the 2016 general election. We show the results in Table A.4, and the columns mirror those in Table 3. The effect of the ID law on turnout in the 2016 general election about a 1 percentage point decrease when we limit the sample only to long-time registrants, which is much smaller than the 2.6 percentage point decrease we observe in Table 3 when we use the full sample.

Table A.4 – Effect of Voter ID Law on General Election Turnout Among Those Without ID, Individual Level, 2008–2016, Including Only Those Registered Pre-2008.

	Voted in General (0-1)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
No DMV Match * Year = 2016	-0.099	-0.097	-0.032	-0.030	-0.020	-0.019	-0.010
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
N	19,836,570	19,836,570	19,790,245	19,790,190	19,836,570	19,836,570	19,790,245
# Voters	3,967,314	3,967,314	3,958,049	3,958,038	3,967,314	3,967,314	3,958,049
Individual FEs	Y	Y	Y	Y	N	N	N
Year FEs	Y	N	N	N	Y	Y	Y
Race by Year FEs	N	Y	N	N	N	N	N
Age by Year FEs	N	N	Y	N	N	N	N
Race by Age by Year FEs	N	N	N	Y	N	N	N
Exact Match on Turnout	N	N	N	N	Y	Y	Y
Exact Match on Race	N	N	N	N	N	Y	Y
Exact Match on Age Bin	N	N	N	N	N	N	Y

Robust standard errors clustered by individual in parentheses. Main effects for No DMV Match and 2016 are absorbed by fixed effects. Exact matching on turnout matches units based on each primary and general election from the 2008 primary through the 2014 general. For exact matching on age, we construct a separate age bin for each group of voters who were under 18 for a given set of elections, so the cohort of voters who became newly eligible to participate in 2010, 2012, 2014, and 2016 each have their own age bin. For voters who were eligible for all elections since 2008, we construct age deciles.

A.8 Effect of Voter ID Law, by Pre-Treatment Turnout

Looking at the first entry in Table A.5, for example, we estimate the difference in turnout among those without ID and those with ID only among voters who had not previously voted in any primary or general election from 2008-2014. We find that the difference in 2016 primary turnout for these types of voters is just 0.4 percentage points. This group has a low baseline probability of voting, so there are few voters who could be deterred from voting because they lack identification. Similarly, looking at the last entry in Table A.5, the effect of the voter ID law on turnout among those without ID is just 1.1 percentage points for voters who have voted in every primary and general election from 2008-2014. For voters who regularly turnout to vote the voter ID law is an insufficient barrier to deter these voters from participating. For example, voters in this group may have been motivated to obtain valid identification before the 2016 primary or they might use no-excuse absentee voting, which does not require presenting a photo ID.

In contrast to those who rarely or always turnout, we find large effects among voters who only occasionally turnout to vote. Among those voters who only participated half of the elections they were eligible to participate in, 2 primary and 2 general elections from 2008-2014, we find a 3.7 percentage point effect of the voter ID laws. The estimates are much noisier in the lower left portion of the table because there are very few treated units who turn out to vote in many primary elections but very few general elections — and there are no treated units who voted in every primary election but no general election from 2008 through 2014.

Table A.6 shows how the effect of the voter ID law on general election turnout varies with an individual's prior turnout history. Again, we find that the voter ID law had a smaller effect among those who rarely participated in previous elections or those who always turned out to vote. The voter ID law caused a 2.3 and 0.8 percentage point decline in 2016 general election turnout among those who voted in no elections and in all elections before the ID law was implemented, respectively. Again, we find a much larger effect for voters who only participate occasionally in elections: among those who participated in half of the potential elections we find a 5.4 percentage decrease in turnout.

Table A.5 – Effect of Voter ID Law on 2016 Primary Election Turnout, by Pre-Treatment Turnout.

	# of Pre-Treatment General Elections				
	0	1	2	3	4
# of Pre-Treatment Primary Elections					
0	-0.004	-0.008	-0.006	-0.020	-0.018
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
1	-0.010	-0.023	-0.023	-0.029	-0.019
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
2	-0.010	-0.017	-0.037	-0.031	-0.021
	(0.014)	(0.006)	(0.003)	(0.002)	(0.001)
3	-0.018	-0.008	-0.027	-0.036	-0.015
	(0.065)	(0.017)	(0.006)	(0.003)	(0.000)
4		0.005	-0.012	-0.017	-0.011
		(0.005)	(0.004)	(0.002)	(0.000)

Each cell estimates the effect of the voter ID law on 2016 primary turnout, estimating the effect separately for different pre-treatment turnout patterns. We construct strata of treated and control units based on the total number of times a voter casted a ballot in a pre-treatment primary election (2008-2014) and pre-treatment general election (2008-2014). We implement the same exact matching procedure described in Section 3. Robust standard errors are in parentheses.

Table A.6 – Effect of Voter ID Law on 2016 General Election Turnout, by Pre-Treatment Turnout.

	# of Pre-Treatment General Elections				
	0	1	2	3	4
# of Pre-Treatment Primary Elections					
0	-0.023	-0.050	-0.045	-0.038	-0.016
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)
1	-0.039	-0.060	-0.055	-0.039	-0.014
	(0.002)	(0.002)	(0.002)	(0.002)	(0.000)
2	-0.048	-0.047	-0.054	-0.039	-0.012
	(0.010)	(0.006)	(0.004)	(0.002)	(0.000)
3	0.005	-0.073	-0.045	-0.040	-0.009
	(0.005)	(0.026)	(0.009)	(0.003)	(0.000)
4		-0.057	-0.031	-0.022	-0.008
		(0.101)	(0.021)	(0.002)	(0.000)

Each cell estimates the effect of the voter ID law on 2016 primary turnout, estimating the effect separately for different pre-treatment turnout patterns. We construct strata of treated and control units based on the total number of times a voter casted a ballot in a pre-treatment primary election (2008-2014) and pre-treatment general election (2008-2014). We implement the same exact matching procedure described in Section 3. Robust standard errors are in parentheses.

A.9 Exploring Heterogeneity in the Effect by Race and Party Registration

In this section, we explore heterogeneity in the effect of the voter ID law for primary elections.

First, in Table A.7 we estimate whether the effect of the voter ID law varies by race, but we use primary election turnout as the outcome rather than general election turnout, as in Table 6 in the main body of the paper. Similar to the effects in general elections, we do not find evidence that the effect of the law varies substantially by race as we implement our most stringent specification (column 7).

Table A.7 – Effect of Voter ID Law on Primary Election Turnout Among Those Without ID, Individual Level, 2008–2016.

	Voted in Primary (0-1)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
No DMV * 2016	-0.071	-0.083	-0.040	-0.050	-0.009	-0.011	-0.008
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
No DMV * 2016 * Black	-0.019	0.023	-0.030	0.008	-0.003	0.005	0.004
	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)
No DMV * 2016 * Hispanic	0.020	0.019	-0.014	-0.011	0.006	0.002	-0.000
	(0.003)	(0.003)	(0.003)	(0.003)	(0.001)	(0.004)	(0.004)
No DMV * 2016 * Other NW	-0.009	0.028	-0.037	-0.002	0.000	0.004	0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.001)	(0.004)	(0.004)
N	33,136,560	33,136,560	33,089,505	33,089,485	33,136,560	33,136,560	33,089,505
# Voters	6,627,312	6,627,312	6,617,901	6,617,897	6,627,312	6,627,312	6,617,901
Individual FEs	Y	Y	Y	Y	N	N	N
Year FEs	Y	N	N	N	Y	Y	Y
Race by Year FEs	N	Y	N	N	N	N	N
Age by Year FEs	N	N	Y	N	N	N	N
Race by Age by Year FEs	N	N	N	Y	N	N	N
Exact Match on Turnout	N	N	N	N	Y	Y	Y
Exact Match on Race	N	N	N	N	N	Y	Y
Exact Match on Age Bin	N	N	N	N	N	N	Y

Robust standard errors clustered by individual in parentheses. Main effects for No DMV Match and 2016 are absorbed by fixed effects. Exact matching on turnout matches units based on all primary and general elections from 2008-2014. For exact matching on age, we construct a separate age bin for each group of voters who were under 18 for a given set of elections, so the cohort of voters who became newly eligible to participate in 2010, 2012, 2014, and 2016 each have their own age bin. For voters who were eligible for all elections since 2008, we construct age deciles.

Next, in Table A.8 we explore whether the effect of the voter ID law varies by party in primary elections. Table A.9 shows the same results by party for the general election. We do not find evidence that the effect of the ID law is meaningfully different for Republicans, Democrats, and unaffiliated registrants. Again, we stress that homogeneity in the effect size does not mean that the law did not affect the composition of the electorate: because those without ID are more likely to be Democrats and unaffiliated voters than those with ID (Table 1), the law seems to have disproportionately deterred Democratic voters. Because those without ID are more likely to be Democrats voters than those with ID, the overall effect of the law decreased (albeit slightly) the share of Democratic voters in the electorate.

Table A.8 – Effect of Voter ID Law on Primary Election Turnout Among Those Without ID, Individual Level, 2008–2016.

	Voted in Primary (0-1)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
No DMV * 2016	-0.048	-0.055	-0.016	-0.022	-0.008	-0.010	-0.009
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
No DMV * 2016 * Dem	-0.051	-0.031	-0.050	-0.031	-0.004	0.000	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
No DMV * 2016 * Unaffil	-0.007	-0.002	-0.041	-0.034	-0.001	0.002	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
N	33,136,560	33,136,560	33,089,505	33,089,485	33,136,560	33,136,560	33,089,505
# Voters	6,627,312	6,627,312	6,617,901	6,617,897	6,627,312	6,627,312	6,617,901
Individual FEs	Y	Y	Y	Y	N	N	N
Year FEs	Y	N	N	N	Y	Y	Y
Race by Year FEs	N	Y	N	N	N	N	N
Age by Year FEs	N	N	Y	N	N	N	N
Race by Age by Year FEs	N	N	N	Y	N	N	N
Exact Match on Turnout	N	N	N	N	Y	Y	Y
Exact Match on Race	N	N	N	N	N	Y	Y
Exact Match on Age Bin	N	N	N	N	N	N	Y

Robust standard errors clustered by individual in parentheses. Main effects for No DMV Match and 2016 are absorbed by fixed effects. Exact matching on turnout matches units based on all primary and general elections from 2008-2014. For exact matching on age, we construct a separate age bin for each group of voters who were under 18 for a given set of elections, so the cohort of voters who became newly eligible to participate in 2010, 2012, 2014, and 2016 each have their own age bin. For voters who were eligible for all elections since 2008, we construct age deciles.

Table A.9 – Effect of Voter ID Law on General Election Turnout Among Those Without ID, Individual Level, 2008–2016.

	Voted in General (0-1)						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
No DMV * 2016	-0.127	-0.132	-0.086	-0.094	-0.031	-0.031	-0.028
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
No DMV * 2016 * Dem	-0.012	-0.002	-0.016	0.003	-0.002	-0.001	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)
No DMV * 2016 * Unaffil	0.054	0.042	-0.042	-0.036	0.001	0.002	0.003
	(0.002)	(0.002)	(0.003)	(0.003)	(0.001)	(0.001)	(0.001)
N	33,136,560	33,136,560	33,089,505	33,089,485	33,136,560	33,136,560	33,089,505
# Voters	6,627,312	6,627,312	6,617,901	6,617,897	6,627,312	6,627,312	6,617,901
Individual FEs	Y	Y	Y	Y	N	N	N
Year FEs	Y	N	N	N	Y	Y	Y
Race by Year FEs	N	Y	N	N	N	N	N
Age by Year FEs	N	N	Y	N	N	N	N
Race by Age by Year FEs	N	N	N	Y	N	N	N
Exact Match on Turnout	N	N	N	N	Y	Y	Y
Exact Match on Race	N	N	N	N	N	Y	Y
Exact Match on Age Bin	N	N	N	N	N	N	Y

Robust standard errors clustered by individual in parentheses. Main effects for No DMV Match and 2016 are absorbed by fixed effects. Exact matching on turnout matches units based on all primary and general elections from the 2008 primary through the 2014 general. For exact matching on age, we construct a separate age bin for each group of voters who were under 18 for a given set of elections, so the cohort of voters who became newly eligible to participate in 2010, 2012, 2014, and 2016 each have their own age bin. For voters who were eligible for all elections since 2008, we construct age deciles.

A.10 Effect of ID Law on Composition of Electorate

To situate the vote reductions due to the voter ID law in a broader context we estimate how the law's effects changed the composition of the North Carolina electorate in the 2016 primary and general elections. In Table A.10 we show the racial and partisan composition of the North Carolina in the 2016 Primary and 2016 General election under the column "With Law." These are the observed shares of those who voted in each election. To estimate how the racial composition of the electorate would have changed had the ID law not been passed, we add the vote reductions from Table 7 – that is, the number of additional voters we estimate would have participated had the law not been passed – to the observed number of voters in each election. We show the estimated racial (Panel A) and partisan (Panel B) composition of the electorate under the counterfactual scenario without the voter ID law. It shows that, because the effects among those without ID are relatively small, along with the fact that those without ID make up a small portion of the electorate, these vote reductions have only a small effect on the overall composition of the electorate, at least along racial and partisan dimensions. We reiterate, that this interpretation of the findings requires relatively strong assumptions about voter behavior in the absence of the law. Specifically, that the law had no effect on the participation decision of those with the required identification.

Table A.10 – Change in Composition of Electorate as a Function of ID Law

	A. Change in Racial Composition			
	2016 Primary		2016 General	
	Without Law	With Law	Without Law	With Law
White	77.32%	77.34%	74.08%	74.11%
Black	19.34%	19.32%	21.56%	21.54%
Hispanic	1.07%	1.07%	1.49%	1.49%
Other Non-White	2.27%	2.27%	2.86%	2.86%
	B. Change in Partisan Composition			
	2016 Primary		2016 General	
	Without Law	With Law	Without Law	With Law
Democrat	41.46%	41.44%	41.80%	41.78%
Republican	36.50%	36.52%	33.64%	33.65%
Unaffiliated	22.04%	22.05%	24.56%	24.57%

Note: Each cell presents our estimates of share of the electorate that belongs to a given category with and without the strict photo ID law. Panel A shows the change in the racial composition of the electorate, while Panel B shows the change in the partisan composition of the electorate as a function of the strict photo ID law. The first two columns show comparisons for the 2016 primary election, while the last two columns show comparisons for the 2016 general election