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Voter Identification and Nonvoting in Wisconsin—Evidence from the 2016 Election

Michael G. DeCrescenzo and Kenneth R. Mayer

ABSTRACT

How much did Wisconsin's voter identification requirement matter in 2016? We conducted a survey of registered nonvoters in the counties surrounding the cities of Milwaukee and Madison to estimate the number of registrants who experienced ID-related voting difficulties in the 2016 presidential election. We estimate that 10 percent of nonvoters in these counties lack a qualifying voter ID or report that voter ID was at least a *partial* reason why they did not vote in 2016, and six percent of nonvoters lacked a voter ID or cited voter ID as their *primary* reason for not voting. Theoretically, we argue that voter ID requirements "directly" affect voters who lack qualifying IDs but also "indirectly" affect voters who are confused about their compliance with the law. We find evidence of such confusion, with many respondents mistakenly believing that they did not have the necessary ID to vote when they actually did. Our analysis permits us to calculate bounds on the possible turnout effect in 2016. Most of our credible estimates suggest that the voter ID requirement reduced turnout in these counties by up to one percentage point.

Keywords: voter identification, turnout, administrative burdens, voting rights, election administration

INTRODUCTION

THE NOVEMBER 2016 PRESIDENTIAL CONTEST was the first major election in which Wisconsin's voter ID requirement was in effect. Statewide turnout was the lowest it had been in 16 years, with an especially notable drop in the city of Milwaukee, where it fell from 66 percent of the voting-age population in 2012 to 56 percent in 2016 (Wisconsin Elections Commission 2018).

The full implementation of Wisconsin's ID requirement offers an opportunity to assess its effects and explore the broader characteristics of voter ID laws. We present the results of a survey of nonvoting registrants in the state's two largest counties (Milwaukee and Dane) that asked about reasons for nonvoting, understanding of the voter ID law, and the forms of ID a respondent possessed. Using a Bayesian analysis, we estimate that a mean of 10.2 percent of nonvoting registrants were *deterred* from voting by the ID law (defined as lacking a qualifying ID or citing lack of ID as a reason for not voting). Using a more restrictive classification (respondents who lacked a qualifying ID or noted that lack of ID was their *main* reason for not voting), a mean of 5.8 percent of nonvoters were *prevented* from voting by the ID law. These estimates are larger among individuals who are black, earn lower incomes, and have less formal education. Credible intervals

Michael G. DeCrescenzo is a PhD candidate at the University of Wisconsin–Madison, in Madison, Wisconsin. Kenneth R. Mayer is a professor of political science at the University of Wisconsin–Madison. He has been an expert witness in federal and state litigation challenging Wisconsin's voter ID requirement.
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indicate that between 8,000 and 17,000 nonvoters in these two counties were deterred from voting, and between 4,000 and 11,000 were prevented from voting. Boundary analyses suggest that registered voter turnout in these two counties may have been reduced by up to one percentage point.

Theoretically, we elaborate on a broader conception of how voter ID requirements and other election laws can impede voters. Voters may be "directly" affected by a voter ID requirement if they lack a qualifying ID, but many additional voters may be "indirectly" affected if the details of the law confound voters' understanding of their compliance with the requirements. Consistent with this argument and with other similar work (Hasen 2016; Hobby et al. 2015), we find evidence that voters are confused about the ID requirement. When asked whether different forms of ID qualify or not under the ID law, respondents classify an average of only 5.4 out of 12 accurately. Individuals who were less knowledgeable of the law were in turn more likely to cite a lack of ID as a reason for not voting. Further, we find that many of the individuals who claim to be affected by the requirement actually report having a qualifying ID, and this pattern is stronger among individuals who were less knowledgeable of the law's details.

Our analysis has its limits. Because our sample is drawn from registered nonvoters, we can only make statements about those who were contemporaneously registered to vote. We do not know many individuals never bothered to register because they lacked (or thought they lacked) a qualifying voter ID.[1] Our estimates apply only to Milwaukee and Dane counties; while we are confident that the effects elsewhere in the state are nonzero,[2] we do not extrapolate to statewide estimates. We cannot definitively control for all possible sources of misreporting or response error, but our findings reflect conservative decisions throughout the analysis are consistent with prior research and are plausible in their magnitude. Finally, our survey does not capture the administrative burdens experienced by those who undertook the steps necessary to obtain a new ID in order to vote. We elaborate on these limitations and discuss potential improvements below.

WISCONSIN'S VOTER ID REQUIREMENT

Prior to enacting its voter ID requirement, Wisconsin law emphasized voter participation and access, with relaxed early voting and absentee voting rules, same-day registration, and local control of election administration. Voters were required to show ID only if they were first-time voters who had not verified their identity when registering by mail. Wisconsin Act 23 (Wisconsin Statutes 5.02(6m)), which became law in May 2011, requires voters to present one of the following forms of identification before casting a ballot:

1. A Wisconsin driver's license
2. A Wisconsin Department of Transportation (DOT) photo ID
3. A receipt for a driver's license or DOT-issued photo ID (used between the time of application and the time that the ID is received)
4. A U.S. military ID
5. A U.S. passport
6. A certificate of naturalization that is less than two years old
7. An ID issued by a federally recognized Native American tribe
8. A qualifying ID card issued by an accredited Wisconsin college or university

IDs in categories 1–4 must be either current or have an expiration date after the previous two-year general election. Student IDs must be unexpired, have an expiration date of two years or less from date of issue, and contain a signature; a person using a student ID is also required to show proof of current enrollment.[3] After reports of military veterans unable to use their Veterans Affairs (VA) IDs to vote in a 2016 primary election (including the uncle of a sitting Wisconsin Supreme Court Justice), the legislature added VA IDs as qualifying form of identification (Marley 2016).

Wisconsin's law is among the strictest in the country. It allows fewer forms of IDs, requires photo ID for mail absentee voting, and does not have an

[1] A qualifying photo ID is not required for voter registration in Wisconsin if the registrant uses the last four digits of their social security number.

[2] More than half of all ID-related rejected provisional ballots cast in 2016 were in counties other than Dane or Milwaukee.

[3] Standard student IDs at many state universities (including the University of Wisconsin–Madison) are not compliant with the statute because they lack a signature or have expiration dates beyond two years from issuance. Students can obtain an additional voting-only ID that contains the necessary elements. See State of Wisconsin Government Accountability Board (2017) for a state guide to student voter IDs.

election-day affidavit exemption for individuals without ID.[4] There is a process by which people without the necessary underlying documentation could obtain an ID for voting, but a federal judge ruled it unconstitutional in 2016, ordering the state Department of Motor Vehicles (DMV) to provide an ID to anyone who asked for one.[5] The process still requires a trip to the DMV to submit forms in person.

The ID law was in effect for a judicial primary in February of 2012 that was held in just six of the state's 72 counties. (Turnout was under three percent.) A series of injunctions in state and federal court blocked the law until the presidential primary election in early 2016 and the general election in November.

THE EFFECTS OF VOTER ID

A large literature has demonstrated that individual decisions to vote, and therefore aggregate turnout, are affected by administrative practices and legal requirements for voting (e.g., Wolfinger and Rosenstone 1980; Leighley and Nagler 1992; Hanmer 2009; Gronke, Galanes-Rosenbaum, and Miller 2007; Green and Gerber 2008; Burden et al. 2014). Voter ID laws can raise barriers for individuals who don't possess a qualifying ID or who lack the documentation required to obtain one. The laws also increase information costs by requiring voters to navigate the details of the law to determine their compliance.

We argue that voter ID requirements affect voting costs through two conceptually distinct pathways. The first is a *direct effect* on people who are kept from voting primarily due to bureaucratic obstacles imposed by the law. Some individuals will not attempt to vote because they lack and cannot obtain ID or are told at the polling place that their ID is insufficient. If ID is a *necessary* condition for voting, we characterize those who do not satisfy that condition as directly affected.

ID laws also have an *indirect effect*. Although possessing a qualifying ID is a necessary condition for voting, mere possession is not a sufficient condition after the law is imposed; people who have qualifying IDs can still have their path to the voting booth impeded by information costs imposed by the law. Voter ID laws contain technical and administrative details that are not widely understood. As a result, voters who possess qualifying IDs could mistakenly believe that they do not.

How might confusion impede someone who actually has a qualifying ID? The devil is in the details. Even a registered voter who possesses a driver's license or state ID might still be confused about the exact circumstances when these common IDs do and do not qualify. For example, WI driver's license holders who move residences must update their address information with the state Department of Transportation but are not required to obtain a new physical license until their current license expires (Wisconsin Statutes 341.335). As a result, many Wisconsinites hold driver's licenses with outdated addresses. Importantly, a driver's license used as a voter ID does *not* need to show the voter's registered address, but otherwise eligible voters may not know this. The number of residents potentially implicated in this detail of the law is far from trivial: the 2012–2016 American Community Survey estimated that each year, 547,819 Wisconsin voting-age residents relocated within-state (U.S. Census Bureau 2016). Voters whose names have changed (e.g., through marriage or divorce) might be able to vote using an ID with their previous name, depending on whether they registered to vote under the new name or if the new name is hyphenated in a way that includes the full previous surname. Again, the numbers are not trivial; Wisconsin recorded 32,385 marriages and 14,986 divorces in 2015 (Wisconsin Department of Health Services 2016). Expired driver's licenses also qualify as long as the expiration date is more recent than the previous two-year November general election, as do suspended or revoked licenses.[6] Wisconsin licenses are valid for eight years. Assuming a regular pattern of license issuance, one-eighth of the state's 4.3 million licenses (about 540,000) will expire each year. Most of these licenses will be renewed (483,000 were renewed in 2017), but many will not be.

Moving, marriage, divorce, and license expiration are ordinary facts of life, but they bear on the

[4]According to the National Conference of State Legislatures as of January 2019, most states with strict photo ID requirements exempt mailed absentee ballots from the ID requirement. All but Wisconsin and Tennessee accept employee IDs issued by a body of federal, state, or local government. Indiana and Tennessee also have an indigence exception (Underhill 2019).

[5]The judge called the program "pretty much a disaster" (*One Wisconsin Institute, Inc. et al. v. Thomsen et al.* 2016: 964).

[6]The minutia can become hyper-technical. Someone whose license has been confiscated by law enforcement can ask for a receipt documenting that the license has been taken away, which can be used as a voter ID.

ability to comply with the voter ID requirement in ways that are neither obvious nor commonly discussed in academic literature. The number of people affected by these technical details, and for whom compliance may not be straightforward, is potentially large.

Research from other states finds evidence that voters are confused by voter ID requirements. In a study of Harris County, Texas, and Texas's 23rd Congressional District, three-quarters of 2016 nonvoters surveyed incorrectly believed that an unexpired Texas driver's license was the only form of ID that was acceptable for voting. Fewer than 20 percent of nonvoters knew what ID requirements were in effect for the election (Jones, Cross, and Granato 2017).

Direct effects are more closely related to bureaucratic hurdles (Herd and Moynihan 2018) that might be mitigated through what Hasen calls a "softening of the harshest aspects of voter identification laws" (Hasen 2016: 102). Indirect effects might be alleviated through voter education efforts or more efficient administrative practices. But both direct and indirect effects impede otherwise eligible people from accessing the voting booth.

Measuring the effects

Estimating the turnout effect of voter ID laws is a challenging empirical problem. The question behind many studies—how many people did not vote *who would otherwise have voted* in the absence of an ID law—is not directly answerable with observable data (McConville, Stokes, and Gray 2018). We know whether someone votes (and therefore know that their intention to vote was not overcome by the ID requirement), but the causes of nonvoting are harder to pinpoint. ID requirements are one of many things that affect turnout. Individuals without ID might not vote because they dislike the candidates, do not think their vote matters, and so on, so they may not have voted even if they possessed a qualifying ID. Furthermore, individuals may possess the documents needed to obtain an ID but lack the ability or inclination to travel to the appropriate government office to get it. Still others might be able to obtain the required documents but decide that the endeavor would be too costly. People may not realize that they possess a valid form of voter ID because they are unaware of the details of the requirement. And election workers might not administer an ID law in an evenhanded or accurate manner (Cobb, Greiner, and Quinn 2010; White, Nathan, and Faller 2015).

Researchers have used four main methods to estimate the effects of ID laws: analyzing the number of provisional ballots cast for ID-related reasons (Hopkins et al. 2017; Pitts 2008, 2013; Stewart 2013); using surveys to identify individuals who lack qualifying forms of ID (Alvarez, Bailey, and Katz 2008; Barreto, Nuño, and Sanchez 2009; Barreto and Sanchez 2012*a*; Barreto and Sanchez 2012*b*; Barreto and Sanchez 2014; Barreto et al. 2019; Hajnal, Lajevardi, and Nielson 2017; Stewart 2013); record-linkage techniques to identify registered voters who lack a form of qualifying ID in government databases (Ansolabehere and Hersh 2017; Government Accountability Office 2014; Hood 2015; Mayer 2015; Stewart 2013); and analyses of aggregate or individual turnout to isolate the effects of ID laws, typically using difference-in-difference methods to compare states that do and do not have strict ID requirements (Erikson and Minnite 2009; Government Accountability Office 2014; Hood and Bullock 2012; Mycoff, Wagner, and Wilson 2009). Although research consistently shows that rates of ID possession are lower among minority and low-income populations, studies of turnout have returned a range of conclusions, from no or inconclusive effects (Mycoff, Wagner, and Wilson 2009; Erikson and Minnite 2009; Grimmer et al. 2018; Cantoni and Pons 2019) to aggregate estimates of a turnout decline up to a few percentage points (Alvarez, Bailey, and Katz 2008; Government Accountability Office 2014; Hood and Bullock 2012).

All of the methods used to study voter ID—the number of provisional ballots, estimates of ID possession, and studies of aggregate turnout—provide insight into the consequences of voter ID laws. They have drawbacks, however. Some methods will underestimate the number of individuals affected because the data are produced only after several self-selection processes (e.g., provisional ballots). Other methods will overestimate the effect on turnout due to unobserved confounders. One way to improve the measurement of voter ID's impact on voters, first employed in a 2015 study of the Texas 23rd Congressional District, is to survey nonvoters from voter files (Hobby et al. 2015; Jones, Cross, and Granato 2017). This approach is consistent with recommendations from Grimmer et al., who describe "custom-sampled surveys of individuals affected by voter ID laws" as an improvement over broad national surveys (2018: 1051). Asking nonvoters directly about their experiences with voter ID requirements provides more leverage to identify direct and indirect effects. We extend this approach using a similar survey instrument in Wisconsin.

DATA AND EMPIRICAL METHODS

Original survey of Wisconsin nonvoters

We surveyed Wisconsin registrants to measure the rate of ID-related nonvoting in the 2016 presidential election. We built our sample from the voter histories of registered Wisconsin voters (the state "WisVote" file), using the voter file generated on February 20, 2017. We limited the voter file to include only registrants from Dane and Milwaukee Counties who did note vote in the 2016 election. These counties contain the two largest metro areas in the state (Milwaukee and Madison) and have the largest low-income and minority populations, which existing research suggests are most likely to be affected by voter ID requirements. Because the sampling frame contains only these counties, we do not extrapolate our estimates to represent the state of Wisconsin as a whole.[7]

We used a stratified design with oversampling from Census tracts with lower aggregate measures of socioeconomic status (SES). We divided the sample into three strata and drew a sample of 2,400 nonvoters in total: 650 from Dane County, 750 from high-SES tracts in Milwaukee County, and 1,000 from low-SES tracts in Milwaukee County. We conducted all analyses using sampling weights to adjust for unequal sampling probability across strata.[8]

We mailed our survey to each sampled individual in March 2017. The survey asked registrants about their engagement with and interest in the campaign, as well as their reasons for not voting. We embedded questions about respondents' knowledge of the voter ID requirement and the forms of ID they possessed. Because the study was supported by a government entity, we did not ask about party affiliation or vote intentions in the 2016 election season. The full questionnaire can be viewed in Supplementary Appendix A.

We received 288 valid responses, with 75 from Dane County and 213 from Milwaukee County. This gives us a nominal response rate of 12.0 percent. The response rate is 27.5 percent after we adjust for deadwood in the sample, which we explain in more detail when we describe our statistical modeling approach below.[9]

Identifying the "affected group"

Because the survey asked respondents several questions about their experiences with voter ID during the 2016 election, we can construct multiple measures of who was affected. We asked respondents why they did not vote, offering voter ID as one of several reasons.[10] These questions were modeled after items routinely used in the Cooperative Congressional Election Study (CCES) and in the November Voting and Registration Supplement to the Census Bureau's Current Population Survey (CPS). Voters could initially select several partial reasons for not voting and then were asked to select their main reason[11] for not voting. Potential reasons

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[7]Our choice to limit the sample to Dane and Milwaukee Counties was driven by two considerations. First, the survey was funded by a government office that was interested in local effects of the ID requirement. Second, we faced a trade-off between a two-county study and a statewide study. We were particularly interested in quantifying the effects among registrants most likely to be affected, who would be concentrated in the state's urban counties. The two-county survey allowed more flexibility in the sampling design but at the expense of our ability to draw statewide inferences. We concluded that estimating individual effects was the more important matter.

[8]Population weights for each sampled individual were generated by the UW Madison Survey Center. For in-sample analysis, we rescale these weights such that the largest weight is equal to 1.0. We show in Supplementary Appendix B that our results are almost identical under other weighting approaches, including poststratification weights that adjust for response rates across strata and a by-stratum estimation method where each stratum is treated as an independent sample.

[9]Supplementary Appendix B contains a section on the demographic composition of the sample. Because there is no Census for our target population (nonvoting registrants in Dane and Milwaukee Counties), we are limited in the explicit judgments we can make about the representativeness of the sample. We were able to compare the racial distribution of our sample to the distribution of *modeled race* as estimated from surnames in the voter file. Sample strata in Milwaukee contain a larger share of whites than the modeled race estimates suggest, which would likely lead us to underestimate voter ID's impact in the sample.

[10]Original text: "There are many reasons why people are not able to vote or choose not to vote. Please tell us whether or not each of the following are reasons why you did not vote in the November 8, 2016 general election." (Underline in original.)

[11]Original text: "Which of the following was the primary or main reason why you did not vote in the recent presidential election? Please check only one." (Underline in original.)

included being ill or disabled, being out of town, not having enough time, not being interested in voting, having a transportation problem that prevented them from getting to the polls, not liking the choice of candidates or issues, being unable to obtain an absentee ballot, lacking a qualifying ID, attempting to vote but being told at the polls that their ID was not qualifying, long lines at the polls, encountering a problem with early voting, and believing that one's vote would not matter. Later in the survey, respondents were asked about the forms of ID they possessed, which we used to determine whether respondents lacked a qualifying voter ID.[12] Tables 1 and 2 summarize these variables with all responses weighted.

Table 1 displays respondents' reasons for not voting. The most common reason for not voting was displeasure with the choice of candidates and issues of the campaigns (cited as a partial reason for not voting by 50.8 percent of the sample and the primary reason for not voting by 33.0 percent of the sample). Other reasons for not voting included lack of interest, a feeling that one's vote did not matter, and other time, location, or ability constraints; 6.5 percent of respondents reported that they did not have adequate ID, and 2.9 percent said that they were turned away at the polls because they lacked ID. Fewer respondents cited voter ID as the main reason they did not vote, with 1.7 percent of the sample saying they lacked adequate ID and 1.4 percent saying that they were turned away at the polls.

The percentage of respondents indicating ID-related reasons for not voting is low but not zero. This makes sense, given what we already know about the impact of voter ID requirements. We have strong a priori expectations that the number of individuals facing ID-related obstacles should be relatively small (Erikson and Minnite 2009). Furthermore, we know that most Wisconsin registrants possess qualifying forms of ID. In litigation over Wisconsin's ID requirement, a federal court concluded that 9.4 percent of registrants in Wisconsin lack a qualifying form of identification (*Frank v. Walker* 2014).

Table 2 shows rates of ID possession in the sample. We find that 3.0 percent of respondents lack all

Table 1. Partial and Main Reasons for Not Voting

	Partial reason (%)	*Main reason (%)*
Unhappy with choice of candidates or issues	50.8	33.0
Not interested	27.5	8.8
Not enough time	26.7	9.3
Vote would not have mattered	26.2	6.6
Away from home	20.1	13.5
Ill or disabled	18.4	13.6
Problem with early voting	12.5	2.9
Couldn't get absentee ballot	8.1	1.3
Transportation problems	7.7	2.1
Did not have adequate photo ID	6.5	1.7
Lines too long	3.0	0.9
Told at polling place that ID inadequate	2.9	1.4
No reason given	-	4.9

Percentages for partial reasons sum to more than 100 because respondents could indicate multiple partial reasons. Estimates reflect sample weighting.

Table 2. ID Possession Among Survey Respondents, Including Forms of ID That Do and Do Not Qualify as Valid Voter IDs in Wisconsin

ID form	*Possess (%)*	*Lack (%)*	*DK (%)*	*NA (%)*	*Qualifying*
WI driver's license	79.7	14.8	0.8	4.6	Yes
U.S. passport	42.3	43.2	0.4	14.1	Yes
WI DOT ID card	21.7	59.2	3.1	15.9	Yes
Military ID	5.7	74.3	0.9	19.1	Yes
Naturalization certificate	3.2	75.7	1.7	19.4	Yes
WI voter ID card	2.4	75.2	1.7	20.7	Yes
Native Am. tribe ID	1.2	78.4	0.4	19.9	Yes
Social Security card	89.0	3.9	0.7	6.4	No
Credit card	73.8	18.2	0.4	7.6	No
Concealed carry permit	6.8	74.4	0.4	18.3	No
Non-WI driver's license	5.6	74.7	0.4	19.3	No
State/federal employee ID	5.0	74.6	0.4	19.9	No

Table includes "Don't know" responses (DK) and non-responses (NA). Estimates reflect sample weighting.

[12]"Currently, do you have each of the following forms of identification?" Respondents could separately indicate that they possessed several forms of ID, only some of which would satisfy the voter ID requirement. The survey does not indicate to the respondent which forms of ID satisfy the voter ID requirement. The qualifying IDs included a Wisconsin driver's license, Wisconsin Department of Transportation ID, a voting-only ID, a military or veteran's ID, a Native American tribal ID, a certificate of recent naturalization, and a U.S. passport. The non-qualifying IDs included a driver's license from another state, a credit card, a permit to carry a concealed weapon, a state or federal government ID, and a Social Security card.

forms of qualifying ID in the survey item.[13] We note that this estimate is lower than the estimates of non-possession produced by expert witnesses on both sides of the federal litigation over Wisconsin's voter ID law (*Frank v. Walker*), suggesting that respondents are not misreporting their ID possession.

We construct two measures of the group of affected citizens. We refer to registrants as *deterred* from voting if they lack a qualifying ID or mention ID as a reason for not voting. We also construct a stricter definition, referring to registrants as *prevented* from voting if they lack a qualifying ID or list voter ID as their primary reason for not voting. We present analyses for both outcome variables throughout the article. In the interest of brevity, we refer to nonvoters more generally as "affected" in contexts where we do not need to distinguish between deterred and prevented classifications.

Even though "prevented" is a more conservative definition than "deterred" and might be interpreted as more robust, we caution against invoking such a heuristic. Electoral reforms can reduce an individual's ability to vote even if they do not constitute an outright ban. Partial reasons for nonvoting remain an important measure of voter ID effects. Furthermore, even if citizens possess a qualifying ID, confusion about the law can lead them to mistakenly believe that they cannot vote (Hobby et al. 2015).

While there is always a possibility for noise in survey responses, closer analysis of our data suggests that these forces do not drive our results (see sections about race and socioeconomics and about confusion). We also find it unlikely that ID-related responses are driven by social desirability because respondents give ID-related responses at a much lower rate compared to other more socially desirable responses (disliking the candidates, away from home, not enough time, etc.). The distribution of responses resembles those of other similar items in the CCES and the CPS for 2016 (see Supplementary Appendix B).

Modeling the impact of voter ID

In this section, we describe a model to estimate the number of individuals affected by the voter ID requirement in the population of these two counties. This process is not as simple as multiplying the number of nonvoters in the voter file by the percentage in the sample who said that they were affected by the voter ID requirement. Not every record in the voter file was eligible at the time of the election. Voter files include deadwood: individuals who are no longer eligible to vote at their registered addresses because they moved, died, or fall into another category of ineligible voters (Pettigrew and Stewart 2016). Identifying this deadwood is crucial to generating population estimates of voter ID effects from our survey results. We build a population model that estimates this eligibility rate as well as the proportion of nonvoters who were affected by the voter ID requirement.

Eligibility rate. To identify deadwood, we tracked survey nonrespondents to identify individuals who no longer lived at the addresses listed in their voter histories. The Survey Center used Lexis/Nexis commercial data to identify nonrespondents who submitted a National Change of Address form with the U.S. Postal Service, registered to vote at another address, appeared on a credit report at a different address, appeared in public records as deceased, incarcerated, in the military and stationed abroad, or underwent a name change. Of the 2,112 nonrespondents, this method identified 1,049 as eligible and 1,063 as ineligible. Counting all respondents as eligible, this gives a point estimate of the deadwood rate of 44.3 percent (or an eligibility rate estimate of 55.7 percent).

Let i index all individuals (respondents and nonrespondents) in the full sample of 2,400. We model the eligibility of each individual in the sample, $Eligible_i$, as a Bernoulli outcome,

$$Eligible_i \sim Bernoulli(\varepsilon), \tag{1}$$

where ε is the population eligibility rate among nonvoters in these two counties.[14]

Response rate. Individuals who remain at their registered address can then respond to the survey or not. In the interest of specifying the full probability, we model the probability that an individual responds, conditional on eligibility, as another Bernoulli outcome.

[13]We code "don't know" responses as lacking ID because if a respondent is unaware whether they possess a form of ID, presumably they would not be able to use it to vote. Non-responses to these questions are more ambiguous, however, so we make the conservative decision to code non-responses as possession. This probably undercounts the extent of ID non-possession.

[14]Although the sample was drawn in February 2017, we must assume that ε is representative of nonvoter eligibility as of the presidential election in November 2016.

$$Respond_i \sim Bernoulli(\rho), \tag{2}$$

where ρ represents the response probability among eligible nonvoters.[15]

Affected rate. Respondents to the survey then indicate whether they were affected by the ID requirement (deterred or prevented). We model the probability that an individual is affected as a final Bernoulli outcome.

$$Affected_i \sim Bernoulli(\pi), \tag{3}$$

where π represents the probability that a randomly selected nonvoter was affected by voter ID, conditional on eligibility. We refer to π as the "affected rate." We generate separate estimates of π for the "deterred" and "prevented" outcome variables.

Population estimate. After estimating these parameters from survey data, we generate population estimates for the number of affected nonvoters in Dane and Milwaukee counties. The voter file contains 229,625 nonvoters for these two counties, but not all of these individuals were eligible at their listed addresses in 2016. We calculate the number of eligible nonvoters in the population by penalizing the number of nonvoters by ε.

$$Number\ Eligible = \varepsilon \times Nonvoters \tag{4}$$

We then calculate the number of nonvoters affected by ID by multiplying the number of eligible nonvoters by the affected rate π.

$$Number\ Affected = \pi \times (Number\ Eligible) \tag{5}$$

We are careful to note that the number of individuals affected by the voter ID requirement is not equivalent to the number of individuals who *would have voted* if not for the requirement. Our survey design does not permit rigorous enough assumptions about counterfactuals to estimate the causal effect on turnout—we cannot know whether affected individuals would have voted if the ID law were not in effect. Absent these counterfactuals, we instead use our estimates in a bounding analysis to simulate a range of plausible turnout effects.

Bayesian priors and estimation

We estimate this model with a Bayesian approach, which offers a number of advantages. Primarily, Bayesian methods allow us to improve our estimates by including prior information from past studies of voter ID, voter registration, and deadwood. This is particularly useful for moderately sized samples such as ours, where priors can stabilize and regularize estimates against sampling error when trustworthy external information about parameters is available. We find that our estimates are consistent with previous studies, which increases our confidence in the reliability of our sample. We also show that our estimates using flat and informed priors are similar, demonstrating that posterior inferences do not merely reflect the priors used.

We design informative prior distributions to reflect conservative assumptions about the unknown parameters in our model. The analysis is most sensitive to the rate at which nonvoters were affected by the voter ID requirement, π, so we take special care to design a prior that minimizes the risk of overestimating this quantity. Our prior always regards smaller values of π as more likely than larger values, and it places 95 percent of the prior probability below the largest credible estimate of π supported by relevant research. When we examine studies of voter ID in Wisconsin, estimates of ID non-possession rates among registered voters range from 4.5 percent (Hood 2015) to 8.5 percent (Mayer 2015), and 9.5 percent in Milwaukee (Barreto and Sanchez 2012*a*). A federal court concluded that 9.4 percent of registrants in Wisconsin lacked qualifying identification (*Frank v. Walker* 2014). With this information, we specify the skeptical prior $\pi \sim$ Beta (1,30), which has an always-decreasing density as π increases, an expected value of 3.3 percent, and 95 percent of its mass below 9.5 percent. This choice of prior is especially conservative because the estimates on which it is based are under-inclusive of the affected population as we define it, which contains both directly and indirectly affected nonvoters. Furthermore, we use the same prior for "deterred" and "prevented" nonvoters, even though existing estimates more closely reflect the narrower "prevented" group.

[15]The exact value of the response rate parameter should not affect our estimates because we employ the canonical assumption in survey research that survey response is independent of item response. Researchers wishing to extend our methods in the future could collect background characteristics on all sampled individuals to model the response rate and modify this independence assumption.

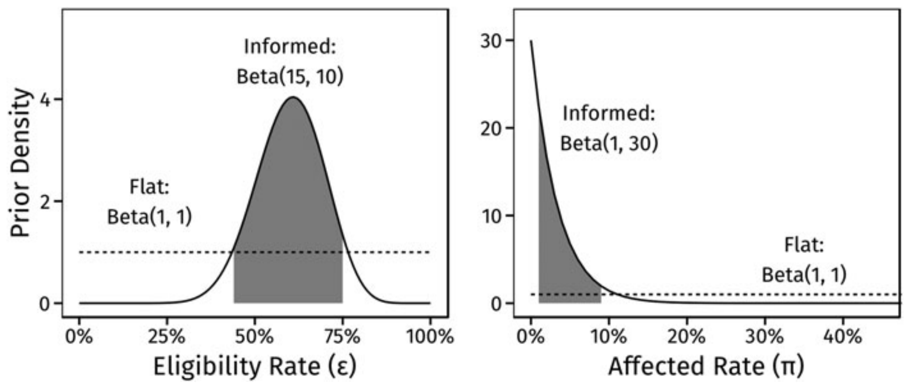

FIG. 1. Flat and informed priors for the eligibility and affected rates. Shaded regions indicate the inner 90 percent of the informative prior distributions.

We also develop a prior for the eligibility rate ε using estimates of voter registration deadwood developed by Pettigrew and Stewart (2016). Their model estimates that the deadwood rate in Wisconsin is roughly 7.5 percent of the total registration file. Assuming that the deadwood rate is about the same statewide as it is in Dane and Milwaukee Counties, this implies that of the 19 percent of registrants in these counties who did not vote in 2016, roughly 61 percent were eligible.[16] Using this information, we place a Beta (15,10) prior on the eligibility rate ε, which has an expected value of 60 percent with 90 percent of its prior mass between 44 percent and 75 percent eligibility. We include this wider variance to account for the possibility that the deadwood rate in Dane and Milwaukee Counties is different from the statewide deadwood rate.

Translating past research into prior distributions is never a precise exercise, but we believe that our approach offers an improvement over flat priors that regard all estimates as equally plausible, especially in a moderately sized sample like ours. We also present estimates using flat priors for the eligibility and affected rates, Beta (1,1), to show that prior information improves our estimates without over-determining them. Figure 1 compares the flat and informative prior distributions for the eligibility rate (ε) and the affected rate (π). The response rate (ρ) is omitted from the plot because we always give it a flat prior.[17]

We fit all Bayesian models with Stan (Carpenter et al. 2016), which generates posterior samples using a variant of Hamiltonian Monte Carlo. We collect 12,000 draws for each model parameter.[18] We incorporate sample weights into the Bayesian analysis by weighting the log likelihood of each observation.[19] The log likelihood of the data (the data's contribution to the log posterior distribution) can be generically expressed as follows:

$$\log[p(y \mid \theta)] = \sum_{i=1}^{n} \ell(y_i \mid \theta) w_i \qquad (6)$$

where each $\ell(y_i \mid \theta)$ and w_i represent the log likelihood and sample weight, respectively, for each outcome observation y_i and parameter vector θ.

[16]If the deadwood rate among nonvoters is $\frac{0.075}{0.19} = 0.39$, then the eligibility rate is 1 minus the deadwood rate.

[17]Additionally, we make the typical assumption in survey research that other model parameters are independent of the response rate. Supplementary Appendix B also contains analyses where all probability parameters are given non-informative Jeffreys priors, Beta (0.5,0.5). Results are nearly identical.

[18]For each model, we generate four Markov chains with 5,000 iterations per chain. The first 2,000 iterations of each chain are used as an adaptive warm-up period to tune the sampling algorithm and before being discarded. Following the advice of Link and Eaton (2011), we do no thinning of parameter chains. We show in Supplementary Appendix B that our chains mix well and exhibit essentially zero autocorrelation despite no thinning, owing to the design of Stan's Monte Carlo algorithm. This results in 12,000 samples per parameter. We also show in Supplementary Appendix B that various Hamiltonian Monte Carlo diagnostics exhibit no problematic behavior.

[19]The most complete way to include weights in Bayesian analysis would be to specify a probability model for the weights (Gelman 2007). Stan's developers recommend pseudo-likelihood as a next-best method for including weights that cannot be estimated de novo (e.g., Survey Weighted Regression, 2017). The analysis in the article uses pre-sample weights, but we show in Supplementary Appendix B that our results are unchanged by various weighting methods.

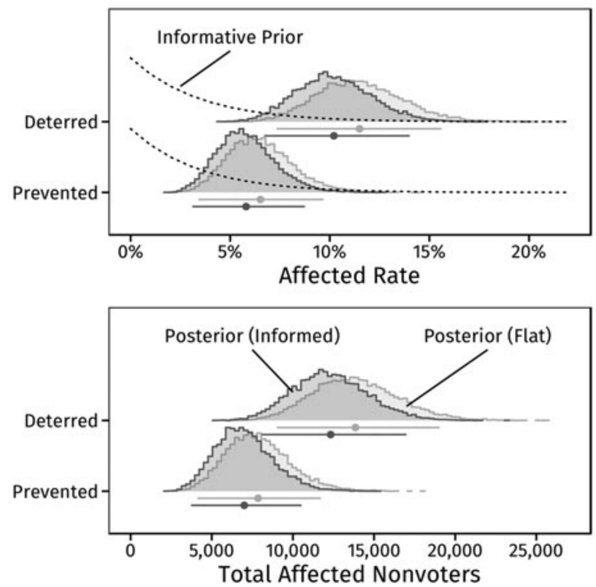

FIG. 2. Posterior estimates of the affected rate (*top*) and total number of affected nonvoters (*bottom*). Each panel shows histograms of posterior samples with means and credible intervals plotted below each histogram.

FINDINGS

Thousands of individuals were impeded by the voter ID requirement

How many nonvoters in Dane and Milwaukee counties were affected by Wisconsin's voter ID requirement? We plot estimates of the affected rate (π) and the total number of affected nonvoters in Figure 2. We show estimates for individuals both "deterred" and "prevented" from voting, using both flat and informed priors.

The top panel of Figure 2 shows our estimates of the affected rate. We visualize the posterior estimates with histograms of Markov chain Monte Carlo samples. Below each histogram, we show a point and error bars for posterior means and 95 percent compatibility intervals. For comparison, we also plot the informative prior distribution (Beta (1,30)) as a dashed line. We do not explicitly plot the flat prior because it has the same density across all supported values. Using flat priors, our mean estimate is that 11.5 percent of nonvoters were deterred from voting due to voter ID, with 95 percent of posterior samples falling between 7.3 and 15.6 percent. Estimates using informed priors are marginally more conservative, with a smaller mean of 10.2 percent and a narrower interval from 6.7 to 14.0 percent. Using the stricter "prevented" definition of the effect, we estimate with flat priors that a mean of 6.5 percent of nonvoters were prevented from voting due to voter ID (3.4 to 9.7 percent). With informed priors, we estimate a mean of 5.8 percent of nonvoters prevented from voting (3.1 to 8.7 percent).

The posterior estimates are similar regardless of the prior used. This is because the data send a strong signal about the affected rate irrespective of the prior. There is not much variance in our estimates because they are close to zero. This is true even for the flat prior, which will naturally have wider variance because it gives greater prior weight to larger values of the affected rate. The informative prior, on the other hand, has the intended effect of regularizing estimates against noise, producing slightly smaller means and smaller variances. This regularization safeguards against overestimating the affected rate due to random sampling error. It is also important to note that the regularization is minor compared to the signal obtained from the data, so the posterior distribution does not merely reflect the prior. The similarity of estimates from flat and informed priors also shows that our data are consistent with previous studies of ID nonpossession in Wisconsin, since models that contain no external information nonetheless produce similar posteriors to models that contain information from past studies.

Estimates of the eligibility rate are not plotted because they are virtually identical across models. All model specifications generate mean eligibility rate estimates of 52.5 percent with credible intervals between 50.2 and 54.8 percent. This is slightly below the Pettigrew and Stewart (2016) estimate of 60.5 percent but entirely consistent with the informative prior.

We use the affected rate and the eligibility rate to calculate the total number of eligible nonvoters in the population who were affected by the voter ID requirement. We plot these estimates in the lower panel of Figure 2. According to our model, thousands of individuals in Dane and Milwaukee Counties were deterred or prevented from voting in 2016 due to voter ID requirements. Using flat priors, we estimate a mean of 13,900 nonvoters deterred from voting (to the nearest hundred, 95 percent interval from 9,000 to 19,000) and a mean of 7,900 nonvoters prevented from voting (interval from

4,100 to 11,700). Estimates from informed priors reflect regularization of the affected rate and are thus slightly lower than the estimates from flat priors: 12,300 nonvoters deterred from voting (95 percent interval from 8,100 to 17,000) and a mean of 7,000 nonvoters prevented from voting (interval from 3,700 to 10,500).

Our models show that Wisconsin's voter ID requirement affected a far greater number of individuals than implied by the 821 ID-related provisional ballots cast in 2016 (of which just 173 were counted) (Wisconsin Elections Commission 2016). Our best estimates using informed priors suggest that thousands of individuals in these two counties alone were deterred or prevented from voting in 2016 by the voter ID requirement. We find that nonvoters report being affected by the ID requirement at roughly twice the rate at which they actually lack ID (3.0 percent in the sample, which is lower than past studies of Wisconsin). We show below in a discussion on "indirect effects" that this difference can be at least partly explained by confusion about the law's details, consistent with our argument that voter ID requirements both directly and indirectly affect voters.

Are these effects real? A look at race and socioeconomics

How confident can we be that the effects we observe are real and not driven by an accumulation of measurement error? Recent controversies in survey research highlight the risks of making inferences about rare events in large datasets, since small data errors can accumulate as sample sizes grow larger (Ansolabehere, Luks, and Schaffner 2015). If the patterns we observe in the data are real, we should be able to observe other implications of the underlying theory and find evidence consistent with the topline results. Furthermore, we should be able to derive implications from alternative explanations (measurement error, misreporting) and show that the data are inconsistent with these notions. An analysis of race and socioeconomics underscores the validity of our data.

What should we observe if our findings are accurate? Previous research suggests that stricter identification requirements raise voting costs disproportionately for nonwhite and lower SES voters. If our results are driven by the real effects of Wisconsin's voter ID requirement, we would expect the affected rate to be higher among these subgroups. If, by contrast, our results are driven by measurement error, we expect these patterns to be attenuated and resemble statistical noise. Further still, if our results are driven by intentional misreporting, social desirability, or expressive responding (Berinsky 2018), we might even expect greater effects among white and higher-SES individuals because the tendency to misreport or engage in expressive behaviors is strongest among higher-SES individuals (Ansolabehere and Hersh 2012; Schaffner and Luks 2018; Sciarini and Goldberg 2016).

Figure 3 puts these contrasting hypotheses to the test, comparing the affected rates across race (black and white), income, and formal education.[20] Point estimates suggest that individuals who are black, lower income, and have less formal education are all more likely to be affected than white, higher income, and higher educated individuals, respectively. We do not observe the reverse pattern that would have strongly indicated expressive responding or social desirability bias. We lose statistical power by dividing our sample into these subgroups, so variation introduced either by sample size or by measurement error is difficult to distinguish formally. However, the point estimates are universally consistent with the hypothesis that the data reflect true effects rather than random measurement error, and the probability of this pattern under measurement error alone is small.[21] While we cannot definitely rule out survey misreporting or response error, these subgroup estimates are consistent with the existing literature and provide reassurance about the quality of our data.

Evidence for ''indirect effects:'' knowledge and confusion

We theorized that voter ID requirements affect voters by directly raising the bureaucratic costs of voting and by indirectly confusing voters about

[20]Confidence intervals are estimated with the Clopper-Pearson method (Clopper and Pearson 1934), which have better coverage in smaller samples and near the probability bounds than intervals based on the approximation of the Normal distribution.
[21]If we define a Bernoulli success as a group comparison where the "theoretically expected" group has a higher estimated affected rate, and we conduct a two-sided significance of the null hypothesis that the expected group in each of 12 comparisons (14 comparisons minus two over-determined comparisons) has a higher affected rate with probability 0.5 (pure noise), the p-value for that test would be 0.0005.

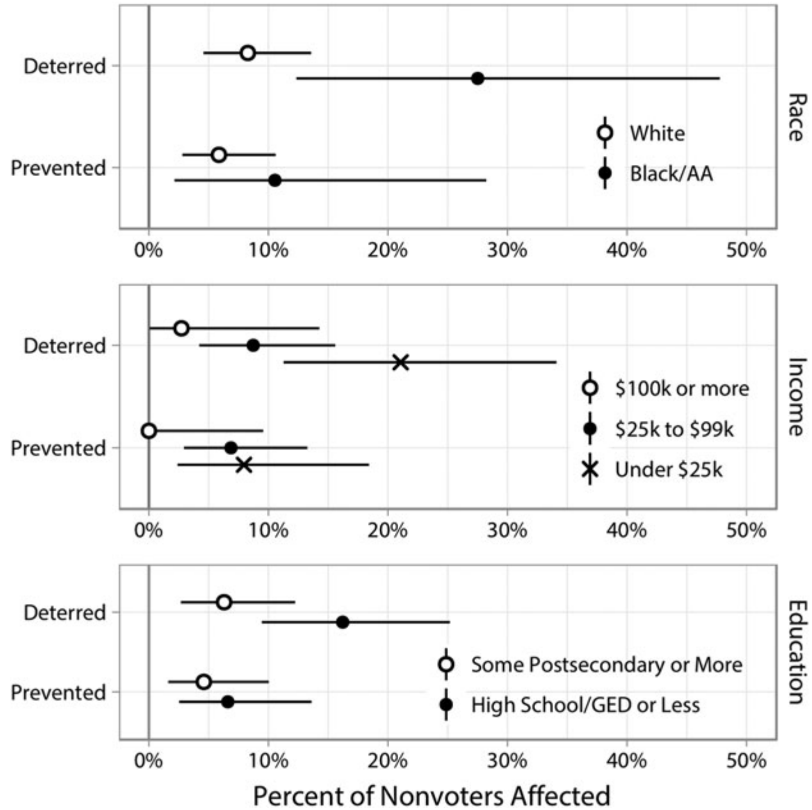

FIG. 3. Estimates of the affected rate (π) within race, income, and education categories.

which IDs are compliant under which circumstances. The details surrounding expiration dates, conforming names and addresses, and the validity of common forms of ID such as university IDs and government employee IDs are complicated, and people may be confused or misinformed about whether they have the necessary ID to vote (Hasen 2016; Hobby et al. 2015; Jones, Cross, and Granato 2017). Our results are consistent with this argument. Many of the individuals we identify as deterred or prevented from voting report that they possess a qualifying form of ID: while roughly 11.2 percent of the sample was deterred and 6.1 percent was prevented from voting due to ID, just 3.0 percent lacked a qualifying ID.

We explore this argument further by measuring respondents' knowledge of the voter ID requirement. We asked respondents to classify 12 forms of ID as satisfying or not satisfying the voter ID requirement. Seven of the 12 forms of ID qualify, and five do not.[22] If confusion about the voter ID requirement drives some respondents to report that their ability to vote was hindered by the law, this would imply that voters who are less knowledgeable of the law are more likely to be affected by it. Furthermore, voters with less knowledge about the law may be more likely to believe that they cannot vote when they in fact possess a qualifying ID.

Figure 4 contains a descriptive picture of the ID classification item. The left panel shows the percent of individuals who classify each form of ID correctly, with each qualifying ID indicated by a dot and each non-qualifying ID indicated by an *x*. We omit nonresponses, so missing data do not "count against" respondents. While almost everyone knew that a Wisconsin driver's license was a qualifying form of ID (about 95 percent), only 70 percent knew that a Wisconsin DOT ID qualifies or that a credit card does not. The typical respondent was uncertain (between 40 and 60 percent correct) about half of the IDs included in the questionnaire, and a majority of respondents were incorrect about

[22]These are the same 12 forms of ID included in our battery of ID possession items.

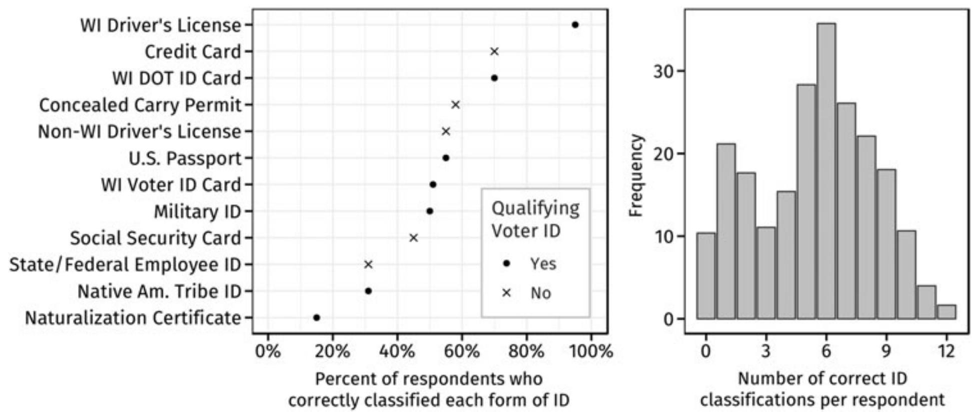

FIG. 4. Results from ID classification task. The *left* panel indicates, for each form of ID, the percent of respondents who correctly classify the ID as qualifying or not qualifying. The *right* panel is a histogram that indicates the number of IDs correctly classified by each respondent.

Social Security cards and government employee IDs (which do not qualify), as well as Native American tribal IDs and naturalization certificates (which do).

The right panel in Figure 4 plots the number of correct respondents at the individual level. Just 15 percent of respondents classified nine or more IDs correctly. The mean number of correct classifications was 5.4 out of 12, or 45% correct. Counting the number of correct responses implicitly penalizes the respondent for item non-response (since non-responses can't be correct), but the impact of this decision is minor. If we omit non-responses, the typical respondent classifies 56% of IDs correctly.

Not only do registrants appear to be confused about which IDs qualify, we also find that respondents who knew less about the law were more likely to be affected by it. We use logistic regressions to estimate the probability that individuals are deterred or prevented from voting as a function of their knowledge of the law, measured as the number of IDs a respondent correctly classified as qualifying or not qualifying. Figure 5 plots predicted probabilities from these regressions with coefficient estimates, standard errors, and *p*-values shown in each panel. The top two panels show the estimated relationship in the full sample. Regardless of whether we measure the effect as "deterred" (left) or "prevented" (right) we find that individuals who are less knowledgeable about the law are more likely to be affected, with both coefficient estimates significant at or below $p = .001$. For the 15 percent of individuals who correctly classify at least nine forms of ID, the predicted probability that they were affected by the ID law was low (below 10 percent). Respondents who classified fewer IDs correctly were more likely to be deterred or prevented from voting. Respondents who classified just two IDs correctly had more than double the predicted probability of being affected as individuals who classified nine or more forms correctly.

We test a stricter implication of the "indirect effects" argument in the bottom two panels of Figure 5. If confusion about the ID requirement leads even *individuals who possess qualifying IDs* to report being affected by the requirement, we should find a similar relationship when we limit the sample only to individuals who possess a qualifying ID. We find relationships of a similar form, but coefficients are weaker and statistically more uncertain ($p < .1$ for "deterred," $p < .05$ for "prevented").[23]

Our results suggest that confusion about the law leads some individuals to misunderstand whether they are able to vote. We cannot make a strict causal inference that variation in the affected rate among ID-possessing respondents is directly attributable to their knowledge of the ID requirement, but these patterns are consistent with the argument that voter ID requirements can affect a broader population of voters than those without a qualifying ID.

[23]All of these regressions are estimated using sampling weights, which downweights the majority of observations. If we assume that the sample design is ignorable (Rubin 1976) and estimate the regression with equal respondent weights, coefficients are essentially identical but *p*-values are smaller.

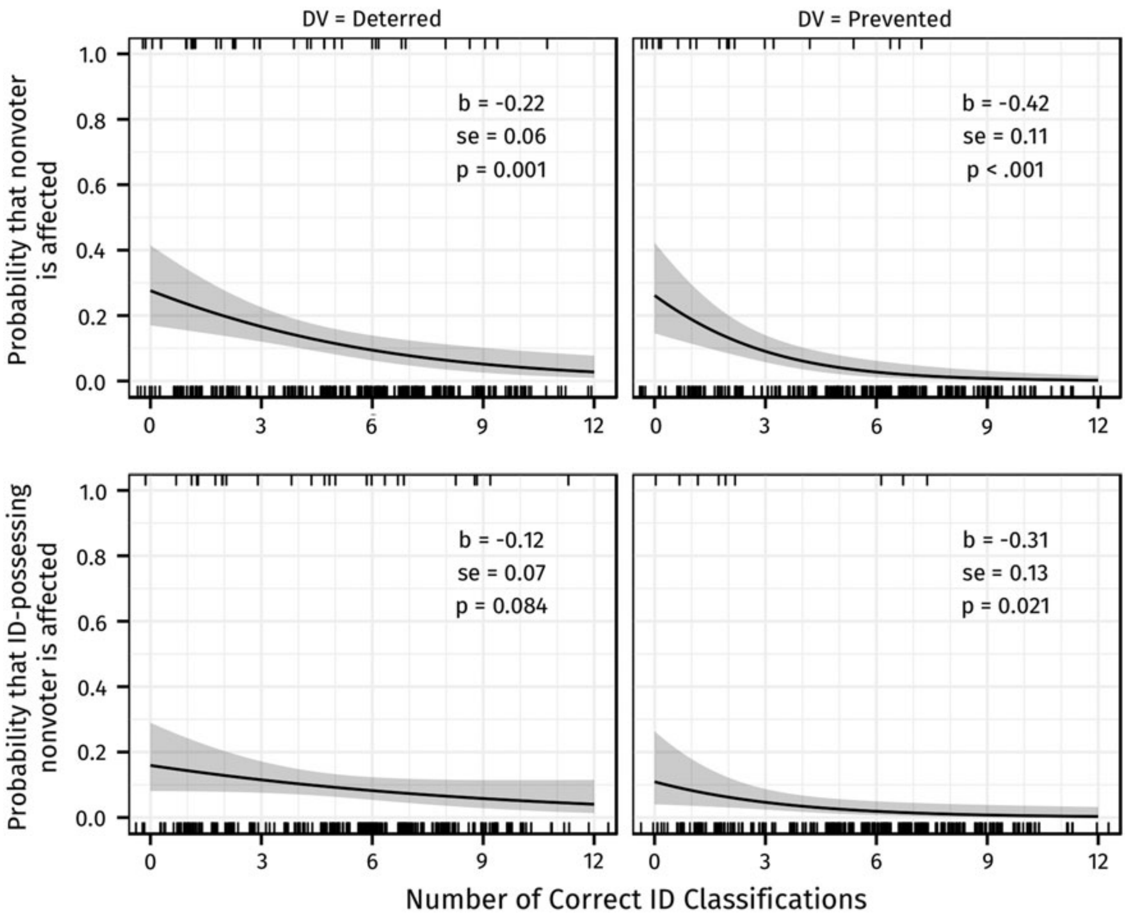

FIG. 5. The relationship between knowledge of the ID requirement and the probability that an individual is affected. Curves and confidence intervals show predicted probabilities from logistic regressions from the full sample (*top*) and limited to individuals who possess qualifying ID (*bottom*). Rugs on the *top* and *bottom* edges of each panel show the observed values of the dependent variable and are jittered for legibility.

These findings provide further reassurance that our results are not driven by misreporting, since we would expect individuals engaging in expressive behavior to be more knowledgeable of the ID requirement.

LESSONS ABOUT TURNOUT, FUTURE RESEARCH, AND POLICY

A simulation of counterfactual turnout

How did Wisconsin's voter ID requirement affect turnout in 2016? This is a difficult counterfactual question. Although we estimate that thousands of registrants were deterred or prevented from voting, we do not know how many of them would have voted if the law were never implemented. Many nonvoters may have had other reasons for not voting. For these individuals, the ID requirement increased the costs of voting, but removing it would not have made the difference.

To estimate turnout effects, we need an estimate of the *counterfactual turnout rate* among affected nonvoters—what turnout among the affected group would have been if no ID requirement existed. While our study design does not permit a direct estimate of the counterfactual turnout rate, we can simulate the aggregate turnout effect at hypothetical levels of counterfactual turnout. Mathematically, this simulation calculates the number of *suppressed votes* as the number of affected individuals in the population, multiplied by the counterfactual turnout rate.

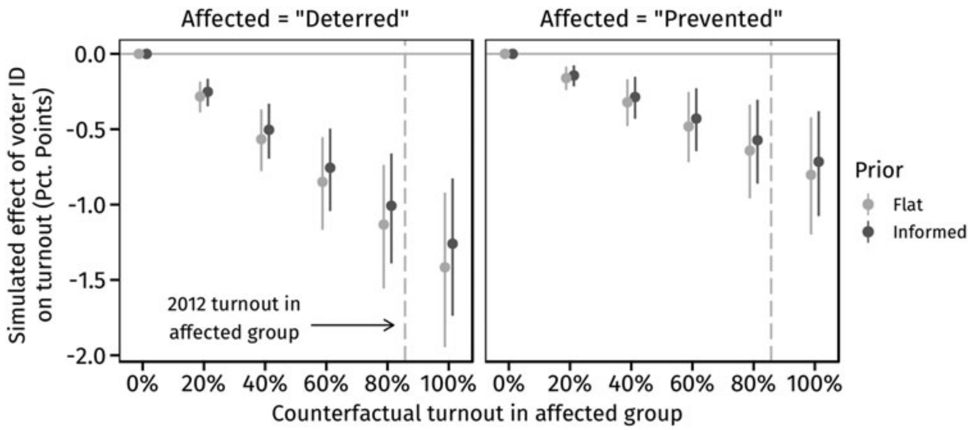

FIG. 6. Simulated effects on voter turnout for hypothetical levels of counterfactual turnout (posterior means and 95 percent credible intervals).

$$Suppressed\ Votes = (Number\ Affected) \times (Counterfactual\ Turnout) \quad (7)$$

We set the counterfactual turnout rate to a series of values between 0 and 1, and we use the simulated number of suppressed votes to calculate the difference between the observed level of registered voter turnout and what turnout would have been under the counterfactual simulation. The method reveals the upper and lower bounds on the turnout effect given the parameters estimated from the above model, and it permits a direct assessment of the turnout effect for a fixed level of counterfactual turnout.

Figure 6 plots the predictions from this simulation. If all affected nonvoters would have voted at 100 percent turnout in the absence of the ID requirement, then turnout in Milwaukee and Dane Counties would have been 0.8 to 1.9 percentage points higher (using "deterred") or between 0.4 and 1.2 percentage points higher (using "prevented"). These are upper-bound predictions on how large the turnout effect could have been, conditional on the estimates from our data. The turnout effect was almost certainly smaller, since a counterfactual turnout rate of 100 percent is unlikely. Respondents to our survey voted in the 2012 presidential election at about 86 percent turnout, and it is likely that turnout would have been lower in 2016 even without the voter ID requirement.[24] If counterfactual turnout in the affected group was just 60 percent, turnout in these two counties would have been between 0.5 and 1.2 percentage points greater (using "deterred") or between 0.2 and 0.7 percentage points (using "prevented"). At the lower bound, the only way to conclude that the voter ID requirement had no effect on turnout among the affected group is to assume that the affected group contains zero people or that counterfactual turnout in the affected group is exactly zero. Both of these assumptions are virtually impossible, so there must have been some nonzero turnout effect. On the upper side, there are essentially no scenarios that support a conclusion that turnout was reduced by two points or more. Most plausible scenarios yield turnout effects that could be as high as one percentage point among registered voters.

Although we are confident that our results reflect real patterns in nonvoting, measurement error may play some role in the effects we find. At the same time, our results reflect conservative modeling assumptions meant to guard against overestimating the effects. Moreover, our results may underestimate the number of individuals affected by the voter ID requirement because our survey cannot measure the decision of unregistered individuals not to register in the first place (Stein and Tchintian 2017).

[24]We restrict this comparison to registrants whose 2012 registrations we could verify. We deem a registrant eligible if their registration date was before the election or if the voter file indicates that they voted in an election prior to 2012. This excludes individuals with registration dates since the 2012 election.

Improvements in research design

The secondary analyses presented reassure us that our core findings are real. Our estimates are consistent with previous studies of ID possession in Wisconsin, and secondary tests are consistent with hypotheses about race, socioeconomics, and knowledge of the ID requirement. Nonetheless, we believe that future studies implementing survey-based methods can improve on our design in a number of ways to identify more precise effects.

First, it is possible to directly confront a "lower-bound" problem in our survey responses. By fielding simultaneous surveys in states that do and do not enforce strict photo ID requirements, researchers can compare the "base rate" of individuals who report being affected by voter ID requirements even in states where no ID requirement exists. This not only would allow researchers to control for survey error, it may also shed light on citizens' knowledge about their voting systems. If voters are confused about a broader set of electoral rules (such as same-day registration, early voting, felon disenfranchisement, etc.), the notion that voters are "indirectly affected" by election laws may be a more widespread phenomenon than the literature currently acknowledges.

We can also collect more detailed information about which IDs registrants possess and their beliefs about whether those IDs satisfy the voter ID requirement (e.g., expiration dates, address changes). Surveys can also ask a broader set of questions about citizen experiences with voter ID laws, including whether voters say that they do or do not need certain IDs to live their lives. Indirect effects also have methodological implications that cannot be ignored. Although record-linkage methods provide accurate estimates of the share of registrants who lack driver's licenses (e.g., Ansolabehere and Hersh 2017), there are strong reasons to believe that voter ID requirements raise voting costs on individuals beyond those lacking ID.

Voter ID in academic and political debate

Our data show that Wisconsin's voter ID requirement impeded many voters' access to the voting booth. We find evidence of both direct and indirect effects, by which outright barriers to voting combine with confusion about the voter ID requirements to reduce the number of eligible people who went to the polls in November 2016. The effects are consistent with other studies of voter ID and with the literature on election administration: electoral reforms can impose a variety of costs on citizens, with larger effects on vulnerable populations. We also find that voter ID laws have indirect effects by raising informational demands on voters even if they possess ID. We make progress exploring survey-based methods for learning about direct and indirect effects, and we believe that future studies can improve upon our instrument to collect more detailed information on the sources of confusion about voter ID.

The number of people affected by voter ID requirements exceeds—by orders of magnitude—the number of cases of voter impersonation that ID laws are purportedly designed to prevent. The literature on vote fraud has repeatedly shown that voter impersonation is exceedingly rare, with just handfuls of confirmed cases over the span of decades (Ahlquist, Mayer, and Jackman 2014; Levitt 2007; Minnite 2010). In federal litigation over Wisconsin's voter ID requirement in particular, the court concluded that "the [state] could not point to a single instance of known voter impersonation occurring in Wisconsin at any time in the recent past" (*Frank v. Walker* 2014: 847). By contrast, we estimate that Wisconsin's voter ID law affected the ability of thousands of registrants to vote in 2016.

SUPPLEMENTARY MATERIAL

Supplementary Appendix A
Supplementary Appendix B

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Address correspondence to:
Kenneth R. Mayer
Department of Political Science
University of Wisconsin–Madison
110 North Hall
1050 Bascom Hall
Madison, WI 53706

E-mail: krmayer@wisc.edu

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