Pollbook Identification: How Electronic Pollbooks Refine the Measurement of Voter ID Laws

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Proposal

This poster presents a working proposal to measure the burden of voter ID laws using novel data generated by electronic pollbooks.

Since *Crawford v. Marion County Election Board*, scholars have gradually refined the measurement of who lacks ID to vote. Scholars initially related aggregate variation in state ID requirements with turnout. Next, scholars associated individual-level measures of driver's license possession and turnout. More recent work gathers affidavits from individuals who vote without ID to distinguish between access and possession of relevant ID.

This project advances the literature by correlating access to ID across elections using electronic pollbooks in Ohio. Electronic pollbooks capture the type of ID voters use to check-in to vote. Using these data, we plan to pre-register a design to measure the disenfranchising effect of Ohio's recent shift from a strict non-photo to strict photo ID law.

Electronic Pollbooks

Data Collection by County and Year

County	2018	2019	2020	2021	2022
Cuyahoga	☑	☑	☑	☑	☑
Butler	☑	–	☑	–	☑
Clark	–	–	–	–	☑
Hamilton	–	–	☑	☑	☑
Lake	–	–	–	–	☑
Lucas	–	–	–	–	☑
Summitt	–	–	☑	–	☑

Primary Outcome of Interest

Y_i^t indicates whether individual i voted in future election t, either the 2023 August special election, 2023 November general election, 2024 presidential primary, or 2024 November general election.

Other Key Variables

We model Y_i^t as a function of ID used to vote in person in prior elections as well as vote history and demographic characteristics, such that:

- $PhotoID_i^t$ indicates whether individual i showed photo ID when voting in person in election t,
- VH_i is a vector indicating whether individual i voted in a set of prior elections, and
- X_i is a vector of individual and Census-level demographic characteristics for individual i, including age and predicted race and ethnicity, as well as the median household income and percentage of people who drive to work.

Turnout Model

Base Model

We initially model Y_i^t as a function of ID used to vote in the 2022 general election.

We define $PhotoID_i^{2022}$ as 1 if individual i showed photo ID when voting in person and 0 if individual i showed non-photo ID. Thus, β measures the difference in turnout among those who previously showed photo ID compared to those who previously showed non-photo ID.

We include county fixed effects, $\alpha_{c(i)}$, to account for county-level determinants of turnout. We also include vote history fixed effects, $\gamma_{f(VH_i)}$, because we expect voters without access to ID will be less frequent voters and that voting is habitual. We define fixed effects for unique combinations of past turnout in the six years prior to the election of interest. In each prior election, we identify whether an individual voted, did not vote, or was not registered to vote.

$$Y_i^t = \alpha_{c(i)} + \beta PhotoID_i^{2022} + \gamma_{f(VH_i)} + \theta X_i + \epsilon_i$$

We will calibrate model performance in Butler and Cuyahoga counties by checking whether $\hat{\beta} \approx 0$ when we estimate

$$Y_i^{2020} = \alpha_{c(i)} + \beta PhotoID_i^{2018} + \gamma_{f(VH_i)} + \theta X_i + \epsilon_i$$

Expanded Model

For the counties in which we observe both 2020 and 2022 pollbook data, we define three strata of in-person voters. First, for individuals who participated only in 2022, the expanded model is the same as the base model. Second, for individuals who participated only in 2020, we substitute $PhotoID_i^{2020}$ for $PhotoID_i^{2022}$. Finally, for individuals who participated both in 2020 and 2022, we estimate the following model:

$$Y_i^t = \alpha_{c(i)} + \beta_1 PhotoID_i^{2020} + \beta_2 PhotoID_i^{2022} + \\ \beta_3 PhotoID_i^{2020} * PhotoID_i^{2022} + \theta X_i + \epsilon_i$$

Photo ID Model

The disenfranchising effect of a strict photo ID law is a function of *current*, not past, access to photo ID. We can model the probability that an individual has *current* access to photo ID based on their access to photo ID in a previous election using historical pollbook data.

Let p_t^{2022} be the probability that individual i who showed photo ID in 2022 has access to photo ID in future election t. Further, let $p_t^{!2022}$ be the probability that individual i who did *not* show photo ID in 2022 nonetheless has access to photo ID in future election t. To learn about the effect of not having current access to photo ID, we wish to estimate:

$$\delta_t = \frac{\beta_t}{p_t^{2022} - p_t^{!2022}}$$

We will use a linked panel dataset of check-in data to calibrate p_t^{2022} and $p_t^{!2022}$ among people who voted in person in multiple elections.

Cuyahoga Case Study

Types of ID Used to Check-In to Vote

Type of ID	2020	2021	2022
Driver License	98.7%	99.1%	99.0%
Utility Bill	0.5%	0.4%	0.4%
Other Government Document	0.3%	0.2%	0.3%
Bank Statement	0.2%	0.1%	0.2%
St/Fed Govt Photo ID	0.1%	0.1%	0.1%
Paycheck	0.1%	0.0%	0.1%
Military ID	0.1%	0.1%	0.1%
Government Check	0.0%	0.0%	0.0%

Photo ID Over Time

	Photo ID in 2020?		
Photo ID in 2022?	Yes	No	Did Not Vote
Yes	98.7%	88.4%	97.9%
	(116,311)	(1,799)	(129,336)
No	1.3%	11.6%	2.1%
	(1,554)	(237)	(2,823)