Zooming in on poll closures - A multilevel approach in the State of Ohio

01/911259 - Philipp Bosch

March 30, 2024

1 Introduction

"The real scandal of this election became clear to me at 6.30 p.m. on election day as I drove a young African-American voter, a charming business student, seven months pregnant, to her polling place at Finland Elementary School in south Columbus [OH]. We arrived in a squalling rain to find voters lined up outside for about a hundred yards. Later the line moved indoors. We were told that the wait had averaged two hours for the entire day. By the time the doors closed at 7.30 p.m., it was considerably longer.[1]*"*

- James K. Galbraith in "Waiting to Vote", *2006*

The question who participates and who abstains in US elections has always been influenced by race (e.g. Abrams, Anderson, Kruse, Richardson, & Thompson, 2020; Verba, Schlozman, Brady, & Nie, 1993). Although minority voter turnout in the US has been converging with that of the white population since the end of the Jim Crow era and the subsequent end of racial segregation by law, the so-called racial turnout gap has never been fully closed. On the contrary, new research shows that this trend has reversed in recent years. While Barack Obama's presidential candidacies in 2008 and 2012 saw record turnout among African American voters, this number collapsed in the following elections, and the turnout gap between black and white voters widened again reaching more than 10% in the 2020 election[2].

In retrospect, the 2012 election is not only notable for its record African American voter turnout. It was also the last presidential election to be fully covered by the Voting Rights Act (VRA). Introduced in 1965 the VRA was designed in a way that jurisdictions with a history of racial discrimination had to undergo a close monitoring process whenever introducing changes to their

[1] Galbraith (2006)

[2] For a detailed breakdown see: `https://www.brennancenter.org/our-work/research-reports/growing-racial-disparities-voter-turnout-2008-2022`

laws and practices pertaining the act of voting. Ironically, the VRA (at least according to the conservative-leaning Supreme Court of 2013) was a victim of its own success. Since the racial turnout gap had all but disappeared in the 2012 election, the judges felt there was no longer any need for this encroachment on the freedom of individual states and counties. On the very day the Supreme Court struck down the VRA in its infamous *Shelby County v. Holder* (2013) ruling, states like Texas and North-Carolina, now freed from federal oversight, made changes to their voting processes which potentially made it harder for minority voters to cast their ballot (Ingraham, 2016).

However, following the ruling, also on a federal level below states, a development took place which had the potential to lower turnout of minority voters in particular. As a report by Pew Trusts states: "In the five years since the U.S. Supreme Court struck down key parts of the Voting Rights Act [in 2013], nearly a thousand polling places have been shuttered across the country, many of them in southern black communities." (Vasilogambros, 2018)

The mechanism why the closure of polling places has the potential to decrease voter turnout is relatively straight forward. It is undisputed in political science that voting entails costs (such as time) for the voter. If the costs of voting surpass the perceived benefits, a rational voter will abstain (Downs, 1957; Riker & Ordeshook, 1968). Closing polling places increases the costs for the voters affected in a way that voters first have to find out where their new polling place is located, second they might need to travel for a longer distance to their new polling booth and lastly, a decreasing number of polling places combined with a constant or growing number of eligible voters raises the risk of queues forming in front of polling places (Brady & McNulty, 2011; Fausset, 2014; Haspel & Knotts, 2005).

Now, if we combine the finding that members of minority groups in particular are sensitive to external shocks to their cost-benefit calculation when it comes to voting(Verba et al., 1993; Leighley & Nagler, 2013) with the fact that in the 2016 presidential election, voters in entirely black neighborhoods waited 29% longer to vote and were 74% more likely to spend more than 30 minutes at their polling place (Chen, Haggag, Pope, & Rohla, 2020), the racial turnout gap puzzle seems all but solved. The political motivation underlying these processes also seems self-evident: Members of minorities (especially African-Americans) still overwhelmingly vote for the Democratic Party.[3] Legislature in states and counties which were formerly covered by the VRA is predominantly in the hands of Republican politicians and law makers. Ergo, the massive loss of polling places between 2012 and 2016 constitutes politically motivated vote suppression.

However, such a clear causal link is not supported by scientific research. Neither by utilizing fine-grained data on the level of voters (voter files) and polling places (geo coordinates) in the State of North Carolina (Shepherd, Fresh, Eubank, & Clinton, 2021) nor by using self reported closures of polling places between elections in a nationwide study (Squires, 2021), researchers could find clear evidence of deliberate manipulation in the sense of votes suppression.

Also in my own master's thesis[4], I was unable to establish any such correlation using a novel and comprehensive data set of 440,000 geo coded polling places, spanning 4 elections and 35 federal states. So why is it worth taking a second look and zooming in on the state of Ohio in particular?

Part of the answer is given by the findings depicted in Figure 1. Although the findings from my master's thesis do not provide any evidence of systematic targeting of black neighborhoods, it turned out that some states closed significantly more polling places than others between the election of 2012 and 2016. One of them is Ohio. Ohio is of particular interest in this regard, as

[3]87% of African American voters identified with the Democratic party in 2016 (Doherty, Kiley, Tyson, & Johnson, 2016)

[4]Replication material and thesis can be found here: `https://github.com/philbosch/Master_thesis/`

the decision which polling place is closed or relocated is within the purview of each of the state's 88 counties. To be more precise, within each county, so-called Board of Elections (BOEs) are responsible. These consist of four members - two from each major party. Thus, the difficult-to-measure hypothesis of politically motivated Republican legislators at the lowest federal level cannot apply in the case of Ohio. Difficult-to-measure in this context means that since Kimball and Kropf (2006) no comprehensive study of the party affiliation of "street level bureaocrats" was conducted.

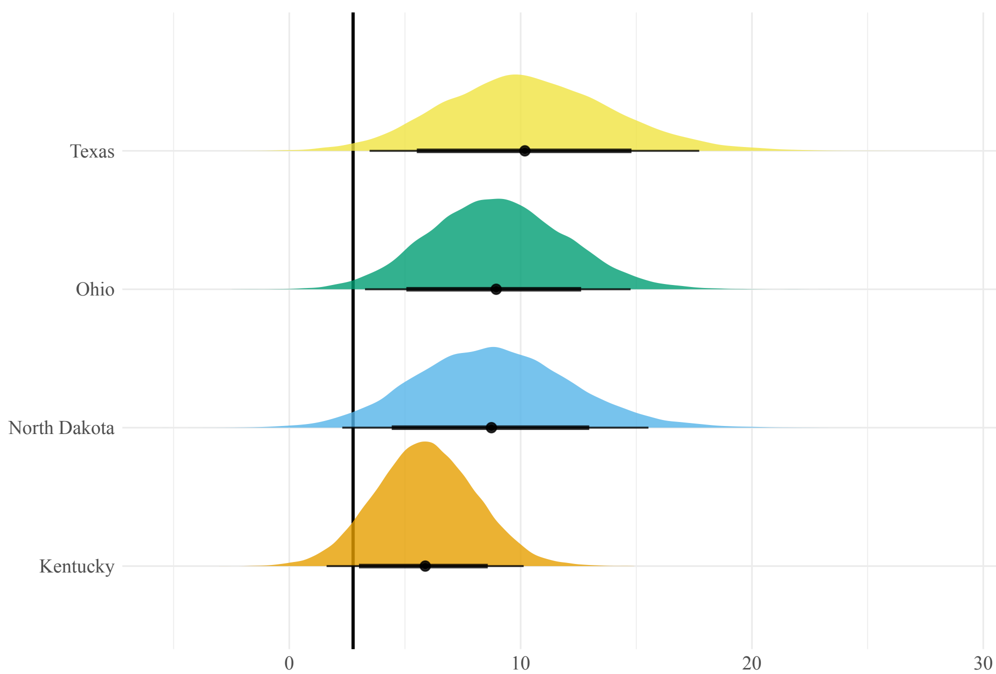

Figure 1: Posterior Distribution of Random Intercept

Note: Black vertical line corresponds to population intercept

Therefore, if in a state like Ohio there is evidence that a significant number of polling places were closed in minority neighborhoods, this speaks more for utility maximizing and complaint minimizing (but not politically motivated) bureaucrats on the ground. Although this changes the motives behind poll closures, the outcome is no less bad, as it infringes upon the constitutionally guaranteed right to vote, regardless of one's race. Evidence for such behavior is for example that individuals with low socio-economic status are less likely to file complaints towards local administrations (Mladenka, 1980; Jones, Greenberg, Kaufman, & Drew, 1978). Therefore, closing polling places in minority neighborhoods might cause less backlash from citizens then closing polling places in predominantly white neighborhoods.

But there are at least two other reasons why Ohio is of interest for a more in-depth examination. One of them is simply political relevance. Ohio is a so-called Battle Ground and Bellwether state. This means that Ohio is one of the few states that is still contested by US presidential candidates and in every election between 1964 and 2016, the winner of Ohio also won the presidential election. [5]

The second reason to pick Ohio comes from a data and modeling perspective. Since the data quality for some states was insufficient in my master's thesis, I was forced to aggregate the geo-coded addresses of polling places at the county level. This is justifiable per se, as the decision of which polling places should be closed is made at county level. Within counties, however, there is an enormous variance in the ethnic composition of neighborhoods. It is therefore quite possible that important neighborhood information was lost in my master's thesis as a result of the county-level aggregation.

Fortunately, the data situation for the state of Ohio for the 2012 and 2016 elections is superb. All of the 36,266 addresses (for four different elections) could be geo-referenced using the Google Maps API. This allows me to actually focus on individual polling stations and their neighborhoods in the analysis at hand.

Consistent with the model of my master's thesis, I use a Bayesian multilevel model. The difference is that this time the unit of observation is in-

[5]for a more in-depth analysis see: `https://www.npr.org/2024/03/23/1240249291/ohio-bellwether-battleground-election`

dividual polling stations, which are nested within counties. Accordingly, I model the probability that a polling place closes or relocates between the 2012 and 2016 election dependent on the racial composition of the neighborhood surrounding it.

2 Data & Model

2.1 Data

To trace whether a polling place closes or relocates from one election to another I rely on a novel dataset which I constructed during my master's thesis. The raw data stems from The Center for Public Integrity (Rebala et al., 2022) and contains partially fragmented addresses of more than 300,000 polling places across thirty-five states and four federal elections in the U.S.. As mentioned, for some states the quality of addresses was not sufficient to infer exact geo coordinates. Fortunately, this does not apply to the state of Ohio, where every single polling place address could be reverse geo-coded via the Google Maps API to retrieve the exact location.

Looking at the raw number of polling places on a state level, the number of voting precincts declined from 9,318 to 8,887 between 2012 and 2016. However, voting precincts cannot be used as a one-to-one mapping for physical polling places (e.g. buildings). Often voters of different precincts are assigned to the same physical polling place. Reduced to unique addresses the number of polling places declined from 4,687 to 4,182 between 2012 and 2016.

Figure 2 gives a graphical overview of this development at the level of counties. Although not all counties closed polling places, a general trend becomes obvious. Out of 88 counties, 71 counties decreased the number of physical voting locations from 2012 to 2016. As comparing the raw number of polling places between counties might be misleading due to a difference in population size, I have normalized the difference between the two elections to reflect the percentage change in the number of polling places per voter.

In Summit County, (dark green in the south of Cleveland on the map) for example 161 polling places served 418,582 eligible voters in 2012. The number of polling places increased to 183 in 2016 while the number of eligible voters remained virtually unchanged at 423,955. This results in a decrease of voters per polling place of around 11%.

The extreme counter-example is Marion County (dark red north of Columbus). There, the ratio of voters to polling places increased by 166%. 24 polling places served 51,902 eligible voters in 2012 compared to 9 polling places for 51,814 prospective voters in 2016. At least in these two counties, the African-American population did *not* suffer particularly from the closure of polling places. In Summit County 13% of eligible voters in the 2016 election were African-Americans compared to only 6% in Marion County.

To actually zoom in on single polling places and not suffer from ecological fallacy by aggregating on county level, I utilize the features of the spatial data I created during the geo-coding process. For each latitude & longitude pair of a polling place in 2012 I create a spatial buffer zone of 10 meters surrounding the polling place. In a next step, I check whether this buffer zone contained a polling place in the 2016 election. I had to use such an approach, as there is no unique identifier which remains stable for polling places across elections. Moreover the buffer zone helps to reduce errors due to small differences in the geo-coordinates like a new entrance to the building between elections. Finally, to derive at the dependent variable for my analysis I create a binary variable `moved_or_closed` for each polling place. `1` if no polling place was found in the buffer zone for 2016 and `0` if there still was a polling place.

Of the 4,687 polling places in 2012 a total of 1,244 ($\tilde{2}6\%$) actually closed or moved according to my operationalization. Figure 3 shows that at the first glance there is no clear clustering of closures and re-locations of polling places across Ohio.

In order to enrich the dataset of polling places with information of the

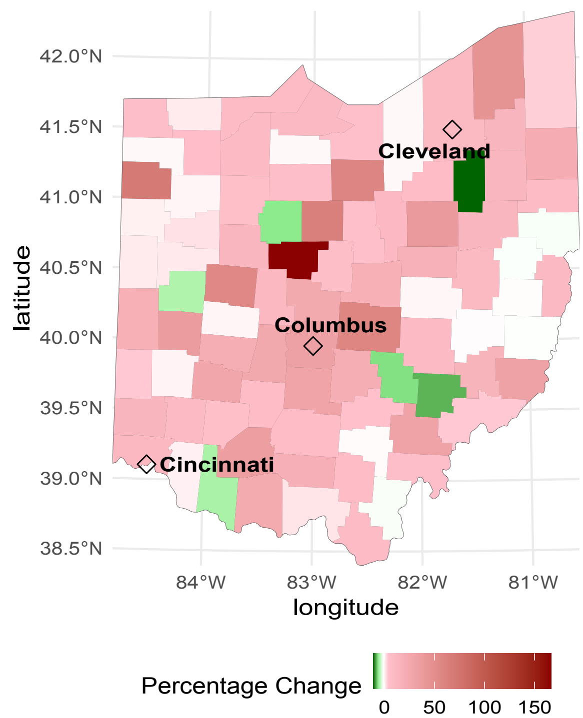

Figure 2: Change in Voters per Polling Place by County in Ohio (2012 to 2016)

socio-demographic composition of the neighborhood surrounding the polling place, I use data from the US census bureau. Even though the unit "polling place" is not an administrative variable for which socio-demographic information is available in the census data, the geo-reference of the polling places allows me to create such data from other official census units. Therefore, I use census "block groups". These block groups are the smallest statistical unit for which the census bureau collects sample data. In Ohio 9,238 block groups exist with a median of 1,093 inhabitants residing inside. The most populous block group in my sample consists of 9,740 residents and is located in Columbus, the capital of Ohio. Compared to the size of voting precincts (the area one polling place serves) which should comprise a maximum of 1,400 voters in Ohio block groups seem like a reasonable proxy. Keeping in

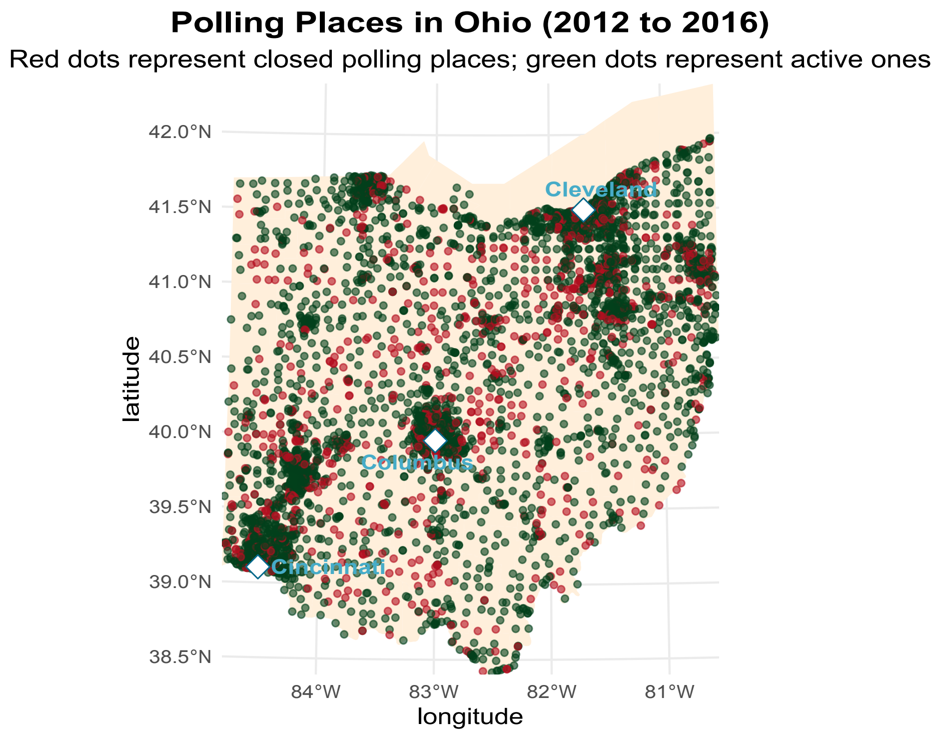

Figure 3: Individual closures & re-locations of polling places from 2012 to 2016

mind, that only a fraction of the population in a block group can be regarded as eligible to vote (i.e. is of voting age).[6]

Figure 4 serves as an overview how these block groups differ in their racial composition. The map illustrates why counties are not an appropriate level of aggregation for studying the socio-demographic aspects of poll closures. Within the same county, there are block groups that are inhibited exclusively by non-white citizens and others were all inhabitants identified as caucasian. Thus, given that polling place closures are determined at the county level, but the effects only manifest at the neighborhood or block group level, aggregation should be avoided.

[6]for details about the legal setup see:`https://www.ohiosos.gov/globalassets/elections/directives/2022/eom/dir2022-10-ch06.pdf`

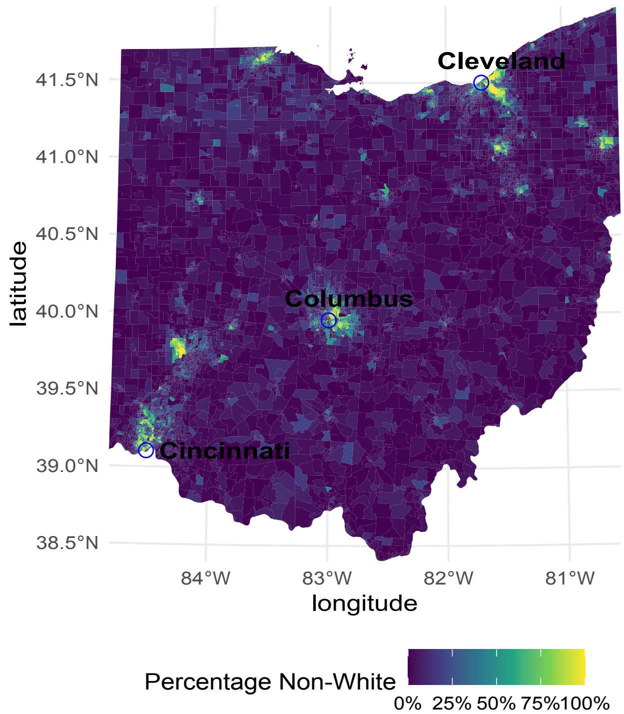

Figure 4: Percentage of Non-White Inhabitants by Block Group in Ohio

Cities are marked with blue points

To combine the latitude and longitude data of polling places with their surrounding block groups, I conduct another spatial join. After this join, three polling places out of the 4,687 appear to be in block groups which are not inhabited. One of them is for example located at an Airport. For these three polling places I retrieve the block group which spatial centroid is the closest and use the socio-demografic information of this block group as a substitute.

Finally, to produce the complete data set for my analysis, I add information about the change in population between 2012 and 2016 for each block group. This information is important for the model, to assess whether polling places were cut to reflect a (expected) change in demand. On the level of counties I also include the state spending per citizen for the year 2016. Most often, County Boards of Elections argue that they have to close polling places due to budgetary constraints. Therefore, I would expect that counties with less budget close polling places at a higher rate.

2.2 Model

Although the aggregation of poll closures to the county level should be avoided, counties still are a decisive entity in the whole process of poll closures. Thus, counties must also be included as a nesting structure in a model that analyses the individual probability of a polling place being closed or not. Not least because the nested structure of the data violates one of the basic assumptions of standard regression models. Namely, the assumption of independence (or lack of correlation) of the residuals (Bressoux, 2020; Gelman & Hill, 2009). In other words: As the closure of polling places is decided on the level of counties, the variation within a county will be lower than the variation between counties.

Since the dependent variable of interest is binary in nature (closed/relocated or not) and keeping the mentioned multilevel structure in mind, a multilevel logistic regression approach is an appropriate modeling choice. Formalized, the basic model without predictors on the county level unfolds like this:

$$
\begin{aligned}
Y_{ij}|\beta_{0j}, \beta_1, \beta_2 &\sim \text{Bernoulli}(\pi_{ij}) \\
\log\left(\frac{\pi_{ij}}{1-\pi_{ij}}\right) &= \beta_{0j} + \beta_1 X_{ij1} + \beta_2 X_{ij2} \\
\beta_{0j}|\beta_{0c}, \sigma_0^{ind} &\sim \mathcal{N}(\beta_{0c}, \sigma_0^2) \\
\beta_{0c} &\sim \mathcal{N}(\log(\frac{1}{3}), 1^2) \\
\beta_1 &\sim \mathcal{N}(0, 0.24^2) \\
\beta_2 &\sim \mathcal{N}(0, 5.51^2) \\
\sigma_0 &\sim \text{Exp}(1)
\end{aligned}
\tag{1}
$$

Let Y_{ij} be the binary outcome of a polling place's closure, with i indexing the polling places and j indexing the counties. The model assumes that:

1. Each polling place's closure outcome, Y_{ij}, follows a Bernoulli distribution with success probability π_{ij}, which is a function of the explanatory variables and random effects. This captures the binary nature of the outcome (closed vs. not closed).

2. The logit transformation of the success probability, π_{ij}, is modeled as a linear combination of the block group's proportion of non-white residents, X_{ij1}, the neighborhood population growth rate, X_{ij2}, and a random intercept, β_{0j}, which accounts for county-specific variations in closure rates. This transformation ensures that the estimated probabilities are bounded between 0 and 1.

3. The county-specific random intercepts, β_{0j}, are assumed to follow a normal distribution centered around the global intercept, β_{0c}, with a county-level variance, σ_0^2. This represents the variability in closure rates across counties and allows the model to account for the hierarchical structure of the data.

4. The global intercept, β_{0c}, represents the log odds of closure for a typical county (after accounting for the effects of the predictors) and is assigned a normal prior centered around the log odds corresponding to the overall known closure rate. This prior reflects my initial belief about the typical closure rate across counties which is around $\frac{1}{4}$ which translates to $\log(\frac{1}{3})$ in log odds.

5. The coefficients β_1 and β_2 are assigned normal priors with mean zero, indicating no prior preference for the direction or strength of the relationship between the predictors and the outcome. The variances of these priors are chosen to reflect the uncertainty in these effects.

6. The county-level standard deviation, σ_0, is assumed to follow an exponential distribution, which places a higher probability on smaller values, indicating that while there is variability in closure rates between counties, extreme variations are less likely.

To extend this model, I introduce in a second step a group level predictor. Namely, the state budget each county spent in the year 2016. This addition enables an exploration of how financial resources at the county level influence the likelihood of polling place closures, alongside the demographic composition and growth rates at the neighborhood level. Formalized, the model looks like this now:

1. The outcome Y_{ij} still follows a Bernoulli distribution parameterized by π_{ij}, the probability of closure for polling place i in county j.

2. The log odds of the closure probability, π_{ij}, is now modeled as $\log\left(\frac{\pi_{ij}}{1-\pi_{ij}}\right) = \beta_{0j} + \beta_1 X_{ij1} + \beta_2 X_{ij2}$. Here, X_{ij1} represents the proportion of non-white residents, and X_{ij2} represents the growth rate of the neighborhood, similar to the previous model.

3. To introduce the county-level predictor, we now model the county-specific intercepts β_{0j} as a function of the county-level budget, Z_j:

$$\beta_{0j}|\beta_{0c}, \beta_3, \sigma_0^{ind} \sim Normal(\beta_{0c} + \beta_3 Z_j, \sigma_0^2)$$

   Where β_3 is the coefficient estimating the effect of the county budget on the log odds of a polling place being closed.

4. The global intercept β_{0c}, the coefficients β_1, β_2, and now β_3, as well as the standard deviation σ_0, are assigned priors similarly to before, with the addition of β_3 to model the influence of the county budget:

$$\beta_{0c} \sim \mathcal{N}(\log(\frac{1}{3}), 1^2)$$

$$\beta_3 \sim \mathcal{N}(0, 1^2)$$

I fit both models using the `rstanarm` (Goodrich, Gabry, Ali, & Brilleman, 2020) and the `brms` (Bürkner, 2017) package in R (R Core Team, 2021). Thereby I follow the approach laid out in Johnson, Ott, and Dogucu (2022).

3 Results & Discussion

The main finding, which is also depicted in figure 5, is that there seems no indication that poll closures primarily and exclusively happened in minority neighborhoods in Ohio between 2012 and 2016. The fixed effect for the percentage of non-white residents in the block group surrounding a polling place is almost perfectly centered around zero.

Interestingly, however, there is a significant positive correlation between population growth within the block group and the likelihood of a polling place being closed or moved. This is somewhat counter intuitive, as one would expect that with a growing number of inhabitants and voters, rather than closing or moving polling places, authorities should open new ones. Unfortunately, this also gives some indication about the limitations of the data. One explanation could be that as the population grows, local Boards of Elections decide to move the polling place to a larger facility. Although not ideal, this behavior would at least only increase search and travel costs for voters and might in turn decrease waiting time in front of the polls.

To facilitate the interpretation of the effect sizes, it helps to convert log odds into probabilities. Given the estimated effect of population change on the log odds of polling place closure or relocation, $\beta_{\text{pop\_change}} = 0.38$, we examine the impact of a specific increase within the observed range of population change. The distribution of `pop_change` in the dataset is characterized by a minimum of 0.36, a 1st quartile of 0.8926, a median of 0.9993, a mean of 1.0177, a 3rd quartile of 1.1167, and a maximum of 3.3563.

To interpret the model's coefficient in a contextually meaningful way, I consider an increase from the 1st quartile to the 3rd quartile of `pop_change`, which represents a typical range of change. This increase, $\Delta\texttt{pop\_change} = 0.2241$, is used to calculate the specific log odds change induced by such an increase:

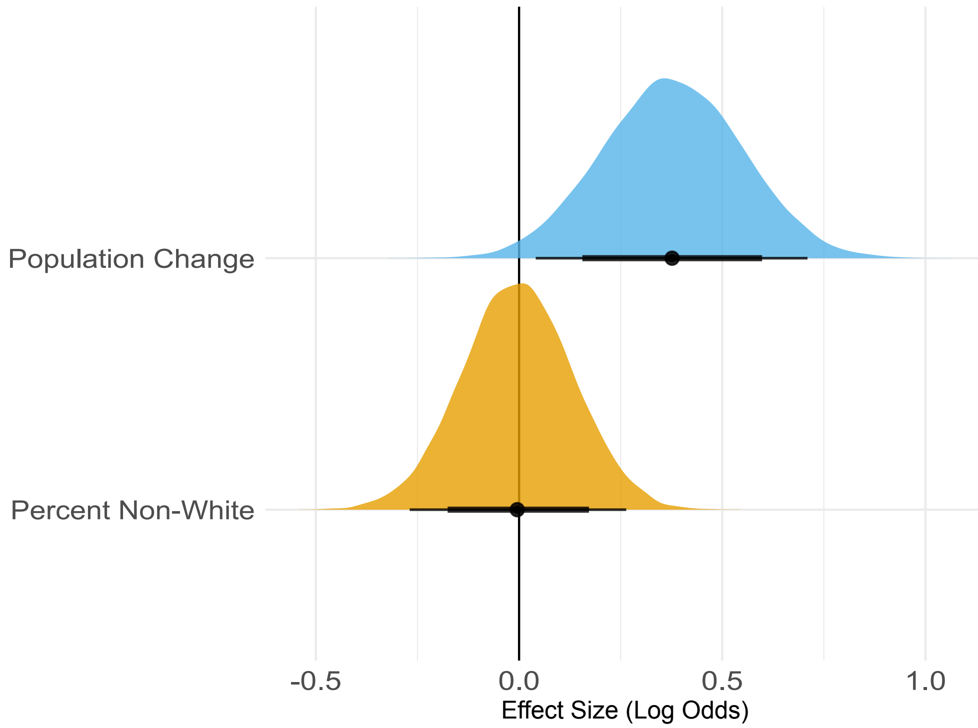

Figure 5: Posterior distributions of effect sizes (log odds) for Percent Non-White & Population Change

Note: 80% and 95% credible intervals shown in black

$$\Delta \log(\text{odds}) = \beta_{\text{pop\_change}} \times \Delta\texttt{pop\_change} = 0.38 \times 0.2241 = 0.085158$$

The baseline probability of closure, corresponding to the average log odds (intercept $\beta_0 = -1.47$), is calculated using the logistic function:

$$P_{\text{old}} = \frac{1}{1 + e^{-\beta_0}} \approx 0.1869 \quad (\text{or } 18.69\%)$$

The new probability of closure, after the specified increase in population change, is:

$$P_{\text{new}} = \frac{1}{1 + e^{-(\beta_0 + \Delta \log(\text{odds}))}} \approx 0.2002 \quad (\text{or } 20.02\%)$$

Thus, the percentage increase in the probability of a polling place closure due to this specific change in population growth is calculated as:

$$\text{Percentage Increase} = \left(\frac{P_{\text{new}} - P_{\text{old}}}{P_{\text{old}}} \right) \times 100 \approx 7.11\%$$

Thus, transitioning from the 1st quartile to the 3rd quartile in terms of population growth corresponds to a 7.11% elevation in the likelihood of a polling place being closed within the data at hand.

Finally, assessing the results of the extended model with the group level predictor of county budget, the results show that this predictor does not help the model and what is more, has no relevance for poll closures. Table 1 shows that the posterior coefficients for the percentage of non-white inhabitants (bg_pct_nonwhite) and change of population remain the same. The coefficient for budget however is close to zero and it's standard error is quite large, which indicates that the effect is not distinguishable from zero. It is worth mentioning, that I had to use the logarithm of the budget in order for the model to converge (i.e. start sampling in the first place).

Table 1: Summary of Model Coefficients

Term	**Estimate**	**Standard Error**
Intercept	-1.95	2.66
bg_pct_nonwhite	-0.00763	0.166
pop_change	0.376	0.170
log(Budget)	0.0602	0.332

Coming to the term "not helping the model" Table 2 shows what is meant by that. The table depicts the between group variance parameters for both models. One would expect that the estimate for Model 2 is lower than for

Model 1 if county budget would help explain the differences in poll closures between countries. As this is not the case, the predictor (at least in it's current operationalization) does not increase the quality of the model.

Table 2: Comparison of Between-Group Variances

Term	**Model 1 Estimate**	**Model 2 Estimate**
SD Intercept County	0.722	0.727

To sum up, zooming in on polling place closures has been fruitful for at least two reasons. For one thing, given that anecdotal evidence from newspapers and reports almost always attributes the closing of polling places to vote suppression, such a causal link (or even correlation) is rarely found in research. Even if it would be nice to explain the racial turnout gap with this one big factor, the issue probably remains highly multi-factorial. On the other hand, much more can be discovered from the data obtained. For example, this geo-referenced data could be used to track not just the closure or relocation of a polling places, but also its accessibility by public transport. As there is an uneven distribution of car ownership in the United States between the majority and minority populations, this could also enhance our understanding of who suffers most from poll closures. A data source such as The Center for Public Integrity is therefore invaluable for such research. It is to be hoped that the collection will continue for the coming elections, allowing better models to be developed over time.

References

Abrams, S., Anderson, C., Kruse, K. M., Richardson, H. C., & Thompson, H. A. (2020). *Voter Suppression in US Elections*. University of Georgia Press.

Brady, H. E., & McNulty, J. E. (2011). Turning out to vote: The costs of finding and getting to the polling place. *American Political Science Review*, *105*(1), 115–134. doi: 10.1017/S0003055410000596

Bressoux, P. (2020). Using multilevel models is not just a matter of statistical adjustment. illustrations in the educational field. *L'Année psychologique*, *120*(1), 5–38.

Bürkner, P.-C. (2017). brms: An R package for Bayesian multilevel models using Stan. *Journal of Statistical Software*, *80*(1), 1–28. doi: 10.18637/jss.v080.i01

Chen, M. K., Haggag, K., Pope, D. G., & Rohla, R. (2020). Racial Disparities in Voting Wait Times: Evidence from Smartphone Data. *The Review of Economics and Statistics*, 1–27. doi: 10.1162/rest_a_01012

Doherty, C., Kiley, J., Tyson, A., & Johnson, B. (2016). *The Parties on the Eve of the 2016 Election: Two Coalitions, Moving Further Apart.* Pew Research Center. Retrieved 2024-03-27, from `https://www.pewresearch.org/politics/2016/09/13/the-parties-on-the-eve-of-the-2016-election-two-coalitions-moving-further-apart/`

Downs, A. (1957). *An Economic Theory of Democracy.* Harper & Row.

Fausset, R. (2014). *Mistrust in North Carolina Over Plan to Reduce Precincts*. The New York Times. Retrieved 2022-03-02, from `https://www.nytimes.com/2014/07/08/us/08northcarolina.html`

Galbraith, J. K. (2006). Waiting to vote. In *Unbearable cost: Bush, greenspan and the economics of empire* (pp. 43–44). London: Palgrave Macmillan UK. Retrieved from `https://doi.org/10.1057/9780230236721_12` doi: 10.1057/9780230236721_12

Gelman, A., & Hill, J. (2009). *Data analysis using regression and multilevel/hierarchical models* (Repr. with corr., 11. print. ed.). Cambridge [u.a.]: Cambridge Univ. Press.

Goodrich, B., Gabry, J., Ali, I., & Brilleman, S. (2020). *rstanarm: Bayesian applied regression modeling via Stan.* Retrieved from `https://mc-stan.org/rstanarm` (R package version 2.21.1)

Haspel, M., & Knotts, G. (2005). Location, location, location: Precinct placement and the costs of voting. *Journal of Politics*, *67*(2), 560–573. doi: 10.1111/j.1468-2508.2005.00329.x

Ingraham, C. (2016). *The 'smoking gun' proving North Carolina Republicans tried to disenfranchise black voters .* The Washington Post. Retrieved 2022-02-23, from `https://www.washingtonpost.com/news/wonk/wp/2016/07/29/the-smoking-gun-proving-north-carolina-republicans-tried-to-disenfranchise-black-voters/`

Johnson, A. A., Ott, M. Q., & Dogucu, M. (2022). *Bayes rules!: An introduction to applied bayesian modeling.* Chapman and Hall/CRC.

Jones, B. D., Greenberg, S. R., Kaufman, C., & Drew, J. (1978). Service delivery rules and the distribution of local government services: Three detroit bureaucracies. *The Journal of Politics*, *40*(2), 332–368.

Kimball, D. C., & Kropf, M. (2006). The street-level bureaucrats of elections: Selection methods for local election officials. *Review of Policy Research*, *23*(6), 1257–1268. doi: 10.1111/j.1541-1338.2006.00258.x

Leighley, J. E., & Nagler, J. (2013). *Who votes now?* Princeton University Press.

Mladenka, K. R. (1980). The urban bureaucracy and the chicago political machine: Who gets what and the limits to political control. *American Political Science Review*, *74*(4), 991–998.

R Core Team. (2021). R: A language and environment for statistical computing [Computer software manual]. Vienna, Austria. Retrieved from `https://www.R-project.org/`

Rebala, P., Levine, C., Hernández, K., Kaneya, R., Ellerbeck, A., Johnston, T., ... Henderson, T. (2022). *U.S. Polling Places (2012-2020).* https://github.com/PublicI/us-polling-places. The Center for Public Integrity.

Riker, W. H., & Ordeshook, P. C. (1968). A Theory of the Calculus of Voting. *American Political Science Review*, *62*(1), 25–42. doi: 10.2307/1953324

Shepherd, M. E., Fresh, A., Eubank, N., & Clinton, J. D. (2021). The Politics of Locating Polling Places: Race and Partisanship in North Carolina Election Administration, 2008-2016. *Election Law Journal: Rules, Politics, and Policy*, *20*(2), 155–177. doi: 10.1089/elj.2019.0602

Squires, J. M. (2021). *Shutting the door on voting: The effects of" the great poll closure".* West Virginia University.

Vasilogambros, M. (2018). *Polling Places Remain a Target Ahead of November Elections* . Pew Trusts. Retrieved 2022-02-10, from `https://www.pewtrusts.org/en/research-and-analysis/blogs/stateline/2018/09/04/polling-places-remain-a-target-ahead-of-november-elections`

Verba, S., Schlozman, K. L., Brady, H., & Nie, N. H. (1993). Race, ethnicity and political resources: Participation in the united states. *British Journal of Political Science*, *23*(4), 453–497. doi: 10.1017/S0007123400006694