Technical Appendix to *Growing Racial Disparities in Voter Turnout, 2008–2022*[*]

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Contents

[*]The full report can be found here: `https://www.brennancenter.org/our-work/research-reports/growing-racial-disparities-voter-turnout-2008-2022`.

A.1 Snapshot Dates

As discussed briefly in the main body of the report, voter file snapshots offer an unparalleled look into the racial turnout gap. It is important to note, however, that these snapshots change every day as voters register or are removed from the rolls. As such, estimates can be slightly different if scholars are working with different snapshots. We follow the advice of Kim and Fraga (2022) and here include the dates of the snapshots used in this report. Unfortunately, Catalist does not report the dates of the snapshots on which their files are based (though they are dated shortly after the election), so we can provide the dates only from the L2-based snapshots.

Table A1: Snapshot Dates

State	2014	2016	2018	2020	2022
AK	2015-03-13	2017-01-27	2019-02-11	2021-02-03	2023-02-18
AL	2015-04-10	2017-03-07	2019-01-27	2021-02-04	2023-01-20
AR	2015-03-24	2017-03-29	2018-09-21	2021-01-19	2023-04-20
AZ	2015-04-22	2017-04-12	2018-09-07	2021-04-27	2023-03-21
CA	2015-05-21	2017-03-25	2019-01-31	2021-02-19	2022-12-19
CO	2015-05-05	2017-02-08	2019-08-31	2020-12-23	2022-12-19
CT	2015-03-25	2017-01-20	2019-06-03	2021-03-30	2023-04-01
DC	2015-03-07	2017-02-15	2019-01-17	2021-01-30	2023-03-11
DE	2015-02-23	2017-01-17	2019-04-02	2021-03-24	2023-04-01
FL	2015-01-28	2017-01-27	2019-02-08	2021-02-04	2023-02-11
GA	2015-05-16	2017-01-27	2018-12-22	2021-02-04	2022-12-23
HI	2015-03-05	2017-03-22	2019-04-05	2021-04-01	2023-03-21
IA	2015-03-25	2017-01-31	2019-03-06	2021-03-04	2023-01-29
ID	2015-02-23	2017-03-20	2019-03-04	2021-03-16	2023-04-20
IL	2015-03-02	2017-03-18	2019-02-21	2021-03-05	2023-03-21
IN	2015-05-06	2017-04-07	2019-02-13	2021-01-15	2023-04-01
KS	2015-02-26	2017-02-16	2019-01-31	2021-03-16	2023-04-01
KY	2015-03-05	2017-03-03	2018-09-29	2021-05-11	2023-04-01

Table A1: Snapshot Dates *(continued)*

State	2014	2016	2018	2020	2022
LA	2015-02-23	2017-02-14	2019-01-15	2021-01-22	2023-01-20
MA	2015-04-02	2017-04-11	2019-02-14	2021-01-19	2023-04-26
MD	2015-02-25	2017-01-20	2018-12-14	2021-02-15	2023-03-21
ME	2015-04-29	2017-04-07	2018-09-26	2021-05-28	2023-04-01
MI	2015-02-28	2017-02-21	2019-03-22	2021-01-30	2023-02-25
MN	2015-03-03	2017-03-10	2019-04-02	2021-02-14	2023-04-01
MO	2015-03-02	2017-02-08	2019-06-03	2021-02-11	2023-02-25
MS	2015-03-17	2017-03-07	2019-03-11	2021-03-23	2023-04-20
MT	2015-03-27	2017-01-25	2019-02-07	2020-12-14	2023-02-25
NC	2015-07-29	2017-01-12	2019-02-01	2021-01-28	2023-02-18
ND	2015-04-15	2017-02-09	2019-03-22	2021-03-18	2023-03-15
NE	2015-03-25	2017-01-13	2019-01-10	2021-01-20	2023-01-16
NH	2015-03-20	2018-08-15	2019-04-10	2021-03-25	2023-05-08
NJ	2015-02-25	2017-03-31	2019-04-03	2021-03-11	2023-02-04
NM	2015-03-19	2017-02-08	2019-02-22	2021-02-25	2023-04-01
NV	2015-01-30	2017-01-13	2019-01-23	2020-12-17	2023-02-04
NY	2015-03-25	2017-03-14	2019-02-27	2021-03-15	2023-03-01
OH	2015-01-08	2017-01-09	2019-01-22	2021-01-07	2023-01-16
OK	2015-03-26	2017-01-12	2019-03-01	2021-02-08	2023-02-25
OR	2015-04-16	2017-01-13	2019-02-24	2021-02-05	2023-03-11
PA	2015-05-01	2017-02-14	2019-09-23	2021-02-17	2023-02-04
RI	2015-03-06	2017-01-18	2019-03-15	2021-02-10	2023-02-25
SC	2015-04-09	2017-02-24	2019-03-12	2021-04-16	2023-03-11
SD	2015-03-13	2017-02-20	2019-01-14	2021-01-22	2023-02-25
TN	2015-02-23	2017-02-17	2019-01-30	2021-03-29	2023-02-04
TX	2015-04-15	2017-03-12	2019-02-24	2021-03-25	2023-03-15
UT	2015-03-06	2017-01-25	2019-03-07	2021-03-26	2023-02-18
VA	2015-04-18	2017-03-29	2019-03-12	2021-02-18	2023-04-01
VT	2015-03-20	2017-02-14	2019-03-08	2021-03-04	2023-02-25
WA	2015-05-05	2017-05-24	2019-01-08	2020-12-09	2023-01-20

Table A1: Snapshot Dates *(continued)*

State	2014	2016	2018	2020	2022
WI	2015-03-03	2017-03-30	2019-02-01	2021-02-24	2023-02-18
WV	2015-03-16	2017-04-03	2019-03-22	2021-03-11	2023-04-20
WY	2015-03-30	2017-02-02	2019-04-02	2021-01-13	2023-04-20

A.2 Alternative Racial Predictions

In the body of this report, we present results in which voters' races are estimated (in non-self-report states) using a BISG algorithm in which the underlying population distribution is drawn from the Citizen Voting Age Population, or CVAP. We argue that this is reasonable because CVAP is a better estimate than total population of the demographics of *potential voters*. In areas with many noncitizens of color, or where children are disproportionately nonwhite, using total population overestimates the nonwhite share of the electorate and biases the turnout gap downward.

Here, we present results supportive of that conclusion. We calculate 2020 turnout rates for each racial group in each county in the six states where self-identified race is available (Alabama, Florida, Georgia, Louisiana, North Carolina, and South Carolina). We then compare the turnout rates that BISG would estimate for each racial group using either CVAP, adult population, or total population as the underlying geographic distribution. We remove the counties where the CVAP of the group of interest is less than 100, and then calculate the absolute value of the "error"—that is, the difference between the *actual* turnout rate based on self-reported data, and the *estimated* turnout rate from BISG. Table A2 presents the mean of these county-level errors (the mean absolute error, or MAE) for each racial group using each estimation strategy.

The above estimates all rely on the methodology developed by Imai and Khanna (2016). In the intervening years, however, researchers have proposed new approaches. In

Table A2: MAE: Different Target Populations for BISG. Counties Weighted Equally.

Race	CVAP	Adult	Total Population	BIRDiE
White	5.3%	7.7%	9.0%	16.9%
Nonwhite	10.8%	19.1%	22.5%	69.2%
Black	14.1%	13.5%	14.5%	28.3%
Latino	6.2%	14.2%	18.3%	14.4%
Asian	18.6%	8.4%	8.8%	288.5%
White–Black Gap	19.3%	21.1%	23.5%	27.5%
White–Nonwhite Gap	16.1%	26.8%	31.6%	86.1%

2023, a team of researchers (McCartan et al., 2023) released a working paper implementing what they call Bayesian Instrumental Regression for Disparity Estimation (BIRDiE). To test whether our approach suffers meaningfully relative to this new approach when aggregated to the county level in states with self-identification on their voter files, we also replicate the MAE analysis using BIRDiE, run at the ZIP code level. Those estimates are presented in the final column.

Table A2 indicates that the CVAP approach is preferable to the other strategies for white and nonwhite turnout. While the error for Black turnout is higher using the CVAP approach than using adult population, it is nonetheless smaller than when race is estimated using total population. Importantly, using CVAP is clearly far superior to approaches including noncitizens for estimating Latinos' race. Although CVAP results in poorer estimates for Asian Americans than the other approaches using alternate target populations, less than 1.5% of the CVAP in this region is Asian. In no case does BIRDiE return better estimates than our primary approach.

Table A3 once again shows the MAE, but this time weights counties by the relative size of the CVAP of interest in each county. When we weight by CVAP, the BISG approach using CVAP as the target population outperforms both of the other approaches for every racial group. In no case does BIRDiE return better estimates than our primary approach.

We thus conclude that using CVAP as the underlying racial distribution for the BISG analyses is justified. However, as we show below in our discussion of the causal effect of *Shelby*

Table A3: MAE: Different Target Populations for BISG. Counties Weighted by CVAP.

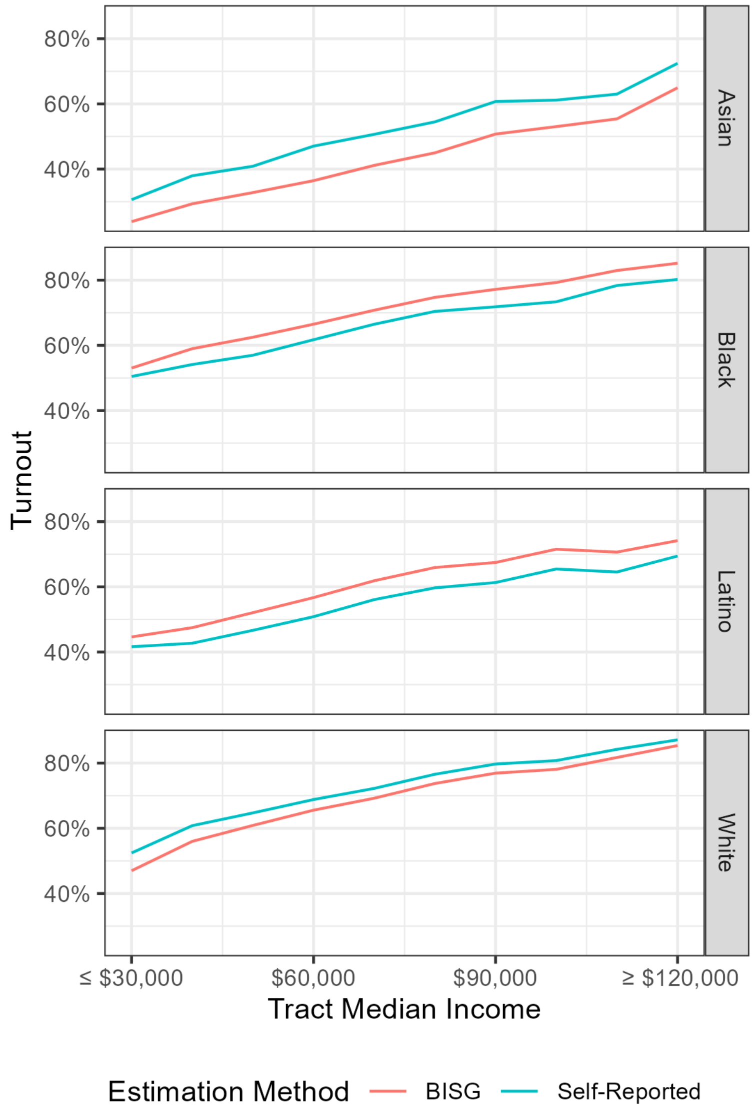
Race	CVAP	Adult	Total Population	BIRDiE
White	2.5%	6.0%	7.5%	16.7%
Nonwhite	4.4%	10.5%	13.1%	29.1%
Black	5.9%	6.3%	7.3%	20.1%
Latino	8.2%	12.7%	14.6%	25.4%
Asian	11.1%	8.4%	8.4%	167.3%
White–Black Gap	9.1%	13.3%	16.3%	11.5%
White–Nonwhite Gap	8.8%	19.2%	23.3%	43.7%

County v. Holder on the racial turnout gap, our results are consistent regardless of how the BISG algorithm is used (due to the computing intensity of the BIRDiE approach and its underperformance in the self-report states, we do not estimate race using BIRDiE for all voters in all states in all years, as we do with the alternative BISG populations).

A.3 Errors Associated with BISG and Socioeconomic Characteristics

Traditional BISG approaches have been shown to have errors correlated with neighborhood socioeconomic characteristics (Argyle and Barber, 2023). In the body of the report, we include turnout rates for neighborhoods at different income and education levels, based primarily on our BISG estimates. Here, we show that there is not a strong relationship between BISG errors and tract-level sociodemographics (income or education) in states with self-reported data. Figures A1 and A2 show that, while there there is consistently a gap between the "true" turnout rate and that estimated by BISG, the gaps are fairly consistent regardless of the demographics of a voter's home Census tract. For this analysis, we retain only the voters who self-identified as white, Black, Latino, or Asian.

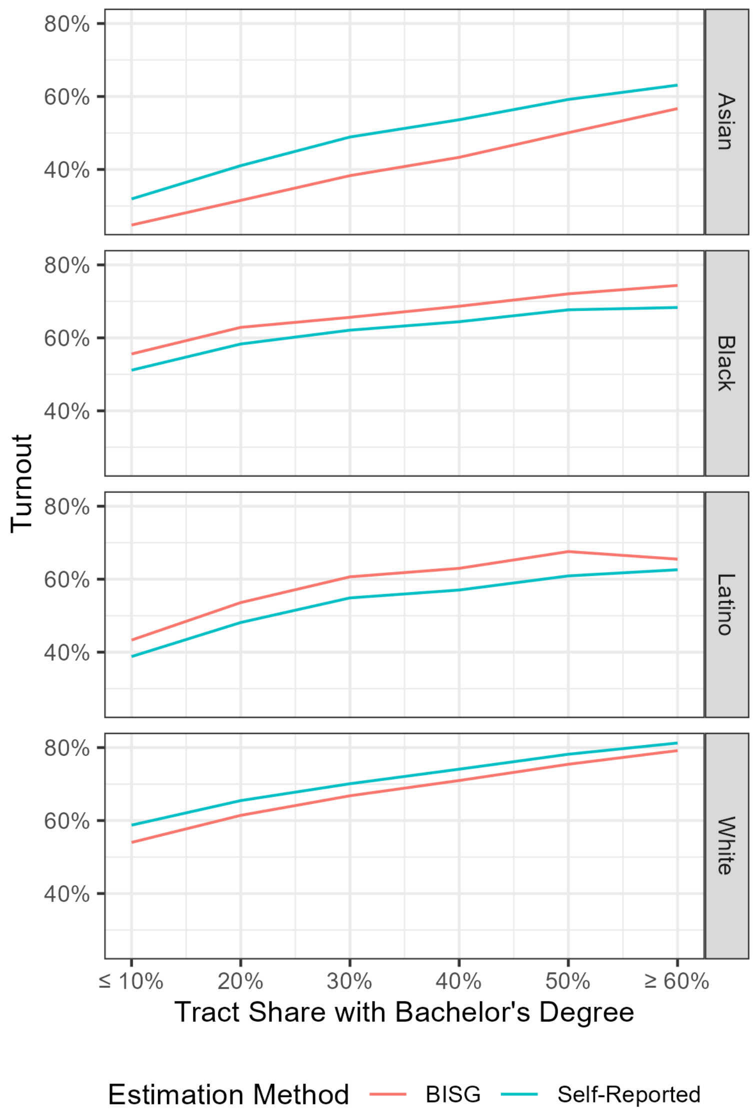
Figure A1: Racial Turnout Rates by Neighborhood Income, Self-Report vs BISG



A.4 Alternative Source for Self-Identification in 2014, 2016

The "processed" voter files from L2 following the 2014 and 2016 elections do not include self-reported race from the six states with self-reported race in their raw files. The processed files do, however, include voters' unique state voter identification numbers, which we can use to merge the processed files with the raw files. This is how we obtain voters' self-reported

Figure A2: Racial Turnout Rates by Share of Tract with Bachelor's Degree, Self-Report vs BISG



race in these two elections. The snapshots do not align perfectly in terms of timing, but we are nonetheless able to match more than the overwhelming majority of all participants to an entry in the raw voter file, where the voter's race (or lack thereof, if they decline to denote it) can be obtained directly. Table A4 shows the share of participants in each state in each year that were successfully matched to the raw voter file. BISG is used to estimate the race of the remaining voters (as it is for those who report "other" for their race, or decline to provide their race). Louisiana stopped using unique statewide IDs in its voter file in 2016,

Table A4: Match Rates Between L2 and Raw Voter Files

	Match Rates	
State	2014	2016
AL	100.00%	99.24%
FL	100.00%	100.00%
GA	99.96%	100.00%
LA	98.43%	88.01%
NC	100.00%	100.00%
SC	98.95%	100.00%

reducing the match rate in that state that year.

A.5 Discussion of Entropy Balancing

We use entropy balancing (Hainmueller, 2012) on pretreatment characteristics to weight control counties. We do this rather than simply condition on covariates (though we do so in our robustness checks) in case the *Shelby County* decision had any post-treatment impact on important socioeconomic characteristics in the formerly covered jurisdictions, which could threaten our causal inference. We rely on the characteristics detailed above as observed in 2012, as they are the latest pretreatment characteristics available. Due to concerns about reversion to the mean when including pretreatment outcome variables in the preprocessing strategy (e.g., Daw and Hatfield, 2018), we do not include outcome variables (white–Black or white–nonwhite turnout gap) in the balancing procedure. Table A5 indicates that the entropic weights are highly successful at removing differences between the treated and control counties along this set of characteristics. After preprocessing our data, we assume that treated and control units would have moved in parallel absent *Shelby County*, conditional on their weights.

Table A5: Balance Table for Entropy Balancing and Genetic Matching

Variable	Covered Counties	Full Set of Uncovered Counties	Entropy Balanced Uncovered Counties	Genetically Matched Uncovered Counties
Share White	66.5%	86.2%*†	66.5%	68.7%*
Share Black	16.7%	3.4%*†	16.7%†	16.3%
Obama 2012 Vote Share	39.9%	37.5%*†	39.9%	40.7%
Population	126,618	78,829*	126,618	114,291
Median Income	$44,689	$46,295*†	$44,689	$43,899
Median Age	39.5	41*†	39.5	38.9*
Share with Bachelor's Degree or Higher	19.1%	19.7%	19.1%	18.4%*

Note:

* Mean different from covered counties (t-test, $p < 0.05$).

† Distribution different from covered counties (Kolmogorov–Smirnov test, $p < 0.05$).

A.6 Alternative Modeling Approaches

As discussed in the body of this report, our results are robust to a wide variety of different modeling specifications. Here, we detail the different approaches we take to estimating the causal effect of *Shelby County* on the racial turnout gap. We discuss the benefits and drawbacks of these different approaches. Ultimately, however, the majority of these robustness checks support our central finding: *Shelby County* increased the racial turnout gap in formerly covered jurisdictions. In the subsections that follow, we generally present the time series and coefficient plots for the different specifications, allowing the reader to see the trends in the data and determine the plausibility of the parallel trends assumption (based on the time series data and the pre-trends tests in the coefficient plots). Except where noted, we include the largest counties, though we always remove all counties with fewer than 100 citizens of voting age of the respective population (all nonwhite for the white–nonwhite gap; Black for the white–Black gap).

Table A6 summarizes the point estimates from each of the methodologies.

Table A6: Coefficients on Outcomes of Interest, Different Models

Model	White–Nonwhite Gap	White–Black Gap
State (No Covariates)		
TWFE	2.46%*	3.11%*
County (No Preprocessing)		
Parallel Trends Assumption Conditional on Covariates	5.36%*	4.96%*
Parallel Trends Assumption Unconditional on Covariates	4.19%*	4.70%*
County (Entropy Balancing)		
Primary Model (All Counties)	2.01%*	2.81%*
Base Period Covariates Averaged for Balancing	2.06%*	2.41%*
Parallel Trends Assumption Conditional on Covariates	2.37%*	3.15%*
Base Period Level Differences Averaged	1.63%*	2.42%*
BISG Target Population: Adult Population	4.48%*	2.83%*
BISG Target Population: Total Population	3.67%*	2.10%*
Former Confederacy Only	2.26%	3.78%*
New Hampshire Considered “Treated”	2.06%*	2.87%*
Uncovered Counties in Partially Covered States as “Untreated”	2.79%*	2.83%*
Weighted by Logged Population	1.69%*	2.50%*
Weighted by Raw Population	-2.38%*	0.90%
Weighted by Raw Population, Largest 5% of Counties in 2012 Excluded	2.48%*	2.64%*
County (Genetic Matching)		
Primary Model	2.02%*	2.58%*
Parallel Trends Assumption Conditional on Covariates	2.52%*	2.91%*

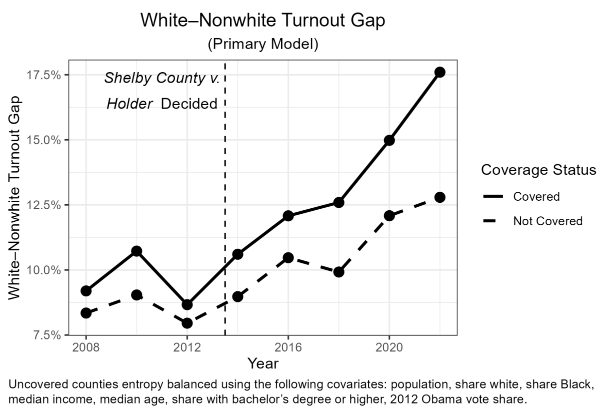
Note:

* Significant at the 95% confidence level.

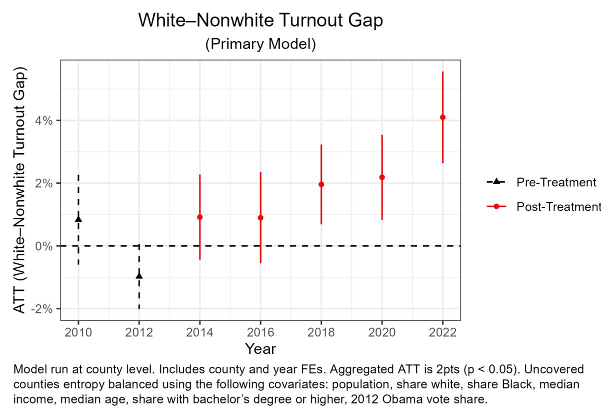
A.6.1 Primary Models from Report

In the body of the report, we present only the time series plot for the white–Black turnout gap models, after balancing the uncovered counties to look similar to the treated ones. Here, we present the time series plots for both dependent variables, along with the coefficient plots for the two-way fixed effects (TWFE) models.

Figure A3: White–Nonwhite Gap, Entropy Balancing Models

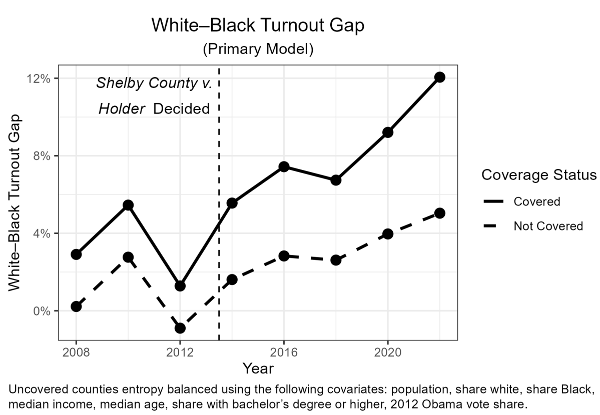


(a) Time Series

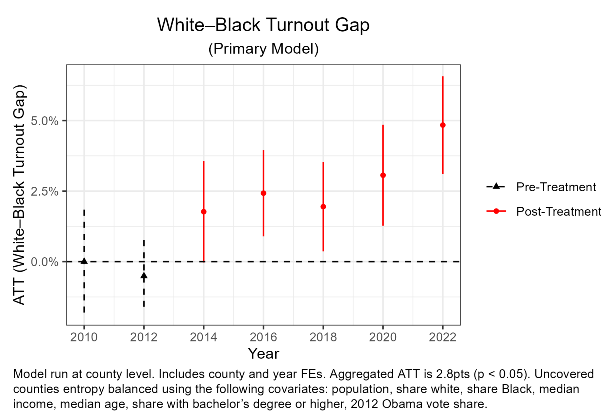


(b) Coefficients

Figure A4: White–Black Gap, Entropy Balancing Models



(a) Time Series

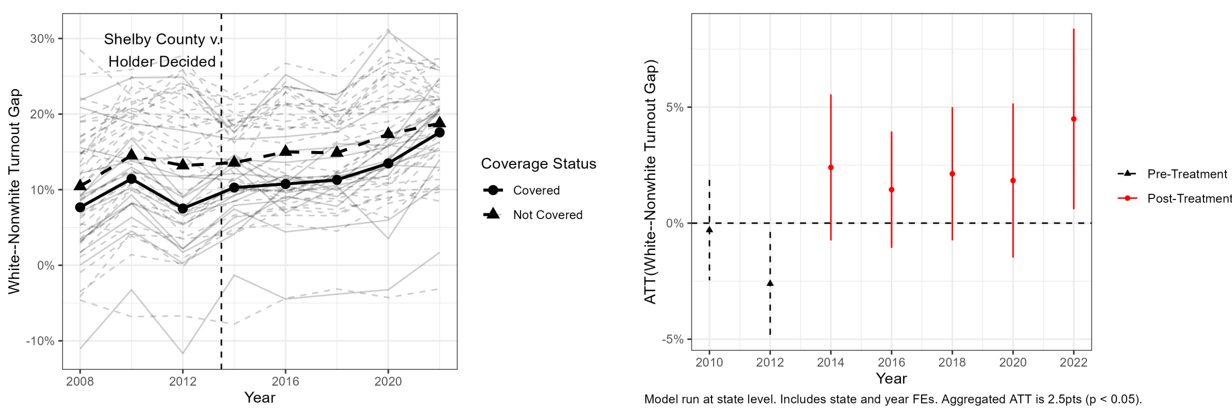


(b) Coefficients

A.6.2 State-Level Models

Elections in the United States are generally run at the county level. Administrators have wide latitude over polling place locations, voter list maintenance, and the training of poll workers. As such, our primary models look at counties as the unit of observation. However, BISG estimates are better estimated as we aggregate up to higher geographic levels. Here, we show that our results generally hold if we instead aggregate the turnout gaps up to the state level. Figures A5 and A6 show that while formerly covered jurisdictions generally had lower turnout gaps prior to *Shelby County* than uncovered ones, that difference shrank substantially in the first post-*Shelby* election and disappeared entirely by 2022. The time series figures also show in light gray the individual states. These models include only year and state fixed effects.

Figure A5: White–Nonwhite Gap, State-Level Models (TWFE)



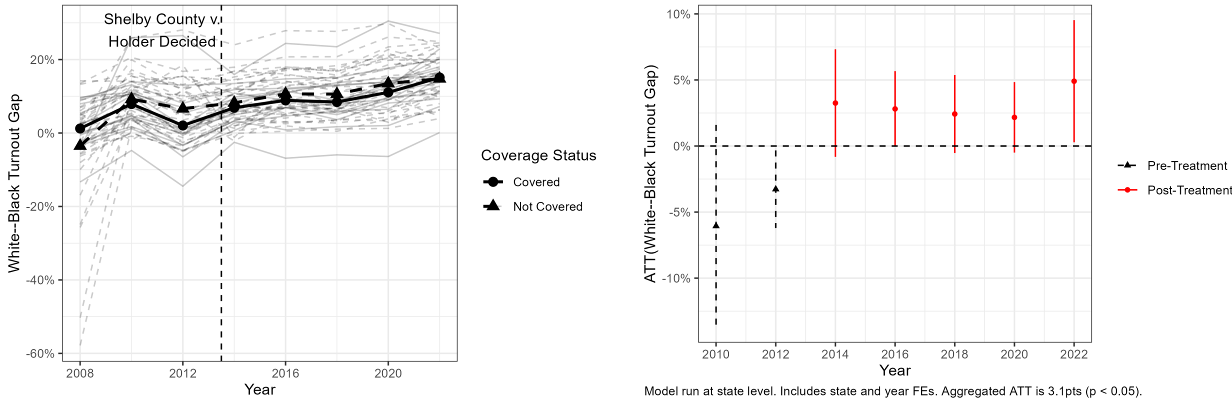
(a) Time Series

(b) Coefficients

A.6.3 County-Level Models, Without Entropy Balancing

In the body of the report, we discuss results in which we preprocess the county-level data using entropy balancing to ensure comparability between treated and control counties. Here, we run a TWFE model in which we condition the parallel trends assumption on covariates; in other words, all counties in the country are given a weight of 1, and we control for the

Figure A6: White–Black Gap, State-Level Models (TWFE)

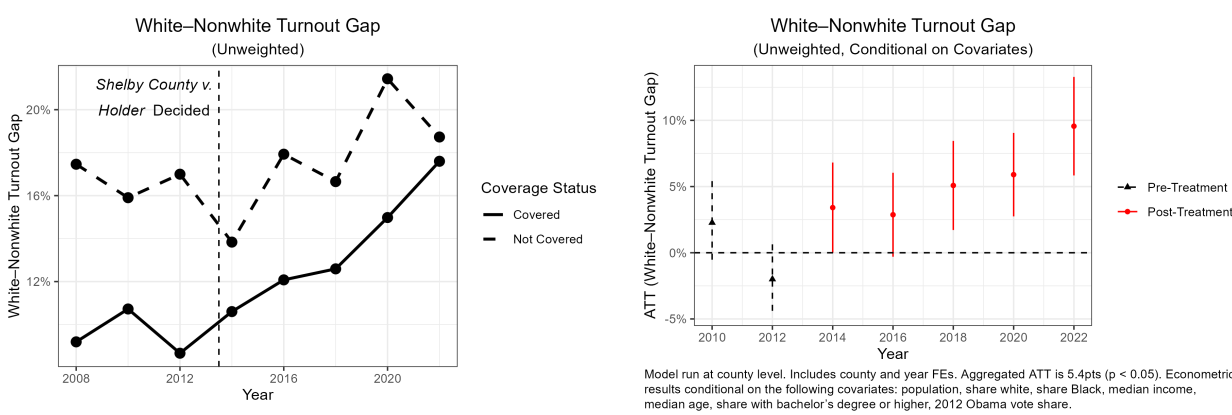


(a) Time Series (b) Coefficients

same things used in the entropy balancing procedure (population, share non-Hispanic white, share non-Hispanic Black, median income, median age, Obama's 2012 vote share, share with a bachelor's degree or higher). For most years, the covariates come from the five-year ACS estimates ending in the election year. The exceptions to this rule are 2008 (we use 2009, as the ACS estimates do not begin until that year) and 2022 (we use 2021, because the 2022 estimates were not yet available at the time of writing).

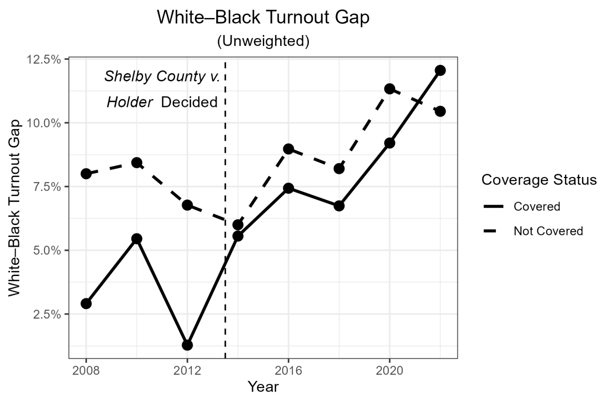
We also present the county-level, unprocessed TWFE model in which we do not condition the parallel trends assumption on the covariates, though note that this likely results in a violation of the assumption based on the pre-trends.

Figure A7: White–Nonwhite Gap, Unprocessed TWFE Models, Conditional on Covariates

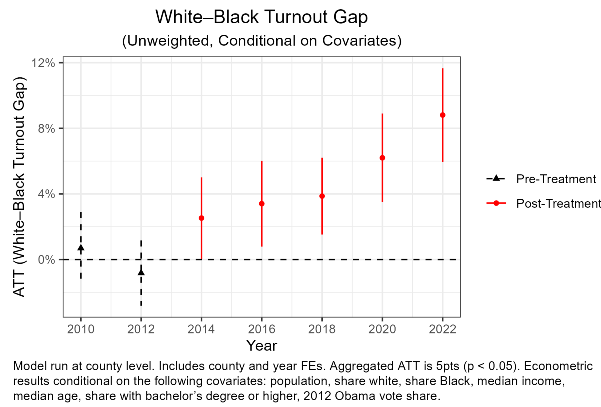


(a) Time Series (b) Coefficients

Figure A8: White–Black Gap, Unprocessed TWFE Models, Conditional on Covariates

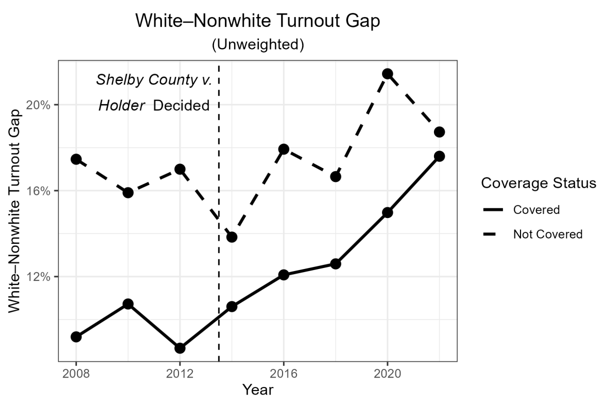


(a) Time Series

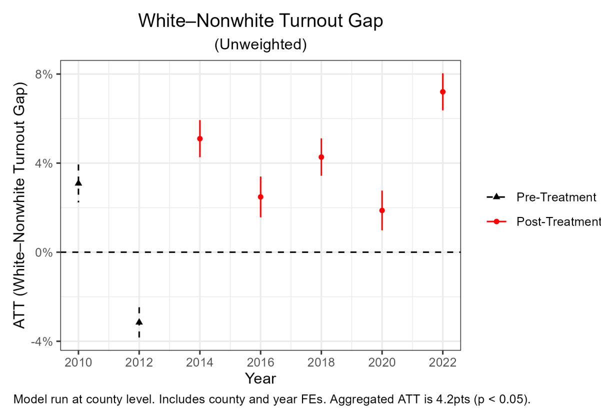


(b) Coefficients

Figure A9: White–Nonwhite Gap, Unprocessed TWFE Models, Unconditional on Covariates



(a) Time Series

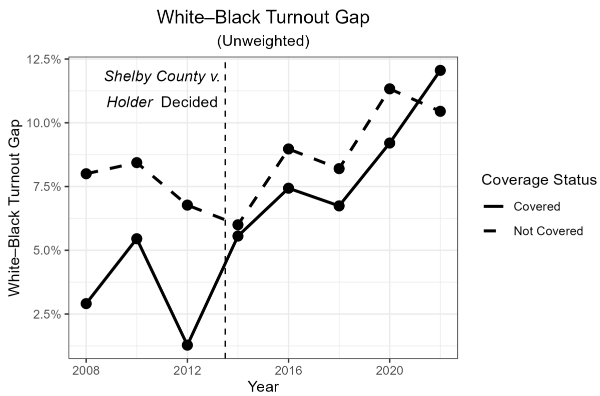


(b) Coefficients

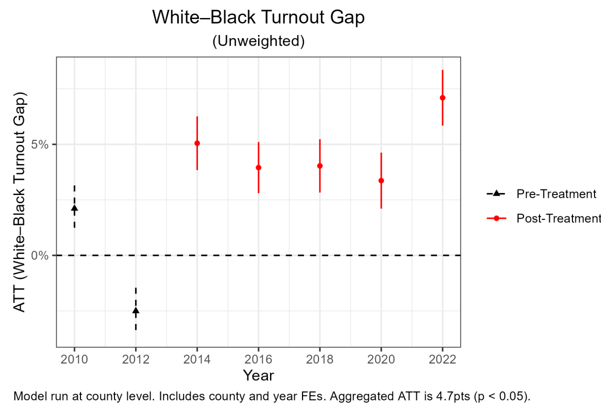
A.6.4 Entropy Balancing, Base Period Covariates Averaged

In the body of the report, we balance treated and control units using their 2012 characteristics, as 2012 is the final pretreatment year. Some researchers (e.g., Daw and Hatfield, 2018), however, have raised concerns about reversion to the mean threatening an approach like this. To test whether using 2012 characteristics alone to balance the treated and control units is driving our results, we here use the average of each county's characteristics from

Figure A10: White–Black Gap, Unprocessed TWFE Models, Unconditional on Covariates



(a) Time Series



(b) Coefficients

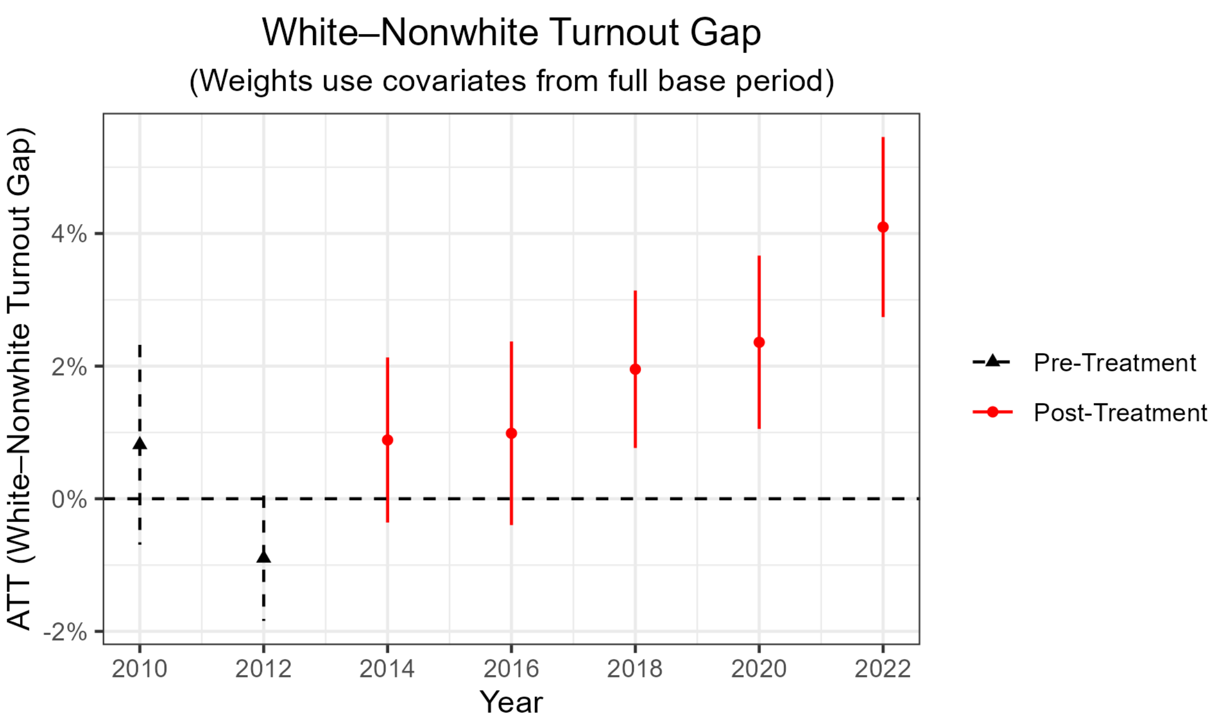
2008, 2010, and 2012 to do the balancing.[1] If some control counties were more similar to treated counties in 2012 by happenstance and thus up-weighted, averaging across the base period should solve this problem. As this approach does not change the time series plots, we do not reproduce them. Figures A11 and A12 indicate that weighting control counties using their average characteristics over the base period does not meaningfully change our results or the validity of the parallel trends assumption.

A.6.5 Entropy Balancing, Parallel Trends Conditional on Covariates

In the body of the report, we do not require that the parallel trends assumption in the entropy-balanced models be conditional on covariates; the time series and coefficient plots do not indicate that imposing this conditionality is necessary. However, to guard against the possibility that treated and control counties that were similar in 2012 might have evolved differently in the post-treatment period, we here produce the results in which the parallel trends assumption is conditional on the covariates used for balancing. As this approach does not change the time series plots, we do not reproduce them. Figures A13 and A14 indicate

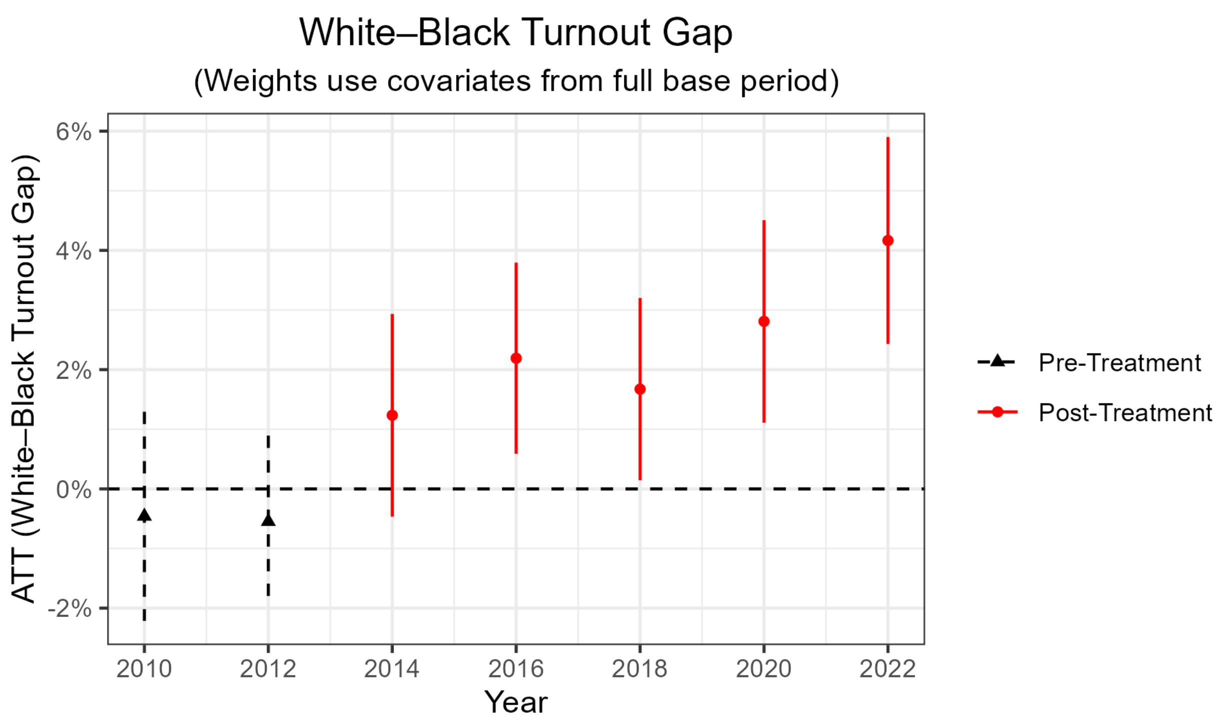
[1] Obama's vote share is averaged across the 2008 and 2012 elections.

Figure A11: White–Nonwhite Gap, Entropy Balancing Models, Balancing Covariates Averaged over Base Period



Model run at county level. Includes county and year FEs. Aggregated ATT is 2.1pts ($p < 0.05$). Uncovered counties entropy balanced using the following covariates: population, share white, share Black, median income, median age, share with bachelor's degree or higher, 2012 Obama vote share.

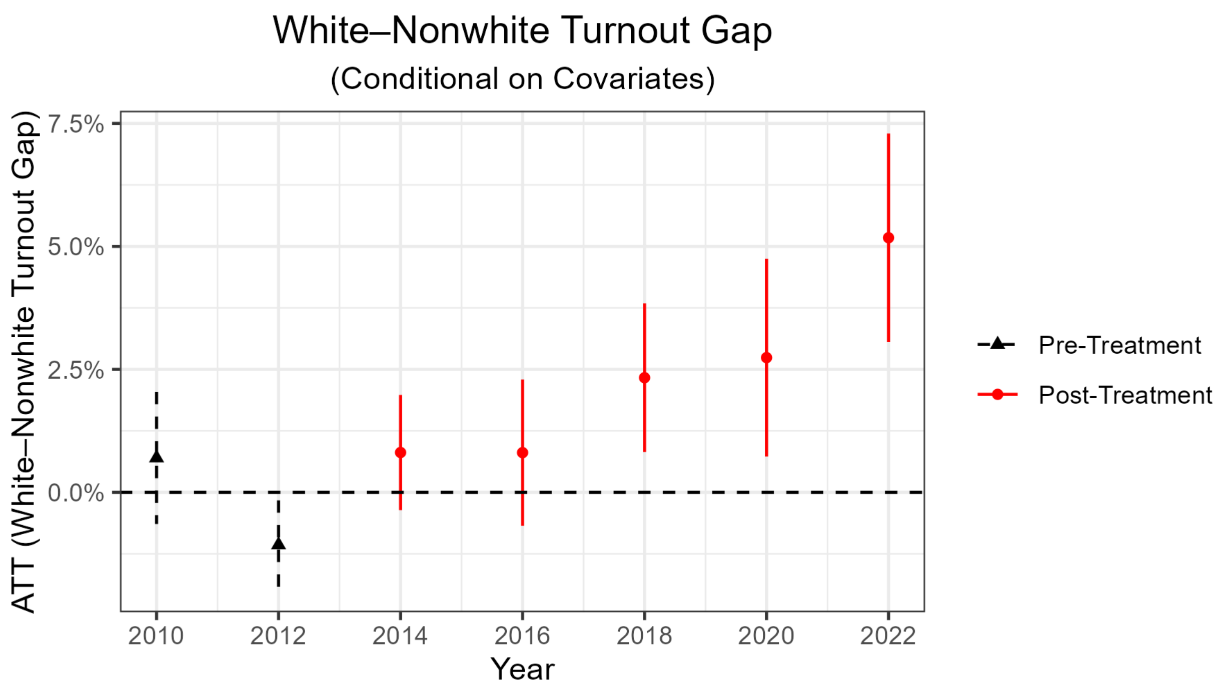
Figure A12: White–Black Gap, Entropy Balancing Models, Balancing Covariates Averaged over Base Period



Model run at county level. Includes county and year FEs. Aggregated ATT is 2.4pts ($p < 0.05$). Uncovered counties entropy balanced using the following covariates: population, share white, share Black, median income, median age, share with bachelor's degree or higher, 2012 Obama vote share.

that conditioning the parallel trends assumption in the entropy-balancing models does not meaningfully impact our conclusions or the plausibility of the parallel trends assumption for the white–nonwhite and white–Black turnout gaps.

Figure A13: White–Nonwhite Gap, Entropy Balancing Models, Parallel Trends Assumption Conditional on Covariates

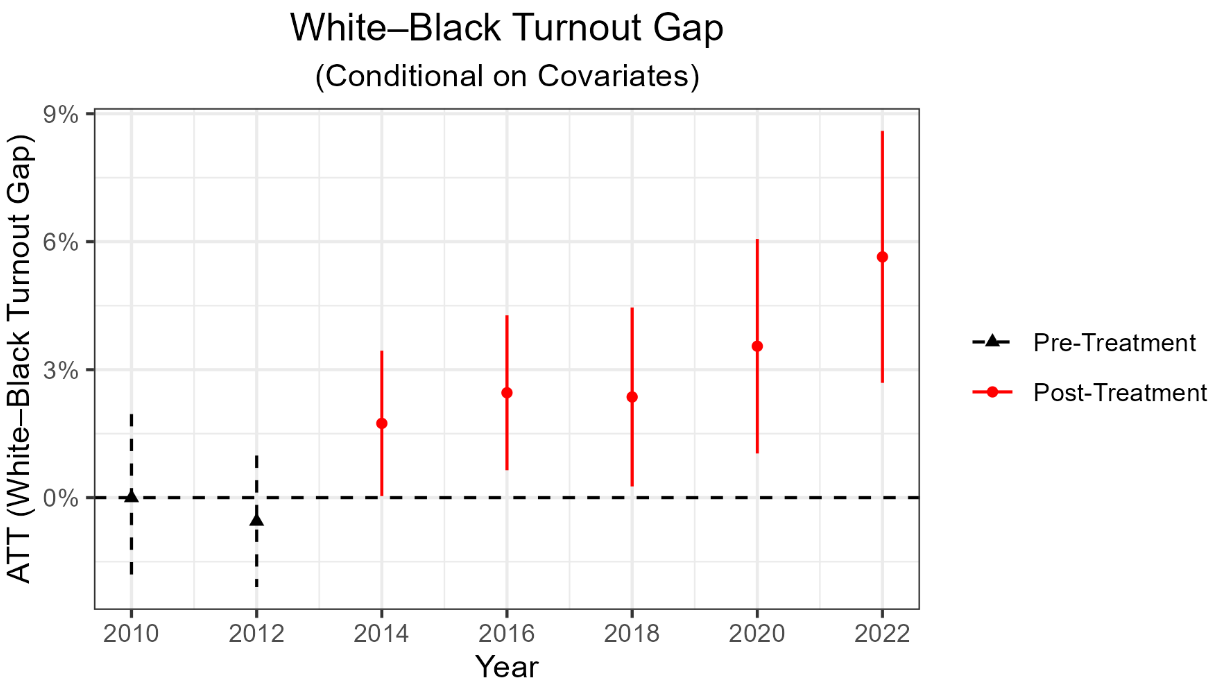


Model run at county level. Includes county and year FEs. Aggregated ATT is 2.4pts ($p < 0.05$). Uncovered counties entropy balanced using the following covariates: population, share white, share Black, median income, median age, share with bachelor's degree or higher, 2012 Obama vote share. Estimates also conditional on preceding covariates.

A.6.6 Entropy Balancing, Level Differences Averaged Across Pre-treatment Period

In the body of the report, we use the `did` package developed by Callaway and Sant'Anna (2021), largely because of its flexibility for estimating different types of difference-in-differences models (such as conditioning the parallel trends assumption on covariates). This approach, however, measures all treatment effects relative to the *final* pretreatment period. In other words, this approach tests whether the turnout gap in formerly covered jurisdictions in the

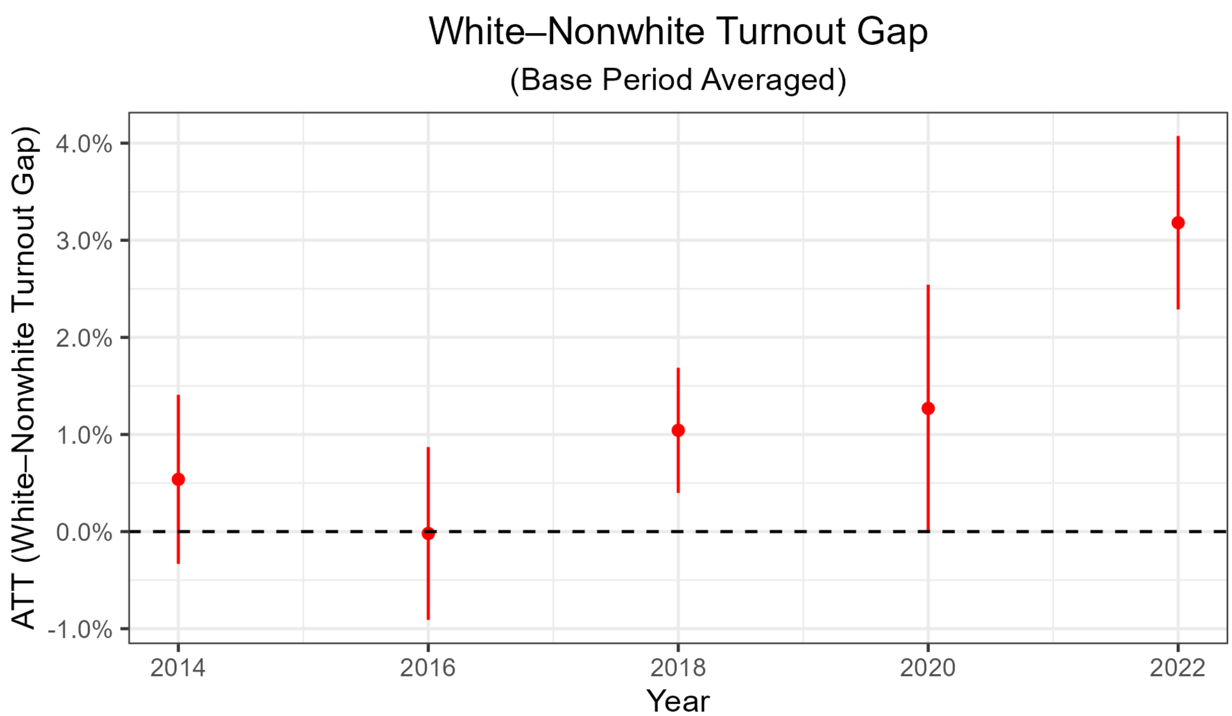
Figure A14: White–Black Gap, Entropy Balancing Models, Parallel Trends Assumption Conditional on Covariates



Model run at county level. Includes county and year FEs. Aggregated ATT is 3.1pts ($p < 0.05$). Uncovered counties entropy balanced using the following covariates: population, share white, share Black, median income, median age, share with bachelor's degree or higher, 2012 Obama vote share. Estimates also conditional on preceding covariates.

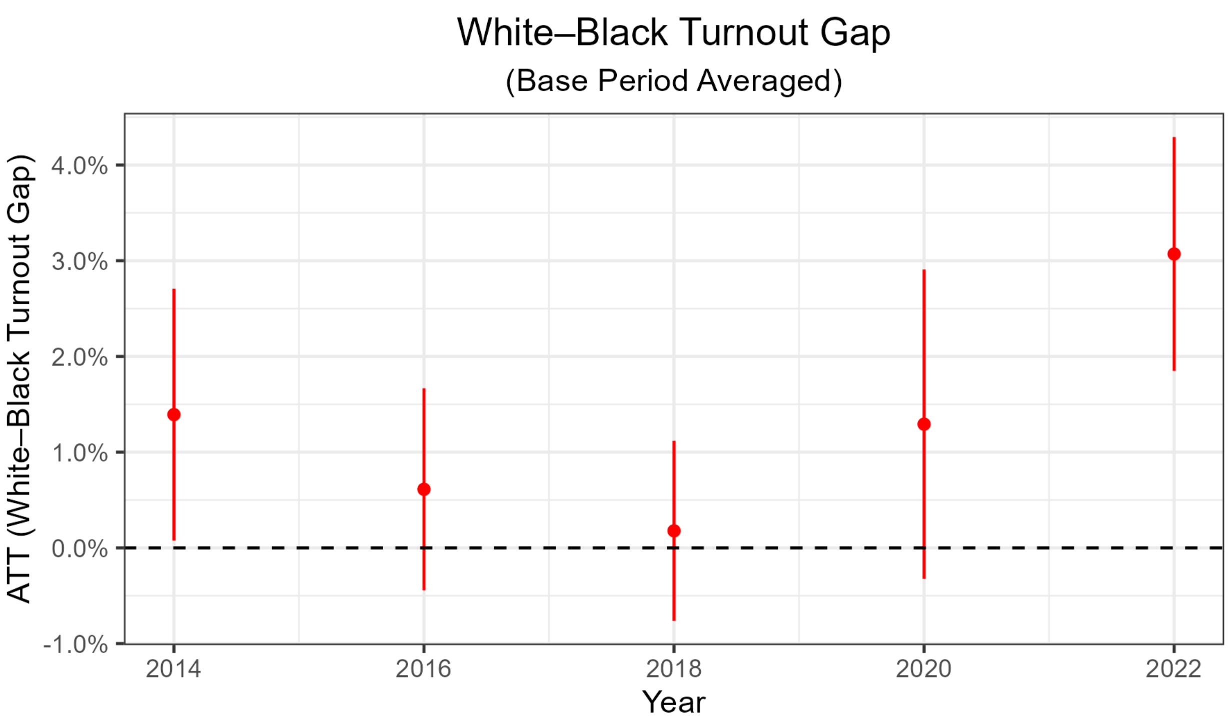
post-*Shelby* era were larger than in 2012, not whether they were larger than the full 2008–2012 period. If the turnout gaps in 2012 were not representative of the pretreatment period, this might lead to biased results. Here, we re-estimate our entropy-balanced TWFE models using the `fixest` package in `R` in which treatment effects are estimated as a deviation from the averaged level differences between treated and control units across the whole base period. As this approach does not change the time series plots, we do not reproduce them. (Because we are using the whole base period as the control set, we cannot estimate placebo coefficients for the pretreatment period as in the figures produced using the Callaway and Sant'Anna (2021) approach).

Figure A15: White–Nonwhite Gap, Entropy Balancing Models, Base Period Gap Averaged



Model run at county level. Includes county and year FEs. Aggregated ATT is 1.6pts ($p < 0.05$). Uncovered counties entropy balanced using the following 2012 covariates: population, share white, share Black, median income, median age, share with bachelor's degree or higher, 2012 Obama vote share.

Figure A16: White–Black Gap, Entropy Balancing Models, Base Period Gap Averaged

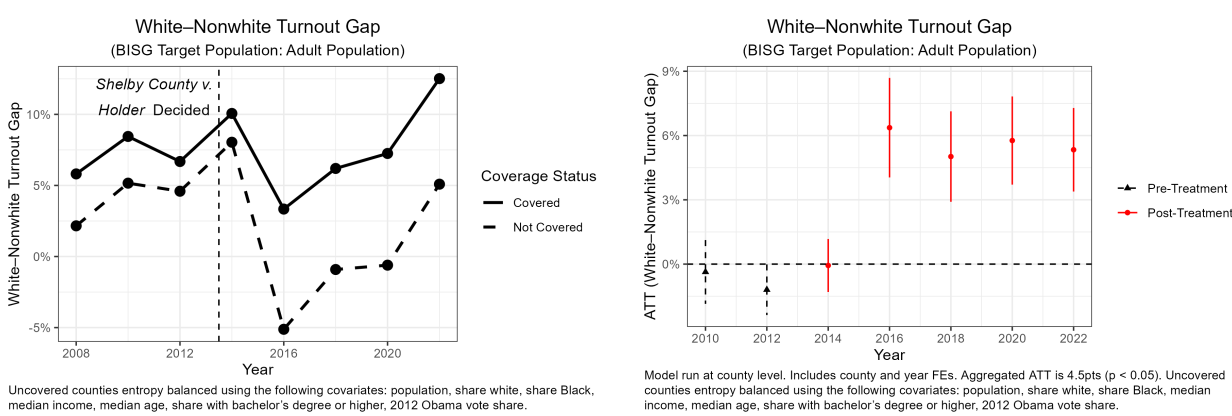


Model run at county level. Includes county and year FEs. Aggregated ATT is 2.4pts ($p < 0.05$). Uncovered counties entropy balanced using the following 2012 covariates: population, share white, share Black, median income, median age, share with bachelor's degree or higher, 2012 Obama vote share.

A.6.7 Alternative BISG Estimations

In the body of the report, we present results where race is estimated using a BISG algorithm where the target geographical population is block-group-level CVAP (though by way of reminder, where self-reported race is available, that is used in all instances). Here, we reproduce our results where race is estimated using adult and total population. In each specification, we continue to rely on entropy balancing to preprocess the data prior to the TWFE model. Given that using CVAP returns the best results in counties where the race of voters is known (see Section A.2), we rely primarily on those estimates in the body of the report. We note the the big shifts from 2014 to 2016 are driven by changes in the source of the geographic data. When we use BISG to estimate race based on adult or total population, these distributions come from the nearest decennial Census. Thus, in 2014 and earlier, voters' races are estimated using 2010 data for their block group; in 2016 and later, 2020 data are used. In our primary approach using CVAP, voters' races are estimated using the 5-year CVAP estimates for their block group ending in the year of the election.

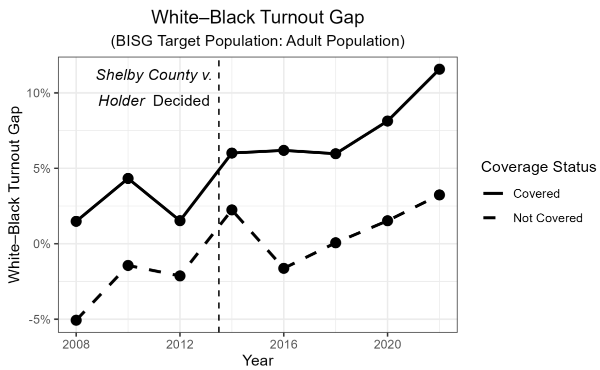
Figure A17: White–Nonwhite Gap, Entropy Balancing Models, BISG Predictions Using Adult Population



(a) Time Series

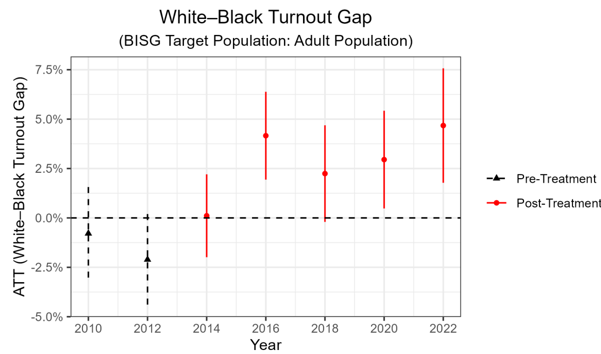
(b) Coefficients

Figure A18: White–Black Gap, Entropy Balancing Models, BISG Predictions Using Adult Population



Uncovered counties entropy balanced using the following covariates: population, share white, share Black, median income, median age, share with bachelor's degree or higher, 2012 Obama vote share.

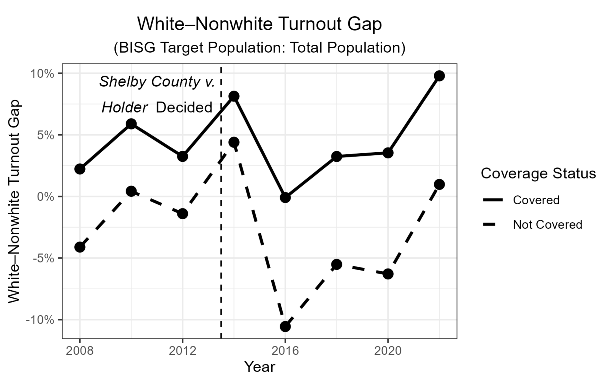
(a) Time Series



Model run at county level. Includes county and year FEs. Aggregated ATT is 2.8pts ($p < 0.05$). Uncovered counties entropy balanced using the following covariates: population, share white, share Black, median income, median age, share with bachelor's degree or higher, 2012 Obama vote share.

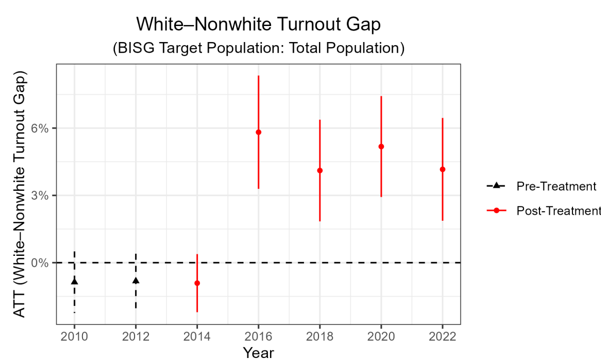
(b) Coefficients

Figure A19: White–Nonwhite Gap, Entropy Balancing Models, BISG Predictions Using Total Population



Uncovered counties entropy balanced using the following covariates: population, share white, share Black, median income, median age, share with bachelor's degree or higher, 2012 Obama vote share.

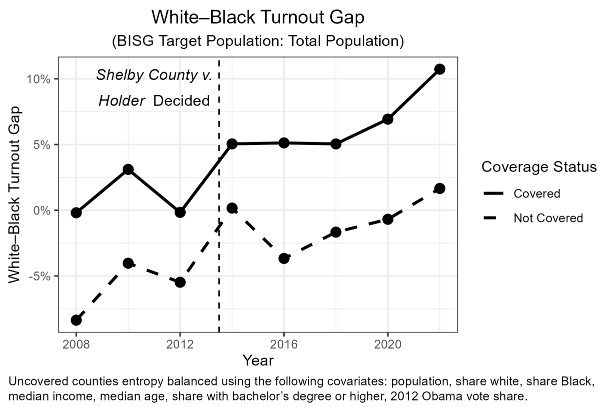
(a) Time Series



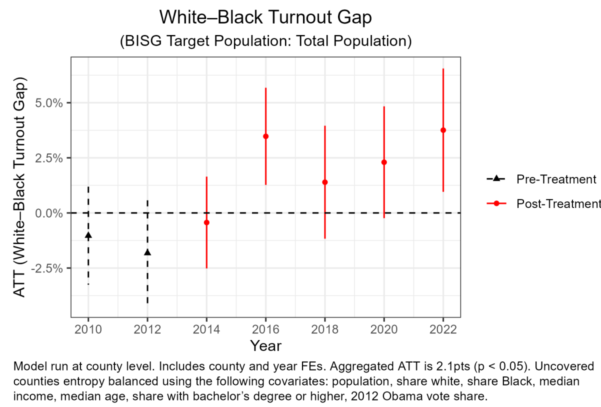
Model run at county level. Includes county and year FEs. Aggregated ATT is 3.7pts ($p < 0.05$). Uncovered counties entropy balanced using the following covariates: population, share white, share Black, median income, median age, share with bachelor's degree or higher, 2012 Obama vote share.

(b) Coefficients

Figure A20: White–Black Gap, Entropy Balancing Models, BISG Predictions Using Total Population



(a) Time Series



(b) Coefficients

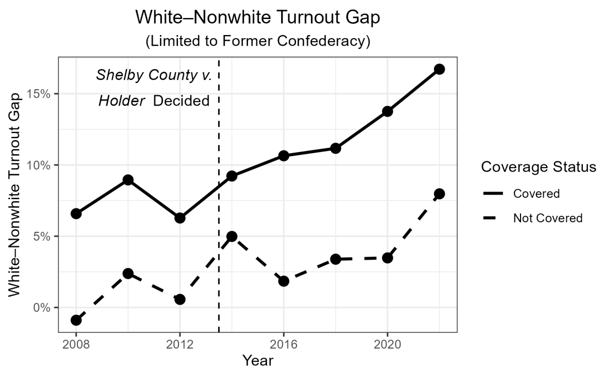
A.6.8 Limiting the Analysis to the Former Confederacy

In the body of the report, we draw our control group from the entire population of counties in the country that were not in states covered in part or whole by Section 5 of the Voting Rights Act. Recent scholarship investigating the impacts of the Voting Rights Act on mid-20th-century social outcomes, however, has compared counties "treated" by Section 5 to only "untreated" counties in the former Confederacy (Bernini et al., 2023) or to counties with pervasive Jim Crow regimes (Eubank and Fresh, 2022), because of their comparable social environments to the covered areas. Functionally, our primary approach using entropy balancing results in a similar specification: the average entropic weight assigned to uncovered counties in the former Confederacy is 2.1, compared with an average weight of 0.55 for uncovered counties elsewhere in the nation. Nevertheless, we here reproduce our results where we limit our analysis to the former Confederacy.

A.6.9 Reclassifying New Hampshire as "Treated"

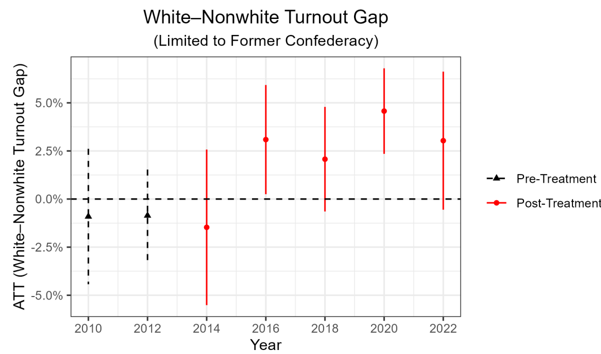
In the body of the manuscript, we consider New Hampshire counties to be "control" units, unaffected by *Shelby County*. The Granite State in unique, however: although it was not covered under the preclearance condition when *Shelby County* was handed down, it *was*

Figure A21: White–Nonwhite Gap, Entropy Balancing Models, Analysis Limited to Former Confederacy



Uncovered counties entropy balanced using the following covariates: population, share white, share Black, median income, median age, share with bachelor's degree or higher, 2012 Obama vote share.

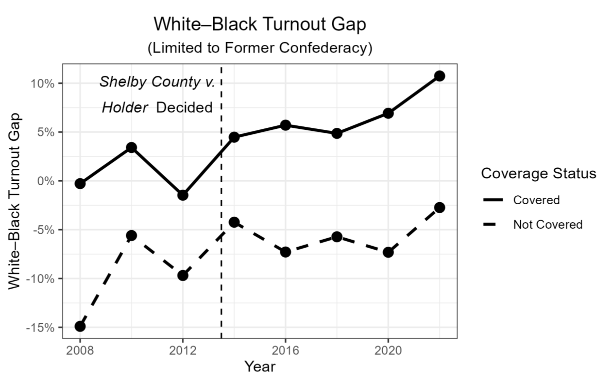
(a) Time Series



Model run at county level. Includes county and year FEs. Aggregated ATT is not statistically significant. Uncovered counties entropy balanced using the following covariates: population, share white, share Black, median income, median age, share with bachelor's degree or higher, 2012 Obama vote share.

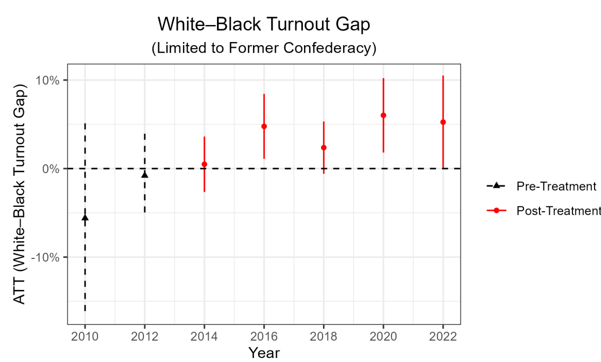
(b) Coefficients

Figure A22: White–Black Gap, Entropy Balancing Models, Analysis Limited to Former Confederacy



Uncovered counties entropy balanced using the following covariates: population, share white, share Black, median income, median age, share with bachelor's degree or higher, 2012 Obama vote share.

(a) Time Series

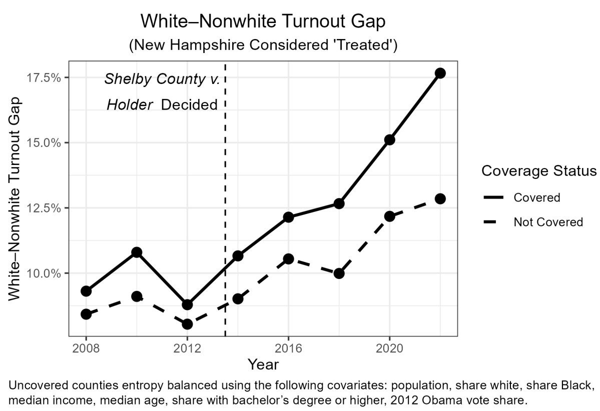


Model run at county level. Includes county and year FEs. Aggregated ATT is 3.8pts ($p < 0.05$). Uncovered counties entropy balanced using the following covariates: population, share white, share Black, median income, median age, share with bachelor's degree or higher, 2012 Obama vote share.

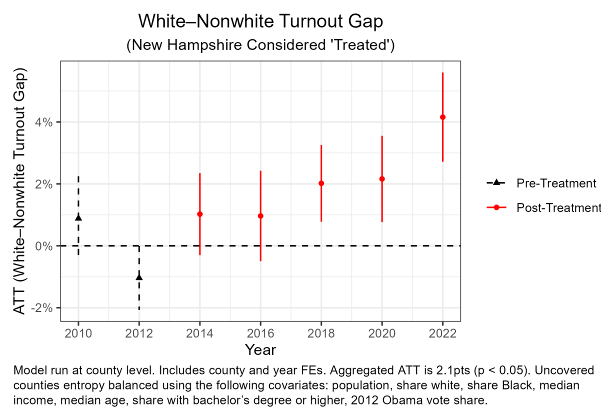
(b) Coefficients

covered until March of 2013.[2] As such, 2014 was the first federal election in which New Hampshire was not subject to Section 5. In that sense, it too was "treated," not by *Shelby County*, but by release from preclearance via a different mechanism. New Hampshire was "bailed out" under Section 4a of the VRA, which allows states to be released from preclearance if they meet certain conditions demonstrating a commitment to protecting the voting rights of minorities. For this reason, we believe that New Hampshire is better understood as a control case than a treated one. Nevertheless, we here show that our results are virtually unchanged if we consider New Hampshire "treated" instead of "control."

Figure A23: White–Nonwhite Gap, Entropy Balancing Models, New Hampshire considered "Treated"



(a) Time Series



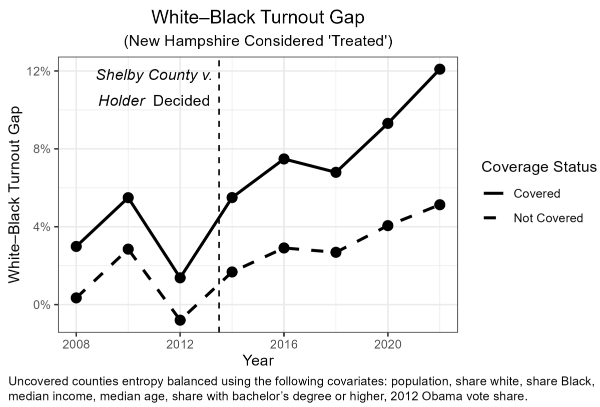
(b) Coefficients

A.6.10 Recoding Uncovered Counties in Partially Covered States

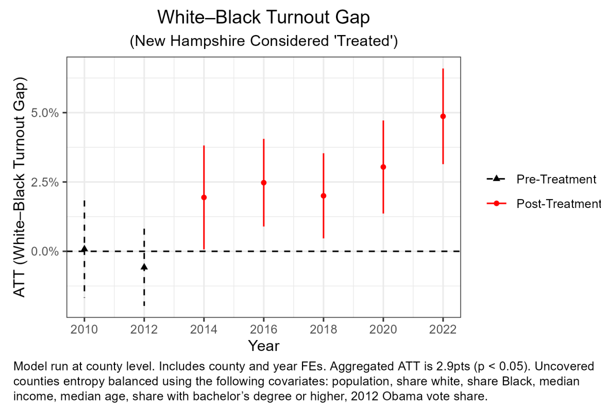
In the body of the report, we consider all counties "treated" by Section 5 of the Voting Rights Act if they were in a state that was only partially covered. For instance, even though only 3 counties in California were covered by the preclearance regime (Kings, Monterey, and Yuba Counties), we consider all counties in the state covered. This is because, according to the U.S. Supreme Court in *Lopez v. Monterey County* (525 U.S. 266 (1999)), all statewide

[2] See `https://campaignlegal.org/press-releases/new-hampshire-becomes-first-state-bailout-voting-rights` for a discussion.

Figure A24: White–Black Gap, Entropy Balancing Models, New Hampshire considered "Treated"



(a) Time Series



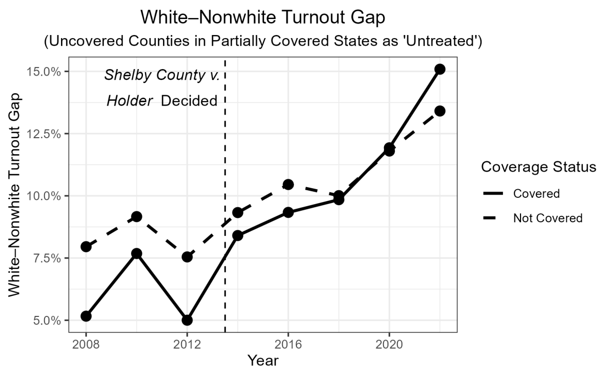
(b) Coefficients

voting policies were subject to preclearance so long as a single county in the state was covered by Section 4b. In other words, *statewide* policy was equally constrained by Section 5 of the Voting Rights Act regardless of whether the state was fully or partially covered by the provision. There are, however, other facets of election administration left up to the counties, such as polling place location. Here, we reclassify uncovered counties in partially covered states as control, and not treated, observations, to test whether these counties are driving our results. This specification results in higher point estimates than our primary models, especially later in the treatment period and for the overall white–nonwhite gap.

A.6.11 Weighting Counties by Population

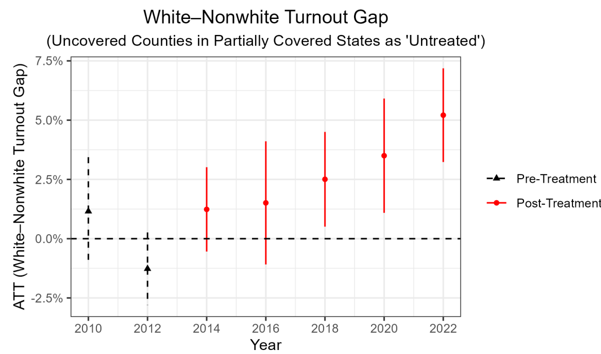
In the body of the report, we weight all counties equally, post–entropy balancing. This is because elections are generally run at the county level in the United States, and thus counties are the natural unit of analysis. We are interested in whether turnout gaps are growing in elections overseen by administrators in small and large counties alike. However, most voters are concentrated in a small handful of very large counties: roughly 23% of Black citizens of voting age in covered areas, for instance, live in just 10 of the nearly 1,300 covered counties. We might thus want to weight our analyses by the relevant population.

Figure A25: White–Nonwhite Gap, Entropy Balancing Models, Uncovered Counties in Partially Covered States as Controls



Uncovered counties entropy balanced using the following covariates: population, share white, share Black, median income, median age, share with bachelor's degree or higher, 2012 Obama vote share.

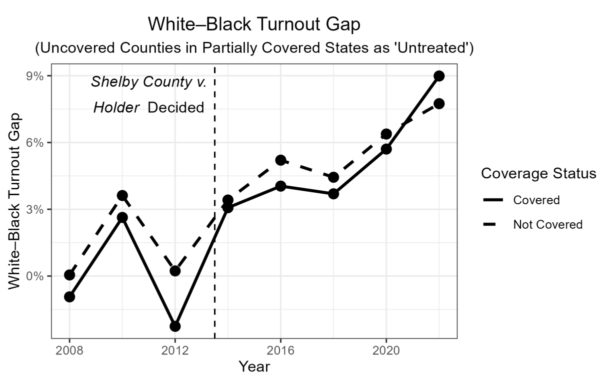
(a) Time Series



Model run at county level. Includes county and year FEs. Aggregated ATT is 2.8pts ($p < 0.05$). Uncovered counties entropy balanced using the following covariates: population, share white, share Black, median income, median age, share with bachelor's degree or higher, 2012 Obama vote share.

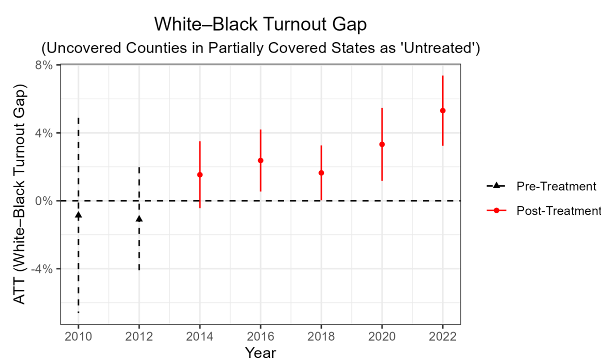
(b) Coefficients

Figure A26: White–Black Gap, Entropy Balancing Models, Uncovered Counties in Partially Covered States as Controls



Uncovered counties entropy balanced using the following covariates: population, share white, share Black, median income, median age, share with bachelor's degree or higher, 2012 Obama vote share.

(a) Time Series

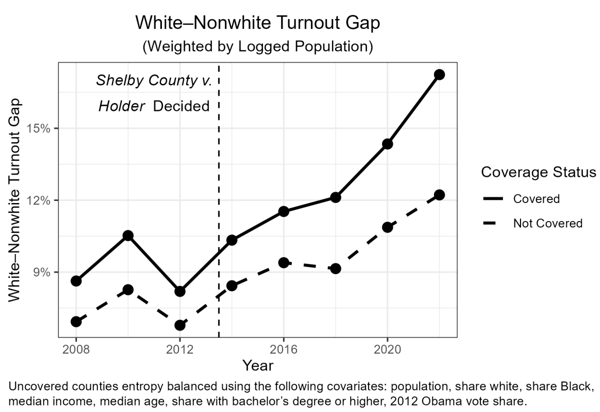


Model run at county level. Includes county and year FEs. Aggregated ATT is 2.8pts ($p < 0.05$). Uncovered counties entropy balanced using the following covariates: population, share white, share Black, median income, median age, share with bachelor's degree or higher, 2012 Obama vote share.

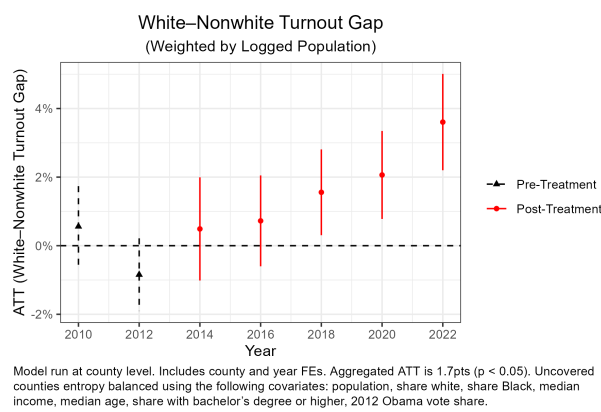
(b) Coefficients

We begin here by weighting counties throughout the country by their logged population of interest (nonwhite CVAP for the overall turnout gap; Black CVAP for the white–Black gap). Weights are scaled within year and treatment status; thus, the sum of the population weights for covered counties is 1 each year (the same is true for uncovered counties). This allows us to multiply the population weights by the entropy balancing weights and retain balanced groups. Using logged population, which grows more slowly than raw population, strikes a balance between weighting large counties more heavily, but not allowing them to completely drive our analyses. These results are consistent with the models in which we weight counties equally.

Figure A27: White–Nonwhite Gap, Entropy Balancing Models, Counties Weighted by Logged Population



(a) Time Series

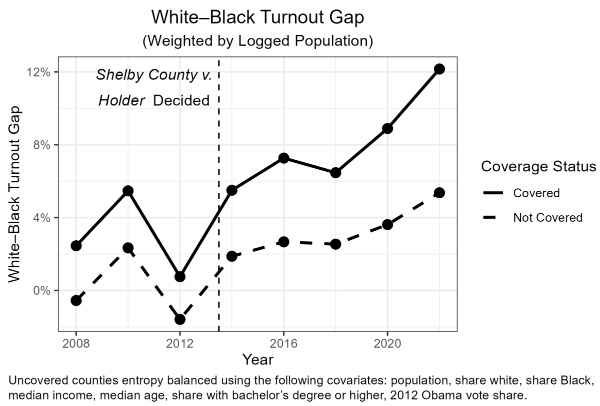


(b) Coefficients

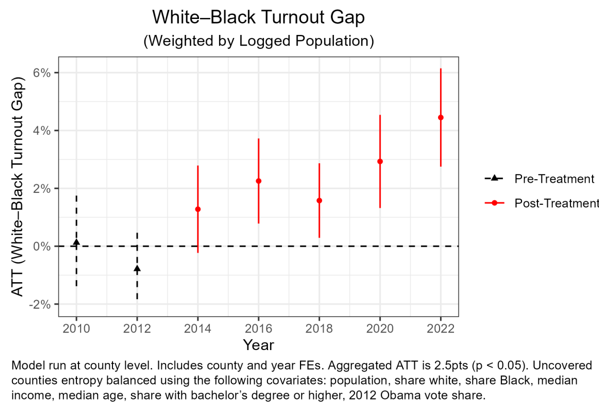
Our results break down, however, when we weight counties by their *raw* population. In fact, weighting by raw population results in *negative* treatment effects for the white–nonwhite turnout gap.

We have strong reason to believe, however, that these results are being overdetermined by the very largest counties in the sample. Los Angeles County, California, for instance, is assigned a population weight that is 863 times the median weight of the treated covered counties in 2022; for Harris County, Texas, that figure is 389. Such an extreme weight means that these results are driven largely by the enormous counties. And while it's possible that

Figure A28: White–Black Gap, Entropy Balancing Models, Counties Weighted by Logged Population

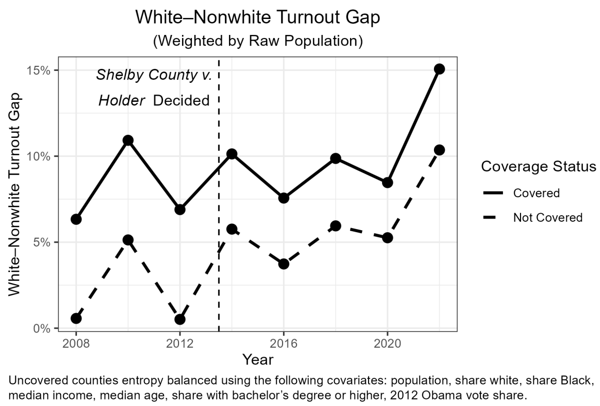


(a) Time Series

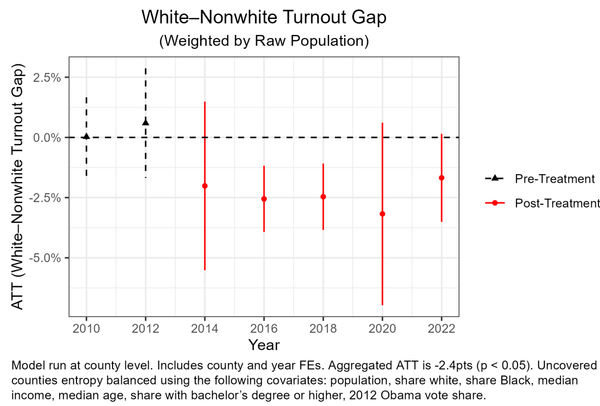


(b) Coefficients

Figure A29: White–Nonwhite Gap, Entropy Balancing Models, Counties Weighted by Raw Population

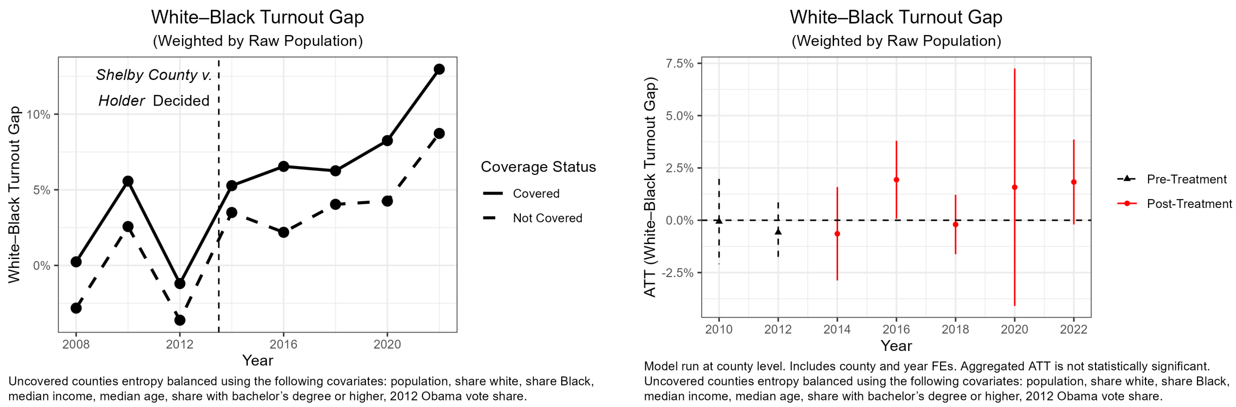


(a) Time Series



(b) Coefficients

Figure A30: White–Black Gap, Entropy Balancing Models, Counties Weighted by Raw Population

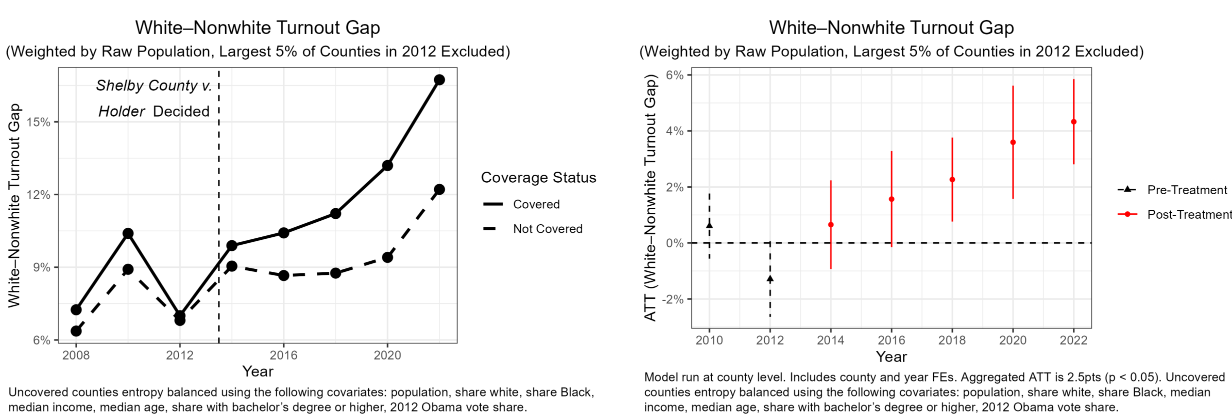


(a) Time Series (b) Coefficients

the effects of *Shelby County* really were different in the very largest counties, it seems that these extreme outliers are in fact outliers. We continue to find that *Shelby County* increased the turnout gap when we exclude the very largest counties.

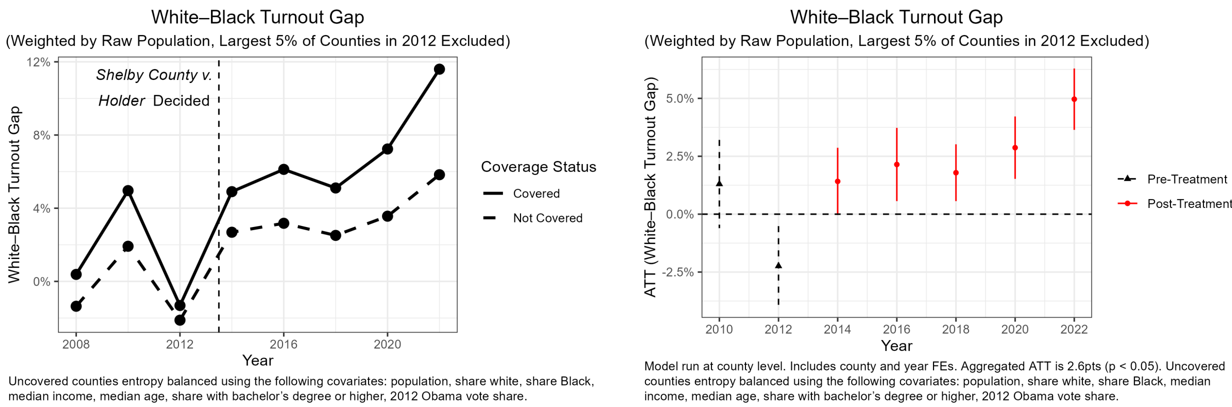
First, when we exclude the 5% of largest counties (based on their nonwhite or Black CVAP in 2012, depending on the model) but continue to weight by raw population, our results remain consistent. In other words, across at least 95% of counties, even when we weight by raw population, *Shelby County* meaningfully increased the racial turnout gap.

Figure A31: White–Nonwhite Gap, Entropy Balancing Models, Counties Weighted by Raw Population, Largest 5% Excluded



(a) Time Series (b) Coefficients

Figure A32: White–Black Gap, Entropy Balancing Models, Counties Weighted by Raw Population, Largest 5% Excluded



(a) Time Series

(b) Coefficients

In Table A7, we present the TWFE models using entropy balanced weights but where the observations are not weighted by population. Instead, we interact the treatment dummy (which is 1 for formerly covered counties for post-2012 years) with the county's population of interest. There are two things worth noting in the table. First, the coefficient on *Covered* $\times$ *Post Shelby County* is significant in both models; this means that there is an identifiable treatment effect of *Shelby County* in smaller counties. The negative, statistically significant coefficient on *Covered* $\times$ *Post Shelby County* $\times$ *Population (100,000s* in model 1 indicates that the effect of *Shelby County* on the white–nonwhite turnout gap was smaller in the largest of counties. Population size does not, however, significantly moderate the effect of *Shelby County* on the white–Black gap.

We thus conclude that, even after we account appropriately for population size, *Shelby County v. Holder* increased racial turnout gaps. Further, we remain convinced that analyzing elections and turnout at the county level *without* weighting by population remains the most theoretically grounded approach. Many of the causal mechanisms through which the consequences of *Shelby County* are effectuated, like redistricting plans and polling place locations, are implemented at the county level, and each county (for the most part) does so independently. There is by now a large body of literature (e.g., Hale, Montjoy and Brown,

Table A7: Treatment Moderated by Population

	White–Nonwhite Gap	White–Black Gap
Population (100,000s)	-0.034**	-0.005
	(0.012)	(0.019)
Covered × Population (100,000s)	0.020	0.029
	(0.013)	(0.022)
Covered × Post Shelby County	0.019***	0.026***
	(0.004)	(0.007)
Post Shelby County × Population (100,000s)	0.006**	0.008**
	(0.002)	(0.003)
Covered × Post Shelby County × Population (100,000s)	-0.006**	-0.002
	(0.002)	(0.003)
County Fixed Effects	✓	✓
Year Fixed Effects	✓	✓
Num.Obs.	24278	18027
R2	0.834	0.776
R2 Adj.	0.810	0.744

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Standard errors clustered by county.

Population is nonwhite CVAP for model 1, Black CVAP for model 2.

2015; Brown, Hale and King, 2019; Moynihan and Silva, 2008; Ferrer, Geyn and Thompson, 2023; Kimball and Baybeck, 2013; Mohr et al., 2019) detailing how voters' experiences are shaped by the county administrators where they live. If county-level administrators are exercising their newfound freedom—intentionally or not—to implement racially discriminatory voting policies that increase the racial turnout gap, this is of substantive interest regardless of the size of the county they oversee. This devolution of responsibility also increases the likelihood of treatment heterogeneity at the county level.

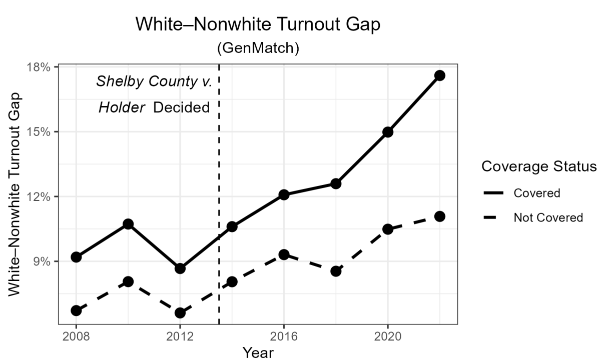
Of course, it remains distinctly possible that the impact of *Shelby County* had a different effect in large counties; there is good theoretical reason to think so. Harris County, Texas, provides a nice example. In 2020, the county introduced new reforms intended to make voting easier. It allowed for drive-through voting and 24-hour early voting and attempted to send all registered voters applications to request absentee ballots. In 2021, Texas passed an omnibus elections bill making voting more difficult, taking "particular aim at voting initiatives used in diverse, Democratic Harris County in the 2020 election" (Ura, 2021). The largest 5% of counties are often majority nonwhite (45% of them are, compared with just 9% of the rest of the counties in the country), are more Democratic (Obama won 75% of these large counties in 2012, compared with 17% of the rest of the country), and are more likely to have local election officials who are people of color.[3] It seems likely that despite state-level policies making voting more difficult in the aftermath of *Shelby County*, these largest counties would have local election officials most committed to mitigating any harm. Further, local and national media are considerably more focused on large counties, which may provide resources for countermobilization or a stronger check against would-be discrimination on the part of local election officials. Future work ought to investigate whether and which of these factors are at play in reducing the impact of *Shelby County* in the largest counties.

[3] https://evic.reed.edu/2022_leo_survey_demography/

A.6.12 Genetic Matching

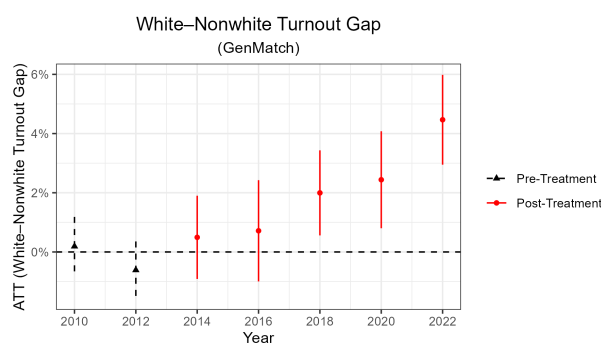
As a final approach, we use a genetic matching procedure (Sekhon, 2011) to match each treated county to one untreated county, using the same set of 2012 characteristics previously described. We conduct matching with replacement, breaking ties randomly. Using this approach, we can adopt the strictest assumption about the parallel trends: that the outcome variable for treated and (matched) control units would have evolved in parallel *unconditional* on any covariates. Table A5 indicates that—like entropy balancing—genetically matching treated and control counties results in a control set substantially similar to the treated group. We also present the results of the matching models in which the parallel trends assumption is conditional on covariates.

Figure A33: White–Nonwhite Gap, Genetic Matching, Parallel Trends Assumption Unconditional on Covariates



Covered counties genetically matched to 1 uncovered county (with replacement) using the following covariates: population, share white, share Black, median income, median age, share with bachelor's degree or higher, 2012 Obama vote share.

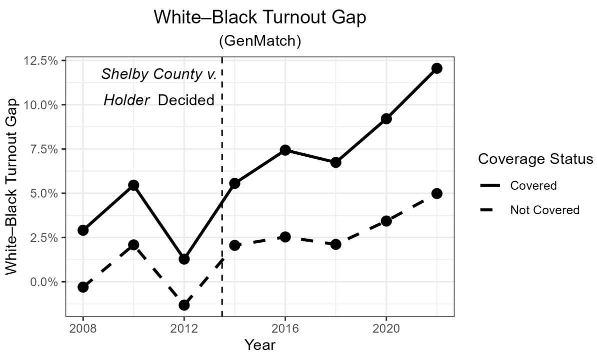
(a) Time Series



Model run at county level. Includes county and year FEs. Aggregated ATT is 2pts ($p < 0.05$). Covered counties genetically matched to 1 uncovered county (with replacement) using the following covariates: population, share white, share Black, median income, median age, share with bachelor's degree or higher, 2012 Obama vote share.

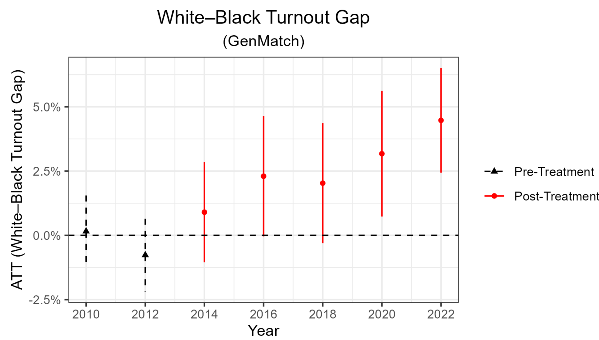
(b) Coefficients

Figure A34: White–Black Gap, Genetic Matching, Parallel Trends Assumption Unconditional on Covariates



Covered counties genetically matched to 1 uncovered county (with replacement) using the following covariates: population, share white, share Black, median income, median age, share with bachelor's degree or higher, 2012 Obama vote share.

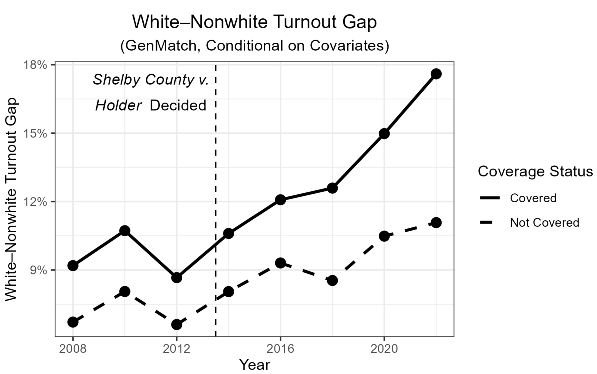
(a) Time Series



Model run at county level. Includes county and year FEs. Aggregated ATT is 2.6pts ($p < 0.05$). Covered counties genetically matched to 1 uncovered county (with replacement) using the following covariates: population, share white, share Black, median income, median age, share with bachelor's degree or higher, 2012 Obama vote share.

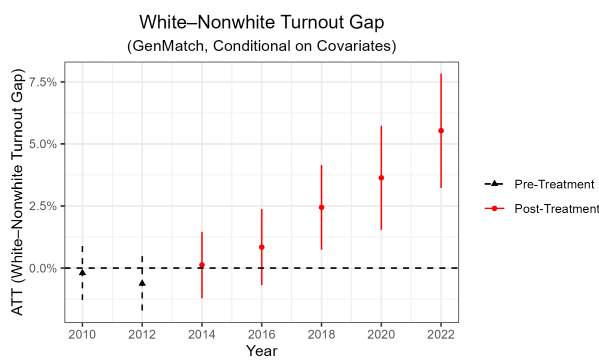
(b) Coefficients

Figure A35: White–Nonwhite Gap, Genetic Matching, Parallel Trends Assumption Conditional on Covariates



Uncovered counties entropy balanced using the following covariates: population, share white, share Black, median income, median age, share with bachelor's degree or higher, 2012 Obama vote share.

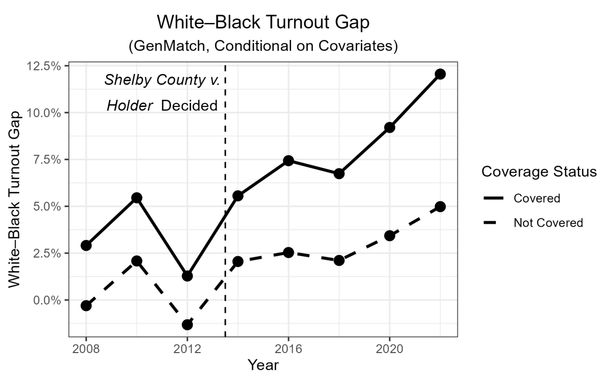
(a) Time Series



Model run at county level. Includes county and year FEs. Aggregated ATT is 2.5pts ($p < 0.05$). Uncovered counties entropy balanced using the following covariates: population, share white, share Black, median income, median age, share with bachelor's degree or higher, 2012 Obama vote share.

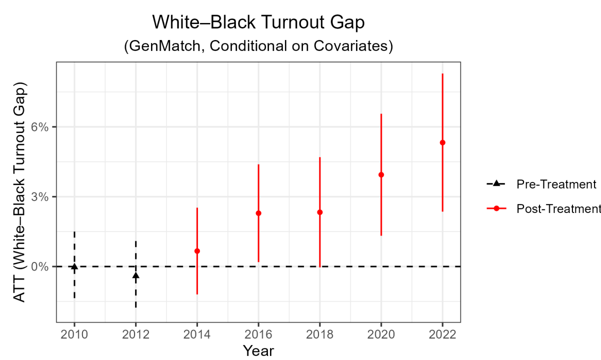
(b) Coefficients

Figure A36: White–Black Gap, Genetic Matching, Parallel Trends Assumption Conditional on Covariates



Uncovered counties entropy balanced using the following covariates: population, share white, share Black, median income, median age, share with bachelor's degree or higher, 2012 Obama vote share.

(a) Time Series



Model run at county level. Includes county and year FEs. Aggregated ATT is 2.9pts ($p < 0.05$). Uncovered counties entropy balanced using the following covariates: population, share white, share Black, median income, median age, share with bachelor's degree or higher, 2012 Obama vote share.

(b) Coefficients

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