PUBLIC POLICY INSTITUTE OF CALIFORNIA

Equity in Voter Turnout after Pandemic Election Policy Changes

Technical Appendices

CONTENTS

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Appendix A. Identifying Race and Ethnicity on the Voter File

Our analysis uses registration file data to understand the equity effects of pandemic election policies. However, most states either do not ask registrants for their race or ethnicity or ask it in a way that does not elicit many responses. In most states, race and ethnicity must be imputed with other information. The current best practice for this imputation is Bayesian Improved Surname Geocoding (BISG) (Elliott et al. 2008, Imai and Khanna 2016). BISG uses registrant surnames matched to race/ethnicity to identify the probability that a particular registrant belongs to a particular racial or ethnic group. It then updates this probability based on the racial/ethnic composition of the registrant's surrounding community. For our work with VoteCal, the California voter file, we impute race and ethnicity using the WRU package for R (Imai and Khanna 2016), with geocoding at the tract level. For our national analysis we use county aggregates from the data vendor Catalist, which employs a proprietary BISG methodology.

BISG estimates contain some bias toward underreporting race/ethnicity (false negatives) in most places. However, because BISG uses location as one factor, it can lead to overreporting (false positives) in places with high concentrations of the race or ethnicity being imputed. For Asian Americans and (especially) Latinos, this context-specific bias is muted because surnames are a reasonably accurate way of identifying race/ethnicity and BISG leans more heavily on surname for those groups. But there is no equally specific list of surnames for the African American community, so BISG relies more on location in that case.

TABLE A1

Share of self-reported race categories classified in each of three BISG groups

Self-Report	BISG		
	Latino	Asian American	African American
American Indian / Alaska Native (N=600)	22%	4%	6%
Asian / Pacific Islander (N=15641)	9%	68%	2%
Black, not of Hispanic Origin (N=5009)	2%	1%	54%
Hispanic (N=23468)	85%	1%	1%
White, not of Hispanic Origin (N=54896)	3%	1%	3%
Multi-racial (N=5096)	23%	7%	10%
Other (N=11467)	42%	7%	10%
NA (N=15248)	28%	12%	8%
NULL (N=413567)	27%	10%	7%

SOURCES: 2018 VoteCal

NOTES: Cell entries are the share of registrants in each self-report category who BISG placed in the race/ethnicity identified at the top of the column. BISG was conducted by WRU package for R (Imai and Khanna 2016). Registrants were assigned to the race/ethnicity with the highest probability. Categories of self-report are listed as coded in VoteCal. BISG categories are identified in column headers and use the terminology from the report. Lightly shaded cells are accurate matches where perfect alignment would produce 100%. The difference between those numbers and 100 is the false negative rate. The values of all other cells are false positive rates.

Table A1 compares the BISG method implemented in the WRU package for R (Imai and Khanna 2016) to the self-reported race/ethnicity in VoteCal, the California voter file. The VoteCal self-reports are not a random sample—about a quarter of VoteCal registrants who identify their race/ethnicity are younger and have higher turnout than those who do not) but they do give a sense of the match. False positives (numbers in unshaded cells) are generally rare. They are more common among BISG-identified Latinos, but mostly in a group of response categories (multi-racial, other, NA, and no response) that are not strictly false positives, plus one category (American Indian) that is a common racial choice for Latinos in the census. False negative rates (100 minus the numbers in shaded cells) are relatively low for Latinos, higher for Asian Americans, and quite high for African Americans, where BISG identifies almost half of self-reported Black registrants as something else.

Despite these sometimes high false negative rates, the low false positive rates suggest the error is evenly distributed among many other groups. Moreover, at the aggregate level the numbers line up well with expectations. Figures A1 through A3 show the correspondence between the California WRU predictions at the tract level and the citizen voting-age population (CVAP) totals from the 5-year American Community Survey of the U.S. Census Bureau. The red line marks equivalence between the two measures, while the green line is a flexible spline fit to the data. For Latinos and Asian Americans, there is a close correspondence at all population shares, with the WRU shares falling below CVAP as would be expected from both a higher false negative than false positive rate and a registered population that must be smaller than the eligible population by definition.

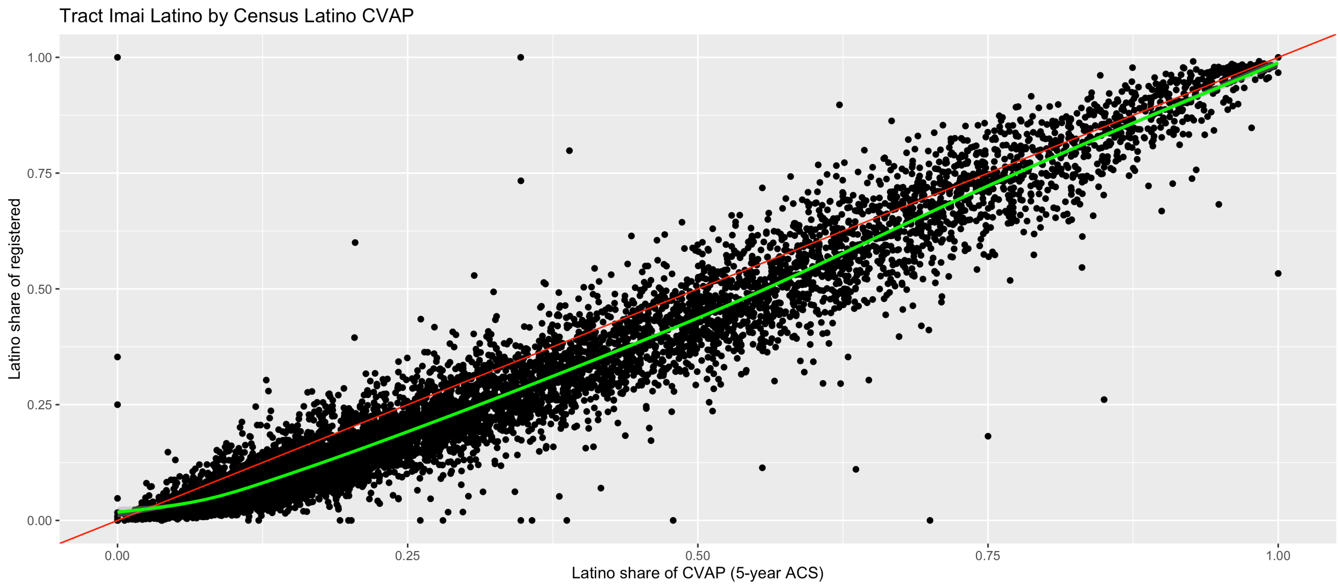
There is a poorer correspondence for African Americans though the correlation is still high (Figure A3). At low African American CVAP shares, the two measures match on average with some error, but at higher CVAP shares the WRU imputation substantially overstates the black share. This is consistent with the geocoding, which will tend to resolve ambiguities in favor of the most prevalent group in an area. (Per Fraga 2016, it might also partly reflect higher registration rates for African Americans in heavily black tracts.)

In all our analyses, we difference out location to ensure that this bias is eliminated as much as possible. For the national analysis we include county fixed effects; for the Los Angeles 2020 primary analysis we compare VBM to non-VBM voters in each part of the county; and for the California analysis of in-person options we analyze both 2016 and 2020 data and include county fixed effects. As confirmation of this general approach to resolving the problem, we dropped the fixed effects and ran our California precinct consolidation analysis within 2016 alone as a placebo. Any differences between counties in that year cannot reflect precinct consolidation policy because all counties took the same basic approach at that time. In these models there are 32 turnout gap differences (4 types of consolidation counties X 4 underrepresented groups, separately for VBM and in-person voter types); 23 of them are statistically significant and 8 have an absolute value larger than 2 percent. Importantly, these differences exist after controlling for vote history and a range of other factors, and might reflect geographic bias in our race imputation. Ignoring these baseline differences could significantly bias our conclusions. The full results of this placebo model are available from the authors by request.

One limitation of the WRU package for R is the age of the Census data it uses. The data come from 2010, and so do not capture changes in the racial and ethnic composition of each tract that have occurred since then. Figures A1 through A3—which compare the WRU estimates to more up-to-date census estimates—suggest the consequence of this time lag may be small. Moreover, our analysis that uses WRU either compares registrants within a single year—in the case of the Los Angeles primary—or compares registrants across a relatively short span of time—in the case of the in-person voting options in 2016 and 2020.

FIGURE A1

Tract-level correspondence between BISG imputations and ACS CVAP rates: Latinos

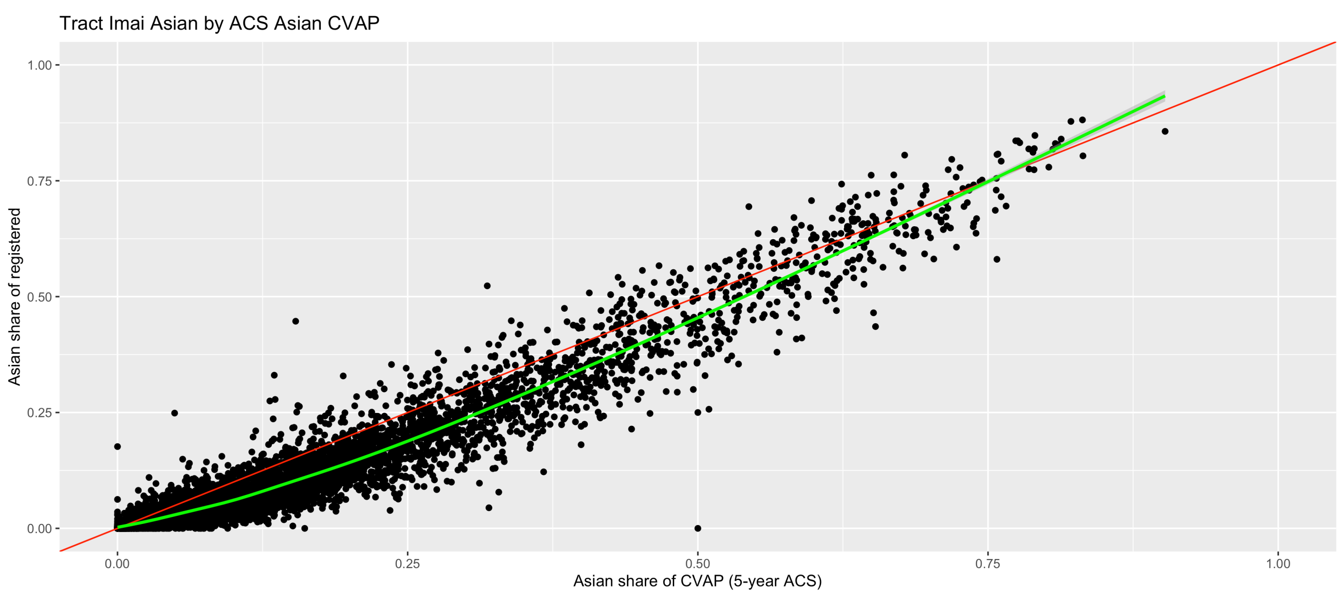


SOURCE: 2018 VoteCal (registration), 2014-2018 American Community Survey (CVAP).

NOTES: Red line marks equivalence. Green line is a spline fit.

FIGURE A2

Tract-level correspondence between BISG imputations and ACS CVAP rates: Asian Americans

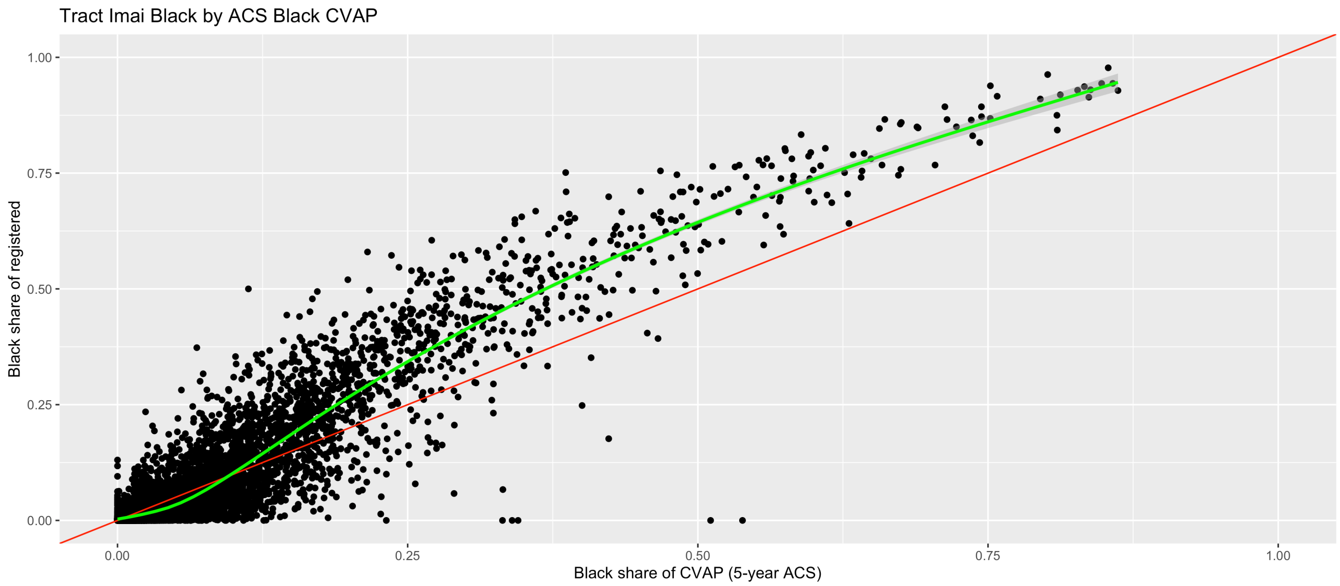


SOURCE: 2018 VoteCal (registration), 2014-2018 American Community Survey (CVAP).

NOTES: Red line marks equivalence. Green line is a spline fit.

FIGURE A3

Tract-level correspondence between BISG imputations and ACS CVAP rates: African Americans



SOURCE: 2018 VoteCal (registration), 2014-2018 American Community Survey (CVAP).

NOTES: Red line marks equivalence. Green line is a spline fit.

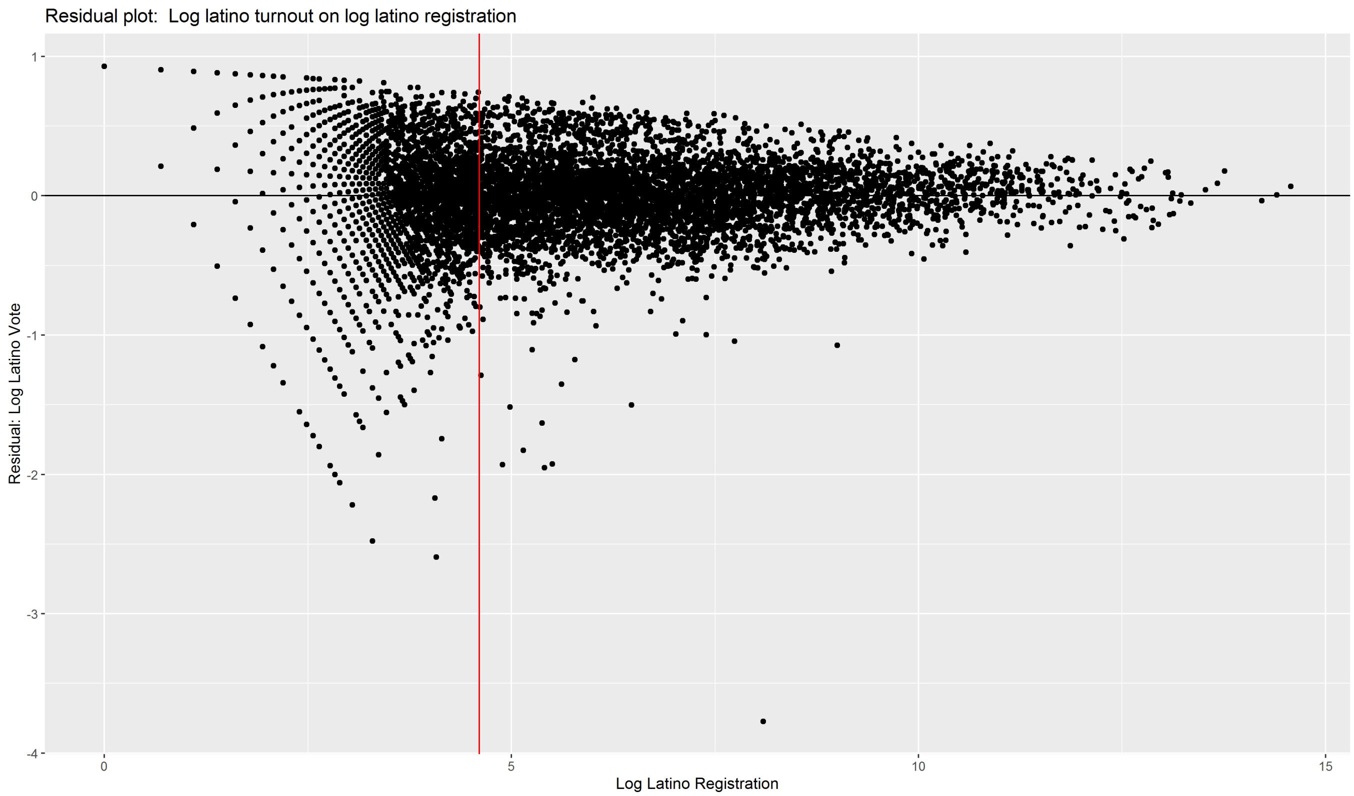
The Catalist data are highly correlated with our WRU estimates for the California counties where we have both. It is also worth noting that Schaffner, et al. (2021) matched Catalist data to Cooperative Congressional Election Study (CCES) survey data and found that 86% of those who identified as black in the CCES were identified as black by Catalist; for Latinos the number was 88%. So if anything the Catalist methodology may have a lower false negative rate than WRU.

The other source of error in our race/ethnicity data stems less from the methodology of imputing race/ethnicity on the voter file and more from the geographic concentration of communities of color. Most counties in the United States have populations of color that are so small that the randomness of small-N samples begins to play a role. Figures A4 through A7 are residual plots from a regression of the log of the number of voters from each group in a county on the log of the number of registrants in each county. The plot shows clear signs of heteroscedasticity for each community of color, as smaller county populations have larger randomness. There are also signs that the Catalist imputation becomes more arbitrary at very low population counts. The same pattern is evident to some extent in the youth data, but less so because very few counties have extremely small populations of young people (Figure A7).

To address this problem, we weight all our county-level regressions by the square root of the number of registrants. This has the effect of significantly downweighting the low-population counties while also tapering the weight for very high population counties. It also mimics the sampling properties that produce the error, since the standard errors shrink as a function of the square root of the number of cases. We also tried dropping counties with fewer than 100 registrants in the relevant racial/ethnic group; this approach produced broadly similar results. The 100-registrant threshold is marked in Figures A4 through A7 with a red vertical line.

FIGURE A4

Tract-level correspondence between BISG imputations and ACS CVAP rates: African Americans

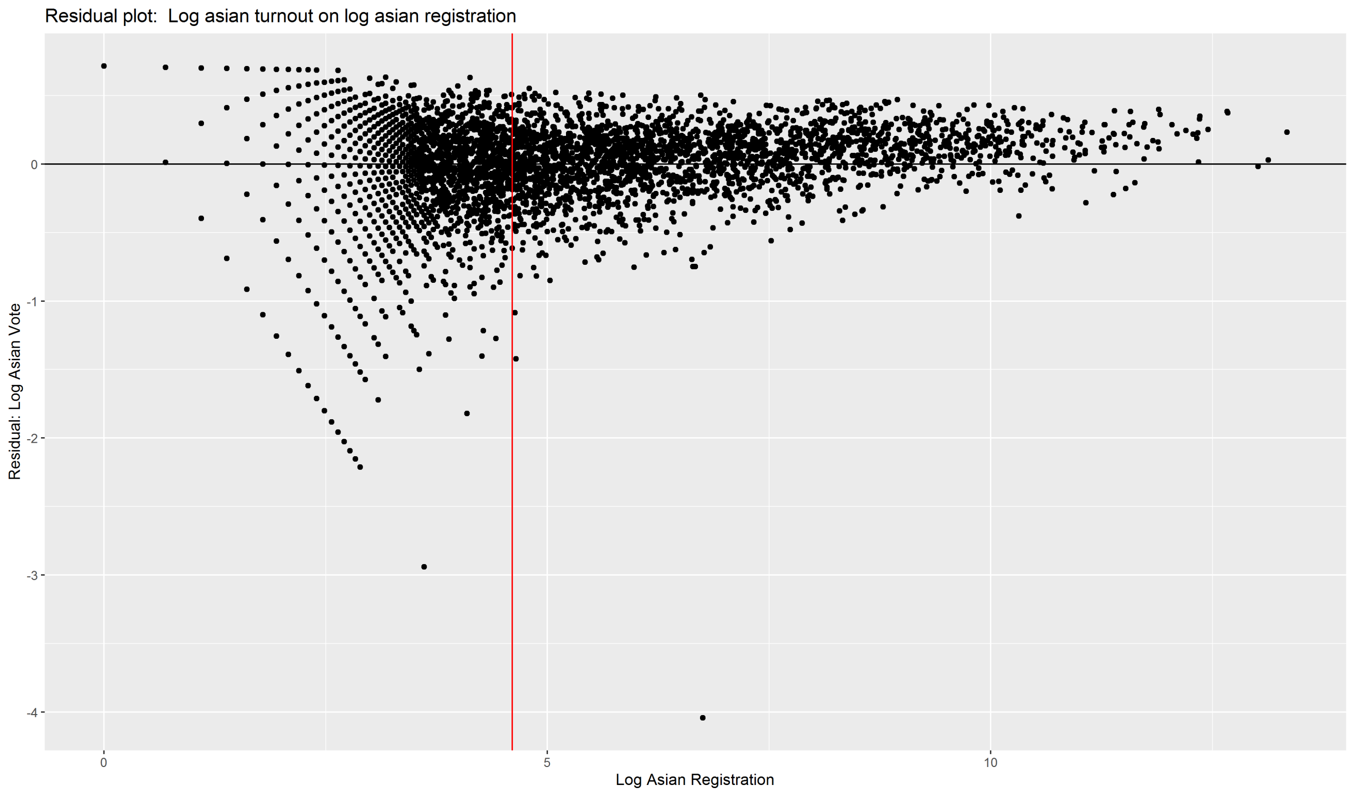


SOURCE: Catalist final county-level data files for the presidential election, 2012-2020.

NOTES: Red line marks counties with 100 Latino registrants.

FIGURE A5

Tract-level correspondence between BISG imputations and ACS CVAP rates: African Americans

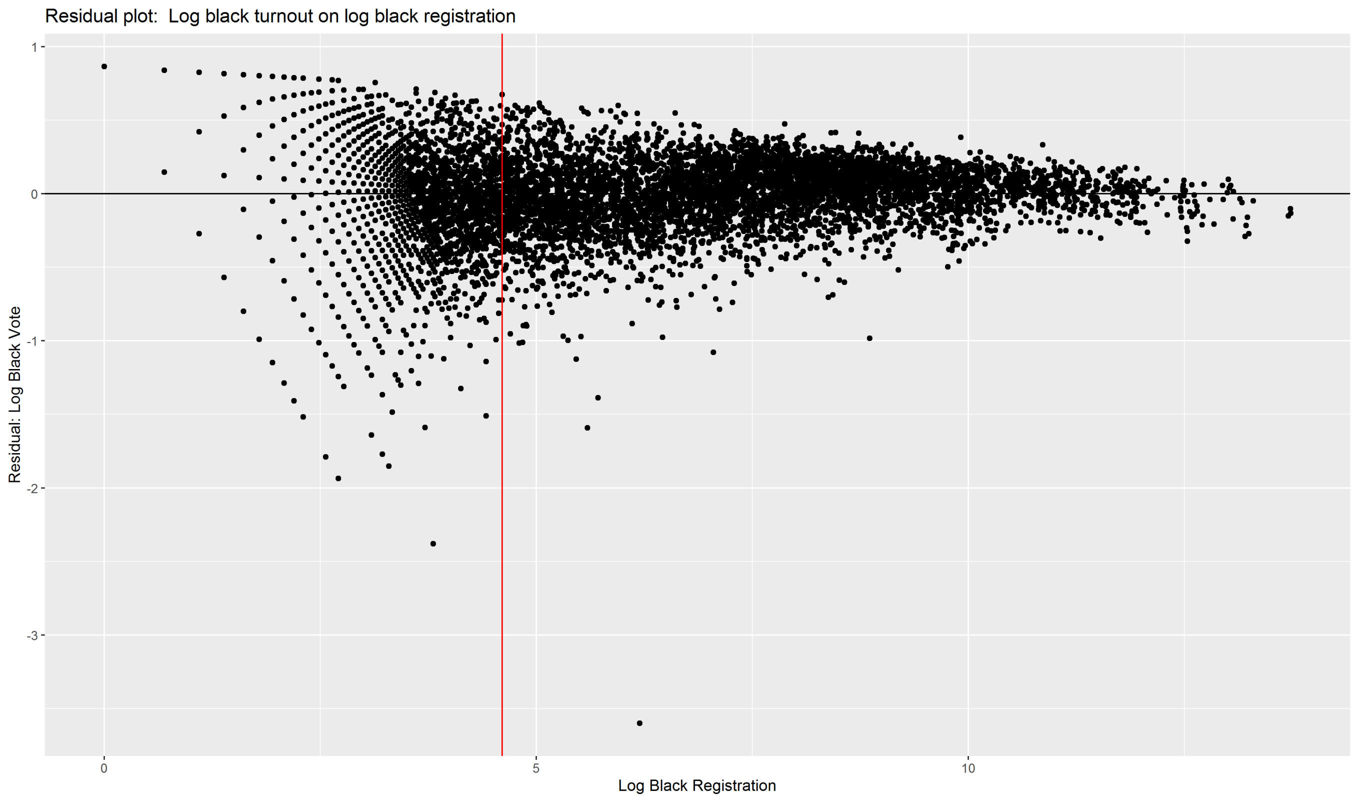


SOURCE: Catalist final county-level data files for the presidential election, 2012-2020.

NOTES: Red line marks counties with 100 Asian American registrants.

FIGURE A6

Tract-level correspondence between BISG imputations and ACS CVAP rates: African Americans

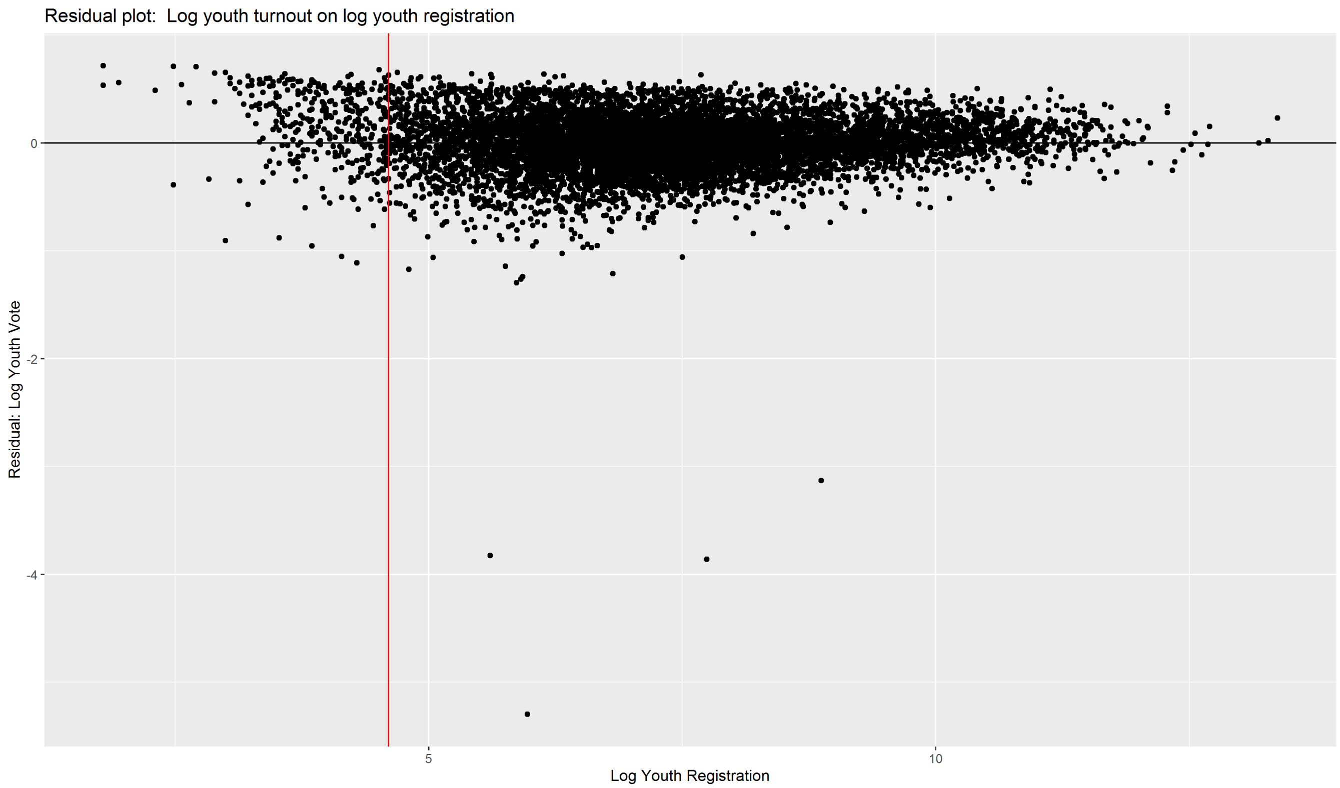


SOURCE: Catalist final county-level data files for the presidential election, 2012-2020.

NOTES: Red line marks counties with 100 African American registrants.

FIGURE A7

Tract-level correspondence between BISG imputations and ACS CVAP rates: Youth



SOURCE: Catalist final county-level data files for the presidential election, 2012-2020.

NOTES: Red line marks counties with 100 young registrants.

Appendix B. Full Model Results

National Universal Vote-by-Mail Analysis

Our national analysis of universal vote-by-mail (VBM) uses county-level voter file aggregates from the data vendor Catalist, based on voter files as they existed just before the 2012, 2016, and 2020 presidential elections.

Lagged Dependent Variable Model

Our main analytical approach is a lagged dependent variable (LDV) model. The LDV model limits the data to post-treatment observations—in this case, observations from 2020 only—and regresses the outcome on multiple pre-treatment lags as a means of identification (O'Neill, et al. 2016). This helps relax the parallel trends assumption of traditional difference-in-differences analysis. Formally the model can be written:

$$v_{c(2020)} = \alpha + \boldsymbol{D}_{\boldsymbol{c}(2020)}\boldsymbol{\delta} + \boldsymbol{X}_{\boldsymbol{c}(2020)}\boldsymbol{\beta} + v_{c(2016)} + v_{c(2012)} + \epsilon_c \qquad \text{(B1)}$$

where $v_{c(2020)}$ is the 2020 turnout gap in county c; $\boldsymbol{D}_{\boldsymbol{c}(2020)}$ is a vector of election reform dummies for county c and $\boldsymbol{\delta}$ a vector of associated coefficients; $\boldsymbol{X}_{\boldsymbol{c}(2020)}$ is a vector of contemporary covariates for county c and $\boldsymbol{\beta}$ a vector of associated coefficients; $v_{c(2016)}$ and $v_{c(2012)}$ are lagged values of $v_{c(2020)}$; α is a global intercept and and ϵ_c is an error term. In addition to universal VBM, $\boldsymbol{D}_{\boldsymbol{c}(2020)}$ includes no-excuse VBM, mailing every registered voter a VBM application, and automatic voter registration. $\boldsymbol{X}_{\boldsymbol{c}(2020)}$ includes the presidential vote margin in the state, the average COVID caseload per 100,000 residents over the month prior to the election, the square root of the number of registrants from the underrepresented group, and the underrepresented group's share of the county's citizen voting-age population (CVAP; see Fraga 2016). We weighted the models by the square root of the number of registrants in the underrepresented group for each regression, for the reasons outlined in Appendix A. The results of this estimation are in Tables B1 and B2.

TABLE B1
Lagged dependent variable models of 2020 turnout gaps

	African American	Latino	Asian American	Youth
Intercept	-0.007	-0.008	0.025	-0.044
	(0.003)	(0.002)	(0.003)	(0.004)
Universal VBM	-0.003	0.019	0.031	0.057
	(0.002)	(0.002)	(0.002)	(0.003)
Universal VBM X California	0.033	0.010	-0.013	-0.025
	(0.003)	(0.002)	(0.002)	(0.003)
No-excuse VBM	-0.012	-0.021	-0.032	-0.003
	(0.001)	(0.001)	(0.002)	(0.002)
VBM applications	0.001	0.008	0.010	0.022
	(0.001)	(0.001)	(0.002)	(0.002)
AVR	0.003	-0.013	-0.009	-0.025
	(0.001)	(0.002)	(0.002)	(0.002)
Statewide presidential vote margin	0.043	-0.023	-0.073	0.083
	(0.004)	(0.006)	(0.006)	(0.007)
COVID caseload (mean-deviated)	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
$\sqrt{registrants}$	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Group share of CVAP	-0.009	0.023	0.042	--
	(0.003)	(0.002)	(0.008)	--
Dependent variable, lag 1	0.933	0.744	0.696	0.773
	(0.022)	(0.018)	(0.019)	(0.014)
Dependent variable, lag 2	0.057	0.203	0.005	-0.004
	(0.020)	(0.016)	(0.019)	(0.011)
RMSE	0.140	0.100	0.217	0.054
N	3044	3078	2536	3105

SOURCES: Catalist (turnout and registration data); David Leip's Presidential Election Atlas (presidential vote margin); New York Times (COVID caseload); National Conference of State Legislatures (election policies); U.S. Election Assistance Commission (election policies)

NOTES: Cell entries are ordinary least squares coefficients. Models are weighted by the square root of the number of registrants in each underrepresented group. Data are limited to the 2020 election.

TABLE B2

Lagged dependent variable models of 2020 turnout

	African American	Latino	Asian American	White	Youth	Senior
Intercept	0.078	0.115	0.271	0.139	0.145	0.165
	(0.006)	(0.005)	(0.006)	(0.007)	(0.005)	(0.007)
Universal VBM	-0.005	0.019	0.021	0.016	0.061	-0.001
	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)
Universal VBM X California	0.053	0.047	0.049	0.033	0.002	0.030
	(0.004)	(0.003)	(0.002)	(0.003)	(0.003)	(0.003)
No-excuse VBM	-0.015	-0.023	-0.050	-0.001	-0.008	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
VBM applications	0.001	0.016	0.009	0.002	0.021	-0.001
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)
AVR	0.002	-0.022	0.005	-0.012	-0.031	-0.004
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Statewide presidential vote margin	-0.046	-0.135	-0.220	-0.110	-0.006	-0.075
	(0.005)	(0.008)	(0.008)	(0.005)	(0.007)	(0.005)
COVID caseload (mean-deviated)	-0.001	0.000	-0.001	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Group share of CVAP	-0.049	0.001	-0.050	0.013	--	--
	(0.004)	(0.003)	(0.010)	(0.004)		
$\sqrt{registrants}$	0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Dependent variable, lag 1	0.817	0.774	0.703	0.813	0.930	0.789
	(0.019)	(0.015)	(0.016)	(0.016)	(0.014)	(0.014)
Dependent variable, lag 2	0.119	0.126	0.056	0.051	-0.081	0.057
	(0.018)	(0.015)	(0.014)	(0.013)	(0.013)	(0.011)
RMSE	0.140	0.107	0.221	0.042	0.061	0.042
N	3044	3078	2536	3105	3105	3105

SOURCES: Catalist (turnout and registration data); David Leip's Presidential Election Atlas (presidential vote margin); New York Times (COVID caseload); National Conference of State Legislatures (election policies); U.S. Election Assistance Commission (election policies)

NOTES: Cell entries are ordinary least squares coefficients. Models are weighted by the square root of the number of registrants in each underrepresented group. Data are limited to the 2020 election.

Difference-in-Differences Model

In addition to the lagged dependent variable approach, we also ran two alternatives. One was a standard difference-in-differences (DID) model. The DID model is identified off disproportionate change in treated units relative to untreated units, after accounting for fixed differences between units and time-varying covariates. This model can be written

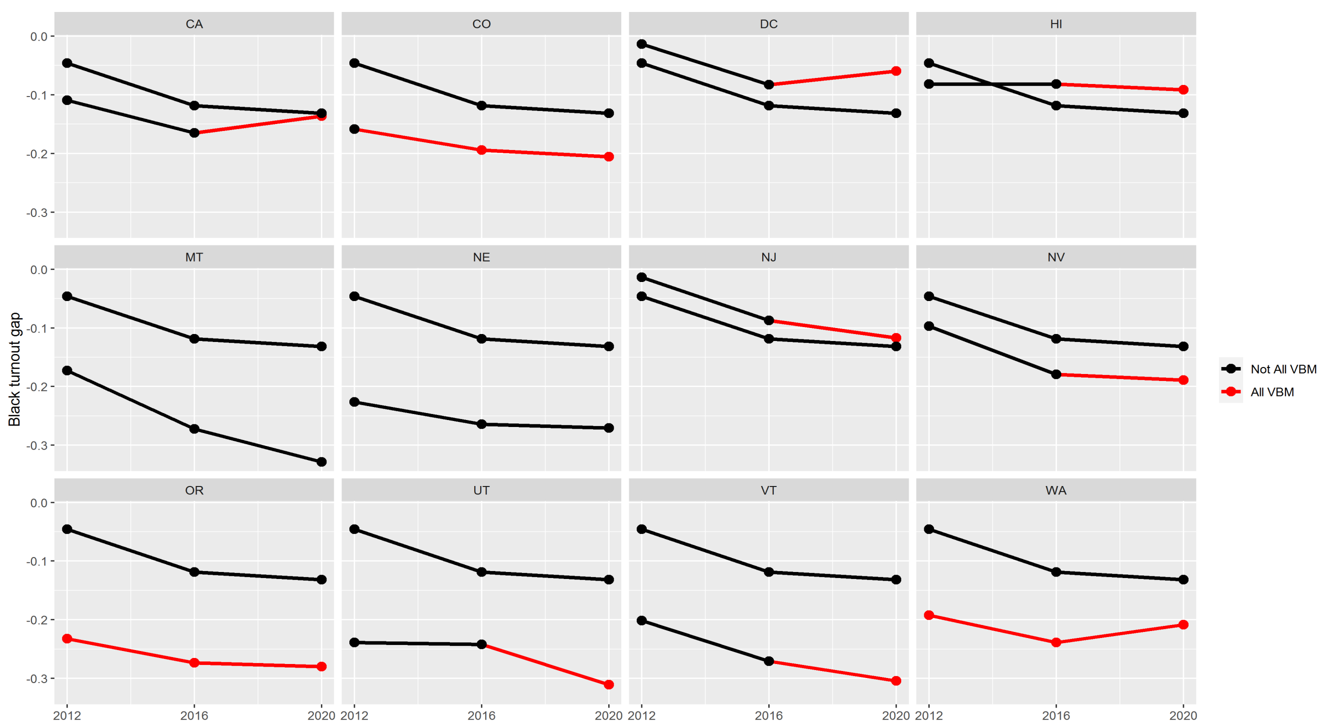
$$v_{ct} = \boldsymbol{D}_{ct}\boldsymbol{\delta} + \boldsymbol{X}_{ct}\boldsymbol{\beta} + \alpha_c + \gamma_t + \epsilon_{ct} \qquad \text{(B2)}$$

where v_{ct} is the turnout gap in county c at time t; $\boldsymbol{D}_{ct}$ is a vector of election reform dummies for county c at time t and $\boldsymbol{\delta}$ a vector of associated coefficients; $\boldsymbol{X}_{ct}$ is a vector of contemporary covariates for county c at time t and $\boldsymbol{\beta}$ a vector of associated coefficients; α_c and γ_t are county and year fixed effects, and ϵ_{ct} is an error term. $\boldsymbol{D}_{ct}$ and $\boldsymbol{X}_{ct}$ contain the same variables as in the lagged dependent variable model, with the omission of the group share of CVAP which is effectively absorbed in the county fixed effect.

This identification strategy is only successful if the parallel trends assumption holds: that in the absence of the treatment, units would change uniformly over time. Figures B1 through B4 show trends in turnout gaps over time by state, and reveal reasons to doubt this assumption for some states. Thus, we place less confidence in these estimates than in the lagged dependent variable and difference-in-differences plus matching methods that take differential trends seriously. Nonetheless, we report the results, which are similar in many but not all cases, for comparison. They can be found in Tables B3 and B4.

FIGURE B1

State-level time trends: African American turnout gap

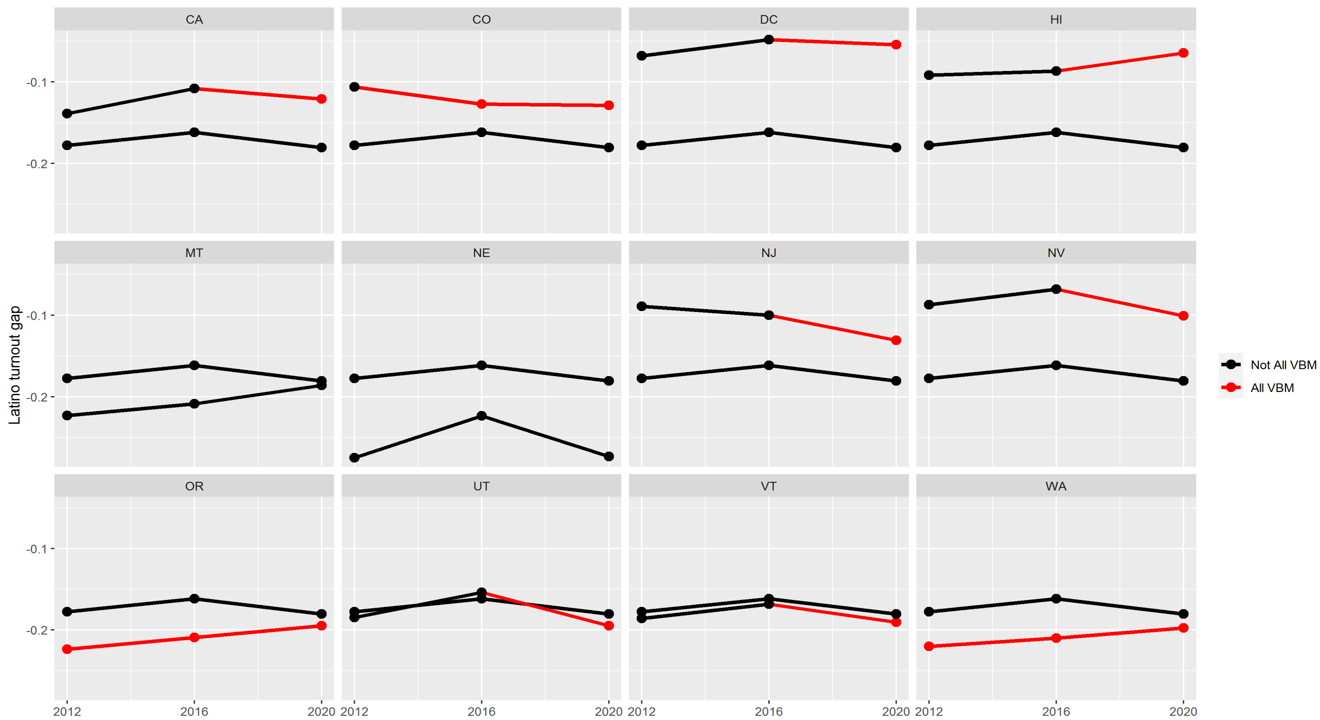


SOURCE: Catalist (turnout and registration data); National Conference of State Legislatures (election policies); U.S. Election Assistance Commission (election policies)

NOTE: Red points mark years with universal VBM in each state, and red lines mark the transition to those systems. The second line in each plot is the average of all other states. State averages are weighted by the square root of the number of registrants in each county to match the models in Tables B3 and B4. Montana's line is all black because it never adopted universal VBM statewide, but only in some counties.

FIGURE B2

State-level time trends: Latino turnout gap

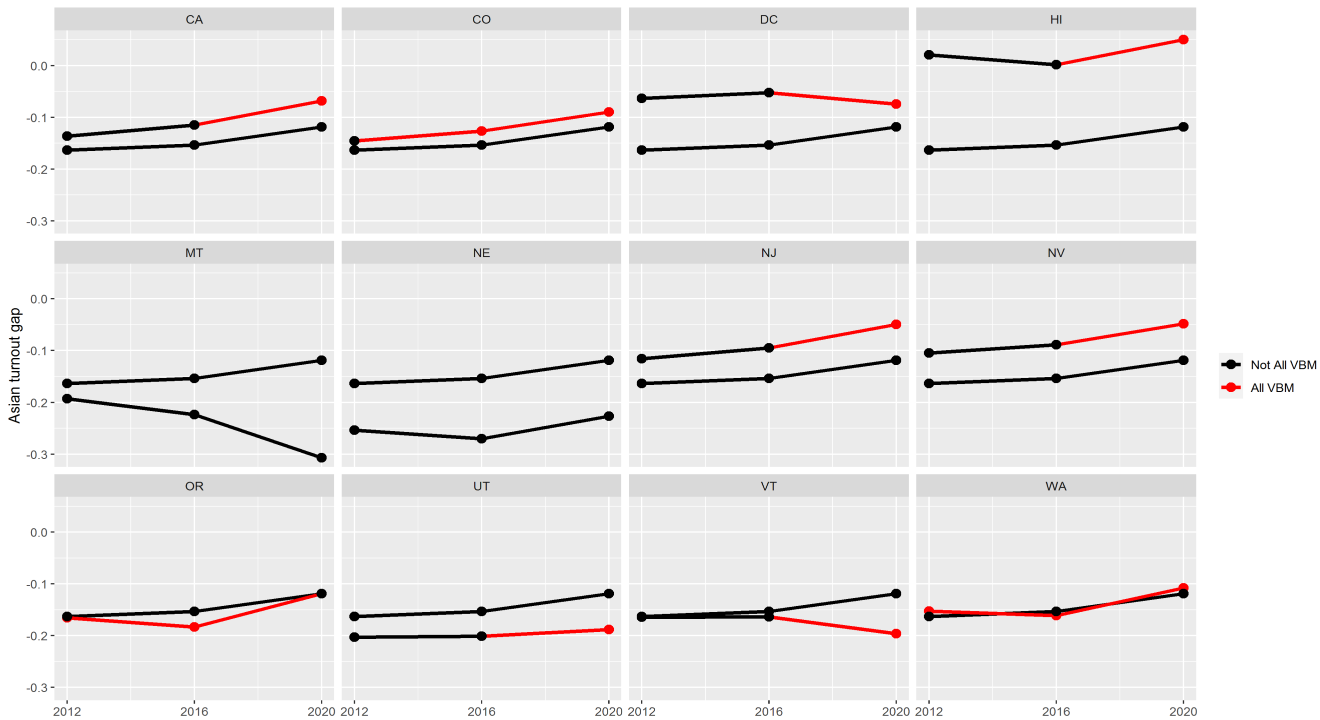


SOURCE: Catalist (turnout and registration data); National Conference of State Legislatures (election policies); U.S. Election Assistance Commission (election policies)

NOTE: Red points mark years with universal VBM in each state, and red lines mark the transition to those systems. The second line in each plot is the average of all other states. State averages are weighted by the square root of the number of registrants in each county to match the models in Tables B3 and B4. Montana's line is all black because it never adopted universal VBM statewide, but only in some counties.

FIGURE B3

State-level time trends: Asian American turnout gap

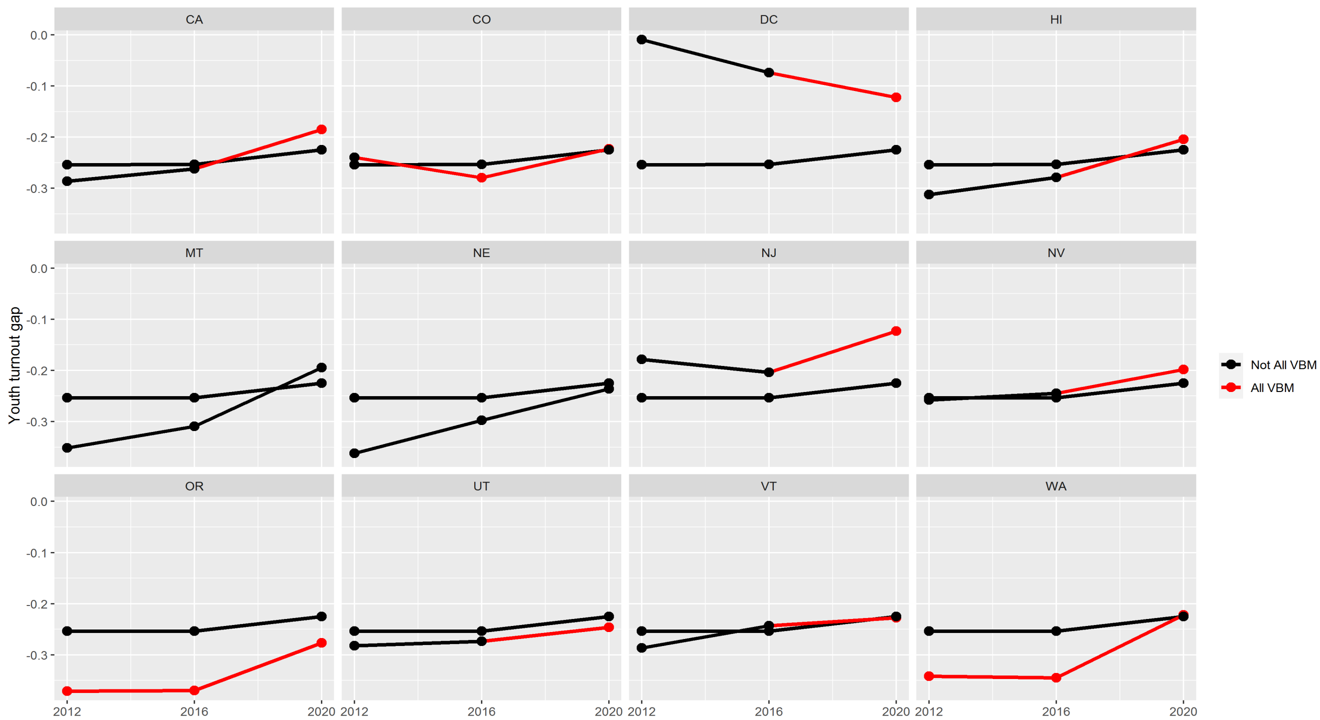


SOURCE: Catalist (turnout and registration data); National Conference of State Legislatures (election policies); U.S. Election Assistance Commission (election policies)

NOTE: Red points mark years with universal VBM in each state, and red lines mark the transition to those systems. The second line in each plot is the average of all other states. State averages are weighted by the square root of the number of registrants in each county to match the models in Tables B3 and B4. Montana's line is all black because it never adopted universal VBM statewide, but only in some counties.

FIGURE B4

State-level time trends: Youth turnout gap



SOURCE: Catalist (turnout and registration data); National Conference of State Legislatures (election policies); U.S. Election Assistance Commission (election policies)

NOTE: Red points mark years with universal VBM in each state, and red lines mark the transition to those systems. The second line in each plot is the average of all other states. State averages are weighted by the square root of the number of registrants in each county to match the models in Tables B3 and B4. Montana's line is all black because it never adopted universal VBM statewide, but only in some counties.

TABLE B3

Difference-in-differences models of turnout gaps, 2016-2020

	African American	Latino	Asian American	Youth
Intercept	0.029	-0.157	-0.094	-0.195
	(0.024)	(0.017)	(0.019)	(0.031)
Universal VBM	-0.006	-0.022	-0.034	0.014
	(0.014)	(0.011)	(0.012)	(0.010)
Universal VBM X California	0.040	0.030	-0.009	0.012
	(0.016)	(0.007)	(0.009)	(0.011)
No-excuse VBM	0.009	-0.020	-0.030	-0.008
	(0.005)	(0.006)	(0.006)	(0.005)
VBM applications	0.002	-0.007	-0.014	0.021
	(0.007)	(0.005)	(0.008)	(0.006)
AVR	0.003	-0.012	0.010	0.011
	(0.007)	(0.008)	(0.010)	(0.006)
Statewide presidential vote margin	-0.042	-0.047	-0.128	0.012
	(0.058)	(0.034)	(0.057)	(0.050)
COVID caseload (mean-deviated)	0.002	0.001	0.006	0.003
	(0.001)	(0.001)	(0.000)	(0.002)
COVID caseload X 2020 Election	0.000	0.000	-0.001	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
$\sqrt{registrants}$	0.000	0.000	0.001	0.001
	(0.000)	(0.000)	(0.000)	(0.000)
County fixed effects	X	X	X	X
Year fixed effects	X	X	X	X
Weighting by $\sqrt{registrants}$	X	X	X	X
RMSE	0.106	0.088	0.198	0.059
N	8735	8787	7681	8831

SOURCES: Catalist (turnout and registration data); David Leip's Presidential Election Atlas (presidential vote margin); New York Times (COVID caseload); National Conference of State Legislatures (election policies); U.S. Election Assistance Commission (election policies)

NOTES: Cell entries are ordinary least squares coefficients with robust standard errors.

TABLE B4

Difference-in-differences models of turnout, 2016-2020

	African American	Latino	Asian American	White	Youth	Senior
Intercept	0.830	0.526	0.590	0.849	0.604	0.845
	(0.020)	(0.027)	(0.036)	(0.029)	(0.034)	(0.034)
Universal VBM	-0.007	-0.042	-0.085	0.015	0.019	0.005
	(0.016)	(0.014)	(0.019)	(0.006)	(0.013)	(0.008)
Universal VBM X California	0.077	0.061	0.049	0.012	0.026	0.035
	(0.016)	(0.013)	(0.016)	(0.008)	(0.014)	(0.015)
No-excuse VBM	-0.009	-0.049	-0.059	-0.016	-0.017	-0.013
	(0.005)	(0.006)	(0.009)	(0.003)	(0.005)	(0.003)
VBM applications	0.013	-0.003	-0.031	0.005	0.016	0.005
	(0.008)	(0.007)	(0.011)	(0.005)	(0.005)	(0.006)
AVR	-0.009	-0.023	0.014	-0.014	-0.002	-0.008
	(0.006)	(0.009)	(0.012)	(0.004)	(0.005)	(0.005)
Statewide presidential vote margin	-0.237	-0.037	-0.069	-0.163	-0.085	-0.137
	(0.044)	(0.056)	(0.117)	(0.024)	(0.031)	(0.044)
COVID caseload (mean-deviated)	0.009	0.008	0.014	0.005	0.009	0.005
	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)
COVID caseload X 2020 Election	-0.001	0.000	-0.001	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
$\sqrt{registrants}$	0.000	0.000	0.000	-0.001	0.000	-0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
County fixed effects	X	X	X	X	X	X
Year fixed effects	X	X	X	X	X	X
Weighting by $\sqrt{registrants}$	X	X	X	X	X	X
RMSE	0.110	0.096	0.202	0.036	0.061	0.038
N	8735	8787	7681	8831	8831	8831

SOURCES: Catalist (turnout and registration data); David Leip's Presidential Election Atlas (presidential vote margin); New York Times (COVID caseload); National Conference of State Legislatures (election policies); U.S. Election Assistance Commission (election policies)

NOTES: Cell entries are ordinary least squares coefficients with robust standard errors.

Difference-in-Differences with Matching

Our second alternative approach for the Catalist data was difference-in-differences with matching (DIDM), implemented through PanelMatch for R (Imai, et al. 2021). DIDM first identifies an untreated comparison group with the same pre-treatment history. If the treatment is denoted as D and implemented at time t in county c, then the comparison set M_{ct} is

$$M_{ct} = \{c' : c' \neq c, D_{c't} = 0, D_{c't'} = D_{ct'} \; for \; all \; t' < t\} \quad \text{(B3)}$$

where D is coded 1 for treated units and 0 otherwise. This comparison group is then further refined in two different ways. The first is by matching each treated unit to the J most similar units from M_{ct}, chosen to minimize the average Mahalanobis distance Ψ:

$$\Psi_{ct}(c') = \frac{1}{L}\sum_{l=1}^{L}\sqrt{\left(\boldsymbol{X}_{c,t-l} - \boldsymbol{X}_{c',t-l}\right)^T \boldsymbol{S}_{c,t-l}^{-1}\left(\boldsymbol{X}_{c,t-l} - \boldsymbol{X}_{c',t-l}\right)} \quad \text{(B4)}$$

where $\boldsymbol{X}$ is a matrix of time-varying variables used for matching, $\boldsymbol{S}$ is the sample covariance matrix of $\boldsymbol{X}$, and L is the number of lags prior to treatment. The other method first estimates the probability of treatment conditional on the matching covariates using a logit regression:

$$Pr(D_{ct}|\boldsymbol{X_c\beta}) = logit^{-1}(\boldsymbol{X_c\beta}) \quad \text{(B5)}$$

Instead of restricting the sample to the J most similar units, this method keeps the entire comparison set and weights the DID estimates by the inverse propensity score. For comparison unit c', the inverse propensity score is:

$$w_{ct}^{c'} \propto \frac{Pr(D_{c't}|\boldsymbol{X_c\beta})}{1 - Pr(D_{c't}|\boldsymbol{X_c\beta})} \quad \text{(B6)}$$

We choose the matching method—including the value of J when using the Mahalanobis distance—to produce the closest covariate balance between the treated and matched control groups. Tables B7 and B8 show the specifications we used, while Tables B9 and B10 show the resulting covariate balances. Where it was impossible to maximize balance across all covariates, we favored specifications that maximized balance for lagged outcomes, since those are most likely to capture unmeasured confounds. Because there was no analog to our regression weighting, we dropped all counties with fewer than 100 registrants in each underrepresented group, but also matched on the square root of the number of registrants. The treatment estimates are in Tables B5 and B6.

TABLE B5

Treatment effects using difference-in-differences with matching: turnout gap

	African American	Latino	Asian American	Youth
California	0.045	0.016	-0.008	0.068
	(0.013)	(0.008)	(0.030)	(0.010)
Other Universal VBM States	0.004	0.008	-0.013	0.070
	(0.013)	(0.008)	(0.015)	(0.010)

SOURCES: Catalist (turnout and registration data); New York Times (COVID caseload); National Conference of State Legislatures (election policies); U.S. Election Assistance Commission (election policies)

NOTES: Cell entries are difference-in-differences estimates following the process described in the text and calculated by PanelMatch for R. The refinement specification for each is detailed in Table B4.

TABLE B6

Treatment effects using difference-in-differences with matching: turnout

	African American	Latino	Asian American	White	Youth	Senior
California	0.046	0.016	-0.026	0.012	0.055	0.002
	(0.026)	(0.008)	(0.090)	(0.022)	(0.015)	(0.008)
Other Universal VBM States	0.006	0.023	-0.009	0.031	0.083	0.015
	(0.013)	(0.010)	(0.024)	(0.007)	(0.011)	(0.007)

SOURCES: Catalist (turnout and registration data); New York Times (COVID caseload); National Conference of State Legislatures (election policies); U.S. Election Assistance Commission (election policies)

NOTES: Cell entries are difference-in-differences estimates following the process described in the text and calculated by PanelMatch for R. The refinement specification for each is detailed in Table B4.

TABLE B7

Matching specifications for national difference-in-difference analysis: turnout gap

	African American	Latino	Asian American	Youth
CALIFORNIA				
Other VBM reforms	YES	YES	YES	YES
Automatic voter registration	YES	YES	YES	YES
COVID factors	Average caseload one month prior	Average caseload one month prior	Average caseload one month prior	Average caseload one month prior
$\sqrt{registrants}$	YES	YES	YES	YES
Group share of CVAP	YES	YES	YES	NO
Number of lagged outcomes	2	2	2	2
Refinement method	Propensity score weighting	Mahalanobis	Propensity score weighting	Mahalanobis
J	N/A	5	N/A	5
OTHER UNIVERSAL VBM STATES				
Other VBM reforms	YES	YES	YES	YES
Automatic voter registration	YES	YES	YES	YES
COVID factors	Average caseload one month prior	Average caseload one month prior	Average caseload one month prior	Average caseload one month prior
$\sqrt{registrants}$	YES	YES	YES	YES
Group share of CVAP	YES	YES	YES	NO
Number of lagged outcomes	2	2	2	2
Refinement method	Mahalanobis	Mahalanobis	Mahalanobis	Mahalanobis
J	5	5	5	5

TABLE B8

Matching specifications for national difference-in-difference analysis: turnout

	African American	Latino	Asian American	White	Youth	Senior
CALIFORNIA						
Other VBM reforms	YES	YES	YES	YES	YES	YES
Automatic voter registration	YES	YES	YES	YES	YES	YES
COVID factors	Average caseload one month prior	Average caseload one month prior	Average caseload one month prior	Average caseload one month prior	Average caseload one month prior	Average caseload one month prior
$\sqrt{registrants}$	YES	YES	YES	YES	YES	YES
Group share of CVAP	YES	YES	YES	YES	NO	NO
Number of lagged outcomes	2	2	2	2	2	2
Refinement method	Propensity score weighting	Mahalanobis	Propensity score weighting	Propensity score matching	Mahalanobis	Mahalanobis
J	N/A	5	N/A	5	5	5
OTHER UNIVERSAL VBM STATES						
Other VBM reforms	YES	YES	YES	YES	YES	YES
Automatic voter registration	YES	YES	YES	YES	YES	YES
COVID factors	Average caseload one month prior	Average caseload one month prior	Average caseload one month prior	Average caseload one month prior	Average caseload one month prior	Average caseload one month prior
$\sqrt{registrants}$	YES	YES	YES	YES	YES	YES
Group share of CVAP	YES	YES	YES	YES	NO	NO
Number of lagged outcomes	2	2	2	2	2	2
Refinement method	Propensity score weighting	Mahalanobis	Propensity score weighting	Propensity score matching	Mahalanobis	Mahalanobis
J	N/A	5	N/A	5	5	5

TABLE B9

Covariate balance for continuous matching variables: turnout gap

	African American		Latino		Asian American		Youth	
	Refined	Null	Refined	Null	Refined	Null	Refined	Null
CALIFORNIA								
Lagged outcomes	0.364	-0.759	0.567	1.907	-0.034	0.691	-0.132	-0.487
Group share of CVAP	0.151	-3.278	0.757	0.899	0.852	0.837	--	--
$\sqrt{registrants}$	0.416	0.221	0.168	0.658	0.730	0.631	0.143	0.657
COVID caseload	-1.548	-3.677	-2.631	-3.913	-0.591	-3.245	-2.263	-4.779
OTHER UNIVERSAL VBM STATES								
Lagged outcomes	-0.131	-0.272	0.249	0.739	0.419	0.812	0.127	-0.278
Group share of CVAP	-0.239	-0.791	0.399	-0.081	0.269	0.580		
$\sqrt{registrants}$	0.158	0.224	0.102	0.359	0.075	0.627	0.068	0.172
COVID caseload	-0.174	-0.114	-0.171	-0.199	-0.564	-0.876	-0.036	0.135

SOURCES: Catalist (turnout and registration data); New York Times (COVID caseload)

NOTES: Cell entries are differences between the treated and matched control groups, in standard deviation units, as calculated by PanelMatch for R. "Null" numbers are the differences between treated units and the comparison set M_{ct}. "Refined" numbers are the same differences after the weighting or subsetting in Table B3 has been applied.

TABLE B10

Covariate balance for continuous matching variables: turnout in underrepresented groups

	African American		Latino		Asian American		Youth	
	Refined	Null	Refined	Null	Refined	Null	Refined	Null
CALIFORNIA								
Lagged outcomes	0.284	0.923	1.322	2.178	0.490	1.176	0.584	0.770
Group share of CVAP	0.472	-3.278	0.754	0.899	0.458	0.837	--	--
$\sqrt{registrants}$	0.458	0.221	0.144	0.658	0.433	0.631	0.132	0.657
COVID caseload	-1.762	-3.677	-2.919	-3.913	-1.694	-3.245	-2.627	-4.779
OTHER UNIVERSAL VBM STATES								
Lagged outcomes	-0.004	-0.058	0.473	0.861	0.460	0.835	0.259	0.301
Group share of CVAP	-0.330	-0.791	0.407	-0.081	0.254	0.580	--	--
$\sqrt{registrants}$	0.134	0.224	0.099	0.359	0.046	0.627	0.055	0.172
COVID caseload	-0.156	-0.114	-0.193	-0.199	-0.612	-0.876	-0.028	0.135

SOURCES: Catalist (turnout and registration data); New York Times (COVID caseload)

NOTES: Cell entries are differences between the treated and matched control groups, in standard deviation units, as calculated by PanelMatch for R. "Null" numbers are the differences between treated units and the comparison set M_{ct}. "Refined" numbers are the same differences after the weighting or subsetting in Table B3 has been applied.

TABLE B10

Covariate balance for continuous matching variables: turnout in overrepresented groups

	White		Senior	
	Refined	Null	Refined	Null
CALIFORNIA				
Lagged outcomes	0.795	1.574	0.970	1.434
Group share of CVAP	0.832	-0.914	--	--
$\sqrt{registrants}$	1.081	0.679	0.246	0.705
COVID caseload	-1.105	-5.119	-2.855	-5.128
OTHER UNIVERSAL VBM STATES	0.034	0.576	0.017	0.638
Lagged outcomes	0.111	0.333	--	--
Group share of CVAP	0.051	0.123	0.049	0.143
$\sqrt{registrants}$	-0.145	0.152	-0.060	0.151
COVID caseload	0.795	1.574	0.970	1.434

SOURCES: Catalist (turnout and registration data); New York Times (COVID caseload)

NOTES: Cell entries are differences between the treated and matched control groups, in standard deviation units, as calculated by PanelMatch for R. "Null" numbers are the differences between treated units and the comparison set M_{ct}. "Refined" numbers are the same differences after the weighting or subsetting in Table B3 has been applied.

Los Angeles Universal Vote-by-Mail Analysis

Los Angeles County committed to a special roll-out of the Voters Choice Act. Voters registered as VBM received a mail ballot as always in the March 2020 primary, but voters who did not request a VBM ballot received a mail ballot anyway if they lived in one of the state legislative or congressional districts shared with Orange County. This opens the opportunity for a difference-in-differences analysis with VBM voters as the control group.

Our data consist of a full copy of the 2020 voter file, subset to LA voters registered in time to participate in the primary election. To identify the effect of universal VBM, we first subset the data to the turnout gap comparison for each case (e.g., African American and non-Hispanic White registrants for the African-American turnout gap). Then we estimate the following logit model:

$$Pr(M_i|\boldsymbol{X_i\beta}) = logit^{-1}(\boldsymbol{X_i\beta}) \tag{B7}$$

where M_i is coded 1 for registrants living in the part of LA County where everyone received a mail ballot, and 0 otherwise. $\boldsymbol{X_i}$ is a vector of covariates that includes age, age squared, gender, party, home ownership, six lagged turnout flags and a flag for new registrants, and a flag for in-person voters. The predicted values from this model serve as propensity scores for matching, using Matching for R. (We did not use PanelMatch because these data are not structured as a time-series cross-section. We also chose to use propensity score matching to make the matching process tractable given the size of our data.)

Once matched, we ran the following linear probability model on the matched data:

$$\begin{aligned} v_i = \alpha + M_i\gamma_1 + PV_i\gamma_2 + U_i\gamma_3 + \\ M_iPV_i\gamma_4 + M_iU_i\gamma_6 + PV_iU_i\gamma_5 + \\ M_iPV_iU_i\gamma_7 + \epsilon_i \end{aligned} \tag{B8}$$

where v_i is a turnout flag for the 2020 primary, PV_i is a flag for in-person precinct voters, U_i is a flag for the demographic group underrepresented by the turnout gap (e.g., African Americans for the African American turnout gap), α is a global intercept, and ϵ_i is an error term. Table B6 contains the full results of Equation B8. Tables B7 through B10 contain covariate balance from the matching across a wide range of variables in our data set, including many we did not explicitly balance on, as calculated by Matching for R. While the matching has the potential to account for non-linear relationships in the data, when we ran Equation B8 with the pre-match data the results were very similar.

TABLE B11

Full results for Los Angeles primary results

	African American	Latino	Asian American	Youth
Intercept	0.589	0.589	0.569	0.638
	(0.001)	(0.001)	(0.001)	(0.002)
Mail ballot district	-0.006	-0.006	0.014	0.003
	(0.002)	(0.002)	(0.002)	(0.002)
Precinct voter	-0.212	-0.208	-0.217	-0.252
	(0.002)	(0.002)	(0.002)	(0.003)
Underrepresented group	-0.115	-0.235	-0.164	-0.330
	(0.003)	(0.002)	(0.003)	(0.003)
Mail X Precinct voter	0.054	0.049	0.059	0.071
	(0.003)	(0.003)	(0.003)	(0.004)
Mail X Underrepresented	-0.004	0.036	-0.027	0.002
	(0.005)	(0.003)	(0.004)	(0.004)
Precinct voter X Underrepresented	-0.007	0.092	-0.009	0.151
	(0.005)	(0.003)	(0.005)	(0.005)
Mail X Precinct voter X Underrepresented	-0.021	-0.011	0.009	-0.031
	(0.007)	(0.004)	(0.006)	(0.007)
RMSE	0.488	0.479	0.484	0.476
N	502372	929432	603388	383562

SOURCE: Political Data, Inc.

NOTES: Cell entries are ordinary least squares coefficients. Data have been pre-matched according to the process described in the text.

TABLE B12

Balance statistics for matched Los Angeles data: African American turnout gap

	Pre-match Difference	Post-match Difference	Pre-match p-value	Post-match p-value
In-person registrant	*-2.44*	*-0.09*	*< 0.001*	*0.721*
Age	*6.74*	*-0.04*	*< 0.001*	*< 0.001*
Age squared	*6.50*	*0.04*	*< 0.001*	*< 0.001*
Female	*0.63*	*0.23*	*< 0.001*	*< 0.001*
Home owner	*20.89*	*1.63*	*< 0.001*	*< 0.001*
Democrat	*-12.83*	*1.05*	*< 0.001*	*< 0.001*
Republican	*18.31*	*-1.44*	*< 0.001*	*< 0.001*
New registrant	*-1.25*	*-0.12*	*< 0.001*	*0.637*
Voted 2018 general	*6.42*	*-0.13*	*< 0.001*	*0.600*
Voted 2018 primary	*7.98*	*-0.16*	*< 0.001*	*0.451*
Voted 2016 general	*7.54*	*0.10*	*< 0.001*	*0.694*
Voted 2016 primary	*5.80*	*0.41*	*< 0.001*	*0.091*
Voted 2014 general	*6.90*	*-0.19*	*< 0.001*	*0.363*
Voted 2014 primary	*10.55*	*-0.08*	*< 0.001*	*0.522*
Voted 2012 general	8.60	1.19	< 0.001	< 0.001
Voted 2012 primary	9.04	1.26	< 0.001	< 0.001
Voted 2010 general	9.43	1.33	< 0.001	< 0.001
Voted 2010 primary	9.15	0.68	< 0.001	0.004
Voted 2008 general	9.35	1.87	< 0.001	< 0.001
Voted 2008 primary: down ballot	2.53	-3.65	< 0.001	< 0.001
Voted 2008 primary: presidential	8.43	1.11	< 0.001	< 0.001
Voted 2006 general	9.82	1.67	< 0.001	< 0.001
Voted 2006 primary	8.53	2.15	< 0.001	< 0.001
Voted 2005 special election	11.59	3.79	< 0.001	< 0.001
Pr(Latino)	13.07	15.39	< 0.001	< 0.001
Pr(Asian)	12.31	13.64	< 0.001	< 0.001
Pr(Other race/ethnicity)	12.03	15.33	< 0.001	< 0.001
Democrat X Pr(Latino)	5.57	10.53	< 0.001	< 0.001
Democrat X Pr(Asian)	5.30	9.18	< 0.001	< 0.001
Democrat X Pr(Other race/ethnicity)	4.79	10.13	< 0.001	< 0.001
Republican X Pr(Latino)	10.13	4.95	< 0.001	< 0.001
Republican X Pr(Asian)	10.79	6.61	< 0.001	< 0.001
Republican X Pr(Other race/ethnicity)	10.78	5.78	< 0.001	< 0.001

SOURCE: Political Data, Inc.

NOTES: Cell entries are comparisons of pre-match and post-match data, as calculated by Matching for R. Differences are standardized mean differences. Variables in italics were included in the propensity score logit regression. P values are based on Kolmogorov-Smirnov tests for continuous variables and t tests for others.

TABLE B13

Balance statistics for matched Los Angeles data: Latino turnout gap

	Pre-match Difference	Post-match Difference	Pre-match p-value	Post-match p-value
In-person registrant	*0.248*	*-0.025*	*0.115*	*0.897*
Age	*4.693*	*-0.301*	*< 0.001*	*0.003*
Age squared	*4.396*	*-0.335*	*< 0.001*	*0.003*
Female	*0.813*	*0.079*	*< 0.001*	*< 0.001*
Home owner	*26.603*	*0.026*	*< 0.001*	*0.010*
Democrat	*-4.693*	*-0.209*	*< 0.001*	*0.233*
Republican	*10.625*	*-0.041*	*< 0.001*	*0.558*
New registrant	*-0.665*	*0.127*	*< 0.001*	*0.498*
Voted 2018 general	*4.927*	*-0.231*	*< 0.001*	*0.176*
Voted 2018 primary	*4.353*	*-0.541*	*< 0.001*	*0.003*
Voted 2016 general	*6.533*	*-0.469*	*< 0.001*	*0.006*
Voted 2016 primary	*3.233*	*-0.674*	*< 0.001*	*< 0.001*
Voted 2014 general	*3.222*	*-0.563*	*< 0.001*	*0.001*
Voted 2014 primary	*5.962*	*-0.234*	*< 0.001*	*0.122*
Voted 2012 general	7.817	1.868	< 0.001	< 0.001
Voted 2012 primary	4.487	-0.245	< 0.001	0.180
Voted 2010 general	7.066	1.073	< 0.001	< 0.001
Voted 2010 primary	4.106	-1.350	< 0.001	< 0.001
Voted 2008 general	8.833	2.919	< 0.001	< 0.001
Voted 2008 primary: presidential	0.366	-3.394	0.020	< 0.001
Voted 2008 primary: down ballot	7.530	1.930	< 0.001	< 0.001
Voted 2006 general	6.586	0.633	< 0.001	0.001
Voted 2006 primary	4.997	0.702	< 0.001	< 0.001
Voted 2005 special election	9.087	3.248	< 0.001	< 0.001
Pr(Black)	-3.319	0.250	< 0.001	< 0.001
Pr(Asian)	8.493	9.284	< 0.001	< 0.001
Pr(Other race/ethnicity)	2.934	4.609	< 0.001	< 0.001
Democrat X Pr(Black)	-5.926	-2.719	< 0.001	< 0.001
Democrat X Pr(Asian)	2.238	4.183	< 0.001	< 0.001
Democrat X Pr(Other race/ethnicity)	-0.537	1.343	< 0.001	< 0.001
Republican X Pr(Black)	4.213	1.869	< 0.001	< 0.001
Republican X Pr(Asian)	9.729	6.137	< 0.001	< 0.001
Republican X Pr(Other race/ethnicity)	6.959	3.910	< 0.001	< 0.001

SOURCE: Political Data, Inc.

NOTES: Cell entries are comparisons of pre-match and post-match data, as calculated by Matching for R. Differences are standardized mean differences. Variables in italics were included in the propensity score logit regression. P values are based on Kolmogorov-Smirnov tests for continuous variables and t tests for others.

TABLE B14

Balance statistics for matched Los Angeles data: Asian American turnout gap

	Pre-match Difference	Post-match Difference	Pre-match p-value	Post-match p-value
In-person registrant	*-1.759*	*-0.013*	*< 0.001*	*0.959*
Age	*6.649*	*-0.088*	*< 0.001*	*< 0.001*
Age squared	*6.542*	*-0.078*	*< 0.001*	*< 0.001*
Female	*0.320*	*0.486*	*< 0.001*	*< 0.001*
Home owner	*35.761*	*0.014*	*< 0.001*	*0.106*
Democrat	*-14.217*	*0.03*	*< 0.001*	*0.814*
Republican	*13.538*	*0.206*	*< 0.001*	*0.265*
New registrant	*0.996*	*0.029*	*< 0.001*	*0.907*
Voted 2018 general	*-0.206*	*0.066*	*0.292*	*0.788*
Voted 2018 primary	*2.774*	*0.029*	*< 0.001*	*0.907*
Voted 2016 general	*1.021*	*0.051*	*< 0.001*	*0.837*
Voted 2016 primary	*-0.878*	*0.302*	*< 0.001*	*0.208*
Voted 2014 general	*2.325*	*0.186*	*< 0.001*	*0.44*
Voted 2014 primary	*6.275*	*0.086*	*< 0.001*	*0.711*
Voted 2012 general	3.177	-0.444	< 0.001	0.078
Voted 2012 primary	4.765	0.257	< 0.001	0.299
Voted 2010 general	3.175	-1.293	< 0.001	< 0.001
Voted 2010 primary	3.798	-1.395	< 0.001	< 0.001
Voted 2008 general	4.298	-0.162	< 0.001	0.521
Voted 2008 primary: presidential	2.028	-1.335	< 0.001	< 0.001
Voted 2008 primary: down ballot	2.848	-1.175	< 0.001	< 0.001
Voted 2006 general	4.287	-0.865	< 0.001	0.001
Voted 2006 primary	3.804	-0.178	< 0.001	0.476
Voted 2005 special election	7.146	2.079	< 0.001	< 0.001
Pr(Black)	3.061	9.86	< 0.001	< 0.001
Pr(Latino)	11.490	12.027	< 0.001	< 0.001
Pr(Other race/ethnicity)	10.619	11.657	< 0.001	< 0.001
Democrat X Pr(Black)	-1.994	6.150	< 0.001	< 0.001
Democrat X Pr(Latino)	3.682	8.289	< 0.001	< 0.001
Democrat X Pr(Other race/ethnicity)	2.698	7.444	< 0.001	< 0.001
Republican X Pr(Black)	6.975	3.891	< 0.001	< 0.001
Republican X Pr(Latino)	9.505	5.395	< 0.001	< 0.001
Republican X Pr(Other race/ethnicity)	10.589	6.348	< 0.001	< 0.001

SOURCE: Political Data, Inc.

NOTES: Cell entries are comparisons of pre-match and post-match data, as calculated by Matching for R. Differences are standardized mean differences. Variables in italics were included in the propensity score logit regression. P values are based on Kolmogorov-Smirnov tests for continuous variables and t tests for others.

TABLE B15

Balance statistics for matched Los Angeles data: Youth turnout gap

	Pre-match Difference	Post-match Difference	Pre-match p-value	Post-match p-value
In-person registrant	*-1.491*	*-0.348*	*< 0.001*	*0.273*
Female	*-0.498*	*-0.475*	*< 0.001*	*< 0.001*
Home owner	*23.942*	*2.597*	*< 0.001*	*< 0.001*
Democrat	*-8.986*	*-0.053*	*< 0.001*	*0.862*
Republican	*11.282*	*0.123*	*< 0.001*	*0.671*
New registrant	*-0.324*	*-0.688*	*0.188*	*0.024*
Voted 2018 general	*5.788*	*0.226*	*< 0.001*	*0.443*
Voted 2018 primary	*5.187*	*0.979*	*< 0.001*	*0.001*
Voted 2016 general	*4.962*	*0.331*	*< 0.001*	*0.273*
Voted 2016 primary	*1.724*	*0.926*	*< 0.001*	*0.003*
Voted 2014 general	*2.594*	*0.846*	*< 0.001*	*0.006*
Voted 2014 primary	*3.188*	*0.685*	*< 0.001*	*0.023*
Pr(NH White)	*-14.181*	*2.626*	*< 0.001*	*< 0.001*
Pr(Black)	*-23.793*	*-0.576*	*< 0.001*	*< 0.001*
Pr(Latino)	*9.973*	*-1.353*	*< 0.001*	*< 0.001*
Pr(Asian)	*24.237*	*-1.037*	*< 0.001*	*< 0.001*
Pr(Other race/ethnicity)	*-1.541*	*-1.320*	*< 0.001*	*< 0.001*
Youth	-2.517	-1.815	< 0.001	< 0.001
Senior	2.517	1.815	< 0.001	< 0.001
Democrat X Youth	-3.450	-1.906	< 0.001	< 0.001
Democrat X Senior	-6.826	1.264	< 0.001	< 0.001
Republican X Youth	2.397	-0.679	< 0.001	0.030
Republican X Senior	10.838	0.400	< 0.001	0.172

SOURCE: Political Data, Inc.

NOTES: Cell entries are comparisons of pre-match and post-match data, as calculated by Matching for R. Differences are standardized mean differences. Variables in italics were included in the propensity score logit regression. P values are based on Kolmogorov-Smirnov tests for continuous variables and t tests for others.

California In-Person Voting Options Analysis

California allowed individual counties to choose one of three options for in-person voting in the 2020 general election: traditional polling places with requirements for number and availability set by law; consolidated polling places available to voters in a certain neighborhood; and consolidated polling places available to any voter in the county. There were also 15 counties that had already adopted the Voter's Choice Act and three counties that had been using only vote-by-mail, with in-person voting only at the county registrar's office, for several years.

The entire voter file is too large to be tractable for matching, but also less likely to have combinations of variables that are unsupported in either the treatment or the control groups. To identify the effect of these in-person options on equity, we combined the 2016 and 2020 California voter files and estimated the following models:

$$\begin{aligned} v_i = \alpha + \boldsymbol{D_c\delta} + \boldsymbol{X_i\beta} + \alpha_c + \gamma_t \ + & \\ black_i * \left(\boldsymbol{D_c\delta^b} + \boldsymbol{X_i\beta^b} + \alpha_c^b + \gamma_t^b\right) + & \\ latino_i * \left(\boldsymbol{D_c\delta^l} + \boldsymbol{X_i\beta^l} + \alpha_c^l + \gamma_t^l\right) + & \\ asian_i * (\boldsymbol{D_c\delta^a} + \boldsymbol{X_i\beta^a} + \alpha_c^a + \gamma_t^a) + \epsilon_i & \qquad \text{(B9)} \end{aligned}$$

$$\begin{aligned} v_i = \alpha + \boldsymbol{D_c\delta} + \boldsymbol{X_i\beta} + \alpha_c + \gamma_t \ + & \\ youth_i * \left(\boldsymbol{D_c\delta^y} + \boldsymbol{X_i\beta^y} + \alpha_c^y + \gamma_t^y\right) & \qquad \text{(B10)} \end{aligned}$$

where $\boldsymbol{D_i}$ is a vector of flags for in-person options; $\boldsymbol{X_i}$ is a vector of covariates that includes gender, party, four lagged turnout flags and a flag for new registrants, and flags for state legislative and congressional races that were ultimately decided by less than 10 percentage points; α_c and γ_t are county and year fixed effects; α is a global intercept; and ϵ_i is an error term. Equation B9 also included age and age squared as covariates, while Equation 10 included race/ethnicity probabilities from the imputation in WRU for R. Equation B10 was run only for registrants who were either seniors or young people ages 18-24. Each model was run separately for VBM and in-person registrants.

The inclusion of the 2016 voter file allows us to account for the possible geographic bias of the race imputation with the county fixed effects, which set a baseline expectation for the turnout gap for a county, conditional on the participation history of its individual registrants. As an extra test, we ran models B9 and B10 separately for each election year without the county fixed and year fixed effects. The 2016 model was a placebo test, since no consolidation had occurred in those counties at that time. The sign of the consolidation effect was flipped in 2020 to positive for Latinos and to negative for Asian Americans, but the same sign flip was present in 2016 when no consolidation effect was possible. This confirms the value of including data from both years in the model to account for these fixed differences. The full results of this model are in Tables B16 through B19.

TABLE B16

In-person voting options: VBM registrants with interactions for voters of color

	Main Effect	Interactions: African American	Interactions: Latino	Interactions: Asian American
Intercept	0.434	-0.148	-0.112	-0.032
	(0.001)	(0.003)	(0.002)	(0.002)
Consolidated countywide	0.001	-0.020	-0.012	0.001
	(0.001)	(0.002)	(0.001)	(0.002)
Consolidated neighborhood	-0.010	-0.019	-0.031	-0.004
	(0.001)	(0.002)	(0.001)	(0.002)
VCA (not Los Angeles)	0.009	-0.013	-0.012	-0.005
	(0.001)	(0.002)	(0.001)	(0.002)
Los Angeles	0.027	-0.021	-0.017	0.004
	(0.001)	(0.002)	(0.001)	(0.002)
Age	0.007	-0.001	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Age squared	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Female	0.009	0.019	0.027	0.014
	(0.000)	(0.001)	(0.000)	(0.001)
Democrat	0.021	0.030	0.022	0.004
	(0.000)	(0.001)	(0.000)	(0.001)
Republican	0.024	-0.038	0.015	-0.005
	(0.000)	(0.003)	(0.001)	(0.001)
Vote lag 1	0.178	0.055	0.044	0.011
	(0.000)	(0.001)	(0.000)	(0.001)
Vote lag 2	0.123	0.029	0.032	0.018
	(0.000)	(0.001)	(0.000)	(0.001)
Vote lag 3	-0.01	-0.008	-0.004	-0.001
	(0.000)	(0.001)	(0.000)	(0.001)
Vote lag 4	0.096	0.049	0.037	0.025
	(0.000)	(0.001)	(0.000)	(0.001)
New registrant	0.171	0.005	0.028	0.025
	(0.000)	(0.001)	(0.001)	(0.001)
Competitive state assembly race	-0.002	-0.001	-0.002	0.007
	(0.000)	(0.001)	(0.001)	(0.001)
Competitive state senate race	-0.003	-0.006	0.000	0.003
	(0.000)	(0.001)	(0.001)	(0.001)
Competitive U.S. House race	0.008	-0.006	0.001	0.008
	(0.000)	(0.001)	(0.001)	(0.001)
Year = 2020	0.007	0.045	0.012	0.036
	(0.000)	(0.002)	(0.001)	(0.001)
County fixed effects	X	X	X	X
RMSE		0.348		
N		27768327		

SOURCE: Political Data, Inc.

NOTES: Cell entries are ordinary least squares coefficients.

TABLE B17

In-person voting options: VBM registrants with interaction for young people

	Main Effect	Youth Interaction
Intercept	0.544	-0.084
	(0.001)	(0.002)
Consolidated countywide	-0.008	-0.003
	(0.001)	(0.002)
Consolidated neighborhood	-0.013	-0.019
	(0.001)	(0.002)
VCA (not Los Angeles)	0.000	-0.007
	(0.001)	(0.002)
Los Angeles	0.021	0.009
	(0.001)	(0.002)
Pr(Black)	-0.013	-0.084
	(0.001)	(0.001)
Pr(Latino)	-0.007	-0.056
	(0.000)	(0.001)
Pr(Asian)	-0.006	-0.006
	(0.000)	(0.001)
Female	-0.001	0.058
	(0.000)	(0.001)
Democrat	-0.004	0.073
	(0.000)	(0.001)
Republican	-0.002	0.053
	(0.000)	(0.001)
Vote lag 1	0.207	0.068
	(0.000)	(0.001)
Vote lag 2	0.144	-0.002
	(0.000)	(0.001)
Vote lag 3	-0.005	0.007
	(0.000)	(0.001)
Vote lag 4	0.097	-0.043
	(0.001)	(0.001)
New registrant	0.257	-0.065
	(0.001)	(0.001)
Competitive state assembly race	0.001	-0.008
	(0.000)	(0.001)
Competitive state senate race	-0.002	0.000
	(0.000)	(0.001)
Competitive U.S. House race	0.007	0.006
	(0.000)	(0.001)
Year = 2020	0.016	0.079
	(0.001)	(0.002)
County fixed effects	X	X
RMSE	0.332	
N	9229791	

SOURCE: Political Data, Inc.

NOTES: Cell entries are ordinary least squares coefficients. Data were limited to seniors and young people.

TABLE B18

In-person voting options: In-person registrants with interactions for voters of color

	Main Effect	Interactions		
		African American	Latino	Asian American
Intercept	0.139	-0.075	-0.025	-0.085
	(0.001)	(0.003)	(0.002)	(0.003)
Consolidated county	0.011	-0.044	-0.010	-0.012
	(0.001)	(0.003)	(0.002)	(0.003)
Consolidated neighborhood	-0.011	-0.030	-0.016	-0.008
	(0.001)	(0.004)	(0.002)	(0.004)
VCA (not Los Angeles)	0.020	-0.030	-0.011	-0.021
	(0.001)	(0.004)	(0.002)	(0.003)
Los Angeles	-0.008	-0.041	-0.017	-0.006
	(0.001)	(0.003)	(0.002)	(0.003)
Age	0.007	-0.003	-0.001	0.001
	(0.000)	(0.000)	(0.000)	(0.000)
Age squared	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Female	0.011	0.026	0.022	0.011
	(0.000)	(0.001)	(0.001)	(0.001)
Democrat	0.029	0.011	0.023	0.012
	(0.000)	(0.001)	(0.001)	(0.001)
Republican	0.037	-0.056	0.001	-0.008
	(0.000)	(0.002)	(0.001)	(0.001)
Vote lag 1	0.236	0.076	0.035	0.028
	(0.000)	(0.001)	(0.001)	(0.001)
Vote lag 2	0.176	0.033	0.004	0.009
	(0.000)	(0.001)	(0.001)	(0.001)
Vote lag 3	-0.023	-0.002	0.008	-0.003
	(0.000)	(0.001)	(0.001)	(0.001)
Vote lag 4	0.271	0.061	0.022	0.032
	(0.000)	(0.001)	(0.001)	(0.001)
New registrant	0.363	-0.034	-0.030	-0.025
	(0.001)	(0.002)	(0.001)	(0.002)
Competitive state assembly race	0.001	0.018	0.000	0.013
	(0.000)	(0.002)	(0.001)	(0.001)
Competitive state senate race	0.001	0.013	0.003	0.008
	(0.001)	(0.001)	(0.001)	(0.001)
Competitive U.S. House race	0.012	-0.018	-0.007	-0.002
	(0.000)	(0.001)	(0.001)	(0.001)
Year = 2020	0.009	0.050	0.003	0.078
	(0.001)	(0.002)	(0.002)	(0.003)
County fixed effects	X	X	X	X
RMSE	0.384			
N	14043462			

SOURCE: Political Data, Inc.

NOTES: Cell entries are ordinary least squares coefficients.

TABLE B19

In-person voting options: In-person registrants with interaction for young people

	Main Effect	Youth Interaction
Intercept	0.229	0.014
	(0.001)	(0.003)
Consolidated county	-0.009	0.013
	(0.002)	(0.004)
Consolidated neighborhood	-0.021	0.009
	(0.002)	(0.004)
VCA (not Los Angeles)	0.005	0.001
	(0.002)	(0.004)
Los Angeles	-0.008	0.004
	(0.001)	(0.003)
Pr(Black)	-0.035	-0.080
	(0.001)	(0.002)
Pr(Latino)	0.013	-0.052
	(0.001)	(0.001)
Pr(Asian)	0.008	-0.063
	(0.001)	(0.002)
Female	0.004	0.047
	(0.000)	(0.001)
Democrat	-0.001	0.095
	(0.001)	(0.001)
Republican	0.004	0.068
	(0.001)	(0.001)
Vote lag 1	0.221	0.166
	(0.001)	(0.001)
Vote lag 2	0.201	-0.011
	(0.001)	(0.002)
Vote lag 3	-0.011	0.026
	(0.000)	(0.002)
Vote lag 4	0.309	-0.197
	(0.001)	(0.001)
New registrant	0.389	-0.104
	(0.002)	(0.002)
Competitive state assembly race	0.002	-0.013
	(0.001)	(0.002)
Competitive state senate race	0.002	-0.005
	(0.001)	(0.002)
Competitive U.S. House race	0.006	0.012
	(0.001)	(0.001)
Year = 2020	0.043	0.067
	(0.001)	(0.003)
County fixed effects	X	X
RMSE	0.332	
N	9229791	

SOURCE: Political Data, Inc.

NOTES: Cell entries are ordinary least squares coefficients.

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