

Supplementary Information

Contents

Changes in Covered Counties	2
Impact on Registrations	2
AME Event Study Plots	3
Alternative Processing Approaches for AME	4
County-Specific Effects	7
Administrative Treatment Effect Event Study Plots	10
Alternative Modelling Approaches for Triple-Differences Model	11
Limiting the Panel to Voters Registered Prior to 2010	15
Multinomial Regression Table	18
References	20

Changes in Covered Counties

Table A1: Changes in Covered Counties

County	Polling Places			Early Voting Days		
	Actual	Expected	Share Open	2018	2016	Change
Bay	6	44	13.6%	10	9	1
Calhoun	6	6	100.0%	15	13	2
Franklin	8	7	114.3%	10	8	2
Gadsden	25	25	100.0%	15	13	2
Gulf	2	10	20.0%	10	8	2
Jackson	3	14	21.4%	10	13	-3
Liberty	7	7	100.0%	13	13	0
Washington	4	12	33.3%	8	13	-5

Impact on Registrations

As discussed in the body of this paper, our estimates all test the effect of the hurricane on turnout as a share of registered voters. This probably leads to an underestimation of the treatment effect. As Figure A1 makes clear, the number of registrations in the weeks before the election in the treated counties was substantially lower than we might have expected based on the rest of the state.¹ Because our estimates exclude the individuals who would have registered and voted in the absence of the storm, our estimated treatment effects are likely highly conservative.

¹Because the storm impacted the registration deadline in some of the treated counties in 2018, we plot the total number of registrations in the 5 weeks prior to election day each year.

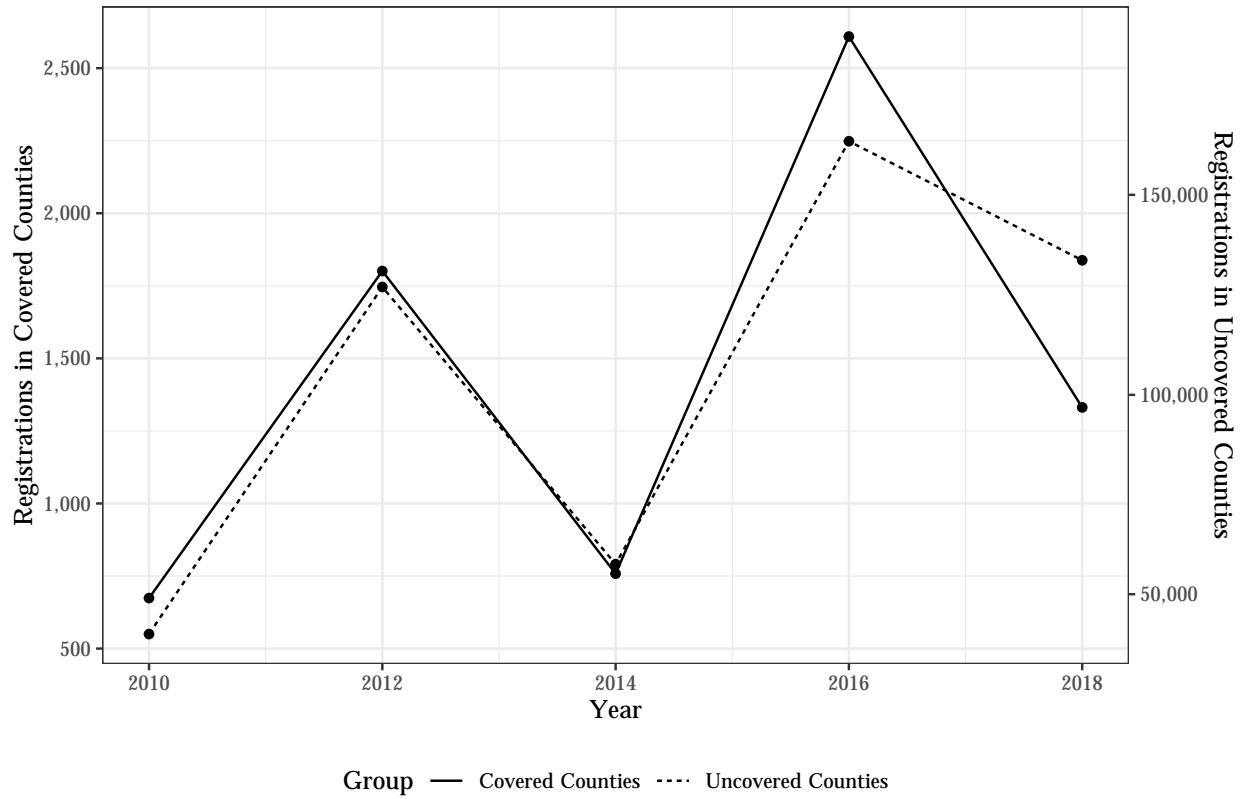


Figure A1: Registrations in Final Weeks Before Election

AME Event Study Plots

In Figure A2 we display the event study plot for the overall treatment effect, as well as the treatment effect for each county individually.

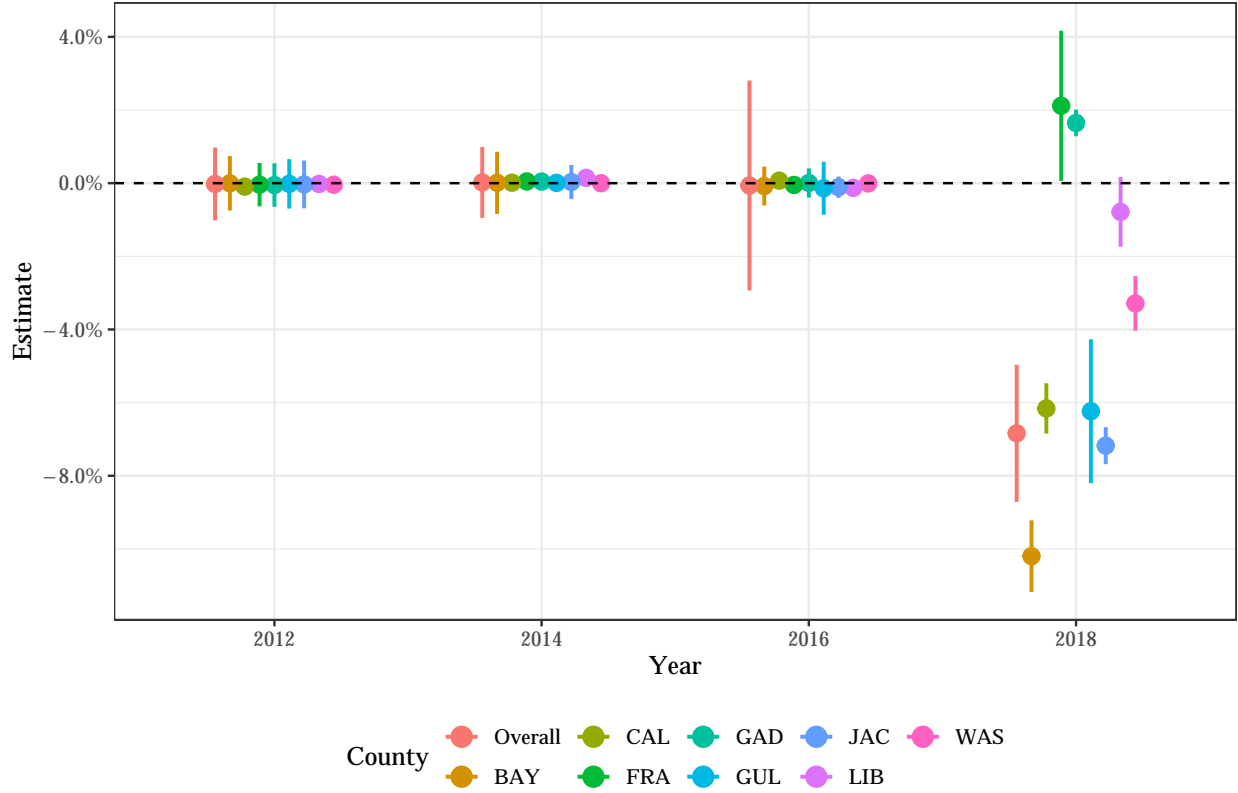


Figure A2: Event Study Plot, Both Treatments Voters

Alternative Processing Approaches for AME

In the body of the paper, we use nearest-neighbor matching and a genetic weighting process. Here, we demonstrate that our primary results are robust to a variety of different pre-processing approaches.

In model 1 of Table A2 we do not process the data in any way before running a difference-in-differences model. In other words, every treated voter and potential control voter is included once, and all voters receive a weight of 1. This is a formalization of the left-hand panel of Figure 2 in the body of the paper. In model 2, we present this same specification but with county linear time trends. Model 3 presents the primary model from the body of this paper, but with county linear time trends.

In model 4, we use an approach called entropy balancing (Hainmueller 2012). In this approach, every treated voter is given a weight of 1, while every control voter receives a unique weight based on their sociodemographic characteristics and past turnout history. Balancing is done using the same covariates used for the primary match in the body of the manuscript.

In model 5, we use propensity score matching (Caliendo and Kopeinig 2008). Each voter’s propensity score is calculated using the same covariates as in the body of the paper. After estimating each voter’s propensity score, we use a nearest-neighbor matching approach. Each treated voter is matched with 5 controls. Matching is done with replacement, and ties are randomly broken.

In model 6, we match treated voters to 5 controls using only individual-level characteristics (race, gender, party affiliation, age, registration date, and historical turnout and vote mode). Control voters must exactly match their treated voters; treated voters who do not exactly match any control voters are dropped. Once again, matching is done with replacement, and ties are randomly broken.

As a reminder, the estimated treatment effect from the body of the paper was -6.8 percentage points. Table A2 makes clear that our results are robust to a variety of preprocessing and weighting approaches. While entropy balancing, propensity score matching, and unmatched models with county linear time trends return more conservative estimates, the unmatched and exact match models without county linear time trends estimate a larger effect. In no case is the estimated effect smaller than -5.5 points or statistically nonsignificant.

Table A2: Alternative Processing Approaches

	Unprocessed	Unprocessed	Primary Model	Entropy Balancing	Propensity Score	Exact Match
Both Treatments \times 2018	-0.099*** (0.009)	-0.055*** (0.014)	-0.068*** (0.014)	-0.063*** (0.009)	-0.063*** (0.009)	-0.072*** (0.015)
Year Fixed Effects	✓	✓	✓	✓	✓	✓
County Fixed Effects	✓	✓	✓	✓	✓	✓
Matched Covariates	✓	✓	✓	✓	✓	✓
County Linear Time Trends		✓	✓			
Cluster Level:	IC	IC	IGC	IC	IGC	IGC
Num.Obs.	60041805	60041805	5925990	60041805	5925990	350970
R2	0.274	0.274	0.280	0.268	0.268	0.330
R2 Adj.	0.274	0.274	0.280	0.268	0.268	0.330

Cluster notation is as follows: I(ndividual); (Matched)G(roup); C(ounty)

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

County-Specific Effects

In the body of this paper, Figure 2 presents the overall pre- and post-treatment trends for treated and control voters. However, lumping each of the treated counties together masks considerable heterogeneity. In Figure A3 we plot the unprocessed and matched turnout trends for treated and control voters, broken out for each of the 8 treated counties. Figure A3 makes clear that the treatment effect varied substantially by county.

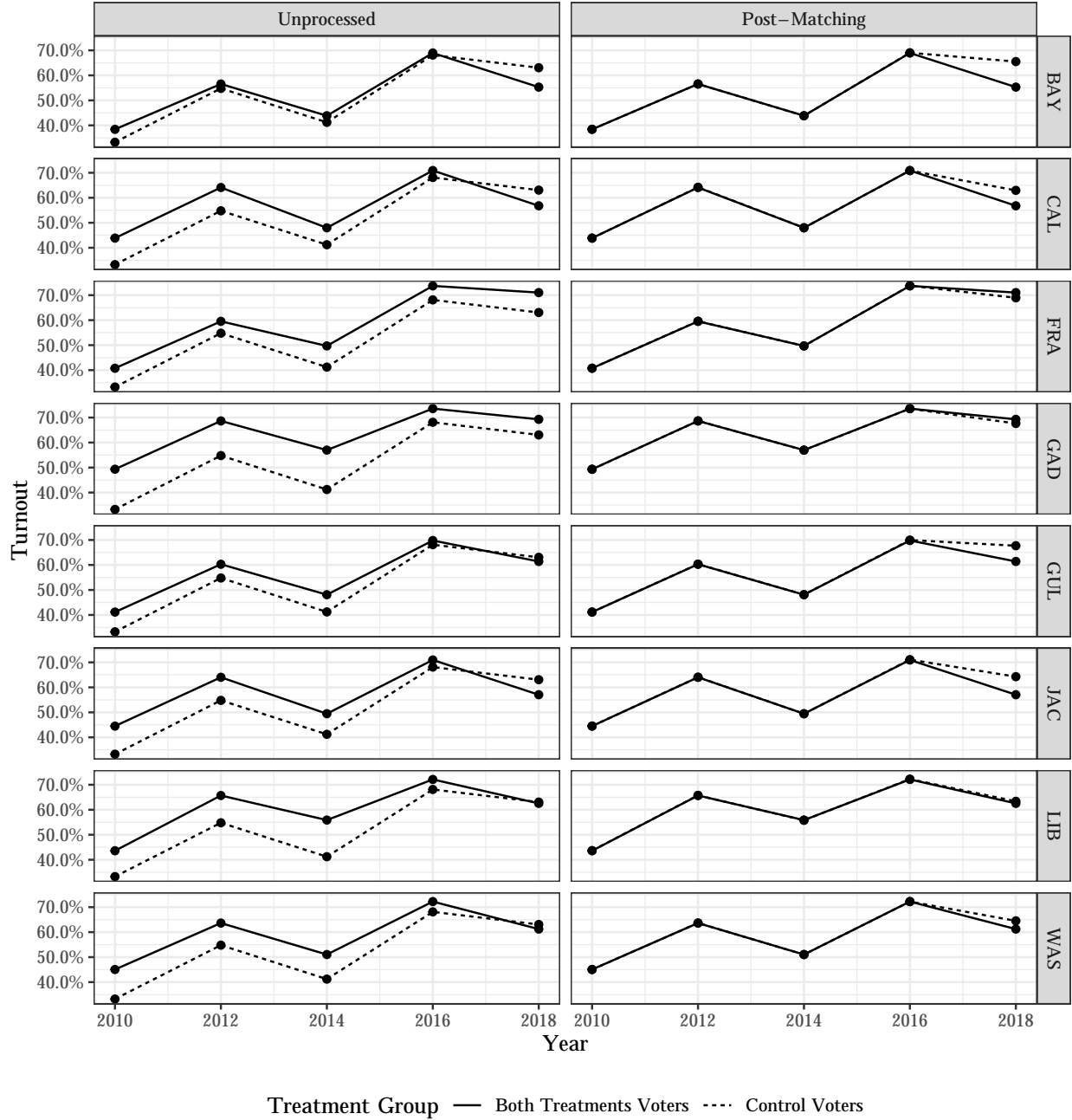


Figure A3: Pre- and Post-Matching County Plots

Table A3 re-estimates model 1 from Table 3 in the body of the paper, but interacts the treatment term with each of the treated counties. This allows us to measure the difference in treatment effect for each county. The reference category in Table A3 is Bay County.

Table A3: Turnout, 2010 — 2018

	Model 1
Both Treatments \times 2018	-0.102*** (0.005)
Both Treatments \times 2018 \times Calhoun	0.040*** (0.005)
Both Treatments \times 2018 \times Franklin	0.123*** (0.011)
Both Treatments \times 2018 \times Gadsden	0.118*** (0.004)
Both Treatments \times 2018 \times Gulf	0.040*** (0.010)
Both Treatments \times 2018 \times Jackson	0.030*** (0.004)
Both Treatments \times 2018 \times Liberty	0.094*** (0.005)
Both Treatments \times 2018 \times Washington	0.069*** (0.005)
Year Fixed Effects	✓
County Fixed Effects	✓
Treated County interacted with County and Year FEs	✓
Cluster Level:	IGC
Num.Obs.	5925990
R2	0.057
R2 Adj.	0.057
Cluster notation is as follows: I(ndividual); (Matched)G(roup); C(ounty)	
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$	

Administrative Treatment Effect Event Study Plots

In Figure A4 we display the event study plot for the administrative treatment effect derived from the triple-differences model, as well as the treatment effect for each county individually. Although the estimates are not perfectly null in the base periods, they corroborate our overall story. There was a clear administrative treatment effect in Bay, Washington, and Liberty Counties, notwithstanding some movement in the pre-treatment periods. As we note in the text, although the 2018 treatment effect for Gadsden County is statistically significant, it is trivial. We therefore conclude that there was no meaningful treatment effect in Gadsden or Jackson Counties.

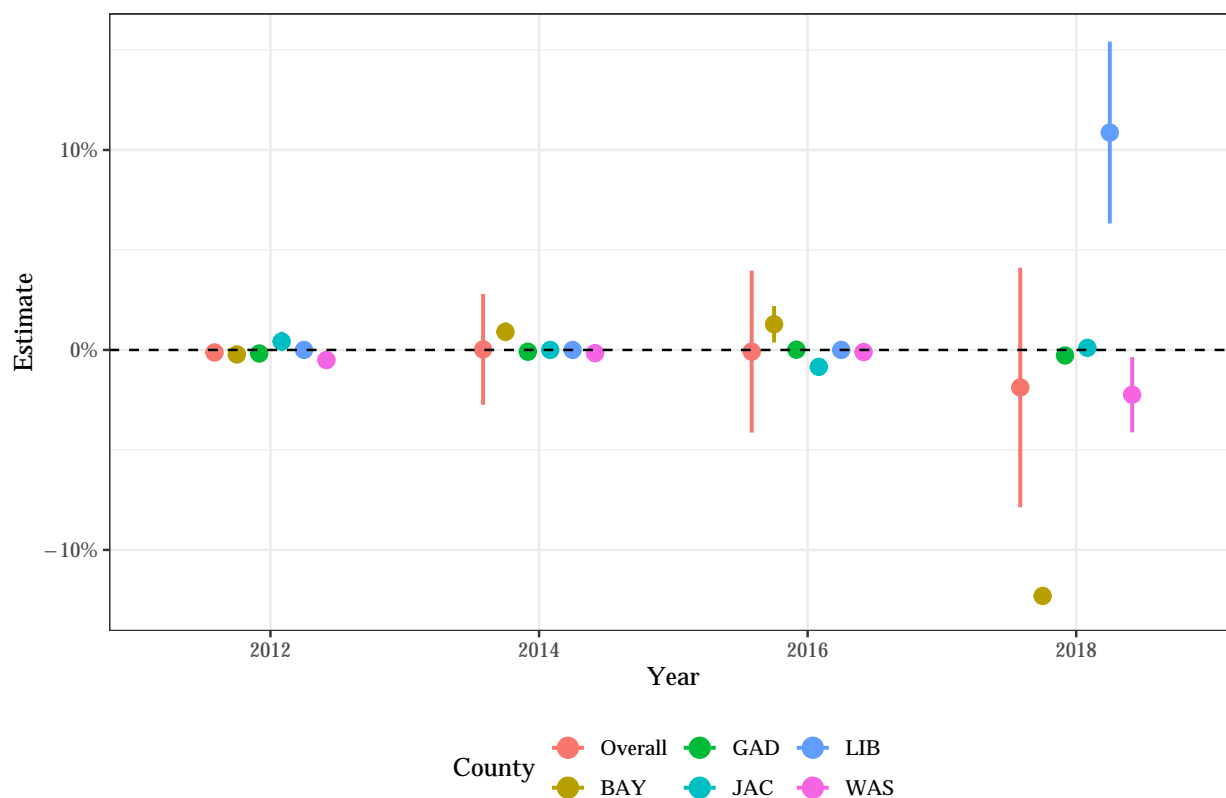


Figure A4: Event Study Plot, Administrative Treatment, Voters in Buffer

Alternative Modelling Approaches for Triple-Differences Model

In the body of this manuscript we match pairs of voters on either side of the administrative county borders in the Florida panhandle to identify the administrative effect of the hurricane. Our pool of voters treated by the administrative and weather effects live within 2.5 miles of a county not covered by the Executive Order, while potential controls—that is, voters treated only by the weather—live within 2.5 miles of a covered county. Each voter in each pair is then matched with 5 voters elsewhere in the state.

Here, we show that our primary results hold even when we include *all* voters who live within 2.5 miles of a covered county, and all untreated voters anywhere. In models 1–4 in Table A4, we present unmatched models. These models include all voters in the state *except* for voters in counties covered by the Executive Order who do not live within 2.5 miles of an uncovered county, and voters in the adjacent, uncovered counties who do not live within 2.5 miles of a county covered by the Executive Order. Model 1 includes neither a county linear time trend nor the covariates used in matching; model 2 adds a county linear time trend to model 1. Models 3 and 4 mirror models 1 and 2, but both include the matching covariates. Models 5–8 mirror models 1–4, but in each case use the matched sets of voters as described in the body of the text. We consistently observe that the administrative treatment effect is highly influenced by the additional distance treated voters had to travel to the closest polling place due to consolidation. In each model in Table A4, the reference county is Bay.

Table A4: Turnout, 2010 — 2018

	Unprocessed	Unprocessed	Unprocessed	Unprocessed	Matched	Matched	Matched	Matched
Administrative Treatment \times 2018	0.034 (0.143)	-0.115 (0.144)	0.034 (0.143)	-0.114 (0.144)	-0.117 (0.215)	-0.122 (0.226)	-0.117 (0.215)	-0.122 (0.226)
Weather Treatment \times 2018	-0.124* (0.048)	-0.026 (0.049)	-0.124* (0.048)	-0.026 (0.049)	-0.103 (0.180)	-0.107 (0.190)	-0.103 (0.180)	-0.107 (0.190)
Gadsden Administrative Treatment \times 2018	-0.161** (0.057)	-0.066 (0.057)	-0.161** (0.057)	-0.066 (0.057)	-0.001 (0.088)	0.015 (0.090)	-0.001 (0.088)	0.015 (0.090)
Jackson Administrative Treatment \times 2018	-0.104*** (0.013)	0.006 (0.013)	-0.104*** (0.013)	0.006 (0.013)	0.042 (0.035)	0.059 (0.033)	0.042 (0.035)	0.059 (0.033)
Liberty Administrative Treatment \times 2018	-0.231** (0.071)	-0.132 (0.071)	-0.231** (0.071)	-0.132 (0.071)	0.102 (0.104)	0.120 (0.105)	0.102 (0.104)	0.120 (0.105)
Washington Administrative Treatment \times 2018	-0.131*** (0.021)	-0.021 (0.021)	-0.131*** (0.021)	-0.021 (0.021)	0.083* (0.032)	0.098** (0.033)	0.083* (0.032)	0.098** (0.033)
Administrative Treatment \times 2018 \times Change in Distance to Closest Polling Place	-0.003*** (0.001)	-0.003*** (0.001)	-0.003*** (0.001)	-0.003*** (0.001)	-0.011* (0.004)	-0.011* (0.005)	-0.011* (0.004)	-0.011* (0.005)
Administrative Treatment \times 2018 \times Relative Rainfall	0.049 (0.093)	0.095 (0.093)	0.049 (0.093)	0.095 (0.093)	0.054 (0.139)	0.050 (0.146)	0.054 (0.139)	0.050 (0.146)
Year Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓
County Fixed Effects	✓	✓	✓	✓	✓	✓	✓	✓
Rainfall and Interactions	✓	✓	✓	✓	✓	✓	✓	✓
Changed Distance to Polling Place and Interactions	✓	✓	✓	✓	✓	✓	✓	✓
Matched Covariates			✓	✓			✓	✓
County Linear Time Trends		✓		✓		✓		✓
Cluster Level:	IC	IC	IC	IC	IGC	IGC	IGC	IGC
Num.Obs.	59167640	59167640	59167635	59167635	473220	473220	473220	473220
R2	0.075	0.076	0.274	0.275	0.071	0.072	0.270	0.270
R2 Adj.	0.075	0.076	0.274	0.275	0.070	0.071	0.269	0.269

Cluster notation is as follows: I(individual); (Matched)G(roup); C(ounty)

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

In Figure A5 we break out the trends for each of the treated counties' turnout, turnout among voters who were treated only by the weather, and voters elsewhere. In the left-hand panel we present the turnout of all voters; in the right-hand panel, we plot the turnout of weather and administratively treated voters and their matched controls. As a reminder, both Calhoun and Gulf Counties are entirely surrounded by other counties covered by the Executive Order, and no registered voters in Franklin County live within 2.5 miles of Wakulla, the nearest county not covered by the Executive Order. As such, these 3 counties are not included.

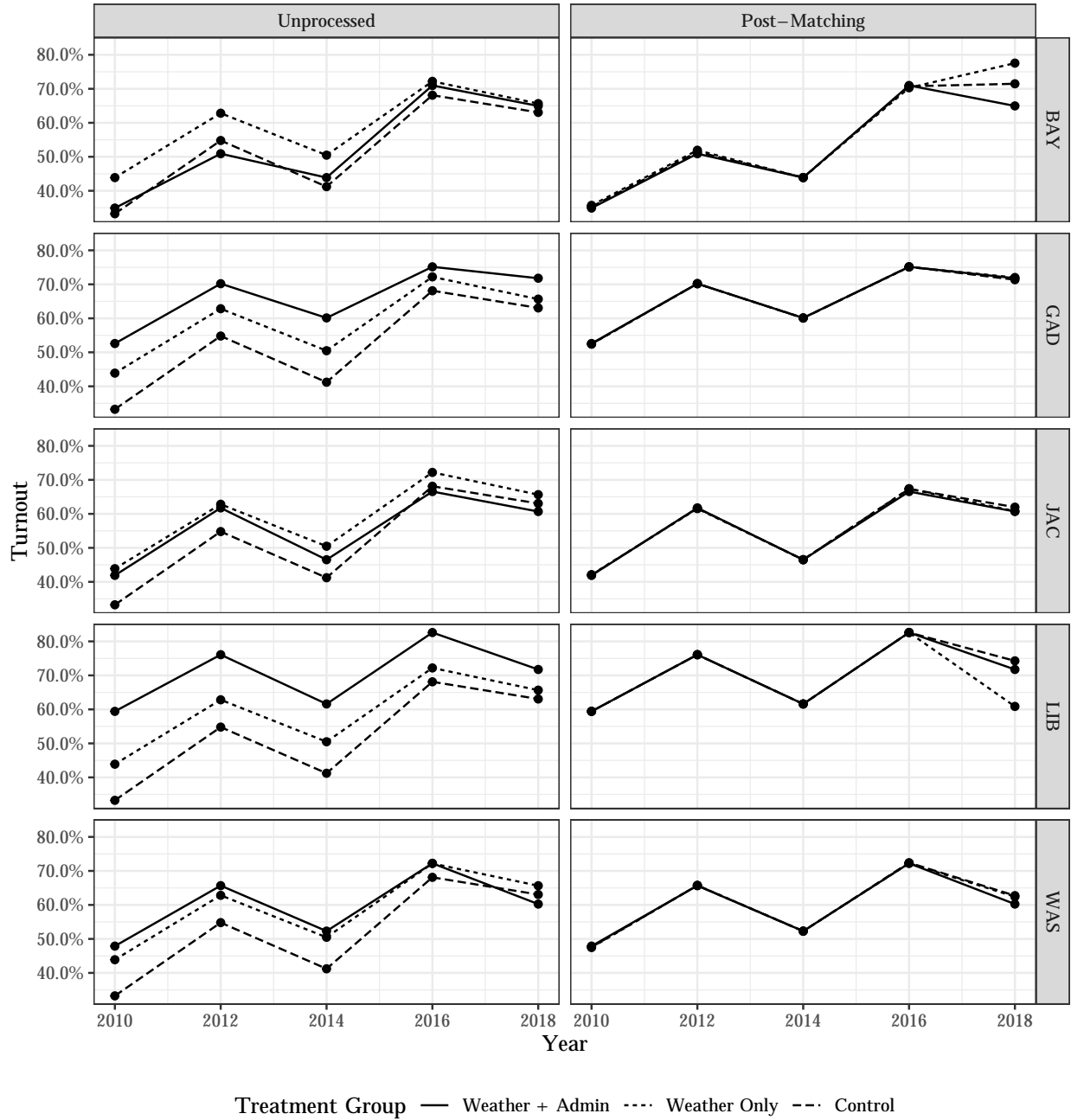


Figure A5: Pre- and Post-Matching County Plots

Figure A5 presents visual corroboration for what we find in the body of the paper—namely, that counties with more closures saw negative administrative treatment effects. The negative administrative treatment effect in Bay County is clearly quite large, while the positive administrative treatment effect is clear for Liberty County. As noted in the paper, weather-

treated voters just outside of Liberty County were subjected to the worst weather of the group; their turnout was evidently severely depressed, although the administrative effect in Liberty mitigated much of this drop. In each county, the matching procedure substantially improves the reasonableness of the parallel trends assumption necessary for valid causal inference.

Limiting the Panel to Voters Registered Prior to 2010

In the body of the manuscript, we include all voters registered as of the 2018 election, including them in the base period regardless of whether they were registered or not. Here, we show that our results do not change when we limit the pool to individuals who were registered prior to the 2010 midterm elections, and thus were registered for the entire study period.

Table A5 presents the results for this restricted pool for the AME of the hurricane. Table A6 presents the results using this pool for the triple-differences models. The point estimate for the AME differs by 0.1 points from the primary model, and the effect of each additional mile on turnout is virtually identical in both models. Somewhat surprisingly, we retain a negative administrative treatment effect for Bay County after controlling for changed distance to polling places. This may point to heterogeneous treatment effects by age that this study does not explore (the treated population retained here is about 4.5 years older than the full population of treated voters registered as of the 2018 election). In Table A6, the reference category is Bay County.

Table A5: Turnout, 2010 — 2018

	Model 1	Model 2	Model 3	Model 4	Model 5
Both Treatments \times 2018	-0.067*** (0.017)	-0.067*** (0.017)	-0.067*** (0.017)	-0.102 (0.061)	-0.062 (0.047)
Both Treatments \times 2018 \times Relative Rainfall				0.018 (0.035)	0.005 (0.028)
Both Treatments \times 2018 \times Change in Distance to Closest Polling Place					-0.007** (0.002)
Year Fixed Effects	✓	✓	✓	✓	✓
County Fixed Effects	✓	✓	✓	✓	✓
Matched Covariates		✓	✓		
CD Competitiveness			✓		
Rainfall and Interactions				✓	✓
Changed Distance to Polling Place and Interactions					✓
Cluster Level:	IGC	IGC	IGC	IGC	IGC
Num.Obs.	4091160	4091160	4091160	4091160	4091160
R2	0.043	0.159	0.159	0.044	0.045
R2 Adj.	0.043	0.159	0.159	0.044	0.045

Cluster notation is as follows: I(ndividual); (Matched)G(roup); C(ounty)

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

Table A6: Turnout, 2010 — 2018

	Model 1	Model 2	Model 3	Model 4
Administrative Treatment \times 2018	-0.030 (0.019)	-0.159*** (0.004)	-0.071* (0.030)	-0.315 (0.206)
Weather Treatment \times 2018	0.008 (0.013)	0.052*** (0.015)	-0.015 (0.035)	0.077 (0.184)
Gadsden Administrative Treatment \times 2018		0.137*** (0.003)	0.049 (0.030)	-0.055 (0.097)
Jackson Administrative Treatment \times 2018		0.176*** (0.003)	0.088** (0.029)	0.103** (0.035)
Liberty Administrative Treatment \times 2018		0.267*** (0.028)	0.179*** (0.041)	0.049 (0.111)
Washington Administrative Treatment \times 2018		0.105*** (0.006)	0.075*** (0.006)	0.111*** (0.031)
Administrative Treatment \times 2018 \times Change in Distance to Closest Polling Place			-0.011* (0.004)	-0.012* (0.005)
Administrative Treatment \times 2018 \times Relative Rainfall				0.163 (0.138)
Year Fixed Effects	✓	✓	✓	✓
County Fixed Effects	✓	✓	✓	✓
Rainfall and Interactions				✓
Changed Distance to Polling Place and Interactions			✓	✓
Cluster Level:	IGC	IGC	IGC	IGC
Num.Obs.	350460	350460	350460	350460
R2	0.039	0.050	0.054	0.057
R2 Adj.	0.038	0.049	0.053	0.056

Cluster notation is as follows: I(ndividual); (Matched)G(roup); C(ounty)

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

Multinomial Regression Table

In Figure 6 in the body of the paper, we show the marginal effects plot based on a multinomial logistic regression. We include the regression table here. While the coefficients have been exponentiated in this table, the standard errors have been left unadjusted.

Table A7: Vote Mode in 2018 (Relative to In-Person on Election Day)

	Abstain	Early	Absentee
Change in Distance to Polling Place (miles)	1.077*** (0.002)	1.068*** (0.002)	1.060*** (0.003)
Distance to Closest Planned Polling Place (miles)	0.959*** (0.004)	0.905*** (0.005)	1.002 (0.004)
White	0.955 (0.043)	1.036 (0.047)	0.953 (0.064)
Black	0.664*** (0.047)	1.051 (0.050)	0.900 (0.069)
Latino	0.957 (0.066)	0.871 (0.074)	0.847 (0.105)
Asian	1.251* (0.091)	1.182 (0.097)	1.081 (0.135)
Male	0.965* (0.015)	1.015 (0.015)	0.993 (0.021)
Democrat	0.802*** (0.024)	0.807*** (0.026)	1.147*** (0.037)
Republican	0.649*** (0.023)	1.242*** (0.024)	1.146*** (0.036)
Age	1.001* (0.000)	1.011*** (0.000)	1.025*** (0.001)
Intercept	0.429*** (0.056)	0.300*** (0.060)	0.011*** (0.086)
Vote-mode in 2010, 2012, 2014, and 2016		✓	
Number of Observations		197533	
McFadden Pseudo R2		0.271	

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

References

- Caliendo, Marco, and Sabine Kopeinig. 2008. “Some Practical Guidance for the Implementation of Propensity Score Matching.” *Journal of Economic Surveys* 22 (1): 31–72. <https://doi.org/10.1111/j.1467-6419.2007.00527.x>.
- Hainmueller, Jens. 2012. “Entropy Balancing for Causal Effects: A Multivariate Reweighting Method to Produce Balanced Samples in Observational Studies.” *Political Analysis* 20 (1): 25–46. <https://doi.org/10.1093/pan/mpr025>.