Supplementary Information

Contents

Changes in Covered Counties

Table A1: Changes in Covered Counties

	Polling Places			Early Voting Days		
County	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.

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[1]Because 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.
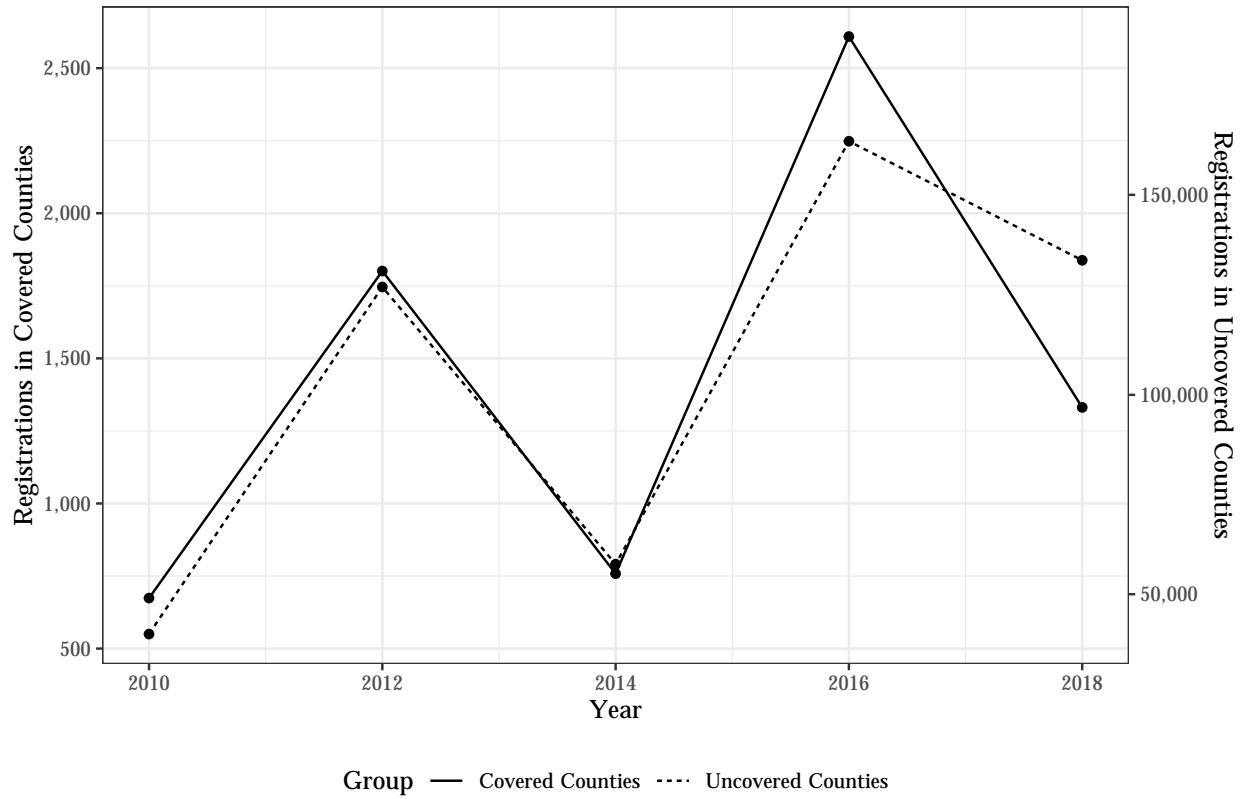
Figure A1: Registrations in Final Weeks Before Election

AME Event Study Plots

In Figure A2 we plot the event study plot for the overall treatment effect, as well as the treatment effect for each county individually.
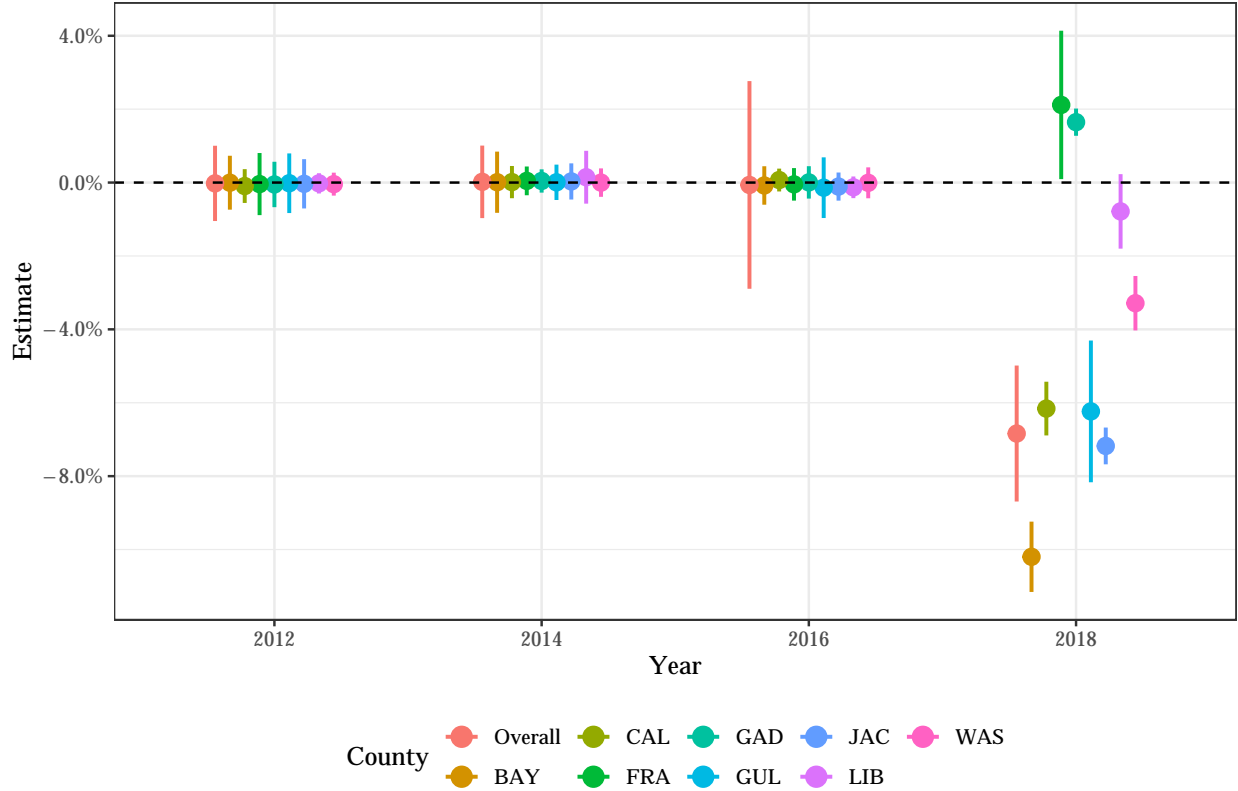
Figure A2: Event Study Plot, Weather + Administrative Treatment, All Treated Voters

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-specific 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, and historical turnout). 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 -6.6 percentage points. Table A2 makes clear that our results are robust to a variety of preprocessing and weighting approaches. Entropy balancing and propensity score matching return estimated effects within 0.1 percentage points of our primary models, as does the matched model including county-linear time trends. Exact matching and unprocessed difference-in-difference approaches return substantially larger treatment effects.

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

Table A2:   Alternative Processing Approaches

	Unprocessed	Unprocessed	Primary Model voted	Entropy Balancing	Propensity Score to	Exact Match
	(1)	(2)	(3)	(4)	(5)	(6)
Treated	0.043***	23.928***	9.900***	0.000	0.001***	0.014***
	(0.001)	(1.310)	(1.685)	(0.0001)	(0.0004)	(0.0004)
2018	0.137***	−0.090***	−0.080***	0.105***	0.105***	0.123***
	(0.0001)	(0.0002)	(0.001)	(0.0002)	(0.001)	(0.001)
Treated × 2018	−0.099***	−0.055***	−0.066***	−0.067***	−0.067***	−0.081***
	(0.001)	(0.002)	(0.001)	(0.0003)	(0.001)	(0.001)
Constant	−0.282***	−94.677***	−80.717***	−0.300***	−0.308***	−0.377***
	(0.001)	(0.364)	(1.525)	(0.001)	(0.002)	(0.002)
Includes Matched Covariates	X	X	X	X	X	X
County Fixed Effects		X	X			
County-Linear Time Trends		X	X			
Observations	60,041,820	60,041,820	5,925,990	60,041,820	5,925,990	5,773,440
R^2	0.152	0.188	0.193	0.161	0.161	0.175
Adjusted R^2	0.152	0.188	0.193	0.161	0.161	0.175

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

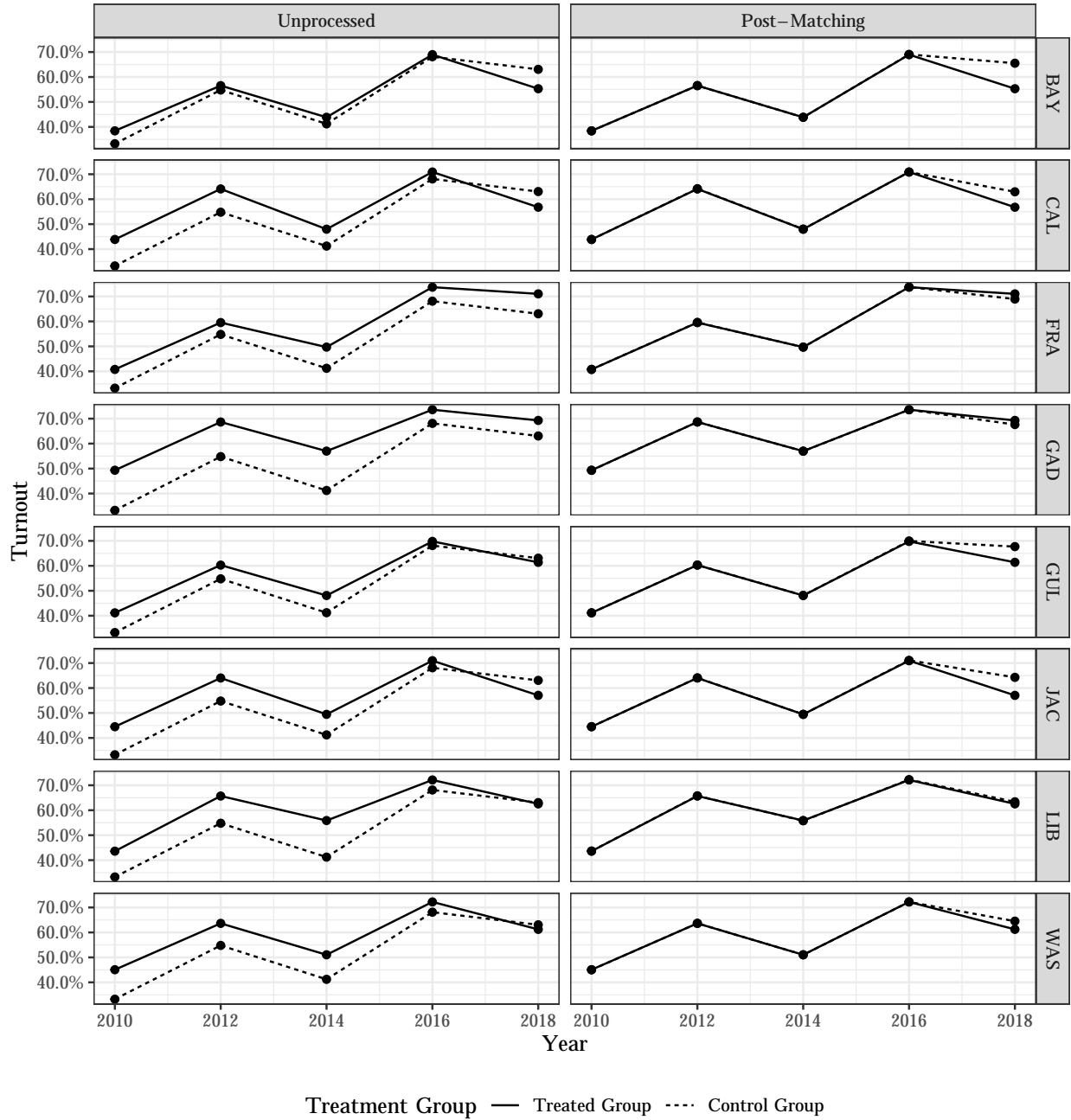A3 makes clear that the treatment effect varied substantially by county.

Figure A3: Pre- and Post-Matching County Plots

Table A3 re-estimates model 1 from Table 2 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
Treated × 2018	-0.102***
	(0.005)
Treated × 2018 × Calhoun	0.040***
	(0.005)
Treated × 2018 × Franklin	0.123***
	(0.011)
Treated × 2018 × Gadsden	0.118***
	(0.004)
Treated × 2018 × Gulf	0.040***
	(0.010)
Treated × 2018 × Jackson	0.030***
	(0.005)
Treated × 2018 × Liberty	0.094***
	(0.005)
Treated × 2018 × Washington	0.069***
	(0.005)
Year Fixed Effects	X
County Fixed Effects	X
Treated County interacted with County and Year FEs	X
Num.Obs.	5925990
R2	0.057
R2 Adj.	0.057

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

As discussed in the body of the paper we argue that the treatment effects are largely moderated by the number of polling places each county kept open, and that these effects were larger than the relative rainfall. In Figures A4 and A5, we plot each county's estimated treatment effect from Table A3 against the relative rainfall experienced by the average voter in each county, and share of polling places that county kept open. The line of best fit is weighted by the number of registered voters in each county. The relationship is clear: while there is virtually no relationship between county rainfall and the estimated treatment effect $(R^2 = 0.03)$, the treatment effect was much larger in counties where more polling places were closed $(R^2 = 0.80)$.
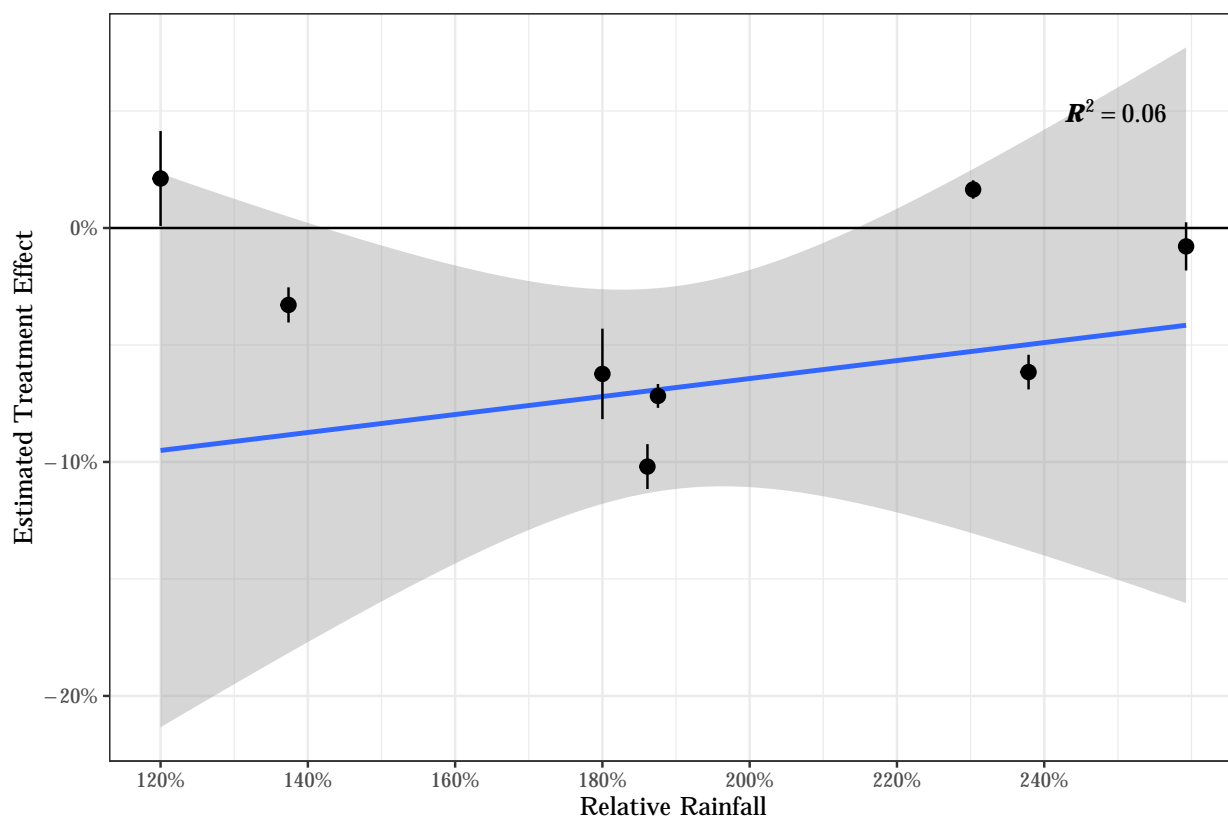

Figure A4: Relationship Between County Treatment Effect and Relative Rainfall
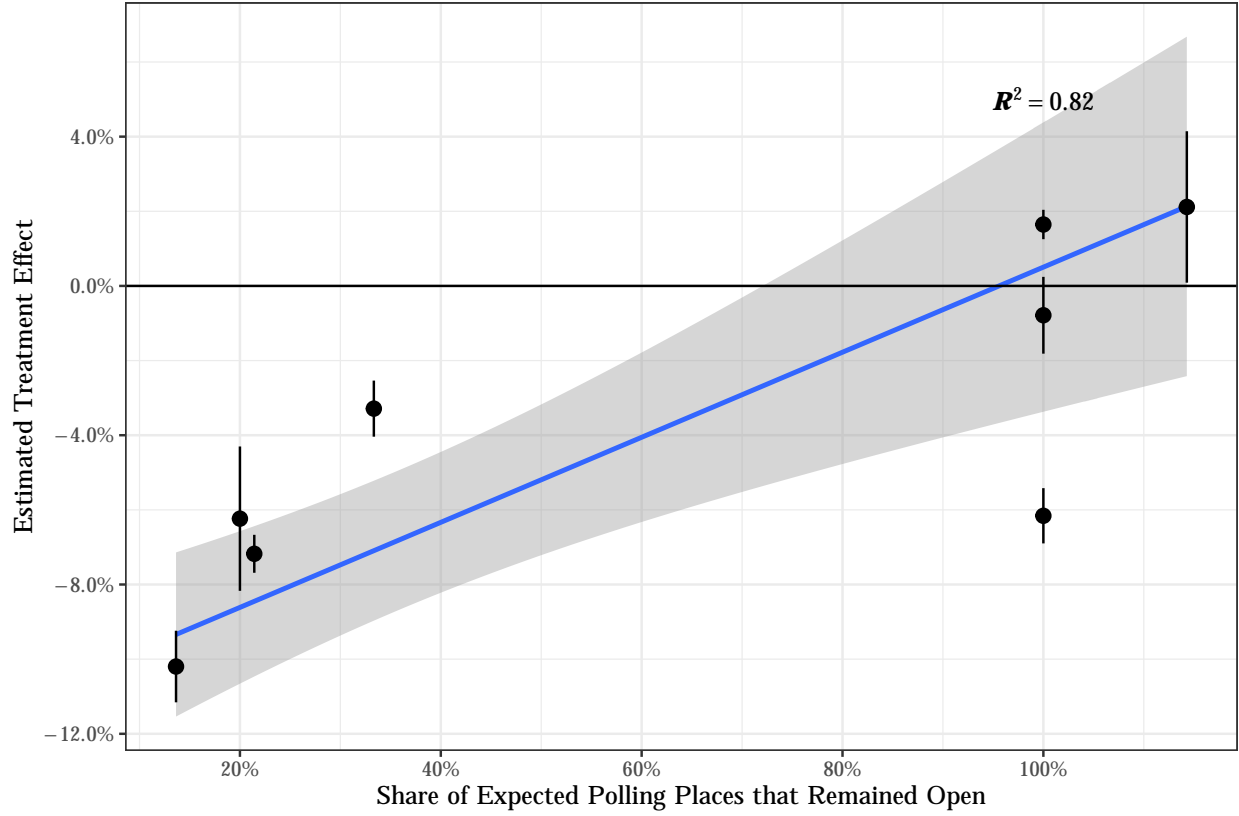
Figure A5: Relationship Between County Treatment Effect and Share of Polling Places Open

Regression Table for Triple-Differences Model

In Table A5 we present the regression table corresponding to Figure 4 in the body of this manuscript. The reference county is Bay.

Administrative Treatment Effect Event Study Plots

In Figure A6 we plot 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, these corroborate our

Table A4: Turnout, 2010 — 2018

	Model 1	Model 2	Model 3	Model 4
Administrative Treatment × 2018	-0.019	-0.123***	-0.036	-0.117
	(0.030)	(0.009)	(0.107)	(0.286)
Weather Treatment × 2018	0.003	0.060	-0.004	-0.103
	(0.025)	(0.034)	(0.108)	(0.280)
Gadsden Administrative Treatment × 2018		0.120***	0.033	-0.001
		(0.009)	(0.113)	(0.170)
Jackson Administrative Treatment × 2018		0.124***	0.037	0.042
		(0.009)	(0.118)	(0.118)
Liberty Administrative Treatment × 2018		0.232***	0.145	0.102
		(0.031)	(0.121)	(0.190)
Washington Administrative Treatment × 2018		0.101***	0.071	0.083
		(0.011)	(0.105)	(0.111)
Administrative Treatment × 2018 × Change in Distance to Closest Polling Place			-0.007*	-0.007*
			(0.003)	(0.003)
Administrative Treatment × 2018 × Relative Rainfall				0.054
				(0.181)
Intercept	0.544***	0.355***	0.400***	-0.815*
	(0.006)	(0.015)	(0.067)	(0.403)
Year Fixed Effects	X	X	X	X
County Fixed Effects	X	X	X	X
Rainfall and Interactions				X
Changed Distance to Polling Place and Interactions			X	X
Cluster Level:	IGC	IGC	IG	IG
Num.Obs.	473220	473220	473220	473220
R2	0.047	0.064	0.068	0.071
R2 Adj.	0.047	0.064	0.067	0.070

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

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 effects for Gadsden and Jackson Counties are statistically significant, they are trivial. We therefore conclude that there was no meaningful treatment effect in those 2 counties.
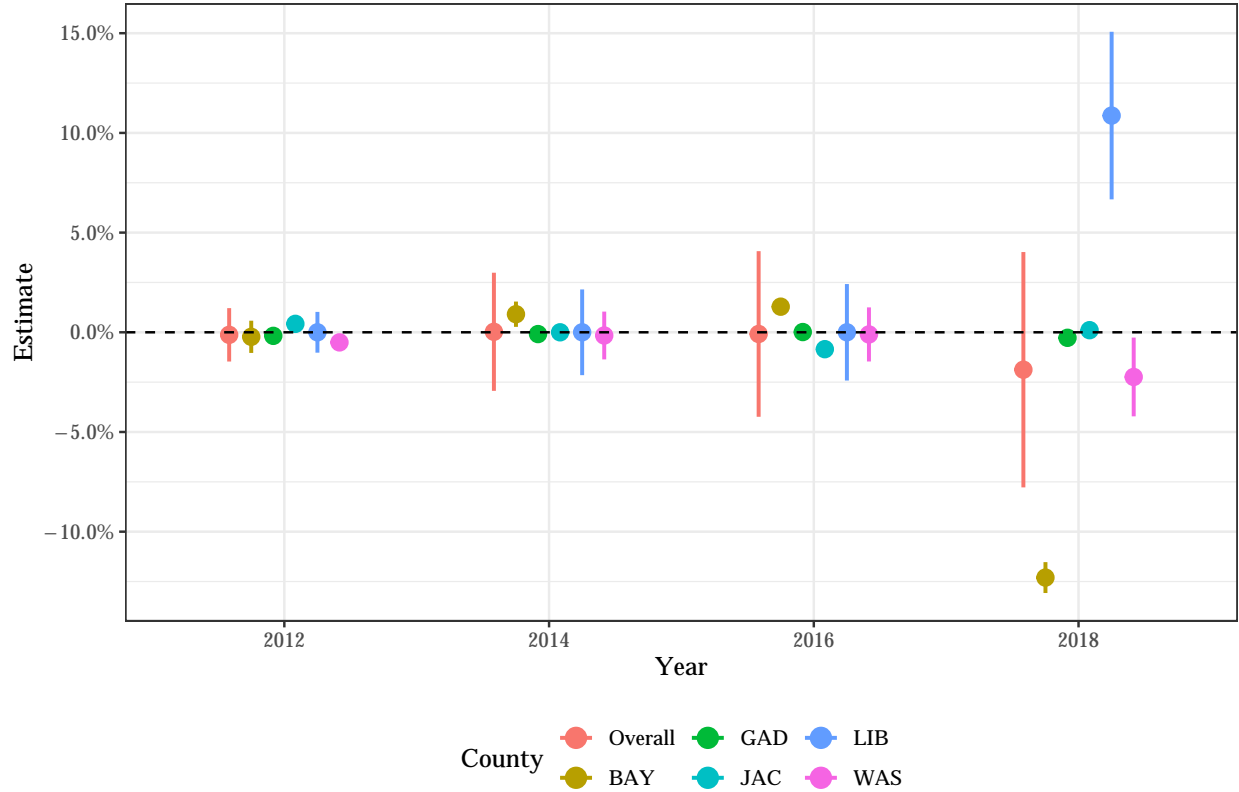

Figure A6: Event Study Plot, Administrative Treatment, Voters in Buffer

Alternative Processing 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 model 1 in Table **??**, we present the results of the unmatched model that does not include a matching procedure. This model includes 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 2 includes a county-linear time trend, and model 3 re-estimates our matched model from the body of the paper with a county-linear time trend.

Models 1 and 3 both continue to identify a negative administrative treatment effect very similar to that included in the body of the paper. Model 2, however, which includes all voters and a county-linear time trend, estimates a nonsignificant administrative treatment effect. Although each model would ideally estimate comparable treatment effects, the benefits provided by the matching procedure ensure that each voter treated only by the weather is similar in terms of past turnout, geography, and rainfall is far superior to one that includes all voters in the buffer treated only by the weather. We conclude that our model is robust to alternative specifications as presented in models 1 and 3, and that model 2 does not invalidate the primary estimates in the paper.

In Figure A7 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 the selected weather-only and control voters for each county. As a reminder, both Calhoun and Gulf Counties are entirely surrounded by other counties covered by the Executive Order,

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Table A5: Turnout, 2010 — 2018

	Turnout			
	(1)	(2)	(3)	(4)
treated_18	0.033	0.033	0.071	0.071
	(0.030)	(0.030)		
panhandle_18	−0.070***	−0.070***	−0.086	−0.086
	(0.022)	(0.022)		
treated_18:treated_rel	−0.015	−0.015	−0.037	−0.037
	(0.017)	(0.017)		
treated_18:treated_change	−0.007***	−0.007***	−0.007	−0.007
	(0.001)	(0.001)		
treated_rel:panhandle_18	0.034***	0.034***	0.048	0.048
	(0.012)	(0.012)		
panhandle_18:treated_change	0.004***	0.004***	0.003	0.003
	(0.001)	(0.001)		
Includes Year Fixed Effects	X	X	X	X
Includes County Fixed Effects	X	X	X	X
Includes changed distance and its interactions			X	X
Includes rainfall and its interactions				X
Observations	473,220	473,220	473,220	473,220
R^2	0.060	0.208	0.061	0.209
Adjusted R^2	0.059	0.208	0.060	0.209

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

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.
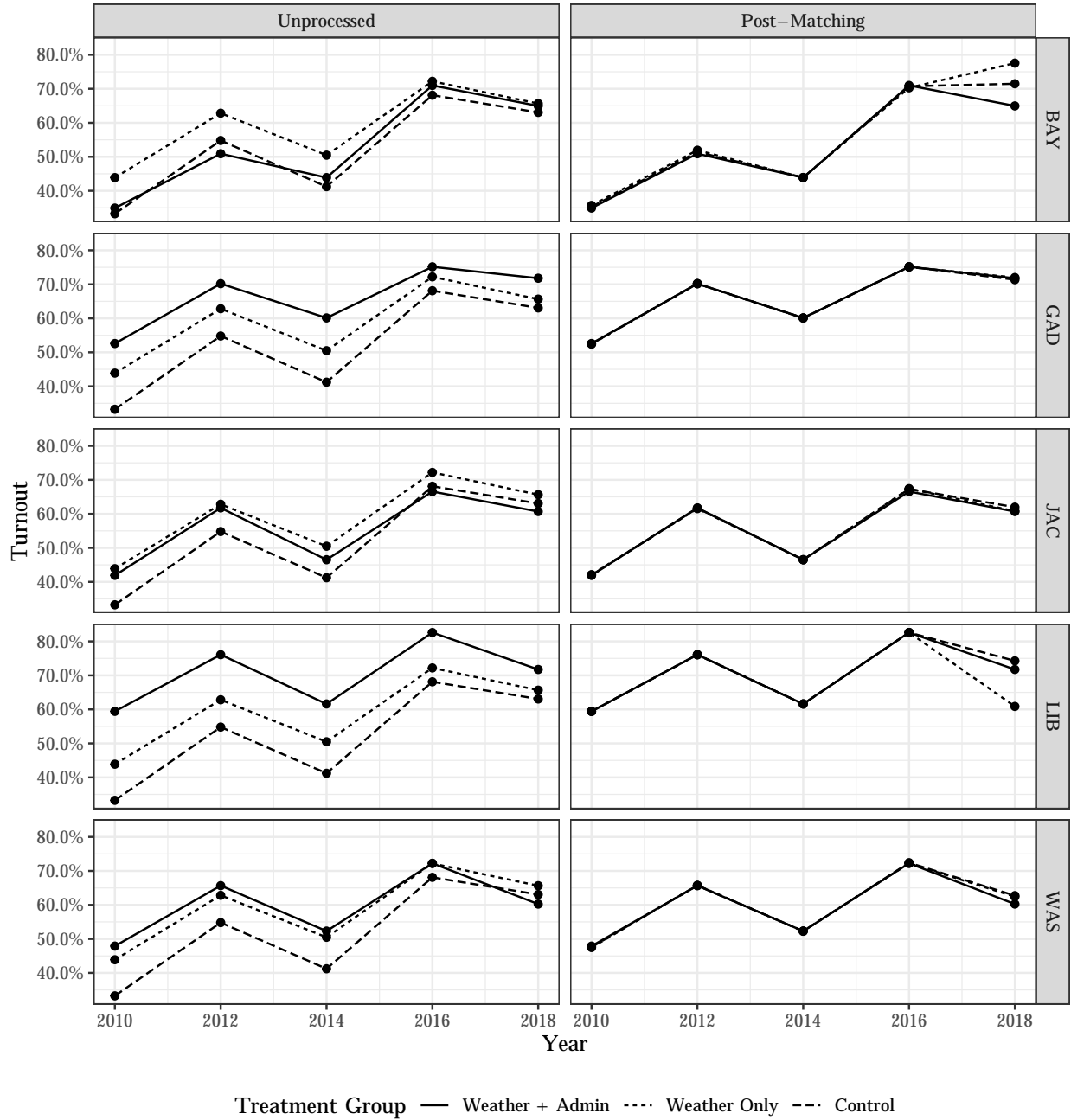
Figure A7: Pre- and Post-Matching County Plots

Figure A7 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. Somewhat surprisingly, the

weather-only matched voters for Bay County saw substantially higher turnout in 2018 relative to the controls elsewhere in the state; however, as discussed in the body of this paper, the weather was relatively mild at the edges of Bay County. Meanwhile, 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.

Multinomial Regression Table

In Figure 5 in the body of the paper, we show the marginal effects plot based on a mulinomial logistic regression. Because those coefficients can be difficult to interpret on their own, we have included the regression table here. While the coefficients have been exponentiated in this table, the standard errors have been left unadjusted.

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.

Table A6: Vote Mode in 2018 (Relative to In-Person on Election Day)

	Abstain	Early	Absentee
Change in Distance to Polling Place (km)	1.047***	1.042***	1.037***
	(0.001)	(0.002)	(0.002)
Distance to Closest Planned Polling Place (km)	0.974***	0.940***	1.001
	(0.003)	(0.003)	(0.002)
White	0.955	1.036	0.953
	(0.043)	(0.047)	(0.064)
Black	0.664***	1.051	0.900
	(0.047)	(0.050)	(0.069)
Latino	0.957	0.871	0.847
	(0.066)	(0.074)	(0.105)
Asian	1.251*	1.182	1.080
	(0.091)	(0.097)	(0.135)
Male	0.965*	1.015	0.993
	(0.015)	(0.015)	(0.021)
Democrat	0.802***	0.807***	1.147***
	(0.024)	(0.026)	(0.037)
Republican	0.649***	1.242***	1.146***
	(0.023)	(0.024)	(0.036)
Age	1.001*	1.011***	1.025***
	(0.000)	(0.000)	(0.001)
Intercept	0.429***	0.300***	0.011***
	(0.056)	(0.060)	(0.086)
Vote-mode in 2010, 2012, 2014, and 2016		X	
Number of Observations		197533	
McFadden Pseudo R2		0.271	

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