Supplementary Information

Contents

1 Administrative Matching Robustness Check

Our models exploring the turnout effects of traffic stops in Hillsborough County, Florida, require that we merge administrative records using the identifiers in the data. This runs the risk of identifying false positives. To test the prevalence of false positives in our administrative matching procedure, we use the test developed by Meredith and Morse (2014). By systematically permuting the birth dates in one set of records, we can see whether false positive matches are a major concern. In Table 1 we begin by merging all names and dates of birth in the traffic stop data with the names and dates of birth in the Hillsborough County registered voter file. We then add and subtract 35 days from the birth dates in the traffic stop data. If there are no false positives, these records should match with no records from the registered voter file.

Table 1: Results of Shifting Birthdates

Group	Number of Matches Between Traffic Stop and Voter File Records
Actual Birthdate	263,152
Birthdate + 35 Days	78
Birthdate - 35 Days	60

As the table makes clear, more than a quarter-million registered voters in Hillsborough County match at least one record in the traffic stop database when merging by first and last name, and date of birth. Once we permute the birth dates, however, the match rate drops dramatically—to 60 or 78, depending on how these dates of birth are permuted. This translates into a false positive rate of roughly 0.03 percent. We consider this rate of false positives too low to meaningfully impact our results.

2 Sensitivity to Narrower Windows

In the individual-level section of this manuscript, voters stopped in the 2 years prior to an election are considered treated, and we draw our controls from the voters stopped 2 years after the election. It is perhaps the case that this large window results in implausible matches; under this design, a treated voter stopped in December of 2012 could draw a control not stopped until October of 2016. Voters stopped nearly 4 years apart from one another might differ in meaningful ways that our matching models cannot capture.

Here, we re-run our matching process on a variety of different windows around the elections. In the most conservative approach, we force voters stopped in the month before an election to match with voters stopped in the month after the election; we then gradually relax this assumption by allowing voters stopped in the 2 months before the election to match to those stopped in the 2 months afterwards, until reaching the two-years used in the manuscript.

Figure 1 shows that our overall treatment effect is remarkably consistent regardless of the size of the window drawn around the election. As we expand the window, we gain more treated voters (and treated voters have a larger pool of potential controls). As such, the confidence interval shrinks, but the treated and control voters are stopped at more distant temporal points from one another. The left-most side of the plot shows that the overall effect is robust to very strict assumptions. In each case, we are re-estimating our primary models in which the covariates used in the matching exercise are also included in the econometric model.

3 Full Regression Tables for Administrative Test

In the body of this manuscript, we present only the overall treatment effects for the police stops in Hillsborough County, which are effectively averaged across all three years. Here, in Tables 2–4, we present the results for each group of treated and control voters. In Table

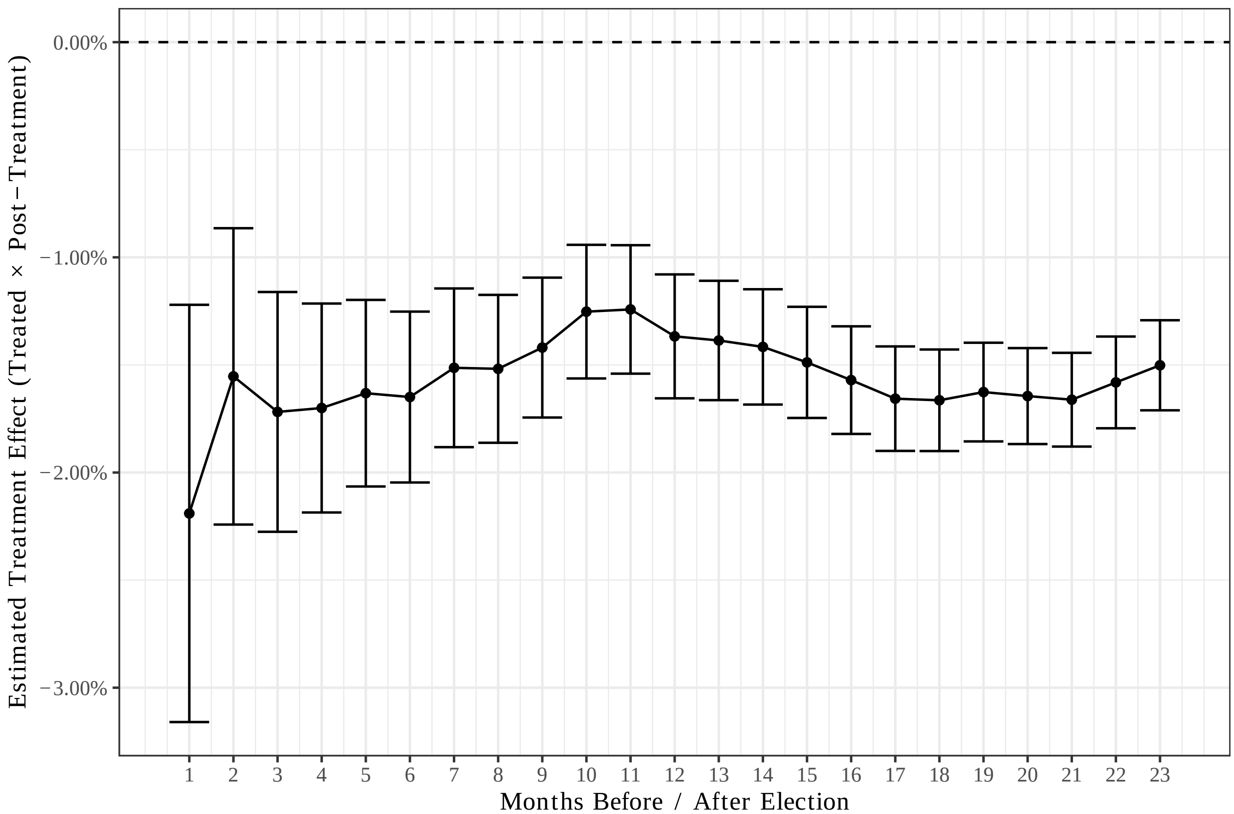

Figure 1: Estimated Treatment Effect for Different Treatment Windows

2, all treated voters were stopped between the 2012 and 2014 elections, and all controls were stopped between the 2014 and 2016 elections. In Table 3, treated voters were stopped between 2014 and 2016, while controls were stopped between 2016 and 2018. Finally, Table 4 presents the treatment effect for voters stopped between 2016 and 2018, relative to their controls stopped between the 2018 and 2020 elections. In every year, there is a statistically significant, negative treatment effect for non-Black voters. In 2014 and 2016, the effect is significantly smaller for Black individuals, though in 2018 the treatment effect for Black and non-Black voters is statistically indistinguishable.

In Table 5, we present the full regression table for the overall models, with all covariates included.

Table 2: Treatment Effect for Voters Stopped before 2014 Election

	Model 1	Model 2	Model 3	Model 4
Treated × Post Treatment	-0.015***	-0.015***	-0.019***	-0.019***
	(0.002)	(0.002)	(0.002)	(0.002)
Treated × Post Treatment × Black			0.010**	0.010**
			(0.004)	(0.004)
Treated	0.000***	0.000***	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Post Treatment	-0.057***	-0.057***	-0.036***	-0.036***
	(0.001)	(0.001)	(0.002)	(0.002)
Black		0.004***	0.053***	0.023***
		(0.001)	(0.002)	(0.001)
White		0.011***		0.011***
		(0.001)		(0.001)
Latino		-0.002**		-0.002**
		(0.001)		(0.001)
Asian		-0.003		-0.003
		(0.002)		(0.002)
Male		0.005***		0.005***
		(0.000)		(0.000)
Democrat		0.003***		0.003***
		(0.000)		(0.000)
Republican		0.006***		0.006***
		(0.001)		(0.001)
Age		0.001***		0.001***
		(0.000)		(0.000)
Registration Date		0.000***		0.000***
		(0.000)		(0.000)
Traffic Stops before Period		-0.002***		-0.002***
		(0.000)		(0.000)
Turnout (t = -3)		0.259***		0.259***
		(0.001)		(0.001)
Turnout (t = -2)		0.324***		0.324***
		(0.001)		(0.001)
Turnout (t = -1)		0.311***		0.311***
		(0.001)		(0.001)
Nhood Median Income		0.000***		0.000***
		(0.000)		(0.000)
Nhood w/ Some College		0.011***		0.011***
		(0.002)		(0.002)
Nhood Unemployment Rate		-0.012**		-0.012**
		(0.004)		(0.004)
Civil Infraction		0.013***		0.013***
		(0.001)		(0.001)
Paid Money on Stop		0.002**		0.002**
		(0.001)		(0.001)
Stopped by Tampa Police Department		0.001*		0.001*
		(0.000)		(0.000)
Treated × Black			0.000	0.000**
			(0.001)	(0.000)
Post Treatment × Black			-0.079***	-0.079***
			(0.003)	(0.003)
Intercept	0.393***	0.001	0.379***	-0.004*
	(0.001)	(0.002)	(0.002)	(0.002)
Year Fixed Effects	✓	✓	✓	✓
Num.Obs.	1020196	1020196	1020196	1020196
R2	0.054	0.574	0.056	0.575
R2 Adj.	0.054	0.574	0.056	0.575

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

Table 3: Treatment Effect for Voters Stopped before 2016 Election

	Model 1	Model 2	Model 3	Model 4
Treated × Post Treatment	-0.003	-0.003	-0.006**	-0.006**
	(0.002)	(0.002)	(0.002)	(0.002)
Treated × Post Treatment × Black			0.009*	0.009*
			(0.005)	(0.005)
Treated	0.000***	0.000	0.000	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Post Treatment	0.367***	0.367***	0.383***	0.383***
	(0.002)	(0.002)	(0.002)	(0.002)
Black		0.005***	0.009***	0.020***
		(0.001)	(0.003)	(0.001)
White		0.007***		0.007***
		(0.001)		(0.001)
Latino		0.009***		0.009***
		(0.001)		(0.001)
Asian		0.014***		0.014***
		(0.002)		(0.002)
Male		-0.011***		-0.011***
		(0.001)		(0.001)
Democrat		0.009***		0.009***
		(0.001)		(0.001)
Republican		0.011***		0.011***
		(0.001)		(0.001)
Age		0.001***		0.001***
		(0.000)		(0.000)
Registration Date		0.000***		0.000***
		(0.000)		(0.000)
Traffic Stops before Period		-0.002***		-0.002***
		(0.000)		(0.000)
Turnout (t = -3)		0.260***		0.260***
		(0.001)		(0.001)
Turnout (t = -2)		0.303***		0.303***
		(0.001)		(0.001)
Turnout (t = -1)		0.316***		0.316***
		(0.001)		(0.001)
Nhood Median Income		0.000***		0.000***
		(0.000)		(0.000)
Nhood w/ Some College		0.030***		0.030***
		(0.002)		(0.002)
Nhood Unemployment Rate		-0.021***		-0.021***
		(0.005)		(0.005)
Civil Infraction		0.027***		0.027***
		(0.001)		(0.001)
Paid Money on Stop		0.007***		0.007***
		(0.001)		(0.001)
Stopped by Tampa Police Department		0.003***		0.003***
		(0.001)		(0.001)
Treated × Black			0.000	-0.001**
			(0.002)	(0.000)
Post Treatment × Black			-0.064***	-0.064***
			(0.003)	(0.003)
Intercept	0.182***	-0.171***	0.180***	-0.175***
	(0.001)	(0.002)	(0.001)	(0.002)
Year Fixed Effects	✓	✓	✓	✓
Num.Obs.	741268	741268	741268	741268
R2	0.084	0.555	0.085	0.556
R2 Adj.	0.084	0.555	0.085	0.556

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

Table 4: Treatment Effect for Voters Stopped before 2018 Election

	Model 1	Model 2	Model 3	Model 4
Treated × Post Treatment	-0.031***	-0.031***	-0.030***	-0.030***
	(0.002)	(0.002)	(0.002)	(0.002)
Treated × Post Treatment × Black			-0.006	-0.006
			(0.005)	(0.005)
Treated	0.000***	0.001***	-0.001	0.001***
	(0.000)	(0.000)	(0.001)	(0.000)
Post Treatment	0.080***	0.080***	0.082***	0.082***
	(0.002)	(0.002)	(0.002)	(0.002)
Black		0.010***	-0.004	0.013***
		(0.001)	(0.003)	(0.001)
White		-0.001		-0.001
		(0.001)		(0.001)
Latino		-0.010***		-0.010***
		(0.001)		(0.001)
Asian		0.002		0.002
		(0.002)		(0.002)
Male		-0.003***		-0.003***
		(0.001)		(0.001)
Democrat		0.013***		0.013***
		(0.001)		(0.001)
Republican		0.011***		0.011***
		(0.001)		(0.001)
Age		0.001***		0.001***
		(0.000)		(0.000)
Registration Date		0.000**		0.000**
		(0.000)		(0.000)
Traffic Stops before Period		-0.002***		-0.002***
		(0.000)		(0.000)
Turnout (t = -3)		0.265***		0.265***
		(0.001)		(0.001)
Turnout (t = -2)		0.298***		0.298***
		(0.001)		(0.001)
Turnout (t = -1)		0.333***		0.333***
		(0.001)		(0.001)
Nhood Median Income		0.000***		0.000***
		(0.000)		(0.000)
Nhood w/ Some College		0.037***		0.037***
		(0.003)		(0.003)
Nhood Unemployment Rate		-0.024***		-0.024***
		(0.005)		(0.005)
Civil Infraction		0.020***		0.020***
		(0.001)		(0.001)
Paid Money on Stop		0.007***		0.007***
		(0.001)		(0.001)
Stopped by Tampa Police Department		0.006***		0.006***
		(0.001)		(0.001)
Treated × Black			0.004	0.000
			(0.002)	(0.000)
Post Treatment × Black			-0.006	-0.006
			(0.004)	(0.004)
Intercept	0.365***	-0.055***	0.366***	-0.056***
	(0.002)	(0.003)	(0.002)	(0.003)
Year Fixed Effects	✓	✓	✓	✓
Num.Obs.	588380	588380	588380	588380
R2	0.041	0.544	0.041	0.544
R2 Adj.	0.041	0.544	0.041	0.544

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

Table 5: Overall Treatment Effect

	Model 1	Model 2	Model 3	Model 4
Treated × Post Treatment	-0.015***	-0.015***	-0.017***	-0.017***
	(0.001)	(0.001)	(0.001)	(0.001)
Treated × Post Treatment × Black			0.005*	0.005*
			(0.002)	(0.002)
Treated	0.000***	0.000	0.000	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Post Treatment	0.062***	0.052***	0.076***	0.066***
	(0.001)	(0.001)	(0.001)	(0.001)
Black		0.006***	0.026***	0.020***
		(0.001)	(0.002)	(0.001)
White		0.007***		0.007***
		(0.001)		(0.001)
Latino		-0.001*		-0.001*
		(0.001)		(0.001)
Asian		0.004***		0.004***
		(0.001)		(0.001)
Male		-0.003***		-0.003***
		(0.000)		(0.000)
Democrat		0.008***		0.008***
		(0.000)		(0.000)
Republican		0.010***		0.010***
		(0.000)		(0.000)
Age		0.001***		0.001***
		(0.000)		(0.000)
Registration Date		0.000***		0.000***
		(0.000)		(0.000)
Traffic Stops before Period		-0.002***		-0.002***
		(0.000)		(0.000)
Turnout (t = -3)		0.248***		0.248***
		(0.000)		(0.000)
Turnout (t = -2)		0.324***		0.324***
		(0.000)		(0.000)
Turnout (t = -1)		0.306***		0.306***
		(0.000)		(0.000)
Nhood Median Income		0.000***		0.000***
		(0.000)		(0.000)
Nhood w/ Some College		0.024***		0.024***
		(0.001)		(0.001)
Nhood Unemployment Rate		-0.018***		-0.018***
		(0.003)		(0.003)
Civil Infraction		0.020***		0.020***
		(0.000)		(0.000)
Paid Money on Stop		0.009***		0.009***
		(0.000)		(0.000)
Stopped by Tampa Police Department		0.005***		0.005***
		(0.000)		(0.000)
Treated × Black			0.002	0.000
			(0.001)	(0.000)
Post Treatment × Black			-0.056***	-0.056***
			(0.002)	(0.002)
Intercept	0.393***	-0.022***	0.386***	-0.025***
	(0.001)	(0.002)	(0.001)	(0.002)
Year Fixed Effects	✓	✓	✓	✓
Num.Obs.	2349844	2349844	2349844	2349844
R2	0.055	0.554	0.055	0.555
R2 Adj.	0.055	0.554	0.055	0.555

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

4 Regression Table for Survey Data

Here we present the regression table reported in the national survey data section of the manuscript. In model 1 we test whether personal or proximal contact with a police stop is differentially associated with turnout for Black and non-Black respondents. In this model, *Stopped in Past 12 Months* captures the relationship between police stops and non-Black respondents; *Stopped in Past 12 Months* $\times$ *Black* tests whether this relationship is different for Black respondents.

Models 2 and 3 whether the relationship is different for other non-white groups. Finally, model 4 tests the relationship between turnout and a historical arrest.

Table 6: Criminal Legal System Contact and 2020 Turnout

	Model 1	Model 2	Model 3	Model 4
Stopped in Past 12 Months	0.023	0.033**	0.037**	
	(0.012)	(0.012)	(0.012)	
Ever Arrested				-0.030**
				(0.011)
Black	0.013	0.032	0.032	0.037
	(0.022)	(0.021)	(0.021)	(0.023)
White	0.039*	0.039*	0.039*	0.037*
	(0.018)	(0.018)	(0.018)	(0.018)
Asian	0.095***	0.084**	0.097***	0.089***
	(0.027)	(0.028)	(0.027)	(0.027)
Latinx	-0.006	-0.006	-0.004	-0.009
	(0.020)	(0.020)	(0.021)	(0.020)
Age	0.001**	0.001**	0.001**	0.001**
	(0.000)	(0.000)	(0.000)	(0.000)
Republican	-0.019	-0.021	-0.021	-0.019
	(0.013)	(0.013)	(0.013)	(0.013)
Other Party	-0.148***	-0.149***	-0.149***	-0.148***
	(0.014)	(0.014)	(0.014)	(0.014)
Income ($10,000s)	0.007***	0.007***	0.007***	0.007***
	(0.001)	(0.001)	(0.001)	(0.001)
Male	-0.014	-0.013	-0.013	-0.008
	(0.008)	(0.008)	(0.008)	(0.009)
Refused Sex Question	0.114	0.114	0.114	0.118

	(0.141)	(0.141)	(0.141)	(0.141)
Ideology Missing	-0.196	-0.194	-0.194	-0.200
	(0.126)	(0.126)	(0.126)	(0.126)
Don't Know Ideology	-0.069	-0.064	-0.064	-0.060
	(0.046)	(0.046)	(0.046)	(0.046)
Extremely Liberal	0.026	0.022	0.024	0.028
	(0.023)	(0.023)	(0.023)	(0.023)
Liberal	0.034*	0.035*	0.035*	0.035*
	(0.016)	(0.016)	(0.016)	(0.016)
Slightly Liberal	-0.030*	-0.030*	-0.030*	-0.030*
	(0.014)	(0.014)	(0.014)	(0.014)
Slightly Conservative	-0.050***	-0.051***	-0.051***	-0.052***
	(0.013)	(0.013)	(0.013)	(0.013)
Conservative	0.017	0.018	0.017	0.018
	(0.015)	(0.015)	(0.015)	(0.015)
Extremely Conservative	0.073***	0.073***	0.073***	0.072**
	(0.022)	(0.022)	(0.022)	(0.022)
Education Missing	-0.196	-0.190	-0.190	-0.184
	(0.375)	(0.376)	(0.376)	(0.376)
No High School Diploma	-0.097***	-0.097***	-0.097***	-0.096***
	(0.017)	(0.017)	(0.017)	(0.017)
Some College, No Degree	0.062***	0.062***	0.062***	0.064***
	(0.013)	(0.013)	(0.013)	(0.013)
Associate's Degree	0.008	0.008	0.008	0.011
	(0.015)	(0.015)	(0.015)	(0.015)
Bachelor's Degree	0.038**	0.038**	0.038**	0.038**
	(0.013)	(0.013)	(0.013)	(0.013)
Post-Graduate Education	0.030*	0.030*	0.030*	0.028
	(0.015)	(0.015)	(0.015)	(0.015)
Stopped in Past 12 Months × Black	0.096**			
	(0.033)			
Stopped in Past 12 Months × Asian		0.124		
		(0.070)		
Stopped in Past 12 Months × Latinx			-0.008	
			(0.034)	
Ever Arrested × Black				-0.011
				(0.031)
Num.Obs.	6846	6846	6846	6846
R2	0.328	0.327	0.327	0.327
R2 Adj.	0.325	0.325	0.324	0.324
F	123.099	122.803	122.634	122.562

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

Model 1 in Table 6 shows that Black individuals who had been stopped by the police (or had a family member stopped) in the preceding 12 months were 9.6 percentage points more likely to vote in 2020, other things equal; they were not related to turnout for non-Black respondents. Police stops are not, however, associated with different turnout effects for other non-white groups. Moreover, as discussed in the body of the paper, historical arrests were uniformly associated with a decrease in turnout of 3 percentage points for Black and non-Black respondents alike.

References

Meredith, Marc, and Michael Morse. 2014. "Do Voting Rights Notification Laws Increase Ex-Felon Turnout?" *The ANNALS of the American Academy of Political and Social Science* 651 (1): 220–49. https://doi.org/10.1177/0002716213502931.