Supplementary Appendix

Data

Voting Data

County-level voting data for 2016, 2012, and 2008 elections were obtained from the Atlas of Presidential Elections (Leip, 2004).

FOP Organizational Data

In January 2016, a hacker leaked a substantial amount of information about the Fraternal Order of Police, including lodge information, membership, and collective bargaining agreements (Swaine and Joseph, 2016). These data were released as a PostgreSQL dump. I geolocated FOP lodges from their addresses to counties and calculated the lodge density per 10,000 adults (visualized in Figure 1). The number of local institutional affiliates, per capita, is a commonly used metric for organizational strength in the political science literature (Gamm & Putnam, 1999; Putnam, 2001; Skocpol et. al., 2006; Satyanath et. al, 2017) and recent empirical work on the political influence of unions in particular (Becker et. al., 2018) indicates that the distribution of union members across a wide number of organizations is a critical determinant of political influence. It seems plausible that a given county's lodge presence affects adjacent counties as well. To address this, I include lodges in adjacent counties (calculated using the Census's county adjacency file) as part of the lodge total – in other words, I use an adjacency weight of one. In practice, the results are not statistically or substantively sensitive to the choice or omission of adjacency weights.

County Control Variables

Demographics

To account for potential observable differences between counties that confound FOP presence, I include a host of socioeconomic and demographic controls. Data about the percentage of non-Hispanic whites, Hispanics, veterans, non-college educated whites, "blue collar workers" (defined as employment in Building and grounds cleaning and maintenance occupations, Natural resources, construction, and maintenance occupations, or Production, transportation, and material moving occupations in any industry), and workers employed in protective services were retrieved from the 2011-2015 American Community Survey. The most recent (2015) county- level estimates of Median Household Income and Poverty were retrieved from the Small Area Income Poverty Estimates program of the US Census. The Rural-Urban County Continuum (RUCC), a 2010 measure of urbanicity ranging from 1 (large metropolitan urban counties) to 9 (rural counties not near any metropolitan areas) was retrieved from the United States Department of Agriculture.

Industry Data

My analysis incorporates data about the concentration and trends in the manufacturing, mining and extraction, and farming and animal husbandry industries from the NAICS to account for pre-treatment economic geography that could be confounded with Fraternal Order of Police presence. For each of the three industries, I collected the county-level location quotient – representing the relative concentration of the industry in the third quarter of 2016 and the 15 year difference in the location quotient (that is, the 2016 level subtracted by the 2001 level; positive values indicating increasing economic dependence on the industry in recent years).

Associational Density

Regions of the country (such as the Midwest) vary in their "joining culture" (Skocpol, 2003). Since these regions mays also have a stronger FOP presence, this associational density may confound the effect of the Fraternal Order of Police. Similarly, regional union density might be associated with both stronger police unions and vote shift to Trump. To address these possibilities, I include 2014 county-level estimates of associational density and labor organization density using updated data from Rupasingha, Goetz and Freshwater (2006). These measures are, respectively, the number of county voluntary associations and the number of labor organizations per 100,000 residents.

Was FOP support Pivotal?

Across various specifications, I find that Fraternal Order of Police presence predicts vote shift from Romney to Trump, consistent with the hypothesis that the FOP endorsement mattered in a climate of politicized policing. The effects of the FOP mobilization in the complete Model (4) are of reasonable magnitude. Moving from no FOP presence to the mean lodge density among counties with any lodges is associated with an increase in the GOP vote swing of about 0.87 percentage points, holding other things constant. One standard deviation above the mean corresponds to a 1.47 percentage point increase in vote swing.

Moreover, the 2016 election was extremely close. While Trump lost the popular vote nationwide by about one-percentage point, his narrow victories in Wisconsin, Michigan, and Pennsylvania proved decisive. To interpret the substantive effect size, I will use the county-level model parameters to estimate the counterfactual election without FOP at the state level, the substantive unit in American Presidential races. Using the Model 4 from Table 2, I calculate the hypothetical counterfactual election results for all counties as though no Fraternal Order of Police lodges existed. Assuming the β I estimated in Model 4 was causal and uniform across counties, I use it to calculate the counterfactual vote share Trump would have received in each county without FOP mobilization. The lodge density in each county multiplied by β gives the estimated change in vote share attributable to FOP. Multiplying this quantity by the total number of votes in the county and aggregating this analysis to the state level provides a back-of- the-envelope indication of the counterfactual electoral map.

Table S3 shows the results of this analysis. I find that Michigan's electoral votes would have gone to Clinton had Trump not gained vote share due to FOP mobilization – while Trump barely won by 0.22 percentage points, he would have barely lost by 0.12 percentage points without FOP support. In several other states, FOP support was nearly pivotal. In Pennsylvania, the margin of Clinton's loss would have narrowed to 0.18 from 0.72; in Wisconsin, 0.57 instead of 0.76. In New Hampshire and Minnesota, Clinton's victory would have been somewhat more comfortable: 0.61 instead of 0.37 in NH and 1.76 instead of 1.5 in Minnesota.

Though Washington D.C. is not included in the main analyses because of collinearity with the "state" fixed effect (there is no "within-state" variation in DC), this table extrapolates the counterfactual results for Washington D.C using its observed lodge density and election results along with the coefficient for lodge density obtained by the main analysis. Furthermore, Alaska is omitted because county-level electoral results are not available at the county-equivalent level (Alaska is not organized into counties).

In the spirit of quantifying uncertainty and accepting variation (Gelman, 2016), I used the β and the standard error from Model 4 to generate a distribution of potential counterfactuals consistent with the model parameters. Sampling 10000 values of β from a normal distribution centered at the model parameter of about 0.9 shown in Model 3, and with a standard deviation equal to the standard error of about 0.23, I calculated the spectrum of potential counterfactual elections incorporating the uncertainty of the β estimate. Figure S1 visualizes the potential outcome for the two states (Michigan and Pennsylvania) in which FOP presence was closest to being pivotal. The blue (red) dashed line represents Clinton's (Trump's) actual vote share. The density plot shows the spectrum of potential Trump vote shares without FOP mobilization. This method allows for quantifying the potential that FOP mobilization was pivotal in a state, by calculating the percentage of simulated samples in which the estimated effect pushed Trump's vote share beyond Clinton's. For Michigan, this probability is about 0.92. For Pennsylvania, it is about 0.10 – only the largest tenth of sampled effect sizes swing the state (and for all other states, including competitive states like Wisconsin or North Carolina, this probability is zero; even the largest sampled effect sizes do not swing the state). This also yields a 99% Confidence Interval of the effect size; for Pennsylvania, given these strong assumptions, the FOP endorsement could have been worth about 0.18% to about 0.89% of vote share. Reassuringly, even the tails of these predicted effects are reasonable (Gelman and Carlin, 2017). Substantively, this exercise tells us that Fraternal Order of Police mobilization could have been pivotal to the electoral votes of at least one state and played an important role in several other states.

Limitations

Endogeneity and Omitted Variable Bias

A potential hazard associated with inferences in the difference-in-differences framework is that the intervention is itself endogenous, thus violating the parallel trends assumption. Applied to this paper, one might worry that FOP lodges happened to be located in places that swung from Romney to Trump for unrelated reasons. Though there is no possibility of simultaneity – diffusion of FOP lodges occurred decades before this Presidential election – it could still be the case that FOP lodges happened to have emerged in places with a proclivity to Trump and not Romney. I have attempted to address this in three ways. First, by including a host of demographic and socioeconomic covariates, I attempt to partial out observable differences between lodges with and without FOP lodges. Included among these covariates are state trend dummies, which have the effect of demeaning each county's swing by the state average swing and accounting for unobserved factors which affect the state as a whole, thus boosting comparability of "treated" and "untreated" counties by looking at the deviation in the swing from Romney to Trump within each state. Second, I use placebo tests to show that FOP presence was not associated with vote swings during an election when FOP did not endorse a candidate, nor was it evident between two Presidential elections in which the GOP candidate in both years was endorsed by FOP. Instead, the effect of FOP mobilization is evident only when moving from a candidate who was not endorsed by FOP (Romney) to a candidate who was endorsed by FOP (Trump). Third and finally, I show evidence consistent with the proposed mechanism: there was heightened political engagement among police officers in 2016.

Measurement Error

Though the number of local institutional affiliates, per capita, is a commonly used metric for organizational strength in the political science literature (Gamm & Putnam, 1999; Putnam, 2001; Skocpol et. al., 2006; Satyanath et. al, 2017), the logged number of lodges per adult undoubtedly does not perfectly capture FOP strength. In the context of the FOP, whether the local is a collective bargaining authority – and the racial composition of local members – could be important moderating factors, though the presence of state fixed effects in all analyses, which use variation between counties within the same state, mitigates this first concern somewhat, since restrictions on police sector collective bargaining vary by state statutes. Moreover, other, smaller police unions endorsed Trump, such as the Cleveland Patrolman's Association (Picciano, 2016);

to the extent that these organizations are substitutes with FOP lodges, I will underestimate the effect of police mobilization. In general, measurement error of the treatment variable would depress the observed coefficient β, biasing it downwards; since a meaningful effect was nonetheless observed, this is not too concerning. These results are robust to using the unlogged lodge density variable, to the omission of adjacency weights, and the use of population weights.

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Figure S1: Counterfactual Elections in two swing states

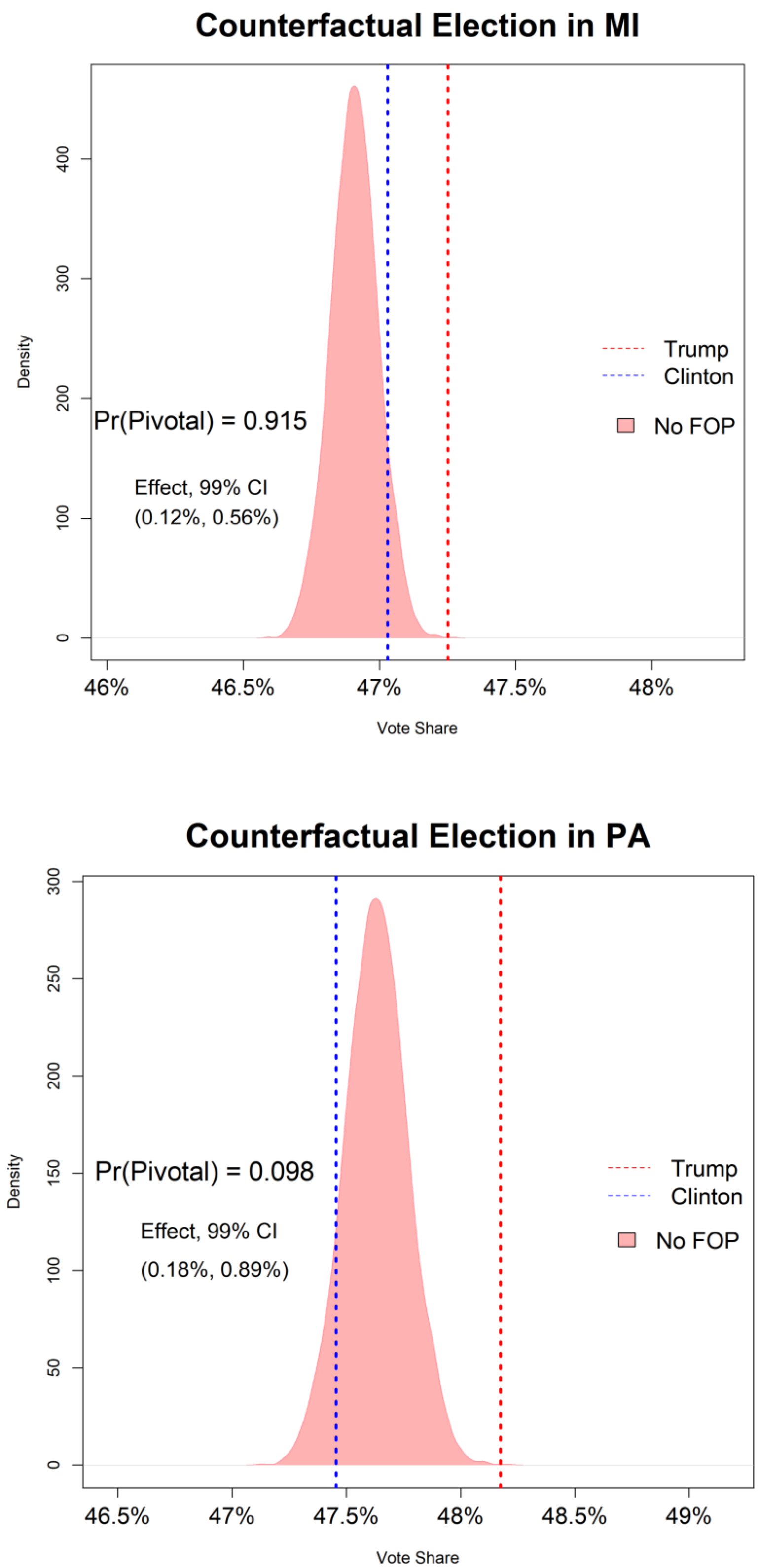

Table S1: Sample o f News Articles with picture of Trump posing with FOP Banner

1. http://www.cleveland.com/court-justice/index.ssf/2016/11/president-elect_donald_trumps.html
2. thinkprogress.org/sessions-cant-be-hold-racist-views-if-police-unions-like-him-says-orrin-hatch-3a28597298ad
3. https://www.yahoo.com/news/emboldened-trump-police-unions-seek-overhaul-obama-reforms-111635272.html
4. http://www.pbs.org/newshour/rundown/police-group-endorse-trump/
5. http://www.reuters.com/article/us-usa-police-trump-insight-idUSKBN15E106
6. https://www.washingtonpost.com/video/politics/nc-fraternal-order-of-police-endorse-trump/2016/08/18/506abd82-657b-11e6-b4d8-33e931b5a26d_video.html
7. http://www.nbcnews.com/news/us-news/black-cops-odds-fraternal-order-police-over-trump-endorsement-n652071
8. http://www.breitbart.com/2016-presidential-race/2016/09/16/fraternal-order-of-police-endorses-donald-trump-he-will-make-america-safe-again/
9. http://www.csmonitor.com/USA/2016/0918/Why-did-the-country-s-largest-police-union-endorse-Donald-Trump-video
10. http://www.washingtontimes.com/news/2016/sep/16/national-fraternal-order-police-endorses-donald-tr/
11. http://www.denverpost.com/2016/10/06/why-would-denvers-police-union-support-donald-trump/
12. http://www.startribune.com/trump-to-briefly-pass-through-minn-for-campaign-fundraiser/390643011/
13. http://www.motherjones.com/politics/2016/09/fraternal-order-police-trump-endorsement-minority-response
14. http://www.stltoday.com/news/opinion/columns/the-platform/editorial-will-police-consent-decrees-be-enforced-in-the-age/article_0e102cb0-ec42-5808-a928-26e95181f6b0.html
15. http://www.msnbc.com/rachel-maddow-show/donald-trumps-stop-and-frisk-policy-raises-eyebrows
16. http://www.phillytrib.com/commentary/coard-fop-oughta-be-arrested-for-endorsing-trump/article_8b01f1b7-fe38-5040-8226-d8764ccaa214.html
17. http://www.latimes.com/nation/politics/trailguide/la-na-trailguide-updates-signs-of-a-shift-in-trump-s-campaign-1471633178-htmlstory.html
18. https://www.theguardian.com/us-news/live/2016/aug/22/hillary-clinton-donald-trump-us-election-news-campaign-live
19. http://www.oregonlive.com/opinion/index.ssf/2016/08/to_russia_with_love_from_trump.html
20. http://www.phillyvoice.com/black-police-officers-voice-opposition-philly-fops-trump-endorsement/

Table S2: Political Behavior Robustness Check

	Pop Mean (12)	Protect. Mean (12)	Pop Mean (16)	Protect. Mean (16)	DiD	p-value
Contacted by Campaign	0.58	0.63	0.44	0.70	0.22	0.00
Vote GOP Pres.	0.38	0.53	0.30	0.60	0.15	0.00
Definitely Vote	0.73	0.80	0.77	0.92	0.07	0.03
Political Sign	0.20	0.23	0.13	0.23	0.06	0.16
Volunteer	0.08	0.06	0.05	0.09	0.06	0.04
Matched Voter File	0.83	0.86	0.66	0.82	0.13	0.00

This table uses an alternative strategy for identifying protective service employees in both the 2012 and 2016 issues of the CCES. As a sensitivity check, to ensure the results shown in the paper are not driven by heterogeneity in the composition of the police officer group in 2012 versus 2016, I separately identified workers in protective services in the CCES 2016 dataset (firefighters, corrections officers, police and law enforcement officers) from raw strings of self-reported occupations. This identified 159 protective services responses in 2016. The analogous calculations shown here demonstrates essentially the same patterns – protective services employees became more politically engaged in 2016 than in 2012, relative to the general population.

Table S3: Counterfactual Election Results without FOP Endorsement

State	Clinton %	Trump %	Counterfact. Trump %	Difference	Margin	Counterf. Margin	Diff/Margin
MI	47.03	47.25	46.91	0.34	0.22	-0.12	1.55
PA	47.46	48.17	47.63	0.54	0.72	0.18	0.76
NH	46.83	46.46	46.21	0.24	-0.37	-0.61	0.67
WI	46.45	47.22	47.03	0.19	0.76	0.57	0.25
FL	47.41	48.60	48.34	0.27	1.19	0.92	0.22
MN	46.44	44.93	44.68	0.25	-1.51	-1.76	0.16
CO	48.16	43.25	42.85	0.40	-4.91	-5.31	0.08
OH	43.24	51.31	50.66	0.66	8.07	7.41	0.08
NC	46.17	49.83	49.53	0.29	3.66	3.36	0.08
AZ	44.58	48.08	47.81	0.27	3.50	3.23	0.08
VA	49.74	44.44	44.03	0.41	-5.31	-5.71	0.08
NJ	54.99	41.00	40.14	0.86	-13.98	-14.85	0.06
RI	54.35	38.95	38.01	0.94	-15.41	-16.35	0.06
DE	53.09	41.71	41.11	0.60	-11.37	-11.98	0.05
NM	48.26	40.04	39.67	0.37	-8.21	-8.58	0.05
IL	55.25	38.36	37.60	0.76	-16.89	-17.65	0.05
IN	37.46	56.47	55.65	0.81	19.01	18.19	0.04
NV	47.92	45.50	45.41	0.09	-2.42	-2.51	0.04
GA	45.35	50.44	50.27	0.18	5.10	4.92	0.03
CT	54.57	40.93	40.49	0.44	-13.64	-14.08	0.03
NE	33.70	58.75	58.05	0.70	25.05	24.35	0.03
KS	35.74	56.16	55.62	0.54	20.42	19.88	0.03
KY	32.68	62.52	61.82	0.70	29.84	29.14	0.02
ME	47.68	45.02	44.96	0.06	-2.66	-2.72	0.02
OK	28.93	65.32	64.52	0.80	36.39	35.59	0.02
AL	34.36	62.08	61.48	0.60	27.73	27.12	0.02
MD	60.33	33.91	33.36	0.55	-26.42	-26.97	0.02
TN	34.72	60.72	60.20	0.52	26.01	25.48	0.02
SD	31.30	61.95	61.36	0.59	30.65	30.05	0.02
LA	38.45	58.09	57.72	0.37	19.64	19.27	0.02
WV	26.18	67.85	67.07	0.79	41.68	40.89	0.02
AR	33.65	60.57	60.07	0.50	26.92	26.42	0.02
SC	40.67	54.94	54.69	0.25	14.27	14.02	0.02
UT	27.17	45.05	44.76	0.29	17.89	17.59	0.02
MO	37.88	56.39	56.09	0.30	18.51	18.21	0.02
IA	41.74	51.15	51.00	0.15	9.41	9.26	0.02
ID	27.48	59.25	58.77	0.47	31.76	31.29	0.01
TX	43.24	52.23	52.10	0.13	9.00	8.87	0.01
WY	21.88	68.17	67.55	0.63	46.30	45.67	0.01
WA	52.54	36.83	36.63	0.21	-15.71	-15.91	0.01
MS	40.06	57.86	57.63	0.23	17.80	17.57	0.01
NY	59.01	36.52	36.22	0.29	-22.49	-22.78	0.01
ND	27.23	62.96	62.53	0.43	35.73	35.30	0.01
MA	60.01	32.81	32.57	0.24	-27.20	-27.43	0.01
VT	56.68	30.27	30.14	0.13	-26.41	-26.53	0.00
OR	50.07	39.09	39.05	0.05	-10.98	-11.03	0.00
DC	90.86	4.09	3.82	0.27	-86.78	-87.04	0.00
MT	35.41	55.65	55.61	0.04	20.23	20.20	0.00
CA	61.48	31.49	31.46	0.04	-29.99	-30.03	0.00
HI	62.22	30.04	30.03	0.01	-32.18	-32.19	0.00