Online Appendix

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Contents

A.1 Additional Descriptive Results About Detainer Requests and Sheriff Elections

A.1.1 Detainer Requests Sent to Sheriffs Over Time

Figure A.1: **The Number of Detainer Requests Sent to Sheriffs, 2006–2015.** The number of detainer requests peaked in 2011. The compliance rate peaked in 2009 and declined from 73% in 2008 and 2009 to 43% in 2015.

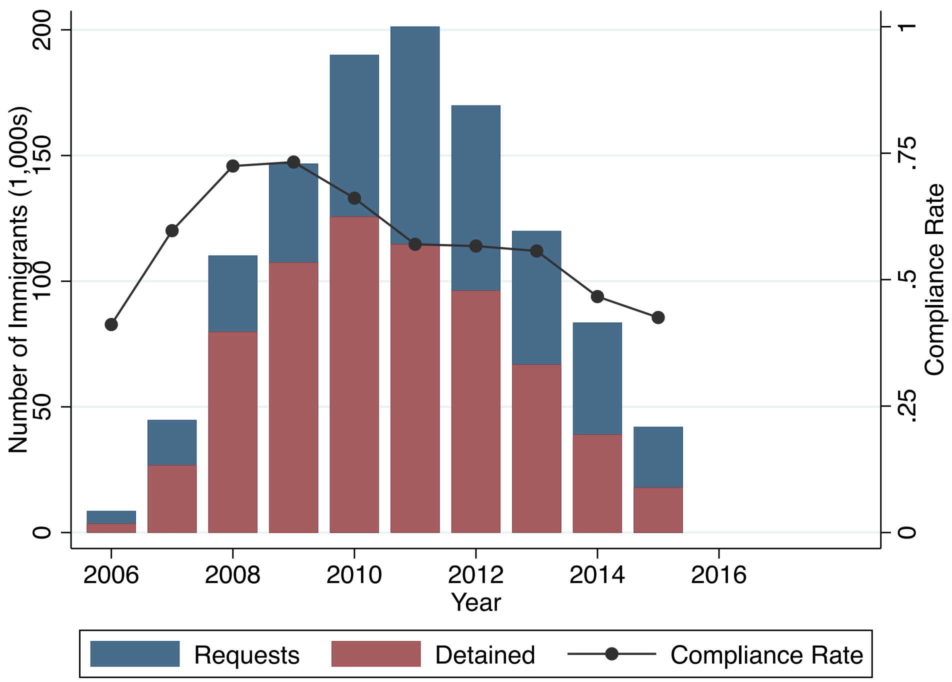
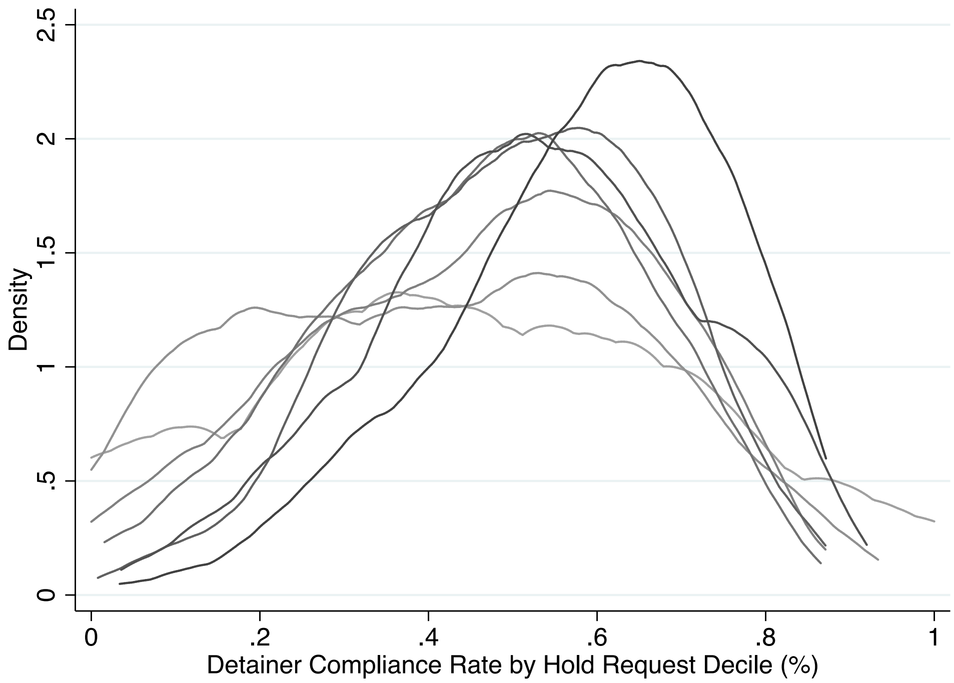


Figure A.1 presents the total number of requests sheriffs received, and the number with which they complied, over time. The number of requests sheriffs received peaked in 2011. The number with which they complied peaked in 2010. The changes through time are in part due to changes in federal policy around the use of detainers. The main program using detainers rolled out in 2008 and ramped up until 2013. Throughout this period, policy changed around who the detainers should be used for, with the most notable change coming in 2015 when the Obama administration ended the use of detainers for immigrants not convicted of a crime.

A.1.2 Distribution of Compliance Rates for Counties with Many and Few Requests

Figure A.2: **The Distribution of Compliance Rates by Request Decile** The distribution of compliance rates in counties that received more requests are plotted in darker shades. The bottom third of counties received no detainer requests, leaving only seven lines. The top three deciles include counties that received 80 requests or more.



An important part of my analysis is a theoretical quantity that I cannot measure: a sheriff's propensity to comply with a detainer request. To interpret the convergence results properly, it is critical to know whether sheriffs actually have control over the propensity to comply. There is quite a bit of legal reasoning and informed discussion of about the freedom sheriffs have to comply or not, but if they do, there should at least be some evidence of differences in propensities to comply from county to county.

If all requests were identical, the rate of compliance across a large number of draws will recover propensity to comply. But some counties receive very few requests. The small number of requests introduces sampling variance that is independent of the variance in propensity to comply across counties. To address this, I plot the distribution of compliance rates by decile of requests received. The plot, Figure A.2, demonstrates that even counties receiving many requests vary quite a lot in the propensity to comply.

A.1.3 Sheriff Election Sample

I gathered the sheriff election data using two strategies. First, I gathered data from state authorities overseeing elections in 15 states where they collected county election results. Since this only represents a small percentage of the overall counties in the country, I also gathered election data directly from counties. I visited every county elections board website for counties with more than 100,000 people as of the 2000 Census. In table A.1, I compare the elections I gathered to all sheriff elections that occurred from 2003 to 2016. Since I was able to get data from most counties with populations over 100,000, I have nearly a census of those elections. My data coverage is also bent toward larger counties because I over sampled them with my strategy. This comparison simply describes the counties for which my analysis applies and provides guidance about the generalizability of my results—it does not implicate the internal validity of my findings.

Table A.1: **Comparison of Election Sample to Universe of Sheriff Elections**

	All Counties		Large & Partisan	
	All	Gathered	All	Gathered
Geographic Region				
Midwest	0.32	0.18	0.26	0.27
Northeast	0.07	0.11	0.24	0.24
South	0.49	0.53	0.41	0.40
West	0.12	0.18	0.09	0.09
Dist to Mex Border, 100s of Miles	8.66	9.95	10.19	10.44
	(3.74)	(3.92)	(4.46)	(4.38)
Population				
All, 1,000s of People	84.01	175.25	345.89	367.52
	(268.82)	(443.86)	(431.20)	(462.30)
Foreign Born, 1,000s of People	8.05	20.93	33.82	37.07
	(69.43)	(121.50)	(81.19)	(88.94)
Politics				
President	0.44	0.44	0.50	0.50
	(0.17)	(0.15)	(0.13)	(0.13)
Governor	0.30	0.27	0.32	0.30
	(0.46)	(0.44)	(0.47)	(0.46)
Num of Counties	3083	1395	420	397
Obs	11142	3500	1560	1216

Standard deviation in parentheses.

In Table A.2, I report descriptive statistics about candidate entry and competitiveness from my sample of sheriff elections. I compare these elections to US House elections for context. I find that

Table A.2: **Sheriff Election Characteristics.** Sheriff elections have fewer candidates than US House elections and winners win with a greater share of the vote. Counties with large populations (more than 100,000 citizens as of 2000) have more races with a Democrat and a Republican.

	All Counties	Large Counties	US House
Partisan Competition			
At Least One Dem	0.60	0.65	0.91
At Least One Rep	0.66	0.80	0.91
Both Parties	0.37	0.48	0.83
Candidate Entry			
One Candidate	0.45	0.43	0.06
Two Candidates	0.46	0.49	0.47
Three Candidates	0.07	0.06	0.32
Competitveness			
Winning Vote Share	0.79	0.78	0.66
	(0.20)	(0.19)	(0.13)
Num of Counties	1282	397	-
Obs	3226	1216	3023

Standard deviation in parentheses. Large counties are those with populations greater than 100,000 as of the 2000 Census. Candidates who receive less than 1% of the vote do not count toward the number of candidates.

open or uncompetitive sheriff elections are more common than open or uncompetitive US House elections, but there is still a large share of sheriff races (55%) that have at least two candidates.

A.1.4 Outcome Descriptives

Table A.3 presents descriptive statistics for all of the main outcomes I study. The table breaks out the outcomes from the 2006-2015 period and 2017-2018 period. The first column reports these statistics for the full population. The second column reports these statistics only for the cases that enter the regression discontinuity design.

Table A.3: **Distributions of Outcomes for Sheriffs.**

	All Counties	RD Sample
2006-2015		
Compliance Rate	0.49	0.50
	(0.33)	(0.29)
	[12473]	[1894]
Detentions per 1k Residents	0.16	0.17
	(1.50)	(0.40)
	[26860]	[2590]
Detainer Requests per 1k Residents	0.31	0.32
	(2.47)	(0.79)
	[26860]	[2590]
287(g) Participant (2015)	0.01	0.04
	(0.11)	(0.19)
	[2164]	[309]
ICE Detention Contract (2015)	0.06	0.09
	(0.23)	(0.28)
	[2164]	[309]
ICE Interrogation (2015)	0.01	0.01
	(0.07)	(0.10)
	[2164]	[309]
ICE Alerts (2015)	0.97	0.97
	(0.18)	(0.17)
	[2164]	[309]
2017-2018		
ICE Arrests per 1k Residents	0.11	0.10
	(0.83)	(0.21)
	[5372]	[697]
Enforcement Scale (2018)	-0.00	0.01
	(0.22)	(0.29)
	[2686]	[347]
287(g) Participant (2018)	0.02	0.05
	(0.16)	(0.21)
	[2686]	[347]
Sanctuary Sheriff (2018)	0.03	0.04
	(0.16)	(0.19)
	[2686]	[347]

Standard deviation in parentheses. Sample size reported in square brackets. RD sample includes counties in which the Democratic vote share in the race that determined the sitting sheriff ranged between 25% and 75%. Candidates who receive less than 1% of the vote do not count toward the number of candidates.

A.1.5 Compliance Rate for Partisan and Nonpartisan Sheriffs Over Time

Figure A.3: **The Overall Rate of Compliance for Partisan and Nonpartisan Sheriffs, 2006–2015.** Nonpartisan sheriffs were more likely to comply prior to 2010. In 2014 and 2015, the compliance rate dropped dramatically for nonpartisan sheriffs, largely drive by policy change in California which whose sheriffs are elected in nonpartisan races.

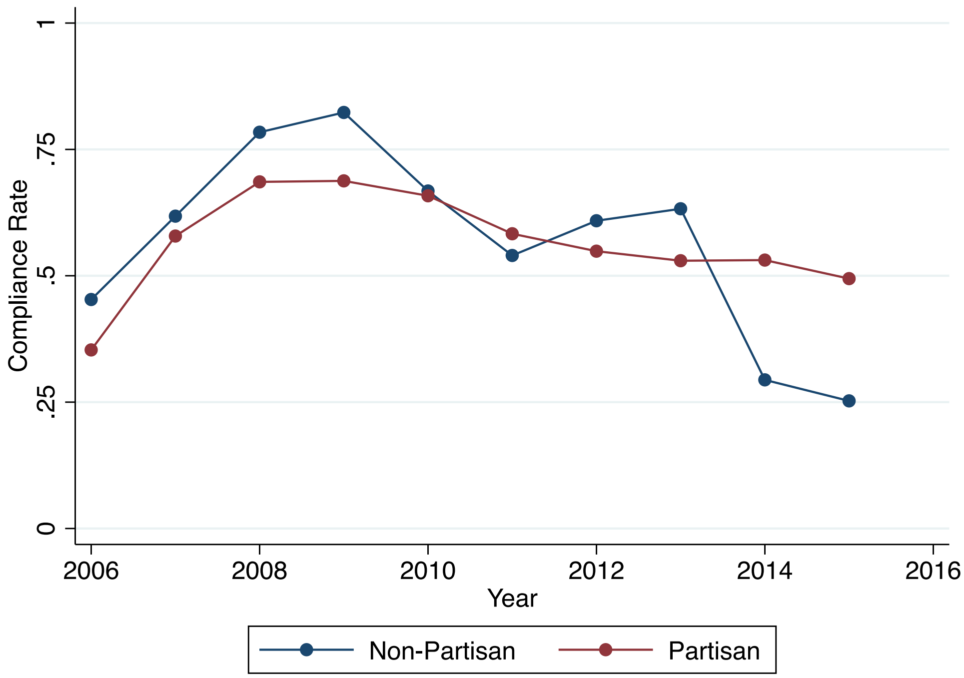


Figure A.3 presents the share of detainer requests sent to sheriffs that resulted detention over time and broken out by partisan and nonpartisan sheriffs. Given the pre-existing differences between states that elect partisan sheriffs and those that do not, I am limited in the causal claims I can make about the institution of partisan sheriff elections. The figure highlights a few interesting patterns, nevertheless. First, the nonpartisan trend drops steeply in 2014. This is largely driven by California which implemented the TRUST act in 2014 requiring sheriffs to limit the cases in which they complied with ICE requests. This is a helpful benchmark, suggesting that compliance is not simply a function of federal policy and that state policy may be able to dramatically change compliance among sheriffs under the right conditions.

A.2 Panel Replication of Main Results

In this section, I present the results of a replication of the main results in the paper using panel regressions rather than a RD design. The panel regressions require a stronger assumption, namely that the counties where the sheriff is from the same party over time were on the same trajectory as counties where the party of the sheriff switched. This assumption pays off in two ways: First, the difference-in-differences design is generally more powerful, reducing the standard errors of the estimate. Second, the estimand is more general than the RDD estimand, allowing researchers to be more confident that the results are not local to a small set peculiar places or points in time.

Across the panel analyses I present, the conclusions are essentially the same as those from the RDD analysis. The main finding continues to be that Democratic and Republican sheriffs comply with detainer requests at essentially the same rate.

A.2.1 Similar Compliance Rate Despite Change in Party of Sheriff

Table A.4 presents a set of difference-in-differences estimates of convergence. The first column reports the estimate from a simple two-way fixed effects estimator with year and county dummies absorbed. The second column includes interactions between year and census region dummies, permitting within-county and within-region-and-year comparisons. The third column presents results from a regression in which the year dummies are interacted with quartiles of county population. The fourth column reports results from a regression in which the year dummies are interacted with region and population quartile dummies. Columns five through eight mimic columns one through four but adjust for county-specific time trends.

Across all of these specifications, the results are largely the same, ranging from a Democratic sheriffs complying 3-percentage-points less to 1-percentage-point less. These effects are all substantively quite small, and all of the confidence intervals overlap zero.

Table A.4: **Effect of Dem Sheriff on Detainer Compliance Rate**

	Detainer Compliance Rate							
Dem Sheriff	-0.03	-0.02	-0.02	-0.02	-0.01	-0.01	-0.01	-0.01
	(0.03)	(0.03)	(0.03)	(0.03)	(0.04)	(0.04)	(0.04)	(0.04)
N	4500	4500	4499	4490	4500	4500	4499	4490
Counties	785	785	785	785	785	785	785	785
County FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	N	N	N	Y	N	N	N
Region-by-Year FE	N	Y	N	N	N	Y	N	N
Pop Quartile-by-Year FE	N	N	Y	N	N	N	Y	N
Pop Quartile-by-Region-by-Year FE	N	N	N	Y	N	N	N	Y
Linear County Trends	N	N	N	N	Y	Y	Y	Y

Robust standard errors clustered by county in parentheses. The reported estimates come from regressions on the full sample of counties with available election results.

A.2.2 Similar Flow of Detainer Requests Despite Change in Party of Sheriff

The effects presented in Table A.5 mimic those in Table A.4 but change the outcome to focus on the behavior of ICE in response to the election of a Democrat. As before, the effects here are substantively quite small and all of the confidence intervals overlap zero. As we found before, this suggests that ICE is not strategically responding to the party of the sheriff by reducing or increasing the number of requests.

Table A.5: **Effect of Dem Sheriff on Number of Detainer Requests per 1,000 Residents**

	Requests per 1,000 Residents							
Dem Sheriff	-0.01	-0.03	-0.01	-0.05	-0.01	-0.02	-0.02	-0.04
	(0.04)	(0.05)	(0.04)	(0.05)	(0.05)	(0.05)	(0.05)	(0.06)
N	6170	6170	6170	6155	6170	6170	6170	6155
Counties	1013	1013	1013	1013	1013	1013	1013	1013
County FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	N	N	N	Y	N	N	N
Region-by-Year FE	N	Y	N	N	N	Y	N	N
Pop Quartile-by-Year FE	N	N	Y	N	N	N	Y	N
Pop Quartile-by-Region-by-Year FE	N	N	N	Y	N	N	N	Y
Linear County Trends	N	N	N	N	Y	Y	Y	Y

Robust standard errors clustered by county in parentheses. The reported estimates come from regressions on the full sample of counties with available election results.

A.2.3 Similar Number of Detentions Despite Change in Party of Sheriff

The effects presented in Table A.6 also follow those in Table A.4 but change the outcome to be something measured for all counties regardless of whether the county received any requests. As we saw before, the results suggest that Republicans are not meaningfully more likely to produce detentions for ICE than Democratic sheriffs.

Table A.6: **Effect of Dem Sheriff on Number of Detentions per 1,000 Residents**

	Dententions per 1,000 Residents							
Dem Sheriff	-0.01 (0.03)	-0.03 (0.03)	-0.01 (0.03)	-0.03 (0.03)	-0.00 (0.03)	-0.01 (0.03)	-0.01 (0.03)	-0.02 (0.03)
N	6170	6170	6170	6155	6170	6170	6170	6155
Counties	1013	1013	1013	1013	1013	1013	1013	1013
County FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	N	N	N	Y	N	N	N
Region-by-Year FE	N	Y	N	N	N	Y	N	N
Pop Quartile-by-Year FE	N	N	Y	N	N	N	Y	N
Pop Quartile-by-Region-by-Year FE	N	N	N	Y	N	N	N	Y
Linear County Trends	N	N	N	N	Y	Y	Y	Y

Robust standard errors clustered by county in parentheses. The reported estimates come from regressions on the full sample of counties with available election results.

A.3 Extension of Convergence Estimates to 2017 and 2018

A.3.1 Data on Sheriff Immigration Enforcement, 2017 and 2018

One concern I addressed in the paper is whether convergence is local to times when a Democrat is president. In order to tease this out I gathered two additional datasets: one on ICE arrests, and one on policies selected by the sheriff that relate to immigration enforcement. The arrests data come from TRAC, run from October 2014 to May 2018, and include the total of arrests made by ICE in a local jail by county and year. Unlike the detainer data, I cannot exclude city jails in this data, I cannot tell which arrests began with a detainer request, and I do not know the number of requests sent to these facilities.

The enforcement policy data come from two sources. First, I scraped a list of all participants in 287(g) in 2018 using archived copies of the ICE website in the Wayback Machine.[22] 287(g) is a program through which ICE grants local police officers and sheriffs the authority to behave as an ICE officer. I then limited this list to participating sheriffs. Second, I collected a list of all the sheriffs identified by the anti-immigration advocacy organization Federation for American Immigration Reform (FAIR) as overseeing sanctuary policies.[23] Putting these two lists together, I construct an enforcement scale in which 287(g) counts as a 1, sanctuary status counts as a -1, and sheriffs participating in neither are counted as 0s.

A.3.2 Infeasible to Test for Convergence in ICE Arrests from 2017 and 2018

For the analysis of arrests, I total up the number of arrests from 2014 through 2016 by county as well as all arrests in 2017 and 2018. I then focus on places with competitive sheriff races in 2016. This allows me to use the 2014 through 2016 data as a pre-treatment measure of arrests and net out the ICE arrests driven by factors other than the sheriff in some specifications following the approach I used in the main analysis.

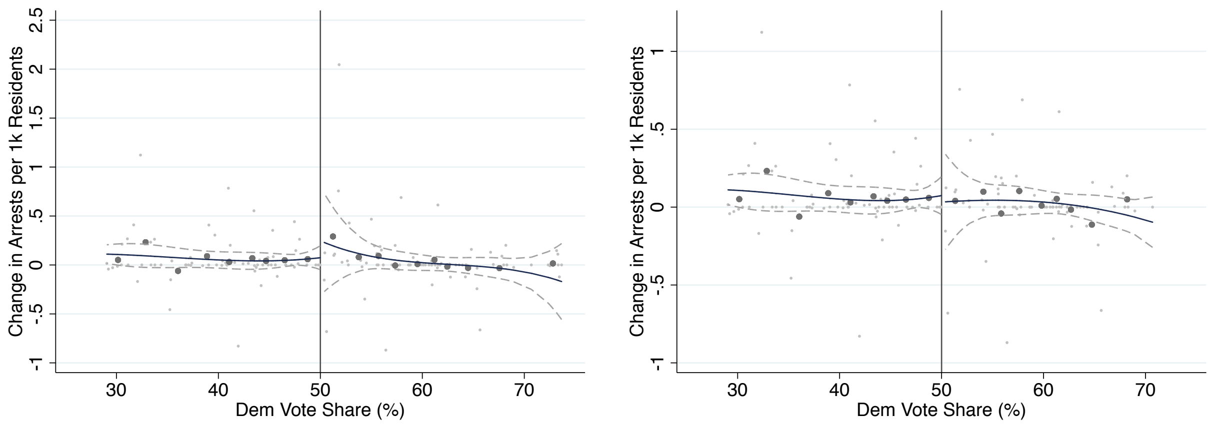
This analysis, first presented graphically in Figure A.4 and then formally in Table A.7, suggests that the effect of electing a Democratic versus Republican sheriff on ICE arrests in 2017 and 2018 is not large enough to be detected in the data. This does not mean that there is no effect or that it is small. In fact, the difference at the threshold stands out as quite large relative to the natural variation of changes in the arrests per 1,000 residents. A key contributor to this estimated difference is Oklahoma County, OK, which barely elected a Democratic sheriff in 2016 and also had a dramatic increase in ICE arrests in 2017 and 2018. According to contemporaneous local reporting based on data from a source separate from the data I am using,[24] the number of detainer requests sent to the Oklahoma County jail increased from 109 to 746 in 2017. This single case appears to be driving the results. When I remove this case, as I do in the figure on the right, Republicans and Democrats appear to lead counties in which ICE arrests a similar number of undocumented migrants. If this is simply irregular behavior by ICE, or a type of action they took independent of the party of the sheriff, a larger number of cases would make that clear and this outlier would not make it difficult to draw meaningful inferences. But, given this data challenge, it is impossible to

[22] `https://archive.org/web/`

[23] The details behind FAIR's measure are described and documented at http://fairus.org/sites/default/files/2018-05/Sanctuary-Report-FINAL-2018.pdf. In most cases, they describe a county as a sanctuary when the county has a stated policy against complying with some form of detainers, but this information occassionally comes from sources other than the sheriff themselves.

[24] `https://newsok.com/article/5583647/immigration-arrests-holds-increase-in-wake-of-enforcement-priority-shift`

Figure A.4: **Electing a Democratic or Republican Sheriff Does Not Meaningfully Effect ICE Arrest Rates, 2017-2018.** Each of the large dots represent binned averages of the underlying data. The small dots are the raw data. The blue line comes from a third-order polynomial regression of compliance rate on Democratic vote share fit separately for counties with Democratic and Republican winners. A plot with all counties with competitive elections included is on the left. A plot excluding Oklahoma County, OK is on the right.



rule out meaningful differences between Republican and Democratic sheriffs in terms of the number arrests made in 2017 and 2018.

Further, ICE arrests are determined in equilibrium. In the same way that Democratic and Republican sheriffs at the 50-50 threshold could take different actions and end up with the same compliance rate due to strategic changes by ICE, the number of arrests could be similar for Democrats and Republicans at the 50-50 threshold because of strategic choices made by both the sheriffs and ICE. I cannot tease out these types of strategic adjustment without additional data on ICE's behavior. In order to focus on the choices sheriffs make more directly in this 2017-2018 period, I turn to data on the policy choices they make.

A.3.3 Sheriff Immigration Enforcement Policies in 2018 Are More Consistent with Convergence than Meaningful Divergence

In Table A.8, I present estimates of convergence in terms of the immigration enforcement scale I constructed from sheriff policies active in 2018. I also present results for each of the policies that go into the scale. The point estimates that suggest Democrats may score slightly lower on the score at the 50-50 threshold. The estimates range from -0.08 to 0 or approximately -0.3 to 0 standard deviations. The theoretically feasible effects range from -2 to 2, but more than 90% of sheriffs choose neither 287(g) nor sanctuary. More sheriffs could choose to offer sanctuary or opt into 287(g), but if we take the population participation rates as given and assume only Democrats offer sanctuary and only Republicans join 287(g), this full divergence would produce average effects of around -0.15. Four of my five estimates are closer to complete convergence than the divergence scenario I laid out, and two of them have confidence intervals that do not include the full separation effect. All of this evidence is consistent with convergence, though it is only suggestive.

As a more formal check of this logic, I switch to an explicitly Bayesian framework. I define two alternative models: Model 0 in which policy selection is independent of party, and Model 1 in which only Democrats select sanctuary policies and only Republican join 287(g). Across both

Table A.7: **Effect of Democratic Sheriff on ICE Arrests, 2017 and 2018.** During the first two years of a new Republican presidency, ICE arrested a similar number of migrants in similar counties when represented by Democratic sheriffs or Republican sheriffs.

	Arrests per 1,000 Residents								
Dem Sheriff Win	0.72 (0.29)	0.52 (0.23)	0.80 (0.38)	0.63 (0.29)	0.30 (0.23)	0.23 (0.17)	0.33 (0.29)	0.28 (0.22)	0.74 (0.32)
N	78	159	159	159	78	159	159	159	80
Deg of Running Var Func	1	3	3	5	1	3	3	5	CCT
Spline	Y	N	Y	N	Y	N	Y	N	Y
Lagged DV	N	N	N	N	Y	Y	Y	Y	N
Bandwidth	10	25	25	25	10	25	25	25	10

Robust standard errors clustered by election in parentheses. The reported estimates come from regressions on the full sample of elections held between a Republican and a Democrat. Spline means that the regression is run separately on both sides of the cut point between a Republican and Democratic win. Lagged DV refers to the inclusion of the lagged dependent variable.

models, I hold constant the average participation rate in 287(g) and the share of counties operating as sanctuaries, meaning that the only thing that changes is where the probabilities of participation are independent of party or not. I then estimate the probability that the effect I observe arises from each model beginning with a prior that these are the only two possible descriptions of the world and both are equally likely. Formally, I define

$$Z \sim \pi$$
$$f(\tau) = (1-\pi) f_0(\tau) + \pi f_1(\tau)$$

where f_0 is the density under Model 0 and f_1 is the density under Model 1. This implies that

$$P(Z=0|\tau=\hat{\tau}) = \frac{(1-\pi) f_0(\hat{\tau})}{(1-\pi) f_0(\hat{\tau}) + \pi f_1(\hat{\tau})} = \frac{1}{\frac{\pi}{1-\pi}\frac{f_1(\hat{\tau})}{f_0(\hat{\tau})} + 1} = \frac{1}{\frac{\pi}{1-\pi}\frac{1}{LR} + 1}$$

where $\hat{\tau}$ is the estimated treatment effect under the RDD and LR is the likelihood ratio of the effect under the alternative models. I calculate this likelihood ratio by simulating the empirical distribution each RDD estimator under the two models, calculating the mean and variance of these empirical distributions, and using a normal approximation to these distributions to extract the density at the value of the estimated effect. Table A.9 reports the probability estimates derived from plugging in the estimated likelihood ratio and my prior.

I find that the effects are generally much more consistent with complete convergence with the probability ranging from 44% to 80%.

Table A.8: **Effect of Dem Sheriff on Stated Policies in 2018**

	Effect by Policy				
Enforcement Scale [-1, 1]	-0.05	-0.08	-0.00	-0.05	-0.01
	(0.06)	(0.05)	(0.07)	(0.06)	(0.05)
287(g) [0, 1]	-0.05	-0.06	0.00	-0.04	-0.00
	(0.05)	(0.04)	(0.06)	(0.04)	(0.05)
Sanctuary County [0, 1]	-0.01	0.02	0.00	0.01	0.01
	(0.04)	(0.04)	(0.04)	(0.04)	(0.03)
N	188	347	347	347	183
Deg of Running Var Func	1	3	3	5	CCT
Spline	Y	N	Y	N	Y
Bandwidth	10	25	25	25	CCT

Robust standard errors in parentheses. The reported estimates come from regressions on the full sample of elections held between a Republican and a Democrat. Spline means that the regression is run separately on both sides of the cut point between a Republican and Democratic win.

Table A.9: **Probability of No Effect versus Partisan Separation for Trump Era Sheriff Enforcement Policy.** The observed effect of electing a Democratic sheriff on active enforcement policies in 2018 is more probable if all sheriffs were equally likely to participate in any enforcement program than if only Democrats lead sanctuary counties and only Republicans lead 287(g) counties, holding the average participation rate constant across both scenarios.

Regression Degree	Bandwidth	Spline	Estimate	P(Z=0 | Est=b)
1	25	Y	-0.05	0.69
3	25	N	-0.08	0.45
3	25	Y	-0.00	0.77
5	25	N	-0.05	0.67
CCT	CCT	Y	-0.01	0.81

Each cell reports a probability that the correct model is simple partisan separation a likelihood ratio test with either partisan separation or partisan separation and increased intensity as the null hypothesis and no effect as the alternative hypothesis. Partisan separation means that all Democrats have 0% probability of participating in 287(g) and all Republican sheriffs have a 0% probability of leading sanctuary counties. No effect means that Republicans and Democrats have an equal probability of participating in any program. The average participation rate is held constant across programs in each scenario The regressions mirror the .

A.4 Additional Statistical Results

A.4.1 RD Balance Table on Lagged Detainer Compliance Rate

The key assumption behind the regression discontinuity design is that counties that just barely elect a Democrat are just like those that just barely elect a Republican in terms of all things not impacted by the outcome of the election. The best test of this is whether counties on either side of the cutoff were similar in terms of pre-treatment outcomes. I present tests of this in Table A.10.

For elections held early in the study window, like those held in 2004 or 2006, most counties had received no detainer requests before the election, so they are not included in the analysis. This smaller sample means that I have noisier estimates. Across all five estimators, I cannot reject the null of perfect balance. Since the third-order polynomial with a 25% bandwidth results in the best balance, I choose that as my preferred specification for discussion in the body of the paper.

The specifications reported in column one and two, while not meaningfully different from zero given the sampling error, are far enough from zero that it is worth adjusting for these remaining imbalances. Accordingly, I adjust for these imbalances in columns five through eight in the main analysis in the body of the paper.

Table A.10: **Balance on Pre-Treatment Detainer Compliance Rate**

	Pre-Treatment Detainer Compliance Rate				
Dem (All)	0.06	0.07	-0.02	0.02	-0.01
	(0.07)	(0.06)	(0.09)	(0.07)	(0.09)
Dem (Large)	0.03	0.01	-0.05	0.01	-0.19
	(0.08)	(0.07)	(0.10)	(0.08)	(0.11)
N (All)	1007	2041	2041	2041	746
N (Large)	583	1203	1203	1203	301
Elections (All)	264	538	538	538	196
Elections (Large)	155	319	319	319	147
Deg of Running Var Func	1	3	3	5	CCT
Spline	Y	N	Y	N	Y
Bandwidth All (Large)	10	25	25	25	7 (5)

Robust standard errors clustered by election in parentheses. The reported estimates come from regressions on the full sample of elections held between a Republican and a Democrat as well as a subsample of elections held in counties with population greater than 100,000 as of the 2000 Census. Spline means that the flexible regression the outcome on Democratic vote share was fit separately on both sides of 0.

A.4.2 Partisan Convergence in Large vs All Counties

Table A.11 presents the effect of electing a Democratic sheriff on detainer request compliance rates in all counties in the election sample as well as only the counties with more than 100,000 residents as of 2000. One of the challenges to the validity of my main estimates is the fact that counties that receive no request drop out entirely. If ICE responds to Democratic sheriffs by sending fewer requests, some of these counties could drop out of the analysis altogether. Counties with larger populations are, simply by the fact of having more people, more likely to have at least one person ICE seeks to detain in a year. Accordingly, estimates based only on large counties are less likely to be missing in the data even if ICE were changing the number of requests they send.

Table A.11: **Effect of Dem Sheriff on Detainer Compliance Rate**

	Detainer Compliance Rate								
Dem (All)	-0.01	-0.04	-0.00	-0.01	-0.02	-0.03	0.01	-0.00	-0.06
	(0.05)	(0.04)	(0.06)	(0.05)	(0.05)	(0.04)	(0.06)	(0.05)	(0.05)
Dem (Large)	-0.01	-0.05	0.02	-0.01	-0.05	-0.04	-0.03	-0.01	-0.05
	(0.06)	(0.05)	(0.07)	(0.06)	(0.06)	(0.05)	(0.07)	(0.05)	(0.06)
N (All)	947	1894	1894	1894	722	1467	1467	1467	766
N (Large)	605	1237	1237	1237	457	941	941	941	465
Elections (All)	346	688	688	688	257	523	523	523	274
Elections (Large)	209	430	430	430	154	318	318	318	154
Deg of Running Var Func	1	3	3	5	1	3	3	5	CCT
Spline	Y	N	Y	N	Y	N	Y	N	Y
Year-Specific Lag DV	N	N	N	N	Y	Y	Y	Y	N
Bandwidth All (Large)	10	25	25	25	10	25	25	25	8 (8)

Robust standard errors clustered by election in parentheses. The reported estimates come from regressions on the full sample of elections held between a Republican and a Democrat as well as a subsample of elections held in counties with population greater than 100,000 as of the 2000 Census. Spline means that the flexible regression the outcome on Democratic vote share was fit separately on both sides of 0. Year-Specific Lag DV refers to the inclusion of the lagged dependent variable interacted with a fully-saturated set of year-by- election-year dummies.

Table A.12: **Effect of Democratic Sheriff on Detainer Compliance Rate, Post-2012.** Democratic and Republican sheriffs representing similar counties at similar times comply with immigration detainer requests at a similar rate between 2013 and 2015. The estimates are consistent with Democrats complying slightly less than Republicans, but the estimates are also consistent with no difference, and are inconsistent with large differences.

	Detainer Compliance Rate [0,1]								
Dem Sheriff Win	-0.07	-0.07	-0.07	-0.05	-0.07	-0.10	-0.04	-0.06	-0.09
	(0.07)	(0.06)	(0.09)	(0.07)	(0.08)	(0.06)	(0.10)	(0.08)	(0.08)
N	404	810	810	810	376	775	775	775	414
Elections	220	437	437	437	202	414	414	414	225
Deg of Running Var Func	1	3	3	5	1	3	3	5	CCT
Spline	Y	N	Y	N	Y	N	Y	N	Y
Year-Specific Lag DV	N	N	N	N	Y	Y	Y	Y	N
Bandwidth	10	25	25	25	10	25	25	25	10

Robust standard errors clustered by election in parentheses. The reported estimates come from regressions on the full sample of elections held between a Republican and a Democrat. Spline means that the flexible regression the outcome on Democratic vote share was fit separately on both sides of 0. Year-Specific Lag DV refers to the inclusion of the lagged dependent variable interacted with a fully-saturated set of year-by- election-year dummies.

A.4.3 Convergence Similar after 2012

The main analysis estimates differences between Republican and Democratic sheriffs at the 50-50 threshold using all years for which I have data. Assuming the partisan gap is stable over time, this approach maximizes the precision of my estimates. But, there are a few reasons to think the effect may vary over time. One concern is that the politics of local immigration enforcement may have become more partisan in 2012 and 2013 (Gulasekaram and Ramakrishnan 2015). Also, the roll out of Secure Communities was not complete until 2013. In order to test whether convergence is local to the period before 2013, I replicated the main estimates using only data from 2013-2015.

Table A.12 presents the results from the post-2012 analysis. I find that, while the reported effects are slightly more negative that those based on all years, the confidence intervals are much wider and still include zero. While we cannot rule out small amounts of divergence, we can still safely rule out most meaningful levels of divergence.

A.4.4 Partisan Convergence Holds Across Measures of Detentions

In Table A.13, I estimate the effect of electing a Democratic sheriff on the rate of ICE detention from the county's jails. While there appears to be some residual imbalance at the threshold, the effect is consistently close to zero after adjusting for pre-treatment outcomes. This is holds across all three alternative versions of the detention rate.

Table A.13: **Effect of Dem Sheriff on Alternative Versions of Detention Outcomes.** Democratic and Republican sheriffs representing similar counties at similar times oversee jails that provide ICE a similar number of detentions.

	Dem Sheriff Win								
Detentions per 1k Residents	0.11	0.03	0.15	0.09	0.01	-0.00	0.03	0.02	0.11
	(0.07)	(0.06)	(0.09)	(0.07)	(0.04)	(0.04)	(0.06)	(0.04)	(0.09)
Detentions per 1k Foreign Born	4.03	1.32	7.00	3.82	0.76	0.53	1.95	0.86	7.07
	(1.94)	(2.03)	(2.83)	(2.10)	(1.10)	(1.14)	(2.03)	(1.47)	(3.02)
log(Detentions + 1)	0.12	-0.10	0.06	0.01	-0.16	-0.09	-0.05	-0.09	-0.10
	(0.38)	(0.34)	(0.48)	(0.39)	(0.20)	(0.18)	(0.26)	(0.20)	(0.40)
N	1346	2590	2590	2590	1271	2396	2396	2396	-
Elections	460	882	882	882	431	813	813	813	-
Deg of Running Var Func	1	3	3	5	1	3	3	5	CCT
Spline	Y	N	Y	N	Y	N	Y	N	Y
Year-Specific Lag DV	N	N	N	N	Y	Y	Y	Y	N
Bandwidth	10	25	25	25	10	25	25	25	-

Each cell reports an estimate of the effect of electing a Democratic sheriff. Robust standard errors clustered by election in parentheses. The reported estimates come from regressions on the full sample of elections held between a Republican and a Democrat. Spline means that the flexible regression the outcome on Democratic vote share was fit separately on both sides of 0. Year-Specific Lag DV refers to the inclusion of the lagged dependent variable interacted with a fully-saturated set of year-by- election-year dummies.

A.4.5 Similar Number of Requests Across Threshold Holds Across Measures of Requests

One concern that arises with the main analysis is that the ICE may be strategically adjusting the number requests it sends to sheriffs in response to changes in the compliance rate. I report one test of this possibility in the body of the paper, but the results are noisy. In Table A.14, I present estimates of the effect of electing a Democratic sheriff on the number of detainer requests ICE sends to sheriffs. The effects on detainer requests per 1,000 residents are generally close to zero. Once I adjust for the pre-treatment request rate, the remaining imbalance and noise goes away, and it becomes clear that the effect is null. A similar pattern shows up in the second row when estimating the effect on the number of requests per 1,000 foreign born residents. Given the number of counties with small foreign born populations, the estimates are quite noisy and suggest an increase in requests for counties in which Democrats win a narrow victory. This appears to be due to imbalance at the threshold and goes away when I adjust for pre-treatment request rates. Estimates of the effect on log(requests + 1) are similar though harder to interpret since the large number of counties with no requests in a given year means that I cannot simply take the log of requests.

Table A.14: **Effect of Dem Sheriff on Alternative Versions of Detainer Requests.** Democratic and Republican sheriffs representing similar counties at similar times oversee jails that receive a similar number of detainer requests.

	Dem Sheriff Win								
Requests per 1k Residents	0.12	-0.02	0.22	0.09	-0.02	-0.02	0.01	-0.02	0.16
	(0.11)	(0.12)	(0.16)	(0.12)	(0.06)	(0.06)	(0.09)	(0.07)	(0.15)
Requests per 1k Foreign Born	5.27	0.59	10.01	4.60	0.47	0.85	2.10	0.94	10.50
	(2.71)	(3.72)	(4.33)	(3.07)	(1.53)	(1.50)	(2.66)	(1.95)	(4.25)
log(Requests + 1)	0.20	-0.06	0.17	0.07	-0.10	-0.03	-0.06	-0.08	0.02
	(0.40)	(0.36)	(0.51)	(0.41)	(0.20)	(0.18)	(0.27)	(0.21)	(0.42)
N	1346	2590	2590	2590	1271	2396	2396	2396	-
Elections	460	882	882	882	431	813	813	813	-
Deg of Running Var Func	1	3	3	5	1	3	3	5	CCT
Spline	Y	N	Y	N	Y	N	Y	N	Y
Year-Specific Lag DV	N	N	N	N	Y	Y	Y	Y	N
Bandwidth	10	25	25	25	10	25	25	25	-

Robust standard errors clustered by election in parentheses. The reported estimates come from regressions on the full sample of elections held between a Republican and a Democrat as well as a subsample of elections held in counties with population greater than 100,000 as of the 2000 Census. Spline means that the flexible regression the outcome on Democratic vote share was fit separately on both sides of 0. Year-Specific Lag DV refers to the inclusion of the lagged dependent variable interacted with a fully-saturated set of year-by- election-year dummies.

A.4.6 Effect of Democratic Sheriff on Contributors to the Number of Requests

As presented in Figure 1, a number of decisions must be made by ICE and sheriffs for someone to ultimately be detained and deported. I gathered data on each of these decisions. In Table A.15, I report the effect of electing a Democratic sheriff on the number of cases that pass each decision point. I find no meaningful effect of electing a Democrat on any of these outcomes.

Table A.15: **Effect of Dem Sheriff on Number of Detainer Requests**

	Contributors to Num of Requests				
	BG Checks	Imm BG Checks	No Requests	Num Requests	Num Comply
Dem (All)	-839.79	-0.66	-0.17	10.01	7.00
	(728.41)	(10.79)	(0.11)	(4.33)	(2.83)
Dem (Large)	109.69	-3.36	-0.07	2.19	2.21
	(292.22)	(5.39)	(0.08)	(2.49)	(1.66)
N (All)	1162	1162	2590	2587	2587
N (Large)	462	462	1420	1420	1420
Counties (All)	593	593	882	881	881
Counties (Large)	239	239	460	460	460
Deg of Running Var Func	3	3	3	3	3
Spline	Y	Y	Y	Y	Y
Bandwidth	25	25	25	25	25

Robust standard errors clustered by election in parentheses. The reported estimates come from regressions on the full sample of elections held between a Republican and a Democrat as well as a subsample of elections held in counties with population greater than 100,000 as of the 2000 Census.

A.4.7 Effect of Democratic Sheriff on Compliance Rate by Most Serious Crime

In Table A.16, I report the effect of electing a Democratic sheriff on the compliance rate with requests for different types of immigrants. The first column simply replicates the main finding from the body of the paper. The second through fifth columns report the effect on the rate at which a sheriff complies with detainer requests for immigrants who are not convicted of any crimes, convicted of misdemeanors, convicted of non-aggravated felonies (serious but nonviolent offenses), and aggravated felonies (murder, rape, drug or human trafficking, etc.), respectively. The results are noisy, but are consistent with the main convergence result.

Table A.16: **Effect of Dem Sheriff on Detainer Compliance Rate**

	Detainer Compliance Rate				
	All	No Crime	Misd.	Non-Agg Felony	Agg Felony
Dem (All)	-0.00	-0.03	0.06	0.02	0.02
	(0.06)	(0.09)	(0.07)	(0.07)	(0.07)
Dem (Large)	0.02	0.00	0.05	-0.02	0.00
	(0.07)	(0.09)	(0.08)	(0.08)	(0.08)
N (All)	1894	1472	1285	976	1236
N (Large)	1237	966	885	765	898
Counties (All)	688	535	491	398	479
Counties (Large)	430	335	318	289	324
Deg of Running Var Func	3	3	3	3	3
Spline	Y	Y	Y	Y	Y

Robust standard errors clustered by election in parentheses. The reported estimates come from regressions on the full sample of elections held between a Republican and a Democrat as well as a subsample of elections held in counties with population greater than 100,000 as of the 2000 Census.

A.4.8 Effect of Democratic Sheriff on Stated Policies

Drawing on data from the Immigrant Legal Resource Center (ILRC), I estimate the effect of electing a Democratic sheriff on the stated policies in the county. The policies I include in the analysis are, from column one to column four, not having a 287(g) agreement with ICE, not having a detention contract with ICE, not alerting ICE about inmate release, and limits on ICE interrogations in the jail. In some counties, these policies are already set by the state and cannot be impacted unilaterally by a sheriff. The surveyed states and counties about policies in 2015, gathering only a snapshot in time of the policies.

Table A.17 presents the results. The results are noisy, but in row one and columns one a two, where the estimates are more precise, I estimate effects of electing a Democratic sheriff that are close to zero.

Table A.17: **Effect of Dem Sheriff on Stated Policies**

	Policy			
	No 287(g)	No Detention	No Alerts	Interog Limits
Dem (All)	-0.04	0.00	-0.01	0.02
	(0.04)	(0.05)	(0.10)	(0.01)
Dem (Large)	-0.08	0.04	0.20	0.04
	(0.11)	(0.15)	(0.18)	(0.04)
N (All)	309	309	309	309
N (Large)	144	144	144	144
Deg of Running Var Func	3	3	3	3
Spline	Y	Y	Y	Y
Bandwidth	25	25	25	25

Robust standard errors clustered by election in parentheses. The reported estimates come from regressions on the full sample of elections held between a Republican and a Democrat as well as a subsample of elections held in counties with population greater than 100,000 as of the 2000 Census.

A.4.9 Effect of State Policy on Convergence

Alabama, Arizona, Colorado, New Hampshire, Ohio, South Carolina, and Virginia passed laws that constrained the role a sheriff plays in the cooperative with ICE. I use these states (with the exception of New Hampshire and Virginia which are not in my data) to estimate the effect of state-level constraints on sheriff divergence. Table A.18 presents the results. My prefered specification, a triple differences approach, is reported in column 4. I find little evidence that state-level policy plays an important role in producing the convergence I observe.

Table A.18: **Effect of Dem Sheriff on Compliance Rate, State Detainer Policy vs No Policy**

	Detainer Compliance Rate			
Dem X Sate Policy	0.04	0.03	0.03	0.01
	(0.03)	(0.03)	(0.03)	(0.06)
Dem	-0.07	-0.06	-0.04	-0.03
	(0.01)	(0.01)	(0.01)	(0.03)
State Policy	-0.02	-0.02	-0.01	0.02
	(0.02)	(0.02)	(0.02)	(0.04)
Counties	852	852	852	852
N	4567	4567	4567	4567
Year FE	N	Y	Y	Y
County FE	N	N	N	Y
County Controls	N	N	Y	N

Robust standard errors clustered by county in parentheses. The reported estimates come from counties with sheriff term limits in Colorado, Indiana, and New Mexico.

A.4.10 Effect of Electing Democratic Representative on Sanctuary Policy Roll Call Votes

In table A.19, I report the formal statistical results that accompany Figure 3 from the body. Replacing a Republican member of the US House with a Democrat results in a large drop in the probability that the representative will vote for measures that punish local sanctuary policies. In all four columns, I estimate a third order polynomial regression separately on both sides of the threshold using elections in which the Democrat received between 25% and 75% of the vote.

Table A.19: **Effect of Dem House Member on Anti-Sanctuary Voting**

	Anti-Sanctuary Vote			
	2007	2012	2013	2017
Dem	-0.25	-0.51	-0.44	-0.88
	(0.17)	(0.15)	(0.15)	(0.10)
N	311	332	309	246
Deg of Running Var Func	3	3	3	3
Spline	Y	Y	Y	Y

Robust standard errors in parentheses. The reported estimates come from regressions on the full sample of elections held between a Republican and a Democrat.

A.4.11 Sheriff Campaign Donation Analysis

In table A.20, I report the average difference between CF Scores for Republican and Democratic sheriff candidates. The first column presents the simple difference. The second column presents the average difference between Democrats and Republicans running in the same county. The third column presents the average difference when the Republican and Democrat are running against one another in the same election. The CF Scores are likely quite imprecise estimates of the sheriff candidate's underlying preference for certain type of candidates in some cases, given how few donations many of the sheriff candidates make. Yet, it is valuable to note that Democrats make donations that place them noticeably to the left of Republicans.

Table A.20: **Differences in CFScore from Sheriff's Personal Political Contributions by Party.**

	CFScore		
Dem	-1.43	-1.46	-1.55
	(0.03)	(0.08)	(0.07)
N	1186	1053	256
County FE	N	Y	N
Election FE	N	N	Y

Robust standard errors in parentheses.

A.5 Details for Mechanisms Analyses

A.5.1 Votes Used in the US House Analysis

In my analysis of roll call votes in the US House of Representatives, I draw on four votes:

- 2007, House Vote 485: Amendment on an appropriations bill blocking federal resources from going to localities that fail to share requested information on the immigration status of people they know to be unauthorized.
- 2012, House Vote 366: Amendment to a DHS appropriations bill restricting the use of fund for terminating the 287(g) program which facilitates cooperation between ICE and local law enforcement agencies.
- 2013, House Vote 195: Amendment to a DHS appropriations bill that would strike \$43,592,000 in funding for the 287(g) program and send 10% of that amount to the Office of Civil Rights and Civil Liberties.
- 2017, House Vote 342: A bill known as Kate's Law that would take numerous measures to penalize local and state governments for enacting a variety of sanctuary policies.

A.5.2 Questions Used in the CCES Analysis

In my analysis of within-county partisan differences in immigration-related policy views, I drew on five questions:

- 2006 (1): Another issue is illegal immigration. One plan considered by the Senate would offer illegal immigrants who already live in the U.S. more opportunities to become legal citizens. Some politicians argue that people who have worked hard in jobs that the economy depends should be offered the chance to live here legally. Other politicians argue that the plan is an amnesty that rewards people who have broken the law. What do you think? If you were faced with this decision, would you vote for or against this proposal?
- 2010 (2), isolating responses to the fifth bullet: What do you think the U.S. government should do about immigration? Select all that apply.
  - Fine Businesses
  - Grant legal status to all illegal immigrants who have held jobs and paid taxes for at least 3 years, and not been convicted of any felony crimes.
  - Increase the number of guest workers allowed to come legally to the US.
  - Increase the number of border patrols on the US-Mexican border.
  - Allow police to question anyone they think may be in the country illegally.
  - None of these.
- 2012 (3): What do you think the U.S. government should do about immigration? Select all that apply. Deny automatic citizenship to American-born children of illegal immigrants.
- 2012 (4): What do you think the U.S. government should do about immigration? Select all that apply. Prohibit illegal immigrants from using emergency hospital care and public schools.
- 2014 and 2016 (5): What do you think the U.S. government should do about immigration? Select all that apply. Identify and deport illegal immigrants.

A.5.3 Questions Used in the Joint CCES and Sheriff Analysis

I use two items from the CCES for the joint CCES and sheriff analysis. They come from a single question in which the survey begins:

"What do you think the U.S. government should do about immigration? Select all that apply." I analyze whether the respondent agreed or disagreed with two policies:

- Increase the number of border patrols on the US-Mexican border.
- Allow police to question anyone they think may be in the country illegally.

The questions I use from Farris and Holman (2017) are

- Federal spending on tightening border security and preventing illegal immigration should be increased.
- In routine patrols, law enforcement should be allowed to inquire about a person's citizenship status.