METHODOLOGICAL APPENDIX

A Short Note on Statistical Significance

In all the analyses (see below), I've taken something of a heretical view on statistical significance: I don't care that much about it. This has nothing to do with any of the discussions about null hypothesis testing, *p*-hacking, or similar issues roaring through some bruising scholarly debates about the scientific soundness of quantitative analyses. It has everything to do with the fact that comparative state-level analyses of the sort I do throughout the book do not really fit into the logic behind traditional statistical significance testing. The traditional approach of analyzing 50-state data as if the key task is to estimate population parameters from sample data using null hypothesis testing makes no statistical sense at all. An analyst can readily generate a population parameter from population data, and that's basically what we have in the analyses discussed below. In that case, worrying about the probabilities of whether the null hypothesis would hold up in some alternate sampling universe seems not just pointless, but senseless.[1] Comparative state politics scholars have tried to make exactly this point on numerous occasions, but tradition—not to mention reviewers and editors—have insisted that we go on reporting *p* values as if they were actually meaningful ("all hail $p < .05$" is about as close to a religious catechism that social science has). For those clutching frequentist pearls over the thought of regression tables with asterisks, don't worry, I've included them. Just be warned that I haven't paid that much attention to them.

What I have paid attention to is estimator variation, because this most definitely is important. This attention is most sustained in the chapter 4 analyses, where I ran something like 100,000 regressions just so I could examine the distributions of individual predictors over a massive range of alternate model specifications. I went to that extreme in Chapter 4 because the theoretical stakes there are highest—there are huge, ongoing debates about what drove the mass incarceration phenomenon and I didn't want to put a thumb on the scale for any of them (parameter values are dependent on model specification, and these can vary dramatically with even fairly modest specification changes in model specification).[2] As I say in the text, I wanted the variables representing these alternate theoretical claims to duke it out on their own. While not always going to the trouble of extreme bounds analysis, at a minimum for most other analyses I tried to at least generate a range of estimators using varying estimation approaches with varying underlying assumptions. This was simply an attempt to see what predictors look stable and what predictors go wobbly when the assumptions change. And, yes, I've also had an eye on the traditional standard error, not in sense of hoping it gets across some desirable minimum relative to the coefficient estimate (all hail $p < .05$!), but just to get a rough sense of how much trust to invest in an inference. I've gone to some pains in the text to acknowledge that all my statistical models—like everyone else's—are almost certainly wrong in some sense. The world is a complex place and capturing it in even broad strokes within a statistical model in a meaningfully useful way is not easy. The argument that my statistical analyses can be treated as useful and taken seriously is predicated on nothing more—and nothing less—than a claim that I've used the data and applied the methods fairly and transparently. If I somehow completely missed something and failed to do that, I'm hoping the safety net provided—making the data and code available to anyone who wants to dig in—will ensure appropriate corrections surface at some point.

CHAPTER 4 ANALYSES

Table S4.1 reports the summary results of an extreme bounds analysis (EBA) for a series of cross sectional (OLS) models where the dependent variable is state-level incarceration rates. The EBA was set up so that for each year models were iteratively estimated using 10 predictors—this number was chosen as a maximum because it seemed reasonable given the number of degrees of freedom available (N = 50 for each individual regression, N = 49 whenever partisan control was included because Nebraska was dropped as it has a non-partisan government). For each year 16,277 regressions were run, which represent all possible combinations of the variables in a 10-predictor model. Violent crime was included in every model (see text), all other variables were iteratively entered through these combinations and were included in 8,100 regressions. The cells in Table S4.1 report the percent of the cumulative distribution function of a variable that is positive. For example, in 1980 violent crime had a positive coefficient in 97.4 percent of the regression models in which it was included, and marijuana legalization was positive in 42.3 percent of the models it was included in. As discussed in the text, the object of this exercise was to see what variables were stable and consistent in a directional sense, i.e., variables that were close to 100 percent (consistently positive) or zero percent (consistently negative) as reported in Table S4.1.

Table S4.2 reports the results of cross sectional (OLS) regressions in each of the years indicated in the first row. The dependent variable is state-level incarceration rates and the independent variables are the eight variables that emerged from the EBA analysis (see Table S4.1) as most stable and robust predictors (see text). Unstandardized coefficients are reported and their associated standard errors immediately below. N = 49; Nebraska is dropped from the analyses because it has no score on the partisan control measure because it has a non-partisan legislature.

Table S4.1: Extreme Bounds Analysis Summary

	1980	**1985**	**1990**	**1995**	**2000**	**2005**	**2010**	Avg
Violent Crime	97.4	97.8	97.9	94.5	61	81	74.5	86.3
Property Crime	95.8	92.4	83.2	76.9	87	87	86.4	86.95714
Marijuana Legalization	42.3	35.6	34.8	15	13	17	10.9	24.08571
Percent Black Male	99.9	97.2	99.1	93.2	98.5	94.6	99.2	97.38571
Percent Young	92.6	80.3	34.3	68.5	85.2	74.8	48.7	69.2
Poverty Rate	70.4	36.2	39	64.2	97.5	94	99.7	71.57143
GINI	47.8	83.6	92.8	90.3	88.2	97.6	91.9	84.6
Partisan Control	7.4	48.8	13.9	20.7	24.4	10.2	10.1	19.35714
Percent Conservative	97.7	86	78	87.3	85.4	92.9	97.5	89.25714
Judicial Selection	91.8	89.3	70	90.33	97.7	96.6	95.4	90.16143
Three Strikes Law	56.9	23.3	10.9	27.7	15.7	14.2	33.8	26.07143
Racial Diversity	77.3	95.2	90.3	98.9	98.1	96.7	84.7	91.6
State Culture	99.9	99.7	97.7	98	94.1	93	97.4	97.11429
Percent Black Legislators	33.4	40.8	74	76.9	79.1	54.4		59.76667
Punitiveness	59	29.3	25.7	52.7	58.3	46.6	80.12	50.24571
Number of Regression Models Run	16277	16277	16277	16277	16277	16277	8177	
Total Number of Regression Models Run								105839

Table S4.3 reports the results of a set of panel models predicting state-level incarcerations between 1980 and 2010. The big difference between the models is the estimation technique used. Traditionally, panel analyses of state-level data boil down to a choice between Random and Fixed Effects estimators as OLS approaches almost always violate assumptions about the error term in regression approaches (tests reported below the table confirm this). Fixed Effects approaches are often considered the “gold standard” fix to these problems, they do so by time demeaning the data by each state and thus capture the within-state variation for analysis.

Table S4.2

	1980	1985	1990	1995	2000	2005	2010
Violent Crime	0.090***	0.123***	0.100*	0.055	-0.061	0.039	0.042
	-0.024	-0.039	-0.05	-0.072	-0.119	-0.112	-0.13
Percent Black Male	4.318*	1.754	8.791**	7.323*	12.351**	5.982	8.437*
	-2.246	-3.333	-3.81	-4.109	-4.839	-4.412	-4.533
Percent Conservative	2.104	2.5	0.061	2.393	4.796	3.61	4.037*
	-1.611	-3.046	-2.238	-3.093	-4.538	-2.748	-2.306
Gini	51.392	194.202	684.019	521.407	489.835	767.733	327.449
	-292.594	-294.90	-512.592	-538.37	-572.489	-513.536	-475.13
Partisan Control	-46.442**	-14.941	-65.233	-70.384	-55.571	-49.906	-48.014
	-21.131	-29.995	-39.319	-52.184	-56.29	-48.908	-49.964
Judicial Selection	8.119	11.11	1.783	45.648	92.296**	72.033*	85.712**
	-13.562	-21.503	-26.669	-34.141	-43.948	-42.196	-41.796
State Culture	8.528**	7.768	8.254	15.000*	14.624	11.356	17.538*
	-3.169	-4.763	-5.667	-7.834	-9.906	-8.912	-9.295
Racial Diversity	20.207	154.23	50.729	294.435**	339.523**	268.827**	140.858
	-78.661	-115.0	-128.204	-133.819	-151.105	-130.539	-143.0
Constant	-42.885	-116.9	-253.434	-284.537	-331.58	-441.598	-205.2
	-132.923	-141.63	-250.923	-292.868	-370.364	-269.977	-282.64
Observations	49	49	49	49	49	49	49
R^2	0.72	0.646	0.678	0.714	0.643	0.65	0.666
Adjusted R^2	0.664	0.575	0.614	0.656	0.572	0.58	0.6
Residual Std. Error (df = 40)	32.56	49.91	61.975	77.609	99.69	93.291	93.707
F Statistic (df = 8; 40)	12.835***	9.125***	10.529***	12.465***	9.006***	9.287***	9.985***
Note:	*p**p***p < .01						

Table S4.3: Panel Models of State-Level Incarceration Rates, 1980–2010

	Between	**Fixed Effects**	**Random Effects**	**First Differences (no lags)**	**First Differences (Lag = t-3)**
Violent Crime	0.072	0.100***	0.107***	0.027**	0.060***
	-0.068	-0.014	-0.014	-0.012	-0.012
Percent Black Male	7.347**	-5.396	4.324*	12.171	-8.167
	-3.384	-4.857	-2.529	-10.173	-10.441
Gini	614.972	251.947***	261.804***	61.215*	54.401
	-540.174	-60.507	-60.151	-36.434	-37.393
Partisan Control	-89.092	-61.777***	-61.488***	-11.159**	-12.965**
	-56.957	-6.57	-6.517	-5.514	-5.659
Percent Conservative	2.097	-0.529*	-0.465*	-0.009	-0.210**
	-2.651	-0.279	-0.277	-0.086	-0.089
Judicial Selection	38.276		55.521**		
	-27.433		-24.773		
State Culture	12.171*		19.391***		
	-6.184		-4.719		
Racial Diversity	202.567	38.487	54.007**	-6.757	79.763***
	-122.403	-28.586	-27.089	-21.869	-22.445
Counter (Year)		9.766***	9.250***		
		-0.404	-0.367		
Constant	-288.411		-188.815***	9.032***	7.764***
	-275.81		-39.076	-0.607	-0.623
Observations	49	1,519	1,519	1,470	1,470
R^2	0.734	0.782	0.78	0.009	0.033
Adjusted R^2	0.681	0.774	0.779	0.005	0.029
F Statistic	13.788*** (df = 8; 40)	751.897*** (df = 7; 1463)	5,344.384***	2.229** (df = 6; 1463)	8.390*** (df = 6; 1463)
Note:	*p < .10 **p <.05, ***p <.01				

Lagrange Multiplier Test for OLS versus Random Effects: 78.56, p <.01 – indicates support for Random Effects over OLS.

Lagrange Multiplier Test for OLS versus Fixed Effects: F = 39.58, df1 = 46, df2 = 1463, p <.01 – indicates support for Fixed Effects over OLS.

Hausman Test for Random versus Fixed Effects: chisq = 11.82, df = 7, p =.10. The p value is borderline here, but by traditional rules of thumb ($p < .05$ required to reject null) this would justify using a random effects model (the null is that Random Effects is the preferred consistent estimator).

The big issue with Fixed Effects is that this data transformation means dropping all time invariant measures. Random Effects allow those time invariant variables to be retained and base estimates on a weighted mean of the between and within estimates. I included a counter variable (i.e., year) in both the Random Effects and Fixed Effects models to pick up any overtime trend that is not accounted for by the variables included in these models.

The difference models consist of annual changes rather than levels, e.g., rather than using the annual data it uses the difference between year t and year t-1. I ran two versions of the differenced models, one with no lags and one where all predictors were lagged three years. The idea here was to construct a model that allowed time for incarceration rates to adjust to changes rather than expecting them to instantaneously respond to a shift in, say, crime rates. The choice of lag length is, admittedly, arbitrary, but is similar to lags used in other studies where lags of 1 to 3 years are typical.[3] I wanted to run differenced models because I'm not entirely convinced these data are stationary. Arguably stationarity is not a huge concern in a series where N (i.e. the number of states) is greater than T (the total years included), and other scholars who have run panel analyses on state-level incarceration rates in roughly comparable time periods have reported Augmented Dickey Fuller tests suggesting state-level incarceration rates are stationary.[4] Stationarity tests I conducted proved maddeningly inconclusive (stationary under some assumptions, non-stationary under others), not hugely surprising as these tests are notoriously under-powered in this sort of N>T situation. Given the possibility—however remote—of hanging inference on spurious regressions (a *very* bad thing), I ran the differenced models because differencing is widely considered the best solution to non-stationary data. There are huge downsides to this. Effectively it means throwing away a lot of information that is awfully useful given my explanatory target, and it also significantly changes interpretation—the differenced models are dynamic models, i.e. models of change across time, and the data transformation involved means ignoring how variation in levels plays into explaining incarceration rates. I also report between estimates, an approach that is rarely reported in published studies. These simply use the state-level averages of the variables for each state for the entire time period—a huge drawback of this procedure is that rather than having N≈1,500 observations you end up with the average of 49 states (Nebraska is missing again because of partisan control), so N=49. In other words, it means throwing out most of the variation in the data in favor of grand averages. I wanted to include this, though, for comparison to the "snapshot" cross-sectional models reported in Table S4.2, which give a sense of the movement across time underlying these grand averages.

The main object in running so many different panel estimation approaches was to get a sense of what predictors consistently punch through under differing sets of assumptions about the nature of the data and the modelling approach, i.e., I wanted to root out robust and stable predictors rather than put all my inference eggs in one basket of assumptions. I should also point out that this far from exhausts the possible estimation approaches—the big two not included are an error correction model and/or or model with a lagged dependent variable. I rejected the former as IMOHO it's overly complicated, or at least hard to explain to a general audience, and it also creates some interpretation issues. The use of ECMs in panel analysis is a topic of considerable debate among methodologists way smarter than me and I'll just let them get on with it. I didn't use the lagged DV approach here because that lag gobbles up a huge proportion of the variance and leaves little for the other variables to get traction on. The lagged DV represents *all* causes of incarceration rates at t-1 and as those causes almost certainly include long term trends this approach basically means ending up with a model that will explain everything and nothing—the lag soaks up huge chunks of the explanatory variance without telling us anything useful (basically it says states with high incarcerations last year have high incarceration rates this year—not exactly a shocker), while leaving the rest of the variables have problems latching onto the variance crumbs left over. I freely acknowledge arguments exist that these or other approaches could/should have been used. In response I would say most published studies that I am aware of rely on one estimation approach rather than the catholic approach adopted here. Tables S4.3 and S4.4 (see below) represent a mix of classic, mainstream, and cutting-edge approaches to panel analysis that collectively represent what I consider to be a defensible platform for the inferences made in the text.

Table S4.4 reports the results of a Between-Within-Idiosyncratic BWI group panel model of incarceration rates. This is a modelling approach for panel data sets suggest by Duxbury.[5] Its big attraction here is that it allows me to assess the impact of a variable between units (here that means states), within units across time, and as a common trend, i.e., a relationship that effects all units similarly across time. It also can incorporate time invariant variables so both state culture and judicial selection can be included. Importantly it does all this simultaneously, i.e., in the confines of a single model. In general terms, what Table S4.4 contains is the output of a model that includes the between and fixed effects estimates as well as pulling out common across-time trends (the latter is more crudely included in the models in Table S4.3 with the counter variable). The BWI model is one of a class of group panel models suggested by Duxbury and the BWI was specifically chosen through the model selection procedure outlined in his article. Decomposing the variance in incarceration rates indicates that ≈47 percent of the variance is among states (see Intraclass correlation coefficients below), ≈12 percent is idiosyncratic to states, with the remaining ≈40 percent attributable to time trends. Auxiliary Hausman tests suggest that Random Effects coefficients might be inconsistent and that a model including idiosyncratic (i.e., within) transformations are preferred. Interestingly, Duxbury's exemplar of model specification and application just happens to be for state-level incarceration rates, so even though my model specifications and time periods are different, it is not too surprising the model selection path set out in his paper leads me straight to an identical estimation approach. Intercepts are being allowed to vary by time and state in this model.

Table S4.4: Between-Within-Common Group Panel Model of Incarceration Rates, 1980–2010

Variable	Coefficient/ Standard Error
Violent Crime (Between)	0.07
	-0.07
Violent Crime (Within)	0.08***
	-0.02
Violent Crime (Common Trend)	0.08
	-0.06
Percent Black (Between)	7.14**
	-3.32
Percent Black (Within)	1.4
	-4.72
Percent Black (Common Trend)	96.33**
	-46.68
Percent Conservative (Between)	2.16
	-2.7
Percent Conservative (Within)	3.35***
	-0.57

Percent Conservative (Common Trend)	-1.05**
	-0.52
Gini (Between)	556.15
	-523.61
Gini (Within)	300.62***
	-74.81
Gini (Common Trend)	528.59***
	-147.99
Partisan Control (Between)	-94.04
	-57.3
Partisan Control (Within)	-39.17***
	-6.56
Partisan Control (Common Trend)	-277.58***
	-38.72
Racial Diversity (Between)	208.15*
	-121
Racial Diversity (Within)	55.59*
	-30.3
Racial Diversity (Common Trend)	480.04***
	-177.83
State Culture	12.49**
	-6.29
Judicial Selection	38.91
	-27.4
Constant	-252.98
	-272.29
Observations	1,519
Log Likelihood	-8,154.20
Akaike Inf. Crit.	16,356.40
Bayesian Inf. Crit.	16,484.22
R-2 Total	.74
R-2 Within	.79
R-2 Time	.99
R-2 Idiosyncratic	.08
R-2 Between	.68
Note:	*p < .10 **p < .05 ***p < .01

Intraclass Correlations Coefficients (ICC) for Incarceration rates:

Between ICC: .47

Idiosyncratic: .12

Time: .40

Hausman Test for Random Effects v. 1-way Fixed Effects: chi squ. 70.58, df = 4, $p < .01$.

Hausman Test for 2-way Fixed Effects v. Random Effects Within Model: chi squ. 344.12, df = 4, $p < .01$

CHAPTER 5 ANALYSES

Table S5.1 reports the results of a series of panel Granger causality tests between state-level incarceration rates and social capital. The alternative hypothesis is Granger causality for at least one state, Z = the standardized test statistic recommended by Dumitrescu and Hurlin.[6] I am using standard statistical significance as a cutoff here—I'm not being consciously hypocritical in light of my soap boxing on *p*-values (see above), this is just how Granger causality tests traditionally work.

Table S5.1 Granger Causality Tests between Incarceration Rate and Social Capital

Lag	**Does incarceration rate Granger cause social capital?**	**Does social capital Granger Cause incarceration rate?**
1	Z = 2.27, $p = 0.02$	Z = 3.03, $p = 0.00$
2	Z = 1.8, $p = 0.06$	Z = 1.08, $p = 0.27$
3	Z = 3.74, $p = 0.00$	Z = 2.24, $p = 0.02$
4	Z = 1.71 $p = 0.08$	Z = 2.52, $p = 0.01$
5	Z = 2.90, $p = 0.00$	Z = 3.30, $p = 0.00$
6	Z = 2.37, $p = 0.01$	Z = 3.24, $p = 0.00$
7	Z = 2.81, $p = 0.00$	Z = 1.23, $p = 0.21$

Table S5.2 reports the results of three OLS regression models (these are just pooled panels) where past values of social capital (t-1) and incarceration rates (t-1, t-2, and t-3) are used to predict current values of social capital (t). The lagged variable of social capital is assumed to be picking up all causes of social capital at t-1 except the lagged incarceration rate variable. The lag is also assumed to be taking care of any big statistical issues that crop up with panel data.[7]

The coefficients for lagged social capital and lagged incarceration rates remains substantively the same regardless of lag length used, so the short run effect seems stable. To calculate the short run effects of incarceration rates on social capital stocks I start by plugging in the means to the model results. For example:

Assuming incarceration rates have no effect (b = 0), estimated social capital = .03 + (.91 * .19) = .20. This is what we'd expect if social capital is simply a product of past values of social capital (and whatever causes it) plus some random error. Assuming lagged incarceration rates do have the effect estimated by the model (b = -.00014), then the model estimates social capital drops to ≈.16 (.03 + (.91 * .19) + (-.00014 * 320.45)). So, if the estimated effect is correct an average incarceration rate lowers estimated social capital by ≈.04—the difference between social capital estimates when assuming that the lagged incarceration rate variable is zero and assuming that the lagged incarceration rate coefficient is valid. That represents a 22 percent decrease in the average social capital score being attributed to incarceration. At 800 inmates per 100,000 population the model estimates social capital at .09, i.e., it effectively predicts social capital in the average state will be cut in half.

The same logic is used to calculate the numbers behind the graph presented in Chapter 5. First, I calculate a 25-, 50-, 75-, and 100-percent increase in the average incarceration rate, which works out to be 400.56, 480.67, 560.78, and 640.9. Then I simply plug those numbers into the regression formula and crank through the calculations to estimate social capital under each of those incarceration rate levels.

It's probably important to underline that everything above is really only calculating the short-term effects of incarceration on social capital. This is because this is essentially a dynamic model where the effect of incarceration rates are also being captured in part by the lagged social capital variable. The long run effect of incarceration rates can be calculated by dividing the incarceration rate coefficient by 1 minus the social capital coefficient. For the mean value of incarceration rates the long run effect on estimated social capital is: (-.00014 / (1 - .914)) * 320.45. That estimate = -.52.[8]

Table S5.2. Predicting Social Capital Using Lagged Incarceration Rates

Variable	**t-1**	**t-2**	**t-3**
Lagged Social Capital	0.918^{***} (-0.009)	0.921^{***} (-0.009)	0.914^{***} (-0.01)
Lagged Incarceration Rate	-0.0001^{**} (-0.0001)	-0.0001^{**} (-0.0001)	-0.0001^{**} (-0.0001)
Constant	0.037^{*} -0.022	0.035 -0.022	0.036 -0.022
Observations	1,248	1,200	1,152
R^2	0.929	0.924	0.917
Adjusted R^2	0.929	0.924	0.917
Residual Std. Error	0.267 (df = 1245)	0.269 (df = 1197)	0.274 (df = 1149)
F Statistic	$8,125.159^{***}$ (df = 2; 1245)	$7,281.497^{***}$ (df = 2; 1197)	$6,350.110^{***}$ (df = 2; 1149)

$^{*}p < .05$

I also want to emphasize that these estimates are for more for expository purposes than supporting any grand claims about the precise impact of incarceration rates on social capital. Unlike the quantitative analyses in other chapters there just are not a ton of well-specified, theoretically grounded statistical models out there for state-level social capital, at least not in the sense of the rich literatures on state-level incarceration rates, economic performance, and political engagement, all of which provide ample guiding baselines for specifying a statistical model. Lacking that, I'm using the blunt instrument of a lagged dependent variable as a sort of super control to try and isolate the effect of incarceration. I'm also aware that given the results of the Granger causality test there’s a reasonable argument that this whole analysis should be set up as a structured equation model or as a set of simultaneous equations. While that might please the methods nerds, those sort of models on panel data raise a host of hairy issues that get in the way of trying to communicate results. I confess I’m falling back on this simpler approach in no small part because it makes exposition easier. As reported in the text, the key inferences drawn from the analyses are that (a) there are reasonable and empirical arguments that higher incarceration rates tend to corrode social capital (and that declines in social capital tend to lead to higher incarceration rates), and that (b) whatever the exact point estimate of incarceration rates on social capital there’s similar grounds to suggest that it is pretty substantive.

CHAPTER 6 ANALYSES

Table S6.1 reports the results of a series of panel models predicting per capita Gross State Product. All monetary variables are adjusted to real dollars using the Berry, Fording, and Hanson state-level consumer price index (see Table S1). Like the models reported in Table S4.3, these models differ only in their estimation approach—see the discussion associated with Table S4.3 for a description of these different approaches. These models (except for the between model) also included time dummies which are not reported. I'm not really worried about stationarity here as the number of cross-sectional units (N = 49 states, Nebraska gets dropped because it has no score on the partisan control variable) is more than double the number of time units (T = 18 years). Unstandardized coefficients are reported with standard errors included directly below. The only model that indicates a positive relationship here is the between model, indicating that overall, per capita GSP is positively associated with the size of a prison population *across* states. In other words, if you just take state averages, a higher average GSP is positively associated with a higher average ex-prisoner population. That relationship flips when variation *within* states becomes the main analytic target. Within states this relationship is clearly and consistently negative—the fixed effects model captures this effect most directly, but the random effects, and even first differences, return extremely similar estimates. Roughly speaking for every percentage point increase in the proportion of the ex-prisoner population per capita GSP drops by approximately $3,000. The central takeaway from these models is that states with higher GSP tend to have higher prison populations (the between model), but increasing prison populations within a state tends to decrease GSP.

Table S6.1: Panel Models of Per Capita GSP, 1980–1997

	Between	**Random Effects**	**Fixed Effects**	**First Differences**
Percent Ex-Prisoners	583.538	-2,856.530***	-3,018.421***	-2,942.552*
	-1380.324	-704.061	-840.19	-1570.134
Taxes as Pct of GSP	-394.072	297.919	239.257	-939.368***
	-717.559	-221.867	-255.473	-139.18
Percent With HS Diploma	123.916	-9.83		
	-82.43	-66.358		
Partisan Control	2743.029	533.029	-749.759	468.966
	-2231.129	-633.832	-657.617	-739.215
Total Deposits	0	0.00002***	0.00002***	0.00001**
	0	0	-0.00001	0
Higher Education Expenditures	2.26	18.138***	30.747***	1.226
	-3.476	-2.094	-2.814	-1.857
Elementary Education Expenditures	-1.406	-2.125**	-2.215**	-0.161
	-3.743	-0.99	-0.995	-0.636
Heath Expenditures	12.878	10.942***	7.275*	22.138***
	-9.347	-3.717	-3.984	-2.487
Welfare Expenditures	-1.533	-6.092***	-5.912***	0.019
	-3.1	-1.088	-1.172	-1.014
Highway Expenditures	-6.205	-3.329**	-1.081	2.895***
	-4.101	-1.63	-1.775	-1.078
1980 Per Capita GSP	0.781***	0.684***		
	-0.117	-0.05		
Constant	2926.911	5190.5		589.252***
	-7155.001	-5247.79		-96.567
Observations	49	882	882	833
R2	0.928	0.602	0.563	0.306
Adjusted R2	0.907	0.589	0.522	0.284
F Statistic	43.307*** (df = 11; 37)	1,291.477***	39.922*** (df = 26; 807)	14.224*** (df = 25; 807)
Note:	**p***p****p* <0.01			

There are just a couple of notes on the other variables. Percent with a high school diploma has no temporal variation in the data I have so this variable gets dropped in the fixed effects and first differences models. The same is also obviously true of 1980 per capita GSP.

Table S6.2 reports the same set of panel models as S6.1 with two big exceptions. The first is the dependent variable. Rather than GSP per capita, the target explanatory variable is the annual percent growth in GSP. The second is that I'm not reporting a first differences model. This is simply because percent growth *is* a difference variable—it expresses an annual change as a percentage—and I worried that first differencing this could lead to difficulties in interpretation. For example, a state that maintains a healthy 5 percent growth rate in consecutive years would have a zero in first differences (5 minus 5 = 0). A state whose economy shrank by three percent in consecutive years would also have a zero (-3 minus -3 = 0). In short, doing this would amount to a sort of second differencing where states in pretty different economic places end up looking the same. As in Table S6.1, year dummies were used for random and fixed effects, and unstandardized coefficients are reported with the associated standard errors immediately below. Though not statistically significant (see note on significance above), the coefficients for the proportion of a state's population that are ex-prisoners echo the results in Table S6.1. The between model indicates above state average GSPs are positively associated with above state average ex-prison populations. As soon as within state variation is introduced, the coefficient flips. The fixed effects model (the most conservative presented) estimates a nearly one-to-one relationship, i.e., that a one percentage point increase in the ex-prison population within a state is associated with roughly a 1 percentage point drop in GSP growth.

Table S6.2: Panel Models of Annual Per Capita GSP Growth, 1980–1997

	Between	**Random Effects**	**Fixed Effects**
Percent Ex-Prisoners	0.418	-0.306	-0.975
	-0.587	-0.429	-0.758
Taxes as Pct of GSP	-0.439	-0.361**	-0.824***
	-0.305	-0.151	-0.23
Percent With HS Diploma	0.057	0.046	
	-0.035	-0.03	
Partisan Control	0.561	1.174**	0.848
	-0.948	-0.468	-0.593
Total Deposits	0	0	0
	0	0	0
Higher Education Expenditures	-0.001	0.002	0.006**
	-0.001	-0.001	-0.003
Elementary Education Expenditures	0.002	0.001	-0.0004
	-0.002	-0.001	-0.001
Heath Expenditures	0.005	-0.001	-0.007*
	-0.004	-0.003	-0.004
Welfare Expenditures	-0.002	-0.002***	-0.003***
	-0.001	-0.001	-0.001
Highway Expenditures	-0.002	-0.003**	-0.003**
	-0.002	-0.001	-0.002
1980 Per Capita GSP	-0.0001	0.00002	
	-0.00005	-0.00003	
Constant	2.018	-0.806	
	-3.04	-2.543	
Observations	49	882	882
R2	0.344	0.365	0.382
Adjusted R2	0.149	0.344	0.326
F Statistic	1.762* (df = 11; 37)	489.393***	19.202*** (df = 26; 807)
Note:	*p**p***$p < 0.01$		

Table S6.3 Reports the results of a Between-Within-Idiosyncratic BWI group panel model of state economies (see discussion of this estimation approach in text accompanying Table S.4.). In the per capita GSP measure, variance is heavily concentrated between states—approximately 50 percent of the variation is between, 18 percent is idiosyncratic (within states), and 32 percent is across time. Of the within variance, 63 percent is idiosyncratic with the rest temporal. In other words, if you look at state economies, you find most differences between states, but with a healthy chunk of differences within states across time, as well as a general trend across time. There's a little different story in the model looking at the annual growth in GSP. In that variable only six percent of the variance is between, a third is temporal, and 60 percent idiosyncratic. Of the within variance, nearly two-thirds is idiosyncratic. In other words, economic growth, or contraction relative to a states' historical per capita GSP is mostly about what's going on within a state across time.

These results, as you'd expect, largely confirm those already reported in Table S6.1 and S6.3. Between estimates indicate higher ex-prisoner populations are positively associated with economic performance. Within estimates are negative (and have a bigger estimated impact). The difference is that common trend estimate. In the per capita GSP model what this is suggesting is that growth in prison populations nationally is associated with a substantial increase in per capita GSP. As time is presumably accounted for (time and year intercepts are being allowed to vary in these models), this is a little puzzling. Within states across time the relationship is clearly negative, but within the nation as a whole the relationship is positive. This is not the case with the annual growth model, where the within and common estimates are both negative (indeed, the common estimate is eye popping). I don't want to over-interpret anything here, and it is quite possible the positive within estimate is a statistical artifact. My case that this isn't just hand waving away contradictory evidence is the consistency of the story coming out of the other models. In other words, I'm genuinely trying to report what the analyses suggest is the rule rather than the exception.

Specifically, I'm interpreting the cumulative weight of evidence presented in Table S6.3, S6.2, and S6.1 as pointing pretty consistently to the inference that between state differences suggest larger ex-prison populations are positively associated with economic performance, but just as consistently to inference that the same relationship is negative within states across time. These analyses and this key inference are what underpin some of the key arguments made in chapter 6.

Table S6.3: Between-Within-Common Group Panel Model of State Economies, 1980–1997

	Per Capita GSP	**Annual GSP Growth (%)**
Percent Ex-Prisoners (Between)	514.638	0.442
	-1370.518	-0.571
Percent Ex-Prisoners (Within)	-3,012.819***	-0.98
	-840.105	-0.757
Percent Ex-Prisoners (Common)	7269.408	-5.873
	-7838.719	-26.007
Taxes as Pct of GSP (Between)	-410.722	0.53
	-605.585	-0.96
Taxes as Pct of GSP (Within)	224.755	0.805
	-255.382	-0.592
Taxes as Pct of GSP (Common)	-1292.389	40.272
	-3790.371	-37.952
Partisan Control (Between)	2656.579	-0.255
	-2304.199	-0.259
Partisan Control (Within)	-744.295	-0.858***
	-657.385	-0.23
Partisan Control (Common)	-6372.374	-18.803
	-11439.12	-12.575
Deposits (Between)	0	0
	0	0
Depositions (Within)	0.00002***	0
	-0.00001	0
Deposits (Common)	0.0001	0
	-0.0002	0
Higher Ed Expenditures (Between)	1.71	-0.001
	-3.496	-0.001
Higher Ed Expenditures (Within)	30.801***	0.006**
	-2.811	-0.003

Higher Ed Expenditures (Common)	-22.897	-0.08
	-36.481	-0.121
Elementary Ed Expenditures (Between)	-0.679	0.002
	-2.877	-0.001
Elementary Ed Expenditures (Within)	-2.262**	-0.0002
	-0.979	-0.001
Elementary Ed Expenditures (Common)	2.482	0.008
	-3.362	-0.011
Health Expenditures (Between)	14.997	0.006
	-11.952	-0.005
Health Expenditures (Within)	6.965*	-0.007**
	-3.972	-0.004
Health Expenditures (Common)	37.266	0.024
	-63.365	-0.21
Welfare Expenditures (Between)	-1.767	-0.002*
	-3.174	-0.001
Welfare Expenditures (Within)	-5.907***	-0.003***
	-1.171	-0.001
Welfare Expenditures (Common)	-0.901	0.03
	-5.638	-0.019
Highway Expenditures (Between)	-6.167	-0.001
	-4.214	-0.002
Highway Expenditures (Within)	-0.995	-0.003**
	-1.773	-0.002
Highway Expenditures (Common)	19.125	-0.001
	-27.151	-0.09
GSP Per Capita 1980	0.757***	-0.00005
	-0.107	-0.00004
Pct Population With HS Diploma	131.686	0.066*
	-85.958	-0.036
Constant	1439.74	-1.004
	-7324.814	-6.334
Observations	882	882
Log Likelihood	-8261.526	-2269.807
Akaike Inf. Crit.	16589.05	4605.613
Bayesian Inf. Crit.	16746.86	4763.425
Note:	*p**p***$p < 0.01$	*p**p***$p < 0.01$

CHAPTER 7 ANALYSES

Table S7.1 reports the results of a series of panel analyses on the state-level outcomes for all presidential contests between 1980 and 2008—I couldn't include later presidential contests because of data availability on the estimates of ex-prisoners. The model specification is drawn directly from DeSart (see discussion in text), I've just added state culture and the percent of a state's population with a prison record. There are some differences that should be noted with the DeSart model, most importantly that I used different polling data (see variable description). This was a purely practical decision based on data availability. While there might be something wrong with my analysis or interpretation, DeSart's model has proven itself capable of being a highly accurate predictor of historical state-level presidential outcomes, which is exactly what I was looking for to isolate the impact of ex-prisoners on those elections.

The use of the previous election's outcome as an independent variable—in other words using the dependent variable at t-1 to predict the dependent variable at t—means these are technically dynamic lagged models. Conceptually, what this means is that the lagged variable is accounting for *all* causes of the previous presidential outcome, and the other estimates are capturing the unique impact of the variables on Democratic vote share above and beyond all those previous causes. In other words, the coefficients represent an estimated effect of a one-unit increase in the independent variable on the change in the dependent variable between time t and t+1. This is thus an estimate of a short term effect; a long rung effect can be recovered by dividing the estimated coefficient by 1 minus the lagged dependent variable. As I've already hinted at in discussions on previous statistical models, there's a whole literature out there debating the merits of lagged dependent variables in panel models and their implications for interpretation and more technical issues such as heteroscedasticity. Last time I checked, those debates were still not fully resolved, and whatever path I take here—or even multiple paths—is likely to end up offending somebody's methodological preferences. What I'm doing is mostly relying on the OLS estimates, even though I'm not panel correcting the standard errors (this is mostly done for statistical testing purposes and see above for my heresy on that front). What I really want to do is use the fixed effects model because that explicitly captures the within state effects, but using lags in fixed effects (and random effects) models is argued by some with way more expertise than me as a big no-no. That pushes me towards the OLS model, which has long-been argued as a good choice for dynamic panel models (i.e., panel models with a lagged dependent variable), even though it arguably violates some key assumptions.[9]

As Table S7.1 shows, there's quite a bit of stability in the coefficients across several modeling approaches, but that unfortunately does not extend to the ex-prisoners variable, which is highly similar in the OLS and random effects models, but much bigger in the fixed effects model. In the between model it's basically zero, but I don't care too much about that—as I explicitly state in the text, what I'm mostly interested in is the within variation. If faith is vested in the OLS coefficient the long term effect of a 1 percentage increase in the ex-prisoner population is an increase of a 1.68 percent in the Democratic presidential candidates voting share (the estimated coefficient is .125, the lagged DV coefficient is .875, so long run effect is .124/ (1-.875) = 1.68). Whether such faith is justified is an entirely different matter. The ex-prisoner coefficient is by traditional standards not statistically significant ($p > .05$), and even by my I've-got-the-population-so-alpha-be-damned approach, there's clearly a lot of potential variation around the estimate. I'm certainly not ruling out the possibility that the actual effect is bupkis as I try to make clear in the text. Again, what I really want to do is trust the fixed effects model, which is designed to explicitly model what happens when ex-prison populations move away from their in state means. That model's result is eye-popping—it suggests that for every 1 percentage point increase in ex-prisoner population the Democratic candidate's vote share increases by nearly 2 percentage points. That is clearly enough to decide elections in swing states. Even though this is the only estimate of ex-prisoners that meets traditional statistical significance thresholds, the fact is I just don't trust it. This isn't just for technical reasons, subjectively it just seems proportionally out of whack. Which is a nice way of saying that even though it provides me with some statistical justification for making an attention grabbing "ex-prisoners decide presidents" claim, there's just not enough consistency across the models for me to crawl out on that limb. The finding is clearly dependent on the assumptions underlying the model and, as I've tried to make clear in previous analyses, I place greater trust in findings that are more consistent and robust regardless of what starting assumptions are made. Again, $p < .05$ sometimes just does not deserve that asterisk.

Table S7.2 reports the results of a series of panel models predicting state turnout in presidential elections between 1980 and 2000.

Note that two states not included in the analyses using voter registration variables—North Dakota does not have voter registration and no data is reported for Wisconsin, which had a liberal same day registration policy for the time period studied. There was also some missing data for 2008, hence 1980–2004 time period (i.e., these are balanced panels where N = 48, T = 7, and N = 336, which contrasts with Table S7.1 which has balanced panels where N = 50, T = 8 and N = 400).

Table S7.1 Ex-Prisoners and Support for Democratic Presidential Candidates

	Between	**OLS**	**Random Effects**	**Fixed Effects**	**First Differences**
Presidential Poll		-0.566***	-0.566***	-0.420***	-0.110***
		-0.035	-0.035	-0.037	-0.042
Dem. Vote Share Prev. Election	1.076***	0.875***	0.875***	0.516***	-0.116**
	-0.025	-0.03	-0.03	-0.048	-0.056
Consecutive Terms		-0.713***	-0.713***	-0.398***	0.525***
		-0.134	-0.134	-0.129	-0.139
Home State	-3.757**	2.957**	2.957**	4.570***	3.768***
	-1.773	-1.183	-1.183	-1.214	-1.079
Percent Ex-Prisoners	0.008	0.206	0.206	1.905***	0.755
	-0.466	-0.394	-0.394	-0.474	-1.648
State Culture	-0.327***	-0.317***	-0.317***		
	-0.068	-0.092	-0.092		
Constant	-1.517	33.072***	33.072***		1.351***
	-1.214	-1.962	-1.962		-0.451
Observations	50	400	400	400	350
R2	0.978	0.732	0.732	0.524	0.174
Adjusted R2	0.976	0.728	0.728	0.449	0.162
F Statistic	506.402*** (df = 4; 45)	178.991*** (df = 6; 393)	1,073.947***	75.852*** (df = 5; 345)	14.532*** (df = 5; 344)
Note:	**p****p*****p* < .01				

Lagrange Multiplier Test for OLS versus Random Effects: -0.23, *p* = .59 – indicates support for OLS over Random Effects.

Lagrange Multiplier Test for OLS versus Fixed Effects: F = 2.31, df1 = 48, df2 = 345, *p* <.01 – indicates support for Fixed Effects over OLS.

Hausman Test for Random versus Fixed Effects: chisq = 111.86, df = 5, *p* < .01. – indicates support for Fixed Effects over Random Effects, but note this is a dynamic model with a lag, so the OLS estimates are arguably the best approach.

Table S7.2: Turnout in Presidential Elections as Percent of Registered Voters, 1980–2004

	Between	**Random Effects**	**Fixed Effects**	**Differences**
Percent Ex-Prisoners	-0.008	-0.035***	-0.029***	0.014
	-0.022	-0.009	-0.01	-0.028
State Culture	-0.001	-0.008**		
	-0.004	-0.003		
Percent With HS Diploma	0.005***	-0.001	-0.003***	-0.001
	-0.002	-0.001	-0.001	-0.001
Days Before Election Req. to Register	0.001	-0.0003	-0.001	-0.0003
	-0.001	-0.001	-0.001	-0.001
Absolute Difference In Pres Polls		-0.002***	-0.003***	-0.001**
		-0.001	-0.001	-0.001
Constant	0.280*	0.920***		-0.005
	-0.165	-0.082		-0.007
Observations	48	336	336	288
R^2	0.36	0.156	0.175	0.023
Adjusted R^2	0.301	0.143	0.027	0.009
F Statistic	6.053*** (df = 4; 43)	61.098***	15.068*** (df = 4; 284)	1.686 (df = 4; 283)
Note:	*p**p***$p < 0.01$			

Lagrange Multiplier Test for OLS versus Random Effects: 9.89, p <.00 – indicates Random Effects over OLS.

Lagrange Multiplier Test for OLS versus Fixed Effects: F = 5.08, df1 = 46, df2 = 284, p <.00 – indicates support for Fixed Effects over OLS.

Hausman Test for Random versus Fixed Effects: chisq = 42.69, df = 5, p < .00—indicates support for Fixed Effects over Random Effects.

The dependent variable is measured as a proportion, so 0.5 indicates half or 50 percent of the registered voters cast a ballot. What that means in terms of interpreting the numbers is that an estimated coefficient of 0.01 translate into a 1 unit increase in the associated independent variable associates with a 1 percentage point increase in turnout. For example, the -.029 coefficient for ex-prisoners for the fixed effects model is associated with a reduction in turnout of ≈3 percentage points.

The control variables used are education (percent with a high school diploma), ease of registration (days before election required to register), and the competitiveness of the presidential election (absolute difference in poll numbers). As far as I am aware, there is no universally agreed upon "standard" turnout model, but these seemed to represent a reasonable set controls that reflect mainstream approaches in the literature.[10]

DATA SOURCES AND CODE

Throughout the book I tried to cite specific sources for data and have drawn mostly from sources such as federal and state governments and related organization (e.g. Bureau of Justice Statistics, National Bureau of Economic Research, National Center for State Courts, Council of State Governments), and publicly accessible data either compiled by academics as part of peer reviewed research or widely relied on by scholars of comparative state politics (e.g. The Correlates of Policy Project). A special thanks to Peter Enns and Daniel Hawes who generously provided me with their public opinion and social capital data – I cannot say enough about scholars who will go out of their way to share their data on the basis of nothing more than an email sent out of the blue.

There are inevitable caveats that come with a massive data collection project like this. For one thing, not all sources agree. Take, for example, incarceration rates, the most critical measure used. Specific estimates of incarceration rates depend on, among other things, the jurisdiction covered (federal, state, local, or some combination), the date the prison population census was taken (e.g. beginning or end of year), and the definition of the population being studied, which can be defined as all those under jurisdiction, those serving sentence of more than one year (i.e. felons), and whether or not private institutions are or are not counted. While I've tried to maintain a consistent definition of what I mean when I say incarceration rate, some of the studies cited inevitably are using different—and perfectly legitimate—numbers. To try and maintain transparency I have included a complete list of all data, variables, and their sources in Table S1.

The data as well as all the code used for the analyses reported are archived here: https://doi.org/10.7910/DVN/JVXHIF. The analyses were conducted using R version 3.6.1, mostly in the summer of 2021. Given that the backwards compatibility of newer versions of R, at least in my experience, can be far from perfect, in addition to the data and code I've also provided the analysis output files in the archive site. The latter are the files output directly from the statistical code used to put together the tables reported above. These output files are labelled as they are presented in the methodological appendix (Table S1 etc.), and the process used to generate them is in the R code (most commonly this is with the stargazer package). These output files are what I used as the key source for the inferences reported in the book (and above).

Table S1: Variables, Measures, and Data Sources

Variable	Measure	Source
Incarceration Rate	Prisoners serving sentences of > 1 yr under the jurisdiction of state authorities per 100,000 residents.	Carson, E. Ann and Mulako-Wangota, Joseph. Bureau of Justice Statistics. (Imprisonment rates of total jurisdiction population). Generated using the Corrections Statistical Analysis Tool (CSAT) - Prisoners at **www.bjs.gov**. (13-Apr-21).
Percent Young	Percent state population between 15 and 34	Calculated by author from: National Bureau of Economic Research: http://www.nber.org/data/seer_u.s._county_population_data.html
Percent Black Male	Percent State Population that is Black male	Calculated by author from: National Bureau of Economic Research http://www.nber.org/data/seer_u.s._county_population_data.html
Total Population	Total state population	National Bureau of Economic Research: http://www.nber.org/data/seer_u.s._county_population_data.html
Property Crime Rate	Property crime rate per 100,000 pop: Arson, burglary, larceny, and motor vehicle theft	Jordan, Marty P., and Matt Grossmann. 2020. *The Correlates of State Policy Project v.2.2*. East Lansing, MI: Institute for Public Policy and Social Research (IPPSR). http://ippsr.msu.edu/public-policy/correlates-state-policy Original Source: U.S. Department of Justice, Uniform Crime Reporting Statistics - UCR Data Online. "Estimated property crime rate by state."

		https://www.ucrdatatool.gov/Search/Crime/State/TrendsInOneVar.cfm
Violent Crime Rate	Violent crime rate per 100,000 pop: murder, nonnegligent manslaughter, forcible rape, robbery, and aggravated assault	See above
State Culture	Sharkansy's scale of Elazar's political culture typology, scale assigns scores between 1 and 9 to each state, where 1 = Pure moralistic, 5 = Pure Individualistic, and 9 = Pure Traditionalistic	[1]Sharkansky, Ira. 1969. The utility of Elazar's political culture: A research note. *Polity*, *2*(1), 66-83 Sharkansky did not have estimates for every state, estimates for those states were taken from calculations reported in: Koven, Steven, and Christopher Mausolff. 2002. "The Influence of Political Culture o State Budgets." American Journal of Public administration. 32: 66-77. Cole, Constance Didlake. 2006. "A Content Analysis by Political Cultures and Values of State Compliance Documents for the Federal Legislation, No Child Left Behind." PhD diss., University of Tennessee, 2006. https://trace.tennessee.edu/utk_graddiss/2128/
Judicial Democracy	0-1 scale where 1 = judges for courts of original jurisdiction are elected (partisan or non-partisan elections), 0.5 = judges are appointed but must face periodic retention (uncontested reappointment) elections, 0 = judges selected through some appoint system that does not involve general elections.	Source: National Center for State Courts, "Judicial Selection in the States." http://judicialselection.us/ Note—the source is descriptive and historical rather than quantitative. What I sought to extract was the primary election method used during the historical period of interest for courts of jurisdiction, though this inevitably led to some subjective scoring, I tried to minimize this by visiting various state court websites, though even this did not always resolve the problem. For example, Kansas has a split system where its 31 court districts use different selection methods—roughly half use partisan elections and the other half use judicial commission/appointment. I scored this as a partisan election system, though there is obvious room for debate on that. Also, the further back in time the more likely the source I used is not fully capturing what was going on. Despite these limitations I am

		reasonably confident that, at a minimum, the resulting measure accurately reflects the basic selection approach used in most states for most of the time period covered.
GINI coefficient	0 to 1 scale where 0 = income is distributed completely equally, 1 = one person receives all income	Frank, Mark W. "U.S. State-Level Income Inequality Data." http://www.shsu.edu/eco_mwf/inequality.html
Partisan Control	This is the Ranney Index, a 0 to 1 scale where 0 = unified Republican Party control of state government (GOP majorities in legislature and Republican governor), .5 divided control, 1 = unified Dem control. I used the 4-year moving average of this score included in the Michigan Correlates of Policy.	Original sources: Ranney, Austin. 1976. "Parties in State Politics." In Politics in the American States, 3rd ed., edited by Herbert Jacob and Kenneth Vines. Boston, MA: Little, Brown & Co. Klarner, Carl, 2013, "Other Scholars' Competitiveness Measures." https://doi.org/10.7910/DVN/QSDYLH, Harvard Dataverse, V1
Marijuana Decriminalization	1 = marijuana possession criminal act, 0 = not criminal act	Marty and Grossman 2020. Original Source: Caughey, Devin, and Christopher Warshaw. 2015. "The Dynamics of State Policy Liberalism, 1936–2014." American Journal of Political Science, September. Doi: 10.1111/ajps.12219. https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/ZXZMJB
Unemployment	Percentage of state's labor force that is out of work.	Bureau of Labor Statistics. 2012. "Labor Force Statistics from the Current Population Survey." Originally provided by Stateminder: A data visualization project from Georgetown University. http://stateminder.org/ (no longer accessible online) For 2005–2017: University of Kentucky Center for Poverty Research. 2019. "UKCPR National Welfare Data, 1980–2017." Lexington, KY. http://ukcpr.org/resources/national-welfare-data
Poverty Rate	Estimated percent of individuals living in poverty.	Marty and Grossman 2020. Original source: University of Kentucky Center for Poverty Research. 2019. "UKCPR National

		Welfare Data, 1980–2017." Lexington, KY. http://ukcpr.org/resources/national-welfare-data
Conservative	Percent of state's population who identify as conservative	Marty and Grossman 2020. Original Source: Enns, Peter K., and Julianna Koch. "Public Opinion in the U.S. States: 1956 to 2010." State Politics & Policy Quarterly 13.3 (2013): 349–372.
Punitiveness	Percent state population approving punitive approaches to criminal justice	Received directly from Peter Enns, June 14, 2021. This measure is described in: Enns, Peter K. 2016. *Incarceration Nation*. New York: Cambridge University Press.
Percent Black Legislature	Percent of members of state legislature that are Black	Hawes, Daniel, 2017, "Replication Data for: Social Capital, Racial Context and Incarcerations in the American States", https://doi.org/10.7910/DVN/B8NR76, Harvard Dataverse, V1, UNF:6:8O7UDMjjfEzvfUPL7GZRfA== [fileUNF]
Three Strikes	1 = 3 strikes law 0 = no 3 strikes	Hawes, Daniel, 2017, "Replication Data for: Social Capital, Racial Context and Incarcerations in the American States", https://doi.org/10.7910/DVN/B8NR76, Harvard Dataverse, V1, UNF:6:8O7UDMjjfEzvfUPL7GZRfA== [fileUNF]
Social Capital	Hawes, Rocha, Meier (2013) state social capital index	Hawes, Daniel, 2017, "Replication Data for: Social Capital, Racial Context and Incarcerations in the American States", https://doi.org/10.7910/DVN/B8NR76, Harvard Dataverse, V1, UNF:6:8O7UDMjjfEzvfUPL7GZRfA== [fileUNF]
Racial Diversity	Blau index of racial diversity	Hawes, Daniel, 2017, "Replication Data for: Social Capital, Racial Context and Incarcerations in the American States," https://doi.org/10.7910/DVN/B8NR76, Harvard Dataverse, V1, UNF:6:8O7UDMjjfEzvfUPL7GZRfA== [fileUNF]
Divorce Rate	Divorces per 1,000 population	Hawes, Daniel, 2017, "Replication Data for: Social Capital, Racial Context and Incarcerations in the American States", https://doi.org/10.7910/DVN/B8NR76, Harvard Dataverse, V1,

		UNF:6:8O7UDMjjfEzvfUPL7GZRfA== [fileUNF]
Disenfranchised	Voting ineligible felons per 100,000 population	Hawes, Daniel, 2017, "Replication Data for: Social Capital, Racial Context and Incarcerations in the American States", https://doi.org/10.7910/DVN/B8NR76, Harvard Dataverse, V1, UNF:6:8O7UDMjjfEzvfUPL7GZRfA== [fileUNF]
State Level Social Capital	Overall Index of state-level social capital	The Geography of Social Capital in America. SCP Report No. 1-18, April 2018. https://www.jec.senate.gov/public/index.cfm/republicans/2018/4/the-geography-of-social-capital-in-america
Putnam Index	Robert Putnam's state-level social Index	The Geography of Social Capital in America. SCP Report No. 1-18, April 2018. https://www.jec.senate.gov/public/index.cfm/republicans/2018/4/the-geography-of-social-capital-in-america Original source: *Putnam, Robert*. 2000. Bowling Alone. New York: Simon and Schuster.
Penn State Social Capital	State social capital index calculated mean of county-level social capital index	Rupasingha, A., Goetz, S. J., & Freshwater, D. (2006, with updates). The production of social capital in US counties. *Journal of Socio-Economics*, 35, 83-101. doi:10.1016/j.socec.2005.11.001 https://aese.psu.edu/nercrd/community/social-capital-resources
GSPPctGrowth	Annual percent growth in gross state product	Bureau of Economic Analysis. "GDP by State." https://www.bea.gov/data/gdp/gdp-state
Taxes GSP	Tax revenue as a percent of gross state product. Note that in the Michigan Correlates of Public Policy data set the decimal seems to be in the wrong place, e.g., in 1978 for	Marty and Grossman 2020. Data drawn from: Klarner, Carl. 2013. "State Economic Data", https://doi.org/10.7910/DVN/KMWN7N, Harvard Dataverse, V1

	Alabama the percent of gsp in taxes is listed as 52.01, in the Klarner data set it is listed as 5.201. Moving the decimal by one in the Michigan data set yields the same estimates as those reported by Klarner and that is what I use.	
HS Diploma	Percent of population that has a high school diploma or higher. Note: this is based on decennial census data	Marty and Grossman 2020.
GSP Total	Gross State Product in dollars	Marty and Grossman 2020. Original source: US Department of Commerce Bureau of Econom 2012. "NAICS Per Capita GDP by state/SIC Per by state." Accessed at: http://www.bea.gov/regional/downloadzip.cfm. Note: there is a discontinuity in this data as industry definitions changed in 1997. Prior to 1997 the Standard Industrial Classification (SIC) system was used, from 1997 on the North American Industry Classification System was used.
State CPI	State level consumer price index. This is the index used to deflate dollars to make state-to-state and year-to-year comparisons, i.e., monetary values are divided by the state cpi to arrive at an estimate of constant dollars that account both for inflation across time and cost of living differences across states.	Marty and Grossman 2020. The index was originally formulated by: Berry, William D., Richard C. Fording, and Russell L. Hanson. 2000. "An Annual Cost of Living Index for the American States, 1960–95," *The Journal of Politic*s, 60(2): 550-67. The index was updated by Klarner 2013.

DEP	Year-end deposits in commercial banks.	FDIC. Historical Bank Data. https://banks.data.fdic.gov/bankfind-suite/historical
Total HighEd Expenditure	Total per capita expenditure on higher education	U.S Census Bureau. "Data Base on Historical Finances of State Governments: State_Govt_Finances Fiscal Years 1942–2009." https://www.census.gov/programs-surveys/gov-finances/data/historical-data.html Note: dollars are deflated using Berry, Fording, and Hanson state-level cpi (see above).
Total Highways Expenditure	Total per capita expenditure on highways	U.S Census Bureau. "Data Base on Historical Finances of State Governments: State_Govt_Finances Fiscal Years 1942–2009." https://www.census.gov/programs-surveys/gov-finances/data/historical-data.html Note: dollars are deflated using Berry, Fording, and Hanson state-level cpi (see above).
Elem Educ Expenditure	Total per capita expenditure on elementary and secondary education	U.S Census Bureau. "Data Base on Historical Finances of State Governments: State_Govt_Finances Fiscal Years 1942–2009." https://www.census.gov/programs-surveys/gov-finances/data/historical-data.html Note: dollars are deflated using Berry, Fording, and Hanson state-level cpi (see above).
Health Total Expenditure	Total per capita expenditure on health	U.S Census Bureau. "Data Base on Historical Finances of State Governments: State_Govt_Finances Fiscal Years 1942–2009." https://www.census.gov/programs-surveys/gov-finances/data/historical-data.html Note: dollars are deflated using Berry, Fording, and Hanson state-level cpi (see above).
Welfare Expenditure	Total per capital expenditure on welfare	U.S Census Bureau. "Data Base on Historical Finances of State Governments: State_Govt_Finances Fiscal Years 1942–2009." https://www.census.gov/programs-surveys/gov-finances/data/historical-data.html

		Note: dollars are deflated using Berry, Fording, and Hanson state-level cpi (see above).
Pct Ex-Pris	Percent of State Population With a Prison Record	Shannon, S. K., Uggen, C., Schnittker, J., Thompson, M., Wakefield, S., & Massoglia, M. (2017). The growth, scope, and spatial distribution of people with felony records in the United States, 1948–2010. *Demography*, *54*(5), 1795-1818. https://read.dukeupress.edu/demography/article/54/5/1795/167743/The-Growth-Scope-and-Spatial-Distribution-of
DCarter	Percent of statewide presidential vote going to Democratic candidate	Atlas of U.S. Presidential Elections. https://uselectionatlas.org/
Pres Poll	Percent of voters indicating support for Democratic candidate 6–7 months before election (March or April poll figures depending on data availability)	Gallup. “Gallup Presidential Election Trial-Heat Trends, 1936-2008.” https://news.gallup.com/poll/110548/gallup-presidential-election-trial-heat-trends.aspx
DemPrevElect	Percent of statewide presidential vote received by Democratic candidate in previous presidential election	Atlas of U.S. Presidential Elections. https://uselectionatlas.org/
Consec Terms	Number of consecutive Democratic (positive numbers) or Republican (negative numbers) presidential administrations	Compiled by author.
Home State	Dummy variable where 1 = home state of Dem candidate, -1 = home state of Rep candidate, 0 = other	Compiled by author.
Turnout as Reg Voters	Turnout as percent of registered voters	Atlas of U.S. Presidential Elections. https://uselectionatlas.org/
Days Before Electtoregister	Number of days before general election	Council of State Governments. *Book of the States*. Various years.

	that voter registration is required	https://issuu.com/csg.publications/stacks/46495f12f95847e6935d331969ed650a
Abs Oct Poll Diff	Absolute difference between poll standings of Democratic and Presidential candidates in October before general election	Gallup. "Gallup Presidential Election Trial-Heat Trends, 1936-2008." https://news.gallup.com/poll/110548/gallup-presidential-election-trial-heat-trends.aspx
Total Reg	Total number of registered voters	Atlas of U.S. Presidential Elections. https://uselectionatlas.org/
VAP	Percent of the voting age population registered to vote	Calculated by the author by data sourced from: VAP: Shannon, S. K., Uggen, C., Schnittker, J., Thompson, M., Wakefield, S., & Massoglia, M. (2017). The growth, scope, and spatial distribution of people with felony records in the United States, 1948–2010. *Demography*, *54*(5), 1795–1818. Registered voters: Atlas of U.S. Presidential Elections. https://uselectionatlas.org/

Notes

[1] Gill, J. (2001). Whose variance is it anyway? Interpreting empirical models with state-level data. *State Politics & Policy Quarterly*, *1*(3), 318–338.
[2] I've tried, with absolutely no success, to draw attention to the problem of inadvertently or explicitly confirming prior beliefs through model specification. See: Smith, K. B., & Granberg-Rademacker, J. S. (2003). Money only matters if you want it to? Exposing the normative implications of empirical research. *Political Research Quarterly*, *56*(2), 223–232.
[3] E.g., Enns, P. K. (2016). *Incarceration nation*. Cambridge University Press. p. 141.
[4] See: Enns 2016; Hawes, D. P. (2017). Social capital, racial context, and incarcerations in the American states. *State Politics & Policy Quarterly*, *17*(4), 393–417.
[5] Duxbury, S. W. (2021). A General Panel Model for Unobserved Time Heterogeneity with Application to the Politics of Mass Incarceration. *Sociological Methodology*, *51*(2), 348–377.
[6] See: Dumitrescu, E. I., & Hurlin, C. 2012. "Testing for Granger non-causality in heterogeneous panels." *Economic modelling*, *29*(4), 1450–1460.
[7] There's a long-standing argument to this effect. See: Beck, N., & Katz, J. N. 1995. "What to do (and not to do) with time-series cross-section data." *American political science review*, *89*(3), 634–647.
[8] For a quick, reasonably straightforward explanation of this from one such expert see: Allison, P. (2015). Don't Put Lagged Dependent Variables in Mixed Models. Statistical Horizons. https://statisticalhorizons.com/lagged-dependent-variables/).

[9]For discussions on the relevant methodological issues, see: Whitten, G. D., & Williams, L. K. (2011). Buttery guns and welfare hawks: The politics of defense spending in advanced industrial democracies. *American Journal of Political Science*, *55*(1), 117–134; Raffalovich, L. E., & Chung, R. (2014). Models for pooled time-series cross-section data. *International Journal of Conflict and Violence (IJCV)*, *8*(2), 209–221; Beck, N., & Katz, J. N. (2011). Modeling dynamics in time-series–cross-section political economy data. *Annual Review of Political Science*, *14*, 331–352.

[10] For an overview of aggregate-level turnout statistical models, see: Geys, B. (2006). Explaining voter turnout: A review of aggregate-level research. *Electoral studies*, *25*(4), 637–663. The studies in Geys's review do not use political culture, but this variable is not unheard of in state-level studies. E.g.: King, J. D. (1994). Political culture, registration laws, and voter turnout among the American states. *Publius: The Journal of Federalism*, *24*(4), 115–127.