Web Appendix A. Multilevel Regression with Post-stratification

To estimate state-level support for the death penalty, we employ multilevel regression with poststratification (MRP).

Part 1 – Multilevel Regression

The first step of MRP is to estimate a multilevel regression with data from public opinion polls taken over a given period of time. Respondents' answers to the question of interest constitute the dependent variable, and they are modeled as a function of random effects (or random intercepts) for demographic and geographic characteristics. The results of this analysis are estimates of support for each combination of demographic characteristics ("cells") that are common for all geographic units, as well as geographic effects that are common to all demographic units.

We do not perform the multilevel regression component of MRP because Shirley and Gelman (2011) provide these estimates. We refer the reader to Shirley and Gelman (2011) for full details on their estimation, but describe here some of the important components of their model.

Data. Shirley and Gelman collect data from all GSS surveys between 1974 and 2000, which contain responses to the question, "Do you favor or oppose the death penalty for persons convicted of murder?" In addition, they collect all Gallup polls taken after 2000 asking the question, "Are you in favor of the death penalty for persons convicted of murder?" This process results in 34 different polls between 1953 and 2006, with the largest gap between polls being

from 1960-1965. The data ranges from 445 to 3085 respondents per survey, with a total number of respondents of 58,253 (Shirley and Gelman 2011, 10).

Multilevel Regression Model. Shirley and Gelman specify a multilevel regression in which responses are a function of demographic and geographic variation. The demographic variables include: gender (2 categories), race (black and non-black), age (4 levels: 18-29, 30-44, 45-64 and 65+), and education (5 levels: less than high school, high school diploma, some college or trade school, college graduate, and graduate degree). The geographic variables include regional and state-level effects, where the state-level intercepts are modeled as a function of Republican vote share in the most recent presidential election and the proportion of years for which the death penalty was legal between 1953 and 2006. The multilevel model also includes year intercepts as well as interactions among gender, race and year. Finally, Shirley and Gelman specify a dynamic model in which the year intercepts are modeled as an AR(1) process. The model is formally defined in a three-page equation in Shirley and Gelman (2011, 14-16), and they estimate it via MCMC Gibbs sampling.

Part 2 – Post-stratification

As noted above, Shirley and Gelman provide the cell estimates for demographic and geographic combinations. We then employ data from the Census and the American Community Survey to post-stratify the estimates into state-level estimates. Specifically, we rely on the 1980, 1990, and 2000 Censi, as well as the 2009 American Community Survey.¹ Using demographic estimates from these sources, we identify the proportion of each state represented by each demographic combination from the multilevel model. For the years in which we have a Census or the ACS, we

¹ For the Censi, we use the 5% probability sample.

use the estimates from that survey. For other years, we use a weighted average of the two nearest surveys. So, for example, in 1981, we estimate the demographic makeup of a state as:

0.9*1980 Census + 0.1*1990 Census,

and so forth. This results in estimates of state demographics that are changing linearly over time.

With these demographic estimates for each state, we construct state-level opinion by weighting each cell from the multilevel regression by its proportional representation in the state, and adding in the state-level intercept shifts from the multilevel regression model. Finally, we take the three-year moving average of these state-level public opinion estimates.

Web Appendix B

In a recent working paper, Alesina and La Ferrera (2011) suggest that if juries are racially biased, then higher courts should be more likely to overturn cases where the defendant is a minority and the victim is white than where both the defendant and victim are white. The authors find strong evidence of this phenomenon in the federal courts but not in the state courts, where the estimates have the expected signs but are not statistically significant. We have followed Alesina and La Ferrara's (2011) coding procedures on race and ethnicity for a random sample of 100 cases from each of the four selection systems between 1996 and 2006. (There were only 93 cases in reappointment systems during this time period and thus we have a total of 393 cases.) Among the first 50 per system, we were able after great difficulty to collect these data for all defendants and for the victim(s) in 81.5% of the cases. Concerned that the missing data on victims was not random and finding, like Alesina and La Ferrara, that the ethnicity of the defendant alone predicted how race would affect a judge's decisions, we collected only the defendant's minority status for the remaining cases. In total we have data on the defendant's minority status for 2,378 judge votes. For these observations, the variable *Minority Defendant* is set to 0 if the individual sentenced to death is a non-Hispanic white and 1 if they are Black, Hispanic, Native American, or "other," where the last category consists of two individuals of Pakistani descent and two of Indian descent. In 47.6% percent of the cases, the defendant is a minority. Web Appendix Table B1 presents these results.

	Coefficient (Standard Error)	Marginal Effect
Minority Defendant	-0.189	-0.027
	(0.118)	0.021
Nonpartisan election	2.492***	0.293
Nonpartisan election	(0.760)	0.200
Commission/Retention election	0.194	0.027
Commission/Retention election	(0.962)	0.027
Reappointment	-1.374	-0.228
Reappointment	(1.039)	-0.220
Death penalty support \times Nonpartisan election	-0.046	-0.007
Death penalty support x nonpartisan election		-0.007
Death negative support of Commission/	(0.036)	0.000
Death penalty support × Commission/	0.020	0.003
Retention election	(0.033)	
Death penalty support × Reappointment	0.094**	0.014
	(0.041)	
Death penalty support × Partisan election	0.114**	0.016
	(0.045)	
Republican party	0.574***	0.082
	(0.178)	
Reselection proximity	0.142	0.020
	(0.129)	
Retiring judge (by party)	-0.067	-0.010
	(0.217)	
Lame-duck (by party)	0.799	0.115
	(0.739)	
Case Specific Variables		
Cop kill	1.095***	0.157
	(0.309)	
Rape	0.310*	0.044
	(0.160)	
Rob	0.371***	0.053
	(0.122)	
Multiple victims	0.033	0.005
	(0.126)	
Female victim	0.094	0.014
	(0.145)	
Number of grounds	0.931***	0.134
	(0.108)	
Homicide rate	0.107	0.015
	(0.069)	0.0.0
Time trend	0.028	0.004
	(0.064)	0.004
Constant	-3.052	
Constant	(2.518)	
	(2.010)	
Observations	2,397	

Web Appendix Table B. Ethnicity and Death Penalty Decisions

Notes: The dependent variable is Pr(Uphold Death Penalty = 1). Analysis conducted with random intercepts for the state- and judge-levels. ***p <0.01, **p <0.05, *p < 0.10, two-tailed.

The table indicates that, all else equal, judges are 2.7-percent more likely to overturn a death sentence when the defendant is of a racial or ethnic minority group than they are when the defendant is white. The effect of a minority defendant, however, is not statistically significant (p=0.11, two-tailed). More important for the purpose of this paper is that the effects of the judicial systems, both in terms of the main effects as well as how they interact with public opinion, are largely similar to the ones uncovered when the defendant's race is not a control variable. Judges facing nonpartisan elections are still far more likely to uphold death sentences than judges facing partisan elections, just as the Partisan Signals prediction suggests. Additionally, consistent with the Dynamic Representation and Indirect Accountability perspectives, a change in the level of public opinion still has a positive and statistically significant impact on judges in partial election and reappointment systems. The one exception to the previous results is that for this subset of the data, when we control for whether the defendant is a minority, the main effect of commission-retention systems is no longer statistically significant; however, as discussed in the main text, this result is generally not as robust as the findings for the other systems. Outside of this one exception, however, Web Appendix Table B establishes that even after controlling for the defendant's race, the findings of the main analyses are sustained.

Web Appendix C. Post-Bird Robustness Checks

	Truncated Public Opinion				Year Indicators		Clustered Standard Errors		Case REs
	Random	Judge Fixed	State Fixed	Random	Judge Fixed	State Fixed	Judge Fixed	State Fixed	Random
	Intercepts	Effects	Effects	Intercepts	Effects	Effects	Effects	Effects	Intercepts
	Coefficient (Standard Error)	Coefficient (Standard Error)							
Nonpartisan election	2.038***	1.542**	1.644***	2.734***	2.421***	2.854***	2.352**	2.601***	2.631***
	(0.637)	(0.703)	(0.582)	(0.480)	(0.540)	(0.422)	(1.120)	(0.969)	(0.460)
Commission/Retention election	1.484**	1.359	1. 034*	1.701***	1.348**	1.396***	1.179	1.295	1.545***
	(0.707)	(0.892)	(0.589)	(0.506)	(0.630)	(0.392)	(1.064)	(0.785)	(0.495)
Reappointment	-0.437 (0.940)			-0.705 (0.709)					-0.816 (0.699)
Death penalty support ×	0.127***	0.115***	0.107***	0.094***	0.099***	0.052**	0.104***	0.099***	0.103***
Partisan election	(0.003)	(0.029)	(0.023)	(0.023)	(0.027)	(0.022)	(0.040)	(0.032)	(0.017)
Death penalty support ×	0.052**	0.055**	0.056***	-0.016	0.008	-0.062***	0.010	-0.011	-0.008
Nonpartisan election	(0.021)	(0.023)	(0.019)	(0.020)	(0.026)	(0.020)	(0.023)	(0.021)	(0.012)
Death penalty support ×	0.054***	0.064***	0.037**	-0.001	0.010	-0.052***	0.018	0.002	0.011
Commission/Retention election	(0.018)	(0.022)	(0.009)	(0.019)	(0.026)	(0.019)	(0.021)	(0.017)	(0.010)
Death penalty support ×	0.115***	0.100***	0.071**	0.106***	0.120***	0.019	0.125**	0.077	0.116***
Reappointment	(0.031)	(0.036)	(0.029)	(0.028)	(0.036)	(0.027)	(0.051)	(0.051)	(0.021)
Controls	Included	Included							
Constant	-4.352***	-5.102***	-3.941***	-2.258***	-6.641***	-1.602***	-7.241***	-2.138**	-2.820***
	(0.769)	(1.011)	(0.704)	(0.514)	(0.925)	(0.421)	(1.306)	(0.859)	(0.489)
Observations Notes: The dependent variable is	4,099	3,718	4,088	9,576	9,279	9,576	9,279	9,576	9,576

Notes: The dependent variable is Pr(Uphold Death Penalty = 1). ***p <0.01, **p <0.05, *p < 0.10, two-tailed.

	Pre-Bir	rd Split	Post-Bird Split	
	1980-1982	1983-1986	1987-1996	1997-2006
	[1A]	[1B]	[2A]	[2B]
Nonpartisan election	-4.111	0.410	4.167***	2.638***
	(2.731)	(1.980)	(1.212)	(0.589)
Commission-Retention system	-11.260***	-6.677***	-0.068	1.922***
	(2.307)	(2.085)	(1.041)	(0.625)
Reappointment	5.461***	14.326***	5.822***	-0.718
	(1.634)	(4.750)	(1.632)	(0.730)
Partisan	-0.582 (1.473)		0.636 (1.010)	
Death penalty support × Partisan election	-7.667	-1.631	8.542***	12.971***
	(6.859)	(5.192)	(2.459)	(2.610)
Death penalty support ×	3.814	-4.112	-5.447*	2.105*
Nonpartisan election	(7.082)	(5.010)	(3.198)	(1.268)
Death penalty support ×	29.699***	17.650***	7.457***	2.445**
Commission-Retention system	(6.516)	(5.299)	(2.160)	(1.161)
Death penalty support ×	-74.517***	-66.360***	-11.290**	14.756***
Reappointment	(20.120)	(19.962)	(5.472)	(2.556)
Controls	Included	Included	Included	Included
Constant	-279.542** (134.991)		-33.450 (30.733)	
Observations	2,878		9,576	

Web Appendix D. Pre-versus Post-Rose Bird Robustness Checks

Notes: The dependent variable is Pr(Uphold Death Penalty = 1). Analysis conducted with random intercepts for the state- and judge-levels. Standard errors given below coefficients. ***p <0.01, **p <0.05, *p < 0.10, two tailed.