The Politics of Selecting the Bench from the Bar: The Legal Profession and Partisan Incentives to Introduce Ideology Into Judicial Selection

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Online Appendix

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Appendix A Linking Lawyers To Their Contribution Records

In order to link records between DIME and the Martindale-Hubbell Directory, we developed a customized probabilistic record-linkage algorithm. The algorithm works as follows. First, it queries the DIME database for records that identify donors as attorneys by filtering on individuals who either (1) have a self-reported occupation that matched against a list of relevant search terms (e.g., lawyer, attorney, "atty," judge, etc.), (2) have a self-reported employer that matched against a pre-compiled list of law firms or contained terms commonly used by the legal industries such as "law offices" or "LLP,"[1] or (3) list "Esq." or "J.D." as a title. The algorithm then cycles through each record in the Martindale-Hubbell directory searching for the set of potential matches in the DIME database. The algorithm narrows the set of possible matches by comparing values for first, last and middle name, suffix, title, address, city, state and zip codes, firm/employer, and geographic proximity. To adjust for slight variations in reporting, the algorithm fuzzy-matched on both names and addresses using the Jaro-Winkler algorithm. Name matching was further conditioned on information frequency of first and last names obtained from the Social Security Administration and the U.S. Census, respectively.[2] We measured geographic proximity as the distance between geo-coordinates of the address in the Martindale-Hubbell database and the geo-coordinates of records from the DIME database. If a set of records assigned to a single ID in the DIME data exceeded the predefined threshold, it was identified as a match.

As we note above, there was significant variance in reporting across state bar associations and across individuals. Several of the fields therefore required additional processing and disambiguation. Specifically, we first standardized names and parsed into separate fields for first, last, middle, suffix, and title. Second, we standardized address strings (i.e., "street" becomes "st"). Third, we used automated disambiguation techniques to standardize entries for employer, law schools and undergraduate institutions, and practice areas.[3] For instance, the listings for law professors were

[1]In order to further narrow the search on attorneys, we screened out records with occupational titles commonly used by paralegals and staff at law firms.

[2]Social Security Administration data on name frequency were accessed at http://www.ssa.gov/OACT/babynames/limits.html. Census data on the frequency of surnames were accessed at https://www.census.gov/genealogy/www/data/2010surnames/dist.all.last.

[3]Information on practice areas was compiled from written descriptions and lacked structured categorizations. After applying standard techniques to clean and normalize the text, we grouped entries into a more general set of 31

derived from a partial list of law schools. As a result, most law professors employed at the missing universities were grouped into the catch-all employment categorization. We were able to extract the remaining law professors by searching the fields on employment and title for terms that could be used to identify them as law professors.

We used an automated coding procedure based on the gender ratios of first names based on census data or, when available, gender-specific titles (e.g., Mrs., Mr., Jr., Sr.) reported in either the contribution records. We do not assign labels to individuals for whom the automated coding scheme did not reach a threshold of being 95 percent confident of the person's gender. In total, we were able to assign gender to 98.6 percent of the sample. The gender coding scheme is identical to that used to identify gender in the DIME database of contribution records.[4]

In addition to the eight variables fields described in the text, a significant percentage of listings included even more information voluntarily provided by the attorney, such as (9) detailed employment history, (10) judicial clerkships along with the name of judge, (11) lists of prominent clients, and (12) prominent cases argued. Since lawyers choose to provide the information and others do not, some items are incomplete sources of information. When available, record-linkage algorithm referenced items (9) and (10) as a way to augment matching algorithm. However, we do not include any information from items (9) through (12) in the main analysis.

Missingness in Martindale-Hubbell One limitation of the Martindale-Hubbell database is potential missingness in the data. To our knowledge, no study has systematically assessed the completeness in legal directories such as the Martindale-Hubbell. Thus, we do not know the exact extent of underreporting or precisely which types of lawyers are most likely to be missing.

A challenge in examining missiningness in the data is that there exists no official tally of lawyers to compare against. Estimates of the number of lawyers in the U.S. can vary considerably. For example, the Bureau of Labor Statistics (BLS) estimates there to be about 600,000 lawyers employed in the labor force, whereas the American Bar Association (ABA) estimates there to be more

categories.

[4]When validated on the set records from the NPPES database of licensed medical doctors which provided information on gender, it successfully classified gender in 99.4% of cases.

than 1.2 million lawyers.[5] This discrepancy is in part explained by methodological differences but is also a matter of scope in defining lawyers as a group.

The BLS estimates appear to exclude individuals practicing law outside the confines of legal practices, which could explain why its population estimate is so low. The ABA uses a broader definition. Its estimates are constructed by summing the populations of lawyers active in each state as reported by state bar associations. This approach can be prone to double-counting, owing to lawyers to be members of multiple state bar associations. The ABA does adjust for out-of-state members of state bar associations, but it is difficult to keep track of members who have moved to different state. The Martindale-Hubbell directory appears to have dropped cases where lawyers would might otherwise be double-counted by the ABA.

We cannot know for sure whether some types of attorneys are more likely to be missing than others. However, a reasonable expectation is that lawyers in private practice are more likely to be captured by the directory than lawyers employed in-house or in government positions. The reason for this is two-fold. First, lawyers in private practice have incentives to make sure they are listed in legal directories so that potential clients will be able to find them more easily. The same is not true of many other lawyers. Second, bar membership is always a requisite for lawyers practicing as in-house counsels, which may make them more less visible to state bar associations.

[5] http://www.americanbar.org/resources_for_lawyers/profession_statistics.html

Appendix B Self-Selection into the Donor Population

A potential concern is selection bias due to some attorneys contributing (and therefore being included in DIME) but not others. However, attorneys are extremely active contributors, even compared to similar professions. In an exhaustive search of the contributor database, we identified 422,362 attorneys listed in the Martindale-Hubbell database, which corresponds to a participation rate of 43.3%, an order of magnitude greater than the participation rate among the voting age population (Bonica, 2014).[6,7]

Regarding judges who are donors, a potential selection problem concerns regulations that prohibit federal and some state judges from making political contributions.[8] Fortunately, a majority of judges were active donors prior to joining the bench. With regard to state high courts, of the 70 state justices first elected to office since 2001, 66 (or 94%) appear in DIME as campaign contributors. The pattern is more muted, but still apparent for federal judges. Nearly 65% of sitting U.S. Court of Appeals judges are found in the DIME database as contributors, with the share rising to 81% of those appointed since 2001.

Despite the high participation rates, self-selection into the donor population could still bias results. We attempt to correct for this using a Heckman selection model (Heckman, 1979). The first stage of the Heckman correction models the probability of selection into sample, while the second stage incorporates the transformed predicted probabilities from the first stage probit model as additional covariates. Results from the first-stage probit model are reported in Table A1. Here, the outcome variable, donor status (i.e., an indicator of whether the individual appears in the DIME data), is regressed on variables that capture gender, age, geography, area of employment, career

[6]A fraction of these donors (6.5%) gave only to corporate or trade groups and thus were not assigned ideal point estimates.

[7]We deliberately calibrated the algorithm to be less "greedy" in identifying matches so as to minimize false matches at the expense of reducing the overall linkage rate. Given the large sample size, this decision reflects our attempt to prioritize minimizing bias over increasing the sample size. In general, false matches are more likely to introduce bias than are missed matches. (Missed matches would be more or less random, whereas false matches would incorporate more people who could be confused with the population of interest.) As a result, the number of lawyers identified by the record-linkage algorithm represents a conservative estimate of the percentage of attorneys making contributions.

[8]Federal judges currently on the bench are barred from making political contributions by the Code of Conduct for U.S. Judges, Canon 5. However, the code of conduct does not bar political activity earlier in their careers.

status, and some basic measures of quality of legal education.[9] Model 2 further includes the Democratic vote share in the last Presidential election for the individual's Congressional district, which captures how liberal (or conservative) the jurisdiction is. (Results from the second-stage model are reported in the main text.)

Both models raise the possibility of selection bias: several of the variables are predictive of the propensity to donate. For example, those who are partners in law firms or those who graduated from top ("T14") law schools are *more* likely to make political contributions than are other kinds of attorneys. Women, government lawyers, prosecutors and public defenders, corporate (in-house) counsel, and those who attended law schools not ranked in the top 100 are *less* likely to contribute. Being located in more liberal Congressional districts is also associated with an increased propensity to donate, as seen in Model 2.

To aid with the identification of the Heckman correction model, we rely on an exclusion restriction assumption involving a single variable, the number of top state executive offices (attorney general, lieutenant governor, secretary of state, state treasurer, and auditor) that are elected in the individual's state.[10] The logic of using this variable is as follows. When selected via elections, races for these state executive offices are typically high-profile events fueled by intense fundraising efforts that often attract a sizable number of new donors. However, whether a state holds elections for executive office is an institutional feature typically determined closer to the state's founding and does not appear to be related with variation in contemporary partisan leanings across states. Whereas increased campaign activity is likely to slightly increase the probability that an individual donates, there is no obvious mechanism whereby holding competitive elections for state executives would bias latent ideological preferences of donors in the state. The F-statistic for the number of

[9] For legal education, we group together law schools that are in the top 14 (or "T14"). The composition of these has remained stable ever since rankings have been kept. Law school attended is observed for 92% of the sample, of whom 13% attended a "T14" law schools. In cases where law school is not reported, we assume lawyers attended non-"T14" law school. For career status, we identify the largest law firms (a.k.a. "Big Law" firms) by tabulating the number of lawyers in the Martindale-Hubbell database listing each law firm as their employer. We define Big Law as the top 100 firms by number of employees as determined from the Martindale-Hubbell data.

[10] Fifteen states have appointed secretaries of state (AK, DE, FL, HI, MD, ME, NH, NJ, NY, OK, PA, TN, TX, UT, VA), six states have appointed attorneys general (AK, HI, ME, NJ, TN, WY), 12 states have appointed treasurers (AK, GA, HI, MD, ME, MI, MN, MT, NH, NJ, TN, VA), 25 states have no elected auditors or comptrollers (AK, AZ, CA, CO, CT, FL, GA, HI, ID, IL, KS, LA, MD, ME, MI, NH, NJ, NV, OR, RI, SC, TN, TX, VA, WI), and seven states have no elected lieutenant governors (AZ, ME, NH, OR, TN, WV, WY).

	Model 1	**Model 2**	**Model 3**	**Model 4**
Judge	-0.134**	-0.142**		
	(0.008)	(0.009)		
Fed. CoA			0.006	-0.007
			(0.087)	(0.087)
Fed. District Court			-0.184**	-0.195**
			(0.038)	(0.038)
State Higher Court			0.039	0.024
			(0.071)	(0.071)
State Lower Court			-0.094**	-0.085**
			(0.011)	(0.011)
Fed. Mag.	-0.484**	-0.509**	-0.481**	-0.506**
	(0.032)	(0.032)	(0.032)	(0.032)
Fed. Admin. Judge	-0.454**	-0.472**	-0.451**	-0.468**
	(0.084)	(0.085)	(0.084)	(0.085)
State Admin. Judge	-0.334**	-0.342**	-0.332**	-0.339**
	(0.057)	(0.057)	(0.057)	(0.057)
Female	-0.336**	-0.340**	-0.337**	-0.340**
	(0.003)	(0.003)	(0.003)	(0.003)
Years since Admitted	0.068**	0.069**	0.068**	0.068**
	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Years since Admitted^2	-0.001**	-0.001**	-0.001**	-0.001**
	(0.00001)	(0.00001)	(0.00001)	(0.00001)
Top 14 Law School	0.323**	0.340**	0.324**	0.341**
	(0.004)	(0.004)	(0.004)	(0.004)
$>$ 100 Ranked Law School	-0.099**	-0.084**	-0.098**	-0.084**
	(0.003)	(0.003)	(0.003)	(0.003)
Num Elected Execs	0.038**		0.038**	
	(0.001)		(0.001)	
Constant	-1.327**	-1.001**	-1.325**	-0.999**
	(0.006)	(0.026)	(0.006)	(0.026)
State Fixed Effects		✓		✓
Log Likelihood	−606942.7	−600758.9	−607014.5	−600850.5
Chi-square	102024.4*	114391.9*	101880.9*	114208.7*
N	974419	974419	974419	974419

*p $<$ .01

Table A1: First-stage Results: Probit regression, whether an individual contributes (is in DIME database) as outcome variable.

elected executives is 553.9, which easily exceeds the F-statistic > 10 rule of thumb for exclusion restrictions. However, the number of elected executives only weakly correlates with donor status at r=0.026. On the other hand, it is all but unrelated with DIME scores at r=0.006.

Appendix C Measure Validation

Comparison with Candidate Scores for Lawyers We were able to identify 2,876 attorneys in our data that had run for elected office and raised funds from enough donors to be assigned an independent DIME score as a candidate. Of this group, 149 also have DW-NOMINATE scores. The overall correlation between contributor and candidate DIME scores is $\rho = 0.93$. The within party correlations are $\rho = 0.83$ for Democrats and $\rho = 0.76$ for Republicans. The corresponding correlations with DW-NOMINATE scores are $\rho = 0.90$ overall, $\rho = 0.52$ for Democrats, and $\rho = 0.53$ for Republicans.

Comparison with Appointee-Based Measures In order to compare the DIME scores with existing measures judicial preferences, we calculated scores for judges appointed to the federal bench between 1987 and 2012 using the methodology described in Giles et al (2001,2002)—the same methodology underlies the widely-used Judicial Common-Space Scores (Epstein et al). The scores are assigned based on the common-space DW-NOMINATE scores of those involved in the nomination process. If one or both home-state Senators are of the same party as the president, the nominee is assigned the NOMINATE score of the home-state Senator (or the average if both senators are from the President's party). If neither home-state Senator is a member of the President's party, the nominee is assigned the NOMINATE score of the President.

The overall correlation between the contributor DIME scores and the appointment based measures is $\rho = 0.67$ for Federal Circuit Court judges and $\rho = 0.58$ for Federal District Court judges. The weaker associations are to be expected. Indirect measures based on those involved in the appointment process tend to be less reliable measures of preferences as compared to more direct measures based on revealed preferences (see Bonica and Woodruff 2014). This is made apparent when examining the residuals between the two measures. The circuit court judges with the largest residuals were Helene White (DIME $= -0.86$; GH $= 0.72$) and Barrington Parker Jr. (DIME $= -0.58$; GH = 0.72) and William Byrd Traxler, Jr. (DIME $= 1.14$; GH $= -0.45$). In each case, the nominee had first been appointed to the district court by a president of one party before being elevated to the circuit courts by a president of the other party—the same is true for Justice

Sonia Sotomayor. Further examination of the judges' backgrounds and the circumstances of their nominations reveals to the DIME scores to be clear winners in terms of face-validity.

Appendix D Robustness of Measures to Strategic Giving

One concern with using campaign contributions as the underlying data source is that donors might give for strategic reasons, rather than due to genuine ideological leanings. Detailed discussion of the robustness of DIME scores to strategic giving can be found in Bonica (2014) for donors in general and Bonica and Woodruff (2015) specifically in the context of state judges. Borrowing from those papers, we note several points that address the concern of strategic giving here. First, the scores for individual donors and recipients have been shown to be robust to controlling for candidate characteristics related to theories of strategic giving, such as incumbency status. Second, there is a strong correspondence between contributor and recipient scores for candidates who have both fundraised and made donations to other candidates, indicating that independently estimated sets of ideal points reveal similar information about an individual's ideology. Third, the DIME scores are strongly correlated with vote-based measures of ideology such as DW-NOMINATE scores, providing strong evidence of their external validity. Lastly, estimated scores for candidates that have campaigned for judicial and non-judicial office are robust to changes in office type.

Bonica (2014) and Bonica and Woodruff (2015) further note that the estimation model does not strictly assume that ideological proximity is the sole determinant of contribution behavior, given that it allows for error. While the model "operates on the assumption that contribution decisions are spatially determined, strategic giving will only bias the candidate estimates if the resulting spatial errors violate normality assumptions" (Bonica and Woodruff, 2015). Indeed, most accounts of strategic behavior are actually largely compatible with ideological giving. That is, strategic incentives would serve largely to motivate contributors to engage in *more* funding activity but would not necessarily influence *which* candidates to support.

Excluding donations to judicial candidates Lastly, as our analysis focuses on donor DIME scores recovered for attorneys and judges who have personally contributed to other candidates and campaigns, we consider whether there are any specific reasons to expect lawyers and judges to meaningfully differ from other types of donors. For example, it may be the case that lawyers face pressure to contribute to the campaigns of sitting judges. When we re-estimate the DIME scores for lawyers with contributions to judicial candidates excluded, however, the resulting scores correlate with the original scores at $\rho = 0.99$. Moreover, re-estimating the scores with all contributions to state elections excluded (i.e. federal contributions only) produces scores for lawyers that correlate with the original score at $\rho = 0.97$. As a result, it seems extremely unlikely that any analysis would be sensitive to these concerns.

Appendix E Consideration of Alternative Mechanisms

Other mechanisms could explain why judges might differ from the underlying population of attorneys. One important alternate explanation is that judges are selected on the basis of other characteristics that do vary according to ideology—that is, that judges are recruited or selected for reasons that appear to be apolitical but that vary according to political beliefs. Selection on these sorts of variables would have the effect of skewing the ideological distribution of judges (vis-a-vis attorneys), without necessarily implicating an ideologically-based selection mechanism.

The most obvious example of such characteristics would be demographic. Ever since the Carter Administration started aggressively recruiting women and ethnic minorities (Clark, 2002), Presidents and other executives have tried to make the judiciary more reflective of the population as a whole. In addition, numerous studies have identified that women and minority judges vote in a more liberal direction on certain issues once they are appointed (Boyd, Epstein, and Martin, 2010; Cox and Miles, 2008). Making the judiciary more demographically representative could therefore have the effect of selecting also on ideology. We can, however, rule out this particular explanation: because women and minorities vote (if anything) in a more liberal direction, such a mechanism would mean that more liberals are selected vis-a-vis the population of attorneys. We see no evidence of this. To the contrary, the judiciary is *more conservative* than the overall potential pool of attorneys.

Another example is selecting judges on the basis of superior credentials. For example, conservatives being on average being more likely to attend highly rated law schools than liberals would explain our results. Under such a scenario, the selection on quality of education would have the effect of introducing into the courts more conservatives, even if no ideological selection was in effect. In terms of evidence, the data are more mixed, but still point toward this being an unlikely explanation. Table 1 in the main text shows that who attend elite law schools are more liberal than their counterparts. In addition, as we show in the main text, there are substantial differences across the selection of conservatives and liberals *even conditional on education*. Thus, education appears not to be the decisive factor here.

Within this category of explanations, we consider the most likely explanation to be that the pool of judges is simply older than the rest of the population. As we see in Table 1 in the main text, those who are older tend to be more conservative. If judges are much older than lawyers, then this could plausibly explain why judges as a whole tend to be more conservative. We note, however, that the effect of age does not diminish the effect of the judge variable, suggesting that judges are more conservative even when conditioning on age.

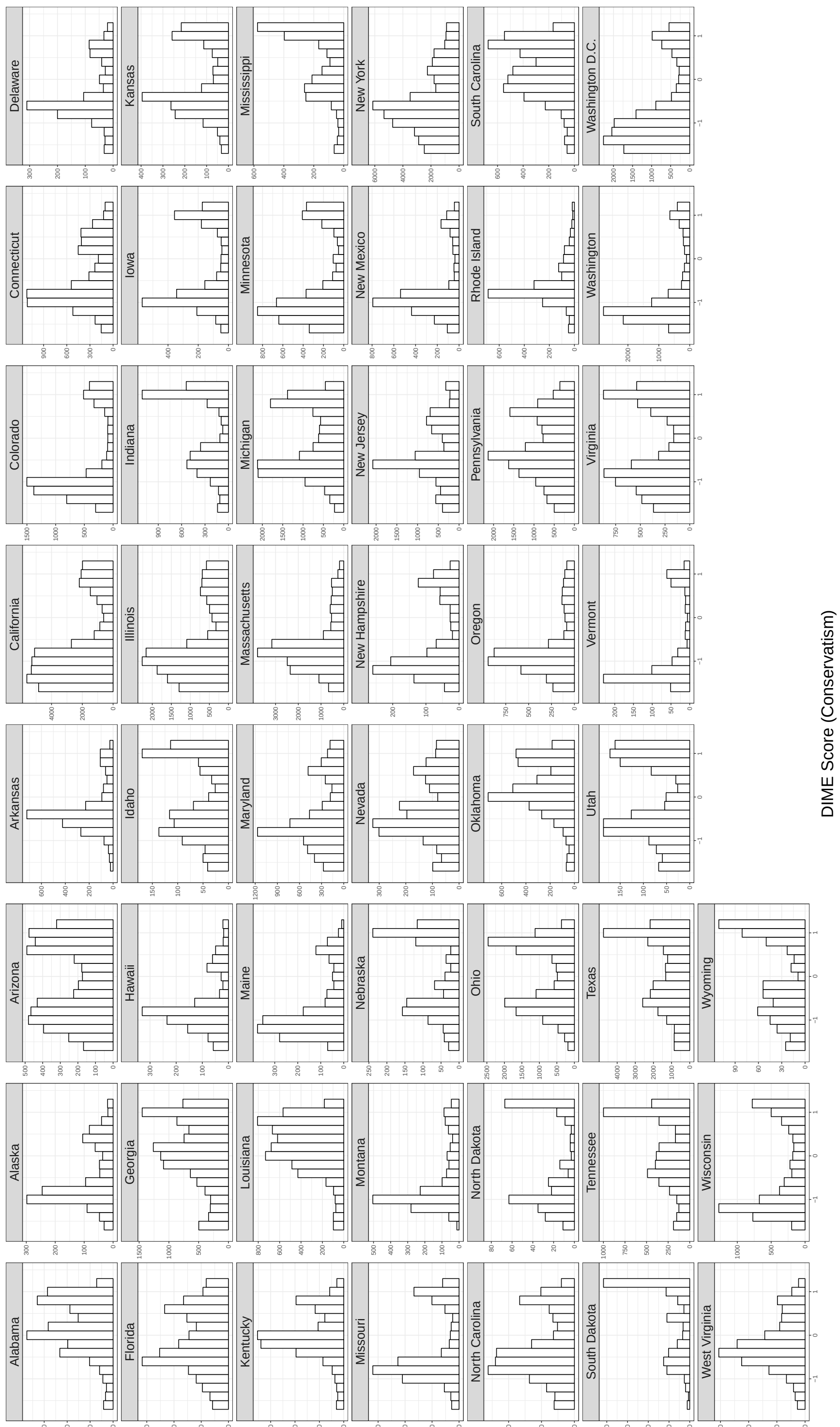
Appendix F Distribution Comparisons of Judges with Politicians and Attorneys by State

Table A2: Comparing Attorney and Politician Distributions with Judges

	Attorneys		Politicians	
	KS P-value	Overlap Coef	KS P-value	Overlap Coef
US	0.00	0.83	0.00	0.85
AK	0.12	0.90	0.00	0.62
AL	0.00	0.82	0.00	0.46
AR	0.05	0.89	0.00	0.59
AZ	0.00	0.83	0.00	0.83
CA	0.00	0.68	0.00	0.75
CO	0.00	0.79	0.00	0.69
CT	0.00	0.79	0.00	0.68
DE	0.40	0.77	0.00	0.63
FL	0.00	0.87	0.00	0.60
GA	0.00	0.84	0.00	0.75
HI	0.07	0.80	0.02	0.72
IA	0.93	0.90	0.00	0.73
ID	0.19	0.77	0.00	0.65
IL	0.00	0.81	0.00	0.76
IN	0.46	0.90	0.00	0.74
KS	0.47	0.88	0.00	0.55
KY	0.00	0.90	0.00	0.80
LA	0.06	0.85	0.00	0.56
MA	0.19	0.89	0.46	0.86
MD	0.00	0.81	0.08	0.84
ME	0.00	0.78	0.01	0.54
MI	0.00	0.90	0.00	0.84
MN	0.01	0.80	0.05	0.83
MO	0.01	0.87	0.00	0.71
MS	0.46	0.82	0.00	0.68
MT	0.21	0.83	0.00	0.54
NC	0.02	0.85	0.00	0.63
ND	0.15	0.67	0.80	0.82
NE	0.56	0.86	0.00	0.50
NH	0.18	0.73	0.00	0.57
NJ	0.14	0.88	0.00	0.73
NM	0.00	0.77	0.00	0.67
NV	0.31	0.88	0.00	0.70
NY	0.00	0.82	0.00	0.81
OH	0.00	0.88	0.00	0.86
OK	0.04	0.89	0.00	0.62
OR	0.00	0.84	0.00	0.61
PA	0.00	0.86	0.00	0.82
RI	0.76	0.83	0.00	0.78
SC	0.37	0.90	0.00	0.68
SD	0.08	0.58	0.00	0.66
TN	0.01	0.83	0.00	0.76
TX	0.00	0.86	0.00	0.70
UT	0.90	0.85	0.00	0.56
VA	0.00	0.75	0.35	0.88
VT	0.13	0.73	0.01	0.48
WA	0.00	0.76	0.00	0.60
WI	0.00	0.74	0.00	0.59
WV	0.04	0.80	0.00	0.61
WY	0.70	0.88	0.06	0.72

Appendix G Attorney Ideology by State

Figure A1: Distribution of estimated DIME scores for attorneys, by state. Increased value of ideal points indicates a more conservative ideology.



Appendix H Most Lawyers (and Judges) Give Exclusively to One Party

Figure A2: Distribution of political contributions by lawyers, 1979-2012

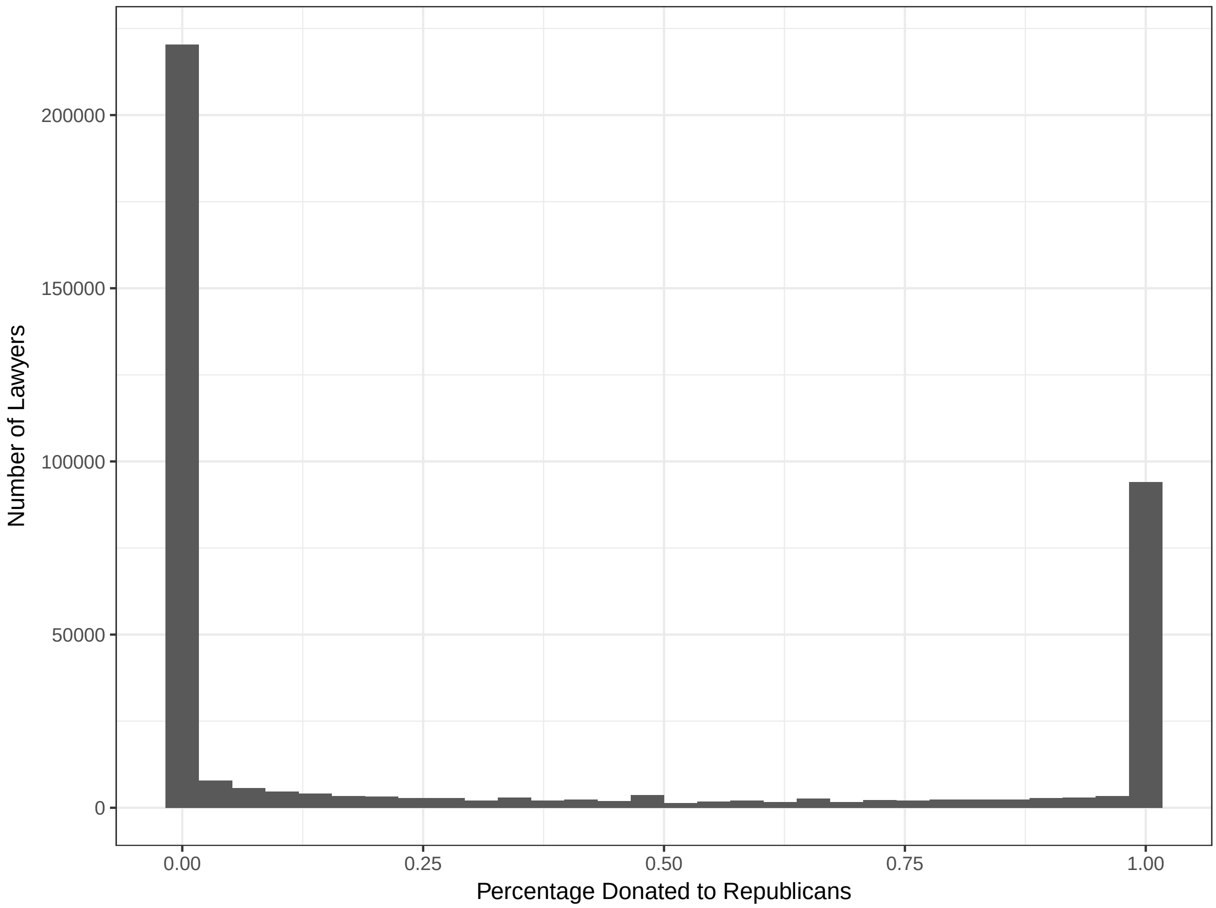
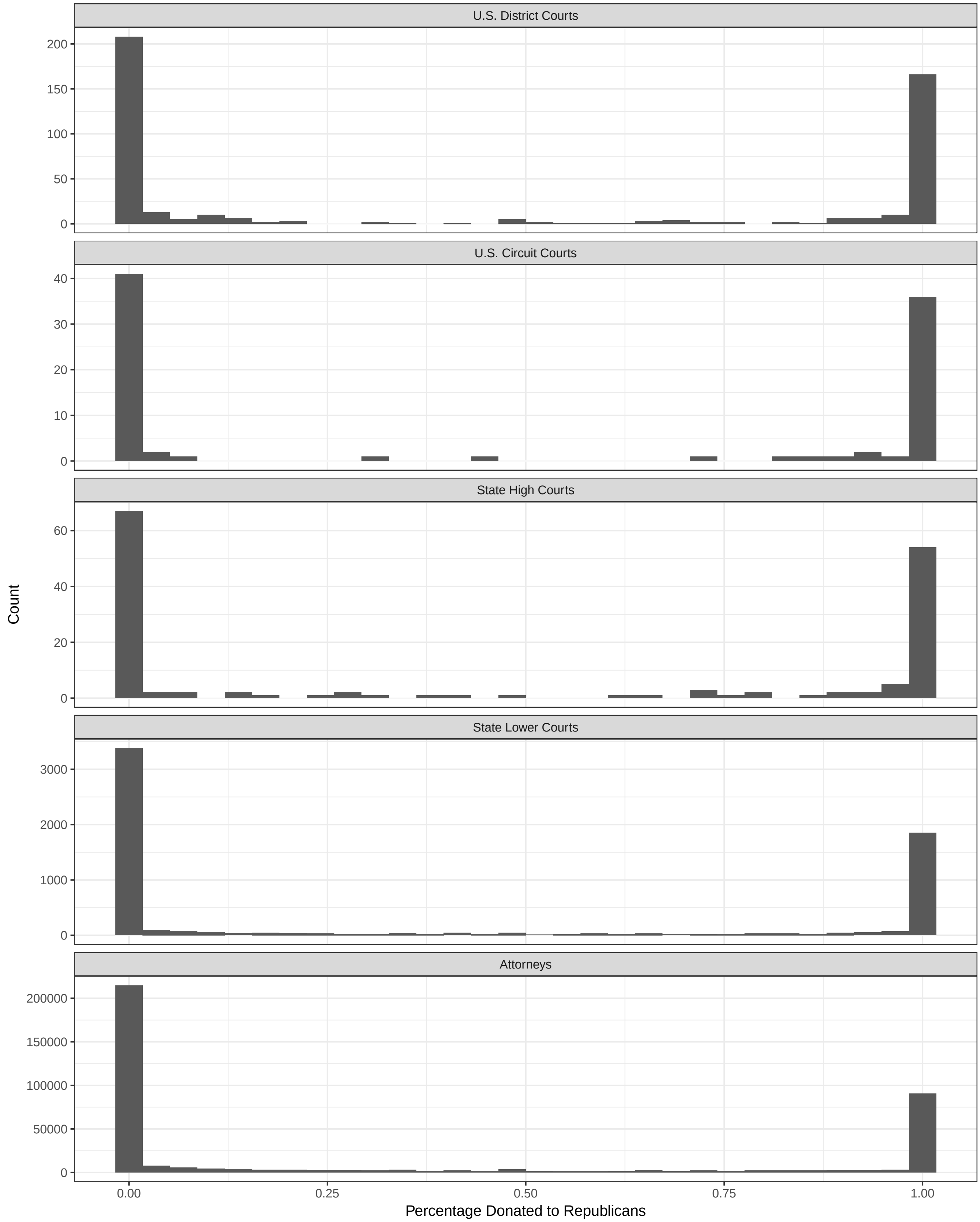


Figure A3: Distribution of political contributions by Judges, 1979-2012



Appendix I First-stage Results From Heckman Model of Attorney Ideology

Table A3: First-stage Results: Probit regression, whether individual contributes (is in DIME database) as outcome variable.

	YS	
	Model 1	**Model 2**
Constant	-1.339**	-1.510**
	(0.006)	(0.009)
Female	-0.317**	-0.322**
	(0.003)	(0.003)
Years since Admitted	0.070**	0.071**
	(0.0003)	(0.0003)
Years since Admitted^2	-0.001**	-0.001**
	(0.00001)	(0.00001)
Government Lawyer	-0.335**	-0.370**
	(0.008)	(0.008)
Corporate (in house counsel)	-0.296**	-0.252**
	(0.007)	(0.007)
Big Law Firm (top 100)	0.238**	0.200**
	(0.006)	(0.006)
Solo-practice	-0.007*	0.002
	(0.003)	(0.003)
Law Professor	-0.016	-0.005
	(0.014)	(0.014)
Partner	0.312**	0.299**
	(0.007)	(0.007)
Prosecutor/District Attorney	-0.215**	-0.208**
	(0.010)	(0.010)
Public Defender	-0.279**	-0.277**
	(0.020)	(0.020)
Top 14 Law School	0.290**	0.266**
	(0.004)	(0.004)
> 100 Ranked Law School	-0.091**	-0.083**
	(0.003)	(0.003)
CD Dem. Pres. Vote Share		0.296**
		(0.009)
N. Elected State Execs.	0.031**	0.027**
	(0.001)	(0.001)
Log Likelihood	-601966.500	-599933.300
N	974413	970567

$^{**}p < .01$; $^{*}p < .05$

Appendix J Modeling Judicial Ideology without Selection Bias Correction

Table A4: Model Results Without Selection Bias Correction: OLS, Contributor CFscore as outcome variable

	Model 1	**Model 2**	**Model 3**	**Model 4**
Judge	0.156**	0.120**		
	(0.008)	(0.008)		
State Lower Courts			0.100**	0.104**
			(0.010)	(0.010)
State High Courts			0.257**	0.201**
			(0.063)	(0.059)
Fed. District Courts			0.260**	0.189**
			(0.037)	(0.035)
Fed. CoA			0.392**	0.379**
			(0.077)	(0.073)
Fed. Admin. Judge	0.218*	0.130	0.215*	0.128
	(0.090)	(0.086)	(0.090)	(0.086)
State Admin. Judge	-0.073	-0.054	-0.075	-0.055
	(0.060)	(0.057)	(0.060)	(0.057)
Fed. Mag.	0.133**	0.069*	0.130**	0.067
	(0.036)	(0.034)	(0.036)	(0.034)
Female	-0.340**	-0.306**	-0.339**	-0.305**
	(0.003)	(0.003)	(0.003)	(0.003)
Years since Admitted	0.002**	0.003**	0.002**	0.003**
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Years since Admitted^2	0.0001**	0.00004**	0.0001**	0.00004**
	(0.00001)	(0.00001)	(0.00001)	(0.00001)
Top 14 Law School	-0.266**	-0.147**	-0.267**	-0.148**
	(0.004)	(0.004)	(0.004)	(0.004)
>100 Ranked Law School	0.100**	0.065**	0.100**	0.065**
	(0.003)	(0.003)	(0.003)	(0.003)
Constant	-0.354**	-0.514**	-0.356**	-0.516**
	(0.006)	(0.023)	(0.006)	(0.023)
State Fixed Effects		✓		✓
R-squared	0.060	0.156	0.059	0.156
N	395252	395252	395252	395252

**$p < .01$; *$p < .05$

Appendix K Selection Model With Lawyers Admitted to the Bar within the Last 15 Years Excluded

Table A5: Probit regression, whether individual contributes (is in DIME database) as outcome variable (>= 15 Years since Bar Admission)

	Model 1	**Model 2**	**Model 3**	**Model 4**
Constant	-1.383**	-1.021**	-1.377**	-1.015**
	(0.012)	(0.030)	(0.012)	(0.030)
Judge	-0.147**	-0.157**		
	(0.009)	(0.009)		
Fed. Admin. Judge	-0.457**	-0.479**	-0.454**	-0.475**
	(0.084)	(0.085)	(0.084)	(0.085)
State Admin. Judge	-0.372**	-0.383**	-0.369**	-0.379**
	(0.058)	(0.058)	(0.058)	(0.058)
Fed. Mag.	-0.492**	-0.523**	-0.489**	-0.519**
	(0.033)	(0.033)	(0.033)	(0.033)
State Lower Court			-0.104**	-0.096**
			(0.011)	(0.011)
State Higher Court			0.034	0.003
			(0.071)	(0.071)
Fed. District Court			-0.205**	-0.220**
			(0.039)	(0.039)
Fed. CoA			-0.015	-0.027
			(0.088)	(0.088)
Female	-0.329**	-0.332**	-0.330**	-0.333**
	(0.004)	(0.004)	(0.004)	(0.004)
Years since Admitted	0.069**	0.070**	0.069**	0.069**
	(0.001)	(0.001)	(0.001)	(0.001)
Years since Admitted^2	-0.001**	-0.001**	-0.001**	-0.001**
	(0.00001)	(0.00001)	(0.00001)	(0.00001)
Top 14 Law School	0.299**	0.325**	0.300**	0.326**
	(0.005)	(0.005)	(0.005)	(0.005)
$>$ 100 Ranked Law School	-0.100**	-0.085**	-0.099**	-0.085**
	(0.003)	(0.003)	(0.003)	(0.003)
Num Elected Execs	0.048**		0.048**	
	(0.001)		(0.001)	
State Fixed Effects		✓		✓
N	716062	716062	716062	716062
Log Likelihood	-476725.600	-471476.100	-476813.600	-471587.800
Chi-square	37152.6** $(df = 10)$	47651.7** $(df = 60)$	36976.7** $(df = 13)$	47428.2** $(df = 63)$

$^{**}p < .01$; $^{*}p < .05$

Table A6: Second-stage Results: OLS, Contributor DIME score as outcome variable (>= 15 Years since Bar Admission)

	Model 1	**Model 2**	**Model 3**	**Model 4**
Judge	0.108**	0.126**		
	(0.009)	(0.013)		
State Lower Courts			0.068**	0.112**
			(0.011)	(0.012)
State High Courts			0.279**	0.213**
			(0.067)	(0.059)
Fed. District Courts			0.195**	0.208**
			(0.039)	(0.038)
Fed. CoA			0.379**	0.384**
			(0.082)	(0.073)
Fed. Admin. Judge	0.058	0.145	0.059	0.161
	(0.094)	(0.091)	(0.094)	(0.091)
State Admin. Judge	-0.186**	-0.016	-0.185**	-0.003
	(0.064)	(0.063)	(0.064)	(0.063)
Fed. Mag.	-0.150**	-0.043	-0.040	0.102*
	(0.040)	(0.044)	(0.040)	(0.051)
Female	-0.467**	-0.306**	-0.464**	-0.293**
	(0.009)	(0.024)	(0.009)	(0.024)
Years since Admitted	0.015**	-0.010	0.015**	-0.012*
	(0.002)	(0.005)	(0.002)	(0.005)
Years since Admitted^2	-0.0001**	0.0002**	-0.0001**	0.0002**
	(0.00002)	(0.0001)	(0.00002)	(0.0001)
Top 14 Law School	-0.158**	-0.143**	-0.161**	-0.155**
	(0.008)	(0.021)	(0.008)	(0.021)
$>$ 100 Ranked Law School	0.046**	0.055**	0.047**	0.058**
	(0.004)	(0.007)	(0.004)	(0.007)
Constant	-1.013**	-0.280	-0.998**	-0.198
	(0.061)	(0.159)	(0.061)	(0.160)
State Fixed Effects		✓		✓
N	716062	716062	716062	716062
R-squared	0.053	0.148	0.052	0.148
ρ	0.604	-0.024	0.595	-0.099
Inverse Mills Ratio	0.560*	-0.019	0.550*	-0.077
	(0.038)	(0.107)	(0.037)	(0.108)

**p < .01; *p < .05

Appendix L Alternative Specification of Selection Model with Binary Outcome Variable

Table A7: Second-stage Results: Binary Indicator for Donor is Conservative (DIME score > 0) as outcome variable

	Model 1	**Model 2**	**Model 3**	**Model 4**
Judge	0.079**	0.177**		
	(0.012)	(0.011)		
Fed. CoA			0.417**	0.429**
			(0.100)	(0.100)
Fed. District Court			0.187**	0.307**
			(0.050)	(0.049)
State Higher Court			0.259**	0.208*
			(0.081)	(0.086)
State Lower Court			0.038**	0.126**
			(0.014)	(0.014)
Fed. Mag.	-0.131**	0.313**	-0.133**	0.310**
	(0.047)	(0.049)	(0.047)	(0.049)
Fed. Admin. Judge	-0.024	0.369**	-0.026	0.366**
	(0.117)	(0.124)	(0.117)	(0.124)
State Admin. Judge	-0.288**	0.074	-0.289**	0.072
	(0.083)	(0.083)	(0.083)	(0.082)
Female	-0.514**	-0.157**	-0.514**	-0.154**
	(0.005)	(0.021)	(0.005)	(0.021)
Years since Admitted	0.032**	-0.038**	0.032**	-0.038**
	(0.001)	(0.002)	(0.001)	(0.002)
Years since Admitted^2	-0.0003**	0.001**	-0.0003**	0.001**
	(0.00002)	(0.00002)	(0.00002)	(0.00002)
Top 14 Law School	-0.137**	-0.323**	-0.138**	-0.325**
	(0.011)	(0.007)	(0.011)	(0.007)
>Ranked Law School	0.054**	0.103**	0.054**	0.103**
	(0.006)	(0.004)	(0.006)	(0.004)
Constant	-1.470**	0.656**	-1.472**	0.658**
	(0.037)	(0.073)	(0.037)	(0.072)
State Fixed Effects		✓		✓
N	974419	974419	974419	974419
Log Likelihood	-855467.7	-836159.2	-855588.8	-836262.5
ρ	0.759*	−0.713*	0.761*	−0.716*
	(0.030)	(0.035)	(0.030)	(0.034)

$^{**}p < .01$; $^{*}p < .05$

Note: The outcome variable is assigned a value of 1 if Contributor DIME score is positive and 0 otherwise. This specification codes 257,327 individuals (65%) as liberal and 137,927 (35%) as conservative. This provides a near one-to-one mapping to coding donors based on whether they had given more money to Democrats or Republicans. The models are fit using a maximum-likelihood estimator (in place of the Heckmann two-step estimator) that allows for binary outcomes in the selection model.

Appendix M Selection Model With DIME scores Recalculated with Selected Groups of Candidates Excluded

Table A8: Second-stage Results: OLS, Contributor DIME Score as Outcome Variable

	All Candidates	**Excluding Conts. To Judicial Candidates**	**Federal Candidates Only**
Fed. CoA	0.385**	0.431**	0.435**
	(0.084)	(0.091)	(0.096)
Fed. District Court	0.284**	0.277**	0.266**
	(0.041)	(0.043)	(0.047)
State Higher Court	0.193**	0.258**	0.250**
	(0.069)	(0.075)	(0.084)
State Lower Court	0.145**	0.185**	0.172**
	(0.012)	(0.013)	(0.033)
Fed. Mag.	0.329**	0.333**	0.234**
	(0.044)	(0.049)	(0.082)
Fed. Admin. Judge	0.365**	0.376**	0.243
	(0.097)	(0.104)	(0.126)
State Admin. Judge	0.117	0.109	0.023
	(0.065)	(0.069)	(0.091)
Female	-0.128**	-0.144**	-0.344**
	(0.016)	(0.019)	(0.026)
Years since Admitted	-0.034**	-0.035**	-0.011
	(0.003)	(0.004)	(0.006)
Years since Admitted^2	0.0005**	0.001**	0.0002**
	(0.00004)	(0.00005)	(0.0001)
Top 14 Law School	-0.310**	-0.327**	-0.237**
	(0.015)	(0.018)	(0.039)
$>$ 100 Ranked Law School	0.107**	0.118**	0.101**
	(0.005)	(0.006)	(0.014)
Constant	0.642**	0.624**	-0.144
	(0.108)	(0.122)	(0.263)
State Fixed Effects	✓	✓	✓
N	395187	382024	261134
R^2	0.156	0.152	0.118
ρ	-0.773	-0.763	-0.338
Inverse Mills Ratio	-0.770*	-0.797*	-0.328
	(0.069)	(0.079)	(0.138)

$^{**}p < .01$; $^{*}p < .05$

Appendix N Judicial Selection Model with Alternative Measures of State Ideology

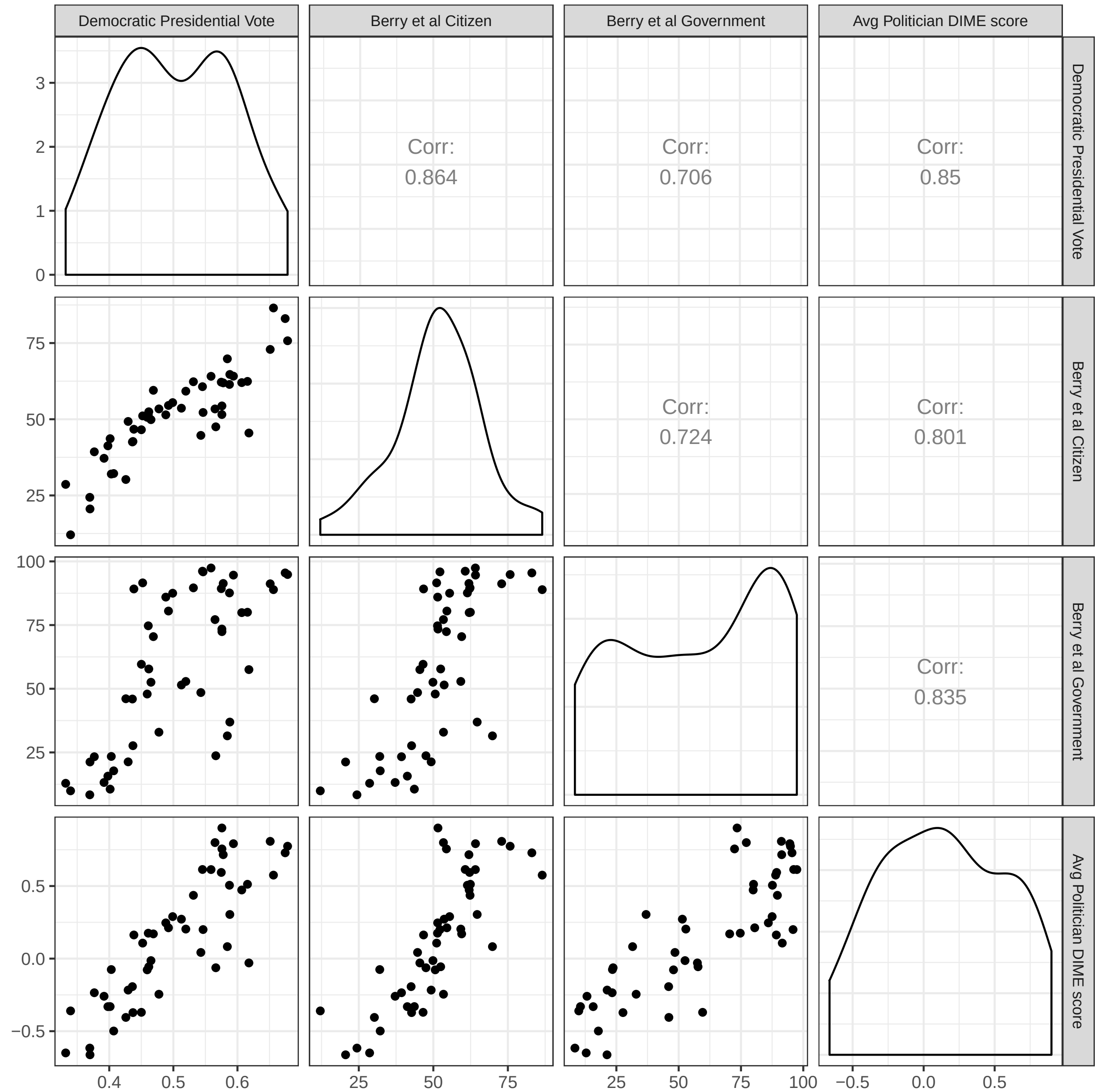


Figure A4: Comparison of Measures of State-Level Ideology

Note: Each row and column corresponds to a different state-level measures of ideology. The first row/column reports the average state-level presidential two-party vote shares for the 2004, 2008, and 2012 election cycles. The second and third row/column report the Berry et al. (2013) measures of citizen and state governmental ideology. The measures of state governmental ideology take partisan control of state legislatures into account. The fourth row column reports the average DIME scores for all elected politicians in the state. This measure is used in the main analysis. The lower-left panels plot the bivariate relationship between the corresponding row and column. The upper-right panels reports the Pearson correlations. The diagonal panels display the kernel density of state-level estimates for a given measure.

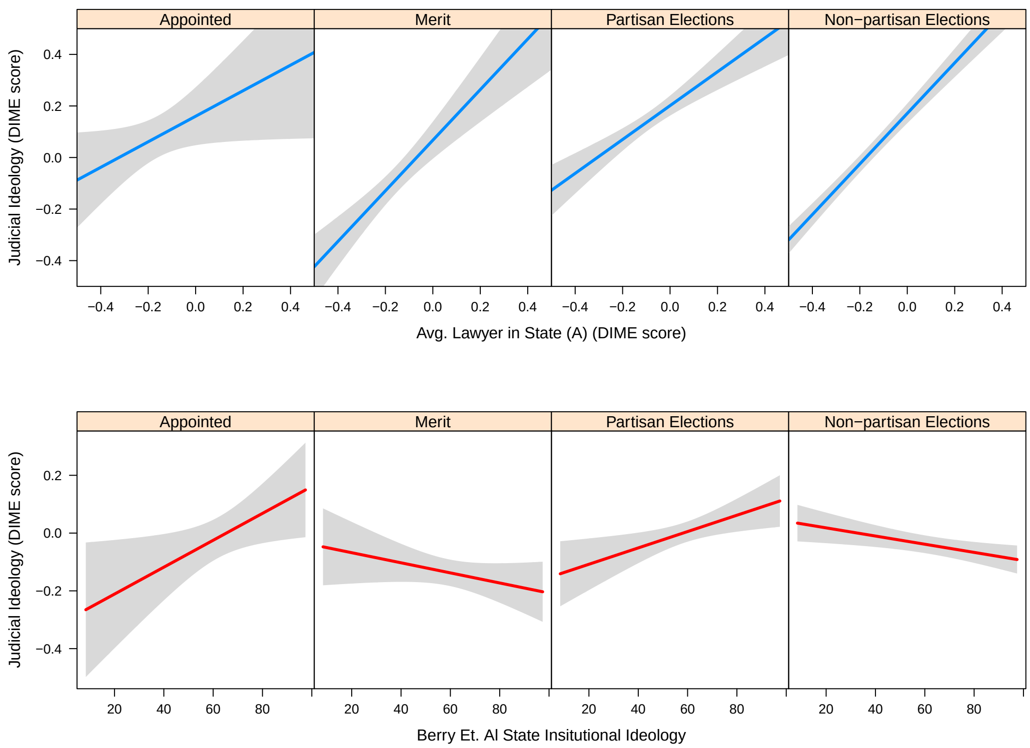


Figure A5: Predicted judicial ideology by (1) lawyers' ideologies (top) and (2) Berry et. al's measures of state government ideology (bottom) by judicial selection mechanism.

Appendix O Comparison of Lawyer DIME Scores to Party Registration

Here we compare the DIME scores for attorneys against party registration data. Party registration data offer the best opportunity to externally validate the measures of lawyer ideology against a corresponding individual-level measure of preferences. Only a fraction of states record party registration data on their voter rolls, and of those that do, most do not make this information publicly available. One exception is Florida. We were able to match 47,601 lawyers in our dataset to their party registration in the Florida voter file, 21,359 of whom have corresponding DIME scores.

The results confirm that the DIME scores are a reliable indicator of partisanship for attorneys. The results also suggest that relying on party affiliation alone would fail to capture important variation in political preferences, both within-party and for registered independents. The average DIME scores by partisan affiliation is -0.476 for Democrats, 0.684 for Republicans, and -0.333 for registered Independents.

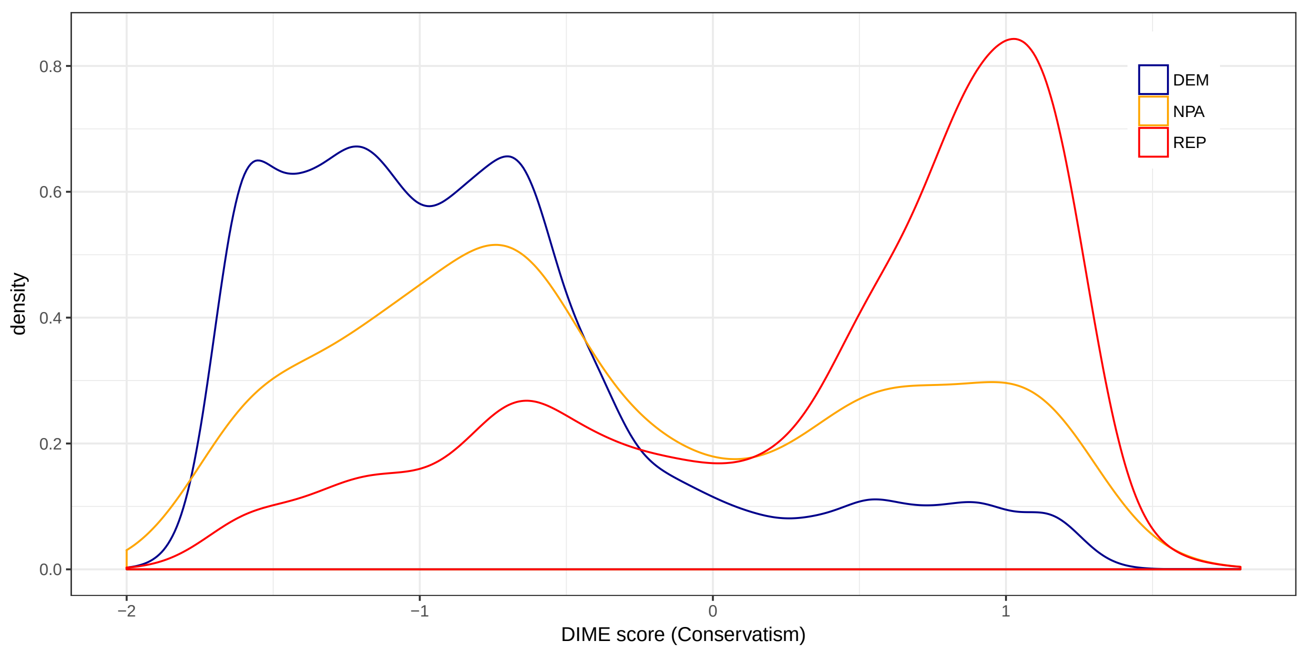


Figure A6: DIME Score Distributions by Party Registration (Florida). Sources: Florida Secretary of State, Martindale Hubbell, and DIME.

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