Supplemental Appendix to "A Common-Space Scaling of the American Judiciary and Legal Profession"

Adam Bonica* Maya Sen†

* Assistant Professor, 307 Encina West, Stanford University, Stanford CA 94305 (bonica@stanford.edu, http://web.stanford.edu/~bonica).

† Assistant Professor, 79 John F. Kennedy St., Harvard University, Cambridge MA 02138 (maya_sen@hks.harvard.edu, http://scholar.harvard.edu/msen).

Appendix 1 Predicting Coded Case Directionality For Unanimous and Nonunanimous Cases

We further consider whether the findings from Table 1 hold for the set of cases that were decided unanimously and hence would be uninformative in the context of MCMC-IRT estimation (Martin and Quinn, 2002). We re-estimate Model 3 from Table 1 separately for unanimous votes and report the results in Table A1. The relationship between attorney ideology and the directionality of case outcomes remains. This suggests that even unanimous cases are not devoid of ideological content, a finding that would be unrecoverable using standard ideal point estimation techniques. Table A1 reports results for nonunanimous cases.

Table A1: Predicting liberal-conservative direction codings from attorney ideal points for unanimous case outcomes: Logit

	Model 1	Model 2	Model 3	Model 4
(Intercept)	0.21	0.03	0.03	-0.46
	(0.12)	(0.16)	(0.12)	(0.87)
DIME score of Petitioning Atty.	0.30	0.34		
	(0.12)	(0.14)		
DIME score of Respondent Atty.		-0.36		
		(0.14)		
(DIME score of Petitioning Atty. − DIME score of Respondent Atty.)			0.35	0.30
			(0.10)	(0.11)
AIC	468.19	370.65	368.66	366.56
Log Likelihood	-232.10	-182.33	-182.33	-171.28
Deviance	464.19	364.65	364.66	342.56
Num. obs.	340	273	273	273

Outcome Variable: Direction of case outcome associated with petitioner is conservative.

Table A2: Predicting liberal-conservative direction codings from attorney ideal points for nonunanimous case outcomes: Logit

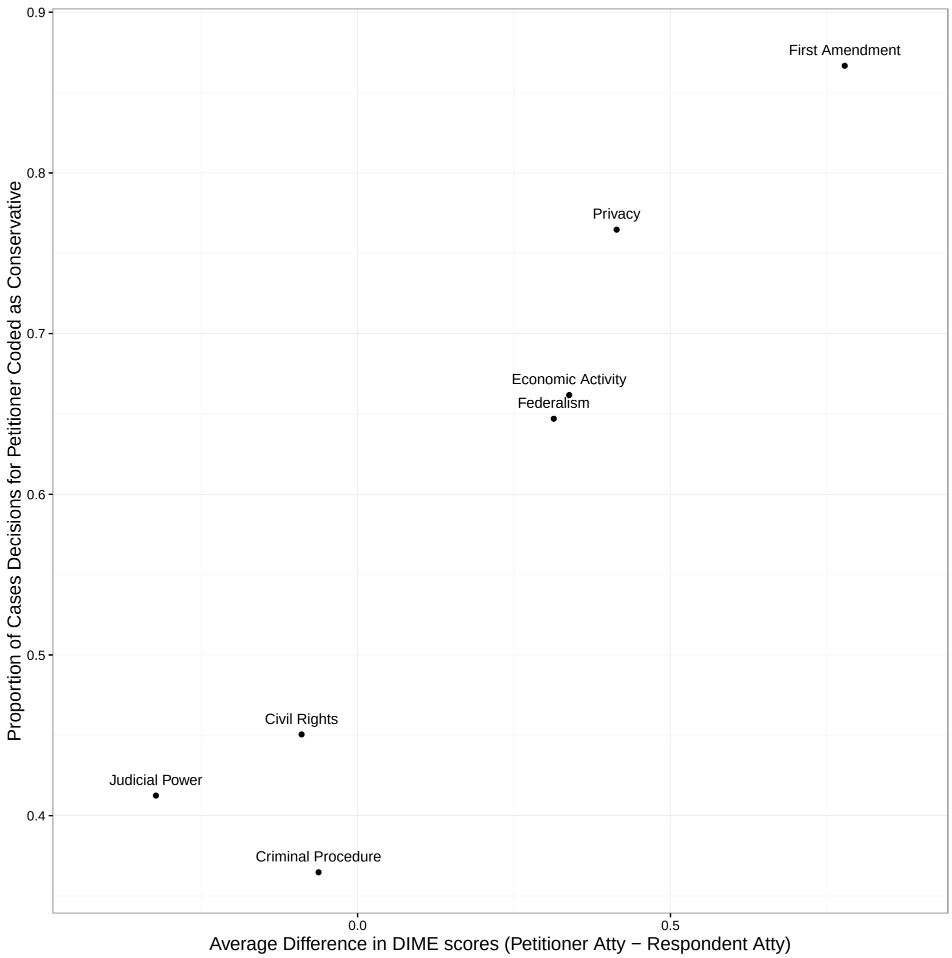
	Model 1	Model 2	Model 3	Model 4
(Intercept)	0.25	0.14	0.01	0.87
	(0.11)	(0.14)	(0.12)	(1.28)
DIME score of Petitioning Atty.	0.55	0.55		
	(0.11)	(0.12)		
DIME score of Respondent Atty.		-0.21		
		(0.12)		
(DIME score of Petitioning Atty. −			0.37	0.37
DIME score of Respondent Atty.)			(0.08)	(0.09)
AIC	554.50	419.68	421.44	382.27
Log Likelihood	-275.25	-206.84	-208.72	-178.13
Deviance	550.50	413.68	417.44	356.27
Num. obs.	417	317	317	317

Outcome Variable: Direction of case outcome associated with petitioner is conservative.

Appendix 2 Case Codings and Petitioner and Respondent Attorney Ideology by Issue Area

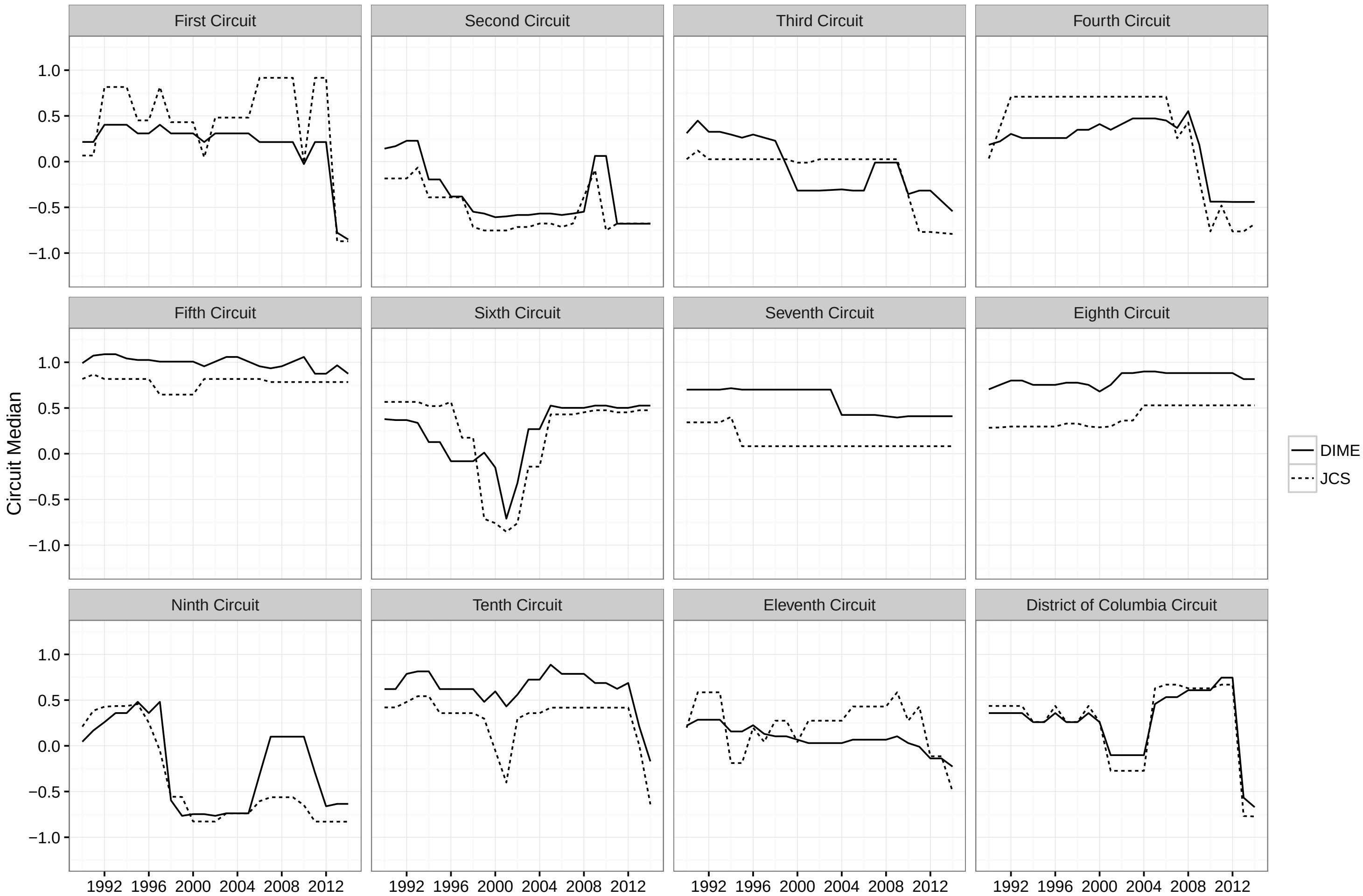
To provide additional substantive context, in Figure A1, we explore the relationship between issue areas cases and attorney ideology. The X-axis is the average difference in DIME scores for the petitioner and respondent attorneys for all cases in a given issue area. The Y-axis is the proportion of case outcomes associated with the petitioner coded as conservative. It reveals a clear relationship between attorney ideology and direction codings. The issue area that most stands out is First Amendment cases. The petitioner attorney is, on average, 0.80 units more conservative than respondent attorneys for these cases. At the same time, a vote cast in favor of the petitioner is coded to be in the conservative direction in 85% of the cases. This is consistent with recent accounts of upswing in conservative first amendment claims being brought before the Court (Savage, 2014). At the other extreme, petitioner attorneys on cases related to judicial power are, on average, significantly to the left of the respondent attorneys in these cases.

Figure A1: Liberal-conservative case codings and petitioner and respondent attorney ideology aggregated by issue areas



Appendix 3 Circuit Court Medians

Figure A2: Circuit court medians (1990-2014).



Note: The JCS scores are rescaled to correspond with DIME scores.

Appendix 4 Multiple Imputation

This appendix provides additional details on the multiple imputation model and results. The multiple imputation was done using the Amelia II package (Honaker, King, and Blackwell, 2011). We include in the model variables capturing (1) the observed DIME and JCS scores, (2) court type, (3) law school attended, (4) birth year, (5) gender, (6) race/ethnicity,[1] (7) prosecutor, (8) public defender, or (9) professorial/adjunct experience, (10) military service, (11) previous employment in the U.S. Attorney's office, (12) whether they were rated "Well Qualified" by the American Bar Association, and (13) whether the judge clerked for a liberal or conservative judge.[2] We also include variables reflecting the political environment at the time of nomination, including (14) divided government and (15) identity of the appointing President. Lastly, we included (16) the DW-NOMINATE for the chair of Senate Judiciary Committee at the time of appointment and (17) the average DW-NOMINATE score for the home-state senators interacted with a variable indicating whether they share the same party as the president.

To deal with sharp shifts that can occur when the partisan control of the presidency changes, we impute estimates for Republican and Democratic administrations separately. Aggregating judicial appointees across administrations of both parties leads to a bimodal distribution of ideal points, which does not fit the normality assumptions made by Amelia. However, the within party distributions more closely approximate a normal distribution. Amelia's framework allows for time-series cross-sectional data structures. We specify the model to treat presidential administrations as cross-sections and allow for time trends with judges grouped by year of appointment. To evaluate the accuracy of the multiple imputation, we "overimpute" the observed values, which gives us predicted values from the multiple imputation model for both the missing and non-missing data and serves as cross-validation check for the accuracy of the imputation model.

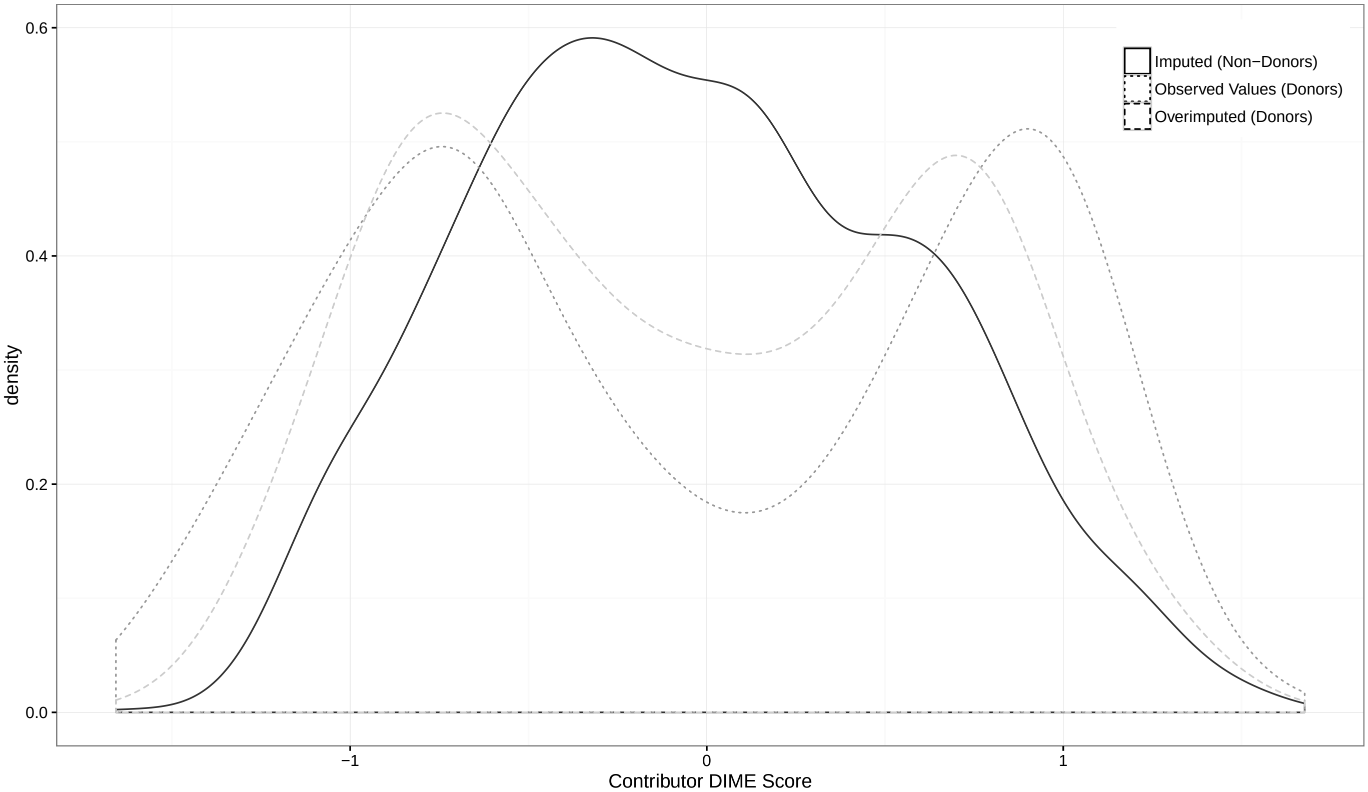
A key assumption built into Amelia is that data are missing at random (MAR). For the MAR assumption to hold, the missingness is random conditional on the observed data. The MAR assumption is distinct from the missing completely at random (MCAR) assumption, which is that the missingness is independent of the observed or missing data. Here, missingness in the data is largely confined to the DIME scores. While some missingness is present in the other variables included in the multiple imputation model, it is rare. The majority of variables (79 out of 89) are fully observed. Of the ten remaining variables, the data is mostly observed. The rate of missingness averaged across the ten variables is just 3.2%. In total, only 0.4% of cells (excluding the DIME scores) have missing data.

As we are primarily tasked with imputing missing DIME scores for judges who are not on record as political donors, we focus our discussion accordingly. One clear pattern is that judges named by recent presidents are much more likely to have donated. Those appointed during the Bush and Obama administrations are more than twice as likely to have donated than those appointed in prior administrations. This does not present a direct threat to the MAR assumption since the missingness depends on the year of appointment, which is fully observed. Instead, the MAR assumption would be threatened if missingness arises due to unobserved differences in the ideological distributions of donors and non-donors. For example, one might conjecture that judges who have never donated are, on average, more moderate than judges who have donated. Unless the differences are captured by other covariates included in the model, the MAR assumption would be violated. While the conjecture is certainly plausible, it is also plausible that these differences will be captured by the rich set of covariates included in the multiple imputation.

Figure A3 compares the distributions for the observed and overimputed values for donors and the imputed values for non-donors. Comparing the overimputed values with the observed values reveals that imputation model does reasonably well in recovering the bimodal distribution observed in the data. The distribution of imputed values for non-donors is noticeably less bimodal. The contrast between overimputed and imputed values is telling. It would seem to be consistent with the conjecture that non-donors tend to be less polarized than donors.

Figure A4 compares the observed values with overimputed values from a model run

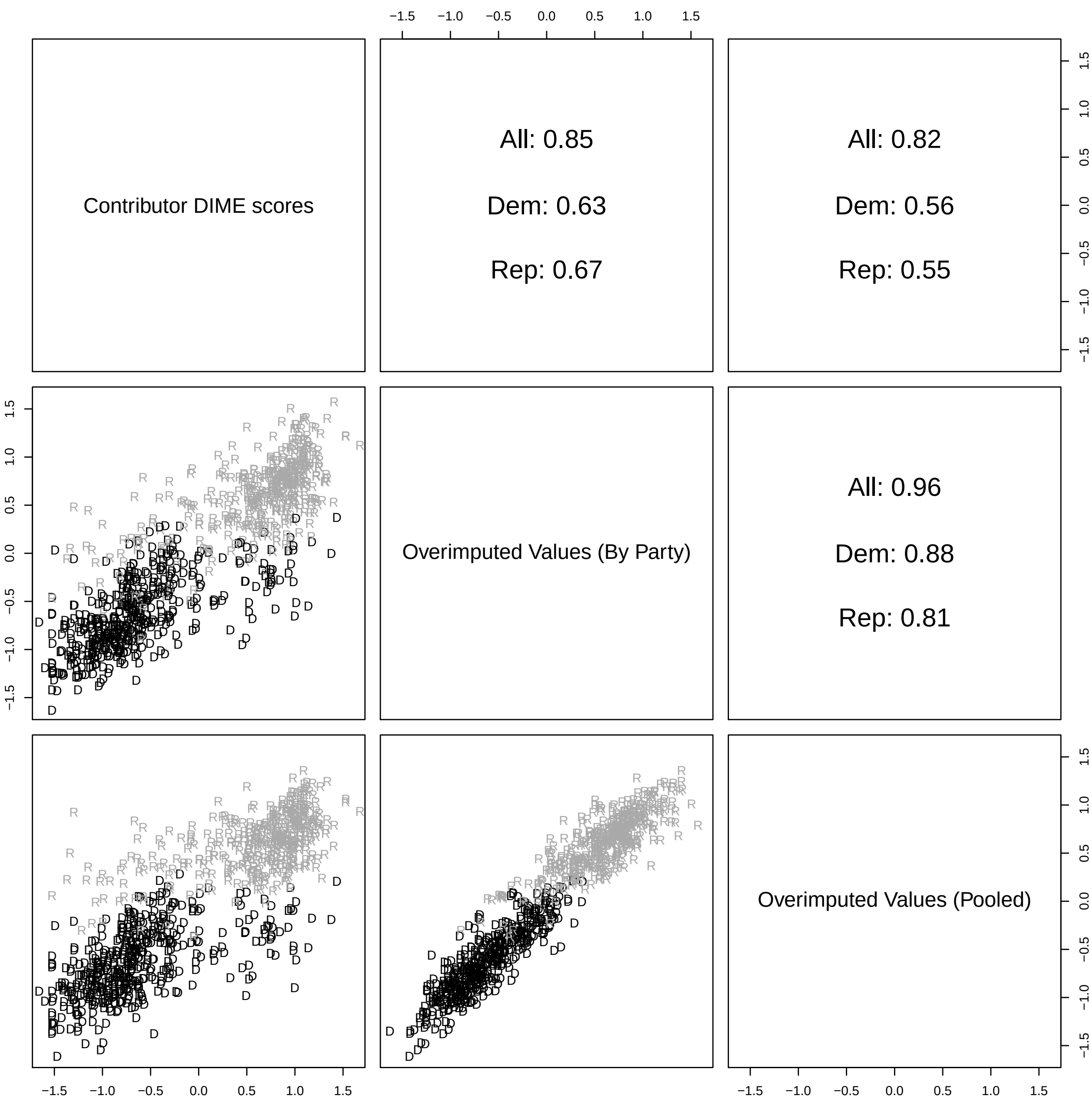
Figure A3: Comparison of distributions of observed, imputed, and overimputed values



separately for each party and from a pooled model run on the full sample. Imputing scores separately by party improves accuracy over a pooled model. But the imputed scores from the party-specific and pooled models are largely consistent, as shown in the middle-right panel.

We further assess the performance of the imputation model conditional on the number of donations made by a judge. Our initial expectation is that the overimputed values should be less accurate for judges who have only given to one or two candidates as compared with judges who were more active donors. We calculate the imputation accuracy for the overimputed values into three groups of judges based the number of recorded contributions: (1) N <= 2 recipients, (3) 2 > N < 10 recipients, and (3) N >= 10 recipients. We find that the accuracy of the imputations does not vary much across groups. The overall correlations for all three groups were basically identical, ranging between $\rho = 0.85$ and $rho = 0.86$. While it is reassuring that imputation model does not appear to be sen-

Figure A4: Pairwise comparisons of observed and imputed DIME Scores from party-specific and pooled models (1980-2014)



sitive to how many times a judge has donated, we note that non-donors might still be systematically different from donors.

Lastly, we acknowledge that multiple imputation is only one of several alternative strategies for dealing with missing data. We believe multiple imputation as implemented represents the best available solution for creating a general resource that can be used "off-the-shelf" similar to how Judicial Common-space scores are currently used by scholars. But we also acknowledge that alternative approaches might be better suited depending on the research question and/or use case. A Heckman-type model is likely to be more appropriate for applications that require researchers to consider more seriously issues related to selection bias. In other applications, non-parametric machine-learning imputation models may be more suitable. To this end, we encourage researchers to think critically about whether the multiple-imputation strategy used here is the best strategy for their purposes and to make use of the accompanying replication data to implement more tailored approaches for dealing with missing data when needed.

Appendix 5 Summary Statistics

Table A3: Characteristics of federal judges named after 1980

	N	Missing	CFscore (Observed)	CFscore (Imputed)	JCS	Age	Female	Black	Hispanic	Asian	Num. Donations (1)	Num. Donations (2-9)	Num. Donations ($\geq$ 10)
Barack Obama	310	0.24	-0.71	-0.72	-0.32	51.90	0.42	0.19	0.11	0.07	0.15	0.33	0.25
George W. Bush	324	0.35	0.64	0.57	0.49	51.00	0.22	0.07	0.09	0.01	0.15	0.31	0.19
William J. Clinton	376	0.43	-0.54	-0.61	-0.32	51.10	0.29	0.16	0.07	0.01	0.18	0.24	0.13
George H.W. Bush	191	0.58	0.57	0.44	0.38	49.60	0.19	0.06	0.04	0.00	0.15	0.20	0.06
Ronald Reagan	377	0.67	0.62	0.60	0.36	50.30	0.08	0.02	0.04	0.01	0.14	0.15	0.04
Male	1,201	0.45	0.09	0.28	0.14	51.30	0.00	0.09	0.06	0.02	0.15	0.25	0.14
Female	377	0.46	-0.42	-0.23	-0.04	49.60	1.00	0.14	0.09	0.03	0.17	0.22	0.10
White	1,273	0.45	0.07	0.27	0.13	51.20	0.22	0.00	0.00	0.00	0.14	0.25	0.14
Black	164	0.48	-0.65	-0.46	-0.13	49.30	0.31	1.00	0.01	0.00	0.22	0.15	0.12
Hispanic	111	0.39	-0.18	-0.08	0.07	50.00	0.31	0.02	1.00	0.01	0.23	0.29	0.06
Asian	32	0.31	-0.72	-0.38	-0.17	48.20	0.38	0.00	0.03	1.00	0.25	0.31	0.09
District Court	1,272	0.45	-0.06	0.14	0.09	50.70	0.24	0.11	0.07	0.02	0.16	0.24	0.13
Circuit Court	306	0.45	0.11	0.25	0.12	51.50	0.24	0.08	0.06	0.02	0.14	0.25	0.14
All	1,578	0.45	-0.03	0.16	0.09	50.90	0.24	0.10	0.07	0.02	0.16	0.24	0.13

Bibliography

Honaker, James, Gary King, and Matthew Blackwell. 2011. "Amelia II: A Program for Missing Data." *Journal of Statistical Software* 45 (7): 1–47. http://www.jstatsoft.org/v45/i07.

Martin, Andrew D., and Kevin M. Quinn. 2002. "Dynamic Ideal Point Estimation via Markov Chain Monte Carlo for the U.S. Supreme Court, 1953–1999." *Political Analysis* 10 (2): 134–153.

Savage, David G. 2014. *Supreme Court faces wave of free-speech cases from conservatives*. http://www.latimes.com/nation/la-na-court-free-speech-20140320-story.html.