**Supplementary Appendix A. Legislative Positions Held by Supreme Court Justices, 1873-2022**

|  |  |  |  |
| --- | --- | --- | --- |
| **Justice** | **Position 1** | **Position 2** | **Position 3** |
| Clifford | State Representative, ME (**4**) | US Representative, ME (**4**) |  |
| Swayne | State Representative, OH (**2**) | Columbus City Council (**1**) |  |
| Davis | State Representative, IL (**1**) |  |  |
| Field | State Assemblyman, CA (**1**) |  |  |
| Chase | US Senator, OH (**6)** |  |  |
| Strong | US Representative, PA (**4**) |  |  |
| Hunt | State Assemblyman, NY (**1**) |  |  |
| Waite | State Representative, OH (**1**) |  |  |
| Woods | State Representative, OH (**5**) |  |  |
| Matthews | State Senator, OH (**2**) | US Senator, OH (**4**) |  |
| Lamar, Lucius | State Representative, GA (**1**) | US Representative, MS (**7**) | US Senator, MS (**8**) |
| Fuller | Augusta Common Council (**1**) | State Representative, IL (**2**) |  |
| Jackson, Howell | State Representative, TN (**1**) | US Senator, TN (**5**) |  |
| White | State Senator, LA (**5**) | US Senator, LA (**3**) |  |
| McKenna | State Assemblyman (**2**) | US Representative, CA (**7**) |  |
| Moody | US Representative, MA (**6**) |  |  |
| Lamar, Joseph | State Representative, GA (**3**) |  |  |
| Pitney | US Representative, NJ (**4**) | State Senator, NJ (**3**) |  |
| Sutherland | State Senator, UT (**4**) | US Representative, UT (**2**) | US Senator, UT (**12**) |
| Black | US Senator, AL (**10**) |  |  |
| Reed | State Representative, KY (**4**) |  |  |
| Byrnes | US Representative, SC (**14**) | US Senator, SC (**10**) |  |
| Burton | State Representative, OH (**1**) | US Senator, OH (**4**) |  |
| Vinson | State Representative, KY (**12**) |  |  |
| Minton | US Senator, IN (**6**) |  |  |
| O’Connor | State Senator, AZ (**6**) |  |  |

Table 1 lists which Supreme Court justices (appointed after 1872) have held legislative positions, which positions they held, and how many years per position (in parentheses).

**Supplementary Appendix B. Matching Protocols**

Using standard statistical estimation procedures in observational studies can create at least two potential problems. First, results can be heavily model-dependent, varying in effect size, statistical significance, and even effect direction depending on the procedure employed and the control variables included (Ho et al. 2007). Second, assuming (as is the case here) that the model includes control variables, there may be a high degree of “imbalance” among the covariates in observational data. Imbalance in this context refers to when covariates differ between what an experimental study would refer to as the “treatment” groups (here those justices with legislative backgrounds) and the “control” groups (those without) (Blackwell et al. 2009), impeding proper estimation. Given the historical sweep of my data, there is good reason to expect such imbalance.

 Both problems can be ameliorated using a variant of nonparametric matching (Ho et al. 2007). Matching brings the logic of experimental treatments to observational studies, aiming to locate pairs of cases that are similar except for the presence of the key independent or “treatment” variable, creating a match. This technique uses one or more algorithms to match as many cases as it can, at which point the procedure generally prunes or discards the remaining cases. As long as the matched dataset remains sufficiently large, gains in covariate balance will offset the loss of statistical power in terms of creating reliable estimates.

 However, creating a dataset of “exact” matches becomes extremely difficult once more than a few covariates are included in the matching process. For example, if one justice-vote in this data was proffered by a Republican appointee ruling in 1904 on an 1888 civil rights law passed by a Democratic Congress, then exact matching would require finding a judge with the same characteristics differing *only* on prior legislative experience. Exact matching can thus quickly grind a dataset down to unusably small numbers, particularly if the model contains continuous variables. Instead, I use an approximate matching method, Coarsened Exact Matching (CEM), that does not require exact matches to improve the data’s balance (Blackwell et al. 2009). The “coarsening” effect of CEM is akin to grouping cases into histograms, at which point matching occurs along the newly created bins rather than exact values. The CEM algorithm I employ automatically coarsens the data (again, similar to how a program might automatically decide how many histogram bins to create), aiming to balance between maintaining adequate dataset size and reducing covariate imbalance (Iacus, King, and Porro 2012). In their use of CEM to estimate the impact of the Solicitor General on the Supreme Court across a variety of dimensions, Black and Owens (2012) reported that this automated process was far easier and more successful at reducing imbalance than setting the coarsening criteria oneself.

**Supplementary Appendix C. Summary Statistics for Matched Data, Main Model**

***Table C.1. Categorical Data***

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | **Frequency (votes)** | **Mean** | **Standard deviation** | **Number** |
| **Strikes down federal law** | 2,489 | 0.297 | 0.497 | 8,366 |
| **Justice has legislative experience, binary** | 2,134 | 0.255 | 0.436 | 8,366 |
| **Partisan orientation** |  | 0.879 | 0.923 | 8,366 |
| *Same party enacted* | 4,164 |  |  |  |
| *Divided gov enacted* | 1,052 |  |  |  |
| *Opposing party enacted* | 3,150 |  |  |  |
| **Issue area** |  | 3.45 | 1.76 | 8,366 |
| *Due process* | 2,076 |  |  |  |
| *Substantive rights* | 1,014 |  |  |  |
| *Equality* | 194 |  |  |  |
| *Economic* | 2,181 |  |  |  |
| *Federalism* | 1,966 |  |  |  |
| *Separation of powers* | 935 |  |  |  |
| **Landmark law** | 4,083 | 0.489 | 0.5 | 8,353 |

***Table C.2. Continuous Data***

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  | **Minimum** | **Maximum** | **Mean** | **Standard deviation** | **Number** |
| **Age of law under review (months)** | 2 | 1463 | 146.907 | 168.828 | 8,366 |
| **Decision year** | 1872 | 2011 | 1943 | 35.293 | 8,366 |

The CEM matching process necessarily prunes some cases from the original dataset to improve balance. Here, no cases after 2011 are matched because the landmark law variable is right censored at 2012. Removing the landmark law control, re-matching, and re-estimating the model does not lead to any substantive differences in the sign, size, or significance of the legislative experience or partisan orientation measures.

**Supplementary Appendix D. Model Comparison Statistics and Interaction Estimates**

***Table D1. Logistic Regression Models, Estimates on the Probability of a Supreme Court Justice Striking Down a Federal Law***

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | (1)Legislative Experience | (2)Elected Office Experience (any) | (3)Congressional Experience (only) | (4)Legislative Experience with Trifecta Measure |
| **Prior legislative experience** | **-0.145\*\***(0.050) | **-0.091\***(0.046) | -0.061(0.056) | **-0.141\*\***(0.050) |
| **Partisan orientation** |  |  |  |  |
| *Law passed under divided government* | **-0.507\***(0.208) | **-0.481\***(0.208) | -0.604(0.368) | -0.072(0.147) |
| *Law passed under opposite Congress/ trifecta* | **0.458\*\*\***(0.117) | **0.38\*\*\***(0.102) | **0.368\*\***(0.109) | **0.429\*\***(0.139) |
| **Law age (months)** | -0.000(0.000) | 0.000(0.000) | 0.0000.000 | -0.000(0.000) |
| **Issue area** |  |  |  |  |
| *Substantive rights* | -0.023(0.191) | 0.081(0.182) | 0.039(0.225) | 0.046(0.199) |
| *Equality* | 0.048(0.455) | 0.016(0.449) | **1.068\***(0.523) | -0.002(0.466) |
| *Economics* | **-0.503\*\***(0.181) | **-0.461\*\***(0.171) | **-0.543\*\***(0.523) | **-0.474\***(0.183) |
| *Federalism* | **-0.543\*\***(0.188) | **-0.577\*\***(0.175) | **-0.641\*\***(0.192) | **-0.547\*\***(0.189) |
| *Separation of powers* | **-0.613\*\***(0.229) | **-0.569\*\***(0.218) | -**0.464\*\***(0.258) | **-0.600\*\***(0.231) |
| **Landmark law** | 0.136(.128) | 0.074(0.121) | -0.007(0.134) | 0.154(0.131) |
| **Decision year** | **0.006\***(0.002) | **0.005\***(0.002) | **0.008\***(0.003) | **0.007\*\***(0.002) |
| *N* | 8,353 | 8,728 | 6,347 | 8,531 |

Robust standard errors clustered on the case in parentheses

\* *p* < 0.05, \*\* *p* < 0.01, \*\*\* *p* < 0.001

Models 1-3 use a partisan orientation variable where a law passed by a Congress of the same party as the justice’s appointing president is the reference category. Model 4 uses a partisan orientation variable where a law passed by a trifecta (Congress and president) of the same party as the justice’s appointing president is the reference category. The reference category for the issue area variable is due process.

***Table D.2. Logistic Regression Models with Interactions Between Legislative Experience and Partisan Orientation Measures***

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | (1)Legislative Experience | (2)Elected Office Experience | (3)Congressional Experience | (4)Legislative Experience with Trifecta Measure |
| **Prior legislative experience, binary** | -0.122(0.066) | -0.102(0.060) | -0.207\*(0.086) | -0.191\*(0.074) |
| **Partisan orientation** |  |  |  |  |
| *Law passed under* *divided government* | -0.553\*\*(0.213) | -0.527\*(0.212) | -0.685(0.390) |  -0.131(0.154) |
| *Law passed under opposite Congress/trifecta* | 0.484\*\*\*(0.127) | 0.381\*\*(0.111) | 0.363\*\*(0.114) | 0.466\*\*(0.151) |
| **Law age (months)** | -0.000(0.000) | 0.000(0.000) | 0.000(0.000) | -0.000(0.000) |
| **Issue area** |  |  |  |  |
| *Substantive rights* | -0.023(0.191) | 0.081(0.182) | 0.042(0.226) | 0.045(0.200) |
| *Equality* | 0.048(0.455) | 0.159(0.448) | 1.085\*(0.522) | -0.002(0.466) |
| *Economics* | -0.503\*\*(0.181) | -0.461\*\*(0.171) | -0.549\*\*(0.181) | -0.474\*\*(0.183) |
| *Federalism* | -0.543\*\*(0.188) | -0.577\*\*(0.175) | -0.640\*\*(0.193) | -0.547\*\*(0.189) |
| *Separation of powers* | -0.613\*\*(0.229) | -0.569\*\*(0.218) | -0.460(0.258) | -0.600\*\*(0.231) |
| **Landmark law** | 0.136(0.128) | 0.074(0.121) | -0.007(0.135) | 0.154(0.131) |
| **Decision year** | 0.006\*(0.002) | 0.005\*(0.002) | 0.007\*(0.003) | 0.007\*\*(0.002) |
| **Interactions** |  |  |  |  |
| *Experience present* x *divided government* | 0.185(0.165) | 0.155(0.156) | 0.233(0.319) | 0.240\*(0.117) |
| *Experience present* x *opposite Congress/trifecta* | -0.107(0.112) | -0.002(0.096) | 0.032(0.151) | -0.069(0.130) |
| *N* | 8,353 | 8,728 | 6,347 | 8,531 |

Robust standard errors clustered on the case in parentheses

\* *p* < 0.05, \*\* *p* < 0.01, \*\*\* *p* < 0.001

Models 1-3 use a partisan orientation variable where a law passed by a Congress of the same party as the justice’s appointing president is the reference category. Model 4 uses a partisan orientation variable where a law passed by a Trifecta (Congress and president) or government of the same party as the justice’s appointing president is the reference category. The reference category for the issue area variable is due process.

**References**

Black, Ryan C., and Ryan J Owens. 2012. *The Solicitor General and the United States Supreme Court: Executive Branch Influence and Judicial Decisions*. Cambridge, UK: Cambridge University Press.

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Iacus, Stefano M., Gary King, and Giuseppe Porro. 2012. "Causal Inference Without Balance Checking: Coarsened Exact Matching." *Political Analysis* 20 (1):1-24.