Social attitudes cannot be predicted from federal court decisions and judge characteristics

William T. Adler, Anna Coenen, Alexander S. Rich, and adviser: Dr. Daniel S. Chen

1 Question

Federal US circuit courts often make rulings in areas that are socially relevant to the American public, such as capital punishment, affirmative action, or racial discrimination. In this project, we seek to measure how these rulings may affect Americans' social and political attitudes. Our goal is to determine whether court rulings tend to move attitudes in the direction "intended" by the ruling or whether rulings tend to move attitudes in the opposite direction or polarize attitudes. We will focus on rulings about gender discrimination and their impact on on attitudes about gender roles.

2 Datasets

To address this question we used two datasets.

First, we used the US General Social Survey (GSS), which is a long running (1972–) survey on social attitudes and behaviors of US American citizens (Smith et al., 2013). In addition to social attitudes, the GSS provides demographic and life-course data about respondents. Each row represents one respondent.

Second, we used a database of federal appeals court cases that were decided at the level of circuit courts (Sunstein, 2007). The cases were separated by issue (e.g. affirmative action, gender discrimination, racial discrimination). The federal court system is divided into 12 circuits, each of which establishes legal precedent for a group of several states. A circuit court case is decided by a randomly assigned panel of three judges chosen from the pool of judges appointed to that circuit. The dataset provides information about the outcome of each case, which is coded as the number of judges who voted in favor the outcome that can be considered to be more "progressive" (for example, pro-affirmative action, and against racial or gender discrimination).

Another dataset was used to assign judge characteristics to each case (Zuk Gary; Barrow, 1997). This included, for instance, the number of panel judges who were female, or who were appointed by a Democratic president. It also included the average number of female judges (and other characteristics) in the pool of judges for that circuit at the time of the ruling.

For our analyses reported below, we focused of the issue of gender discrimination, and restricted ourselves to court case data pertaining to that issue. In total, we used 100 cases (one case per row) that were decided between 1995 and 2004. We chose this subset of cases because it was the subset that had the longest period of intersection with several relevant questions on the GSS.

3 Data preprocessing and independent variables

3.1 GSS predictors

When testing for the impact of course cases in our modeling section below, we controlled for various demographic variables from the GSS. Specifically, we used the following variables as predictors in our model(s).

- age (years)
- sex (male; female)
- education (years)
- race (black; white; other)
- region (New England; Middle Atlantic; Mountain; Pacific; South Atlantic; East-North Central; East-South Central; West-North Central; West-South Central)
- religion (Buddhist; Catholic; Christian; Hindu; inter/nondenominational; Jewish; Muslim; Native American; Orthodox Christian; Protestant; Other Eastern; Other; None)

For discrete predictors, we used one-hot encoding. Continuous variables were standardized to have zero mean and unit variance. Along with these predictors, we also included race-by-region and race-by-religion interactions, and interactions of all demographic predictors with year in which the survey was administered.

3.2 Court case predictors

For each case, we computed the difference between the judge ideology on a given panel and its expected value. To calculate this, we took the proportion of judges who were appointed by Democratic presidents on each panel, and subtracted the expected proportion based on the overall pool of judges in the circuit at the time of the case.

We then grouped court cases by circuit and year, and aggregated them in different temporal time windows ranging from 1 to 10 years. For each time window and each circuit we computed the *number of liberal* and the *number of conservative decisions*, as well as the summed *difference of judge ideology from expectation* value described above.

3.3 Integrating the data sources

We removed GSS data for years in which court data was unavailable, and merged the three court predictors with the GSS demographics predictors by year and circuit (the "circuit" of a GSS respondent was determined by the region they resided in). For each court predictor, we added interactions of court-predictor-by-year, and court-predictor-by-demographic for each demographic variable.

4 Dependent variable: Index of conservative attitudes about gender roles

4.1 Approach

Our dependent variable was people's attitudes towards gender roles. To operationalize these attitudes, we used 7 questions from the GSS that asked for people's opinions on gender roles (see below). To arrive at a single outcome measure, we performed a Principal Components Analysis (PCA) as a method of dimensionality reduction. Before fitting the PCA, we standardized the answers to each question to have variance of 1 and mean of 0. To handle missing data, we excluded every respondent who answered only four or fewer of the 7 questions. Otherwise, missing values were imputed using the average response to a given question by other respondents in the same year.

PCA performs a total least squares regression on a number of variables to find the dimensions that can explain the most (or least) amount of variance in the data. Each principle component is an eigenvector of the data's covariance matrix ($D^T D$) and the amount of variance it explains is the corresponding eigenvalue.

4.2 Resulting measure

The first principle component of the 7 gender questions from the GSS explained 36% of the variance in the data and by examining its coefficients for each question, we confirmed that it captures respondents' level of conservatism regarding gender roles. The following table summarizes the coefficients per question.

GSS Statement	Coefficient of 1st principal component
A working mother can establish just as warm and secure a relationship with her children as a mother who does not work.	-0.53
Because of past discrimination, employers should make special efforts to hire and promote qualified women.	-0.02
I favor the preferential hiring and promotion of women.	0
Most men are better suited emotionally for politics than are most women.	0.3
It is much better for everyone involved if the man is the achiever outside the home and the woman takes care of the home and family.	0.54
Family life often suffers because men concentrate too much on their work.	0.54
A preschool child is likely to suffer if his or her mother works.	0.56

After projecting the question data on this component, participants with more traditional views on gender roles (assigning more domestic responsibilities to women and more professional ones to men) end up with higher values than more progressive respondents. In the rest of this report we will use this measure as our dependent variable, which we refer to as the *gender conservatism index*.

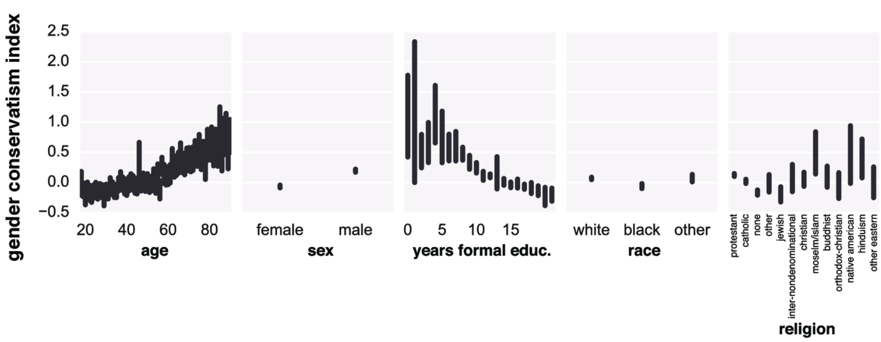

Figure 1: GSS respondents who were older, male, or had fewer years of formal education scored highly on the gender conservatism index. Error bars represent 95% confidence intervals on the bootstrapped mean.

5 Modeling approach

5.1 Main model

Our main challenge in modeling these data was to strike a balance between predictive accuracy and interpretability. On the one hand, we wanted to make sure that our model was not overfitting the data and made good predictions. On the other hand, the question of this project required us to use a method that allowed us to draw inferences about the impact of specific predictors.

To make sure the results were easy to interpret, we chose to model the data using linear regression. To make sure our model does not overfit, we regularized it using L1 regularization (proportion=.9) and L2 regularization (proportion=.1). This elastic net approach gave us the benefit of sparsity of the solution (due to L1 regularization), while stabilizing our estimates from correlated predictors via a small amount of L2 regularization. We chose the total amount of regularization using 10-fold cross-validation within the training set and chose the value that yielded the lowest average error.

5.2 Alternative models

In addition to the regularized linear regression, we also tried a number of other machine learning algorithms to model our data. Each of these approaches yielded similar results as our main analysis regarding the impact of court predictors. Since their outcomes are more difficult to interpret, we chose to present results only from the linear regression.

Specifically, we tried the following algorithms.

- regression with a decision tree
- regression with a random forest
- regression with AdaBoost

In all cases, court-related predictors decreased performance on the validation set.

6 Results

All results reported below are calculated based on ten runs of the model, using a different randomly selected 10% of the GSS data held out as a test set on each run.

6.1 Null model: Demographics only

When predicting the gender conservatism index using demographic predictors alone, we achieved an R^2 of $\sim .11$ on the training set, and $\sim .092$ on the test set.

6.2 Full model: Demographics and court data

We tested two versions of the full model that included the court data in addition to demographic predictors. First, we tested a model with court decisions (no. of conservative/liberal decisions) over different time windows along with the judge ideology predictor (difference from expectation in each time window). Second, we also tested a model with only the judge ideology predictor. Since judges are randomly chosen from a large pool, their impact on attitudes counts as an interesting "natural experiment."

Across all temporal windows tested (1 to 10 years), the addition of information from recent circuit court decisions did not improve the prediction of gender conservatism in our test set. This is illustrated by Figure 2, which shows the R^2 by model type (demographics only or demographics + court), time window, and dataset (training or test). On the test set, the full models' performance is consistently worse than those of the null model.

Although we were unable to detect any impact from the court decisions on the gender conservatism index, a number of demographic variables proved reliably predictive of gender conservatism. As Figure 3 shows, among the most reliable predictors were age, gender, race, education, and religion of the respondent.

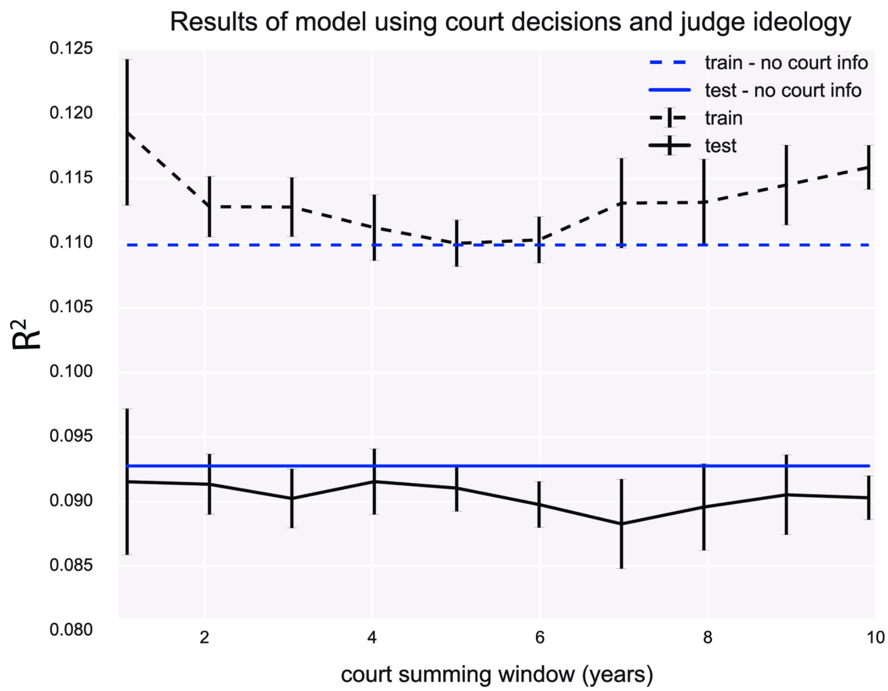

Figure 2: R^2 of null model (no court) and full model on training and test set, by court data summing window.

7 Discussion

Although we used several modeling approaches, we did not find a relationship between federal court rulings dealing with gender discrimination and societal attitudes about gender roles. It may be that most circuit court cases do not reach the public consciousness enough or are not impactful enough to affect attitudes. Alternatively, it is possible that cases in another domain such as affirmative action or the death penalty have a more direct effect on attitudes. Unfortunately, in many domains our current data set did contain sufficient temporal overlap between court cases and relevant GSS questions for a well-powered analysis.

An interesting future direction might be to study this question using supreme court cases, which (sometimes) receive far greater media coverage. For example, did the recent Obergefell v. Hodges ruling alter Americans' views about same-sex marriage? This kind of high-profile case may be the most likely to shift attitudes perceptibly, though this very landmark status also means that such cases are rare, and thus difficult to statistically analyze.

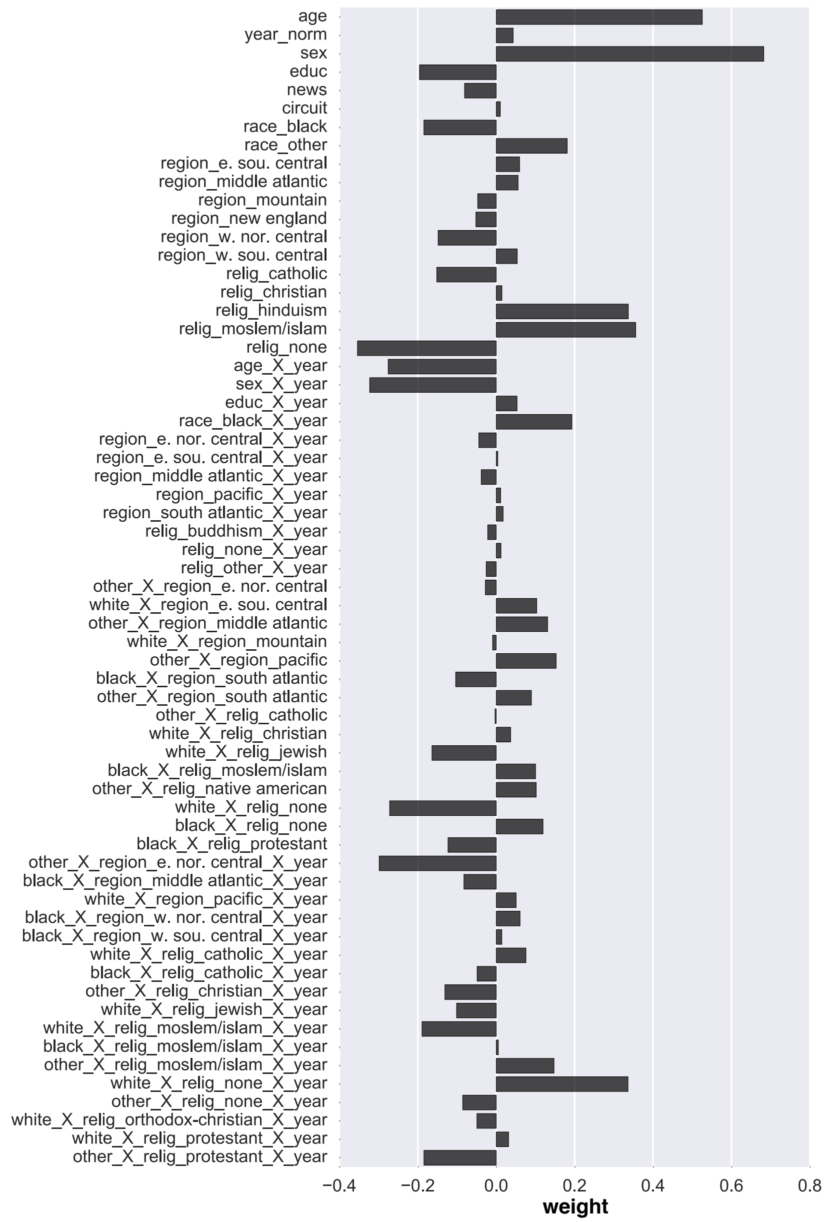

Figure 3: Coefficients of GSS demographic predictors of conservative attitudes about gender roles, from a linear regression model using only demographic predictors from the GSS (and no court data).

References

Smith, T. W., Marsden, P., Hout, M., & Kim, J. (2013). *General Social Surveys, 1972–2012 (Chicago, IL: National Opinion Research Center).*

Sunstein, C. R. (2007). *Are judges political?: an empirical analysis of the federal judiciary.* Brookings Institution Press.

Zuk Gary; Barrow, G. S., Deborah J.; Gryski. (1997). *Multi-User Database on the Attributes of United States Appeals Court Judges, 1801-2000.* ICPSR - Interuniversity Consortium for Political and Social Research. Retrieved from http://dx.doi.org/10.3886/icpsr06796 doi: 10.3886/icpsr06796