One Court, Indivisible? Examining Divisiveness in the Supreme Court

1. Introduction and background

For decades, political division has grown in the United States.[1] This has taken place throughout many facets of American politics and life, particularly at the federal and state levels. These days, it seems virtually impossible for Democrats and Republicans to make law together, let alone be civil and friendly.

While the partisan divide has crept steadily into Congress, the presidency, state legislatures, and personal lives especially through the influence of social media, the judicial branch of the United States aims to stay above the fray. Chief Justice John Roberts told the public in 2016, “We don’t work as Democrats or Republicans,” and Justice Gorsuch repeated the chorus in his confirmation hearing: “I do not see Republican judges, and I do not see Democrat judges. I see judges.”[2] But we know U.S. Supreme Court Justices are, underneath the solemn black robes, human beings like the rest of us. Political pressure reaches them as individuals and in their jobs—it is simply not possible for anyone to completely block out all politics. This raises the question: To what extent, if any, has political divisiveness affected the Supreme Court of the U.S. (SCOTUS)?

The majority of Americans still view SCOTUS as non-partisan, as of 2020.[3] Additionally, historians say that SCOTUS actually used to be for more partisan, particularly in the 19th century, and remains less partisan today than during that time.[4] Throughout this report, I will investigate this question of divisiveness in a modern context—the last 50 years—and from several perspectives of what constitutes divisiveness.

2. Data and methodology

The data are from Washington University Law’s Supreme Court Database and were scraped and compiled by Kaggle user Garrett Fiddler.[5] The dataset contains every SCOTUS opinion since 1970, including some information about the written opinion and the case, such as filing date, opinion type, case parties, and vote counts. Each opinion is listed, meaning that there are 1-4 rows per case.

I performed several recodes in order to manipulate variables into their most useful forms: indicator variables for whether the US was a case party, whether a case party was a corporation, whether the case was decided unanimously, whether the decision was a close vote, and whether a dissenting opinion was filed; categorical variables for the size of the vote majority, simplified opinion type, total number of votes cast, and number of opinions filed in the case. These, along with the date and direction decision (1=conservative, 2=liberal, 3=neither) variables, were the main variables used throughout my analyses.

Before constructing any models, however, I performed exploratory data analysis to look for any trends. As you can see in Figure 1, the number of opinions per year peaked around the 1980s and then looks to be declining since. Rather than choosing a single outcome variable in hopes that it is a fair representation of how divided SCOTUS is, I identified five measures of divisiveness to work with: unanimous vote (binary), close vote (binary: margin smaller than 40/60), dissenting opinion filed (binary), number of opinions filed per case (ordinal categorical: 1-4), and vote margin (ordinal categorical). Mapping out these measures from 1970-2020, there were mixed indications: Most of these measures appeared to trend down, including those that carry opposite messages about divisiveness (Figures 2-6). Behind this, the total number of cases per year has decreased since 1970 (Figure 7), so I needed to control for that change over time in order to get at trends.

3. Analysis and findings

First I performed simple logistic regressions for the binary outcome variables, using year as the sole explanatory variable and a collapsed version of the dataset that contained only one row per case (Tables 1-3). Although with different magnitudes, each of these models found a significant year effect, with every one year advancement associated with an estimated 0.42%, 0.79%, and 1.24% increase in the odds of unanimous vote, close vote, and dissenting opinion, respectively. Analogously, I ran univariate cumulative logit models for the two categorical response variables (Tables 4-5). The number of opinions model had proportional odds while the vote margin model did not, as confirmed with likelihood ratio tests. The models state that for every one year advancement, the odds of the case having a larger number of opinions decreased by around 1.3% (Table 4) and the odds of a larger majority decreased by around 0.8-4.6% (Table 5). All reported effects are significant at α=0.05.

Next, I built upon these models by incorporating other explanatory variables, as described above. Overall, the month variable seemed to lack significance, unlike decision direction, corporate parties, and total votes. When the decision was labeled "conservative" rather than "liberal" *and* when there was a corporate party involved, odds of the vote being unanimous were higher while odds of the vote being close and of a dissenting opinion being filed were lower (Tables 6-8). The cumulative logit models also produced significant effects; their results are summarized in Tables 9-10.

The final step in this model progression was to return to the full dataset with 1-4 opinions per case. I ran several generalized estimating equation (GEE) models, treating the cases as clusters and using the exchangeable correlation structure because of associations between predictor variables, except for the cumulative logit models. At this point I also included opinion-specific variables: the number of opinions the author wrote and the opinion type (majority, dissenting, concurring, or per curiam). These models produced similar coefficient estimates to the multivariate non-clustered models' for the case-level variables. I also performed anova tests on each model and iteratively removed predictors with insignificant effects, in line with the purposeful selection process.

For unanimous and close votes (Tables 11-12), even after adjusting for other predictors, the year effect remained: for every one year advancement, the models estimate the odds of a unanimous vote increase by 1.46% and the odds of a close vote also increase by about 6.9%. The decision direction variable was also highly significant. When the decision was liberal rather than conservative, the odds of the vote being unanimous were about 2.2% lower and the odds of it being close were about 26.4% lower. When one of the case parties was a corporation, the odds of the vote being unanimous were about 4.8% higher and the odds of the vote being close were about 26% lower.

The odds of a dissenting opinion being filed were significantly lower when the decision was liberal rather than conservative, and were even lower (~57%) when the decision was non-political (Table 13). Additionally, the presence of a corporate party was associated with a 41.9% reduction in the odds of a dissenting opinion being filed. For the number of opinions, the odds that the case had more opinions filed were lower in later years and were higher when the decision was not conservative and there was a corporation involved (Table 14). Finally, the odds of the vote margin being in the larger direction have decreased since 1970 by approximately 0.7% per year (Table 15). The vote margin has lower odds of being large when either the US or a corporate are case parties and when the decision is not conservative.

4. Conclusions and future work

For ease of comparison, I compiled the model results for the binary outcome variables into a single table, with the coefficient estimates exponentiated to represent odds ratios (Table 16). As I suspected from the outset, the trends revealed by the models do not all point toward the same conclusion. Divisiveness is a latent variable that can never be directly measured, so we can only try to find proxy variables that give us various perspectives on the question at hand. While I expected the odds of unanimous votes and close votes to exhibit opposite trends, this was not the case—both have increased since 1970; however, their results do diverge when it comes to corporate participation in the lawsuit. When that is the case, unanimous votes become more likely while close votes become less likely. The odds of a dissenting opinion being filed have increased since 1970, as have the odds of the vote margin being smaller, which may indicate growing divisiveness. The number of opinions per case has dropped since 1970, which could be interpreted to mean there is less divergence in thought. Overall, I cannot conclude one way or the other whether SCOTUS has become more divided, as there are signs pointing to either conclusion.

Also available on Kaggle is the same data for all SCOTUS opinions since the court's first in 1791. It would be interesting to perform these analyses on the full dataset. It would also be interesting to use natural language processing on the full opinion texts. These models probably could also stand to have more independent variables because there's more data in the text and also external data that could be merged in, such as divisiveness of Congress or political party in control of the White House.

Works Cited

1. “Political Polarization in the American Public.” Pew Research Center, 2014. Last accessed 4/29/2021. https://www.pewresearch.org/politics/2014/06/12/political-polarization-in-the-american-public/

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4. Sheldon, Rachel. “The Supreme Court used to be openly political. It traded partisanship for power.” Washington Post, 2020. Last accessed 4/29/2021. https://www.washingtonpost.com/outlook/supreme-court-politics-history/2020/09/25/b9fefcee-fe7f-11ea-9ceb-061d646d9c67_story.html

5. Fiddler, Garret. “SCOTUS Opinions. Full text and metadata of all opinions written by SCOTUS justices since 2020.” https://www.kaggle.com/gqfiddler/scotus-opinions?select=opinions_since_1970.csv

Appendix

Figure 1. Bar chart of total opinions per year.

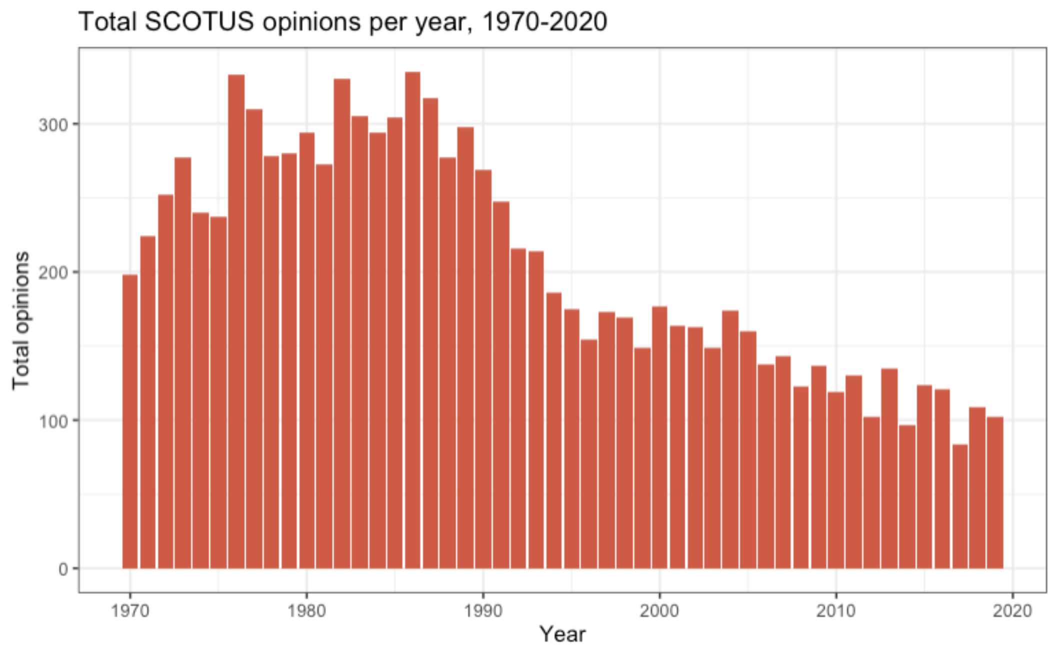

Figure 2. Bar chart of total unanimous decisions per year.

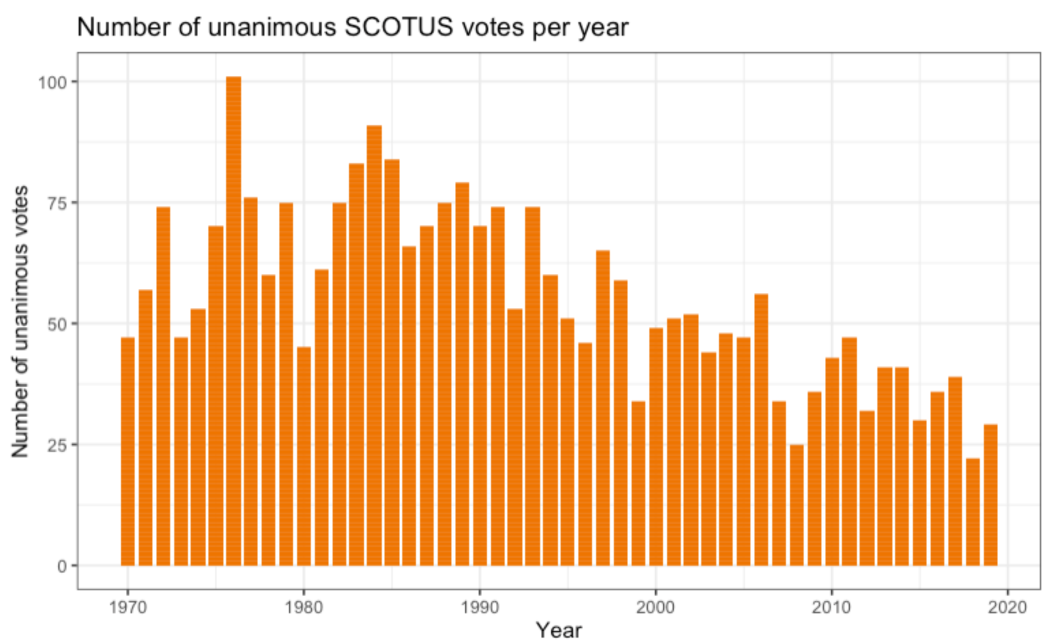

Figure 3. Bar chart of total close votes per year.

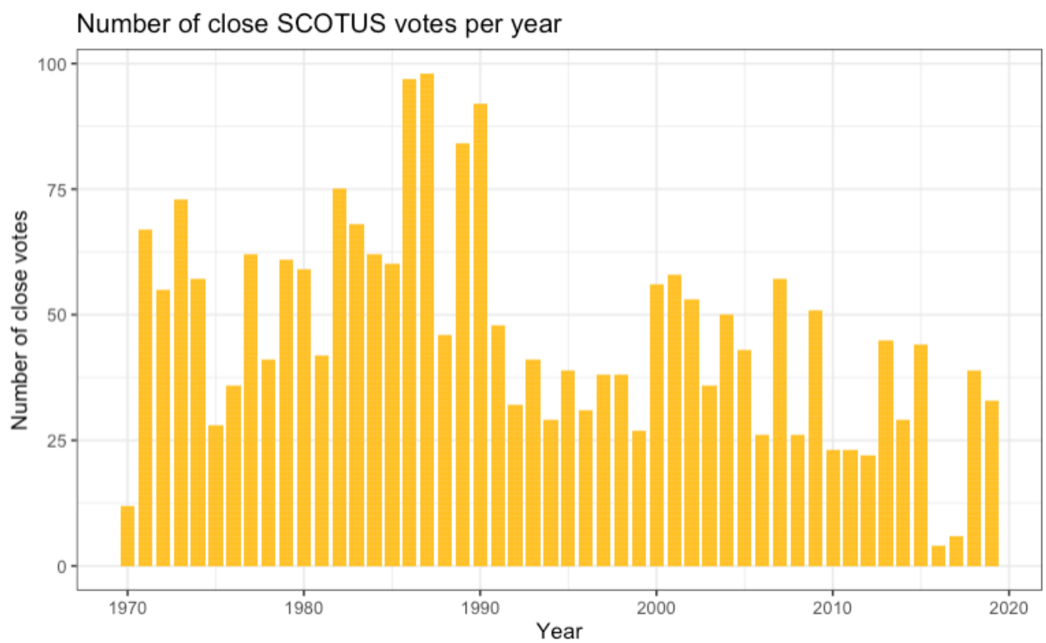

Figure 4. Two-paneled stacked bar chart of opinion types by year.

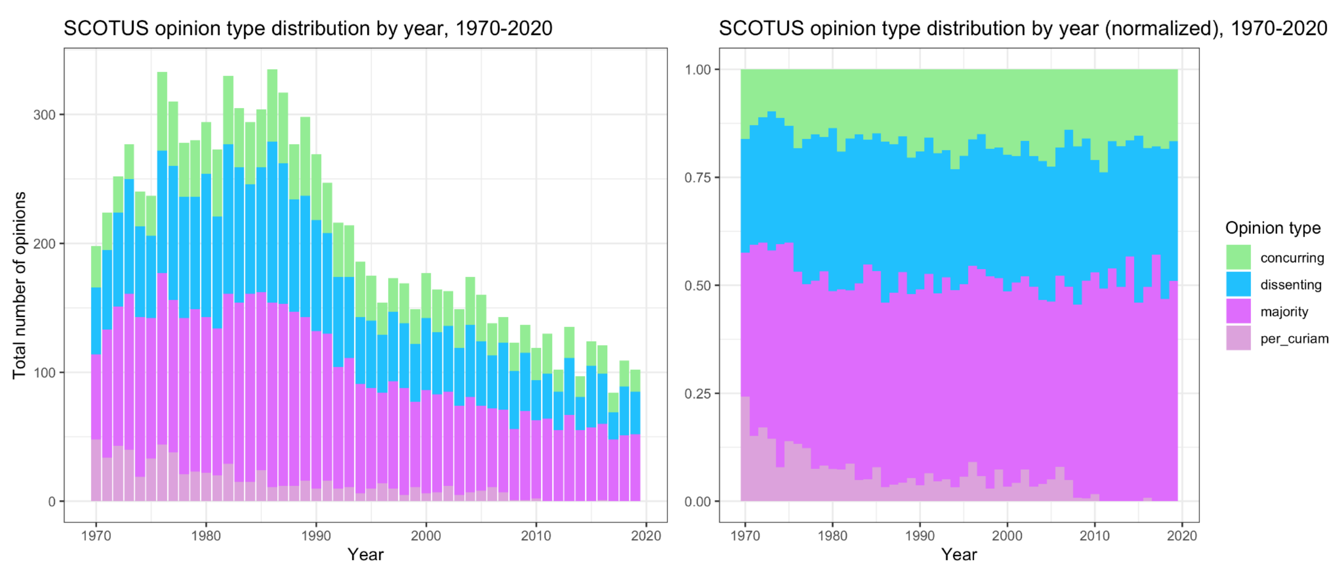

Figure 5. Two-paneled bar chart of opinions per case, by year.

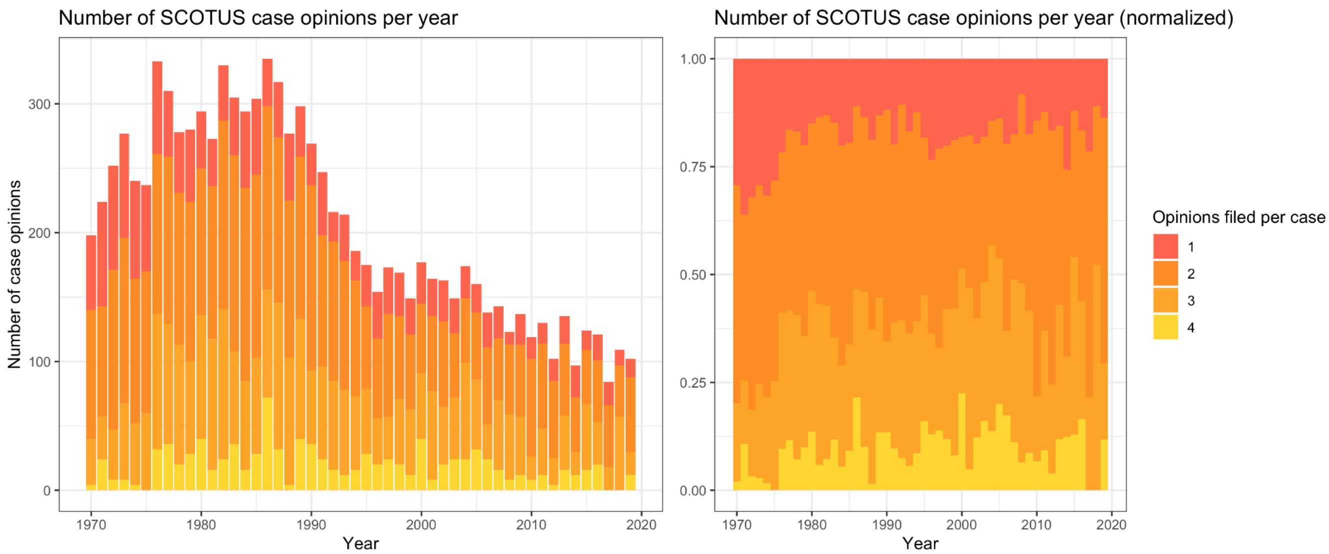

Figure 6. Two-paneled bar chart of vote margin by year.

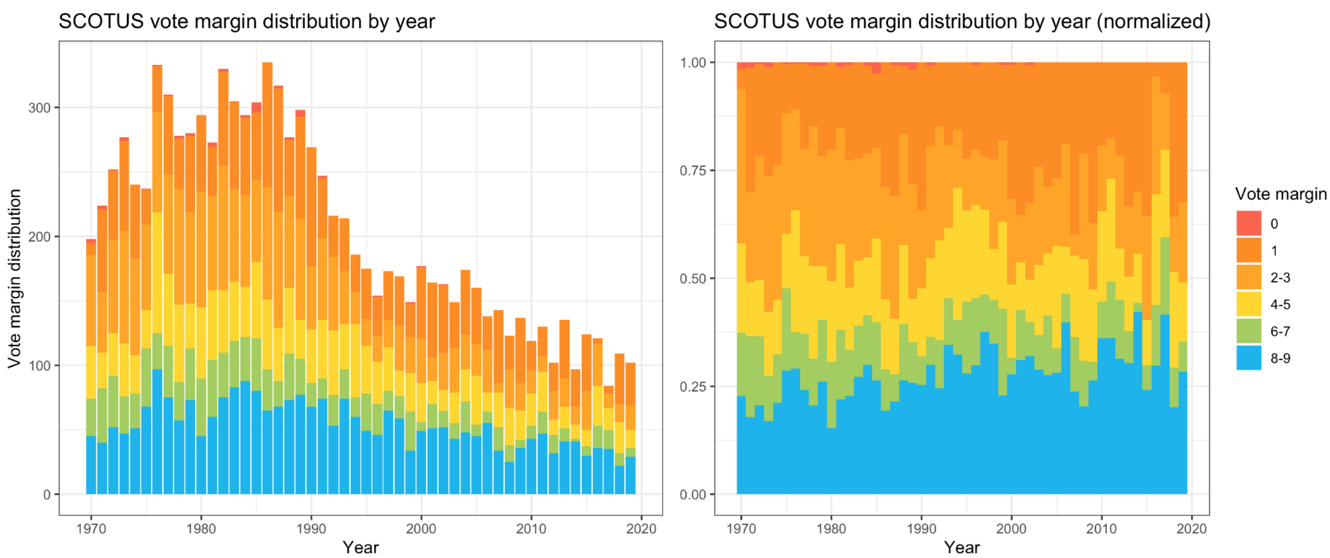

Figure 7. Bar chart of total cases per year.

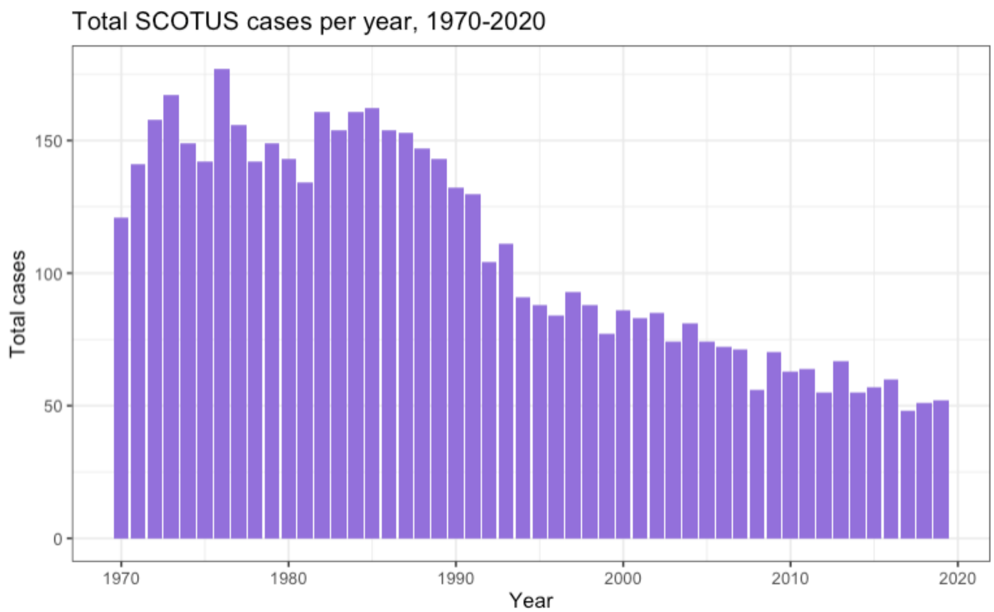

Table 1. Simple logistic regression with unanimous vote as binary outcome variable

```
Call:
glm(formula = V2 ~ V1, family = "binomial", data = datatest1)

Deviance Residuals:
   Min      1Q  Median      3Q     Max
-1.144  -0.994  -0.928   1.340   1.477

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) -24.8620     4.1784   -5.95  2.7e-09 ***
V1            0.0123     0.0021    5.85  5.0e-09 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 7146.6  on 5335  degrees of freedom
Residual deviance: 7112.4  on 5334  degrees of freedom
AIC: 7116

Number of Fisher Scoring iterations: 4
```

Table 2. Simple logistic regression with close vote as binary outcome variable

```
Call:
glm(formula = V2 ~ V1, family = "binomial", data = datatest2)

Deviance Residuals:
   Min      1Q  Median      3Q     Max
-0.701  -0.644  -0.617  -0.596   1.917

Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept) -17.08708    5.23168   -3.27   0.0011 **
V1            0.00783    0.00263    2.98   0.0029 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 5053.4  on 5335  degrees of freedom
Residual deviance: 5044.6  on 5334  degrees of freedom
AIC: 5049

Number of Fisher Scoring iterations: 4
```

Table 3. Simple logistic regression with dissenting opinion filed as binary outcome variable

```
Call:
glm(formula = as.numeric(V2) ~ as.numeric(V1), family = "binomial",
    data = datatest3)

Deviance Residuals:
   Min      1Q  Median      3Q     Max
 -1.22   -1.17   -1.14    1.19    1.22

Coefficients:
               Estimate Std. Error z value Pr(>|z|)
(Intercept)    -8.41433    4.08716   -2.06     0.04 *
as.numeric(V1)  0.00422    0.00205    2.06     0.04 *
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 7397.0  on 5335  degrees of freedom
Residual deviance: 7392.7  on 5334  degrees of freedom
AIC: 7397

Number of Fisher Scoring iterations: 3
```

Table 4. Proportional odds model with number of opinions filed as outcome variable and likelihood ratio test for proportional odds

```
Call:
vglm(formula = V2 ~ V1, family = cumulative(parallel = T), data = datatest4)

Coefficients:
              Estimate Std. Error z value Pr(>|z|)
(Intercept):1  25.5966     3.7879    6.76  1.4e-11 ***
(Intercept):2  27.4247     3.7906    7.23  4.7e-13 ***
(Intercept):3  29.2449     3.7922    7.71  1.2e-14 ***
V1             -0.0132     0.0019   -6.92  4.6e-12 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Names of linear predictors: logitlink(P[Y<=1]), logitlink(P[Y<=2]), logitlink(P[Y<=3])

Residual deviance: 12604 on 16004 degrees of freedom

Log-likelihood: -6302 on 16004 degrees of freedom

Number of Fisher scoring iterations: 3

Likelihood ratio test

Model 1: V2 ~ V1
Model 2: V2 ~ V1
    #Df LogLik Df Chisq Pr(>Chisq)
1 16004  -6302
2 16002  -6302 -2  0.53       0.77
```

Table 5. Cumulative logit model (non-proportional odds) with vote margin as outcome variable and likelihood ratio test for proportional odds

```
Call:
vglm(formula = V2 ~ V1, family = cumulative(parallel = F), data = datatest5)

Coefficients:
               Estimate Std. Error z value Pr(>|z|)
(Intercept):1  88.58450   27.26168    3.25  0.00116 **
(Intercept):2 -15.41630    5.20448      NA       NA
(Intercept):3  12.92522    4.26662    3.03  0.00245 **
(Intercept):4  14.45278    4.08658    3.54  0.00041 ***
(Intercept):5  30.09037    4.18386    7.19  6.4e-13 ***
V1:1           -0.04699    0.01375   -3.42  0.00063 ***
V1:2            0.00699    0.00261    2.67  0.00752 **
V1:3           -0.00677    0.00214      NA       NA
V1:4           -0.00724    0.00205   -3.53  0.00042 ***
V1:5           -0.01487    0.00210   -7.08  1.5e-12 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Number of linear predictors:  5

Names of linear predictors: logitlink(P[Y<=1]), logitlink(P[Y<=2]), logitlink(P[Y<=3]), logitlink(P[Y<=4]), logitlink(P[Y<=5])

Residual deviance: 16379 on 26670 degrees of freedom

Log-likelihood: -8190 on 26670 degrees of freedom

Number of Fisher scoring iterations: 6

Likelihood ratio test

Model 1: V2 ~ V1
Model 2: V2 ~ V1
    #Df LogLik Df Chisq Pr(>Chisq)
1 26674  -8244
2 26670  -8190 -4   108     <2e-16 ***
```

Table 6. Multivariate logistic regression with unanimous vote as outcome variable

```
Call:
glm(formula = unanimous_vote ~ year_filed + factor(scdb_decision_direction) +
    month + usparty + corpparty + total_votes, family = "binomial",
    data = multivartestdata)

Deviance Residuals:
   Min      1Q  Median      3Q     Max
-1.494  -0.993  -0.830   1.282   1.681

Coefficients:
                                  Estimate Std. Error z value Pr(>|z|)
(Intercept)                      -25.54975    4.25012   -6.01  1.8e-09 ***
year_filed                         0.01342    0.00216    6.21  5.4e-10 ***
factor(scdb_decision_direction)2   0.44264    0.05746    7.70  1.3e-14 ***
factor(scdb_decision_direction)3   0.20864    0.27440    0.76  0.44703
month                             -0.00388    0.01039   -0.37  0.70894
usparty                            0.10101    0.07651    1.32  0.18678
corpparty                          0.47320    0.06465    7.32  2.5e-13 ***
total_votes                       -0.21965    0.05667   -3.88  0.00011 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 7146.6  on 5335  degrees of freedom
Residual deviance: 6973.7  on 5328  degrees of freedom
AIC: 6990

Number of Fisher Scoring iterations: 4
```

Table 7. Multivariate logistic regression with close vote as outcome variable

```
Call:
glm(formula = close_vote ~ year_filed + factor(scdb_decision_direction) +
    month + usparty + corpparty + total_votes, family = "binomial",
    data = multivartestdata)

Deviance Residuals:
   Min      1Q  Median      3Q     Max
-0.868  -0.681  -0.607  -0.444   2.830

Coefficients:
                                  Estimate Std. Error z value Pr(>|z|)
(Intercept)                      -19.28162    5.44246   -3.54  0.00040 ***
year_filed                         0.00594    0.00274    2.17  0.03017 *
factor(scdb_decision_direction)2  -0.30865    0.07363   -4.19  2.8e-05 ***
factor(scdb_decision_direction)3  -0.39370    0.36790   -1.07  0.28457
month                              0.03089    0.01294    2.39  0.01699 *
usparty                           -0.25421    0.10050   -2.53  0.01142 *
corpparty                         -0.30351    0.08734   -3.48  0.00051 ***
total_votes                        0.68527    0.09852    6.96  3.5e-12 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 5053.4  on 5335  degrees of freedom
Residual deviance: 4937.5  on 5328  degrees of freedom
AIC: 4954

Number of Fisher Scoring iterations: 5
```

Table 8. Multivariate logistic regression with dissenting opinion filed as outcome variable

```
Call:
glm(formula = as.numeric(dissenting_opinion) ~ year_filed + factor(scdb_decision_direction) +
    month + usparty + corpparty + total_votes, family = "binomial",
    data = multivartestdata)

Deviance Residuals:
   Min      1Q  Median      3Q     Max
-1.385  -1.165  -0.703   1.136   1.848

Coefficients:
                                 Estimate Std. Error z value Pr(>|z|)
(Intercept)                      -7.84648    4.17146   -1.88  0.05997 .
year_filed                        0.00222    0.00212    1.05  0.29423
factor(scdb_decision_direction)2 -0.28251    0.05622   -5.03  5.0e-07 ***
factor(scdb_decision_direction)3 -0.95903    0.28362   -3.38  0.00072 ***
month                             0.00693    0.01012    0.68  0.49335
usparty                          -0.16797    0.07463   -2.25  0.02440 *
corpparty                        -0.49814    0.06473   -7.70  1.4e-14 ***
total_votes                       0.41808    0.05867    7.13  1.0e-12 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 7397.0  on 5335  degrees of freedom
Residual deviance: 7233.2  on 5328  degrees of freedom
AIC: 7249

Number of Fisher Scoring iterations: 4
```

Table 9. Multivariate cumulative logit model (non-proportional odds) with number of opinions filed as outcome variable and likelihood ratio test for proportional odds

```
Call:
vglm(formula = case_opinions_ct ~ year_filed + factor(scdb_decision_direction) +
    month + usparty + corpparty + total_votes, family = cumulative(parallel = F),
    data = multivartestdata)

Coefficients:
                                   Estimate Std. Error z value Pr(>|z|)
(Intercept):1                      24.51664    4.40976    5.56  2.7e-08 ***
(Intercept):2                      28.56377    4.92888    5.80  6.8e-09 ***
(Intercept):3                      39.40856    9.81313    4.02  5.9e-05 ***
year_filed:1                       -0.01114    0.00224   -4.97  6.8e-07 ***
year_filed:2                       -0.01140    0.00248   -4.59  4.4e-06 ***
year_filed:3                       -0.01457    0.00489   -2.98  0.00289 **
factor(scdb_decision_direction)2:1  0.18850    0.05882    3.20  0.00135 **
factor(scdb_decision_direction)2:2  0.16258    0.06683    2.43  0.01499 *
factor(scdb_decision_direction)2:3  0.10280    0.13296    0.77  0.43941
factor(scdb_decision_direction)3:1  1.12001    0.26983    4.15  3.3e-05 ***
factor(scdb_decision_direction)3:2  1.17527    0.43663    2.69  0.00711 **
factor(scdb_decision_direction)3:3  0.13262    0.60718    0.22  0.82710
month:1                             0.00554    0.01052    0.53  0.59842
month:2                            -0.01142    0.01203   -0.95  0.34243
month:3                            -0.05730    0.02304   -2.49  0.01286 *
usparty:1                           0.26445    0.07721    3.43  0.00061 ***
usparty:2                           0.27611    0.09082    3.04  0.00237 **
usparty:3                           0.37729    0.18788    2.01  0.04463 *
corpparty:1                         0.52833    0.06562    8.05  8.1e-16 ***
corpparty:2                         0.67281    0.08446    7.97  1.6e-15 ***
corpparty:3                         1.06569    0.20449    5.21  1.9e-07 ***
total_votes:1                      -0.37457    0.05685   -6.59  4.4e-11 ***
total_votes:2                      -0.55399    0.08397   -6.60  4.2e-11 ***
total_votes:3                      -0.83416    0.21430   -3.89  9.9e-05 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Names of linear predictors: logitlink(P[Y<=1]), logitlink(P[Y<=2]), logitlink(P[Y<=3])

Residual deviance: 12373 on 15984 degrees of freedom

Log-likelihood: -6186 on 15984 degrees of freedom

Number of Fisher scoring iterations: 5
```

Table 10. Multivariate proportional odds model with vote margin as outcome variable

```
Call:
vglm(formula = vote_margin_cat ~ year_filed + factor(scdb_decision_direction) +
    month + usparty + corpparty + total_votes, family = cumulative(parallel = T),
    data = multivartestdata)

Coefficients:
                                 Estimate Std. Error z value Pr(>|z|)
(Intercept):1                     9.75018    3.72004    2.62  0.00877 **
(Intercept):2                    12.99808    3.71782    3.50  0.00047 ***
(Intercept):3                    13.97151    3.71834    3.76  0.00017 ***
(Intercept):4                    14.57542    3.71877    3.92  8.9e-05 ***
(Intercept):5                    15.03983    3.71911    4.04  5.3e-05 ***
year_filed                       -0.00752    0.00189   -3.97  7.0e-05 ***
factor(scdb_decision_direction)2 -0.37565    0.05018   -7.49  7.1e-14 ***
factor(scdb_decision_direction)3 -0.29588    0.23727   -1.25  0.21238
month                             0.01554    0.00896    1.73  0.08287 .
usparty                          -0.15834    0.06643   -2.38  0.01714 *
corpparty                        -0.44741    0.05789   -7.73  1.1e-14 ***
total_votes                       0.07432    0.04999    1.49  0.13711
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Number of linear predictors:  5

Names of linear predictors: logitlink(P[Y<=1]), logitlink(P[Y<=2]), logitlink(P[Y<=3]), logitlink(P[Y<=4]), logitlink(P[Y<=5])

Residual deviance: 16357 on 26668 degrees of freedom

Log-likelihood: -8179 on 26668 degrees of freedom

Number of Fisher scoring iterations: 5
```

Table 11. GEE model with exchangeable correlation structure for unanimous vote outcome variable

```
Call:
geeglm(formula = unanimous_vote ~ year_filed + factor(scdb_decision_direction) +
    corpparty + total_votes + author_ct + opiniontype, family = binomial,
    data = scotus, id = as.factor(scdb_id), corstr = "exchangeable")

 Coefficients:
                                  Estimate   Std.err    Wald Pr(>|W|)
(Intercept)                      -2.77e+01  4.15e+00   44.42  2.6e-11 ***
year_filed                        1.45e-02  2.11e-03   46.88  7.5e-12 ***
factor(scdb_decision_direction)2  4.50e-01  5.62e-02   64.18  1.1e-15 ***
factor(scdb_decision_direction)3  1.96e-01  2.79e-01    0.50    0.482
corpparty                         4.72e-01  6.23e-02   57.42  3.5e-14 ***
total_votes                      -2.22e-01  5.52e-02   16.22  5.6e-05 ***
author_ct                         5.27e-05  2.09e-05    6.34    0.012 *
opiniontypedissenting            -3.89e-01  9.39e-03 1718.07  < 2e-16 ***
opiniontypemajority               9.67e-03  9.01e-03    1.15    0.283
opiniontypeper_curiam             2.10e-01  4.62e-02   20.60  5.7e-06 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation structure = exchangeable
```

Table 12. GEE model with exchangeable correlation structure for close vote outcome variable

```
Call:
geeglm(formula = close_vote ~ year_filed + factor(scdb_decision_direction) +
    month + usparty + corpparty + total_votes + author_ct + opiniontype,
    family = binomial, data = scotus, id = as.factor(scdb_id),
    corstr = "exchangeable")

 Coefficients:
                                  Estimate   Std.err   Wald Pr(>|W|)
(Intercept)                      -2.06e+01  5.64e+00  13.38  0.00025 ***
year_filed                        6.71e-03  2.76e-03   5.91  0.01505 *
factor(scdb_decision_direction)2 -3.06e-01  7.41e-02  17.10  3.6e-05 ***
factor(scdb_decision_direction)3 -3.20e-01  3.85e-01   0.69  0.40696
month                             2.88e-02  1.18e-02   5.99  0.01440 *
usparty                          -2.42e-01  1.03e-01   5.57  0.01831 *
corpparty                        -3.01e-01  8.88e-02  11.45  0.00071 ***
total_votes                       6.59e-01  1.19e-01  30.70  3.0e-08 ***
author_ct                         8.80e-05  2.36e-05  13.91  0.00019 ***
opiniontypedissenting            -1.17e-01  8.56e-03 186.68  < 2e-16 ***
opiniontypemajority              -1.72e-02  8.87e-03   3.78  0.05182 .
opiniontypeper_curiam             1.92e-01  1.14e-01   2.82  0.09328 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation structure = exchangeable
```

Table 13. GEE model with exchangeable correlation structure for dissenting opinion outcome variable

```
Call:
geeglm(formula = as.numeric(dissenting_opinion) ~ year_filed +
    corpparty + factor(scdb_decision_direction) + total_votes +
    author_ct + opiniontype, family = binomial, data = scotus,
    id = as.factor(scdb_id), corstr = "exchangeable")

 Coefficients:
                                  Estimate   Std.err     Wald Pr(>|W|)
(Intercept)                      -3.13e+00  4.45e+00 5.00e-01   0.4811
year_filed                       -1.68e-05  2.25e-03 0.00e+00   0.9940
corpparty                        -4.94e-01  6.75e-02 5.35e+01  2.6e-13 ***
factor(scdb_decision_direction)2 -2.84e-01  5.79e-02 2.40e+01  9.5e-07 ***
factor(scdb_decision_direction)3 -8.12e-01  3.06e-01 7.05e+00   0.0079 **
total_votes                       3.98e-01  6.22e-02 4.08e+01  1.7e-10 ***
author_ct                         1.35e-05  8.67e-05 2.00e-02   0.8764
opiniontypedissenting             4.50e+15  4.47e+05 1.02e+20  < 2e-16 ***
opiniontypemajority              -3.53e-03  2.76e-02 2.00e-02   0.8981
opiniontypeper_curiam            -6.71e-01  8.63e-02 6.05e+01  7.4e-15 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Correlation structure = exchangeable
```

Table 14. GEE model with independence correlation structure and proportional odds for number of opinions per case outcome variable

```
Call:
ordLORgee(formula = case_opinions_ct ~ year_filed + factor(scdb_decision_direction) +
    month + usparty + corpparty + total_votes + author_ct + opiniontype,
    data = scotus, id = as.factor(scdb_id), LORstr = "independence")

Summary of residuals:
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
 -0.846  -0.339  -0.121   0.000   0.466   0.971

Number of Iterations: 1

Coefficients:
                                 Estimate   san.se san.z Pr(>|san.z|)
beta10                           17.10192  4.09842  4.17        3e-05 ***
beta20                           19.55306  4.10080  4.77       <2e-16 ***
beta30                           21.51390  4.10077  5.25       <2e-16 ***
year_filed                       -0.00813  0.00208 -3.91        9e-05 ***
factor(scdb_decision_direction)2  0.15199  0.05435  2.80       0.0052 **
factor(scdb_decision_direction)3  0.86730  0.32239  2.69       0.0071 **
month                            -0.01909  0.00977 -1.95       0.0507 .
usparty                           0.29674  0.07296  4.07        5e-05 ***
corpparty                         0.64407  0.06214 10.36       <2e-16 ***
total_votes                      -0.42454  0.05294 -8.02       <2e-16 ***
author_ct                        -0.00001  0.00007 -0.08       0.9375
opiniontypedissenting            -0.09838  0.03766 -2.61       0.0090 **
opiniontypemajority               1.56330  0.03098 50.46       <2e-16 ***
opiniontypeper_curiam             2.84406  0.08596 33.09       <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Table 15. GEE model with independence correlation structure and proportional odds for vote margin outcome variable

```
call:
ordLORgee(formula = ordered(vote_margin_cat) ~ year_filed + factor(scdb_decision_direction) +
    month + usparty + corpparty + total_votes + author_ct + opiniontype,
    data = scotus, id = as.factor(scdb_id), LORstr = "independence")

Summary of residuals:
   Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
 -0.545  -0.183  -0.131   0.002  -0.003   0.999

Number of Iterations: 1

Coefficients:
                                 Estimate   san.se san.z Pr(>|san.z|)
beta10                            5.98340  3.81952  1.57      0.11722
beta20                           10.23150  3.81253  2.68      0.00728 **
beta30                           11.38507  3.81570  2.98      0.00285 **
beta40                           12.17065  3.81623  3.19      0.00143 **
beta50                           12.76527  3.81642  3.34      0.00082 ***
year_filed                       -0.00704  0.00193 -3.65      0.00026 ***
factor(scdb_decision_direction)2 -0.35580  0.05000 -7.12      < 2e-16 ***
factor(scdb_decision_direction)3 -0.61792  0.20542 -3.01      0.00263 **
month                             0.02673  0.00884  3.02      0.00251 **
usparty                          -0.20615  0.06416 -3.21      0.00131 **
corpparty                        -0.42185  0.05827 -7.24      < 2e-16 ***
total_votes                       0.25954  0.04731  5.49      < 2e-16 ***
author_ct                        -0.00046  0.00007 -6.36      < 2e-16 ***
opiniontypedissenting             1.46303  0.04392 33.31      < 2e-16 ***
opiniontypemajority               0.15116  0.03723  4.06        5e-05 ***
opiniontypeper_curiam            -0.20263  0.08370 -2.42      0.01548 *
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
```

Table 16. Summary of model coefficient estimates for binary outcome variables

	Outcome measure								
	Unanimous vote (OR)			Close vote (OR)			Dissenting opinion (OR)		
Variable	*Model 1*	*Model 2*	*Model 3*	*Model 1*	*Model 2*	*Model 3*	*Model 1*	*Model 2*	*Model 3*
Year	1.0124	1.0135	1.0146	1.0079	1.0060	1.0067	1.0042	*NS*	*NS*
Decision direction (liberal)	-	1.5568	1.5683	-	0.7344	0.7364	-	0.7539	0.7528
Decision direction (apolitical)	-	*NS*	*NS*	-	*NS*	*NS*	-	0.3833	0.4440
US party	-	*NS*	-	-	0.7755	0.7851	-	0.8454	-
Corporate party	-	1.6051	1.6032	-	0.7382	0.7401	-	0.6077	0.6102
Total votes	-	0.8028	0.8009	-	1.9843	1.9329	-	1.5190	1.4888
Author opinion count	-	-	1.0001	-	-	1.0001	-	-	*NS*
Opinion type (dissenting)	-	-	0.6777	-	-	0.8896	-	-	1.0000
Opinion type (majority)	-	-	*NS*	-	-	*NS*	-	-	*NS*
Opinion type (per curiam)	-	-	1.2337	-	-	*NS*	-	-	0.5112

NS = not significant at 0.05 significance level; all other estimates have corresponding p-value < 0.05