Redistricting Reforms Reduce Gerrymandering by Constraining Partisan Actors

Cory McCartan **Christopher T. Kenny** Tyler Simko
Emma Ebowe Michael Y. Zhao Kosuke Imai

PolMeth XLI • July 18, 2024

Problem: Partisan influence over democratic processes

Problem: Partisan influence over democratic processes

- Parties can draw their own congressional districts
  - Often draw to benefit themselves — “partisan gerrymandering”
  - Widespread in 2010 and 2020 redistricting cycles (Kenny et. al, 2023)

Problem: Partisan influence over democratic processes

- Parties can draw their own congressional districts
  - Often draw to benefit themselves — “partisan gerrymandering”
  - Widespread in 2010 and 2020 redistricting cycles (Kenny et. al, 2023)
- Worsened by political polarization and weakened democratic norms

Problem: Partisan influence over democratic processes

- Parties can draw their own congressional districts
  - Often draw to benefit themselves — “partisan gerrymandering”
  - Widespread in 2010 and 2020 redistricting cycles (Kenny et. al, 2023)
- Worsened by political polarization and weakened democratic norms
- *see, e.g.,* January 6, 2021

Solution: Procedural reforms?

Solution: Procedural reforms?

- Limit influence partisan actors have on districting plans
  - Independent map-drawing commissions may reduce direct influence
  - Introduction of court oversight may remedy other biases

Solution: Procedural reforms?

- Limit influence partisan actors have on districting plans
  - Independent map-drawing commissions may reduce direct influence
  - Introduction of court oversight may remedy other biases
- 8 states had some reform between 2010 and 2020

Solution: Procedural reforms?

- Limit influence partisan actors have on districting plans
  - Independent map-drawing commissions may reduce direct influence
  - Introduction of court oversight may remedy other biases
- 8 states had some reform between 2010 and 2020
- **Do reforms work?** So far, correlational evidence only

Challenge: Complex processes, complex outcomes, and limited data

Challenge: Complex processes, complex outcomes, and limited data

Complex processes:
Multi-step & multi-player
Big variety across states

Challenge: Complex processes, complex outcomes, and limited data

Complex processes:
Multi-step & multi-player
Big variety across states

→ Data reduction through a formal model of redistricting processes

Challenge: Complex processes, complex outcomes, and limited data

Complex processes:
Multi-step & multi-player
Big variety across states

Complex outcomes:
A whole redistricting plan
Can’t compare directly

→ Data reduction through a formal model of redistricting processes

Challenge: Complex processes, complex outcomes, and limited data

Complex processes:
Multi-step & multi-player
Big variety across states

→ Data reduction through a formal model of redistricting processes

Complex outcomes:
A whole redistricting plan
Can't compare directly

→ Multiple outcome measures; Redistricting simulation to control for political geography

Challenge: Complex processes, complex outcomes, and limited data

Complex processes:
Multi-step & multi-player
Big variety across states

→ Data reduction through a formal model of redistricting processes

Complex outcomes:
A whole redistricting plan
Can't compare directly

→ Multiple outcome measures; Redistricting simulation to control for political geography

Limited data:
n = 43 states; t = 2 periods

Challenge: Complex processes, complex outcomes, and limited data

Complex processes:
Multi-step & multi-player
Big variety across states

→ Data reduction through a formal model of redistricting processes

Complex outcomes:
A whole redistricting plan
Can't compare directly

→ Multiple outcome measures; Redistricting simulation to control for political geography

Limited data:
n = 43 states; t = 2 periods

→ Data reduction and model-based Bayesian estimation

Challenge: Complex processes, complex outcomes, and limited data

Complex processes:
Multi-step & multi-player
Big variety across states

→ Data reduction through a formal model of redistricting processes

Complex outcomes:
A whole redistricting plan
Can't compare directly

→ Multiple outcome measures; Redistricting simulation to control for political geography

Limited data:
$n = 43$ states; $t = 2$ periods

→ Data reduction and model-based Bayesian estimation

Confounding:
Reformed states skew Democratic

Challenge: Complex processes, complex outcomes, and limited data

Complex processes:
Multi-step & multi-player
Big variety across states

→ Data reduction through a formal model of redistricting processes

Complex outcomes:
A whole redistricting plan
Can't compare directly

→ Multiple outcome measures; Redistricting simulation to control for political geography

Limited data:
$n = 43$ states; $t = 2$ periods

→ Data reduction and model-based Bayesian estimation

Confounding:
Reformed states skew Democratic

→ Differences-in-differences design

Introduction

Treatment Modeling

Estimation

Results

Policy Evaluations

The redistricting game

Round 1

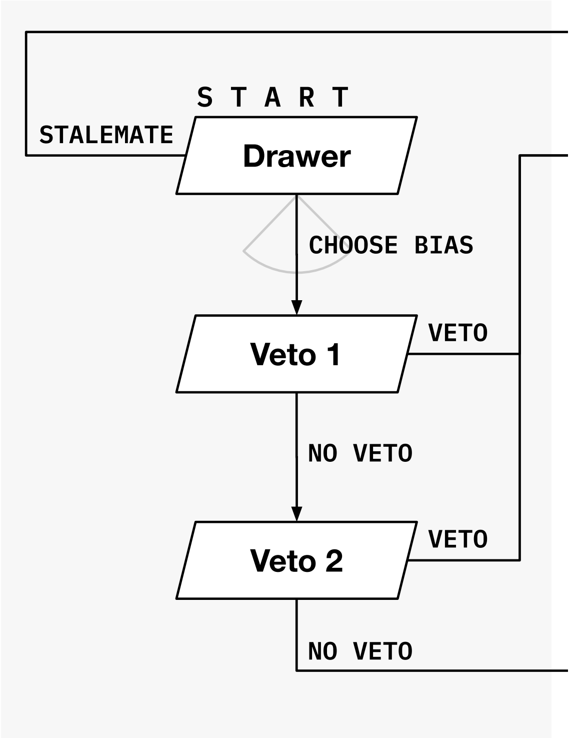
Round 2

Stalemate Procedure

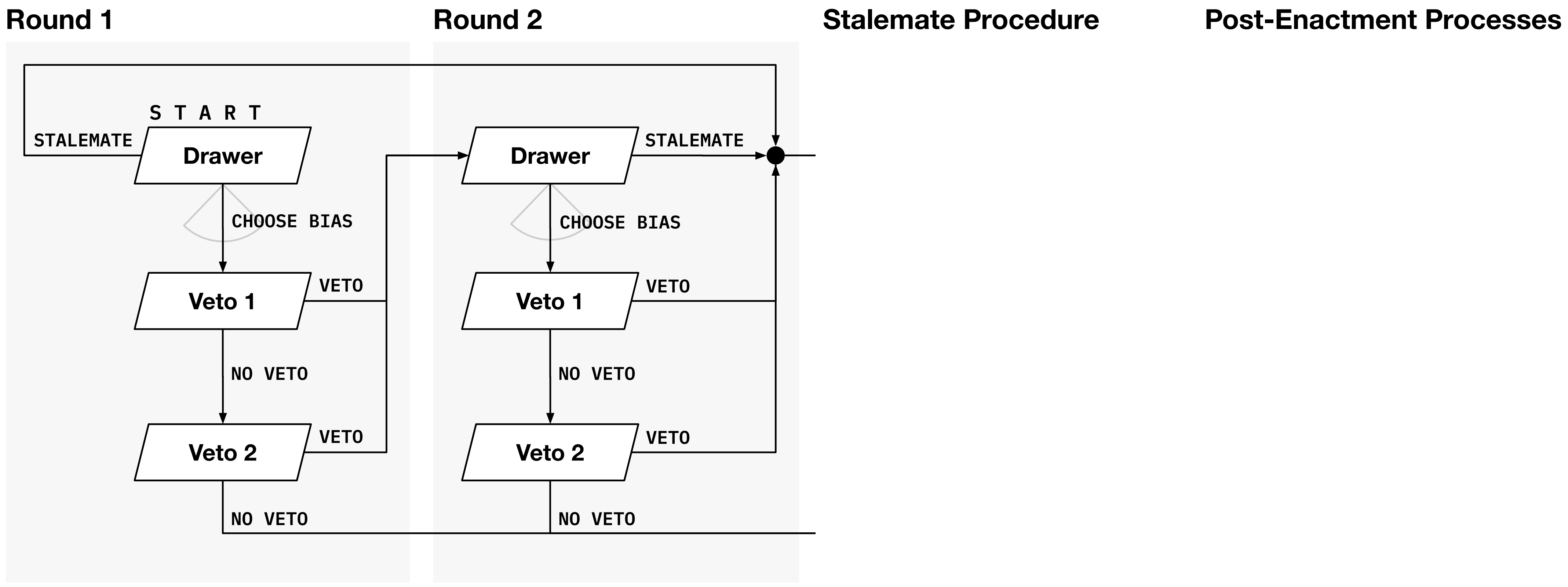
Post-Enactment Processes

The redistricting game

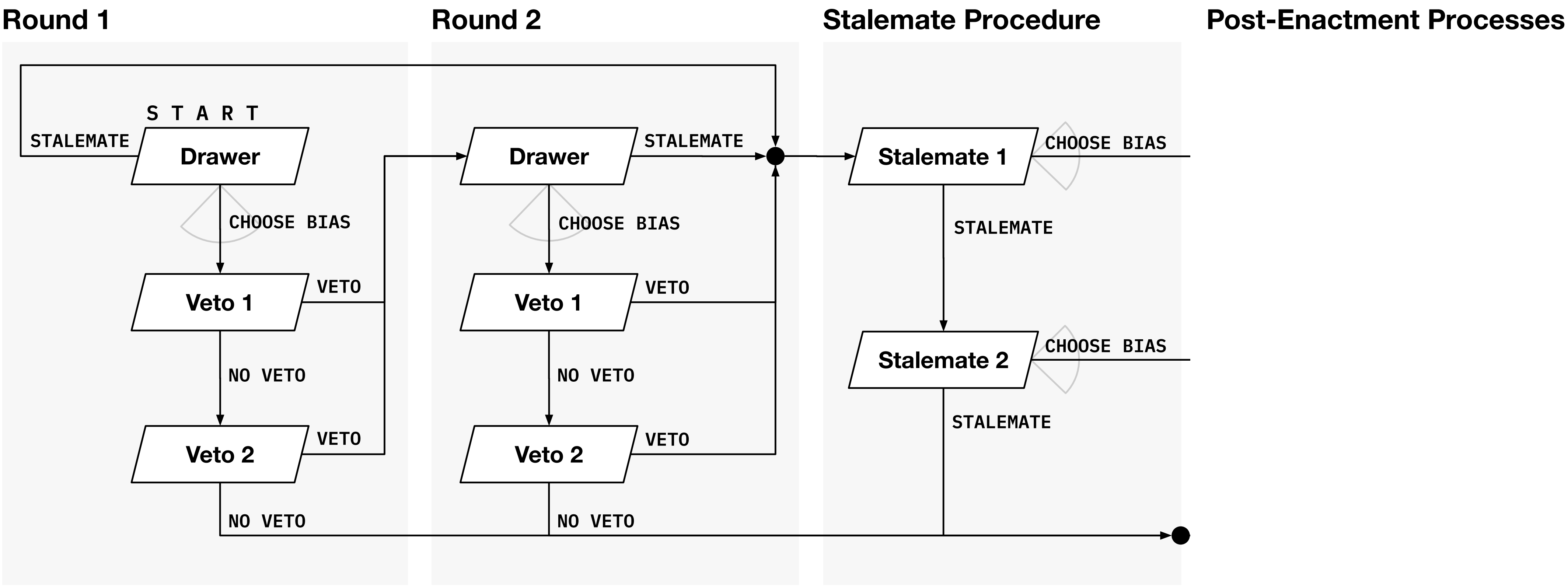
Round 1 | **Round 2** | **Stalemate Procedure** | **Post-Enactment Processes**



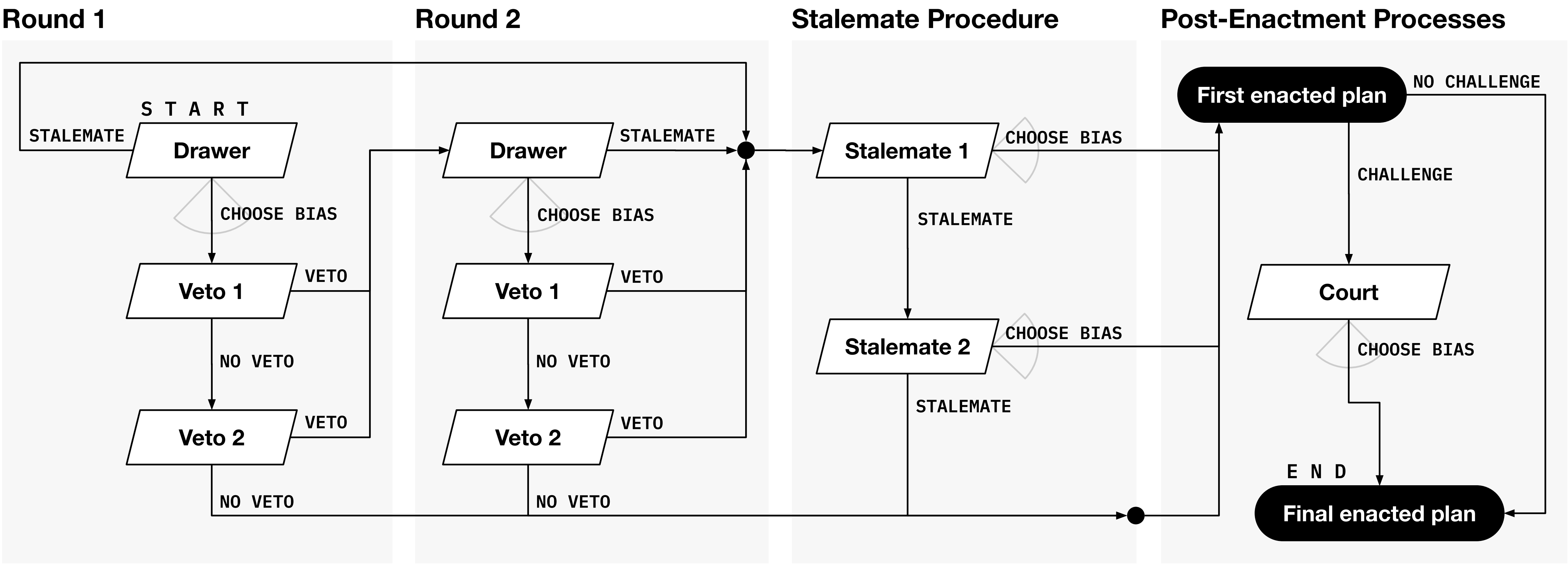
The redistricting game



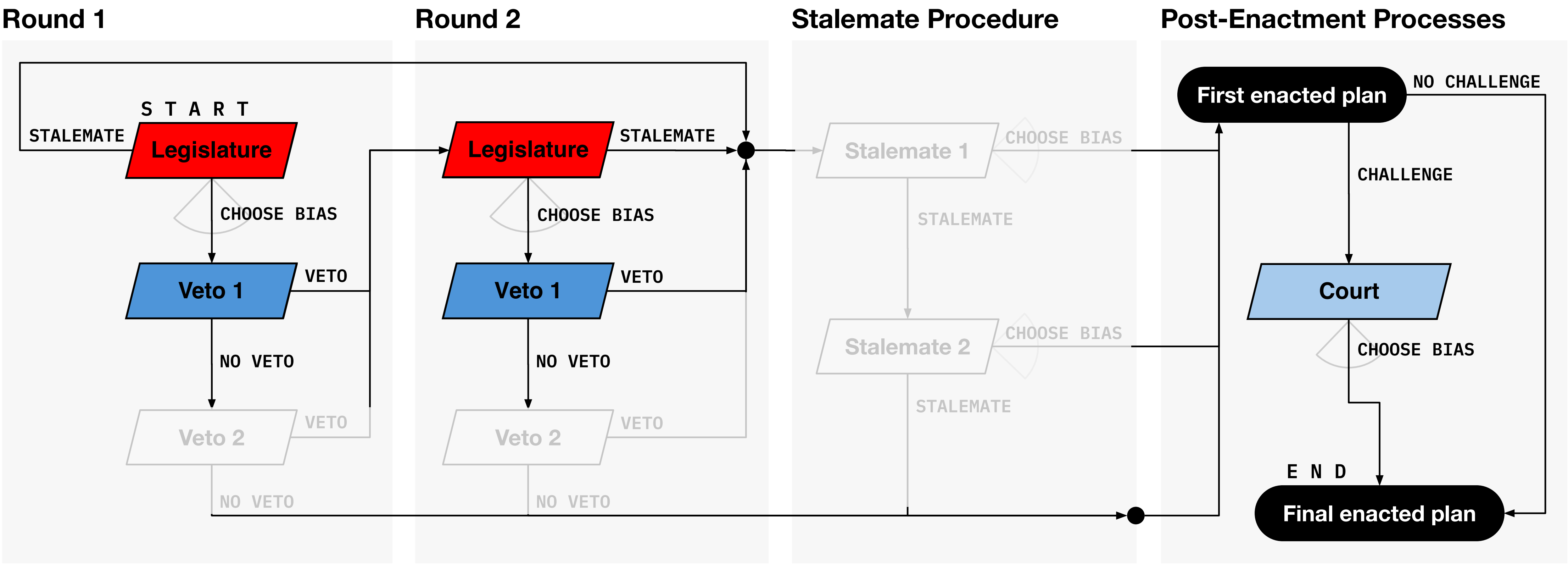
The redistricting game



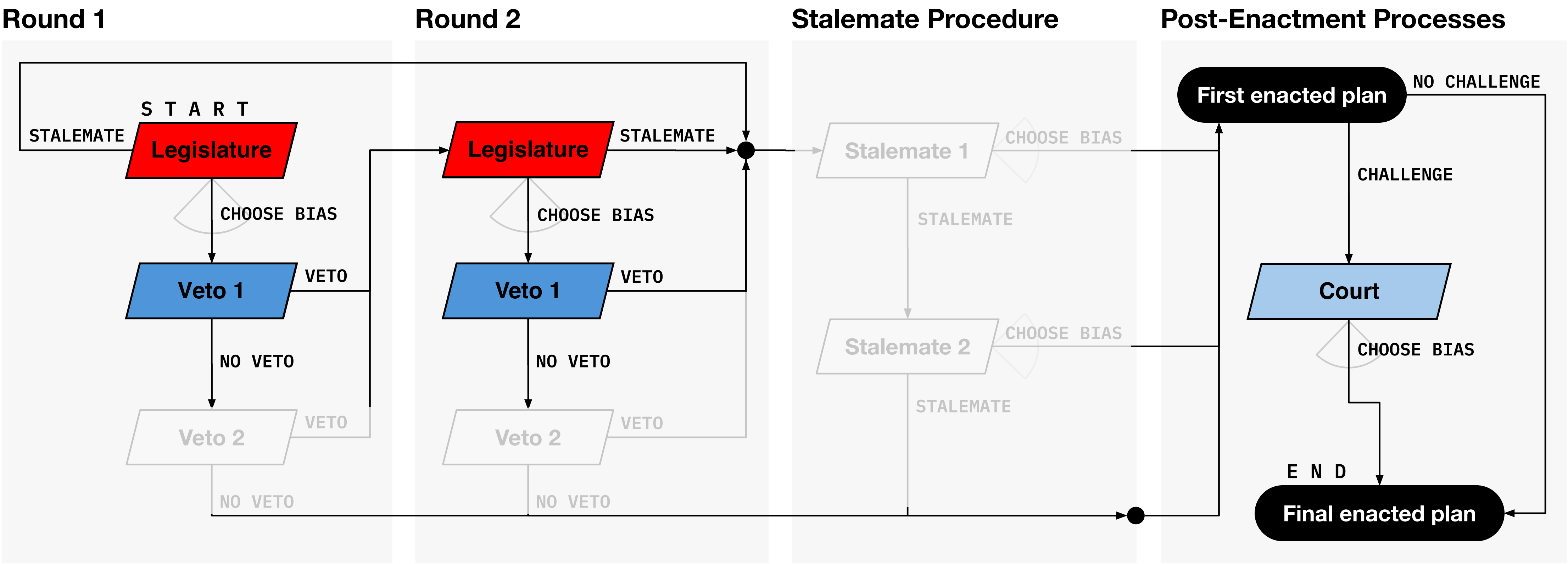
The redistricting game



The redistricting game: Pennsylvania

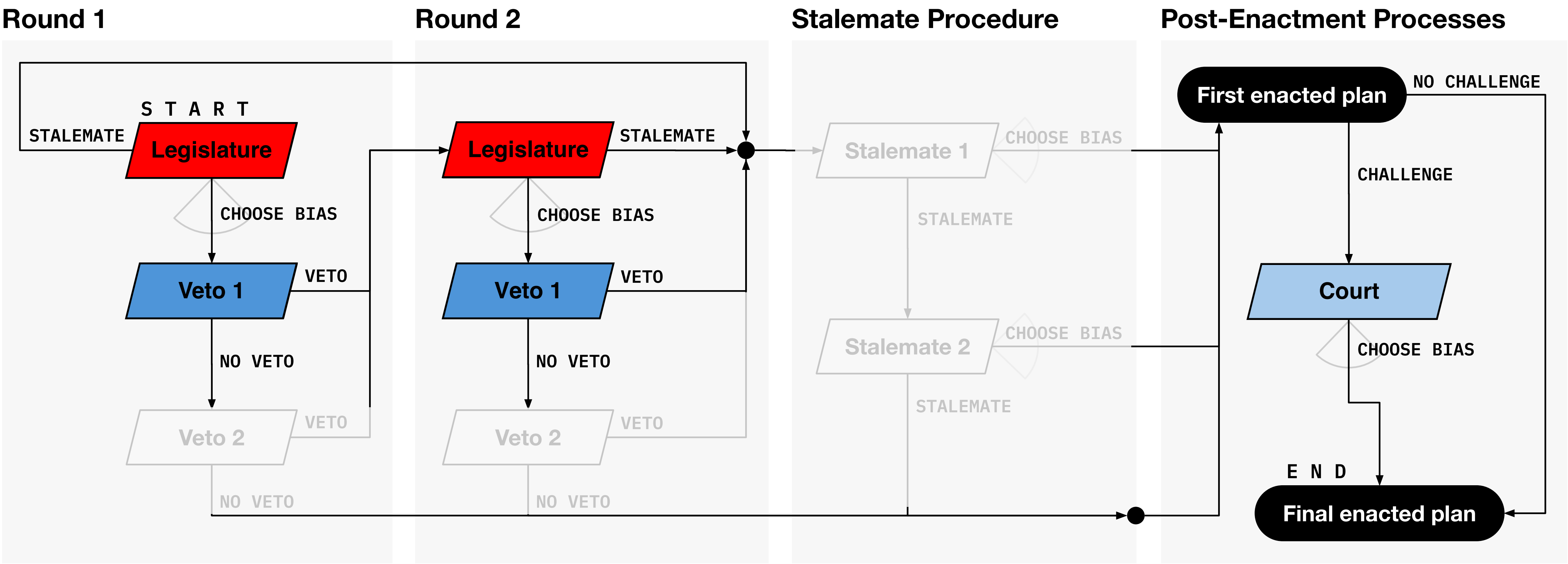


The redistricting game: Pennsylvania



Plan bias = zero-sum utility

The redistricting game: Pennsylvania



Plan bias = zero-sum utility

Equilibrium = **0.6** / **4** (Republican-favoring)
"realized leeway"

Model-based treatment values

- Pennsylvania: **0.6** in 2020 (GOP legislature, Dem. governor)

Model-based treatment values

- Pennsylvania: **0.6** in 2020 (GOP legislature, Dem. governor)
- W. Virginia: from **–3.9** in 2010 (Dem. trifecta)
  to **3.9** in 2020 (GOP trifecta)

Model-based treatment values

- Pennsylvania: **0.6** in 2020 (GOP legislature, Dem. governor)
- W. Virginia: from **–3.9** in 2010 (Dem. trifecta)
  to **3.9** in 2020 (GOP trifecta)
- Michigan: from **3.1** in 2010 (GOP trifecta)
  to **0.0** in 2020 (independent citizen commission)

Model-based treatment values

- Pennsylvania: **0.6** in 2020 (GOP legislature, Dem. governor)
- W. Virginia: from **–3.9** in 2010 (Dem. trifecta)
  to **3.9** in 2020 (GOP trifecta)
- Michigan: from **3.1** in 2010 (GOP trifecta)
  to **0.0** in 2020 (independent citizen commission)
- New York: **–1.6** in 2020 (commission w/ Dem. veto)

Introduction
Treatment Modeling
Estimation
Results
Policy Evaluations

Continuous DiD

Continuous DiD

- Assume institutional features affect outcome only through continuous treatment:

$$Y_{it}(\mathbf{z}) = Y_{it}(\mathbf{z'}) \quad \text{for any} \quad \mathbf{z}, \mathbf{z'} \text{ with } u^*(\mathbf{z}) = u^*(\mathbf{z'})$$

  Can then write potential outcomes as $Y_{it}(d)$ for treatment d

Continuous DiD

- Assume institutional features affect outcome only through continuous treatment:

$$Y_{it}(\mathbf{z}) = Y_{it}(\mathbf{z}') \quad \text{for any} \quad \mathbf{z}, \mathbf{z}' \ \text{ with } \ u^*(\mathbf{z}) = u^*(\mathbf{z}')$$

  Can then write potential outcomes as $Y_{it}(d)$ for treatment d

- Want to estimate $\text{CATE}_{\mathbf{x}}(d, d') = \mathbf{E}[Y_{i1}(d') - Y_{i1}(d) \mid \mathbf{X}_i = \mathbf{x}]$

Continuous DiD

- Assume institutional features affect outcome only through continuous treatment:

$$Y_{it}(\mathbf{z}) = Y_{it}(\mathbf{z}') \quad \text{for any} \quad \mathbf{z}, \mathbf{z}' \text{ with } u^*(\mathbf{z}) = u^*(\mathbf{z}')$$

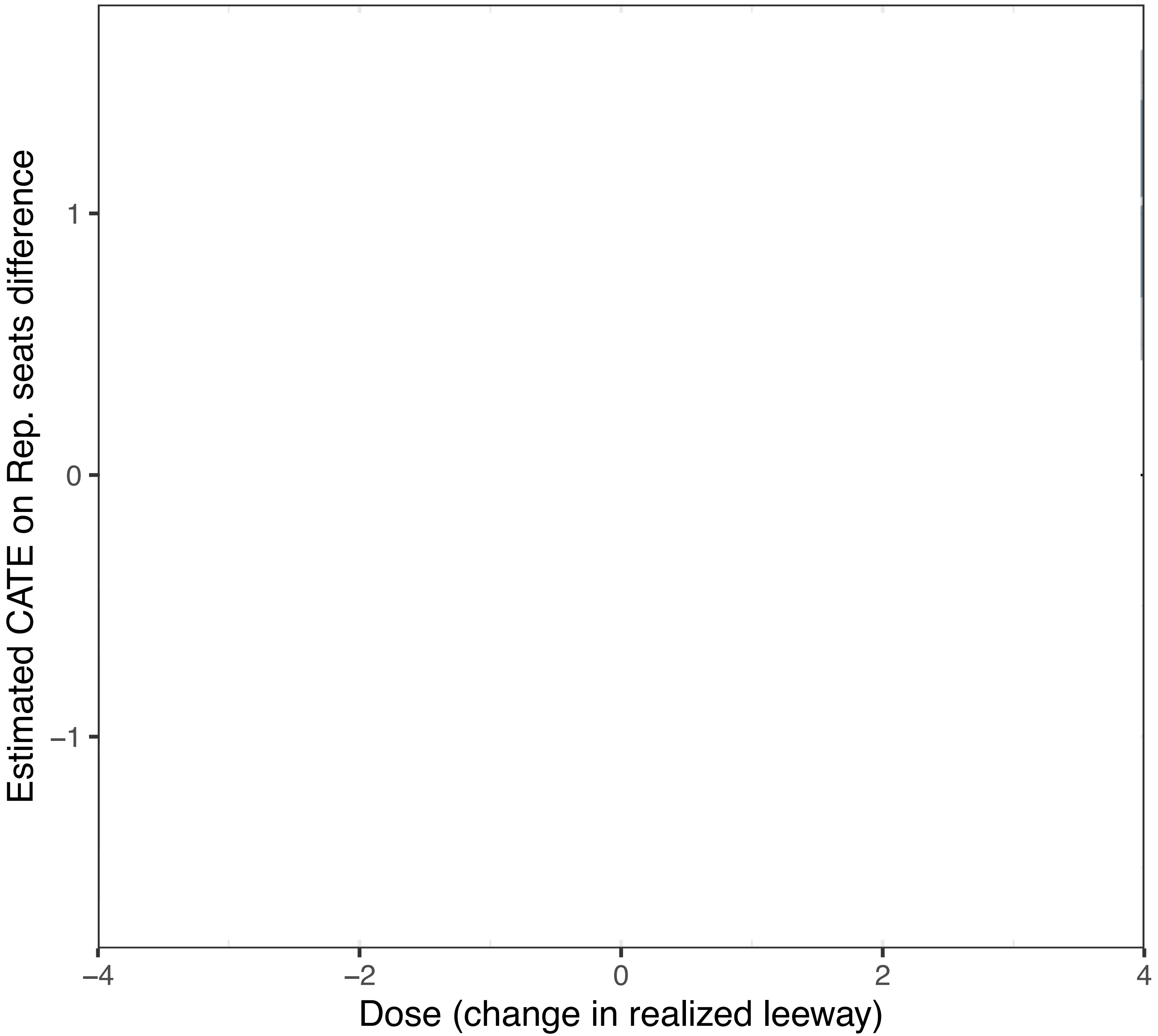
  Can then write potential outcomes as $Y_{it}(d)$ for treatment d

- Want to estimate $\text{CATE}_{\mathbf{x}}(d, d') = \mathbf{E}[Y_{i1}(d') - Y_{i1}(d) \mid \mathbf{X}_i = \mathbf{x}]$
- Assume **strong parallel trends** to identify CATE for any dosage (Callaway et al., 2024)

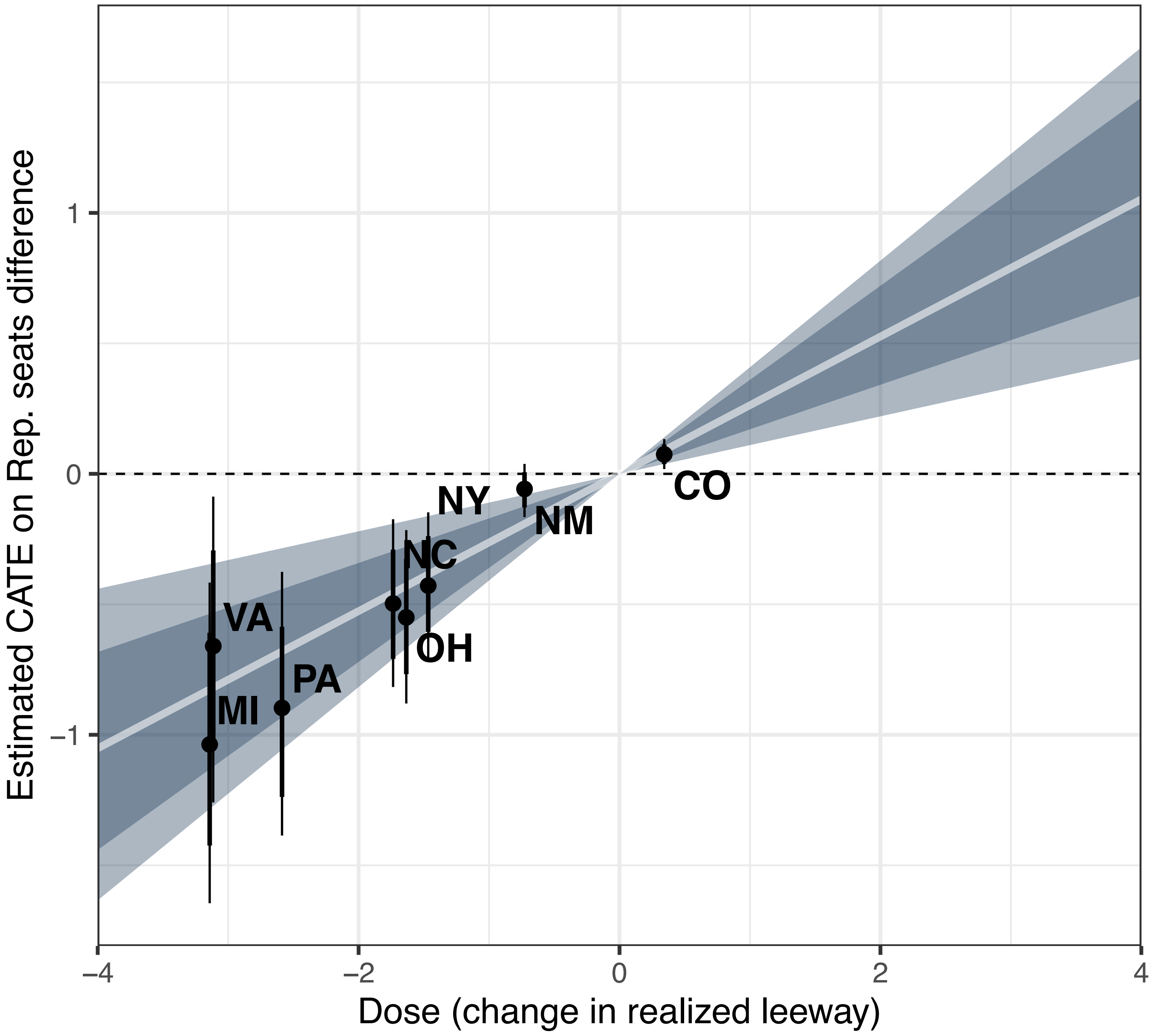
$$\mathbf{E}[Y_{i1}(d') - Y_{i0}(d) \mid \mathbf{X}_i = \mathbf{x}] = \mathbf{E}[Y_{i1}(d') - Y_{i0}(d) \mid \mathbf{X}_i = \mathbf{x}, \mathrm{D}_{i0} = d, \mathrm{D}_{i1} = d']$$

Introduction
Treatment Modeling
Estimation
Results
Policy Evaluations

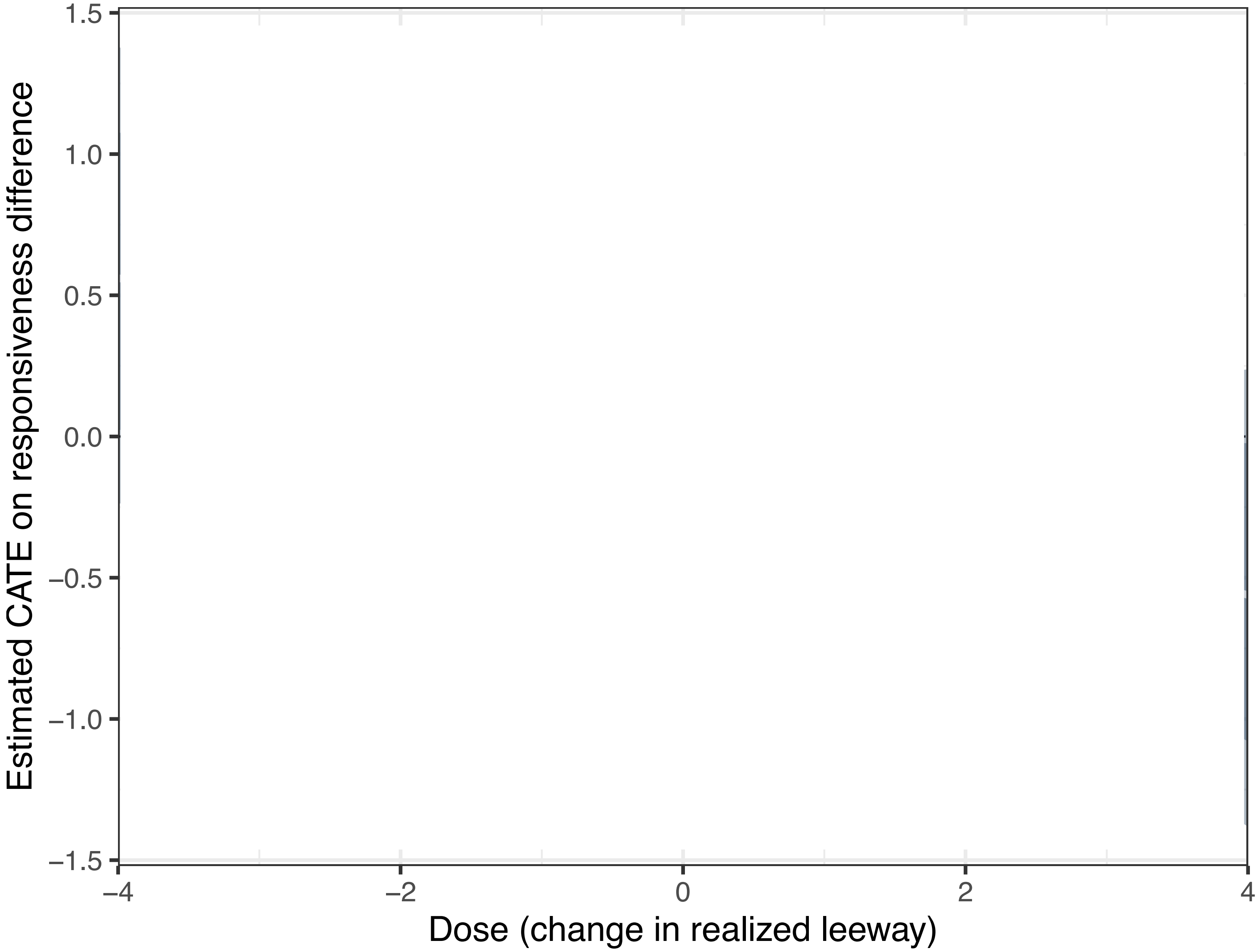
Decreasing leeway reduces partisan bias



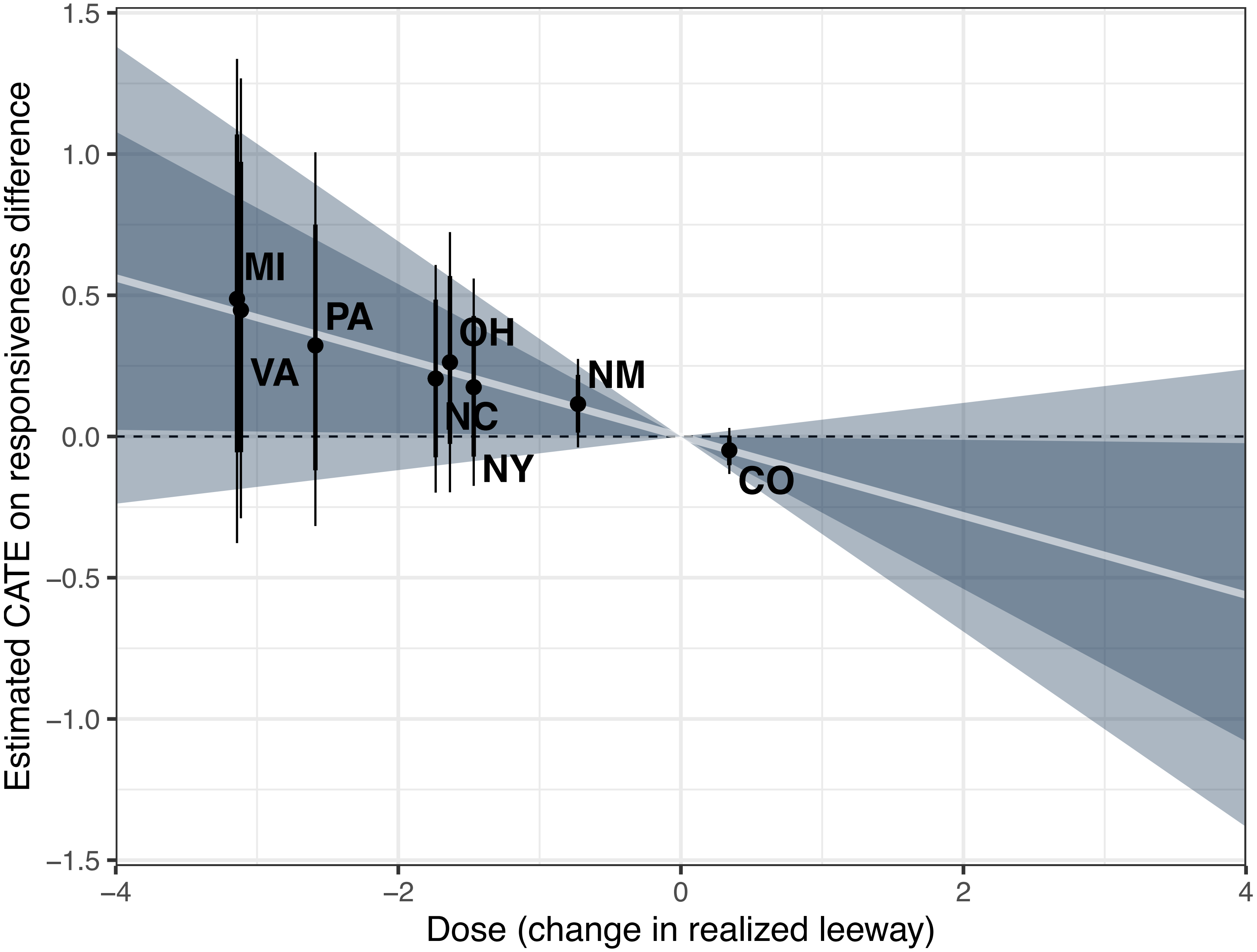
Decreasing leeway reduces partisan bias



Decreasing leeway increases responsiveness



Decreasing leeway increases responsiveness



Treatment Modeling
Estimation
Results
Policy Evaluations

Evaluating reforms with counterfactuals

Estimating Counterfactuals

Reforms

Evaluating reforms with counterfactuals

Estimating Counterfactuals

1. Re-estimate equilibria
    - For a given reform
        - Adopt its institutional coding
        - Apply each state's 2020 observed partisan control

Reforms

Evaluating reforms with counterfactuals

Estimating Counterfactuals

1. Re-estimate equilibria
    - For a given reform
        - Adopt its institutional coding
        - Apply each state's 2020 observed partisan control

Reforms

- New York-style
    - *Stage 1*: independent commission
    - *Stalemate*: legislature + governor veto
    - Court review

Evaluating reforms with counterfactuals

Estimating Counterfactuals

1. Re-estimate equilibria
   - For a given reform
     - Adopt its institutional coding
     - Apply each state's 2020 observed partisan control
2. Predict the outcome model on the counterfactual equilibria

Reforms

- New York-style
  - *Stage 1*: independent commission
  - *Stalemate*: legislature + governor veto
  - Court review

Evaluating reforms with counterfactuals

Estimating Counterfactuals

1. Re-estimate equilibria
    - For a given reform
        - Adopt its institutional coding
        - Apply each state's 2020 observed partisan control
2. Predict the outcome model on the counterfactual equilibria
3. Aggregate nationally

Reforms

- New York-style
    - *Stage 1*: independent commission
    - *Stalemate*: legislature + governor veto
    - Court review

Evaluating reforms with counterfactuals

Estimating Counterfactuals

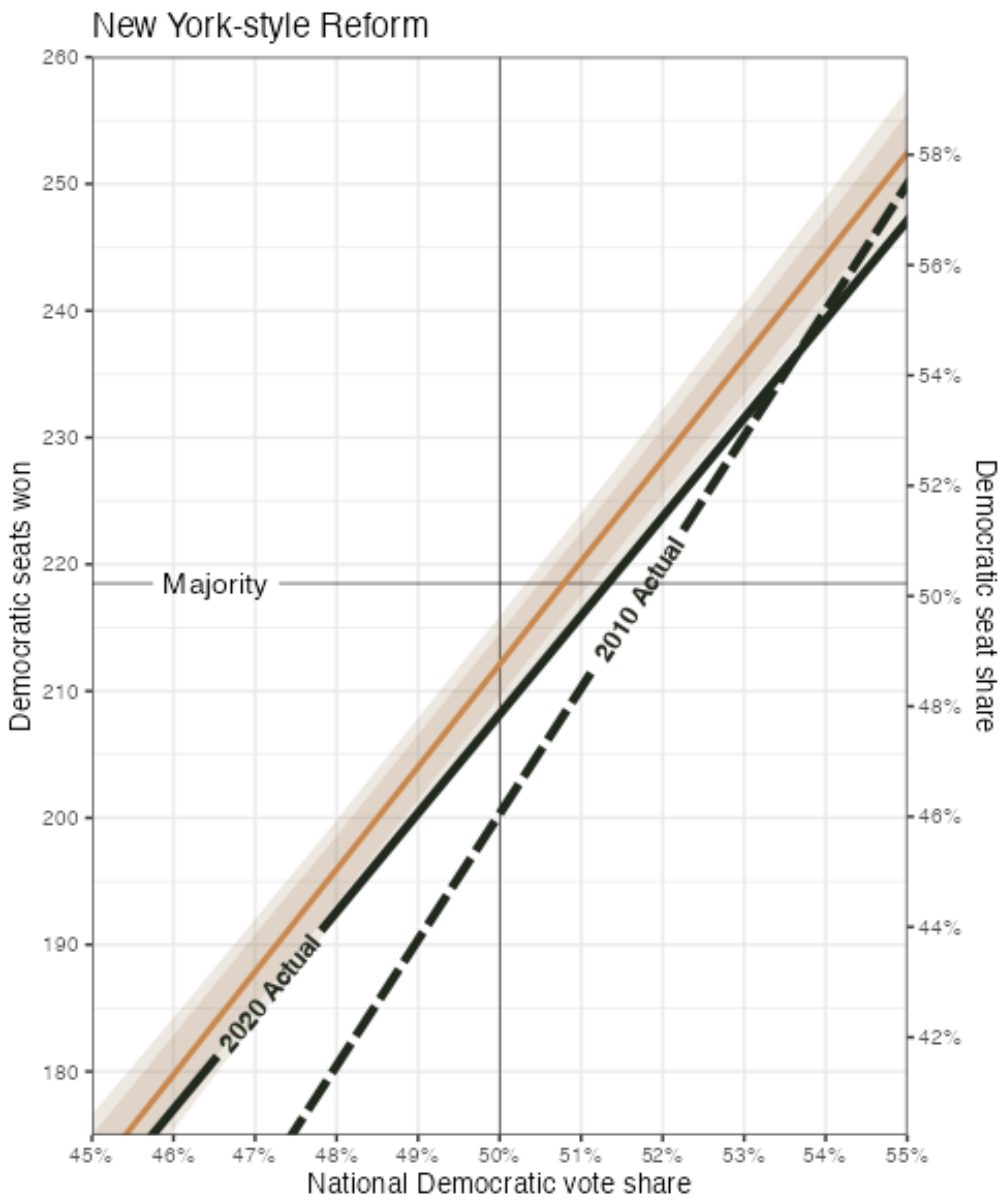
1. Re-estimate equilibria
   - For a given reform
     - Adopt its institutional coding
     - Apply each state's 2020 observed partisan control
2. Predict the outcome model on the counterfactual equilibria
3. Aggregate nationally

Reforms

- New York-style
  - *Stage 1*: independent commission
  - *Stalemate*: legislature + governor veto
  - Court review

ⓘ We evaluate every state adopting this reform from their 2010 process

Reforms improve nationwide partisan symmetry by constraining Republicans



ALARM

Redistricting Reforms

Redistricting Reforms Reduce Gerrymandering

Redistricting Reforms Reduce Gerrymandering by Constraining Partisan Actors

Redistricting Reforms Reduce Gerrymandering by Constraining Partisan Actors

- We use theory to perform dimension reduction of a complex treatment

Redistricting Reforms Reduce Gerrymandering by Constraining Partisan Actors

- We use theory to perform dimension reduction of a complex treatment
- Decreasing partisanship influence in redistricting...
  - reduces partisan bias
  - increases electoral responsiveness

Redistricting Reforms Reduce Gerrymandering by Constraining Partisan Actors

- We use theory to perform dimension reduction of a complex treatment
- Decreasing partisanship influence in redistricting...
  - reduces partisan bias
  - increases electoral responsiveness
- Restrictive reforms would nationally ...
  - help Democrats, decreasing partisan bias
  - increase responsiveness

Redistricting Reforms Reduce Gerrymandering by Constraining Partisan Actors

- We use theory to perform dimension reduction of a complex treatment
- Decreasing partisanship influence in redistricting…
  - reduces partisan bias
  - increases electoral responsiveness
- Restrictive reforms would nationally …
  - help Democrats, decreasing partisan bias
  - increase responsiveness
- More in the paper!
  - Other outcomes (including partisan symmetry)
  - More reform analyses

Continuous DiD(iD)

- Control for changes political geography using redistricting simulation
- Randomly sampled plans provide a nonpartisan benchmark $\tilde{Y}_{it}$
- Additional simulation difference weakens identification condition: Replace $Y_{it}(d)$ with $\Delta Y_{it}(d) = Y_{it}(d) - \tilde{Y}_{it}$

$$\mathbf{E}[\Delta Y_{i1}(d') - \Delta Y_{i0}(d) \mid \mathbf{X}_i = \mathbf{x}] = \mathbf{E}[\Delta Y_{i1}(d') - \Delta Y_{i0}(d) \mid \mathbf{X}_i = \mathbf{x}, \mathrm{D}_{i0} = d, \mathrm{D}_{i1} = d']$$

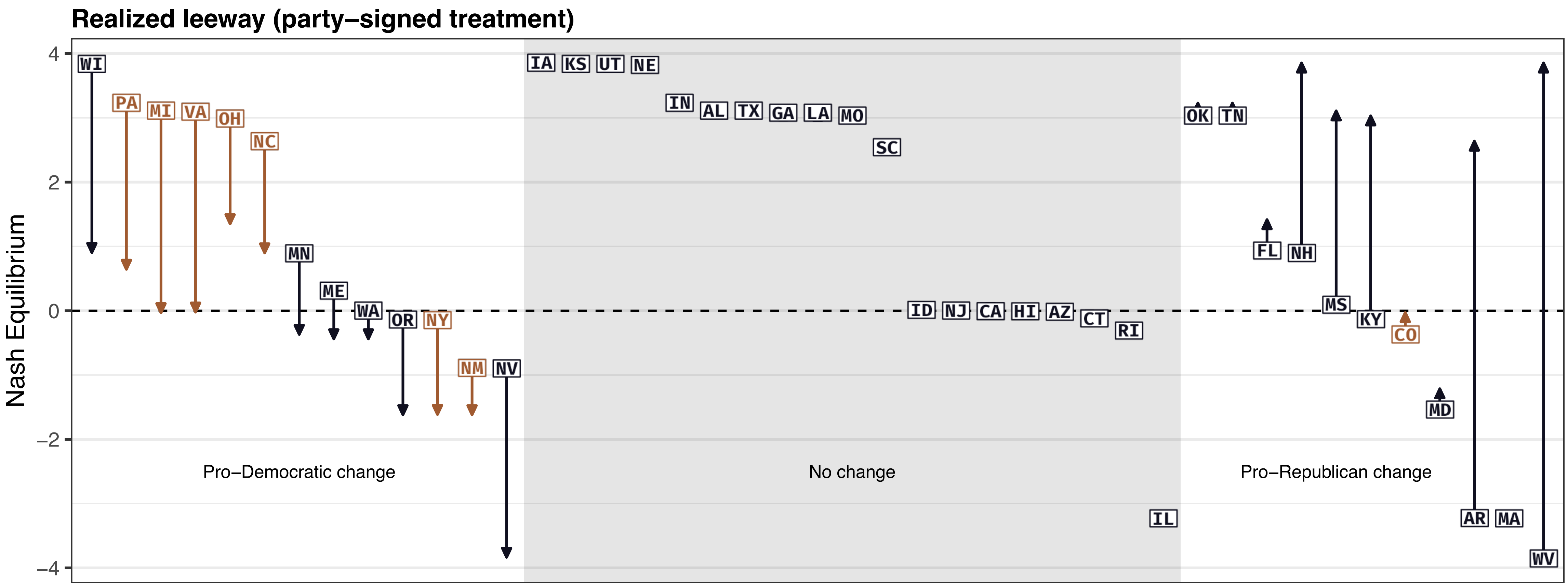
- Identify CATE as

$$\begin{aligned}\mathrm{CATE}_{\mathbf{x}}(d, d') = {} & \mathbf{E}[\Delta Y_{i1} - \Delta Y_{i0} \mid \mathbf{X}_i = \mathbf{x}, \mathrm{D}_{i0} = d, \mathrm{D}_{i1} = d'] \\ & - \mathbf{E}[\Delta Y_{i1} - \Delta Y_{i0} \mid \mathbf{X}_i = \mathbf{x}, \mathrm{D}_{i0} = d, \mathrm{D}_{i1} = d]\end{aligned}$$

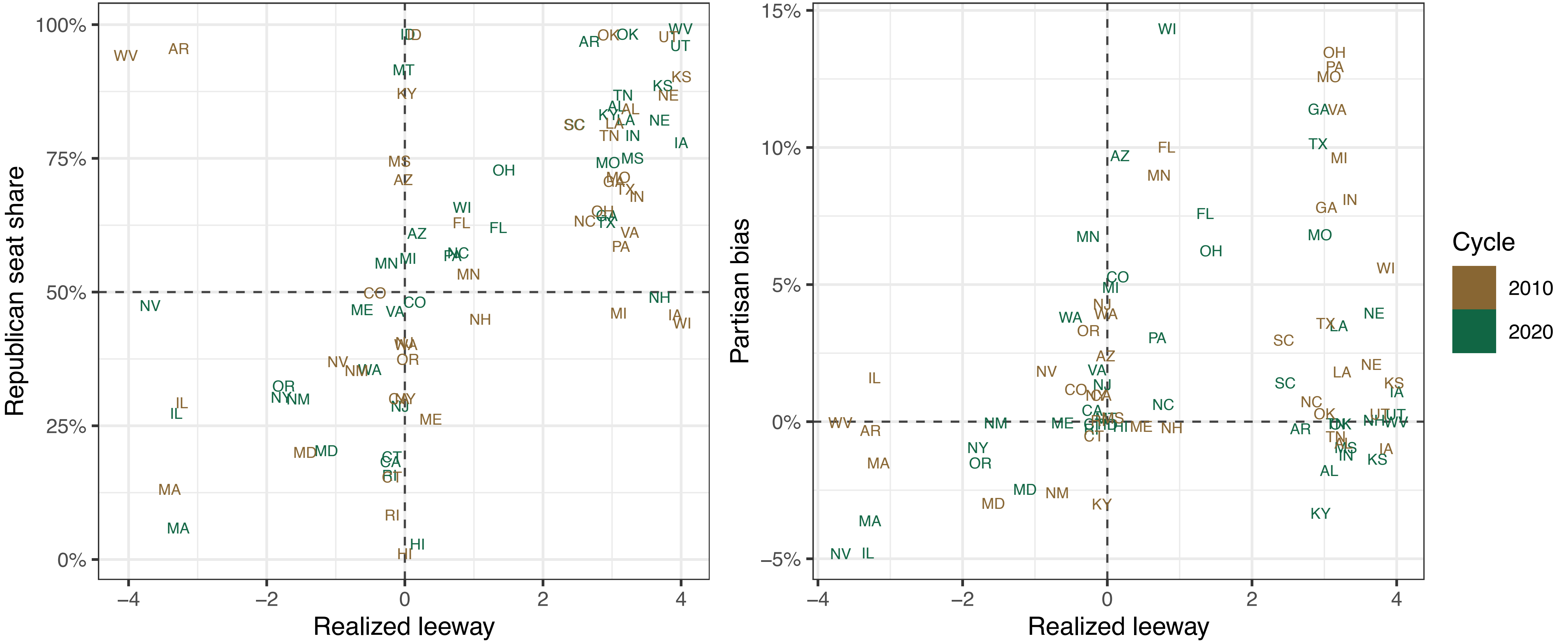
Detailed procedural coding, 2010–2020

State	Year	Drawer	Drawer control	Veto 1	Veto 1 ctrl.	Veto 2	Veto 2 ctrl.	Court review?	Court control	Stalemate 1	Stalemate 1 ctrl.	Stalemate 2	Stalemate 2 ctrl.	Preclearance
Alabama	2010	legislature	republicans	governor	republicans	NA	NA	no	republicans	unclear	NA	NA	NA	yes
Alabama	2020	legislature	republicans	governor	republicans	NA	NA	no	republicans	unclear	NA	NA	NA	yes
Arizona	2010	commission	nonpartisans	NA	NA	NA	NA	maybe	republicans	unclear	NA	NA	NA	yes
Arizona	2020	commission	nonpartisans	NA	NA	NA	NA	maybe	republicans	unclear	NA	NA	NA	yes
Arkansas	2010	legislature	democrats	governor	democrats	NA	NA	maybe	democrats	unclear	NA	NA	NA	yes
Arkansas	2020	legislature	republicans	governor	republicans	NA	NA	maybe	republicans	unclear	NA	NA	NA	yes
California	2010	commission	nonpartisans	voters	NA	NA	NA	yes	republicans	court	democrats	unclear	NA	yes
California	2020	commission	nonpartisans	voters	NA	NA	NA	yes	democrats	court	republicans	unclear	NA	yes
Colorado	2010	legislature	split	governor	democrats	NA	NA	yes	democrats	court	democrats	unclear	NA	no
Colorado	2020	commission	nonpartisans	court	democrats	NA	NA	yes	democrats	commission staff	nonpartisans	unclear	NA	no
Connecticut	2010	legislature	split	NA	NA	NA	NA	no	democrats	commission	nonpartisans	court	democrats	no
Connecticut	2020	legislature	split	NA	NA	NA	NA	no	democrats	commission	nonpartisans	court	democrats	no
Florida	2010	legislature	republicans	governor	republicans	NA	NA	yes	democrats	unclear	NA	NA	NA	yes
Florida	2020	legislature	republicans	governor	republicans	NA	NA	yes	republicans	unclear	NA	NA	NA	yes
Georgia	2010	legislature	republicans	governor	republicans	NA	NA	no	democrats	unclear	NA	NA	NA	yes
Georgia	2020	legislature	republicans	governor	republicans	NA	NA	no	republicans	unclear	NA	NA	NA	yes
Hawaii	2010	commission	nonpartisans	NA	NA	NA	NA	yes	democrats	unclear	NA	NA	NA	no
Hawaii	2020	commission	nonpartisans	NA	NA	NA	NA	yes	democrats	unclear	NA	NA	NA	no
Idaho	2010	commission	split	NA	NA	NA	NA	yes	republicans	commission	split	unclear	NA	no
Idaho	2020	commission	split	NA	NA	NA	NA	yes	republicans	commission	split	unclear	NA	no
Illinois	2010	legislature	democrats	governor	democrats	NA	NA	maybe	democrats	unclear	NA	NA	NA	no
Illinois	2020	legislature	democrats	governor	democrats	NA	NA	maybe	democrats	unclear	NA	NA	NA	no
Indiana	2010	legislature	republicans	governor	republicans	NA	NA	maybe	republicans	commission	republicans	unclear	NA	no
Indiana	2020	legislature	republicans	governor	republicans	NA	NA	maybe	republicans	commission	republicans	unclear	NA	no
Iowa	2010	commission	nonpartisans	legislature	republicans	governor	republicans	no	republicans	legislature	republicans	unclear	NA	no
Iowa	2020	commission	nonpartisans	legislature	republicans	governor	republicans	no	republicans	legislature	republicans	unclear	NA	no
Kansas	2010	legislature	republicans	governor	republicans	NA	NA	no	nonpartisans	unclear	NA	NA	NA	no
Kansas	2020	legislature	republicans	governor	NA	NA	NA	no	nonpartisans	unclear	NA	NA	NA	no
Kentucky	2010	legislature	split	governor	democrats	NA	NA	maybe	democrats	unclear	NA	NA	NA	no
Kentucky	2020	legislature	republicans	governor	NA	NA	NA	maybe	democrats	unclear	NA	NA	NA	no
Louisiana	2010	legislature	republicans	governor	republicans	NA	NA	no	democrats	unclear	NA	NA	NA	yes

Model-based treatment values



Treatment model validation



Treatment model validation

- Equilibrium path from game leads to forecast of which body will end up drawing map
- Compare these forecasts to reality
- Good agreement, with tendency of model to over-predict court intervention

	Most likely in equilibrium			
Final drawer	Legislature	Commission	Court	Total
Legislature	31.9	0.0	19.1	51
Commission	0.0	18.9	3.0	22
Court	1.7	0.0	12.3	14
Total	33.6	18.9	34.4	87

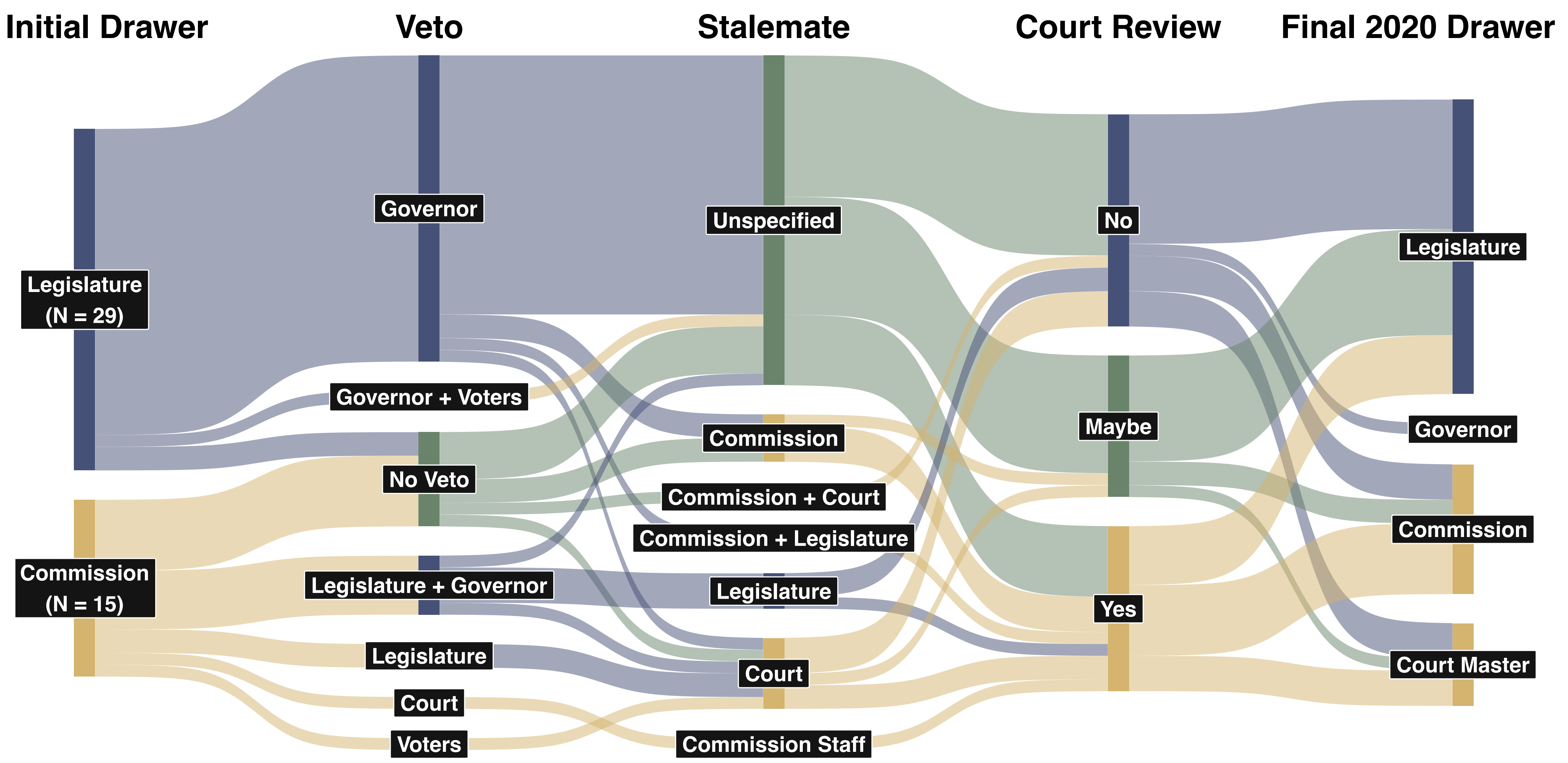
Estimation

- Bayesian linear regression model
- Response is $\Delta Y_{i1} - \Delta Y_{i0}$
- Interact dose (leeway change) with covariates
- Priors for moderate shrinkage

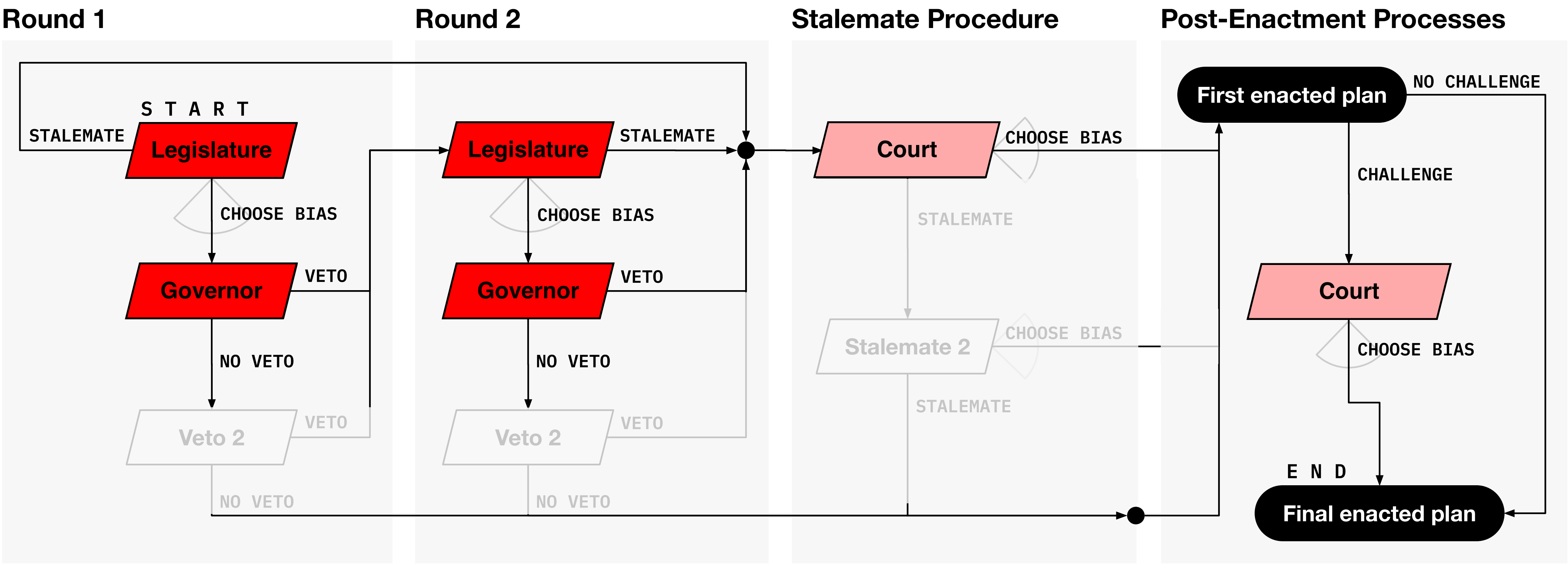
Covariates:

- 2010 leeway
- 2008 Democratic vote share
- Indicator for South
- log(no. of districts in 2020)
- Change in districts 2010–2020
- log(corruption convictions)
- Indicator for ballot initiatives

A menagerie of redistricting processes



The redistricting game: Alabama



Equilibrium = 2.8 / 4 (Republican-favoring)

Reforms reduce gerrymandering and improve nonpartisan outcomes