# Survey weighting and hierarchical regression: some successes and struggles

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# Survey weighting and regression modeling

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  - Hierarchical modeling and poststratification
- Struggle: the Social Indicators Survey of NYC families
- Unrelated topic: interactions in before-after studies
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# National opinion trends

# State-level opinion trends

- Goal: estimating time series within each state
- One poll at a time: small-area estimation
- It works! Validated for pre-election polls
- Combining surveys: hierarchical model for parallel time series
- Straightforward hierarchical modeling + poststratification
- Poststratification cells: sex $\times$ ethnicity $\times$ age $\times$ education $\times$ state

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# Hierarchical modeling to estimate state opinions

- Hierarchical model for the data
  - $\Pr(y_i = 1) = \text{logit}^{-1}((X\beta)_i)$
  - $X$ includes demographic and geographic predictors
  - Hierarchical model for the 50 state coefficients

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| Simulation | $\theta_1$ | $\cdots$ | $\theta_{75}$ |
|---|---|---|---|
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# Poststratification to estimate state opinions

- Implied inference for $\theta_j = \text{logit}^{-1}(X\beta)$ in each of 3264 cells $j$ (e.g., black female, age 18–29, college graduate, Connecticut)
- Poststratification
  - Within each state $s$, average over 64 cells:
    $\sum_{j \in s} N_j \theta_j \Big/ \sum_{j \in s} N_j$
    $N_j$ = population in cell $j$ (from Census)
    1000 simulation draws propagate to uncertainty for each $\theta_j$

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# CBS/New York Times pre-election polls from 1988

- Validation study: fit model on poll data and compare to election results
- Competing estimates:
  - No pooling: separate estimate within each state
  - Complete pooling: no state predictors
  - Hierarchical model and poststratify
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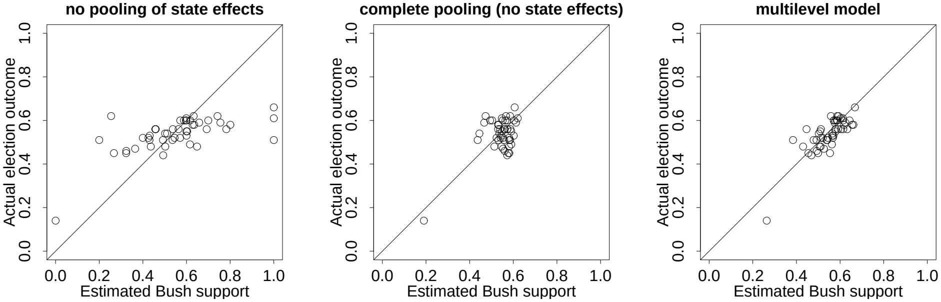
# Validation study: comparison of state errors

1988 election outcome vs. poll estimate



# National opinion trends

# Death penalty opinions from General Social Survey, 1975–2000

- Goal: time series of opinions in each state
- For each state $s$ at time $t$, sum over 64 poststrat cells $j$: $\sum_{j \in s} N_{jt} \theta_{jt} \Big/ \sum_{j \in s} N_{jt}$
- Logistic regression: $\theta_{jt} = \text{logit}^{-1}((X\beta)_{jt})$
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- Estimate the $\beta$'s from the survey data
- We just presented the model in "reverse order"

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# Death penalty opinion trends by state

# Survey weighting is a mess

- Using weights
  - Weighted mean: $\bar{y}_w = \sum_{i=1}^n w_i y_i / \sum_{i=1}^n w_i$
  - Estimating a ratio: $r_w = \sum_{i=1}^n w_i y_i / \sum_{i=1}^n w_i x_i$
  - Estimating anything more complicated: ???
- Regression modeling as an alternative

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# Simple theoretical example

- Survey of a population with 52% women, 48% men
- Simple random sampling, $n = 100$
  - SRS 1: 52 women, 48 men. Weights are $w_i = 1$ for everyone
  - SRS 2: 60 women, 40 men. Weights are $w_i = \frac{52}{60}$ for women, $\frac{48}{40}$ for men
- We know the population proportions, so the selection probabilities are irrelevant
- Weights depend on the entire survey; the $(y_i, w_i)$ paradigm is inappropriate

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- Survey of a population with 52% women, 48% men
- Simple random sampling, $n = 100$
  - SRS 1: 52 women, 48 men. Weights are $w_i = 1$ for everyone
  - SRS 2: 60 women, 40 men. Weights are $w_i = \frac{52}{60}$ for women, $\frac{40}{48}$ for men
- We know the population proportions, so the selection probabilities are irrelevant
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# CBS/New York Times pre-election polls

| id | org | y | state | edu | age | adults | weight |
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- Telephone survey every 2 years of NYC families
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# Poststratification for the CBS polls

- We don't actually use the "weights"
- We model $y$ conditional on the variables used in the weighting
- These define poststratification cells $j = 1, \ldots, J = 3264$
- $2 \times 2 \times 4 \times 4 \times 51$: sex $\times$ ethnicity $\times$ age $\times$ education $\times$ state
- Poststratified average, $\theta = \frac{\sum_{j=1}^{J} N_j \theta_j}{\sum_{j=1}^{J} N_j}$
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- Compare 1999 and 2001 Social Indicators Surveys
- Goal is to estimate $\bar{Y}^{2001} - \bar{Y}^{1999}$, for various survey responses $y$
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# Comparing estimates from weighting and regression

| Question | weighted averages 1999 | weighted averages 2001 | (a) time change in percent | (b) linear regression coefficient of time |
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| Adult in good/excellent health | 75% | 78% | 3.4% (2.4%) | 6.6% (1.4%) |
| Child in good/excellent health | 82% | 84% | 1.7% (1.5%) | 1.2% (1.3%) |
| Neighborhood is safe/very safe | 77% | 81% | 4.5% (2.3%) | 4.1% (1.5%) |

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# Regression models and implied weights

- Fit a regression and poststratify:
  - $\hat{\theta} = \sum_{j=1}^{J} N_j \hat{\theta}_j \Big/ \sum_{j=1}^{J} N_j$
  - From regression, $\hat{\theta}_j$'s are linear combinations of the data $y$
  - We can write $\hat{\theta} = \frac{1}{n} \sum_{i=1}^{n} w_i y_i$
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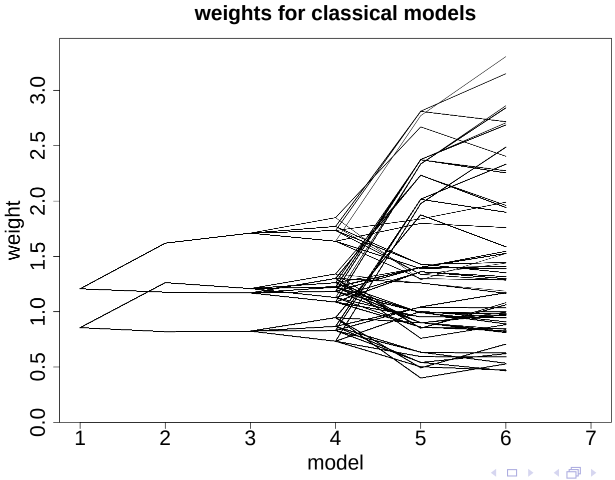

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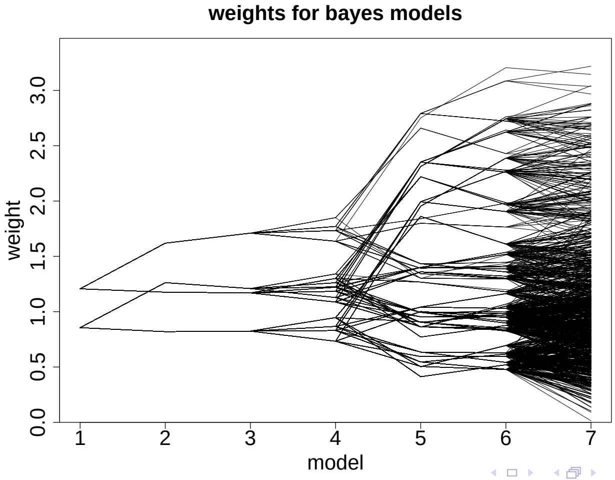

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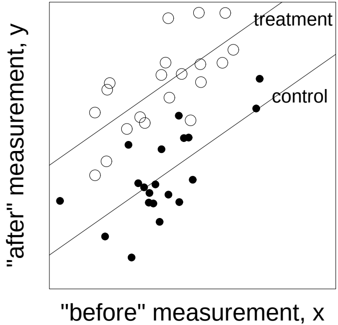

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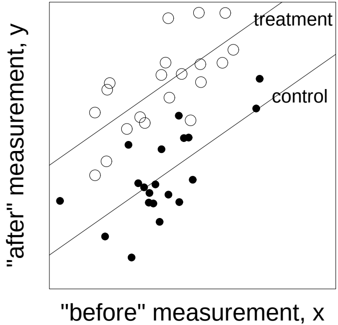

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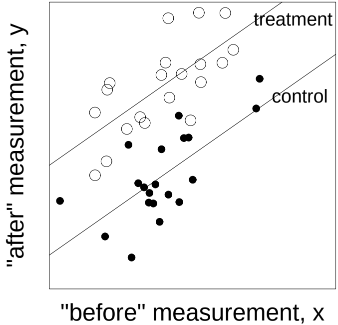

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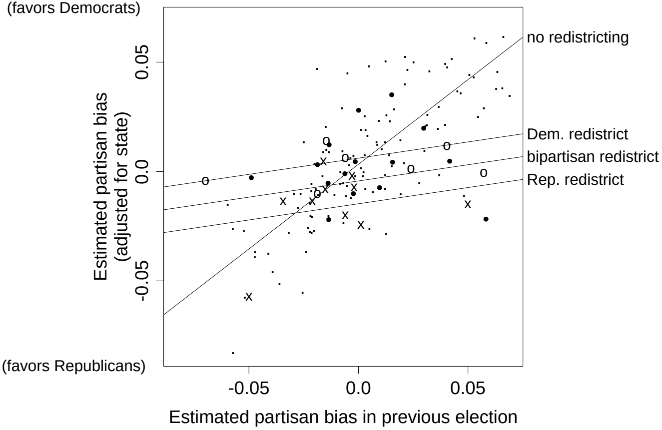
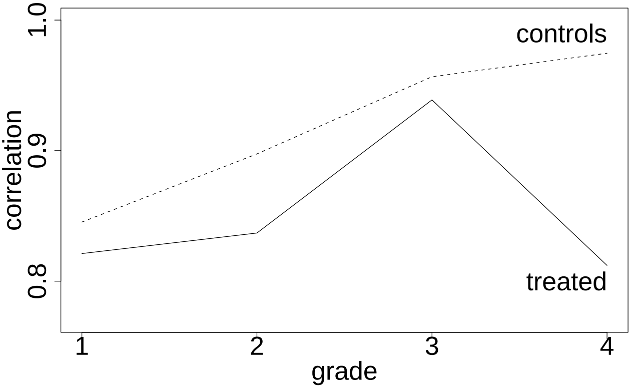
  - Congressional elections with incumbents and open seats

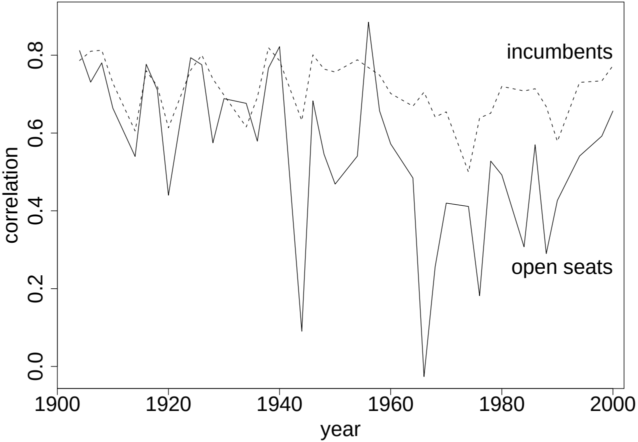
# Observational study of legislative redistricting before-after data



# Experiment: correlation between pre-test and post-test data for controls and for treated units



# Correlation between two successive Congressional elections for incumbents running (controls) and open seats (treated)



# Underlying variance components

Unit-level "error term" $\eta_i$

- For control units, $\eta_i$ persists from time 1 to time 2
- For treatment units, $\eta_i$ changes:
  - Subtractive treatment error ($\eta_i$ only at time 1)
  - Additive treatment error ($\eta_i$ only at time 2)
  - Replacement treatment error
- Under all these models, the before-after correlation is higher for controls than treated units

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# Papers

- State-level estimates from national polls
  - 1997 Poststratification into many categories using hierarchical logistic regression. *Survey Methodology*. (Andrew Gelman and Thomas C. Little)
  - 2004 Bayesian multilevel estimation with poststratification: state-level estimates from national polls. *Political Analysis*. (David K. Park, Andrew Gelman, and Joseph Bafumi)
- Struggles with survey weighting and poststratification
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