# Rich State, Poor State, Red State, Blue State: What's the Matter with Connecticut

### Andrew Gelman Department of Statistics and Department of Political Science Columbia University

13 Aug 2006



- Income and voting: understanding aggregate and individual patterns
- Multilevel modeling and graphical display
- Some politics and some psychology
- Collaborators

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Individual, county, and state-level analyses Multilevel models of individuals within states Understanding the results A trip to Mexico

- I never said all Democrats are saloon-keepers. What I said is that all saloon-keepers are Democrats. — Horace Greeley, 1860
- Pat doesn't have a mink coat. But she does have a respectable Republican cloth coat. — Richard Nixon, 1952
- Like upscale areas everywhere, from Silicon Valley to Chicago's North Shore to suburban Connecticut, Montgomery County supported the Democratic ticket in last year's presidential election, by a margin of 63 percent to 34 percent.
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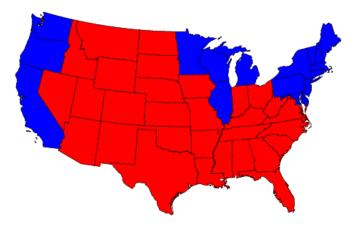
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- Rich states go for the Democrats, but rich voters go for the Republicans. How do we understand this?
- ▶ Why all the fuss since 2000?
- How to reconcile journalists' and social scientists' views about income and political preferences?

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States Individuals Counties

## Richer states now support the Democrats

▶ In each presidential election year, run linear regression:

- y = state vote share for the Republican
- x = average income in the state
- Display time series of estimates ± standard errors (the "secret weapon")
- Quantitative version of looking at a series of red/blue maps
- Also do separate analyses for South, non-South

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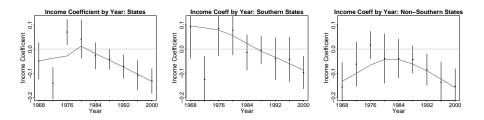
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- "Latte" Democrats vs. "Nascar" Republicans
- Recent trends explain why it's recent news
- Is state-level inequality (rather than average income) the explanation?

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## Richer voters continue to support the Republicans

- National Election Study
- Each election year, logistic regression on individual voters:
- Display time series of estimates  $\pm$  standard errors
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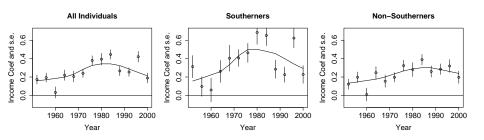
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Andrew Gelman Rich State, Poor State, ...

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- "Fat-cat" Republicans and "working-class" Democrats
- Including ethnicity, sex, education, and age as predictors in the model has little effect on the coefficient for income

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### Richer counties support the Republicans in some states and the Democrats in others

- Within each state, estimate regression on county data:
  - y = county vote share for the Republican
  - x = average income in the county
- Varying-intercept, varying-slope model:

- Fit separate model for each election year ("secret weapon")
- For each state, display time series of estimated  $\beta_s$

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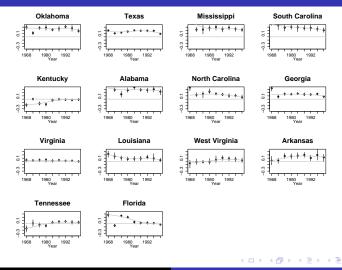
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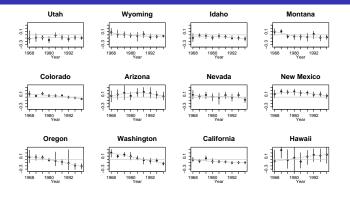
#### Coef of county-level income on county-level vote: South



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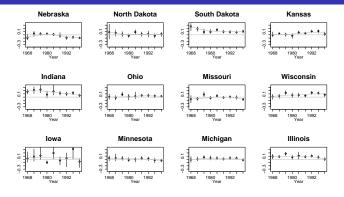
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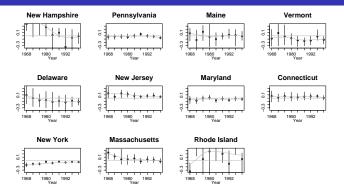


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### Richer counties support the Republicans in some states and the Democrats in others

- In "deep-red" Southern states such as Oklahoma, Texas, Mississippi, etc., richer counties strongly support the *Republicans*
- In "media-center" states of New York, California, Maryland, and Virginia, richer counties slightly support the *Democrats*
- Journalists noticed a pattern (richer counties supporting the Democrats) that is concentrated in the states where the journalists live!

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Varying-intercept model Varying-intercept, varying-slope model Supplementary analyses

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- ▶ Within each state, estimate logistic regression on individuals:
  - ▶ y = vote preference (1 = Rep, 0 = Dem)
  - x = individual income (on a five-point scale)
- Varying-intercept model:

- Use 2000 Annenberg Election Survey (over 100,000 respondents)
- Plot estimated Pr(R vote) vs. income for three representative states

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- Use 2000 Annenberg Election Survey (over 100,000 respondents)
- Plot estimated Pr(R vote) vs. income for three representative states

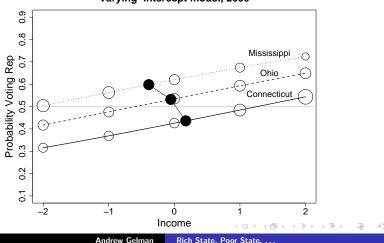
Varying-intercept model Varying-intercept, varying-slope model Supplementary analyses

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- ▶ Within each state, estimate logistic regression on individuals:
  - y = vote preference (1=Rep, 0=Dem)
  - x = individual income (on a five-point scale)
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Varying-intercept model Varying-intercept, varying-slope model Supplementary analyses

#### Richer voters support the Republicans within states



#### Varying-intercept model, 2000

Varying-intercept model Varying-intercept, varying-slope model Supplementary analyses

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- Varying-intercept, varying-slope model:
  - $\Pr(y_i = 1) = \operatorname{logit}^{-1}(\alpha_{s[i]} + \beta_{s[i]} x_i)$
  - s[i] = state containing county i
  - > State-level regression of  $lpha_s$  and  $eta_s$  on state income
- ► Income is coded as -2, -1, 0, 1, 2, so we can interpret both intercepts and slopes
- Plot estimated Pr(R vote) vs. income for 3 representative states
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Varying-intercept model Varying-intercept, varying-slope model Supplementary analyses

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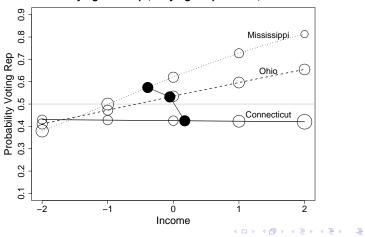
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Varying-intercept model Varying-intercept, varying-slope model Supplementary analyses

### Income matters more in "red America" than in "blue America"



Varying-intercept, varying-slope model, 2000

Andrew Gelman Rich State, Poor State, ...

Varying-intercept model Varying-intercept, varying-slope model Supplementary analyses

#### Income matters more in "red America" than in "blue America"

0.8 0.6 MS 0.4 Slope 0.2 MANJ 0.0 CT 0.2 2.0 2.5 3.0 3.5 Avg State Income (\$10k)

Slope vs. state income, 2000

Andrew Gelman Rich State, Poor State, ...

Varying-intercept model Varying-intercept, varying-slope model Supplementary analyses

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- Excluding African Americans
- Also including sex, ethnicity, age, education, state % black, and state avg. education in the regression
- Estimates since 1968 using National Election Studies
- Exit polls from 2000
- ▶ Exit polls from 2004

Varying-intercept model Varying-intercept, varying-slope model Supplementary analyses

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### Supplementary analyses give the same results

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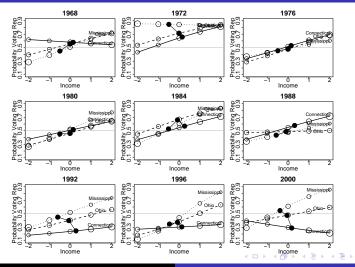
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### Estimates using National Election Studies

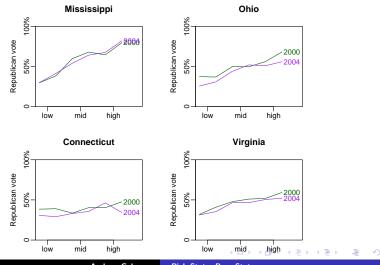


Andrew Gelman

Rich State, Poor State, ...

Varying-intercept model Varying-intercept, varying-slope model Supplementary analyses

#### Income and vote preference from exit polls



Andrew Gelman

Rich State, Poor State, ...

Understanding the differences between states Explaining why journalists (and others) have been confused Conclusions

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- Richer states support the Democrats—even though, within any given state, richer voters tend to support the Republicans.
- The slope within a state is strongest in poor, rural, Republican-leaning "red" states and weakest in rich, urban, Democrat-leaning "blue" states.
- These patterns have largely arisen in the past ten or fifteen years.

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- Positive slopes within states are no suprise
- Between states: state income as product of long-term trends (large cities 50 or 100 years ago, more trade, immigration, ethnic diversity)
- Economic issues are perhaps more salient in poor states, less salient in rich states (that could be "what's wrong with Connecticut")

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### Understanding the differences between states

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# Explaining journalists' confusion

- Statistical explanations
- Political explanations
- Psychological explanations

Understanding the differences between states Explaining why journalists (and others) have been confused Conclusions

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# Statistical explanations for journalists' confusion

#### Red-blue map is misleading

- Overstates "polarization"
- Focus on large land-area states
- Reliance on anecdotes leads to confirmation of what is already "known"
- Aggregation bias: within-state and between-state correlations in different directions

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Understanding the differences between states Explaining why journalists (and others) have been confused Conclusions

- I come from Huntington, a small farming community in Indiana. I had an upbringing like many in my generation—a life built around family, public school, Little League, basketball and church on Sunday. My brother and I shared a room in our two-bedroom house. — Dan Quayle, 1992
- Clinton displays almost every trope of blackness: single-parent household, born poor, working-class, saxophone-playing, McDonald's-and-junk-food-loving boy from Arkansas. — Toni Morrison, 1998
- Lower-than-average income Americans are part of the "mom and apple pie" cluster
- Both sides want to claim the "average American"
- ► 50% of voters support each party, so no easy answers for either side!

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- "Typicality" (Rosch, 1975): robins and penguins
- What does a "typical" Democrat or a "typical" Republican look like?
- Personification of states and counties

Understanding the differences between states Explaining why journalists (and others) have been confused Conclusions

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# Psychological explanations for journalists' confusion

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- I can't believe Nixon won. I don't know anybody who voted for him. — attributed to Pauline Kael, 1972
- It evidently irritates many liberals to point out that their party gets heavy support from superaffluent "people of fashion" and does not run very well among "the common people." — Michael Barone, 2005
- First-order availability bias ("false consensus effect"): most people I know are Democrats, therefore most people are Democrats
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Understanding the differences between states Explaining why journalists (and others) have been confused Conclusions

## Second-order availability bias

- National journalists in New York, California, Maryland, and Virginia live in states where:
  - Rich counties support the Democrats, poor counties support the Republicans
  - There is only a weak relation between income and vote preference
- In contrast, in the deep-red Southern states:

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- Paradoxically, journalists are influenced by their geography—even when they try to generalize to the general population!

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#### Red-state, blue-state in Mexico

#### Background on Mexican elections

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- Every 6 years
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- 2000 and 2006 were the first fair elections; 3 major parties:

- PAN beat PRI in 2000;
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- Income at individual level: middle class and poor
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# Mexican presidential elections

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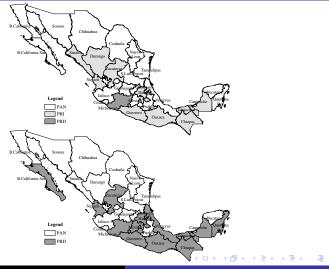
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#### Presidential election results in 2000 and 2006



Andrew Gelman Rich State, Poor State, ...

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- ► 3 parties instead of 2
  - Model a continuous outcome y = 1, 2, 3
  - Logistic regression comparing each party to the other two
  - Ordered logit, estimating cutpoints
- Data issues

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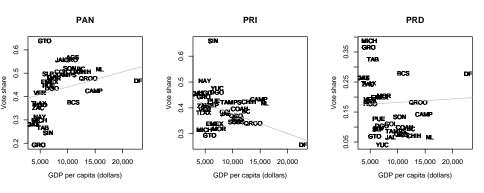
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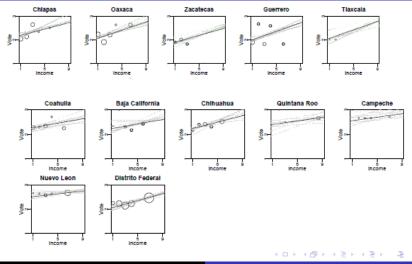
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#### State vote vs. state GDP



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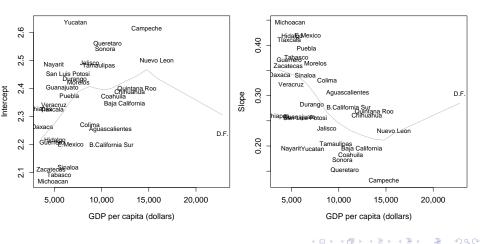
#### Data and fitted lines within poor and rich states



Andrew Gelman Rich State, Poor State, ...

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#### Estimated intercepts and slopes vs. state GDP



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## Summary of results

- Rich voters support more conservative candidates
- Income predicts vote choice more strongly in poor states
- Different from the U.S.

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### Nonlinear relation to state GDP

- Richer states are more conservative and have lower slopes—except for Mexico City, the richest "state"
- Cannot simply display the equivalents of Mississippi, Ohio, and Connecticut

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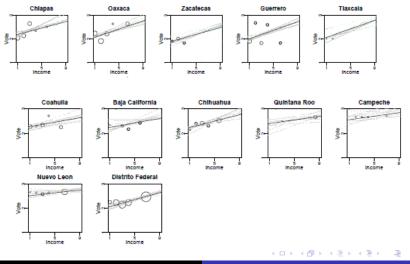
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Introduction

Individual, county, and state-level analyses Multilevel models of individuals within states Understanding the results A trip to Mexico Background on Mexican elections Replicating our analysis Challenges in fitting the model Costs and henefits of Bayesian inforence and multilevel models

# Original fit



Andrew Gelman Rich State, Poor State, ...

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# Fixing the model

#### Add state-level predictors

- GDP per capita (already included in model)
- Indicators for the five regions (including Mexico City)
- ► Collinearity

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# Costs and benefits of Bayesian multilevel modeling

Cost

Can be more more effort to fit

Benefit

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# Costs and benefits of Bayesian multilevel modeling

- Can be more more effort to fit
- Benefit
  - Fewer arbitrary choices (paradoxically, in light of what is sometimes said about subjectivity and prior distributions)

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