# CS2080: Applied Privacy for Data Science
# Attacks on Utility

School of Engineering & Applied Sciences
Harvard University

March 12, 2025

# Housekeeping

- Second call: Please do filling out the mid-semester feedback form (see Henry's post on Ed) **by tonight**
  - Preliminary responses to midterm feedback on next slide
- Add your project ideas to the spreadsheet if you haven't already done so, and express interest in ≥2 other ideas by **Friday night**
- Final project poster session **9am-12pm on Thursday 5/8** and revision of project papers due that night
- Solutions to HWs 1&2 posted on Canvas; others are coming

# Housekeeping

- Preliminary responses to midterm feedback
  - Perusall readings should all be downloadable (let us know if we miss any)
  - Section is the place to get practice problem-solving for HW prep. "probably the most helpful part of the course in terms of understanding"
  - For more depth in theory, see the annotated bibliography and/or take CS2260 in the Fall.
  - We've added HW deadlines to the course Google calendar. We generally are not making use of Canvas.
  - We will more systematically monitor Ed for questions.
  - For HoDP readings, feel free to comment about what you've found clear/unclear/interesting or requests for things for us to go over in lecture.
  - We have been trying release & polish the HWs sooner, to minimize frustrating updates.

# Census DAS Process

"Disclosure Avoidance System"

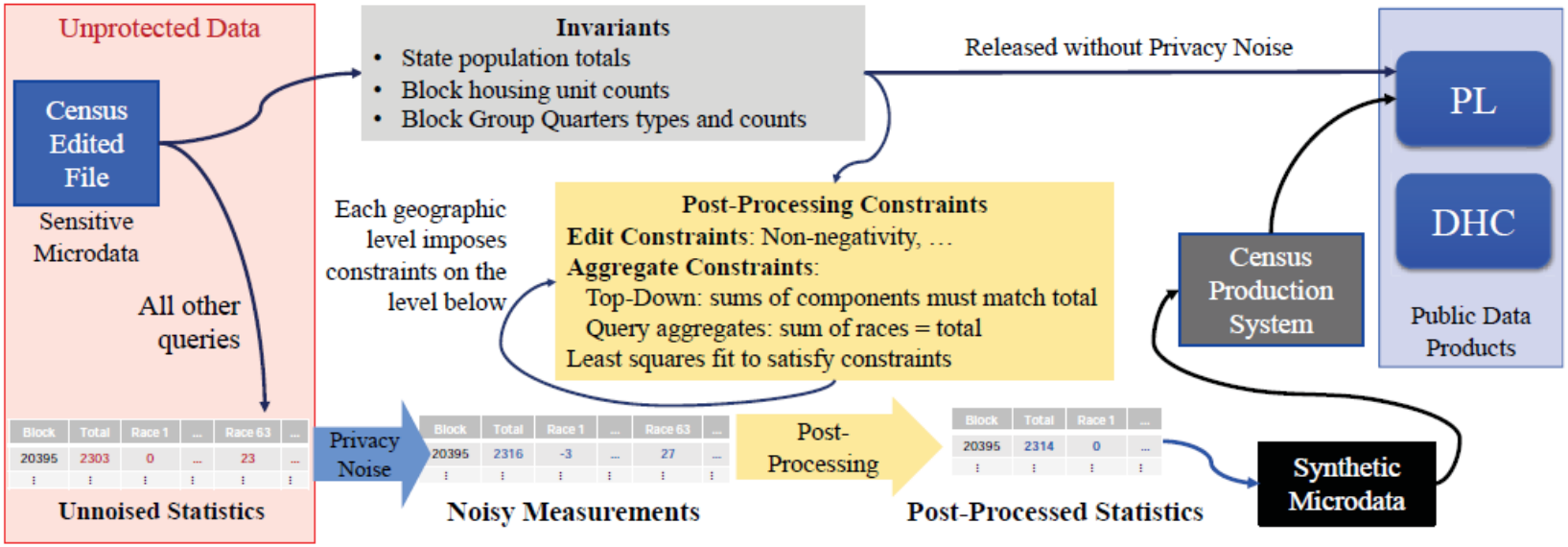


Figure 5-1: Process used to produce privacy-protected data products.

What happens to the **utility** of Census data when DP is applied?

# There are several uses of census data

- Reapportionment
- Redistricting
- Funding allocation (*billions* of $)
- Social science research
- Business decisions
- etc.

https://www.census.gov/programs-surveys/decennial-census/about/why.html

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**How are these uses impacted by DP?**
(i.e., What is the utility of census data protected under DP?)

https://www.census.gov/programs-surveys/decennial-census/about/why.html

# Utility vs. accuracy

- **Accuracy:** how close a published, differentially private estimate is to its non-differentially private counterpart

- **Utility:** “usefulness of a dataset or statistic for various societally beneficial purposes”
  - Sometimes studying utility may require qualitative approaches, but today we’ll stick to quantitative approaches.

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**today**

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# Evaluating ("attacking") utility

1. Choose a dataset to be protected under DP
2. Consider a <u>specific</u> real-world use of that dataset
3. Formulate a metric (broadly defined) that would help understand the <u>utility</u> of the dataset for that specific task
4. Design & run simulations where DP noise is used to protect the data. Compare metrics on the DP-noised data vs. the dataset without protections*

*In practice, it may be hard to get access to the dataset without protections. In such a case, you may simulate the original data first.

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**When would we want to change the comparison in Step 4?**

*In practice, it may be hard to get access to the dataset without protections. In such a case, you may simulate the original data first.

# Part I: Redistricting

# Voting Rights Act (VRA) of 1965

- Landmark legislation passed by Congress & signed into law by President Lyndon B. Johnson during the civil rights movement
- Intended to uphold Black people's rights to vote and stop race discrimination in voting (e.g., literacy tests)
- **Section 2**: prohibits practices that "[result] in a denial or abridgement of the right of any citizen of the United States to vote on account of race or color"


Image: Library of Congress LC-U9-10344-16
Photographer: Marion S. Trikoso

https://www.archives.gov/milestone-documents/voting-rights-act
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**One way to abridge voting rights is to draw districts in a way that intentionally dilutes the voting power of minorities.**

https://www.archives.gov/milestone-documents/voting-rights-act
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# Background on the VRA & gerrymandering

# How will DP applied to the U.S. Census impact the ability to enforce the VRA?

Today we'll see two approaches to answering this question, each with different conclusions.

SCIENCE ADVANCES | RESEARCH ARTICLE

SOCIAL SCIENCES

# The use of differential privacy for census data and its impact on redistricting: The case of the 2020 U.S. Census

Christopher T. Kenny[1], Shiro Kuriwaki[2], Cory McCartan[3], Evan T. R. Rosenman[4], Tyler Simko[1], Kosuke Imai[1,3]*

We will focus on their analyses around the detection of **packing** and **cracking** in plans drawn for the South Caroline State House.

# Simulation setup

**Goal**: Analyze how DP impacts conclusions drawn about racial biases in redistricting plans (specifically “packing” and “cracking”)

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    1. Published Census 2010 data (remember, these data were subject to swapping) ("**Census 2010**")
    2. Published Census 2010 data protected with TopDown, $\boldsymbol{\varepsilon}$ = 4.5 ("**DAS-4.5**")
    3. Published Census 2010 data protected with TopDown, $\boldsymbol{\varepsilon}$ = 12.2 ("**DAS-12.2**")

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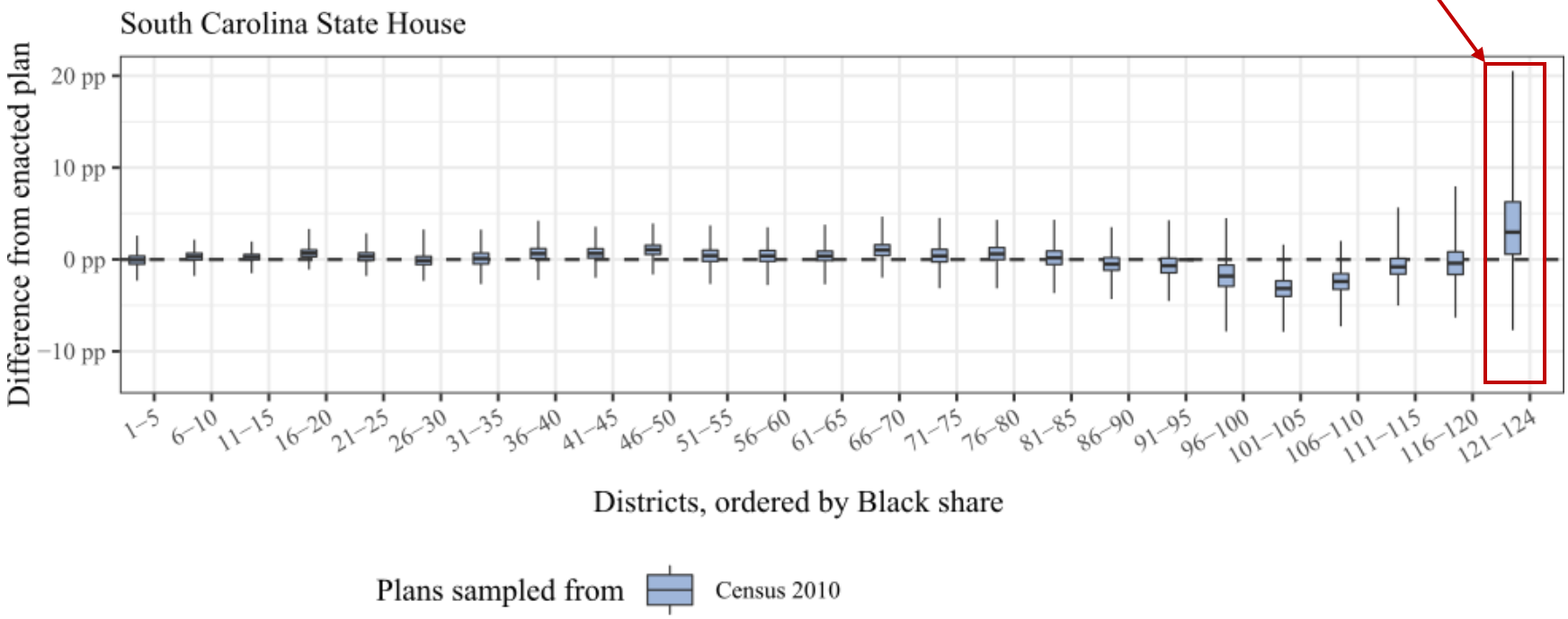
2. Find signals of packing or cracking in 2010 districts (the enacted plan) by comparing between the estimated proportion of Black people in simulated districts using **Census 2010** compared to the enacted plan (also using **Census 2010**)
3. Observe whether signals of packing or cracking found above remain, disappear, or reverse with simulated plans based on **DAS-4.5** or **DAS-12.2**

Difference from enacted plan =
Black share in simulated district – Black share in enacted district


Districts, in *ascending* order of Black share

Boxplot of “difference from enacted plan” among districts in **Census 2010** simulated plans that ranked 121st-124th in Black share



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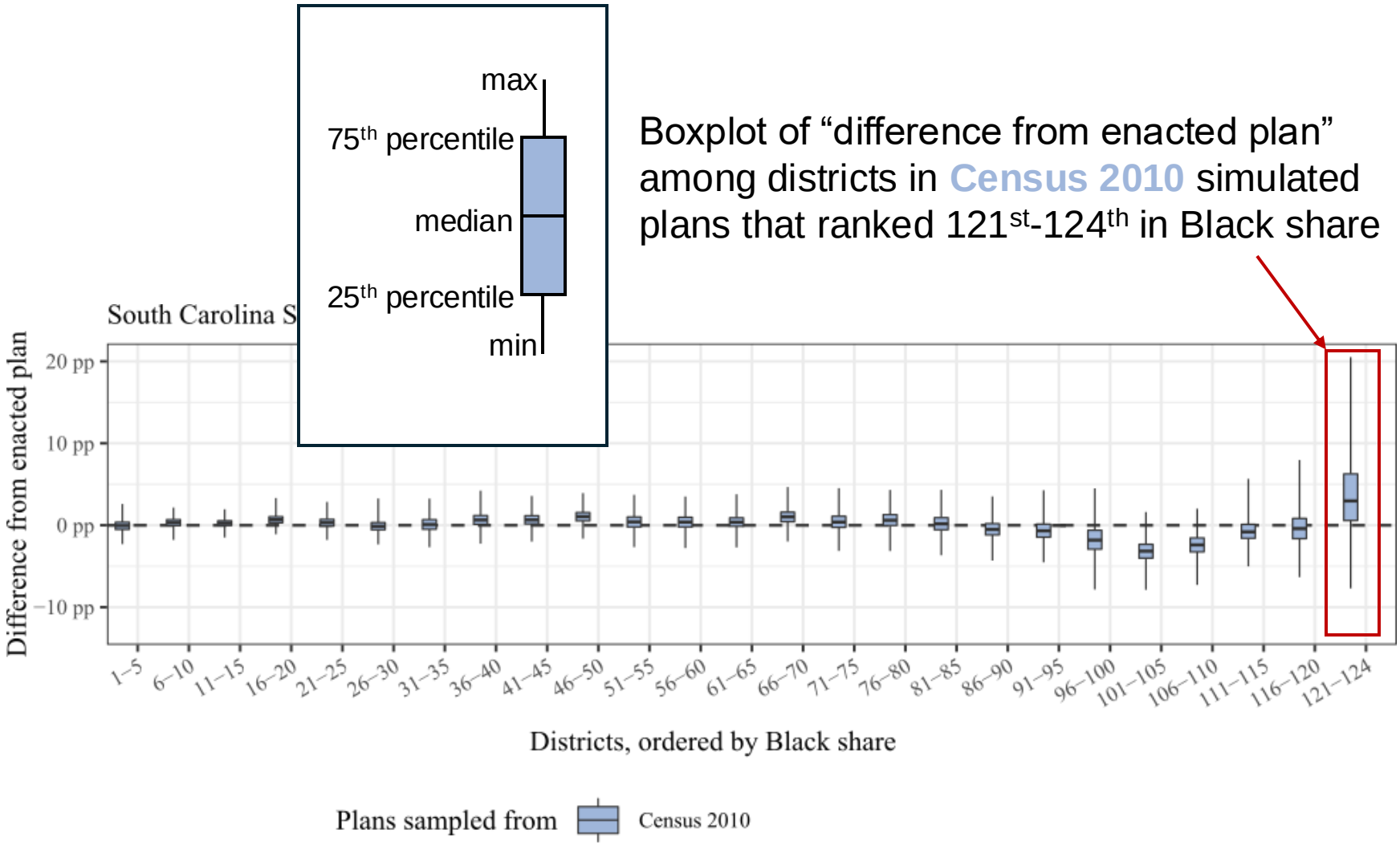
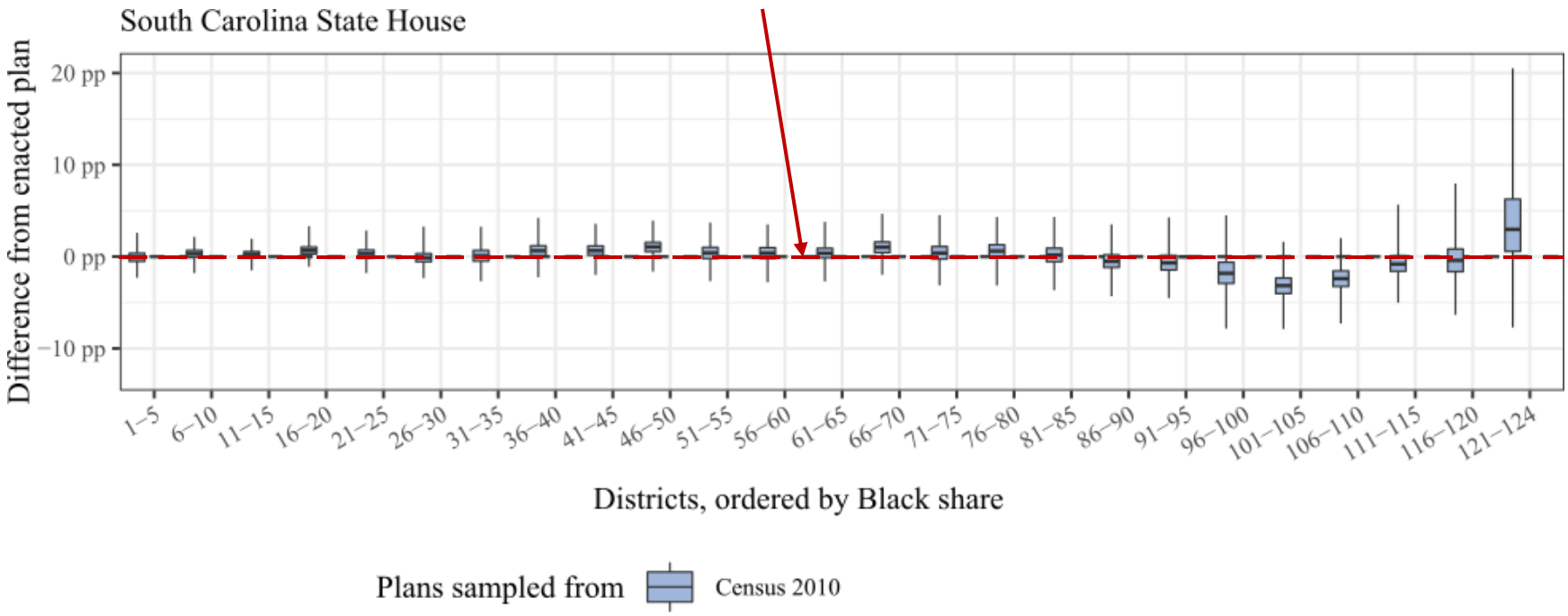


When “difference from enacted plan” > 0, there was higher Black share in simulated plans compared to the enacted plan (i.e., the enacted plan had *lower* Black share than what we would expect from a politically-neutral baseline).
This is evidence of “cracking” in the enacted plan.



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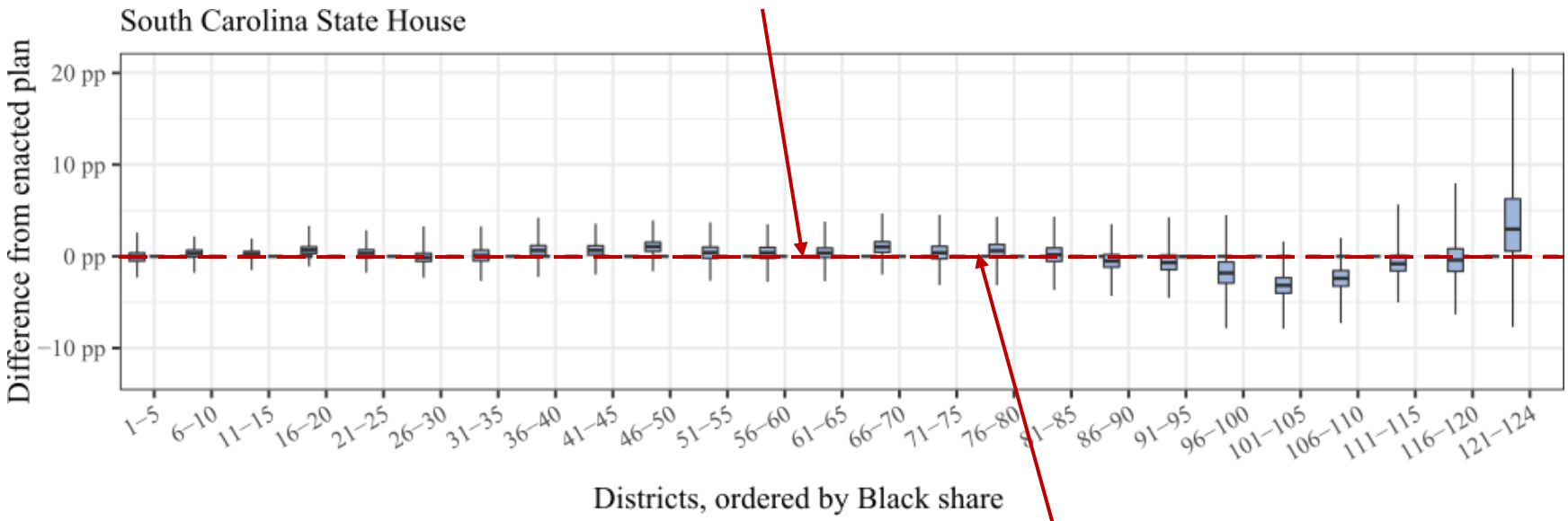
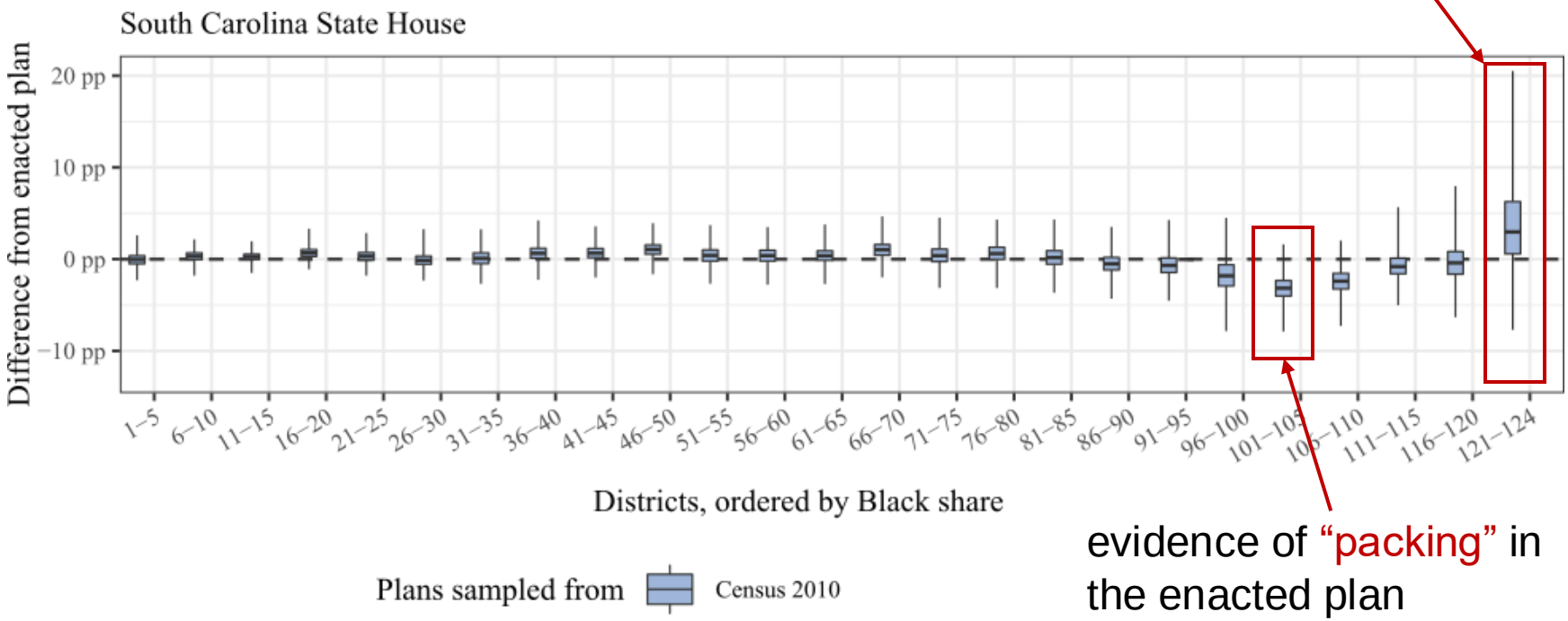
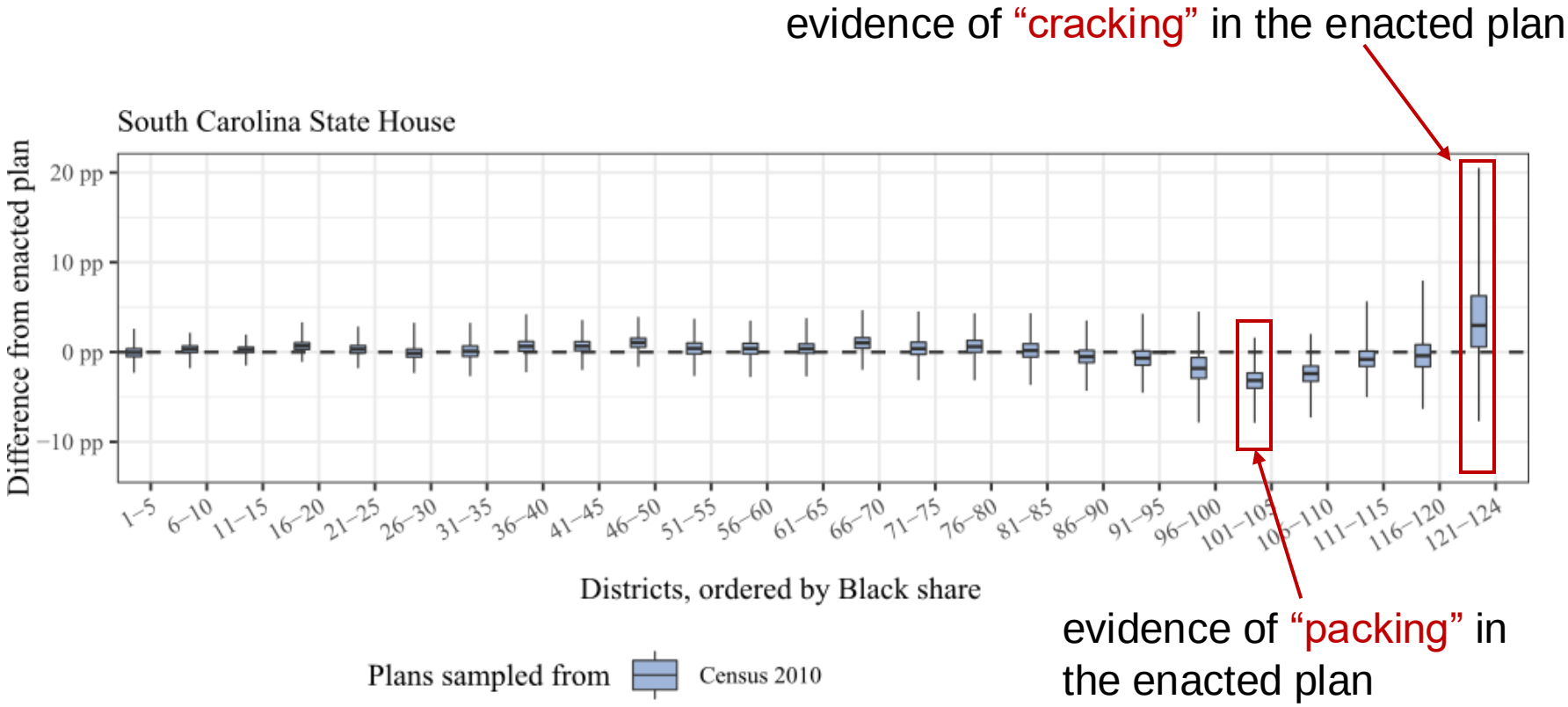



When “difference from enacted plan” < 0, there was lower Black share in simulated plans compared to the enacted plan (i.e., the enacted plan had *higher* Black share than what we would expect from a politically-neutral baseline). In other words, there is evidence of “packing” in the enacted plan.

evidence of “cracking” in the enacted plan

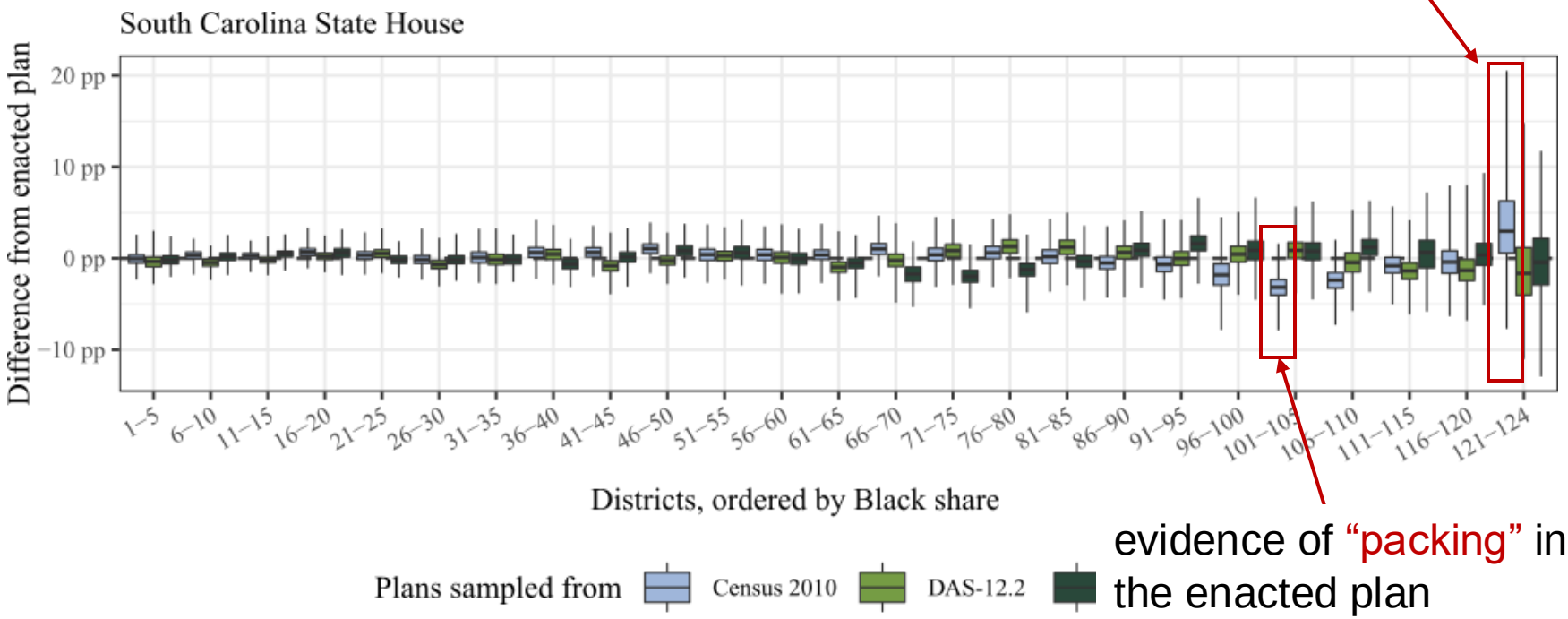



evidence of “packing” in the enacted plan



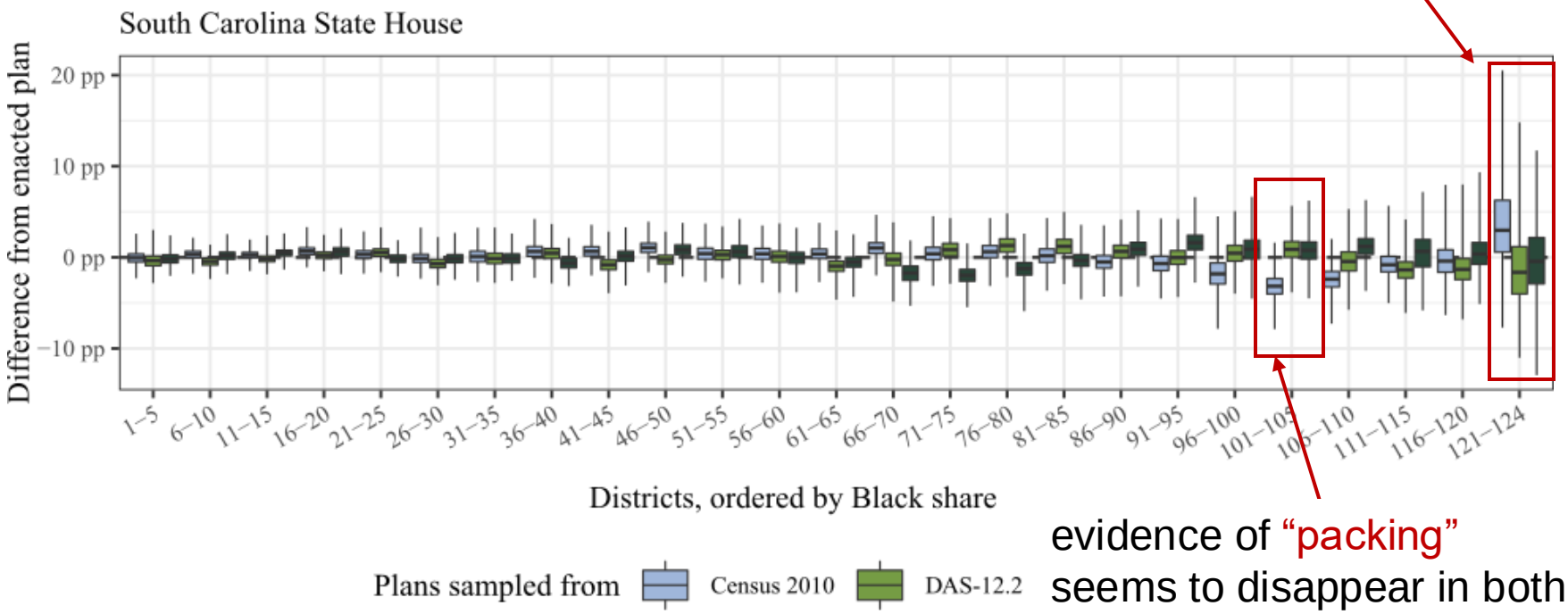

**Can we still detect evidence of cracking and packing using data protected under the new DAS?**

evidence of “cracking” in the enacted plan




evidence of “packing” in the enacted plan

evidence of "cracking" seems to disappear in both DAS's simulated plans

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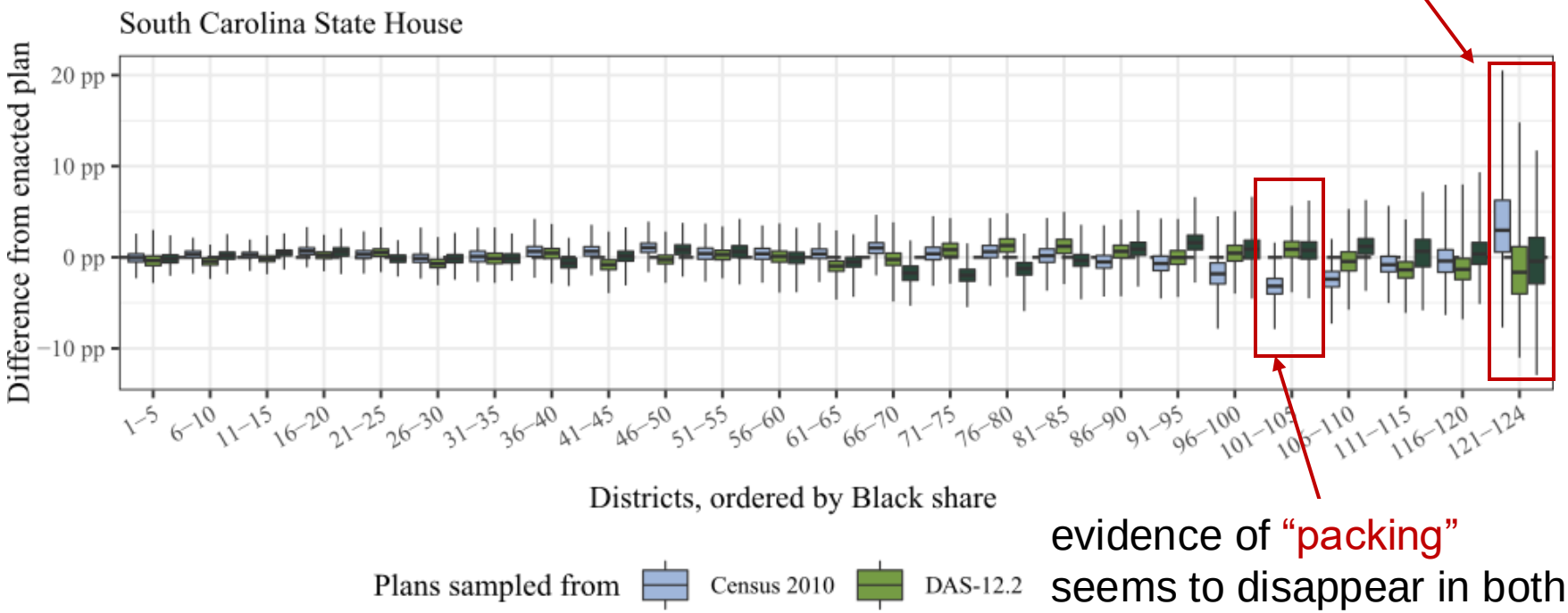
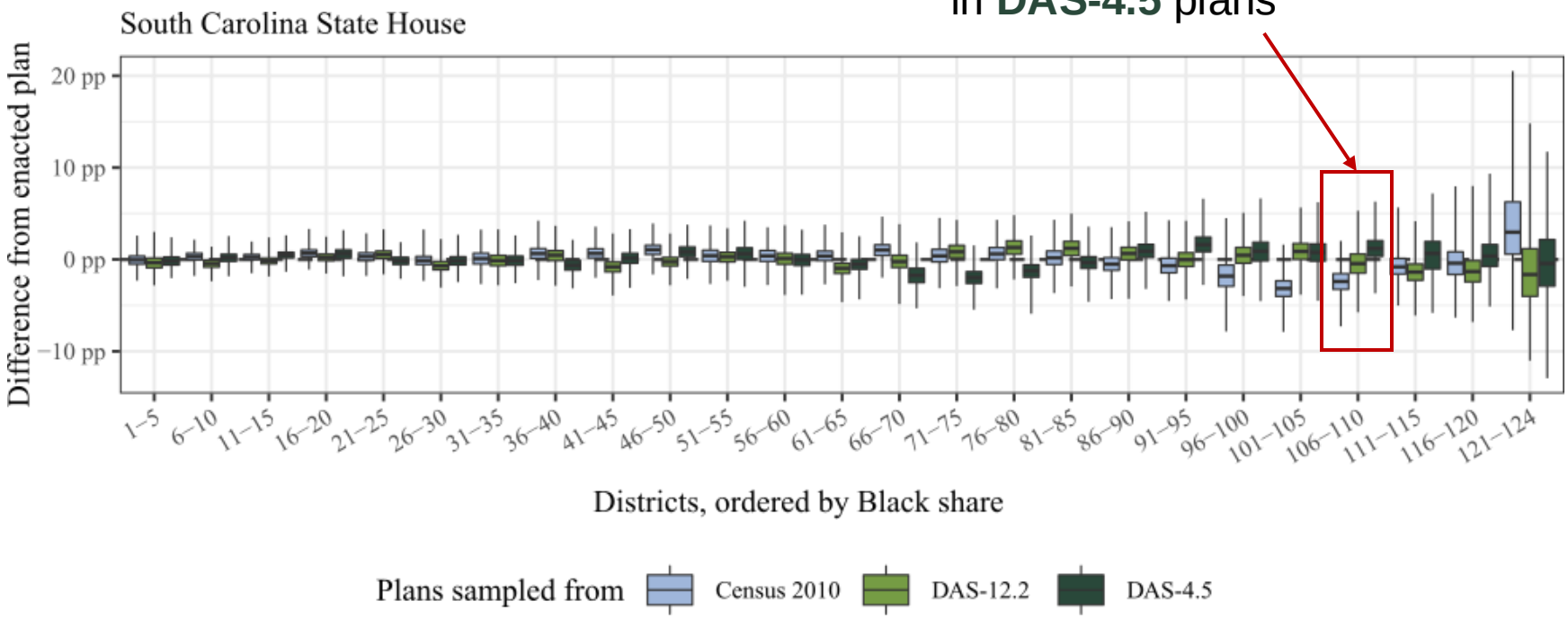



evidence of "packing" seems to disappear in both DAS's simulated plans

**Can you find other disappearances or reversals of evidence?**

evidence of "packing" seems to reverse to evidence of "cracking" in **DAS-4.5** plans



# Census TopDown: The Impacts of Differential Privacy on Redistricting

**Aloni Cohen**
Hariri Institute for Computing and School of Law, Boston University, MA, USA

**Moon Duchin**
Department of Mathematics, Tufts University, Medford, MA, USA

**JN Matthews**
Tisch College of Civic Life, Tufts University, Medford, MA, USA

**Bhushan Suwal**
Tisch College of Civic Life, Tufts University, Medford, MA, USA

We will focus on their **ecological regression** analyses.

# Gingles factors

Demonstrating a violation of Section 2 of the VRA requires showing:

1. It's possible to create a district where the minority group is over 50% of the population
2. The minority group must be "politically cohesive"
3. The majority group also votes together as a bloc, such that it usually defeats the minority group's preferred candidate

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2. The minority group must be "politically cohesive"
3. The majority group also votes together as a bloc, such that it usually defeats the minority group's preferred candidate

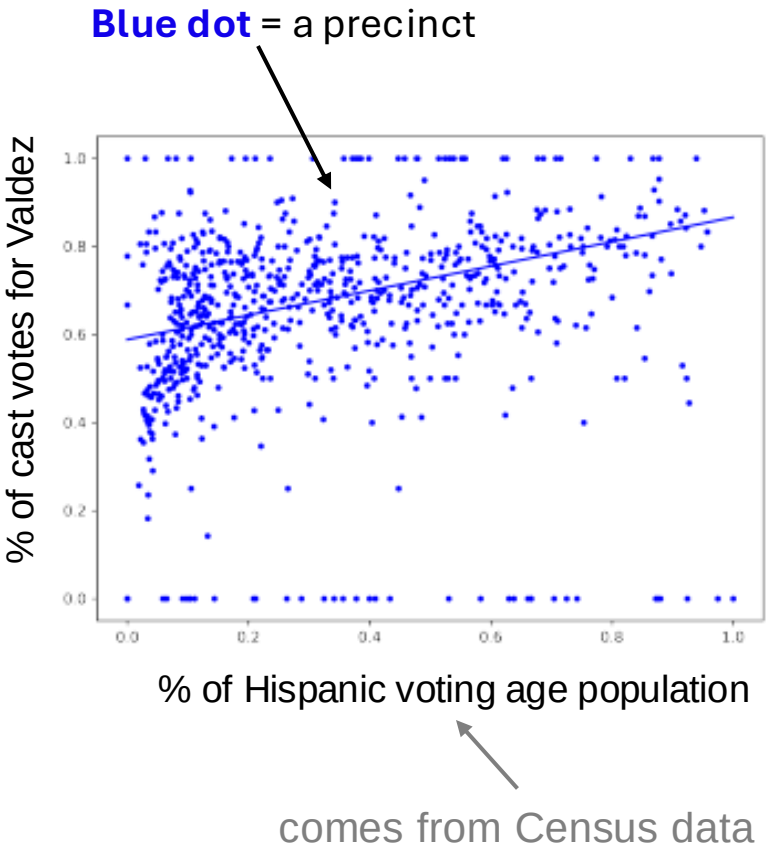
**= racially polarized voting**

# Simulation setup

**Goal**: Analyze whether it's possible to detect racially polarized voting with Census data protected under DP

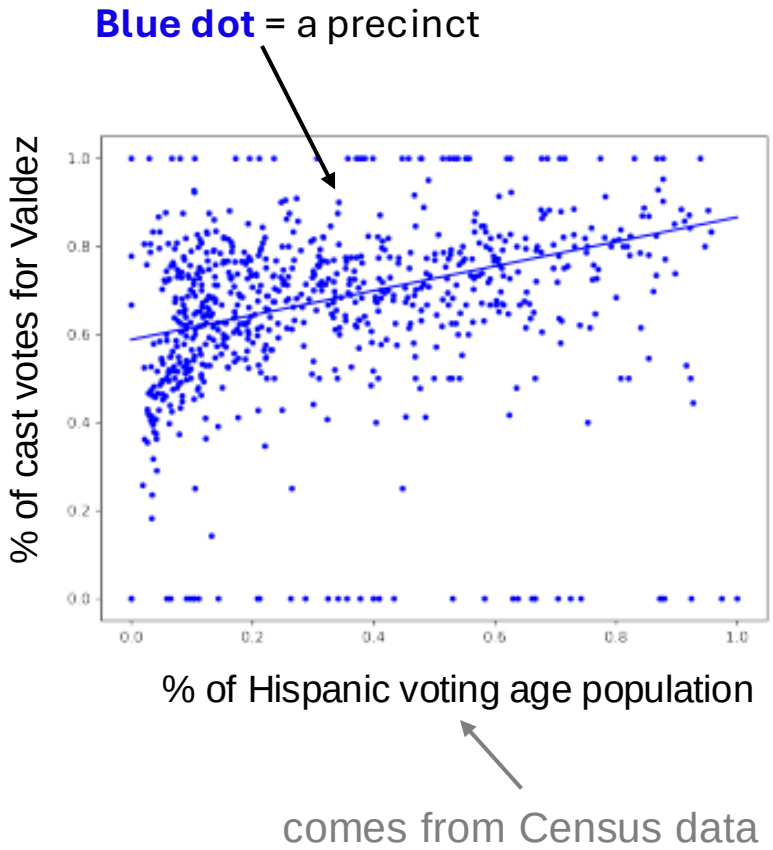
1. Reconstructed block-level 2010 microdata (i.e., person-level data) for Texas (but cannot quantify errors because they do not have access to the Census's microdata files)
2. Ran TopDown 16 times, $\boldsymbol{\varepsilon} = 1$ (equally split across geographical hierarchies)
3. Compared ability to detect racially polarized voting using reconstructed data ("un-noised data") vs. data protected using TopDown ("TopDown data")

# Ecological regression on un-noised data




**Ecological regression** on Dallas County precincts, showing support for Lupe Valdez for governor in the 2018 Democratic primary runoff

# Ecological regression on un-noised data

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Where the regression line intersects with $x = 1$ estimates support for Valdez in a 100% Hispanic population

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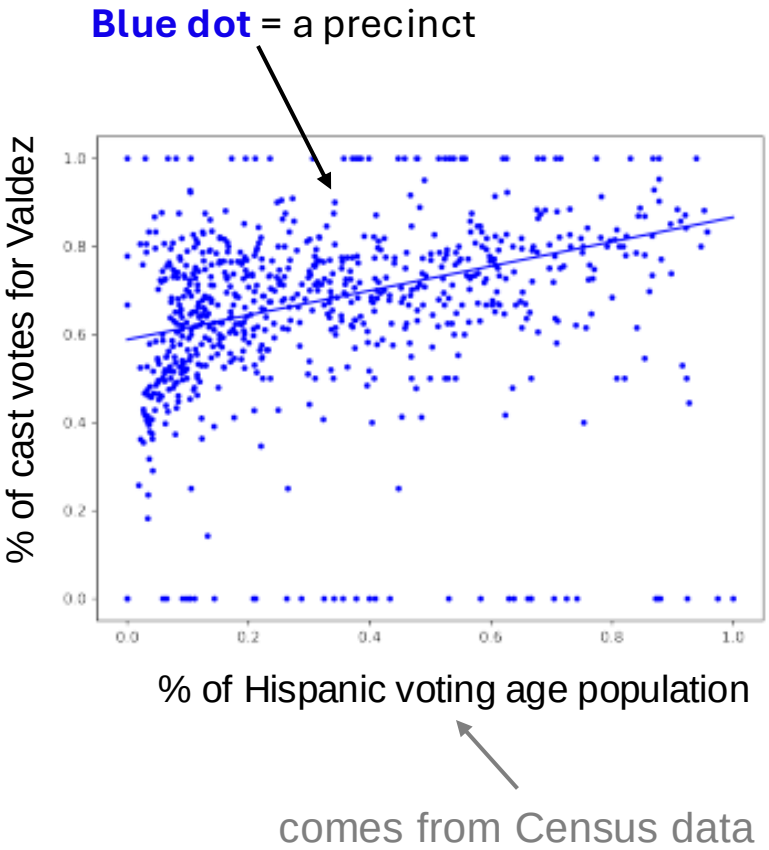


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Where the regression line intersects with $x = 0$ estimates support for Valdez in a 0% Hispanic (i.e., 100% non-Hispanic) population

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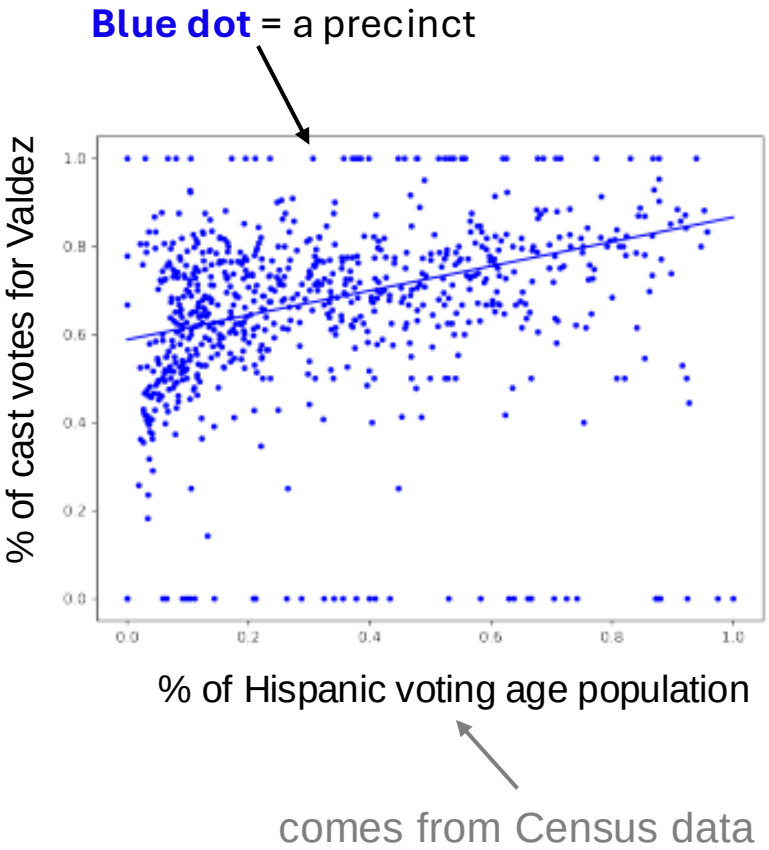


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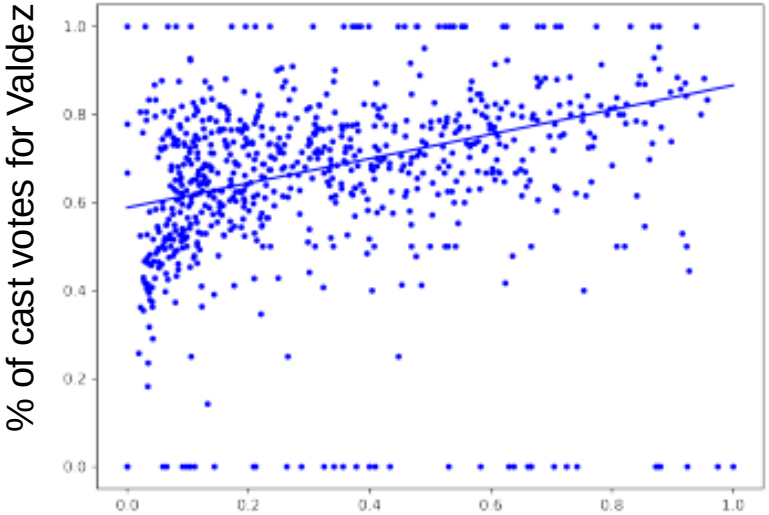
Where the regression line intersects with $x = 0$ estimates support for Valdez in a 0% Hispanic (i.e., 100% non-Hispanic) population

**What does a regression line with a large slope mean?**

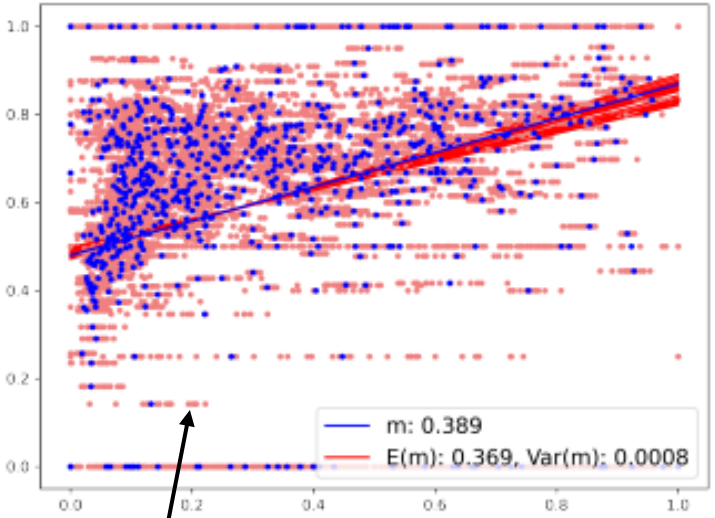
# Ecological regression on un-noised vs. TopDown data

Un-noised data



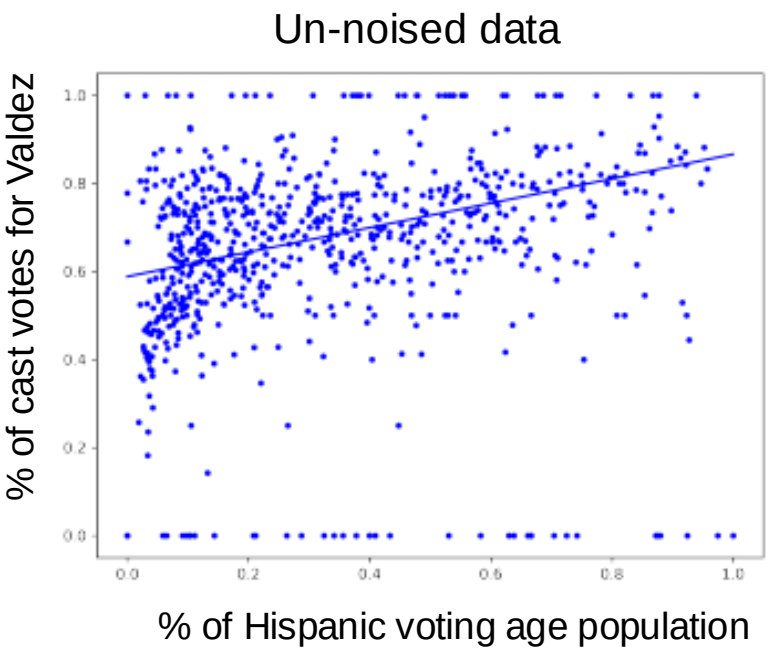

% of Hispanic voting age population

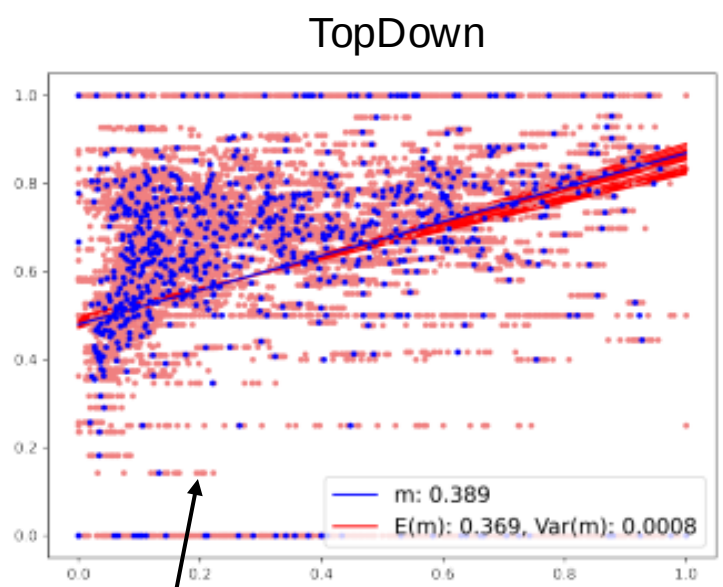
TopDown




**Pink dots** = 16 runs of TopDown
**Red lines** = regression lines corresponding to each of the 16 runs

# Ecological regression on un-noised vs. TopDown data




**Pink dots** = 16 runs of TopDown
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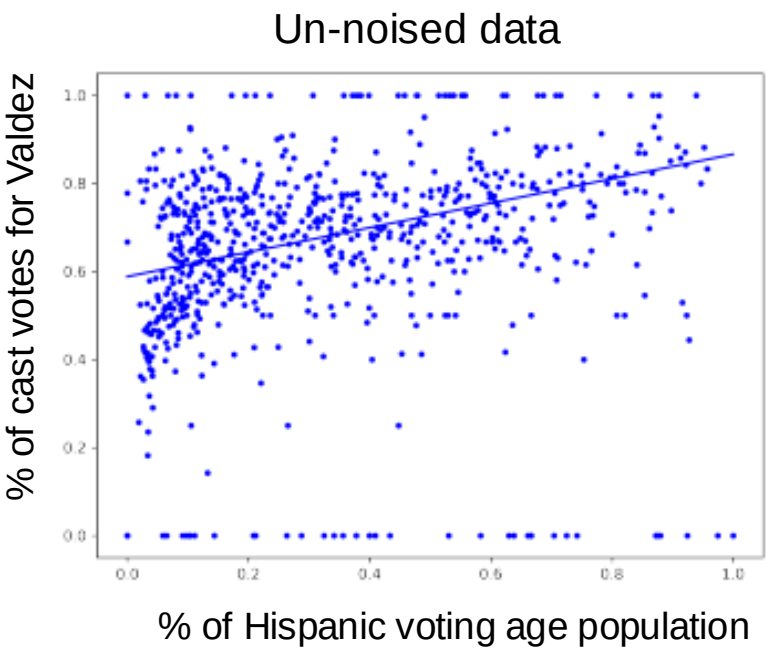
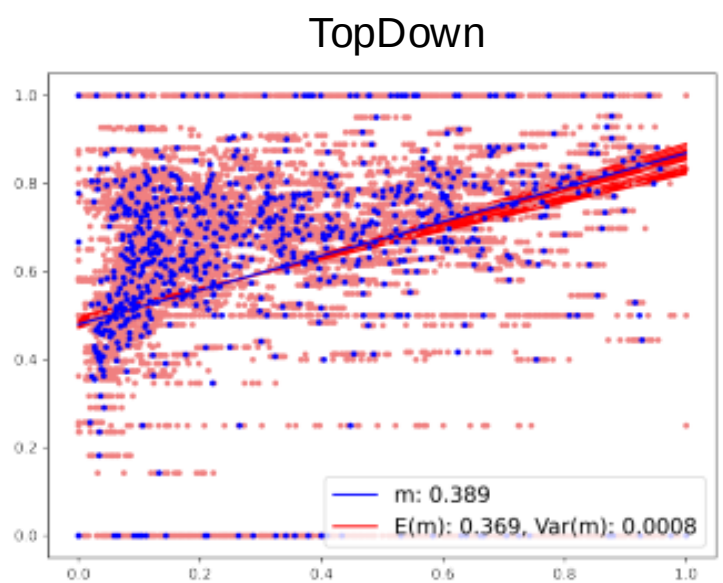
**Why do the pink dots jitter horizontally only?**

# Ecological regression on un-noised vs. TopDown data




**What do you think will happen if we remove precincts with few cast votes?**

# Ecological regression on un-noised vs. TopDown data

## Precincts with fewer than 10 cast votes filtered out


**The blue and red regression lines basically match.**

# Ecological regression on un-noised vs. TopDown data

## Precincts weighted by number of cast votes


**Again, the blue and red regression lines basically match.**

# Part II: Funding Allocation

POLICY FORUM | PRIVACY

# Policy impacts of statistical uncertainty and privacy

Funding formula reform may help address unequal impacts of uncertainty from data error and privacy protections

RYAN STEED , TERRANCE LIU, ZHIWEI STEVEN WU, AND ALESSANDRO ACQUISTI Authors Info & Affiliations

*SCIENCE* • 25 Aug 2022 • Vol 377, Issue 6609 • pp. 928-931 • DOI: 10.1126/science.abq4481

# Title I of the Elementary and Secondary Education Act

- Allocates funding to school districts with children in poverty
- "In 2021, the US federal government appropriated over $16.5 billion in Title I funds…to distribute to over 13,000 local education agencies (LEAs)”

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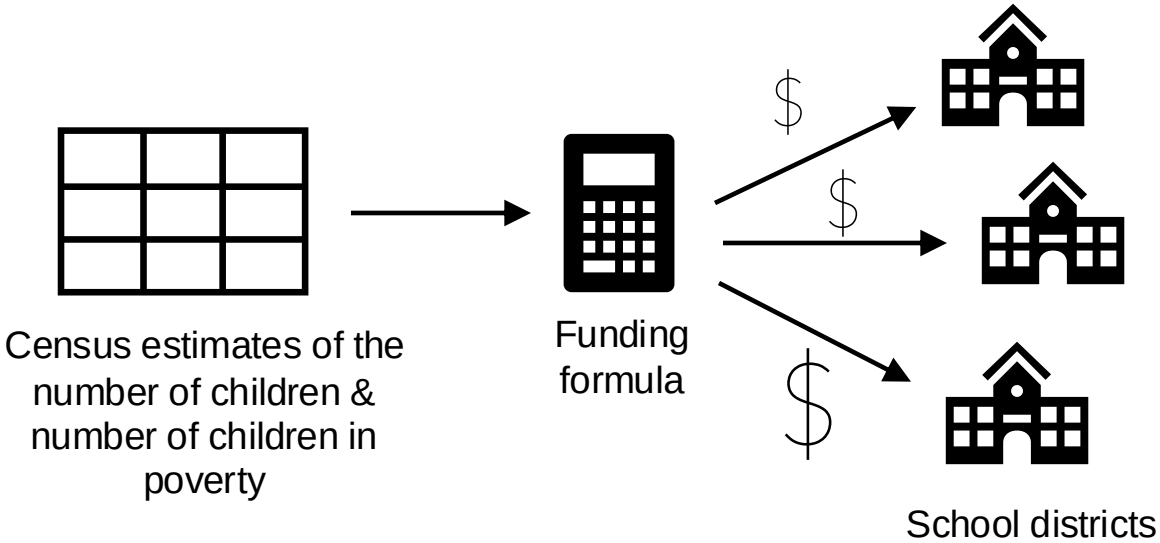
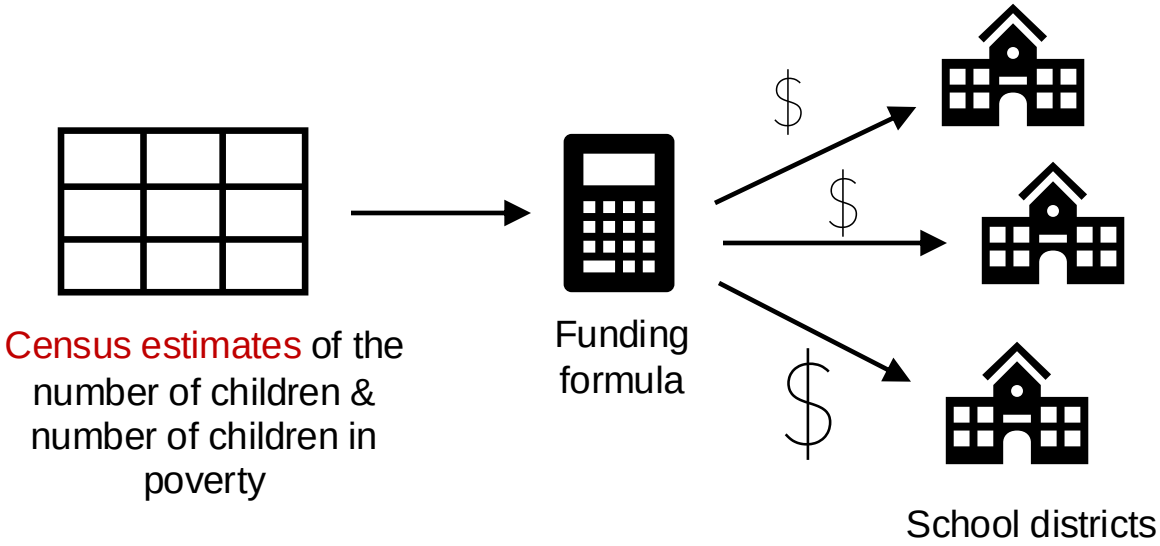


# Title I of the Elementary and Secondary Education Act

- How would funding allocation change if DP were applied to census estimates?
- And how do downstream impacts of DP compare to impacts from other sources of data error?



# Simulate sources of error

Quantifiable error

Data deviations

Privacy deviations

# Simulate sources of error

## Quantifiable error

## Data deviations

e.g., error from other data sources used in the Small Area Income and Poverty Estimates; errors from converting county estimates → school district estimates

*Can model these deviations by sampling from a normal distribution centered at reported estimate*

## Privacy deviations

# Simulate sources of error

## Quantifiable error

## Data deviations

e.g., error from other data sources used in the Small Area Income and Poverty Estimates; errors from converting county estimates → school district estimates

*Can model these deviations by sampling from a normal distribution centered at reported estimate*

## Privacy deviations

e.g., error from DP mechanism

*Can model these by adding Laplace noise to American Community Survey estimates, which are used to generate estimates fed to the funding formula*

# Simulate sources of error

1. Simulate data deviations & privacy deviations
2. Compute formula-based allocations (i.e., entitlements)
3. Compare above allocations to the official allocations

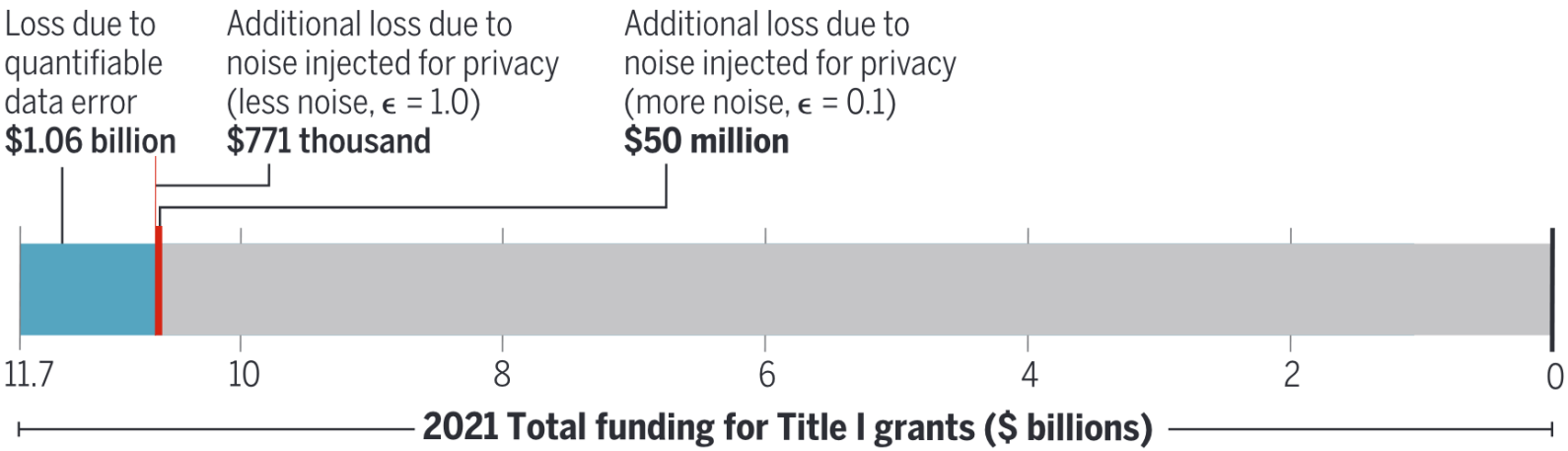
*Repeat 1,000 times*

# Simulate sources of error

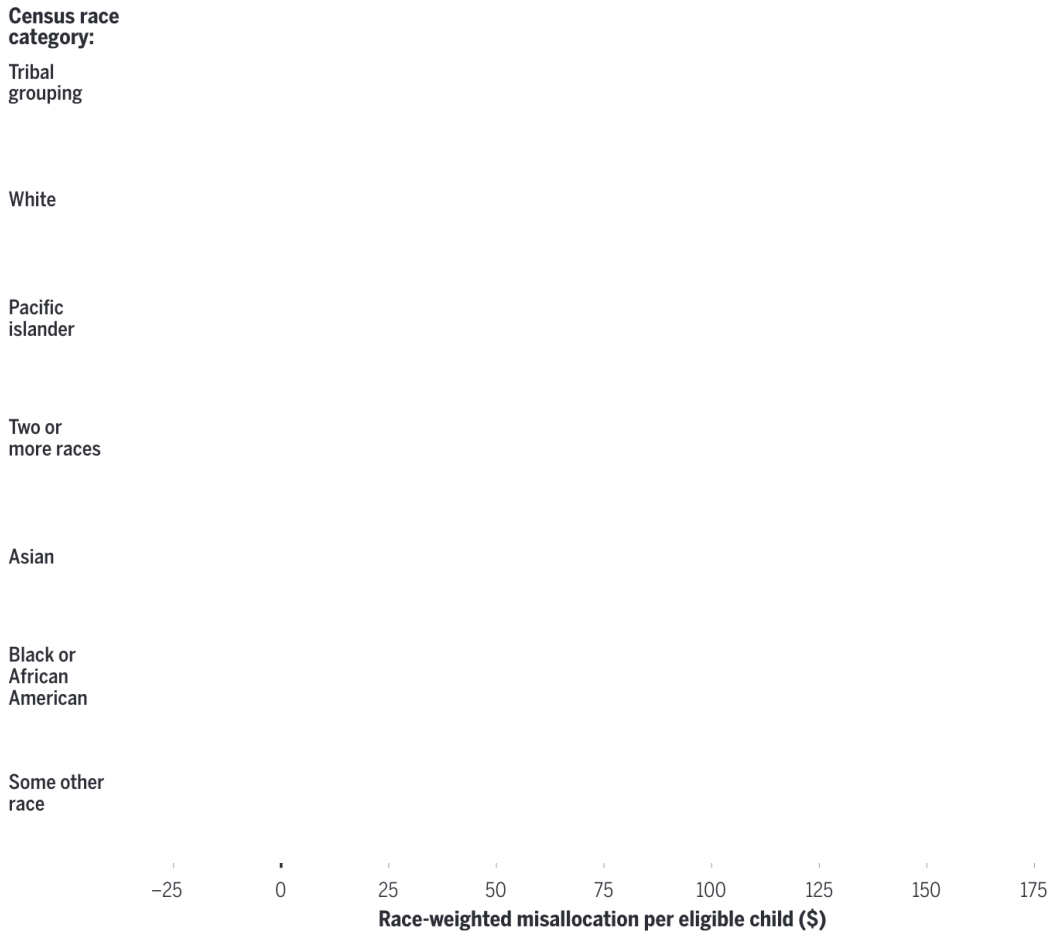
1. Simulate data deviations & privacy deviations (two privacy loss budgets)
2. Compute formula-based allocations (i.e., entitlements)
3. Compare above allocations to the official allocations

*Repeat 1,000 times*

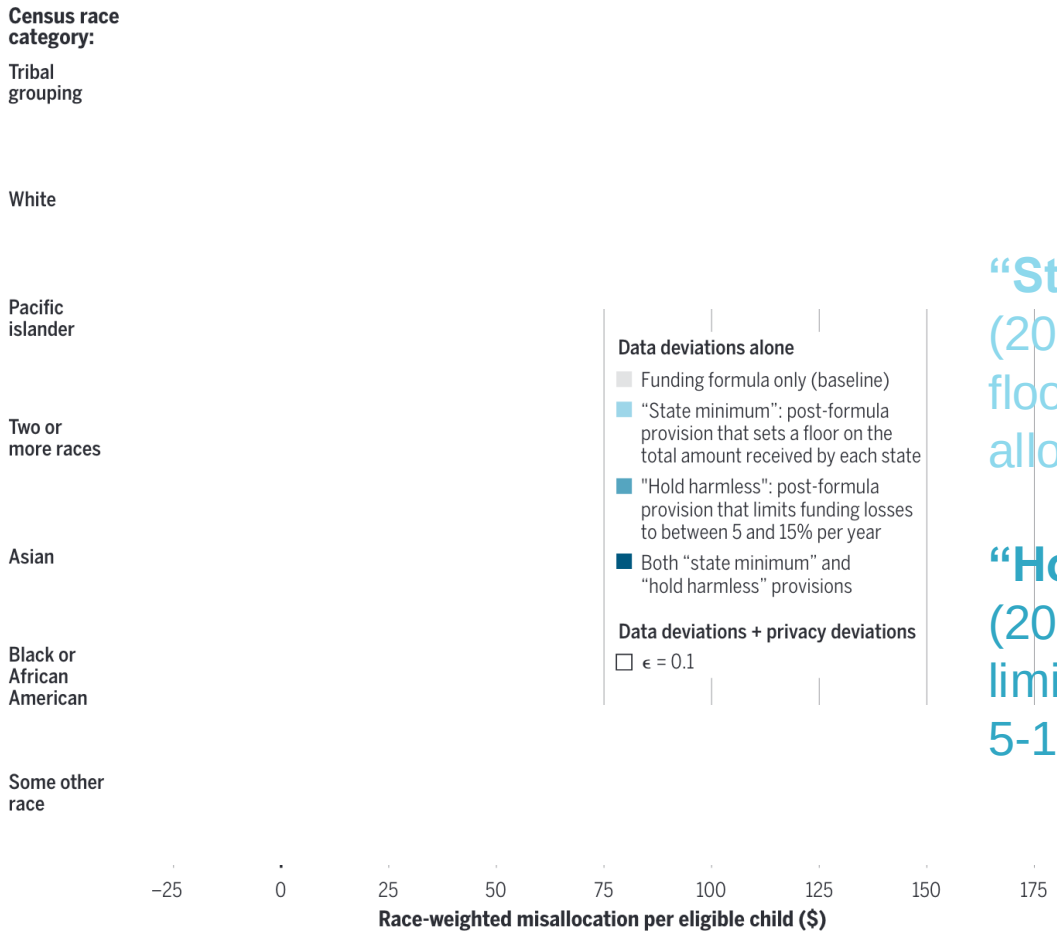
# Results


Loss due to quantifiable data error
$1.06 billion
Additional loss due to noise injected for privacy (less noise, ϵ = 1.0)
$771 thousand
Additional loss due to noise injected for privacy (more noise, ϵ = 0.1)
$50 million
11.7
10
8
6
4
2
0
2021 Total funding for Title I grants ($ billions)

# Results


Census race category:
Tribal grouping
White
Pacific islander
Two or more races
Asian
Black or African American
Some other race
−25
0
25
50
75
100
125
150
175
Race-weighted misallocation per eligible child ($)

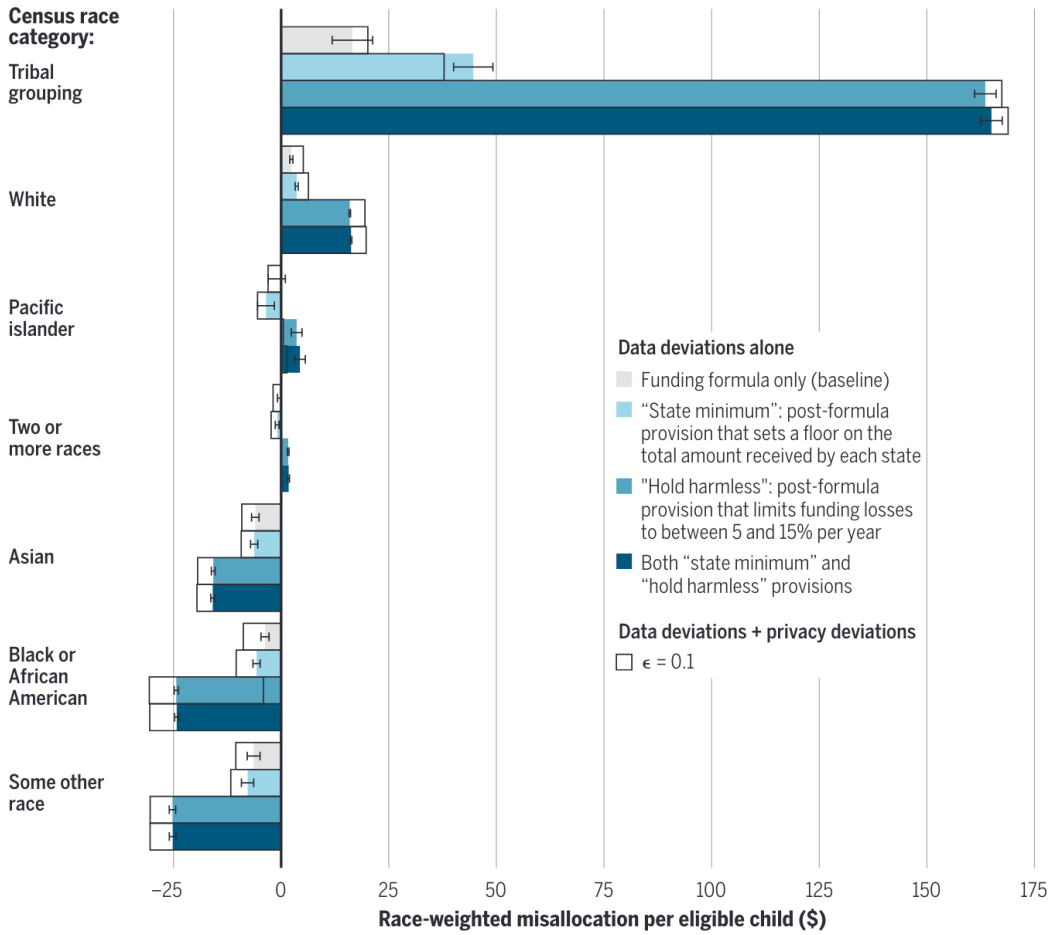
# Results




**"State minimum"** (20 U.S.C. §6333): floor on total state allocation

**"Hold harmless"** (20 U.S.C. §6332): limits funding loss to 5-15%

# Results


Census race category:
Tribal grouping
White
Pacific islander
Two or more races
Asian
Black or African American
Some other race
Data deviations alone
Funding formula only (baseline)
"State minimum": post-formula provision that sets a floor on the total amount received by each state
"Hold harmless": post-formula provision that limits funding losses to between 5 and 15% per year
Both "state minimum" and "hold harmless" provisions
Data deviations + privacy deviations
ϵ = 0.1
−25
0
25
50
75
100
125
150
175
Race-weighted misallocation per eligible child ($)

# Discussion

Choose one deployment from this list:

https://desfontain.es/blog/real-world-differential-privacy.html

and describe how you might attack its utility.

To evaluate utility quantitatively:

1. Choose a dataset to be protected under DP
2. Consider a specific real-world use of that dataset
3. Formulate a metric (broadly defined) that would help understand the utility of the dataset for that specific task
4. Design & run simulations where DP noise is used to protect the data. Compare metrics on the DP-noised data vs. the dataset without protections*

*In practice, it may be hard to get access to the dataset without protections. In such a case, you may simulate the original data first.

# Takeaways

- Utility expresses accuracy's impact on real-world outcomes (among other things, potentially)
- In debates about DP for the U.S. Census, investigations around utility (for redistricting, funding allocation) became cornerstones.
- To evaluate utility quantitatively:
  1. Choose a dataset to be protected under DP
  2. Consider a <u>specific</u> real-world use of that dataset
  3. Formulate a metric (broadly defined) that would help understand the <u>utility</u> of the dataset for that specific task
  4. Design & run simulations where DP noise is used to protect the data. Compare metrics on the DP-noised data vs. the dataset without protections*

*In practice, it may be hard to get access to the dataset without protections. In such a case, you may simulate the original data first.