

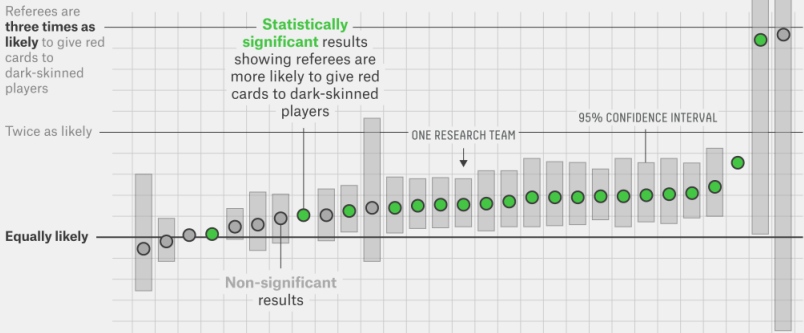
# RESEARCHER CHOICES AND BIAS

Data Analysis for Journalism and Political Communication  
(Fall 2024)

Prof. Bell

## Same Data, Different Conclusions

Twenty-nine research teams were given the same set of soccer data and asked to determine if referees are more likely to give red cards to dark-skinned players. Each team used a different statistical method, and each found a different relationship between skin color and red cards.



FIVETHIRTYEIGHT

SOURCE: BRIAN NOSEK ET AL.

# RESEARCHER CHOICES

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- 5 What statistical analyses do I use?
- 6 How do I handle outliers, missing data, and other peculiarities?



# WHAT IS MY HYPOTHESIS?

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Our goal is to reduce Type I error. Assume that the data is innocent (that the hypothesis is false) until it is proven guilty.

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- The p-value is our chance of committing a Type I error - sending the innocent to jail
- Common p-value cut-offs in scientific research: .01, .05, and .1 indicate **statistical significance**

# MEASURING TYPE I ERROR

**Hypothesis:** A student cheated on an exam.

**P-value (chance that we conclude that student cheated, but they did not):** .50

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**Hypothesis:** A student cheated on an exam.

- The student performed much better on this exam than on previous exams

**P-value (chance that we conclude that student cheated, but they did not): .25**



# MEASURING TYPE I ERROR

**Hypothesis:** A student cheated on an exam.

- The student performed much better on this exam than on previous exams
- The student finished their exam more quickly than other students

**P-value (chance that we conclude that student cheated, but they did not): .15**

# MEASURING TYPE I ERROR

**Hypothesis:** A student cheated on an exam.

- The student performed much better on this exam than on previous exams
- The student finished their exam more quickly than other students
- The student's roommate saw them up all night studying before the exam

**P-value (chance that we conclude that student cheated, but they did not): .40**

# MEASURING TYPE I ERROR

**Hypothesis:** A student cheated on an exam.

- The student performed much better on this exam than on previous exams
- The student finished their exam more quickly than other students
- The student's roommate saw them up all night studying before the exam
- The student missed the same questions as other students

**P-value (chance that we conclude that student cheated, but they did not): .75**

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- We follow the scientific method: Theory  $\Rightarrow$  Hypothesis  $\Rightarrow$  Test  $\Rightarrow$  Analyze  $\Rightarrow$  Report
- But in practice, no analysis plan survives contact with the data

# ARE DEMOCRATS OR REPUBLICANS GOOD FOR THE ECONOMY?

Use FiveThirtyEight's online modeling tool to test what you think is the best approach to answering the question. There are no right or wrong answers - just select the model you think is best, and report your results in the form:

<https://bit.ly/smpa2152>



(The link to the tool is on the form.)

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- Confusing statistical significance with substantive significance

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Suppose you were interested in measuring “study quality,” a variable indicating how well a student studies. What are some ways you would measure this concept?

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- Principles of good operationalization:

- 1 Unambiguous
- 2 Concise
- 3 Familiar
- 4 Available

# EXERCISE: OPERATIONALIZATION

- 1 You want to measure how happy people are
- 2 You want to measure people's driving ability
- 3 You want to measure the political ideology of a member of Congress

# HOW DO I COLLECT MY DATA?

## Data Generating Process

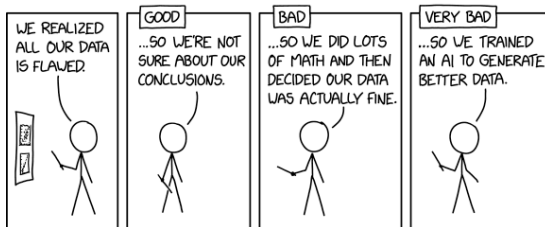
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- No amount of statistical wizardry can compensate for bad data
- The gold standard of data generating processes is the **random sample**

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  - 1 A **random sample** of the population
  - 2 The **sample size** is sufficiently large

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- A failure of each unit to have a uniform probability of being drawn from the population is known as **selection bias**
- Units are “selecting” into our data because they are more observable than other units
- Selection bias reduces our **generalizability** to the population because the data is not representative of the population

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Can I randomly sample 10 students from this class to generalize to:

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Can I randomly sample 10 students from this class to generalize to:

- the population of GW students?
- the population of SMPA students?
- the population of Data Analysis students?

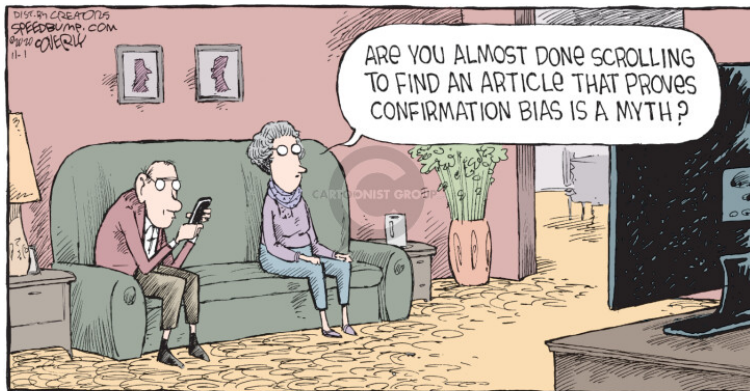
# EXERCISE: SELECTION BIAS

# BIASES IN RESEARCH

- 1 Confirmation bias
- 2 Desirability bias
- 3 Authority bias
- 4 Availability bias
- 5 Certainty bias

# CONFIRMATION BIAS

We privilege evidence that supports our existing beliefs and discount evidence that challenges those beliefs.



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# DESIRABILITY BIAS

We prefer evidence that supports a conclusion we want to be true and discount evidence that undermines that conclusion.

## ***Pandemic in Retreat***

And what else you need to know today.


By David Leonhardt

Feb. 11, 2021

THE MORNING NEWSLETTER

### ***Covid, in Retreat***

New cases in the U.S. have fallen by more than a third in the past month.



A medical worker in a hazmat suit is loading a Covid-19 patient last month. John Moore/Getty Images

By David Leonhardt

Oct. 4, 2020

David Leonhardt

Covid may now be in permanent retreat in the U.S.

It is not over, but after more than a year of death, sickness, grieving and isolation, you're allowed to feel joyful about the progress.

[nytimes.com/2021/05/21/bri...](https://nytimes.com/2021/05/21/bri...)


Change in Daily U.S. Covid-19 Cases and Deaths Since Jan. 1

90%

THE MORNING NEWSLETTER

### ***Omicron Is in Retreat***

What's next?



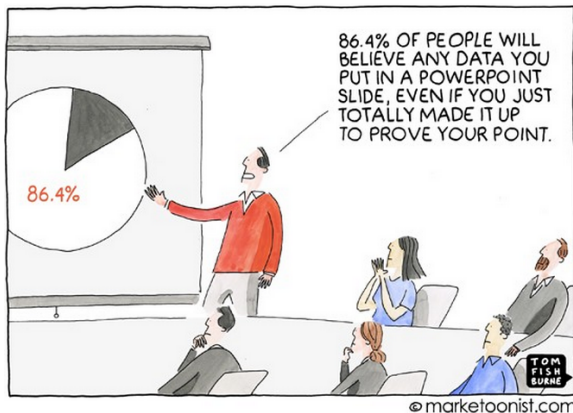
Covid patients at a Brooklyn hospital last week. Yusef J. Blue for The New York Times

By David Leonhardt

Jan. 18, 2022

# AUTHORITY BIAS

We give greater weight to evidence offered by people in positions of authority.



# AVAILABILITY BIAS

We give greater weight to evidence that is most memorable.



# CERTAINTY BIAS

We over- and under-state probabilistic evidence.

**FiveThirtyEight**  
2016 Election Forecast

President  
Updated Nov. 8, 2016

Senate  
Updated Nov. 8

We're forecasting the  
election with three models

● Polls-plus forecast

What polls, the economy and  
historical data tell us about Nov. 8

○ Polls-only forecast

What polls alone tell us about Nov. 8

○ Now-cast

Who would win the election if it  
were held today

🗳️ National overview

## Who will win the presidency?



### Chance of winning





# RETRO REPORT (2021) - WHAT'S IN A NUMBER?



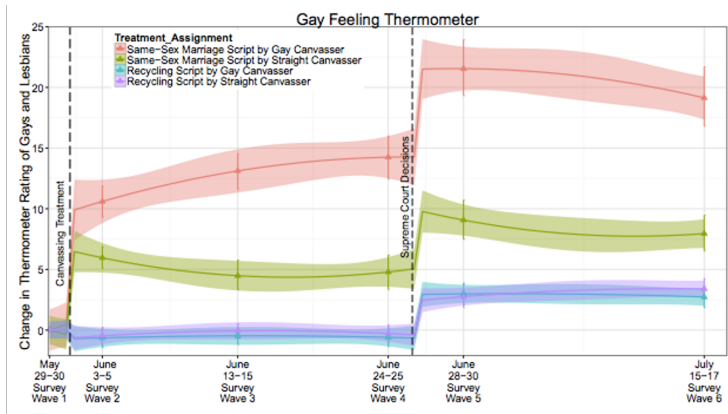
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- Unfortunately, fraud does happen - perhaps more than researchers would like to admit

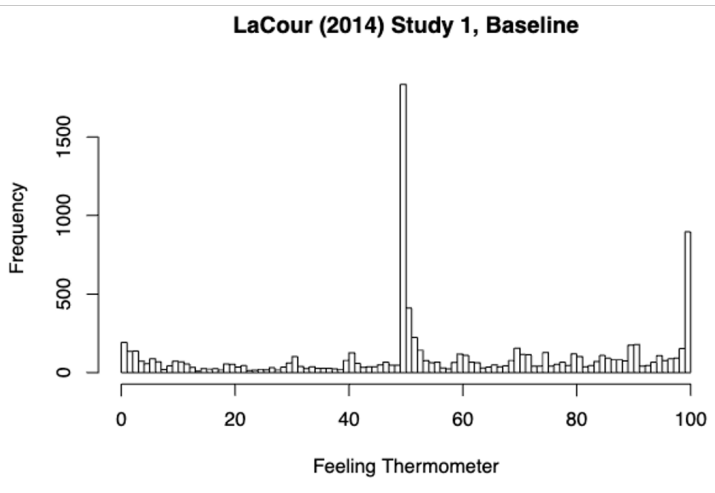
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## Gay Canvassers Scandal



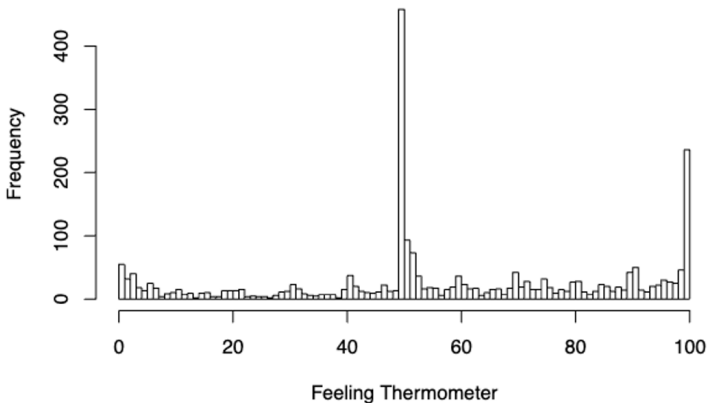
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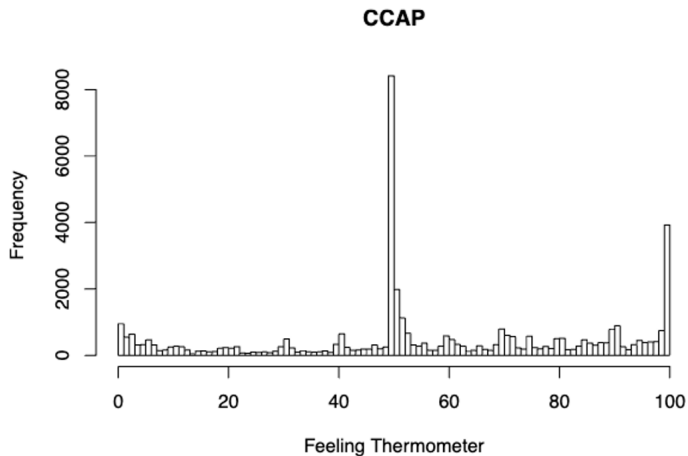
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## Gay Canvassers Scandal

LaCour (2014) Study 2, Baseline



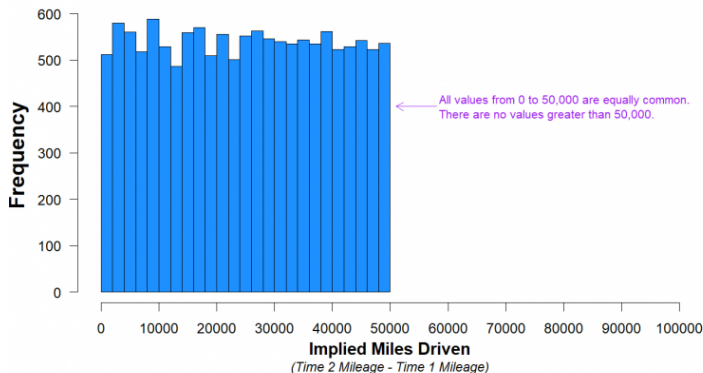
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# FRAUDULENT RESEARCH

## Dishonesty in Dishonesty Research (uncovered by Data Colada)

Figure 1. Histogram of Miles Driven - Car #1 (N=13,488)

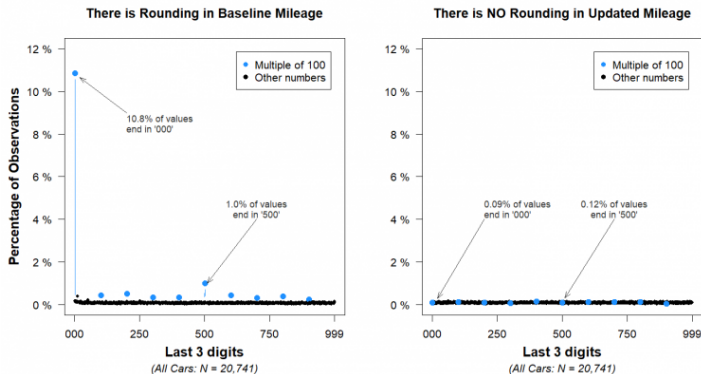




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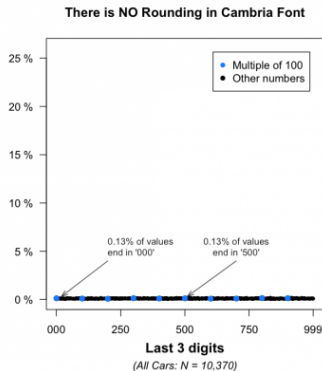
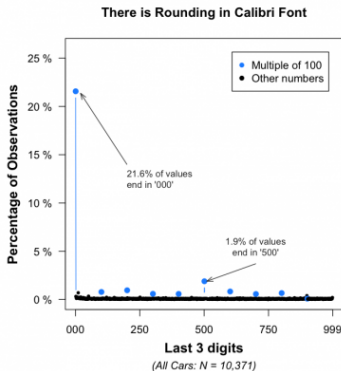
Figure 3. Last Three Digits at Baseline (Time 1) vs Updated (Time 2)



# FRAUDULENT RESEARCH

## Dishonesty in Dishonesty Research (uncovered by Data Colada)

Figure 6. Last Three Digits at Baseline: Calibri vs. Cambria



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  - ▶ Unusual patterns in the data
  - ▶ Non-reproducible outcomes or outcomes not supported by theory
  - ▶ Conflicts of interest
- These “red flags” do not necessarily mean the data is fraudulent – but be vigilant