### **Observational Study**

and

**Experiment** 

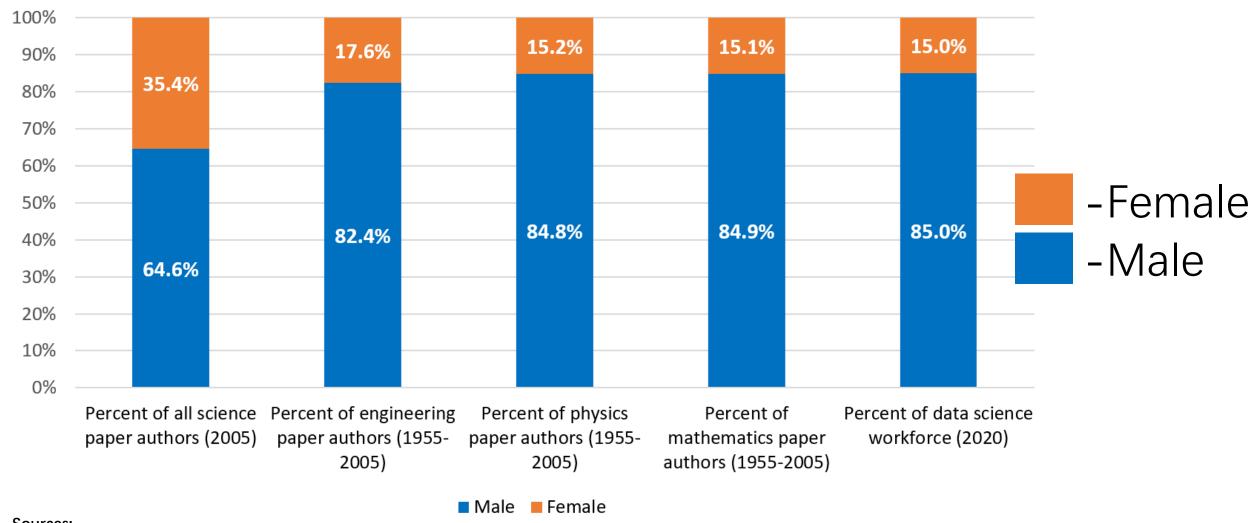
# Topics

- 1. Observational studies vs. experiments
- 2. Components of experiments
- 3. Principles of experimental design
- 4. Describing a completely randomized design

# Topics

- 1. Observational studies vs. experiments
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### Gender Gaps in STEM

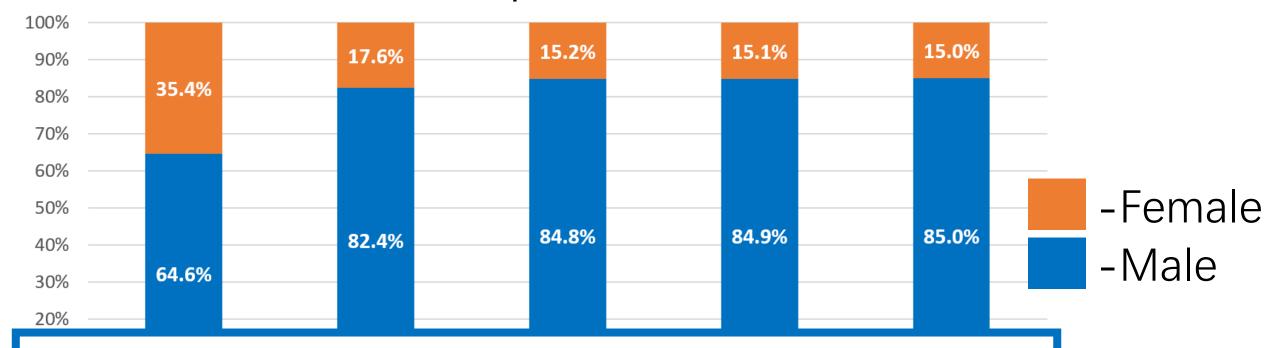


#### Sources:

<sup>-</sup>Huang, J. et al. "Historical comparison of gender inequality in scientific careers across countries and disciplines." Proceedings of the National Academy of Sciences, Mar 2020, 117 (9) 4609-4616; DOI: 10.1073/pnas.1914221117

<sup>-</sup>Boston Consulting Group, "What's Keeping Women out of Data Science?" bcg.com/publications/2020/what-keeps-women-out-data-science.aspx

### Gender Gaps in STEM



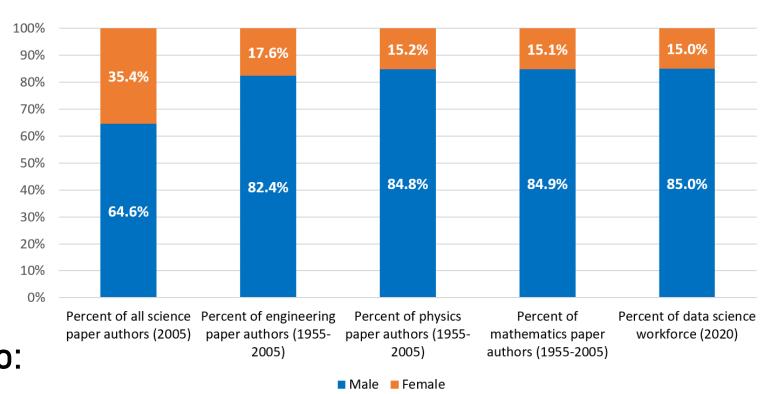
## Today's Key Analysis

Is it possible to find the true cause of these gender gaps in science?

### What causes this trend?

# Possible Cause: Hiring Discrimination

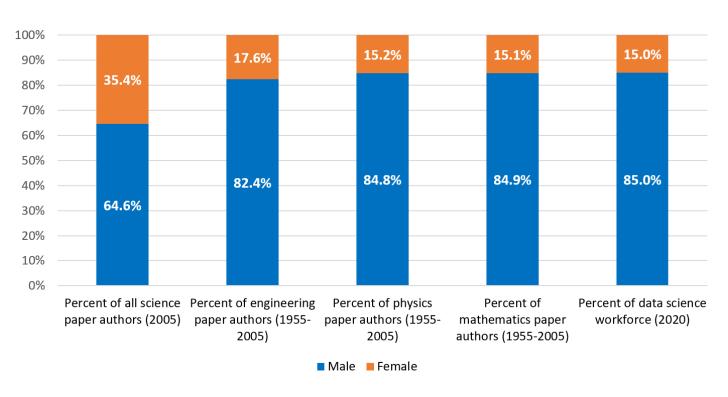
Women are given fewer research and workforce opportunities in STEM due to:



discriminatory practices in research/industry hiring, therefore, fewer women can enter or succeed in the field.

### Can we prove this cause?

From this observed data alone, we cannot prove that hiring discrimination is the cause.



### Why?

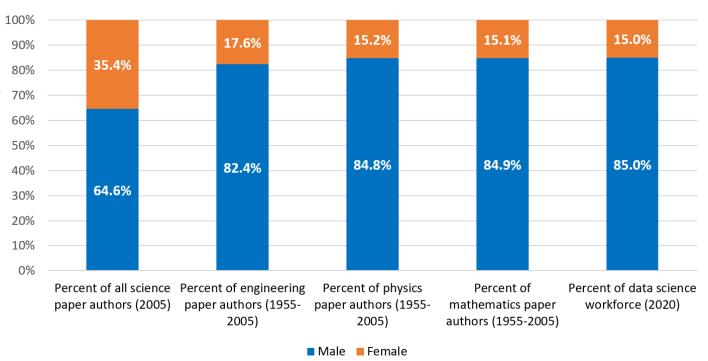
### Can we prove this cause?

Drownings & Ice cream sales

Confounding variable: temperature

Attendance & GPA

Confounding variable: Poverty



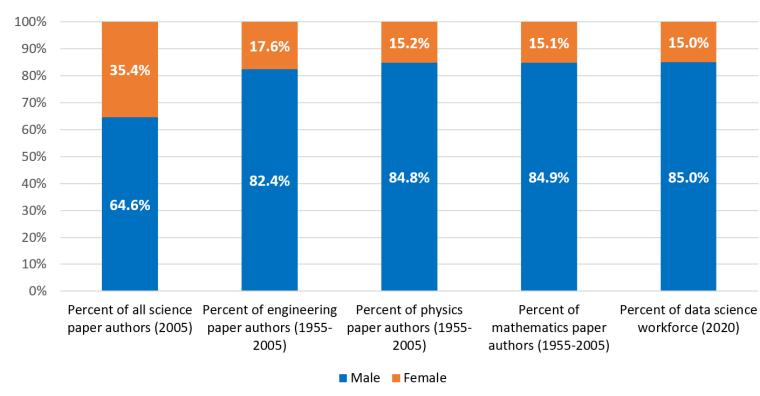
### Confounding variables:

Provide alternative explanations for trends between explanatory (gender) and response (hiring rates) variables.

### Possible Confounding

Variable
Confounding:
Socialization

Women are given fewer research and workforce opportunities in STEM due to:



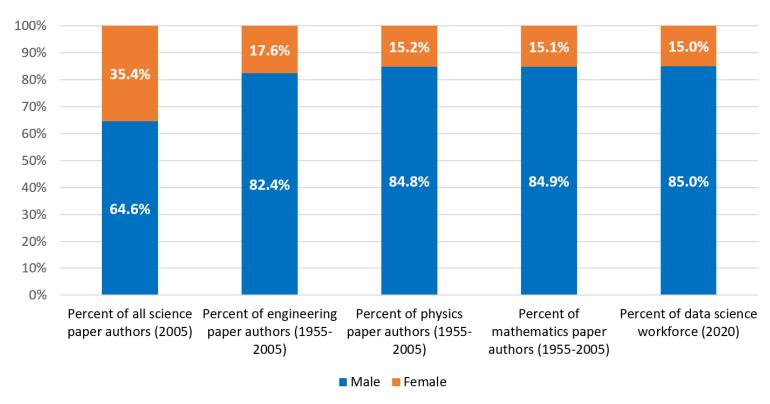
Many girls are not encouraged to pursue STEM subjects when they are growing up. Therefore, fewer women choose to pursue STEM as adults.

# Possible Confounding

Variable

# Confounding: Socialization

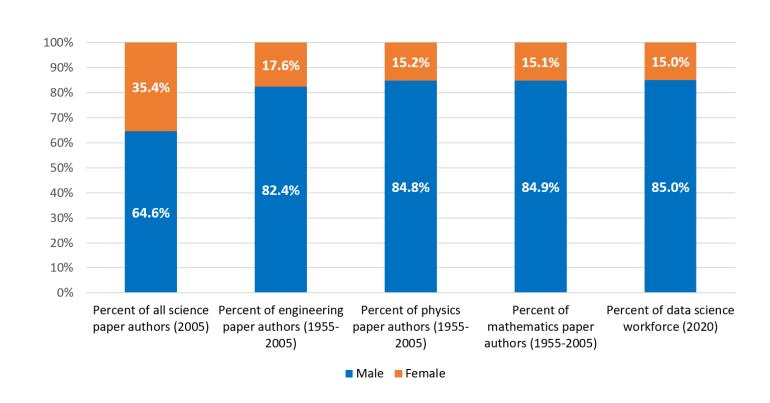
Women are given fewer research and workforce opportunities in STEM due to:



Additionally, We tend to foster boys' belief of talent in STEM which leads more men pursue STEM as adults.

### What causes this trend?

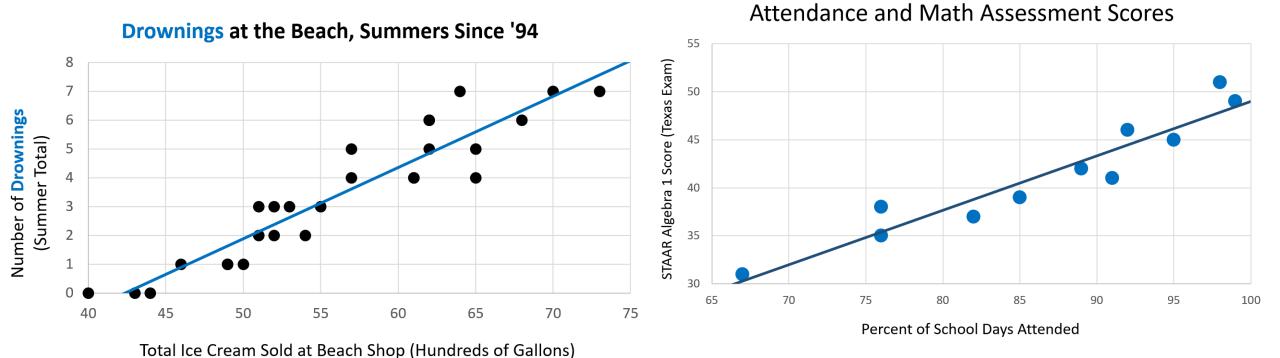
- 1. Hiring discrimination?
- 2. Socialization?
- 3. A combo of #1 and #2?
- 4. Other causes?
- 5. A combo of #1, #2, and other causes?...



We don't know! But maybe we can **test** it...

#### **DEFINITION** Observational study

An **observational study** observes individuals and measures variables of interest but does not attempt to influence the responses.



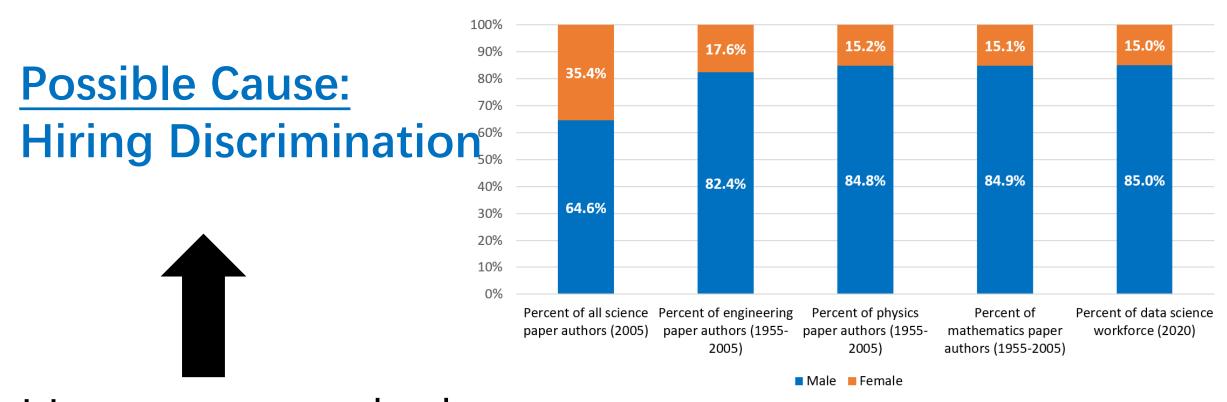
**Cannot** show cause and effect!

### Experimental studies

Experiments: a study in which treatment is imposed on subjects.

-If well designed, experiments can show causeeffect relationships by controlling for confounding variables.

### What causes this trend?



How can we design an experiment to test this?

### **Observational Studies & Experiments**

- Observational Studies cannot show cause and effect because they do not control for confounding!
- If well designed, experiments can show cause and effect by controlling for confounding variables.

# Topics

- 1. Observational studies vs. experiments
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**NEW RESEARCH IN** 

Physical Sciences

Social Sciences

#### **RESEARCH ARTICLE**



# Science faculty's subtle gender biases favor male students

Corinne A. Moss-Racusin, John F. Dovidio, Victoria L. Brescoll, Mark J. Graham, and Jo Handelsman

PNAS October 9, 2012 109 (41) 16474-16479; https://doi.org/10.1073/pnas.1211286109

Edited\* by Shirley Tilghman, Princeton University, Princeton, NJ, and approved August 21, 2012 (received for review July 2, 2012)

Researchers from Yale developed an experiment to test for gender bias in research lab hiring.

# We'll discuss a simplified version of what they did (read paper for full version)

**Paper:** Moss-Racusin, C., Dovidio, J., et al. "Science faculty's subtle gender biases favor male students." *PNAS* October 9, 2012 109 (41) 16474-

16479; <a href="https://doi.org/10.1073/pnas.1211286109">https://doi.org/10.1073/pnas.1211286109</a>

#### Resumé

John Williams

University of Indiana Major: Biology, GPA: 3.5

#### **Experience**

Research Assistant, Summer 2011

Development Intern, Spring 2010

\_\_\_\_\_

#### Resumé

Jennifer Williams

University of Indiana Major: Biology, GPA: 3.5

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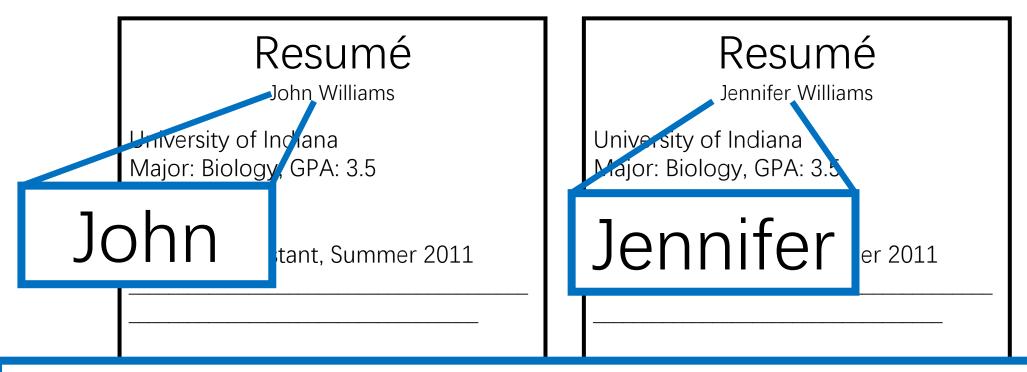
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"have been pretested as equivalent in likability and recognizability..." – study authors









n = 127







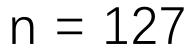










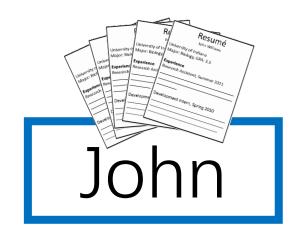


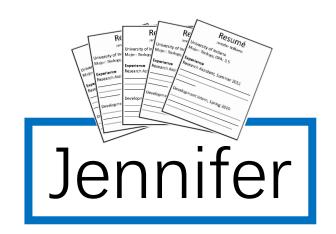


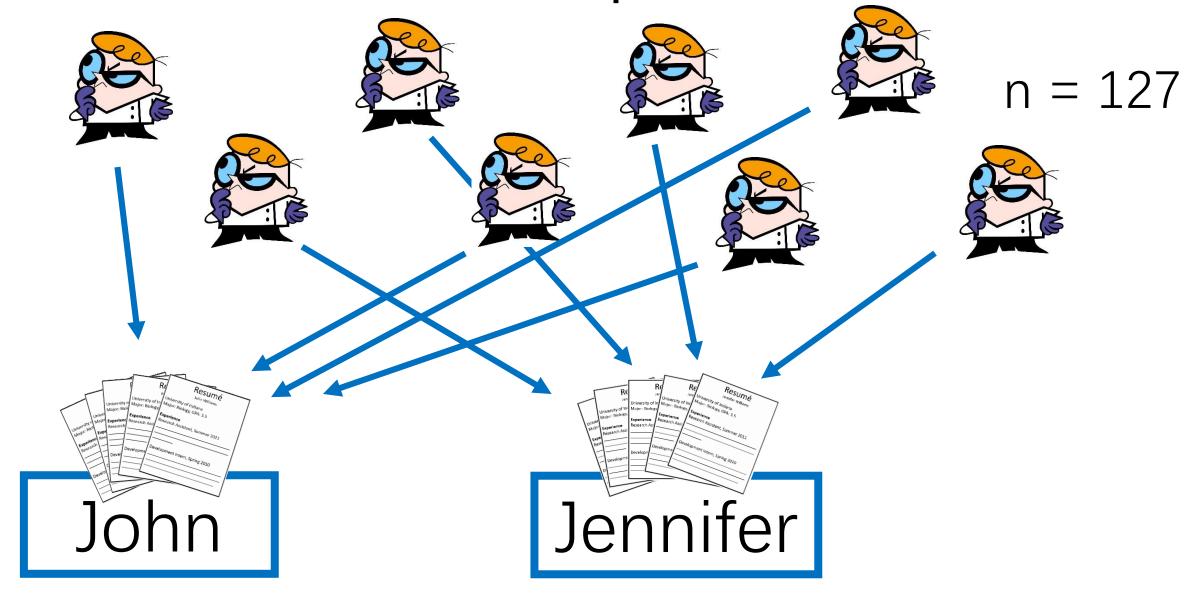


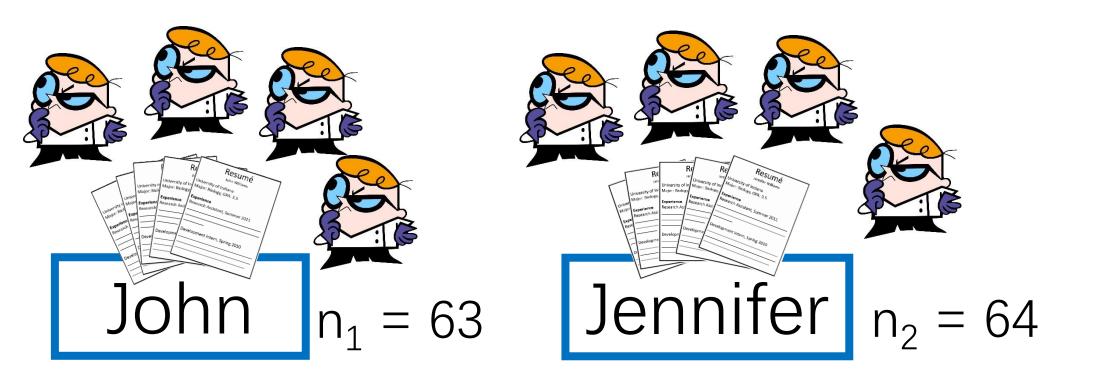






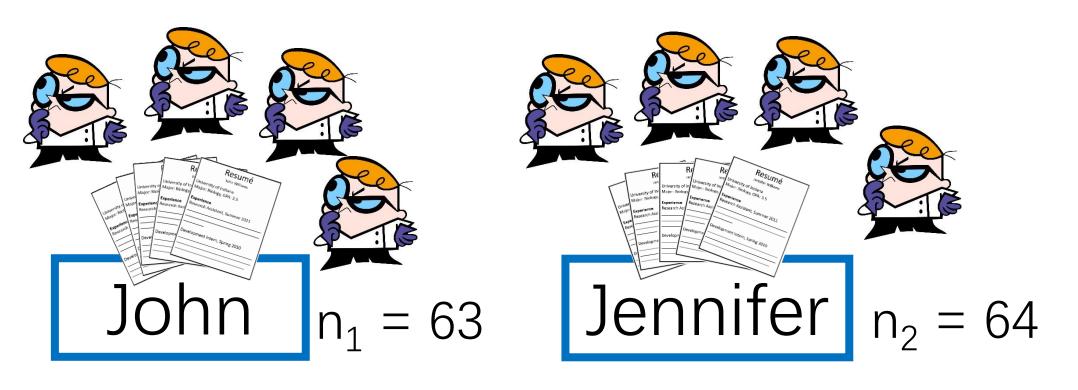






### Measured which group gave the applicant ...

- -Better "hireability" ratings
- -A higher starting salary estimate



### Components of experiments

Experimental units: the individuals/subjects (person, animal, plant, virus, particle, etc.) that are assigned to different treatments.

In hiring study: Science lab faculty

Explanatory variable: the variable that is purposefully manipulated. This is also known as the factor.

In hiring study: Applicant name

### Components of experiments

<u>Treatments:</u> the different **levels** of the explanatory variable in the experiment.

In hiring study: Jennifer/John

Response variable: the measured experiment outcome that is compared between treatment groups.

In hiring study: "Hireability" rating and salary estimate

# Topics

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### Principles of Experimental Design

- Comparison of at least two treatment groups
- Random assignment of experimental units to treatment
- Replication many experimental units in each treatment group
- Control of confounding variables

# Comparison



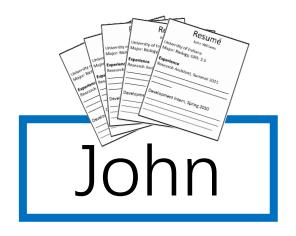


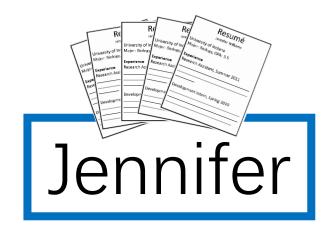




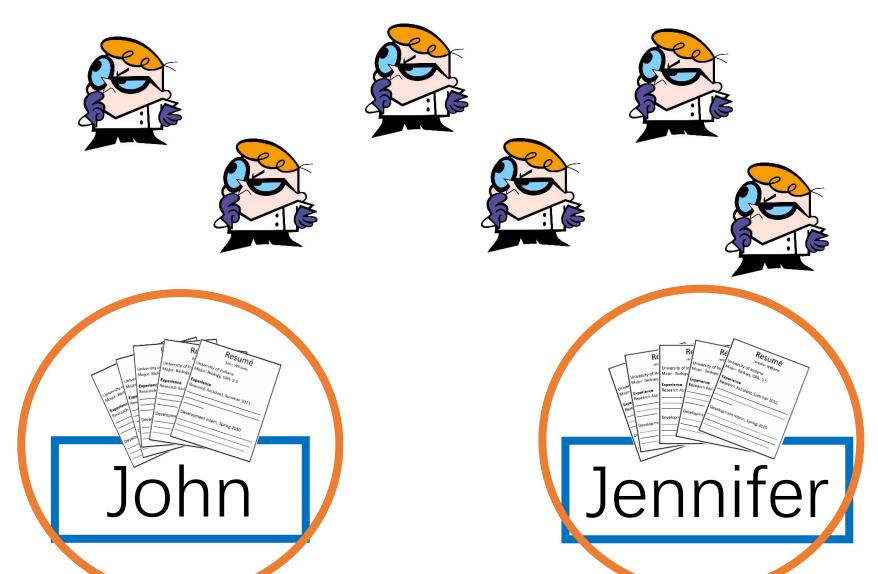








# Comparison



# Comparison

Comparing at least two treatments





# Random Assignment



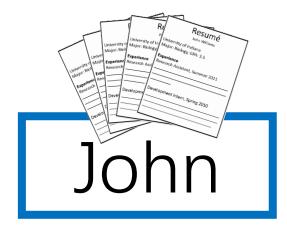


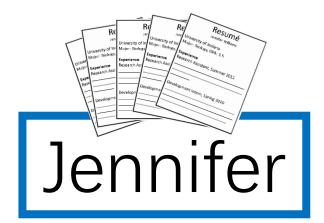




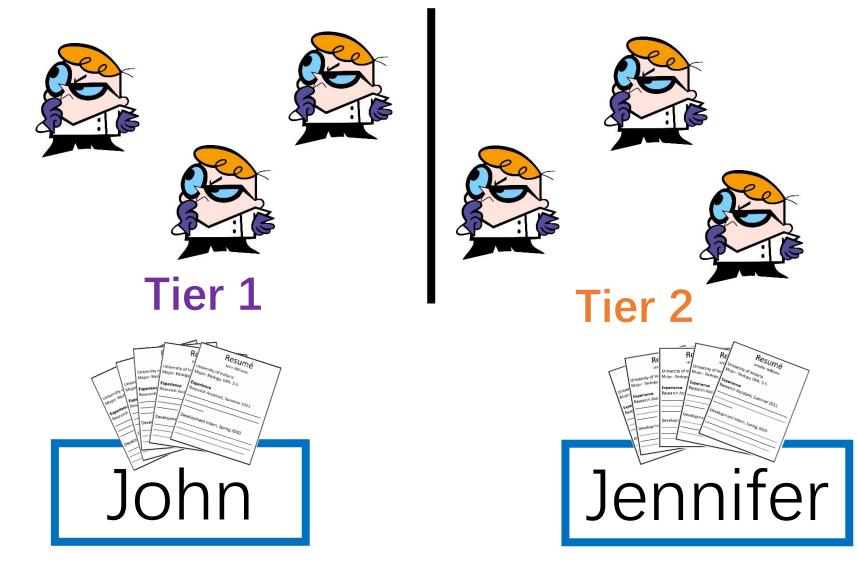








# Random Assignment



# Random Assignment



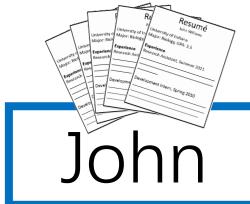


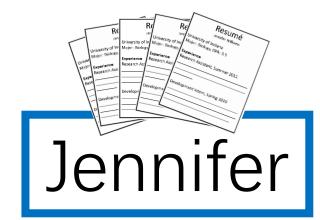


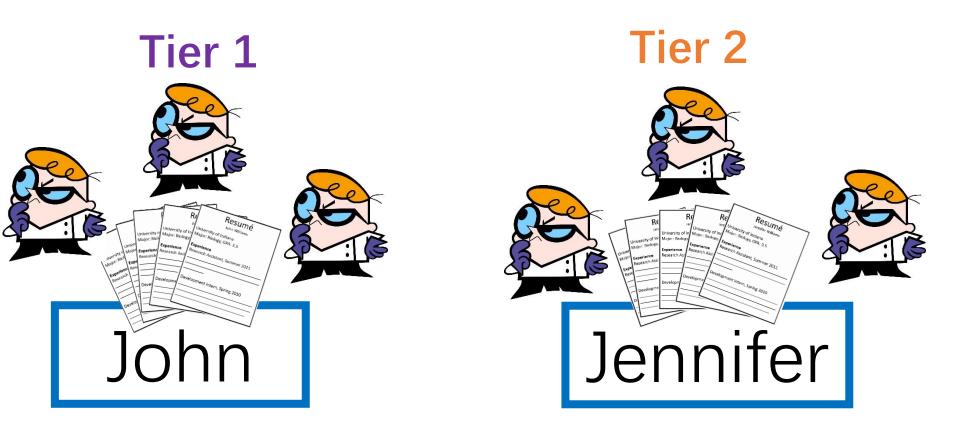


Tier 2

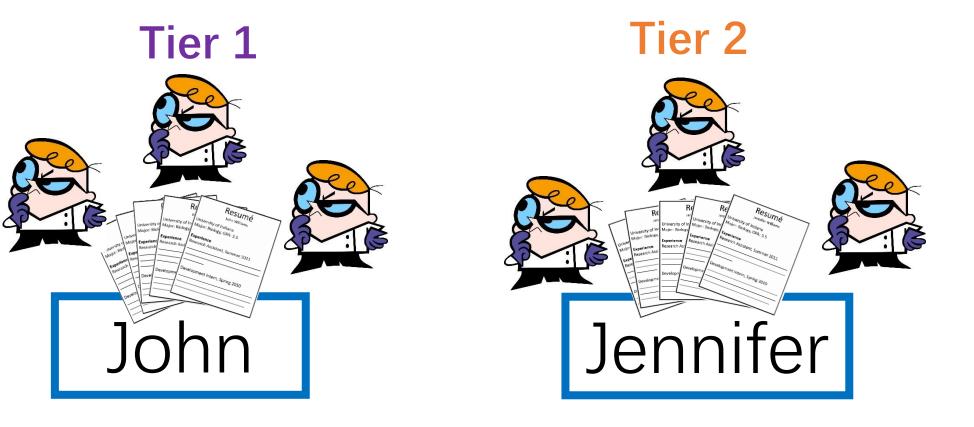
What if I assigned **Tier 1** University labs to get "John" and **Tier 2** labs to get "Jennifer"?







Now we have confounding! Not sure if it's gender or lab quality that causes hiring outcome differences.



Tier



Tier





Tier









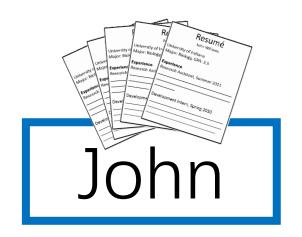


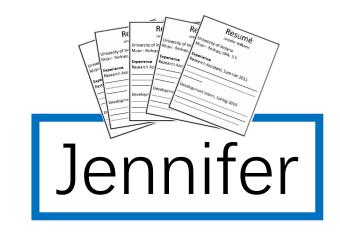
Tier

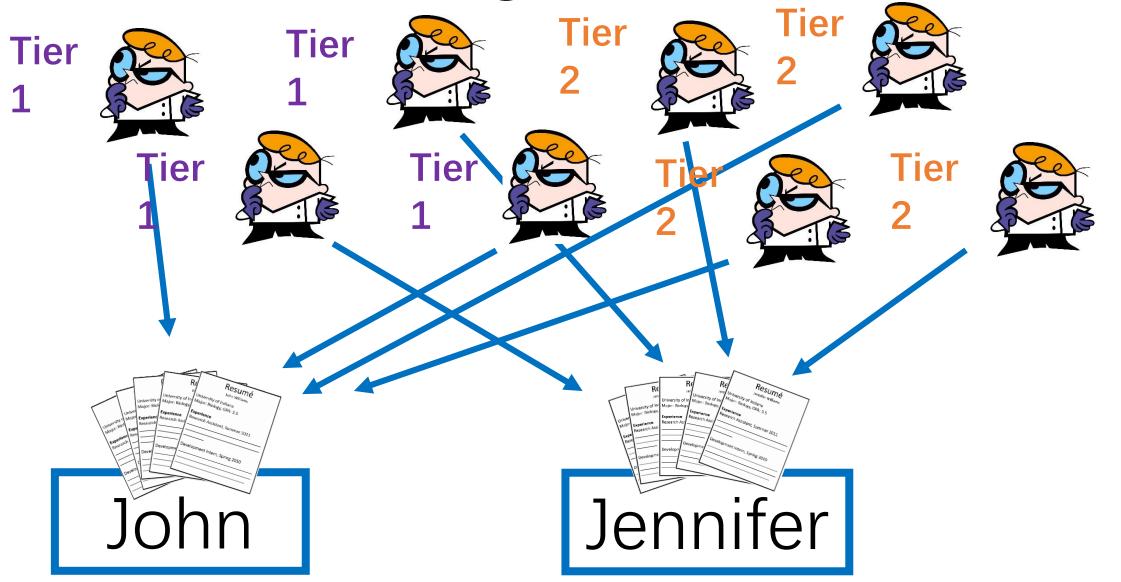


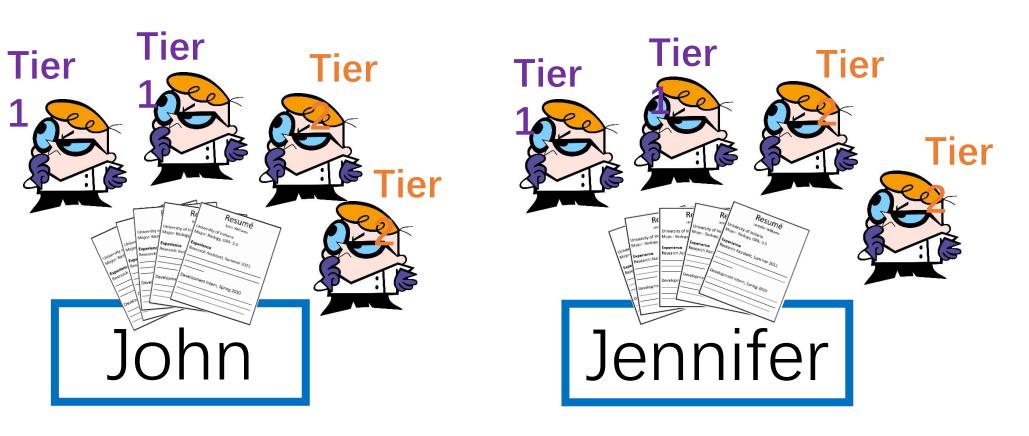
**Tier** 



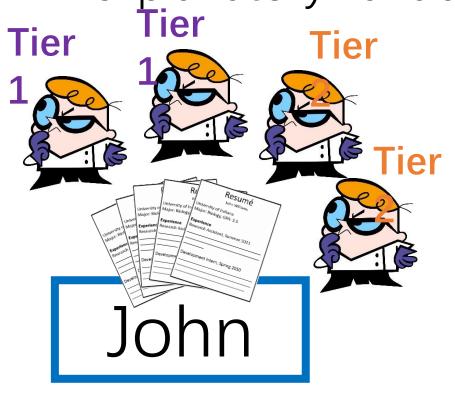


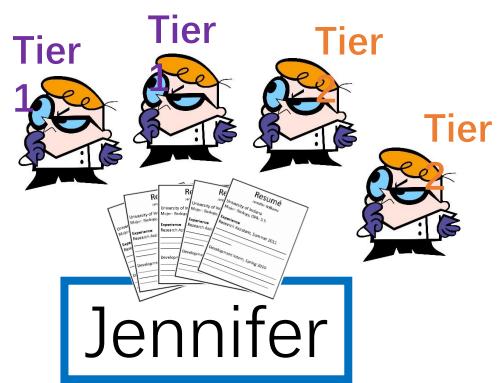






Random assignment tends to **balance** confounding factors, so inferences can be made about the explanatory variable.





## Terminology

Sampling

Random sample

Reduces bias

**Experiments** 

Random assignment

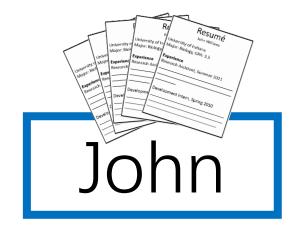
Reduces confounding

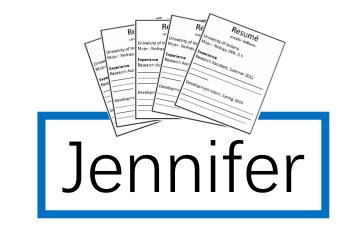
n = 2

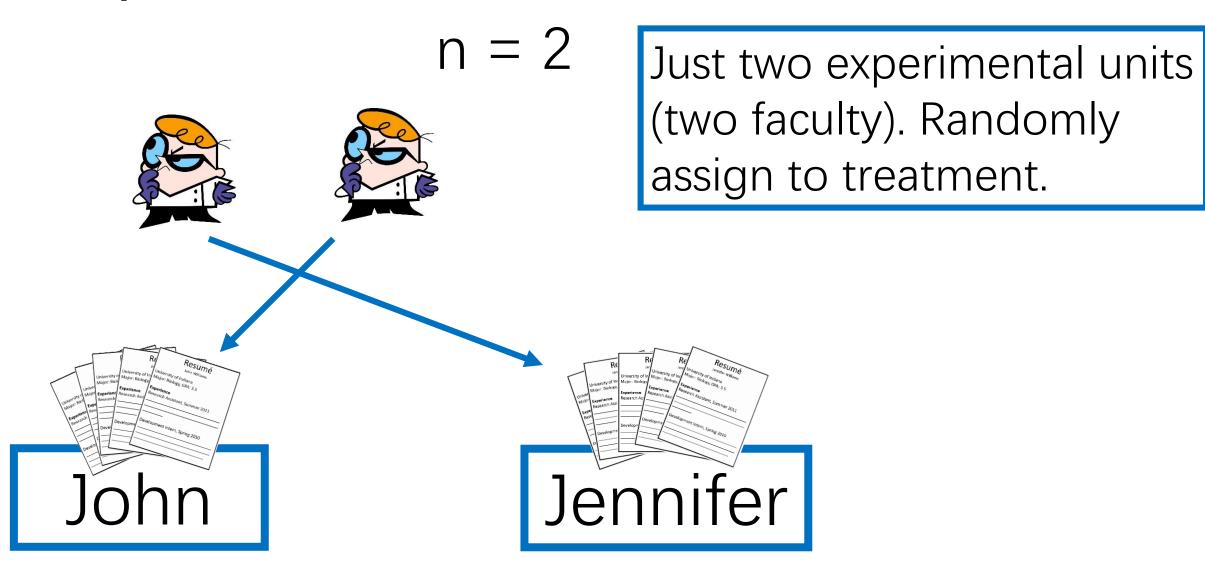


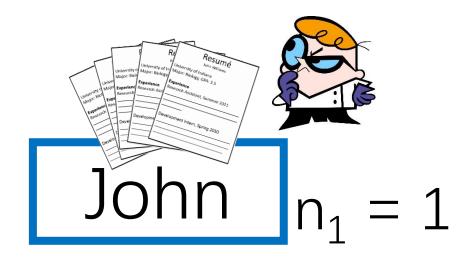


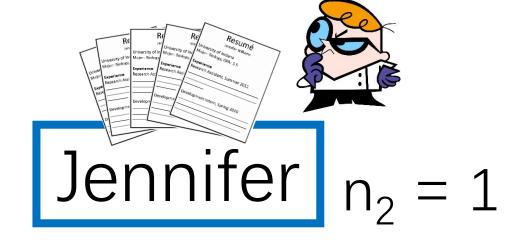
Just two experimental units (two faculty). Randomly assign to treatment.





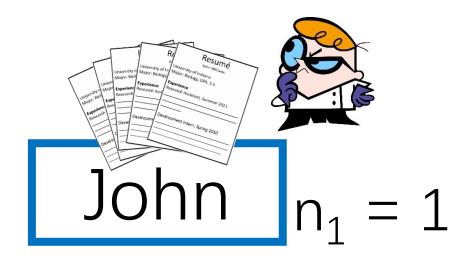


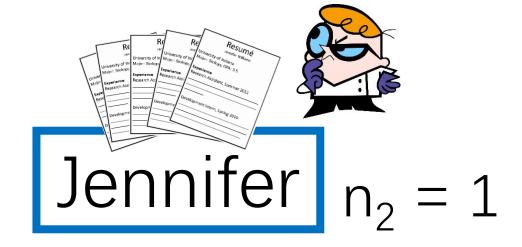




Hard to tell if differences are due to explanatory variable (gender) or chance variation between these two faculty.

**Ex:** maybe one of the faculty members was having a bad morning while reading applications































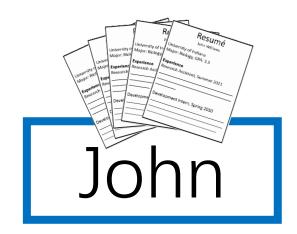
n = 127

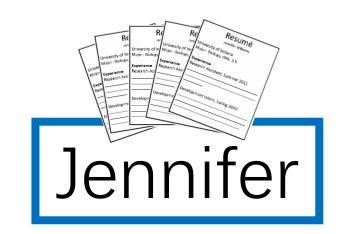


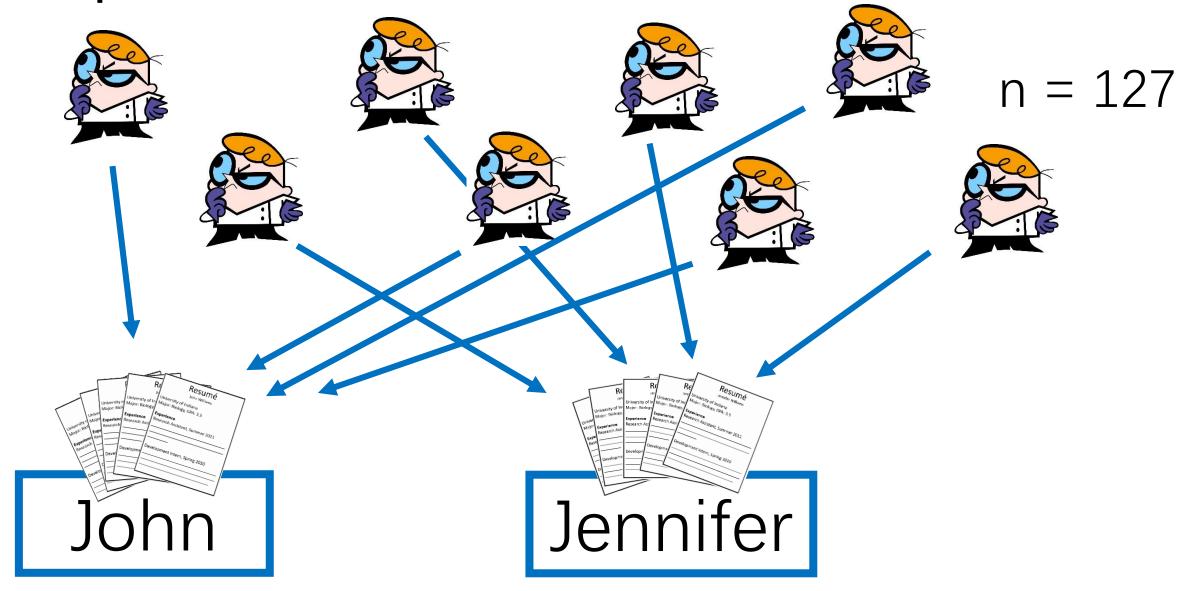




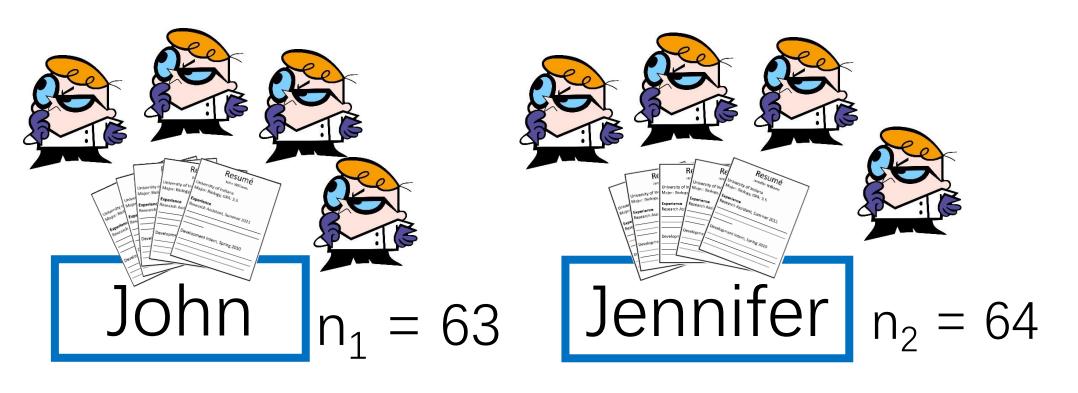








Larger treatment group size reduces the likelihood of differences arising due to chance alone. In other words, it makes our estimates of treatment effect more precise.



### Control

#### Resumé

John Williams

University of Indiana Major: Biology, GPA: 3.5

#### **Experience**

Research Assistant, Summer 2011

Development Intern, Spring 2010

\_\_\_\_\_

#### Resumé

Jennifer Williams

University of Indiana Major: Biology, GPA: 3.5

#### **Experience**

Research Assistant, Summer 2011

\_\_\_\_\_

Development Intern, Spring 2010

### Control

One way they control for confounding factors is by making the application materials completely identical, except for the explanatory variable (gender).

They even control for name likability:

Jennifer/ John "have been pretested as equivalent in likability and recognizability..."

# Topics

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### Completely Randomized Design

Completely randomized design:

An experimental design in which experimental units are assigned to treatments completely at random.

Describe how you would implement a completely randomized design of the Jennifer/John experiment, with 127 science faculty members.

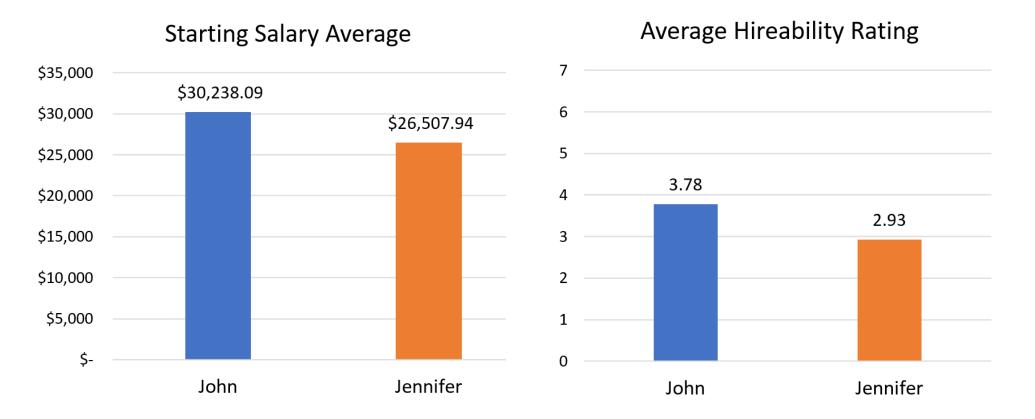
#### **Key Steps:**

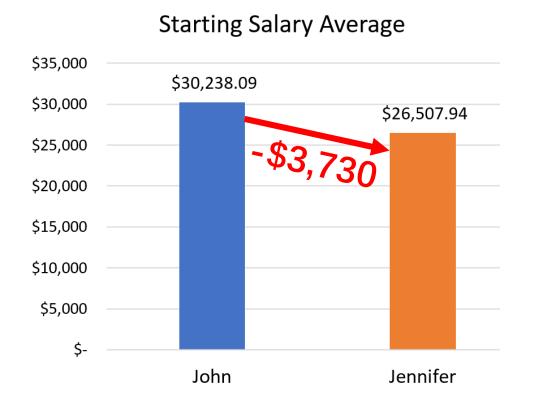
- 1. Assign each experimental unit a number 1 n (sample size).
- 2. Write all the numbers on identical slips of paper, put into a hat, and mix well.
- 3. Draw out  $n_t$  (treatment group size) slips of paper, without replacement. The corresponding units are assigned treatment 1. Draw out another  $n_t$  slips of paper, assign to treatment 2, etc.
- 4. Compare response among treatment groups

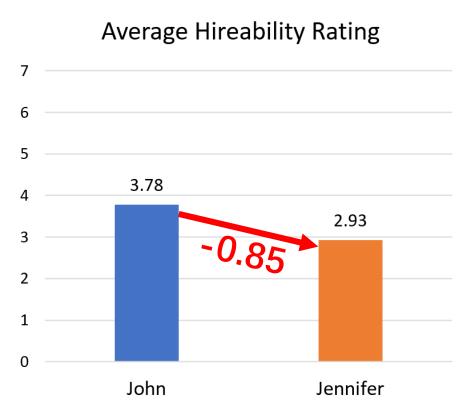
Describe how you would implement a completely randomized design of the Jennifer/John experiment, with 127 science faculty members.

Assign each faculty member an integer, **1-127**. Write integers 1-127 on identical slips of paper, put them into a hat, and **mix well**. Draw out 63 slips (without replacement). The corresponding faculty members will receive "John" application materials. The **remaining** faculty members will receive "Jennifer" application materials. At the end of the experiment, record faculty members' rating of applicants' "hireability" and starting salary estimates. Finally, **compare** these results across the two groups.

# Discussion

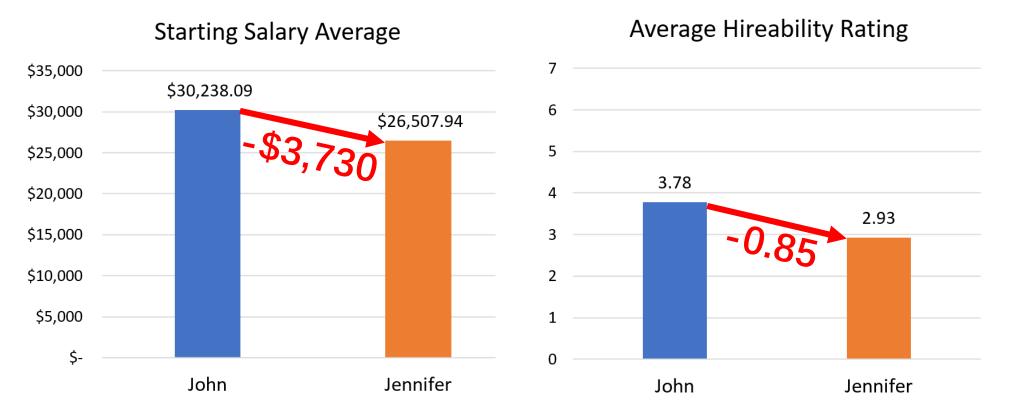




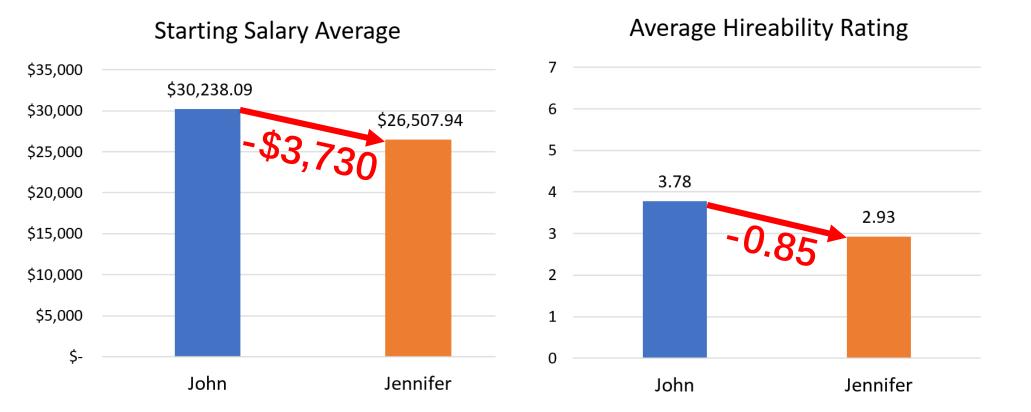


	John	Jennifer	Difference
Hireability	3.78	2.93	-0.85
Salary	\$30,238	\$26,508	-\$3,730

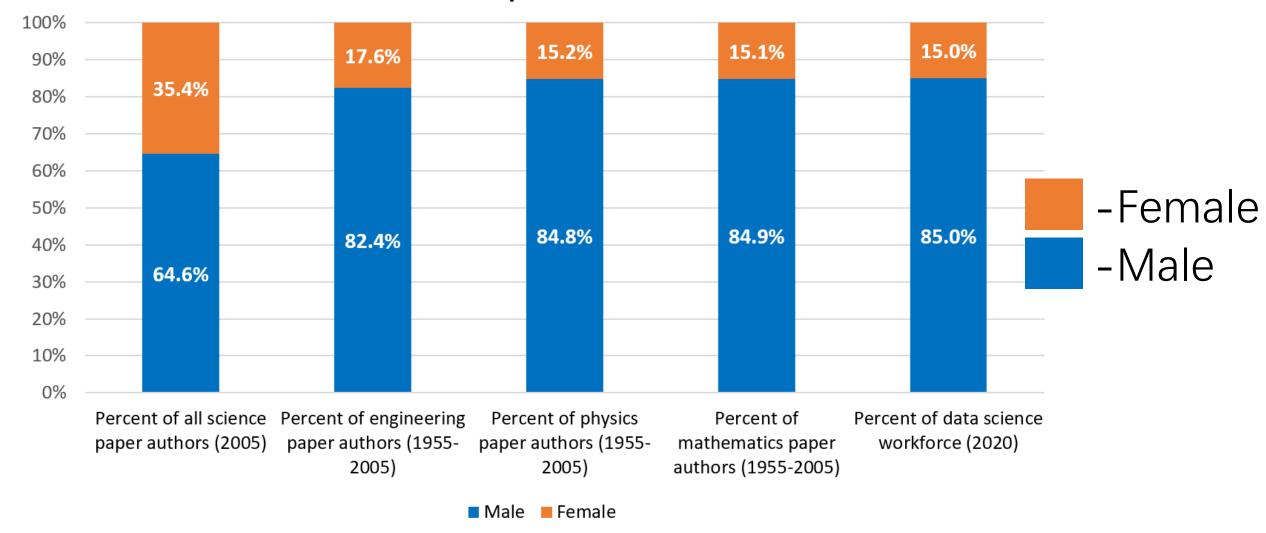
The differences were found to be <u>statistically significant</u>: so extreme that they were unlikely to happen by **chance alone**.



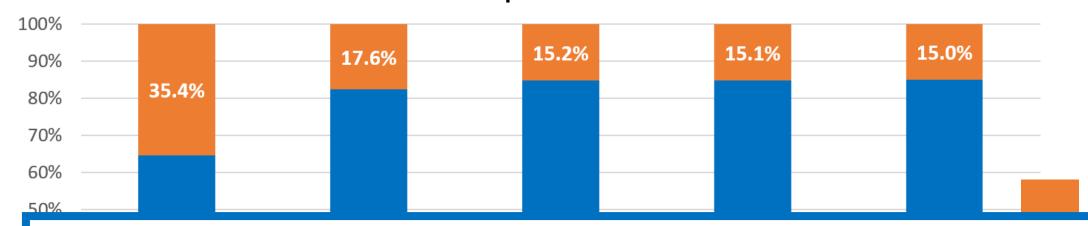
Since this was a well-designed experiment, we can infer that these average differences are caused by gender bias.



### Gender Gaps in STEM



### Gender Gaps in STEM



**Discussion Question:** Is the proven gender bias among the faculty in this study enough to explain the large gender gaps in STEM? Or might there be other causes as well? Explain your reasoning.

2005)

2005)

authors (1955-2005)

(a) Identify the treatments, experimental units, and response variable of the experiment.

Treatments:

Experimental units:

Response variable:

- (b) Does the experiment have a control group? Explain your answer.
- (c) Describe how the treatments can be randomly assigned to the experimental units so that each treatment has the same number of units.

(a) Identify the treatments, experimental units, and response variable of the experiment.

Treatments: 4 different correntrations of Fungus mixture (0, 1.25, 2.5, 3.75 m/L)

Experimental units: 20 individual containers

- Response variable: number of insects that are still alive in each container one week after spraying, ach treatment
- (c) D has the same number of units.

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Treatments:

Experimental units:

Response variable:

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(a) Identify the treatments, experimental units, and response variable of the experiment.

Treatments:

Experimental units:

Response variable:

(b) Does the experiment have a control group? Explain your answer.

(b) Yes, the containers which recieve the O mI/L concentration of fungus mixture. The insects in these containers will not get any of the fungus, which provides the researchers with baseline data to compare the fungus mixtures to.

(a) Identify the treatments, experimental units, and response variable of the experiment.

Treatments:

Experimental units:

Response variable:

- (b) Does the experiment have a control group? Explain your answer.
- (c) Describe how the treatments can be randomly assigned to the experimental units so that each treatment has the same number of units.

(c) Label each of the 20 containers with a number from 1 to 20. Use a random number generator to get 5 integers from 1 to 20, ignoring repeats. Assign those 5 corresponding containers to the first treatment (OMVL). Then use the random number generator to get 5 more integers (ignoring numbers already selected and repeats) and assign the corresponding containers to the second treatment (1.25 ml/L). Use the same process to identify 5 containers for the third treatment (2.5 m/L) and the remaining 5 containers get the fourth treatment (275 m1/L).