

Statistical Literacy Provides Research Opportunities

Milo Schield

**New College of Florida
University of New Mexico**

**Foundations of Causal Inference
Validating claims and evaluating ideas**

July 31, 2025

**[www.StatLit.org/pdf/
2025-Schild-ROSE-Slides.pdf](http://www.StatLit.org/pdf/2025-Schild-ROSE-Slides.pdf)**

Statistics Education: What is the Biggest Problem?

Statistics anxiety. Students don't appreciate. Why?

- Confused with math, poorly taught, unknown..

A different explanation.

Statistics has three definitions

#1: Data summaries “*Everyday stats*” (Ch 1)

#2: Sample summaries (Ch 3)

#3: [small] random sample summaries (Ch 8)

Bait and switch!

Quantitative Gen Ed: Math vs. Statistics

College students: required to take a quantitative course

In mathematics, there are typically separate courses:

- Math for Liberal Arts: for non-Quantitative majors
- College Algebra or Pre-Calc: required for Q majors.

In statistics, there is typically just a single course.

- Introduction to *statistical inference*
Required by stat & Q majors. Taken by non-Q majors

Need a separate course for students in non-Q majors.

Reexamining Statistical Inference

What is *statistical inference*?

- Infer population parameters from sample statistics

Milo: What *kinds of statistical inference* are there?

Chat: There are *two* kinds.

Milo: (Thinking) Conf Intervals & hyp. tests
WRONG!!!

Chat: *Population Inference & Causal inference*

Reexamining Our Students

All US college students

MATH REQUIRED BY US COLLEGE GRADUATES: 2020-2021

CALCULUS	DISCRETE	STATISTICS	OTHER
10%	5%	52%	33%

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Students required to take statistics (by major)

Distribution of US College Graduates Taking Statistics by major: 2020-21

Business	Health	Social Sc.	Biological	Psychology
36%	25%	15%	12%	12%

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Students' Statistical Interest and Needs

What fraction of students want to learn mainly about:

- Population inference (10%?)
- Causal inference (90%?)

What fraction of causal inference are interested in:

- Ideal experiments (10%) Repeatable
- RCT Clinical trials (10%?)
- Quasi-experiments (30%?)
- Observational studies (50%?)

? *Schield estimates. Research needed!*

Students' Statistical Needs Summary

Most students need a course that focuses primarily on

- causal inference
- quasi-experiments and observational studies.

Q. What is the big problem in *observational causation*?

A. CONFOUNDING

In a convenience survey of 100 intro statistical textbooks, only 20 referenced confounding in the index. Of these, most had a single reference.

Statistical Literacy: No agreement on Definition

For me, there are two approaches to statistical literacy:

- Confounder absent
- Confounder focused

Most are confounder-absent

SERJ 2017: Statistical Literacy		
# of appearances in body of paper		
Author	Statistical Literacy	Confound
Schild	58	28
Wild	13	2
Engle	2	2
13 others	<22.4>	0
2 other	0	0
18 papers	89%	17%



Statistical Literacy: Foundations of Causal Inference

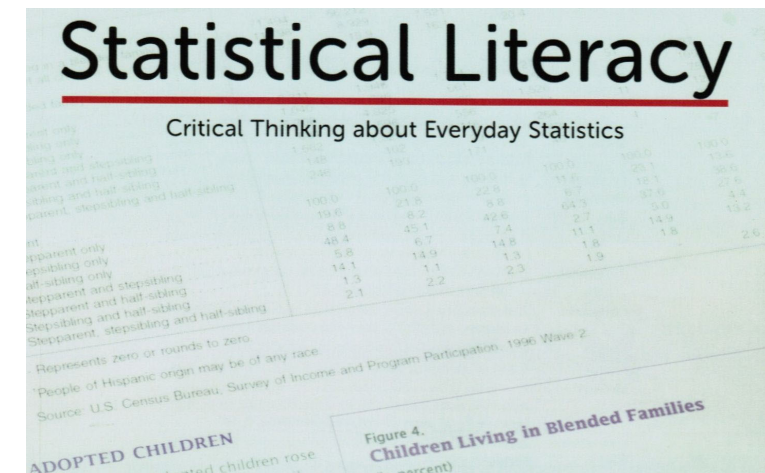
Confounder-based Statistical Literacy focuses on ideas.

Textbook published by Kendall-Hunt: Schield (2023)

- Offered at University of New Mexico (UNM)
required by all undergraduate statistics majors.
- Offered at New College of Florida (NCF)
required by all first-year students.

Statistical Literacy is accessible:

- Doesn't require or use computers.
- Doesn't require or use algebra.



Statistical Literacy: Foundations of Causal Inference

Statistical Literacy focuses on

- multivariable analysis (GAISE 2016 major heading)
- confounding (GAISE 2016 minor heading)
- ‘controlling for’ confounders (GAISE 2016 appendix)

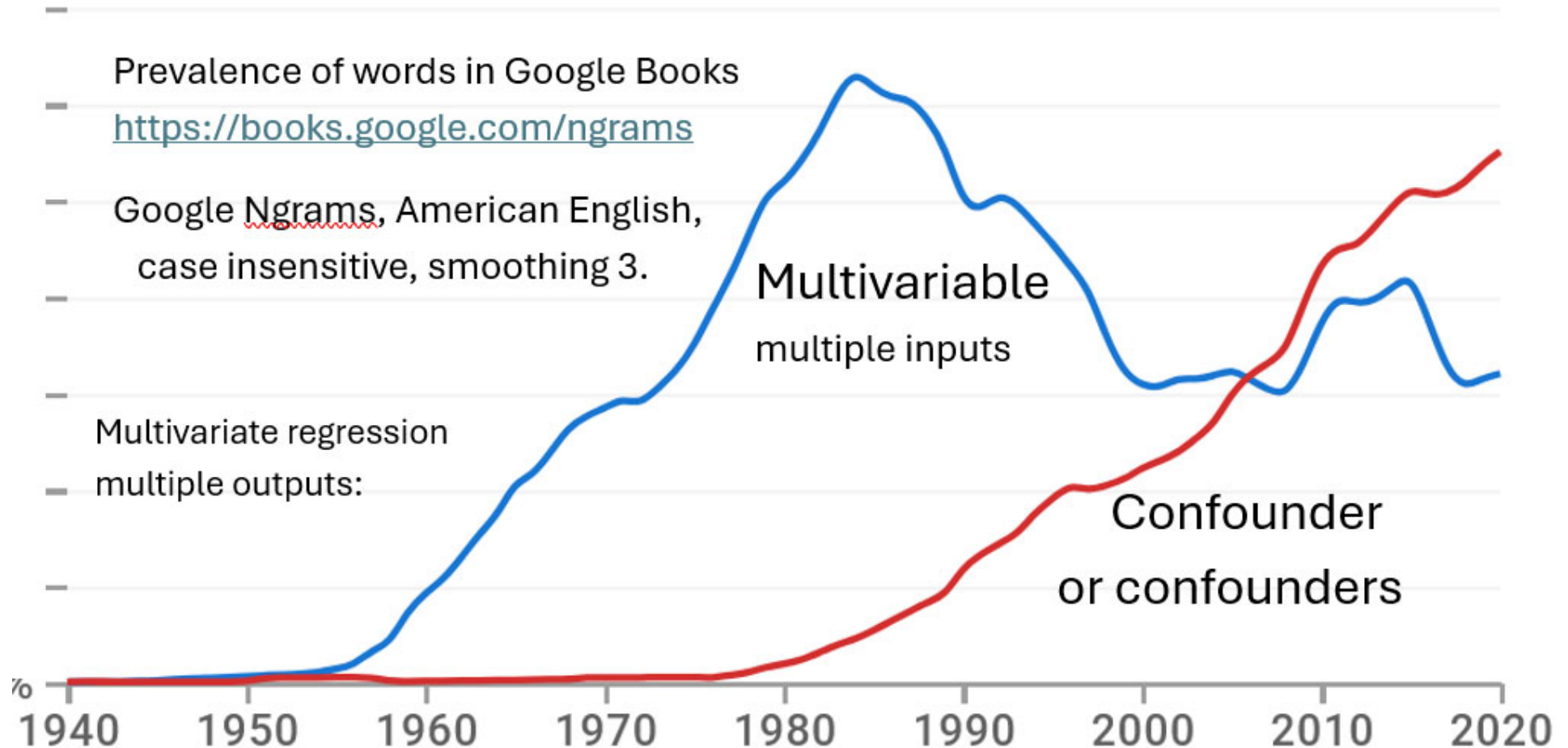
Statistical Literacy may be the only textbook/course that is arguably GAISE 2016 compliant.

Prediction:

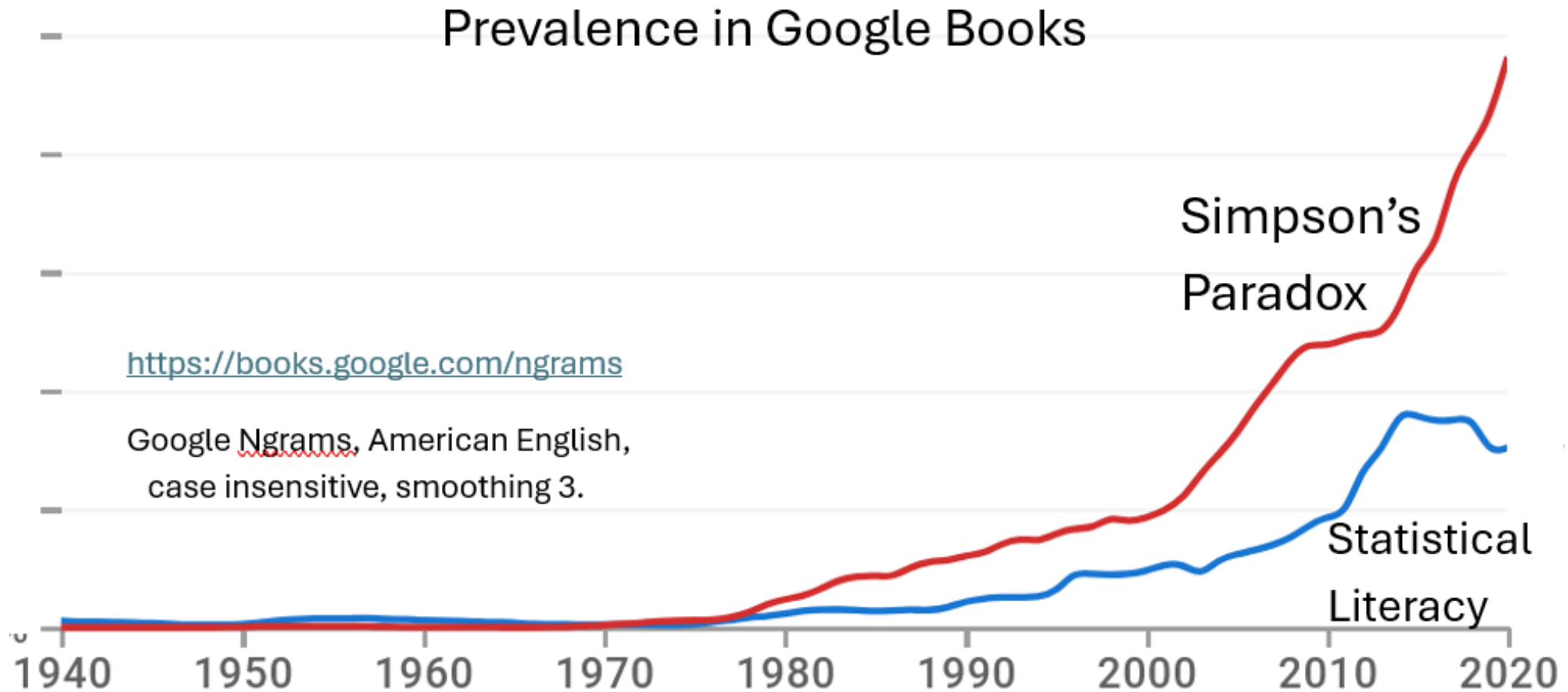
GAISE 2025 will downgrade multivariable & confounding.

Multivariable and Confounder: Prevalence in Google Books

Confounder is 500 times as prevalent in 2020 as in 1940



Prevalence in Google Books: Simpson's Paradox & Statistical Literacy



Textbook Claims Needing Proof, Explanation or Confirmation

P 91: If an event occurs with 1 chance in N , then in N tries, an event is *expected*: at least one is *more likely than not*.

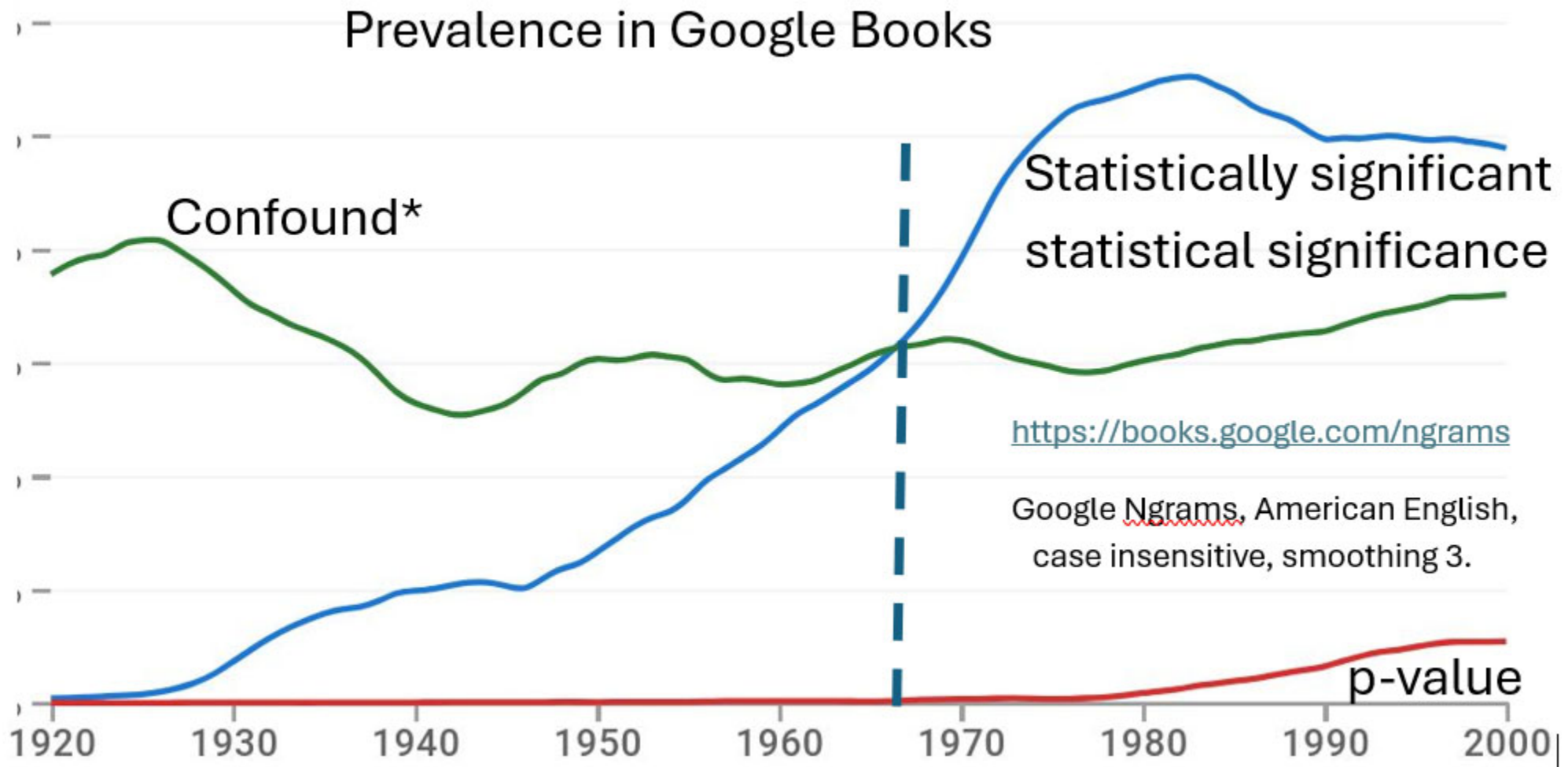
P 138. Std error of median is greater than that of the mean.

Medical tests where sensitivity = specificity:

P. 278. If disease prevalence=50%,
then positive predictive value (PPV) = sensitivity.

P. 278. If confirmation error rate = disease prevalence,
then positive predictive value (PPV) = 50%.

Prevalence in Google Books: Confound vs Statistical Significance



ASA is attempting to discredit the use of 'statistical significance'.

ASA: “P-values do not measure the probability that the studied hypothesis is true, or the probability that the data were produced by random chance alone.”

“Since 0.01 is typically less than common significance levels like 0.05 or 0.01, a p-value of 0.01 is generally interpreted as **strong evidence** against the null hypothesis.”

In practice: *The smaller the p-value, the stronger the evidence against the truth of the null hypothesis.*

Statistical Significance: Underlying Problem

ASA: “*By itself*, a p-value does not provide a good measure of evidence regarding a model or hypothesis.”

Underlying problem: setting a single value for statistical significance regardless of the implausibility of the research hypothesis violates Carl Sagan’s ECREE: “extraordinary claims require extraordinary evidence.”

ASA noted that statisticians often use “... alternative approaches including ... Bayesian methods ...”

Textbook Claim #1 ***Needing Confirmation***

If the test result is positive (statistically significant) and research hypothesis is more likely than not to be true, then we are 95% confident that the Null is false (RH is true).

	RH = False	RH = True	
RESULT	Null=True	Null=False	ALL
NEGATIVE	95	5	100
POSITIVE	5	95	100
ALL	100	100	200
RH=Research Hypothesis 50% chance (RH=True)			
If sensitivity=specificity = 95%, PPV=95%			

Note: Fisher's agricultural experiments were cases where the research hypothesis was *more likely than not* to be true.

Textbook Claim #2 Needing Confirmation

If research hypothesis is unlikely to be true (1%) and if sensitivity=specificity=1-chance (RH=True), then the Positive Predictive Value (PPV) = 50%

	RH = False	RH = True	
RESULT	Null=True	Null=False	ALL
NEGATIVE	9,801	1	9,802
POSITIVE	99	99	198
ALL	9,900	100	10,000
RH=Research Hypothesis 1% chance (RH = True)			
Sensitivity = specificity = 1 - chance (RH=true)			
If sensitivity=specificity = 99%, PPV=50%			

Note: Utt's ESP had a p-value of 10^{-18} . If chance ESP was true were 10^{-99} , a much smaller p-value would be required

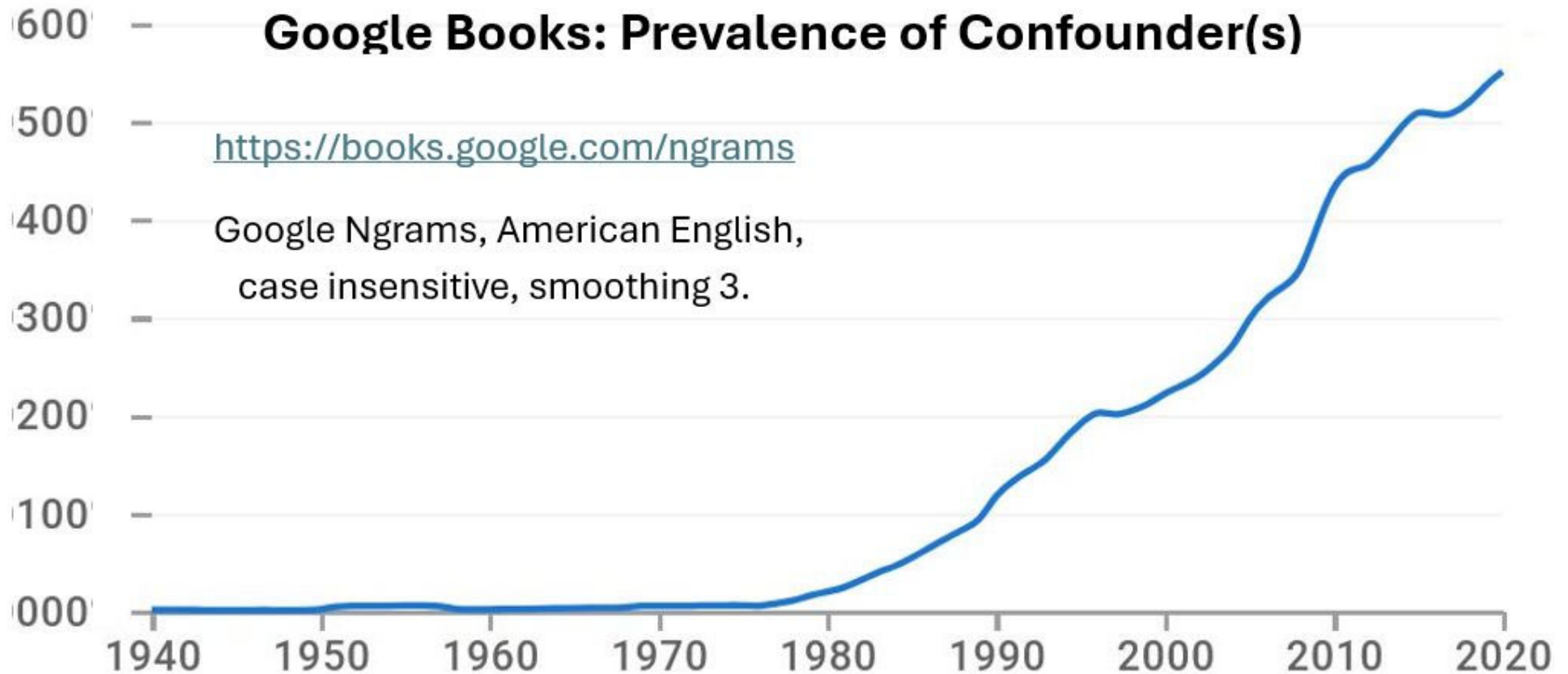
Statistical Significance Conclusion

Using $p\text{-value} < 5\%$ for statistical significance is appropriate if the research hypothesis is more likely than not to be true.

Using 5% for statistical significance when the research hypothesis is plausible is like treating Newtonian physics as valid in ordinary (non-relativistic) situations.

If the research hypothesis is extremely unlikely, disregard the use of ‘statistical significance’. Treat it as irrelevant!

Prevalence in Google Books: confounder+confounders



Using Ratios to Control for Proportional Influences

Compare counts: Students expect California (40M people) to have more unemployed **workers** than Wyoming (0.6M).

Compare ratios: Students are not surprised if Wyoming has a higher unemployment **rate** [per 100] than California.

Comparisons of counts can be influenced by the size of the group in comparing ratios.

But few students recognize that a comparison of ratios can be influenced by related factors.

Comparisons of Ratios: Common in Everyday Media

Women make 76 cents for every dollar a man makes.

Family income for Whites is 60% more than for Blacks.

White households hold 6 times as much wealth as Blacks.

Blacks are twice as prevalent in prison as in the population.

Black Americans: 10% of population; 3% of BS in statistics.

Hispanic/Latine: 20% of population; 10% of BS in statistics.

BS: Bachelor of Science degrees.

OLS Regression

“Bottom Line”

OLS regression is limited. Easily misused.

Don't teach without checking the assumptions.

Plus: That's why OLS regression is taught in a 2nd course.

Minus: 1st course students never learn that a ratio can be influenced by what is – or is not – ‘taken into account’.

Voltaire:

Don't let the perfect become the enemy of the good.

Confounders Solutions: Physical and Mental

CONFOUNDER SOLUTIONS

Inside the Data	Mental: Simple	Mental: Advanced
Effect Size	Selection	Linear Modelling
Controlled Study	Ratios	Logistic Modeling
Study Design	Standardization	Multivariate
----- Hypothetical thinking -----		

Consider study design

Types of Studies: Hard Science vs. Soft Science

Hard Science

Experiment

Researcher assigns/intervenes

Repeatable: Scientific experiment

Randomized: Clinical trial

Other: Quasi-Experiment

Soft Science

Observational

Researcher observes/responds

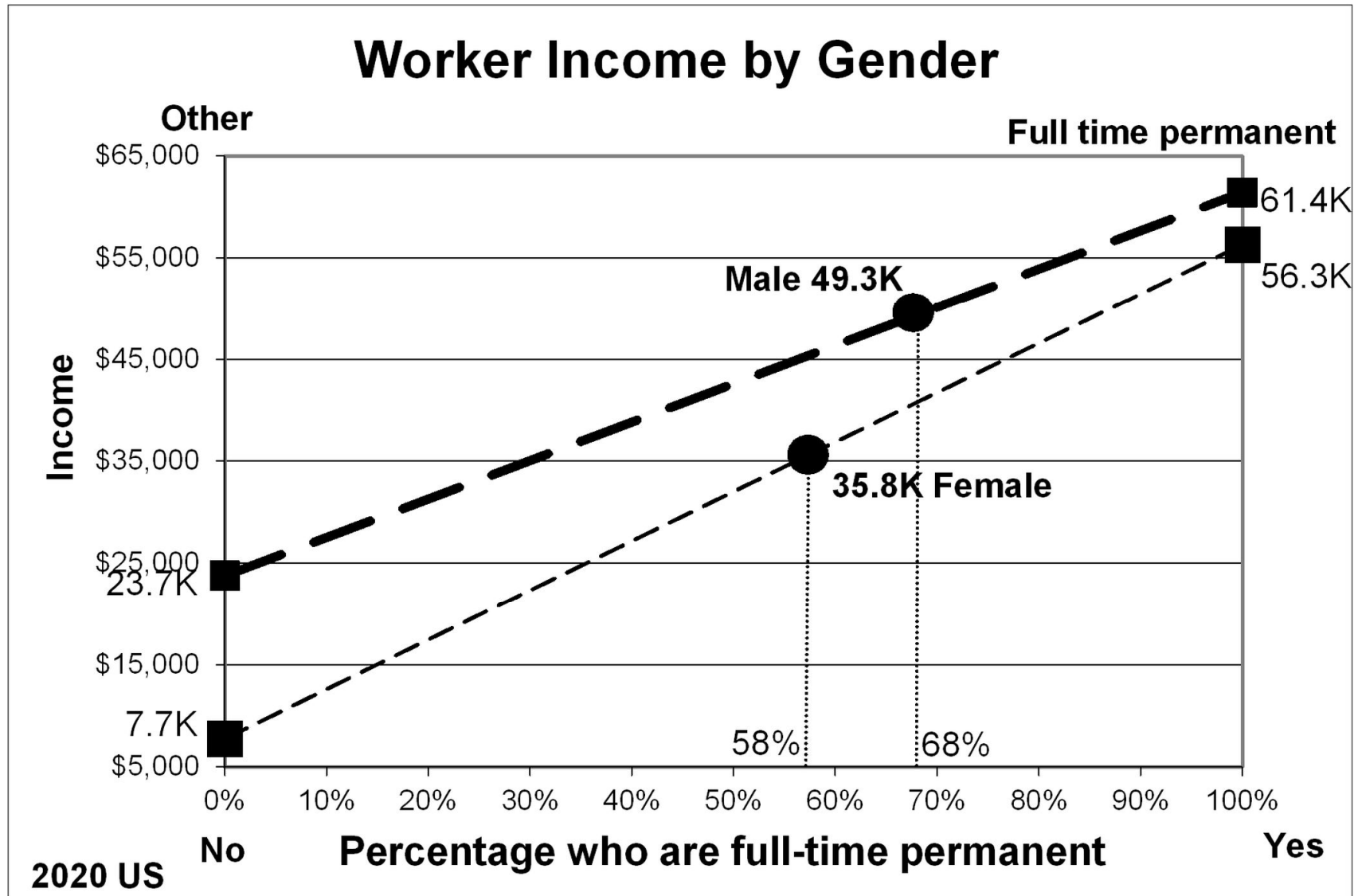
Movie: Longitudinal Study

Snapshot: Cross-sectional study

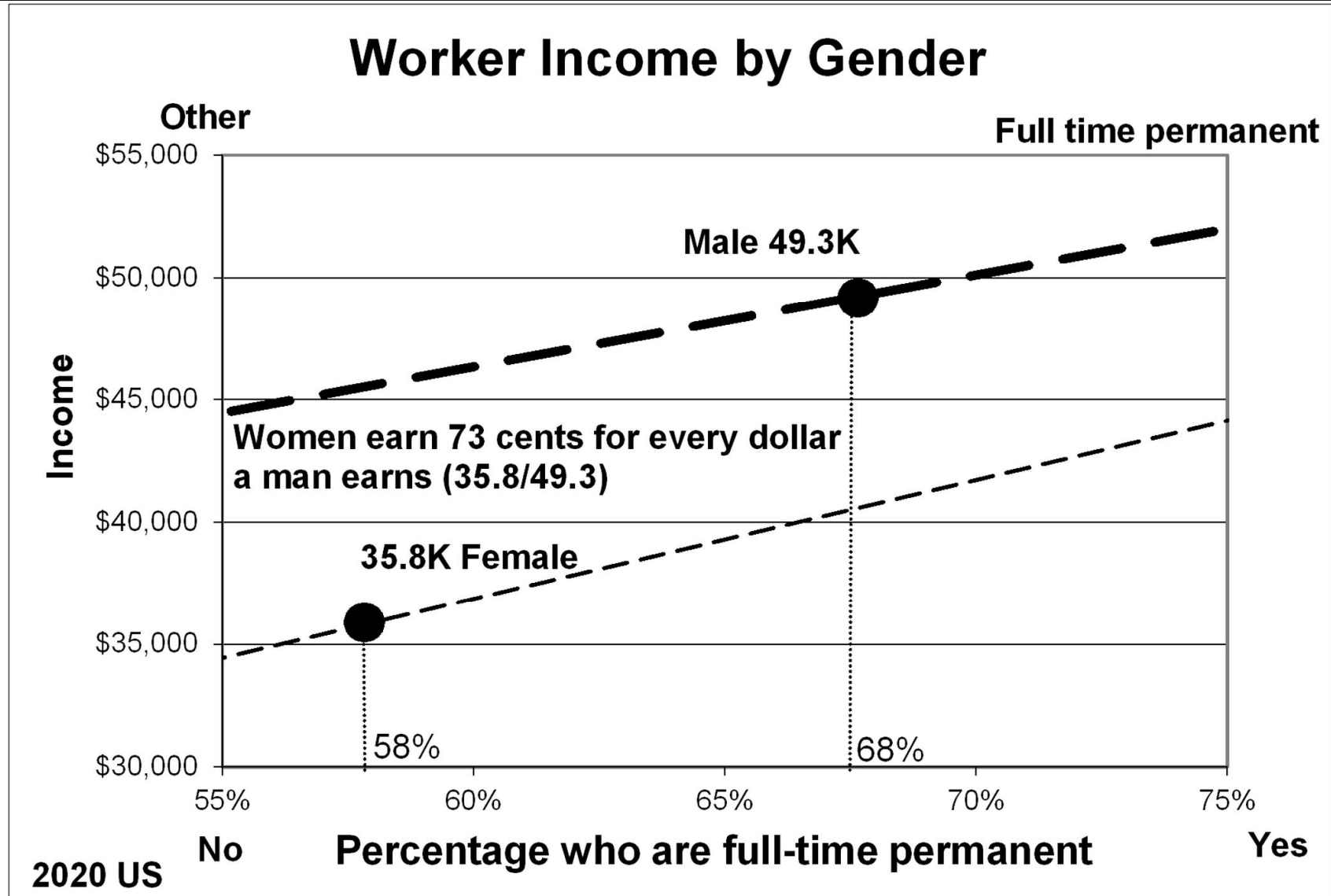
Someone says: Anecdotal

Soft science is more vulnerable to being influenced by confounders than hard science.

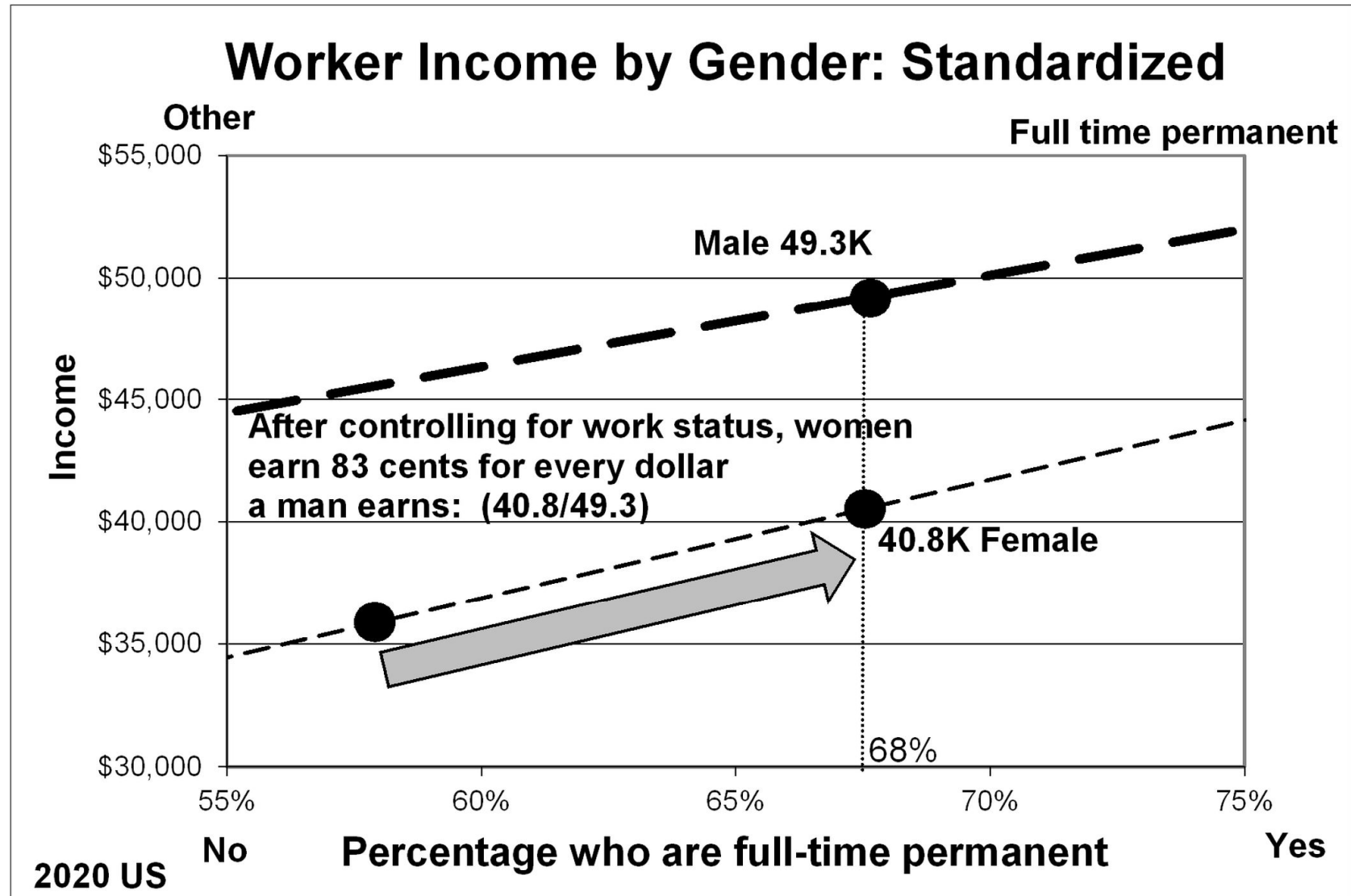
Difference in the “Mix”: Full-time Permanent vs Other



Crude Comparison: Mixed-Fruit Comparison



Standardization: Both Groups the Same 'Mix'



Male-Female Income Gap: Arithmetically

Individual Income by Gender and Work Status			Pctg who are		
2020	Workers	Col %	FT/Perm	Other	FT/Perm
Male	\$64,200	100%	\$79,800	30,900	68%
Female	46,600	73%	73,200	10,100	58%
Difference	17,600	27%	6,600	20,800	
$\text{\$46,600} = .58 * 73,200 + (1 - .58) * 10,100$					
FT/Perm: Full-time permanent					

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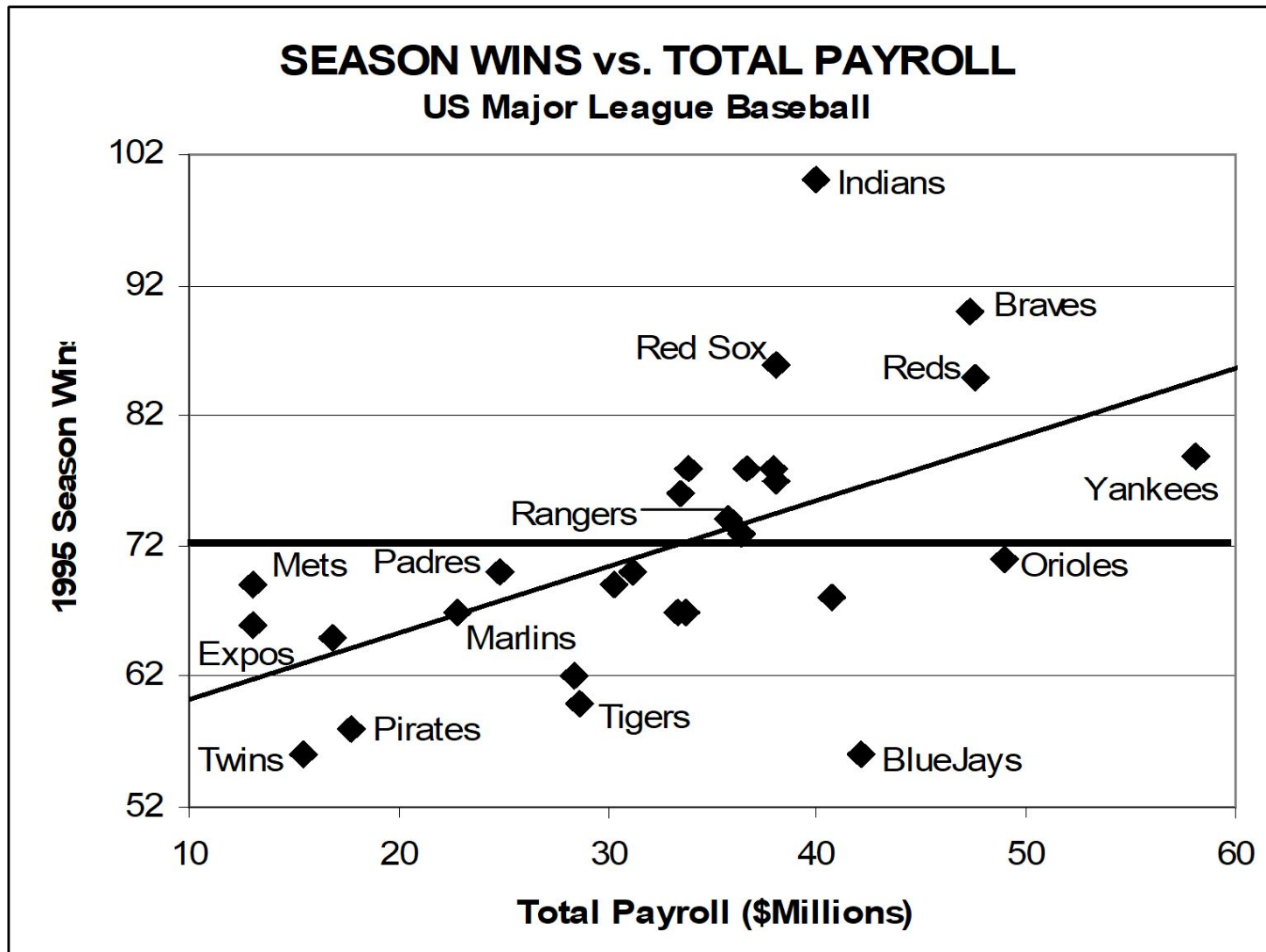
Mean Income by Gender and Work Status			Pctg who are			Worker Income	
2020	Workers	Col %	FT/Perm	Other	FT/Perm	Adjusted	Col %
Male	\$64,200	100%	\$79,800	30,900	68%	\$64,200	100%
Female	46,600	73%	73,200	10,100	58%	53,100	83%
Difference	17,600	27%	6,600	20,800		11,100	17%

Apply male percentage (68%) to females. $\$53,100 = .68 * 73,200 + (1-.68) * 10,100$

Assume mean incomes are 1.3 times medians. Controlling for work eliminates 37% of gap

Table A7: www.census.gov/library/publications/2021/demo/p60-273.html

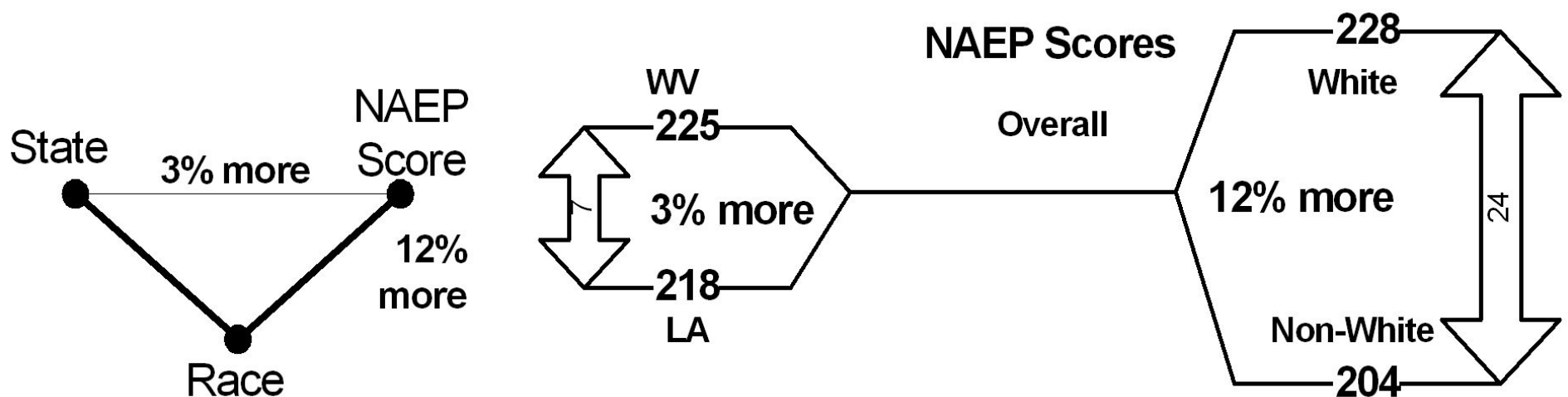
Standardizing: Quantitative Confounder



Cornfield Conditions

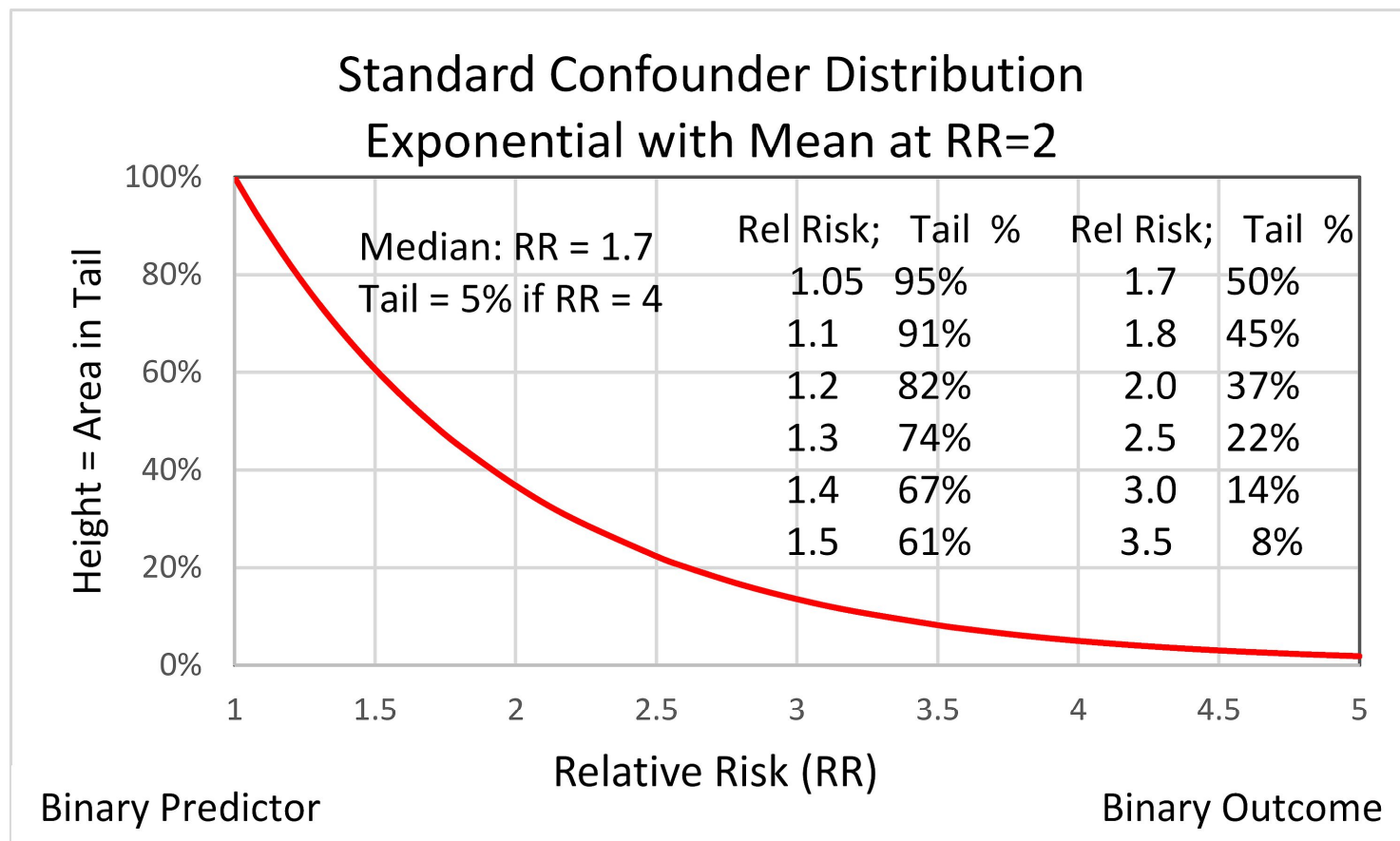
2000 NAEP Math Scores: 4th Graders			
Total	State	Blacks	Whites
218	Louisiana	204	230
225	W. Virginia	203	226

Distribution	
Blacks	Whites
47%	53%
5%	95%



Standard Confounder Distribution

Assume that unknown or unmeasured confounders are exponentially distributed with mean relative risk of 2.



“Confounder-Significant”

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Confounder	----- Minimum Effect Size* -----				
Resistance	Negligible	Weak	Moderate	Strong	Significant
RR	1	1.5	2	3	4
% increase	0%	50%	100%	200%	300%
% decrease	0%	33%	50%	67%	75%

*cross-sectional studies: two-group comparison as scientific evidence for causation

Standard confounder: Schield (2019). Confounding and Cornfield: Back to the Future

Students' Statistical Needs: 2025: New Era for Stat Ed

2025 is the first year that most students are using LLM-AI.

- AI can calculate answers to most homework problems.
- AI can answer essay questions.

Statistics instruction must change.

Statistics instructors must adopt the 2016 GAISE guidelines.

- More focus on ideas; less on calculations
- More focus on observational studies, less on RCT.
- More focus on confounding; less on statistical significance
- More focus on causation; less on prediction

Conclusion

Statistics should offer two intro courses:

- Population inference: 1st course in stat major or minor
- Statistical Literacy: Satisfies QR requirement in Gen. Ed.

All college graduates should know:

- That a comparison of ratios can be confounded.
- What it means to “control for” something quantitatively.
- That confounding is a big problem in modern studies.

Bibliography

Schield (2018). *Confounding and Cornfield: Back to the Future*. ICOTS. Kyoto, Japan.

www.StatLit.org/pdf/2018-Schield-ICOTS.pdf

Schield (2022). *Disparity vs. Discrimination*.

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Schield publications:

- by topic: www.StatLit.org/Schield-Pubs.htm
- by year published:
www.researchgate.net/profile/Milo-Schield

V1 Observational Causation: Adjusting Crude Comparisons 1

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V1 Observational Causation: Adjusting Crude Comparisons 2

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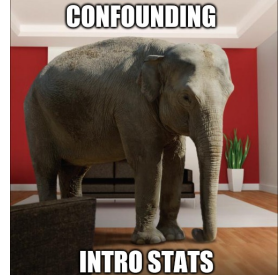
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of appearances in body of paper

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V1 Observational Causation: Adjusting Crude Comparisons 9

Statistical Literacy: Foundations of Causal Inference

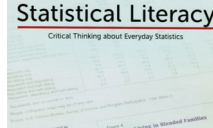
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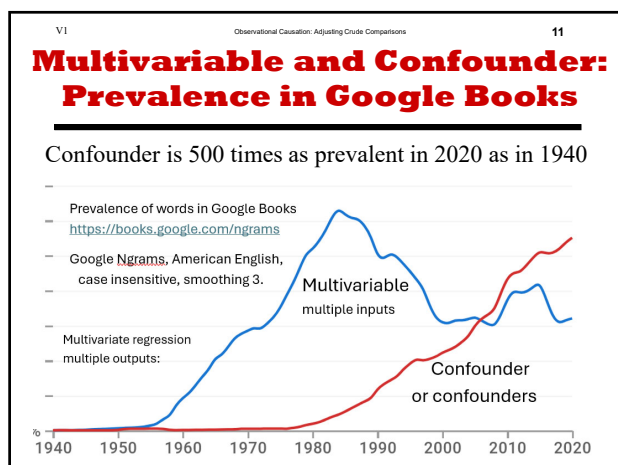
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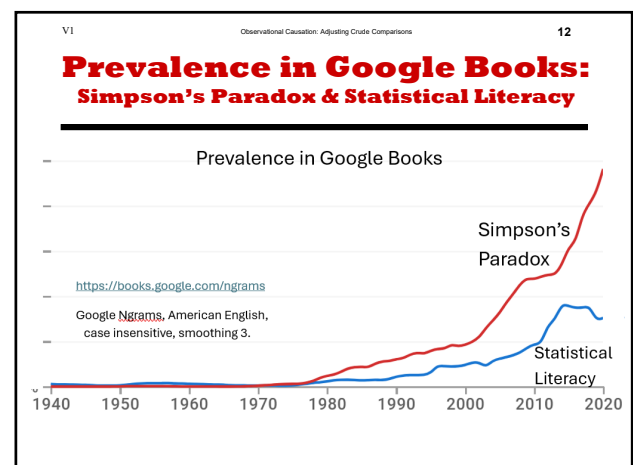
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V1 Observational Causation: Adjusting Crude Comparisons 13

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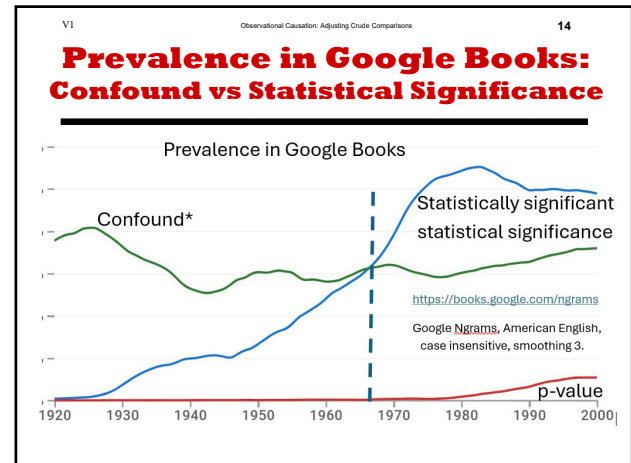
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Underlying problem: setting a single value for statistical significance regardless of the implausibility of the research hypothesis violates Carl Sagan's ECRREE: "extraordinary claims require extraordinary evidence."

ASA noted that statisticians often use "... alternative approaches including ... Bayesian methods ..."

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Textbook Claim #1 Needing Confirmation

If the test result is positive (statistically significant) and research hypothesis is more likely than not to be true, then we are 95% confident that the Null is false (RH is true).

RESULT	RH = False		RH = True	ALL
	Null=True	Null=False		
NEGATIVE	95	5		100
POSITIVE	5	95		100
ALL	100	100		200

RH=Research Hypothesis 50% chance (RH=True)
If sensitivity=specificity = 95%, PPV=95%

Note: Fisher's agricultural experiments were cases where the research hypothesis was *more likely than not* to be true.

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V1 Observational Causation: Adjusting Crude Comparisons 18

Textbook Claim #2 Needing Confirmation

If research hypothesis is unlikely to be true (1%) and if sensitivity=specificity=1-chance (RH=True), then the Positive Predictive Value (PPV) = 50%

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Statistical Significance Conclusion

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Using Ratios to Control for Proportional Influences

Compare counts: Students expect California (40M people) to have more unemployed **workers** than Wyoming (0.6M).

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Comparisons of counts can be influenced by the size of the group in comparing ratios.

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OLS Regression "Bottom Line"

OLS regression is limited. Easily misused.
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Plus: That's why OLS regression is taught in a 2nd course.
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Confounders Solutions: Physical and Mental

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Controlled Study	Ratios	Logistic Modeling
Study Design	Standardization	Multivariate
----- Hypothetical thinking -----		

Consider study design

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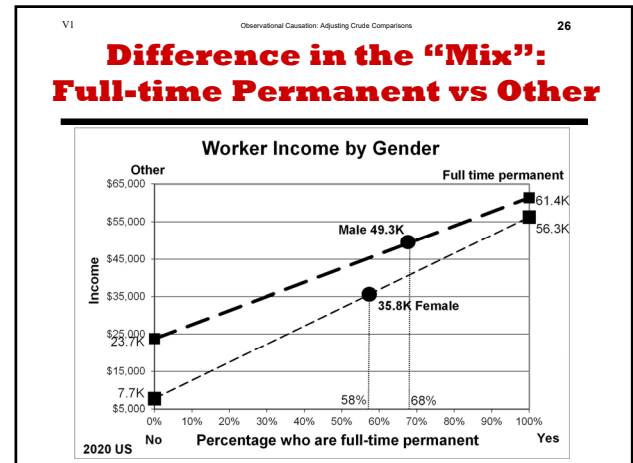
V1 Observational Causation: Adjusting Crude Comparisons 25

Types of Studies: Hard Science vs. Soft Science

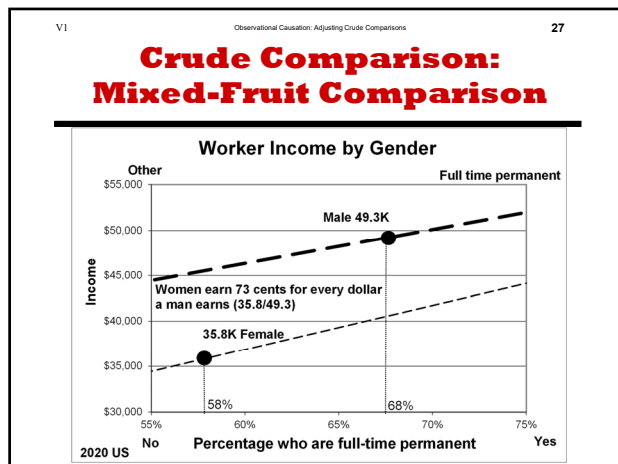
Hard Science	Soft Science
Experiment Researcher assigns/intervenes	Observational Researcher observes/responds
Repeatable: Scientific experiment	Movie: Longitudinal Study
Randomized: Clinical trial	Snapshot: Cross-sectional study
Other: Quasi-Experiment	Someone says: Anecdotal

Soft science is more vulnerable to being influenced by confounders than hard science.

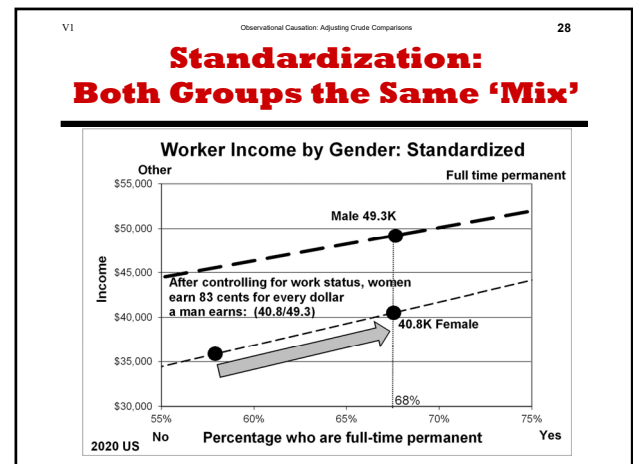
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FT/Perm: Full-time permanent

$\$46,600 = .58 * 73,200 + (1 - .58) * 10,100$

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Male-Female Income Gap: Arithmetically

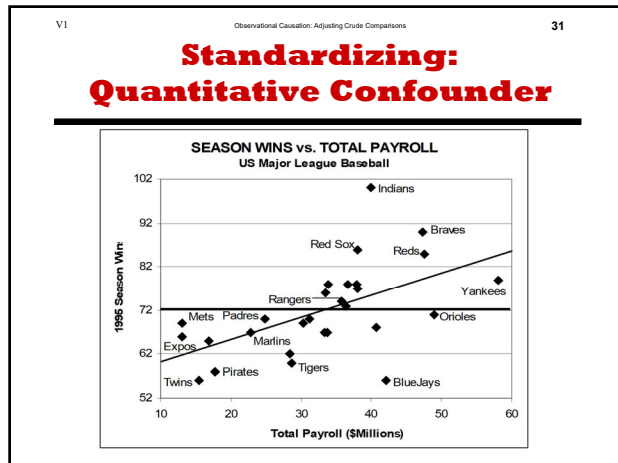
Mean Income by Gender and Work Status			Pctg who are			Worker Income	
2020	Workers	Col %	FT/Perm	Other	FT/Perm	Adjusted	Col %
Male	\$64,200	100%	\$79,800	30,900	68%	\$64,200	100%
Female	46,600	73%	73,200	10,100	58%	53,100	83%
Difference	17,600	27%	6,600	20,800		11,100	17%

Apply male percentage (68%) to females. $\$53,100 = .68 * 73,200 + (1 - .68) * 10,100$

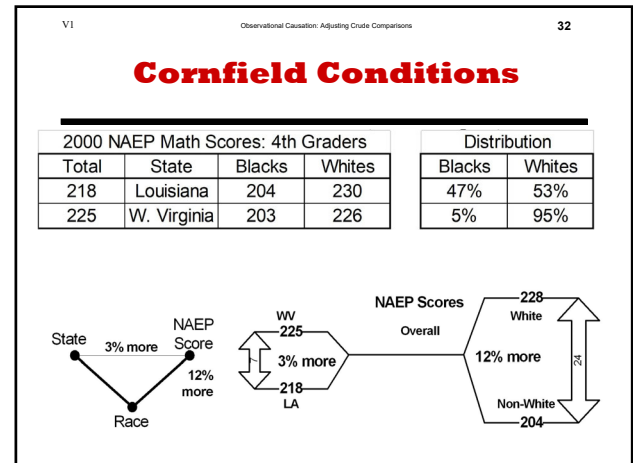
Assume mean incomes are 1.3 times medians. Controlling for work eliminates 37% of gap

Table A7: www.census.gov/library/publications/2021/demo/p60-273.html

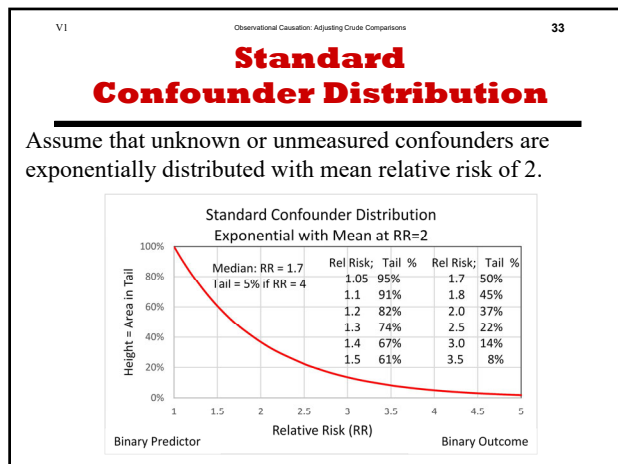
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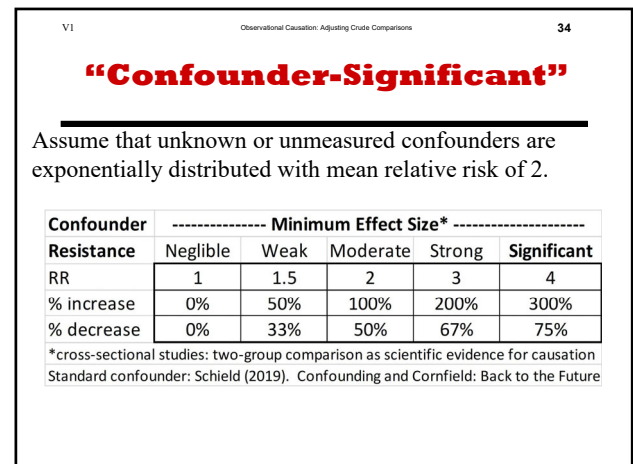
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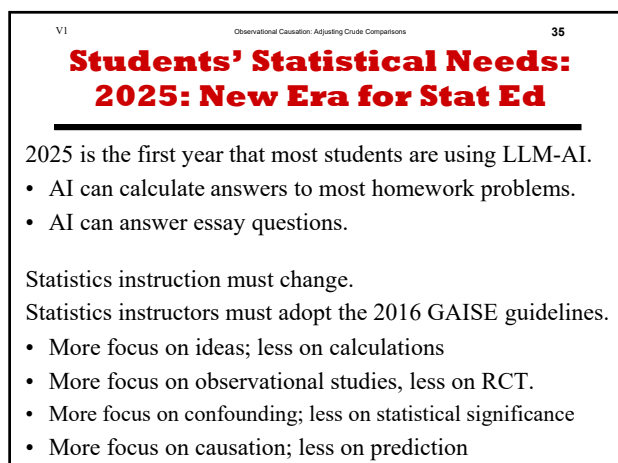
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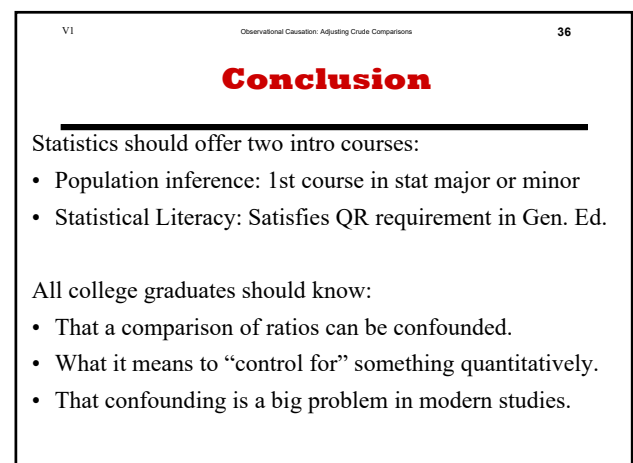
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VI

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