V1

2

4

6

Confounding: A Big Idea

Milo Schield, Augsburg College Member: International Statistical Institute US Rep: International Statistical Literacy Project Director, W. M. Keck Statistical Literacy Project VP. National Numeracy Network Editor: www.StatLit.org

August 1, 2016 www.StatLit.org/pdf/2016-Schield-ASA-Slides.pdf

Core Concepts in Intro Stats

V1

V1

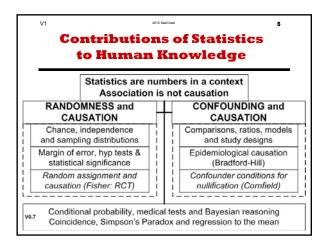
1

McKenzie (2004): Survey of Educators Goodall@RSS (2007) Big Ideas in Statistics Garfield & Ben Zvi (2008): Big Ideas of Statistics Gould-Miller-Peck (2012). *Five Big Ideas* Blitzstein@Harvard (2013): *10 Big Ideas Stat110* Stigler (2016): *Seven pillars of statistical wisdom*

V1 2015 StatChat2 3 Ambiguity of "Importance" **Classifying Important Ideas** Logically Socially Cognitively Topic {Common} Good/Bad* Claim Fallacy Contribution or catastrophe Topic (randomness) or a claim: ME ~ 1/sqrt(n)This paper focuses on claims or relationships having substantial social or cognitive consequences.

2015 SMICTAR2 1A: Fallacies

- 1. Confusion of the inverse: P(A|B) = P(B|A)
- 2. Conjunction fallacy: P(A&B) > P(A)
- 3. P(A&B | C) > P(A | B&C): Three-factor fallacy
- 4. Individual fallacy
- 5. Ecological fallacy
- 6. Simpson's Paradox



#2A: Butterfly Fallacy

One should never trust a statistical association generated by an observational study.

An unknown or unmeasured confounder – regardless of size (a small as a butterfly) – can nullify or reverse an observed association.

V1

8

10

Smoking Causes Cancer: Fisher's Argument

Observational data: Smokers are **10 times** as likely to develop lung cancer as are non-smokers.

7

Some statisticians wanted to support the claim that smoking "caused" lung cancer.

Sir Ronald Fisher (1958) noted that "association was not causation" and that there was a difference (**factor of two**) in smoking preference between fraternal and identical twins.

Smoking Causes Cancer: Cornfield's Reply

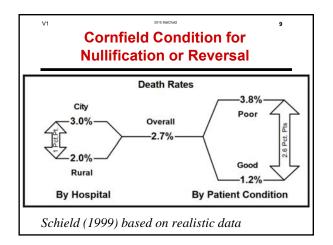
Cornfield et al (1959) argued that to nullify or reverse the observed association, the relative risk of a confounder must exceed the relative risk of that association.

Fisher never replied.

V1

V1

"Cornfield's minimum effect size is as important to observational studies as is the use of randomized assignment to experimental studies." Schield (1999)

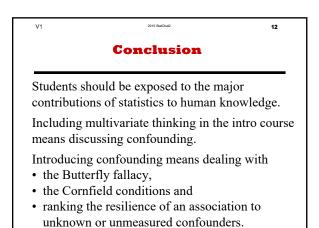


Confounder Distribution: Simple One-Parameter Model

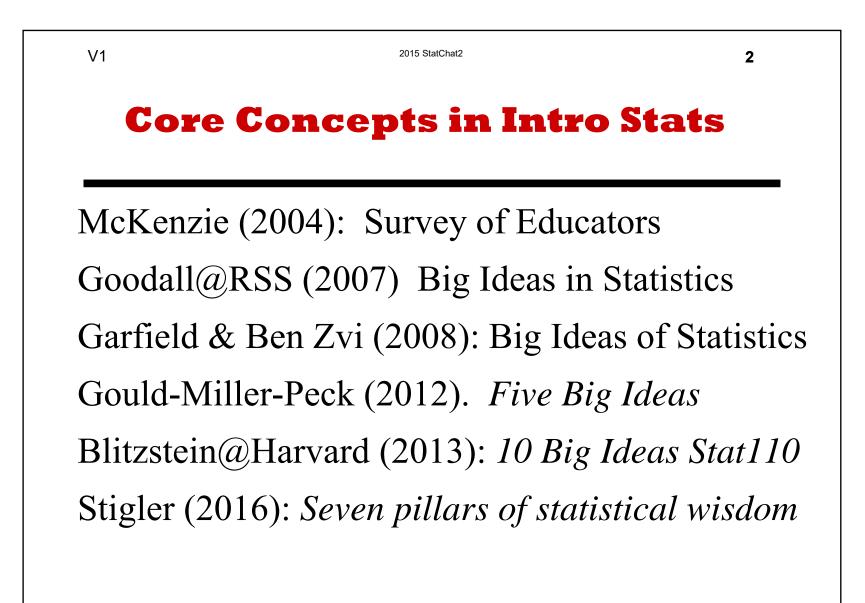
How to deal with unknown or unmeasured confounders? Assume: RR of confounders is distributed exponentially with a minimum RR of one and a mean RR of two.

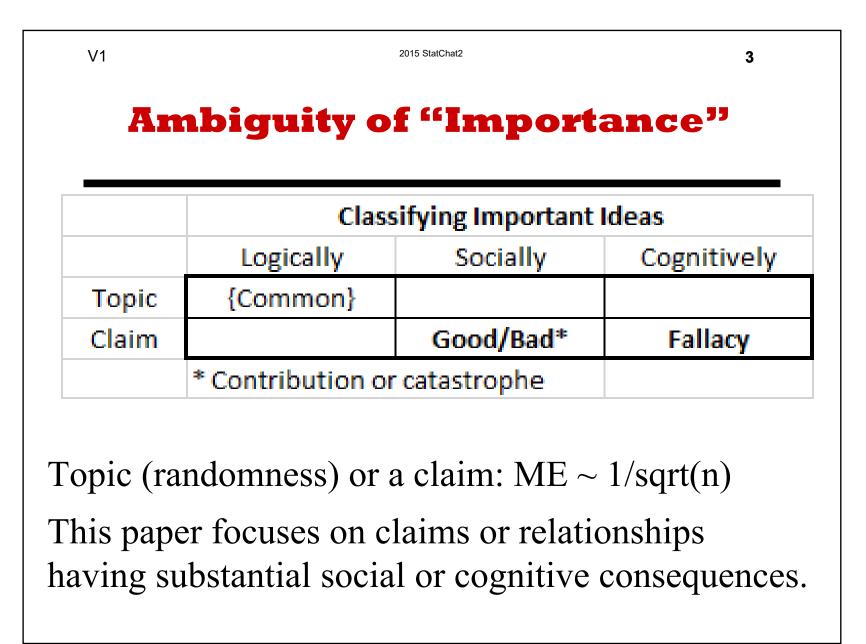
CDF		RR-1	CDF
0.00		0	0.00
0.63		1	0.63
0.86		2	0.86
0.95		3	0.95
0.98		4	0.98
	0.00 0.63 0.86 0.95	0.00 0.63 0.86 0.95	0.00 0 0.63 1 0.86 2 0.95 3

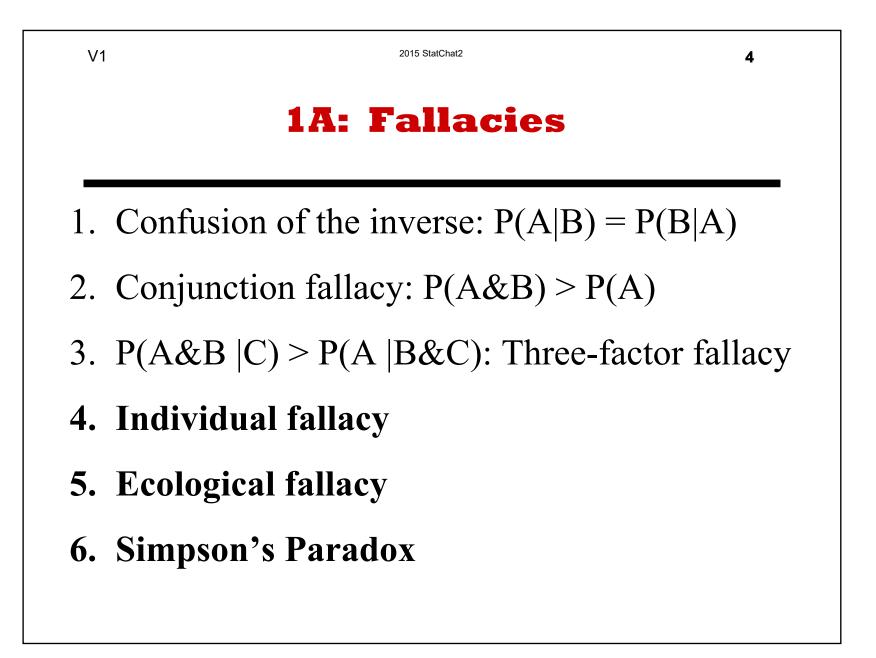
V1 Effect Sizes: Relative Risk 95% Confounder Resistant: Exp20				
	RR of Health Outcome	Women	Men	
Obese vs.	Type 2 Diabetes	12.7	5.2	
non-Obese	Hyptertension	4.2	2.6	
	Heart attack	3.2	1.5	
	Colon Cancer	2.7	3.0	
	Angina	1.8	1.8	
	Gall-bladder	1.8	1.8	
	Ovarian Cancer	1.7		
	Osteoarthritis	1.4	1.9	
	Stroke	1.3	1.3	
	Average	3.4	2.4	

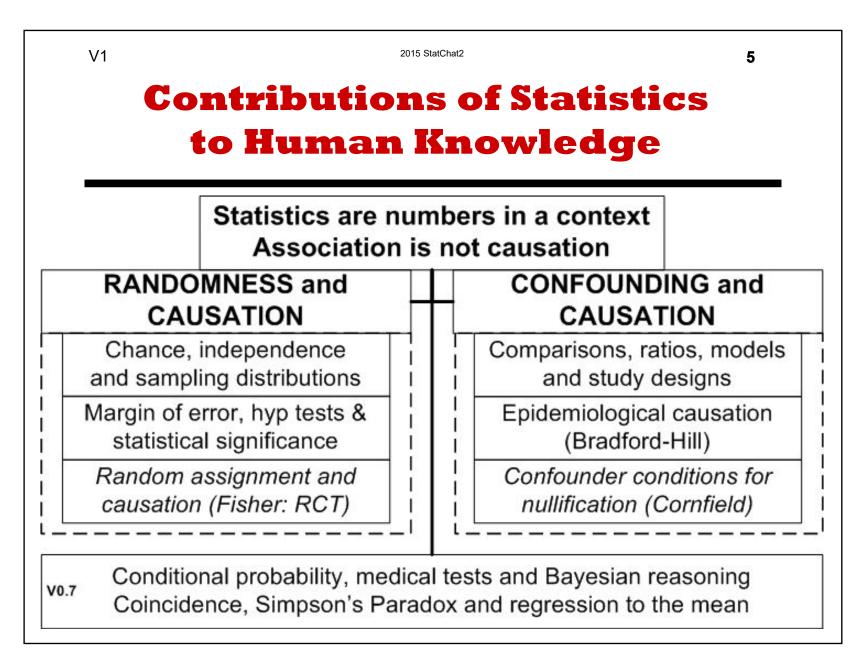


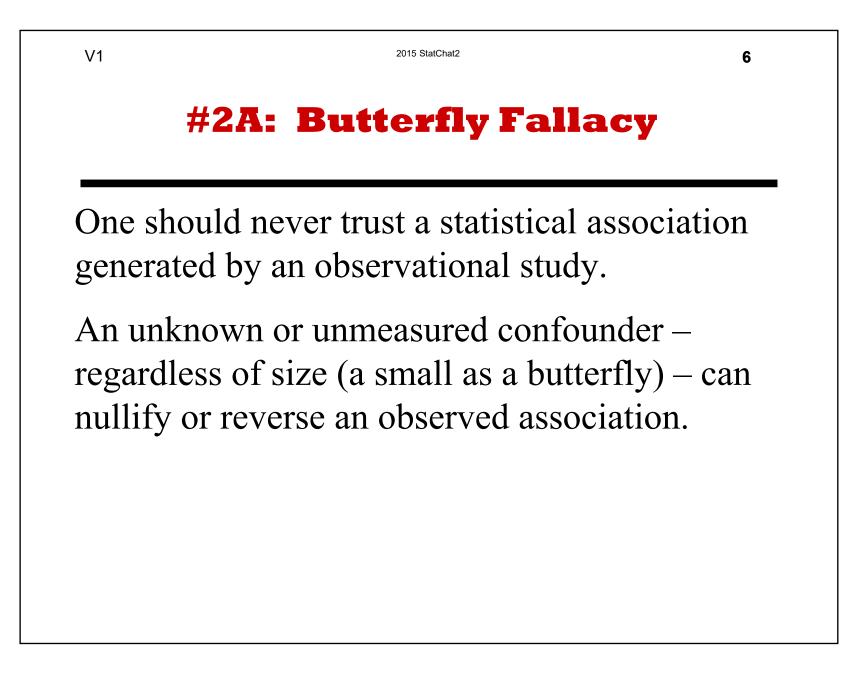


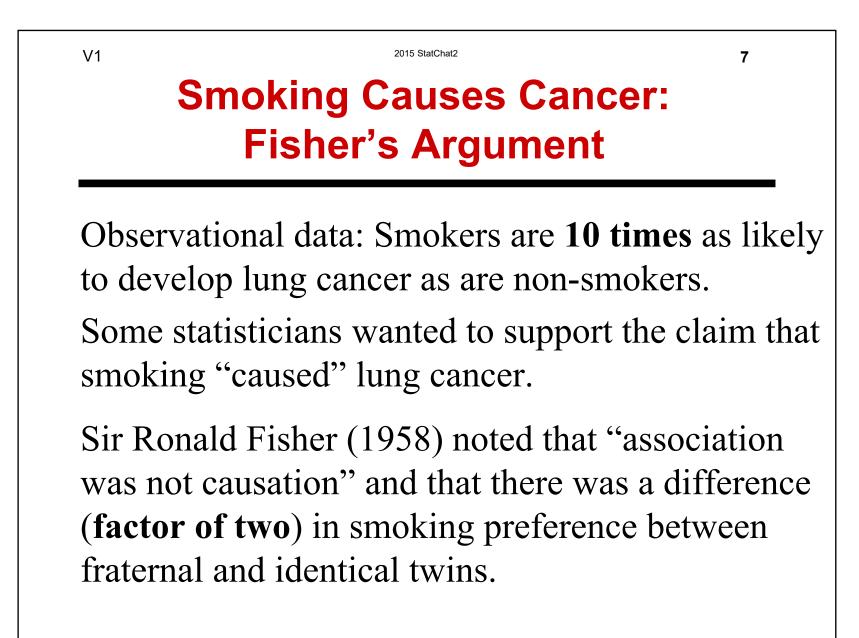


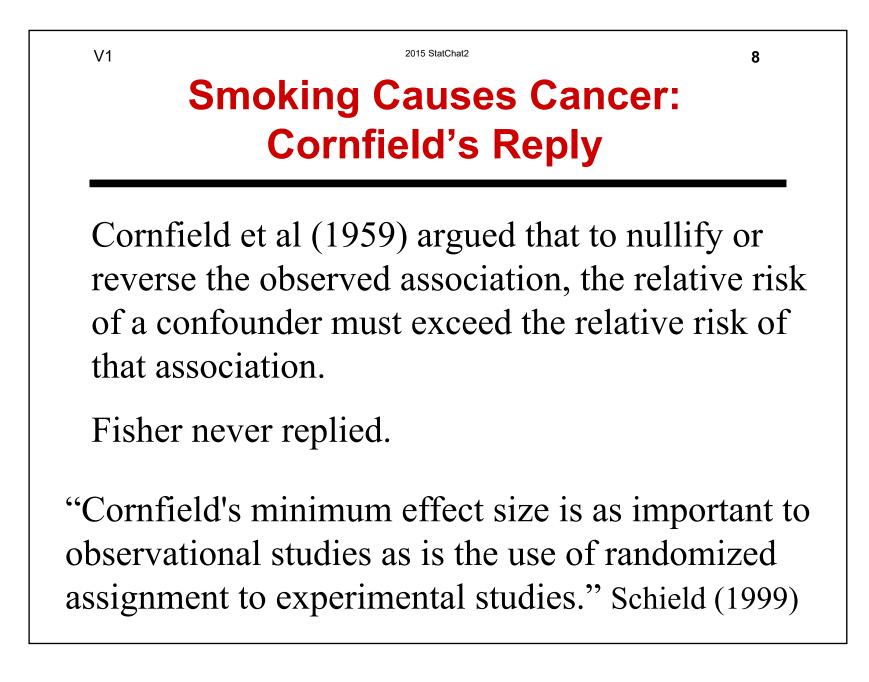


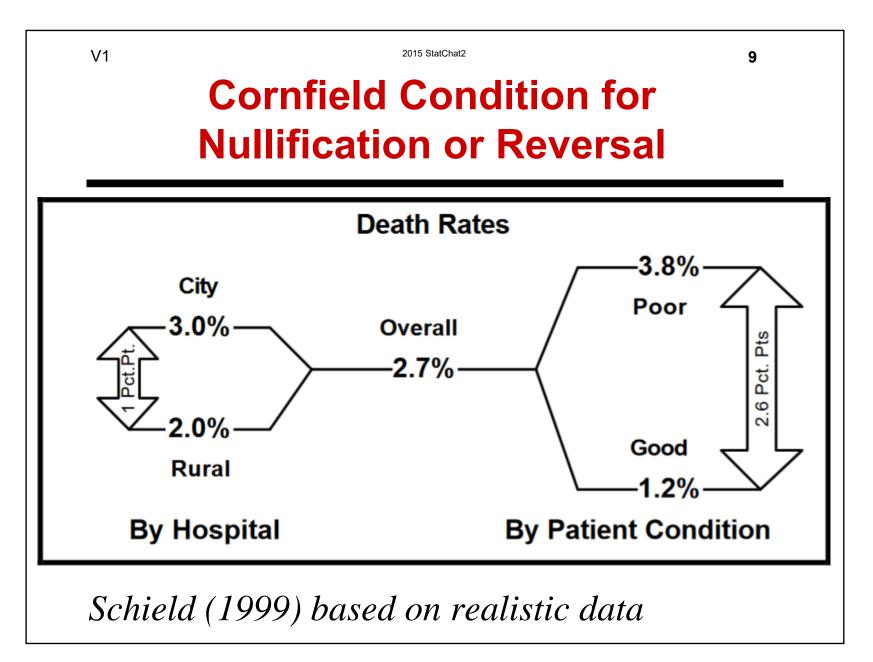












V1 2015 Stat2 10 Confounder Distribution: Simple One-Parameter Model						
How to deal with unknown or unmeasured confounders? Assume: RR of confounders is distributed exponentially with a minimum RR of one and a mean RR of two.						
RR	CDF		RR-1	CDF		
1	0.00		0	0.00		
2	0.63		1	0.63		
3	0.86		2	0.86		
4	0.95		3	0.95		
5	0.98		4	0.98		

V1 2015 2012 11 Effect Sizes: Relative Risk 95% Confounder Resistant: Exp20					
Obese vs. non-Obese	RR of Health Outcome	Women	Men		
	Type 2 Diabetes	12.7	5.2		
	Hyptertension	4.2	2.6		
	Heart attack	3.2	1.5		
	Colon Cancer	2.7	3.0		
	Angina	1.8	1.8		
	Gall-bladder	1.8	1.8		
	Ovarian Cancer	1.7			
	Osteoarthritis	1.4	1.9		
	Stroke	1.3	1.3		
	Average	3.4	2.4		

