February 15, 2015

To the Judea Pearl Causality Prize Committee:

Committee members: Maya Petersen (University of California, Berkeley), Dennis Pearl (Ohio State University, CAUSE, co-chair), Judea Pearl (University of California, Los Angeles, co-chair), Felix Elwert (University of Wisconsin-Madison), Daniel Kaplan (Macalester College), Michael Posner (Villanova University) and Larry Wasserman (Carnegie Mellon University).

Nominee: Dr. Milo Schield, Professor of Business Administration at Augsburg College, Minneapolis, MN. He has written more than 65 papers on various aspects of association, causation and confounding. He is an elected member of the International Statistical Institute (ISI). He has developed teaching materials showing how a confounder can influence the size of a statistic, the size of a statistical association and the statistical significance of an association. His textbook and course are the result of his research, his teaching of introductory statistics, his teaching of critical thinking and an award by the W. M. Keck Foundation "to develop statistical literacy as an interdisciplinary curriculum."

Intended Audience: Undergraduates in non-quantitative disciplines (e.g., Humanities) taking their first course in statistics. Teaching undergraduates involves a radically different approach from teaching graduate students. Most undergraduates taking statistics do so because it is required. Their mathematical background may be limited and they may find algebraic notation off-putting. Nothing in their mathematical experience prepares them for the idea that statistics are different from numbers. Unlike numbers, statistics are collected, organized, summarized and presented in ways that are chosen to support a goal. Numbers aren't confounded, but statistics can be. All this is new to the typical undergraduate.

Nominated Work: Augsburg's undergraduate catalog course, Statistical Literacy (GST 200). This course uses statistical associations as evidence for causal connections. It distinguishes association from causation using ordinary English. It distinguishes confounding and mechanism (a causal mediator): a distinction that students find difficult to understand. It includes elements from epidemiology (Cornfield conditions), from advanced statistics and Econometrics I (fully saturated multivariate OLS regression), from Econometrics 2 (directed path diagrams) and from Schield's research (extended Cornfield conditions). This courses use minimal algebra so it is accessible to students in non-quantitative majors.

Nominating a course is quite different from nominating a textbook. This course has a number of unique components that are carefully designed to work together in support of the overall goal: helping students evaluate the ability (or inability) of a statistical association to support a causal connection. This course has been taught entirely online for the past three years. It has four components:

- 1. The first component is the textbook: *Statistical Literacy 2011: Seeing the Story Behind the Statistics*. This textbook has been in use for over 10 years and has had several revisions. See Appendix B for the chapter highlights and associated page numbers for those topics closely related to this award.
- 2. The second component involves the PowerPoint slides for each chapter and the associated audio by the teacher. The URL's for these materials are also shown in Appendix B.
- 3. The third component involves Moodle exercises. Moodle is a web-based course management system. Students work 30-50 exercises online in the course. Each exercise involves 10 to 20 questions typically multiple choice with two tries. This allows students to get immediate feedback on their strengths and weaknesses. Appendix C highlights those exercises involving causality.

4. The fourth component involves Odyssey challenges. Odyssey is a unique online forum. Every participant is anonymous as is every transaction. All participants grade each other. This gives every participant immediate feedback from at least four reviewers. By including a forum in this course, students must present arguments for their conclusions. Students are given two challenges per week. They must generate their response and must review and grade at least four responses provided by their peers. Evaluating arguments is a new activity for most students. The goal is to help students to evaluate their own arguments before they are submitted. Appendix D highlights some challenges that focus specifically on association, causation and confounding.

Since many elements of this course are new and unique, student feedback is considered essential. Appendix E provides student comments on their understanding (or lack thereof) on association, causation, confounding and mechanism. Appendix F includes a bibliography of Schield's papers organized by topic. Appendix G is a bibliography of related papers by others.

Rationale for nomination: The traditional undergraduate introductory statistics course simply states that "Association is not causation" and focuses primarily on statistical significance. But if undergraduates are to appreciate path analysis and structural equation modeling, they need a much broader background than this association-causation truism and statistical significance.

By showing how a confounder can influence the size of a statistic, the size of a statistical association, and the statistical significance of that association, this introductory course links together two key topics: variation and confounding. These two topics provide the foundation for advanced study on causation.

Teaching Teachers: Seeing how all these items fit together in the course is best understood by having teachers take the course. Only then can they fully understand why certain things are done as they are. But some prospective teachers may not have time to take a full-semester course.

The 11-Steps in in Appendix A have been designed to help prospective teachers understand the materials without taking the entire course. Going through those notes is not an easy task either. Prospective teachers are advised to first review the components of the course: Moodle exercises in Appendix C and Odyssey challenges in Appendix D.

Teachers must recognize that students are expected to *calculate* the numerical effect that controlling for a confounder will have on a statistic and on a statistical association. As such, this course is definitely a numeracy course – and not just a big-ideas course.

With that background, prospective teachers will be better prepared to assimilate the material provided in Appendix A. Once the steps in Appendix A have been reviewed, the following summary may be helpful.

Alignment of Teaching Materials with the Causality Award Criteria: After reviewing the Teacher Notes and the materials in the various appendices, the following summarizes the features of this course and textbook to the 2015 Causality Award Criteria.

- 1. The extent to which the material submitted equips students with skills needed for effective causal reasoning. These include:
 - 1a. Ability to correctly classify problems, assumptions, and claims into two distinct categories: causal vs. associational. RESPONSE: See Step 1 in Appendix B.
 - 1b. Ability to take a given causal problem and articulate in some mathematical language (e.g., counterfactuals, equations, or graphs) both the target quantity to be estimated and the

- assumptions one is prepared to make (and defend) to facilitate a solution.

 RESPONSE: Students articulate a causal problem in words and in triangle path diagrams.

 See Step 2 in Appendix B. In this context, a "solution" involves showing that the observed association will resist nullification or reversal by confounders below a certain minimum size.
- 1c. Ability to determine, in simple cases, whether control for covariates is needed for estimating the target quantity, what covariates need be controlled, what the resulting estimand is, and how it can be estimated using the observed data.
 RESPONSE: In doing Odyssey challenges (Appendix D), students engage in hypothetical thinking to envision plausible confounders: factors which can cause a change in the outcome and are associated with the predictor. They must ensure that these third factors are not mechanisms: factors on the causal path between the predictor and the outcome. As shown in Moodle exercise C3K1, K2 and K3, the students work problems using data to calculate what happens to a statistical association when the influence of a binary confounder is controlled for.
- 1d. Ability to take a simple scenario (or model), determine whether it has statistically testable implications, and apply data to test the assumed scenario.
 RESPONSE: See Moodle exercise C3K1, K2 or K3, where students work problems using data to see what happens when the influence of a binary confounder is taken into account.
- The extent to which the submitted material assists statistics instructors in gaining an understanding of the basics of causal inference (as outlined in 1a-d) and prepares them to teach these basics in undergraduate and lower-division graduate classes in statistics.

 RESPONSE: These materials have been used online by students and in training instructors at other colleges to teach using these materials. Each chapter is summarized using PowerPoint slides and a short audio reviewing the highlights. All materials are available online and have been taught over a dozen times. Teachers have participated in the same Odyssey challenges as the students each grading and being graded by the other. By seeing how confounding influences statistical significance in chapter 7, statistical educators can present their students with a very Big Idea without involving a second course in statistics. Prospective teachers are invited to take Schield's online course which is offered each summer. See www.StatLit.org/Schield.htm

SUMMARY: This course has taken over 10 years to develop. It is based on feedback from over a dozen instructors and student tutors at Augsburg. It has been taken by over a thousand students and by almost a dozen faculty. Statistical educators who have taught the introductory inference course need extensive training and support in order to shift to a course that focuses on causation and confounding. This course provides that support for first-time teachers.

This course provides students and teachers with a foundation for understanding how a statistical association can be used to support the presence of a causal connection. It covers the key elements needed to understand the relationship between association and causation in observational studies. It does so with minimal mathematics, but it introduces some necessary conditions that are very important in evaluating the strength of evidence provided by a statistical association.

This undergraduate course does not involve any confirmatory test of a causal model. This undergraduate course focuses on exploratory causality: what factors should be taken into account in developing a meaningful model of the causality involved. It focuses on necessary conditions to nullify or reverse an observed association. But it provides the foundation needed to take on the advanced topics in a graduate course involving confirmatory causality.

And as a bonus, anecdotal evidence suggests that students find this critical-thinking course more valuable after taking it than they expected to before taking it.

Educating students on the relationship between association and causation in observational studies is not easy. It is much easier – and safer – to simply say: association is not causation. As mathematically-trained statistical educations, we know that this claim is to be interpreted deductively: association is not sufficient for causation. Adopting this book will require new terminology, new lessons, new exercises, new exams – and most importantly – a new style of teaching. Indeed, the McKenzie (2004) survey of the top 30 statistical concepts did not even include confounding as a topic to be considered.

So why would anyone who has taught traditional statistics entertain using a book which highlights the relationship between association and causation? Here are some reasons:

- 1. Students see less value in the traditional introductory statistics course after completing it than they did before they started. See Schau (2003) and Millar (2010).
- 2. Most of the students taking statistics are in majors that use statistical associations as evidence for causal connections in observational studies. These majors include Business, Sociology, Education, Economics and Social Work.
- 3. Preaching the "abstinence approach" (Don't use correlation as evidence for causation) is likely to fall on deaf ears. Our students know that many times correlation is a definite sign of direct causation (drinking hemlock is associated with dying, lightning is associated with thunder, the tides are associated with the position of the moon). So they will act on this basis. Sometimes they will be right: Shellfish should only be eaten in months containing the letter "R".
- 4. Students are going to see epidemiological thinking being used to support causation in public policy. See Wakeford and McElvenny (2007). Indeed they will see statistics like these: 395,000 deaths due to hypertension, 216,000 deaths due to obesity, 191,000 due to high blood sugar, 102,000 due to high salt intake, etc. Schield (2009). Those reading these statistics have no idea that these are based entirely on statistical associations. And they have no idea that they can be influenced by confounders.
- 5. Graduates of traditional courses can still be statistically illiterate. They've never dealt with confounding. They've never seen how ordinary English can be used to imply causation without asserting causation.
- 6. Anecdotal feedback suggests that students see more value in studying statistics after completing this causation-based course than after completing a traditional statistical inference course.

There are a number of steps that should be reviewed and understood in order to teach a course that focuses on using statistical associations as evidence for causal connections. Pages and Figures refer to the Statistical Literacy textbook which is outlined in Appendix B.

Step 1: Grammar of Association and Causation

Pages 19-25 in the textbook introduce association and causation. Pages 24 and 25 introduce the grammar of association and causation. Note the large number of words and phrases that are classified as "Between": implying causation but not asserting causation. See Schield and Raymond (2009)

Students need practice in distinguish association from causation. Pages 55-59 give practice stories. In Appendix C, Moodle exercises C1G and C1K give students immediate feedback on such matters.

Odyssey challenges often start by asking students to identify and distinguish the association from the causal claim. See Appendix D.

Step 2: Introducing Confounding, Path Diagrams, Common Causes and Mechanism

Figure 5 (Pages 26-27) and Table 1 (Pages 33-34) introduce confounding graphically and in a table.

Figures 3 and 4 introduce the first path diagram: the association (the dotted line) between a predictor and an outcome. Figures 9-14 (pages 26-29) introduce the three-body triangle diagrams. Using these triangle diagrams prepares students for more complex diagrams in Econometrics.

Common cause is introduced on page 36; mechanism is introduced on page 38.

Step 3: Students need practice in applying these ideas in various contexts

A survey of students found that most had never heard the words 'confounder', 'confounding' or 'mechanism'. See Appendix E. Of these terms, students have the most difficulty with mechanism. Yet, all-to-often what they propose as a confounder is actually a mechanism. Controlling for a mechanism (a third factor on the causal path between the predictor and outcome) essentially eliminates most – if not all – the association between the predictor and the outcome. Until students recognize the difference between a confounder and a mechanism, they cannot appreciate why controlling for a confounder is OK, but controlling for a mechanism is not.

By definition, a confounder is a factor related to the predictor and to the outcome that wasn't taken into account in forming the association. Typically, the confounder is not in the data. Getting students to imagine plausible confounders takes practice. Few – if any – quantitative courses have students think hypothetically about what could be a plausible confounder.

The Odyssey challenges (Appendix E) typically ask students

- to identify and distinguish association from causation.
- to think hypothetically about what confounder could plausibly have an influence on the association presented in the story.

Students need lots of practice to assimilate these new ideas into their long-term understanding.

Step 4: Understanding Association-Causation in Epidemiology

It is important for instructors to understand why epidemiology is different from statistics and to sensitize students to the use of epidemiological constructs in the everyday media.

- 1. Statisticians typically summarizes the strength of an association using the correlation coefficient whereas epidemiologists seldom if ever use that measure of association. Schield and Burnham (2002) review the relationship between phi and relative risk. They note that phi taken absolutely has a limited range in any 2x2 table with fixed margin counts, whereas a relative phi is linearly related to relative risk.
- 2. Epidemiologists are often successful in using statistical associations as evidence for causal connections because the outcome of an epidemic is unusual and readily identified (e.g., death or a rare disease or condition), there is often a single cause for the epidemic, and that single cause of the epidemic is typically necessary but not sufficient for the outcome. Statistics is typically used in very different situations. The outcome is not always unusual or readily identifiable, there is seldom a single cause, and none of the causes taken individually are necessary.
- 3. Epidemiologists use the "percentage attributable to" as a measure of association between a predictor and outcome. Epidemiologists use this measure of association to calculate the number

of outcome events that are attributable to the predictor. Page 239-244. Social scientists use these measures on a wide variety of outcomes. See Schield (2009, 2011).

Step 5: Understanding Various Ways of Controlling for Confounders

"The goal of a second course in statistics should not be the models for conducting multivariable statistical inference, but should instead be the concepts that underlie the motivation and utility of such models: namely, confounding and variability." Tintle et al (2013). This statement applies equally to any introductory course that focuses on using association as evidence for causation.

Many of the techniques used in experimental design have analogs in observational studies. Page 40 presents five techniques that can be used to control for potential confounders.

Step 6: Understanding how Study Design Controls for Confounders

Page 82-89 introduce various kinds of study design: experimental vs. observational, longitudinal vs. cross-sectional, and controlled vs. uncontrolled. Each kind of study design has different confounders that it either takes control of or controls for. Moodle exercises C2J and C2L (Appendix C) allow students to demonstrate their understanding of these terms.

Students have great difficulty accepting that a controlled study is any study involving two or more groups. See Moodle exercise C2M.

P 90-91 introduces random assignment as a way of statistically controlling for all pre-existing confounders. Students have difficulty applying this in everyday situations. See Odyssey Challenge #1 in Appendix D.

Pages 91-97 present various experiments and studies, and explore the kinds of confounders that a given type of study can control for.

Step 7: Understanding how to apply OLS Regression in an Introductory Course.

By its nature, confounding requires three variables: predictor, outcome and confounder. Modelling this using OLS regression requires at least three variables – and this requires multivariate regression. Multivariate least-squares regression requires dealing with a number of assumptions. This is normally covered in a second statistics course – or an introductory Econometric course – since there isn't time for this in the introductory inference course.

But when the predictor and confounder are both binary, almost all the necessary conditions are automatically satisfied (the model is fully-saturated) and it can be taught in the introductory course. See Schield and Burnham (2003) and Schield (2008)

Step 8: Understanding how Controlling for a Confounder can reverse or nullify an Association.

Pages 142-143 (Tables 13-16) show how controlling for the size of the group can increase, decrease, nullify or reverse an association between two totals. This introduces students to the *per* numbers: per capita and per cent. Students are not surprised that taking into account the size of a group can change the association between totals after converting these totals to rates or ratios. But this review sets the stage for dealing with averages.

Page 144-150 show that taking into account a confounder can influence an average. This is demonstrated for cross-sectional data (Table 17) and for longitudinal data (Table 18). Students find these cases most surprising. They find it hard to accept that a confounder can influence a statistic that has already taken into account the size of a group.

But if students can't work problems, if it won't be on a quiz, test or final, then students are unlikely to really understand what is happening. This has been a perennial problem in previous courses that focus on big ideas. This textbook is arguably the first to provide a way that students – even those who are algebraically challenged – can work problems that calculate the influence of a confounder on a statistic and on a statistical association. The secret is to deal with predictors and confounders that are binary.

Page 145-146 introduce weighted averages using arithmetic. Pages 147-150 introduce weighted averages involving a graphical technique first publicized by Wainer (2002). This technique was presented in more detail by Schield (2004a) in the AAC&U *Peer Review*, at an international IASE roundtable by Schield (2004b) and in the ASA *Stats* magazine by Schield (2006).

Peter Holmes said that seeing Simpson's paradox displayed by this diagram was the first time he really understood Simpson's paradox.

While most students see how a difference in mix can confound an association using this diagram, only a third will use this diagram in working problems. Another third will use the arithmetic of a weighted average, while the rest will use some form of proportional reasoning.

Step 9: Countering the Butterfly Problem with Cornfield's Condition

After seeing how easily a statistic or a statistical association is influenced by even a small confounder (the Butterfly problem), some students declare they will never trust a statistic or a statistical association. This is not a desirable outcome. Statistical educators are not likely to teach this material if it brings our discipline into disrepute.

Statistical educators must spend time reviewing the discussion between Cornfield and Fisher on whether smoking caused lung cancer. Statistical educators must understand Cornfield's necessary condition for nullifying or reversing an association. Only then can they inform students that statistics cannot be nullified or reversed by any confounder – only by those that are larger than the observed association. See Schield (1999b) and Schield and Burnham (2003).

Page 158-159 present Cornfield's necessary condition in a graphical format. Students find this much simpler to understand and to apply than the standardization approach to weighted averages. And in the long run, this will be more helpful.

Pages 170-173 finish the chapter by showing how larger effect sizes have more resistance to confounder influence.

Steps 8 and 9 Repeated when the Outcome is measured using Percentages

Page 308-323 repeat steps 8 and 9 when the outcome is measured using percentages. Educators may wonder why percentages are treated separately from averages. In our experience, students find it difficult to read the weighted-average diagrams when both the horizontal and vertical axis involve percentages. Presenting cases where the y-axis involves averages first seems preferable.

This section includes several situations in which taking into account a confounder nullifies or reverses the observed association. It also recounts the historic argument between Fisher and Cornfield on whether smoking caused cancer. See Schield (1999b) for more details on that argument.

Step 10. Schield's Necessary Condition

Cornfield identified a necessary condition between the confounder and the outcome of interest. Schield and Burnham (2004) identified a similar necessary condition between the confounder and the predictor.

Page 312 presents Schield's necessary condition in a graphical format. For more detail on confounder resistance, see Schield and Burnham (2004) and Schield (2008).

Step 11. Confounder Influence on Statistical Significance

Pages 362-366 show how controlling for a confounder can influence statistical significance using the presence -- or lack – of overlap in 95% confidence intervals. This section is critical. It unifies variation and confounding: the two big topics in statistical literacy. See Moodle exercises C7J and C7L in Appendix C.

Appendix B: Causality Content in Schield's Textbook

CHAPTER	R 1:
14-19	Structure of arguments (reasons/conclusion); CARE: classifying influences
19-24	Distinction between association and causation
24-25	Grammatical signs of association and causation.
26-30	Case studies on distinguishing association from causation.
33-34	Context: spurious association and confounding.
35	Triangle diagrams (directed arrows) [Triangle diagram]
36-37	Common cause [Triangle diagrams]
38	Mechanism: related factor on the predictor-outcome pathway.[Diagram]
39	Influence of confounding in arguments. [Triangle diagram]
55-59	Stories where students practice distinguishing cause from association.
СНАРТЕ	R 2:
80-81	Controlling for confounder can influence* an association.
82-89	Confounder can be controlled by study design.
90-91	Confounders can be statistically <i>controlled for</i> by random assignment [Diagram]
91-94	Analyzes experiments
95	Analyzing the kind of study in cases
96	Distinguishing "control of" from "control for".
97	Benefits of various study designs
СНАРТЕР	R 3: Page 164-195
142-143	Show how controlling for size can influence* an association.
144-145	Show "Simpson's paradox". [Triangle diagram]
145-151	Weighted averages show influence of a binary confounder [Triangle diagram]
152-157	2 ND example of confounding. [Triangle diagram]
157-158	Percentage "explained by" controlling for a confounder.
158-159	First necessary condition for nullification or reversal [Triangle diagram]
161	Wording that indicates control for a possible confounder.
162	Ways of controlling for confounders.
163-164	Examples of change after controlling for related factors.
170-173	Effect sizes and confounder resistance
СНАРТЕБ	R 4: DESCRIBING RATIOS
189-235	Controlling for the size of a group [Part-whole diagrams]
СНАРТЕБ	R 6: INTERPRETING RATIOS
308-323	Confounding and Simpson's paradox [Triangle diagram]
312	Second necessary condition for nullification or reversal.
329-330	Variable with the greater explanatory power
	R 7: RANDOMNESS AND CHANCE
362-366	Confounder influence on statistical significance
367-369	Confounder influence on cases attributed.

Influence*: this stands for "increase, decrease, nullify or reverse"

Appendix B: Causality Content in Schield's Textbook

Online access to textbook chapter materials: slides and associated audio commentary. Materials involving chapters 1, 2 and 3 are most relevant to the teaching of causation.

Introduction: Slides: www.statlit.org/pdf/2009StatLitTextHandoutCh0.pdf

	<u></u>	* *
Chapter 1:	Slides 6up Slides 1up Audio	www.statlit.org/pdf/2009StatLitTextHandoutCh1.pdf www.statlit.org/pdf/2009StatLitTextHandoutCh1-1up.pdf www.statlit.org/Audio/2009StatLitText-Overview-Ch1.mp3
Chapter 2:	Slides 6up Slides 1up Audio	www.statlit.org/pdf/2009StatLitTextHandoutCh2.pdf www.statlit.org/pdf/2009StatLitTextHandoutCh2-1up.pdf www.statlit.org/Audio/2009StatLitText-Overview-Ch2.mp3
Chapter 3:	Slides 6up Slides 1up Audio	www.statlit.org/pdf/2009StatLitTextHandoutCh3.pdf www.statlit.org/pdf/2009StatLitTextHandoutCh3-1up.pdf www.statlit.org/Audio/2009StatLitText-Overview-Ch3.mp3
Chapter 4:	Slides 6up Slides 1up Audio	www.statlit.org/pdf/2009StatLitTextHandoutCh4.pdf www.statlit.org/pdf/2009StatLitTextHandoutCh4-1up.pdf www.statlit.org/Audio/2009StatLitText-Overview-Ch4.mp3
Chapter 5:	Slides 6up Slides 1up Audio	www.statlit.org/pdf/2009StatLitTextHandoutCh5.pdf www.statlit.org/pdf/2009StatLitTextHandoutCh5-1up.pdf www.statlit.org/Audio/2009StatLitText-Overview-Ch5.mp3
Chapter 6:	Slides 6up Slides 1up Audio	www.statlit.org/pdf/2009StatLitTextHandoutCh6.pdf www.statlit.org/pdf/2009StatLitTextHandoutCh6-1up.pdf www.statlit.org/Audio/2009StatLitText-Overview-Ch6.mp3
Chapter 7:	Slides 6up Slides 1up Audio	www.statlit.org/pdf/2009StatLitTextHandoutCh7.pdf www.statlit.org/pdf/2009StatLitTextHandoutCh7-1up.pdf www.statlit.org/Audio/2009StatLitText-Overview-Ch7.mp3

Glossary of terms introduced in chapters 1 and 2.

www.statlit.org/CP/BK/SL2011/SLS2011-Glossary-Ch1+2.pdf

Equations, Glossary and Index

www.statlit.org/pdf/2009StatLitBook-TablesIndex.pdf

Appendix C: Causality Content in Moodle Exercises

Chapter 1: The Story behind the Story

C1G Association vs. Causation (ABC) in longitudinal studies

C1K Common Cause, Confounder or Mechanism

Chapter 2: Take CARE

C2J Longitudinal vs. Cross-SectionalC2L: Experiment vs. Observational studyC2M Study: Controlled vs. Uncontrolled

Chapter 3: Understanding Measurements

C3I Standardize Counts using Ratios

C3J Calculate "Percentage Explained by (Due To)"

C3K Standardize influence of a confounder on averages (1, 2, 3)

C3N Necessary conditions for nullification/reversal

Chapter 6: Understanding Ratios

C6I What percentage of original rate gap is explained by controlling for a confounder?

C6J Standardize influence of a confounder on outcome measured in percents (1, 2, 3).

C6N Necessary conditions for reversal of association

Chapter 7: Chance, Confidence and Statistical Significance

C7J Confounder influence on statistical significance involving percentages

C7L Confounder influence on statistical significance involving averages

The five exercises in bold are presented in detail on the following pages.

Appendix C: Causality Content in Moodle Exercise C3J

Calculate the percentage of the original difference that is explained by (due to) taking into account (controlling for) a confounder. Note: all data is hypothetical.

Suppose the average income before standardization is \$45,000 for men (\$35,000 for women). Suppose standardization takes into account having a permanent (year-round) vs. temporary job suppose the average income after standardization is \$42,000 for men (\$38,000 for women). What is the male-female income gap before standardization? 1. \$2,000 b. \$4,000 c. \$5,000 d. \$10,000	
What is the male-female income gap after standardization? a. \$2,000 b. \$4,000 c. \$5,000 d. \$10,000	B 100%
What is the influence of this standardization on this association? a. Reversed difference b. Decreased difference no reversal c. Increased difference no rev	B 83% ersal
What percentage of the original (unstandardized) difference is "explained by" or "due to" have bermanent job? Pick the closest answer. [A 25 a. Not applicable (need decrease without reversal) b. 20% c. 50% d. 60% e. 80% f] D 67%
Suppose the average income before standardization is \$45,000 for men (\$35,000 for women). Suppose standardization takes into account having a full-time (40 hours/week) vs. part-time journess the average income after standardization is \$42,000 for men (\$40,000 for women). What is the male-female income gap AFTER standardization? 1. \$2,000 b. \$4,000 c. \$5,000 d. \$10,000	
What is the influence of this standardization (controlling for full-time vs. part-time) on this as a Reversed difference b. Decreased difference no reversal c. Increased difference no reversal c.	B 83%
What percentage of the original (unstandardized) difference is "explained by" or "due to" wor ull time vs. part time? Select the closest answer. [B 42] Not applicable (need decrease without reversal) b. 20% c. 50% d. 80% e. 90%	rking %] D 58%
Suppose the average income before standardization is \$45,000 for men (\$35,000 for women). Suppose standardization takes into account having a full-time (40 hours/week) permanent (yea ob. Suppose the average income after standardization is \$40,000 for men (\$42,000 for women standardization) the male-female income gap AFTER standardization? 1. \$2,000 b. \$4,000 c. \$5,000 d. \$10,000	ar round)
What is the influence of this standardization (taking into account hours worked per week and worked per year) on this association? a. Reversed difference b. Decreased difference no reversal c. Increased difference no rev	A 67%
What percentage of the original (unstandardized) difference is "explained by" ("due to") have remanent job? Select the closest answer. [B 25 C 17] a. Not applicable (need decrease without reversal) b. 20% c. 50% d. 80% e. 90%	•

Appendix C: Causality Content in Moodle Exercise C3K1

Standardize the relationship between weight and gender where height is the confounder.

Assume that the outcome of interest is weight. The predictor of interest is gender (male or female). The confounder is height: short (below average) or tall (above average).

Average weights for men: 150 if short and 170 if tall. Average weights for women: 130 if short and 150 if tall.

Suppose that 75% of men are tall and 25% of women are tall – where tall means above average overall. Note: All numbers are hypothetical.

Answer these by reading the results of your graphing or by using proportions or algebra. Pick the answer that is closest to your answer. You can use the graph in the associated resource, but this is optional.

1.	What is the average weight for these men? a. 150 b. 155 c. 160 d. 165 e. 170	D 83%
2.	What is the average weight for these women? a. 130 b. 135 c. 140 d. 145 e. 150	B 92%
3.	What is the difference in their average weights? a. 0 b. 10 c. 20 d. 30 e. 40	D 83%
	Standardize the weights for men and women assuming that 50% of all students are tall. What is andardized average weight for these men? a. 150 b. 155 c. 160 d. 165 e. 170	s the C 83%
5.	What is the standardized average weight for these women? a. 130 b. 135 c. 140 d. 145 e. 150	C 83%
6.	What is the difference in their standardized average weights (in pounds)? a. 0 b. 10 c. 20 d. 30 e. 40	C 92%
7.	What does standardizing do to the original difference in mean weights? a. Increase w/o reverse b. Decrease without reversal c. Nullify d. Reverse (change the signal difference in mean weights?	B 83% gn)
8.	What percentage of the original difference is "explained by" the confounder (height)? a. 25% b. 33% c. 67% d. 75% e. Can't do for this case (Need decrease without revenuent: $(30-20)/30 = 0.33$	B 42% ersal)
9.	The average weight for these men is than that for these women. Pick the closest. a. 30 pounds less b. 20# less c. 10# less d. 10# more e. 20# more f. 30# more.	F 67%
10	 After taking into account height, the average weight for these men is than that for the women. Pick the closest. a. 30 pounds less	se E 75%

Appendix C: Causal Materials in Moodle Exercise C6N

- 1) City Hospital has a 2 percentage point (60%) higher death rate than Rural Hospital. Patients in poor condition are 4.4 percentage points (230%) more likely to die than patients in good condition. City hospital patients are 1.5 percentage points (40%) more likely to be in poor condition than are rural hospital patients. Death is outcome, hospital is predictor and patient condition is the confounder. What necessary conditions for a reversal are present? Select one: a. #1 Outcome: CF > Predictor b. #2 Predictor: CF > Outcome c. Both d. Neither
- 2) City Hospital has a 2 percentage point (60%) higher death rate than Rural Hospital. Patients in poor condition are 1.9 percentage points (55%) more likely to die than patients in good condition. City hospital patients are 60 percentage points (200%) more likely to be in poor condition than are rural hospital patients. Death is outcome, hospital is predictor and patient condition is the confounder. What necessary conditions for a reversal are present? Select one: a. #1 Outcome: CF > Predictor b. #2 Predictor: CF > Outcome c. Both d. Neither
- 3) City Hospital has a 2 percentage point (60%) higher death rate than Rural Hospital. Patients in poor condition are 4.4 percentage points (230%) more likely to die than patients in good condition. City hospital patients are 60 percentage points (200%) more likely to be in poor condition than are rural hospital patients. Death is outcome, hospital is predictor and patient condition is the confounder. What necessary conditions for a reversal are present? Select one: a. #1 Outcome: CF > Predictor b. #2 Predictor: CF > Outcome c. Both d. Neither
- 4) City Hospital has a 2 percentage point (60%) higher death rate than Rural Hospital. Patients in poor condition are 1.9 percentage points (55%) more likely to die than patients in good condition. City hospital patients are 1.5 percentage points (40%) more likely to be in poor condition than are rural hospital patients. Death is outcome, hospital is predictor and patient condition is the confounder. What necessary conditions for a reversal are present? Select one: a. #1 Outcome: CF > Predictor b. #2 Predictor: CF > Outcome c. Both d. Neither
- 5) Murderers who are white are 1.7 percentage points (20%) more likely to get a death sentence than murderers who are black. Murderers who kill a white are 8.6 percentage points (160%) more likely to get a death sentence than are murderers who kill a black. Murderers who are white are 56 percentage points (147%) more likely to kill a white than are murderers who are black. Getting a death sentence is the outcome, the race of the murderer is the predictor and the race of the victim is the confounder. What necessary conditions for a reversal are present? Select one: a. #1 Outcome: CF > Predictor b. #2 Predictor: CF > Outcome c. Both d. Neither
- 6) Murderers who are white are 1.7 percentage points (20%) more likely to get a death sentence than murderers who are black. Murderers who kill a white are 1.6 percentage points (16%) more likely to get a death sentence than are murderers who kill a black. Murderers who are white are 56 percentage points (147%) more likely to kill a white than are murderers who are black. Getting a death sentence is the outcome, the race of the murderer is the predictor and the race of the victim is the confounder. What necessary conditions for a reversal are present? Select one: a. #1 Outcome: CF > Predictor b. #2 Predictor: CF > Outcome c. Both d. Neither

Appendix C: Causal Materials in Moodle Exercise C6N

- 7) Murderers who are white are 7 percentage points (200%) more likely to get a death sentence than murderers who are black. Murderers who kill a white are 8.6 percentage points (160%) more likely to get a death sentence than are murderers who kill a black. Murderers who are white are 5 percentage points (147%) more likely to kill a white than are murderers who are black. Getting a death sentence is the outcome, the race of the murderer is the predictor and the race of the victim is the confounder. What necessary conditions for a reversal are present? Select one: a. #1 Outcome: CF > Predictor b. #2 Predictor: CF > Outcome c. Both d. Neither
- 8) The renewal rate for History magazine was 13 percentage points (26%) higher in February than in January. The renewal rate for History magazine was 55 percentage points (270%) more for Direct sales than for Agency sales. Subscriptions due were 12 percentage points (20%) more prevalent in February than in January. Renewal is the outcome of interest, month is the predictor and type of sales/subscriptions is the confounder. What necessary conditions for a reversal are present? Select one:
- a. #1 Outcome: CF > Predictor
- b. #2 Predictor: CF > Outcome
- c. Both
- d. Neither
- 9) The renewal rate for History magazine was 13 percentage points (26%) higher in February than in January. The renewal rate for History magazine was 11 percentage points (21%) more for Direct sales than for Agency sales. Subscriptions due were 36 percentage points (66%) more prevalent in February than in January. Renewal is the outcome of interest, month is the predictor and type of sales/subscriptions is the confounder. What necessary conditions for a reversal are present? Select one:
- a. #1 Outcome: CF > Predictor
- b. #2 Predictor: CF > Outcome
- c. Both
- d. Neither
- 10) The renewal rate for History magazine was 13 percentage points (26%) higher in February than in January. The renewal rate for History magazine was 11 percentage points (21%) more for Direct sales than for Agency sales. Subscriptions due were 12 percentage points (20%) more prevalent in February than in January. Renewal is the outcome of interest, month is the predictor and type of sales/subscriptions is the confounder. What necessary conditions for a reversal are present? Select one:
- a. #1 Outcome: CF > Predictor
- b. #2 Predictor: CF > Outcome
- c. Both
- d. Neither

Appendix C: Causal Materials in Moodle Exercise C7J

Moodle C7J Pick the closest answer.

- 1. New problem. Suppose that 100 randomly-sampled male college students, 20 have a regular part-time job. Among 100 randomly-sampled female college students, 15 have a regular part-time job.
- 1. What is the conservative Margin of Error with 95% confidence for each group?

a. 0.8% b. 1% c. 8% d. 10% e. 18%

D 80%

2. What is the estimated percentage of male college students who have a regular part-time job?

a. 2% b. 10% c. 20% d. 25% e. 50%

C 80%

3. What is the lower end of the conservative 95% confidence interval for men?

a. 10% b. 16.02% c. 16.2% d. 19% e. 19.9%

A 80%

4. What is the upper end of the conservative 95% confidence interval for women?

a. 15.1% b. 18% c. 18.8% d. 25% e.30%

D 60%

- 5. In estimating the percentage who work, do the conservative 95% confidence intervals for men and women overlap?

 a. Yes

 b. No

 A 80%
- 6. Is the difference in the percentage who work between men and women statistically significant?

a. Yes b. No B 80%

- 7. Assume the same size sample for both groups. What is the minimum sample size required to make the estimated difference statistically significant? E.g., make the allowable margin of error no more than half the difference between the two sample proportions. Use the conservative approach for the margin of error. Pick the closest answer.
- a. less than the actual number b. 144 c. 225 d. 400 e. 1600

E 20%

- 8. New problem. Suppose that among 400 randomly-sampled male college students, 40 have a regular part-time jobs. Among 400 randomly-sampled female college students, 29 have a regular part-time jobs. What is the conservative Margin of Error with 95% confidence for each group? 1/v400 = 0.05 = 5%.
- a. 0.5% b. 1% c. 5% d. 10% e. 40%

C 20%

- 9. Is the difference in the percentage who work between men and women statistically significant?
- a. Yes b. No B 40%
- 10. Assume the same size sample for both groups. What sample size is required to make the estimated difference statistically significant? E.g., Make the allowable margin of error no more than half the difference between the two sample proportions.
- a. less than the actual number b. 225 c. 800 d. 900 e. 1,600 f. 6,400

E 0%

Appendix C: Causal Materials in Moodle Exercise C7L

Moodle C7L GST 200

The average time worked per week is 12 hours for 25 randomly-sampled men (10 hours for 25 randomly-sampled women). The standard deviation is 3 hours per week for each randomly-sampled group.

- 1. What is the 95% margin of error for each group? Pick the closest number.
- a. 0.2 hours b. 0.6 hours c. 1 hour d. 1.2 hrs e. 6 hrs
- 2. What is the best estimate of the average number of hours worked for all the men in the population from which the sample was taken? Pick the closest number.
- a. 9 hrs b. 12 hrs c. 12.03 hrs d. 12.3 hrs e. 15 hours
- 3. What is the lower left end of the 95% confidence interval for men? Pick the closest number.
- a. 6 hrs b. 10.8 hrs c. 11.2 hrs d. 11.92 hrs e. 13.2 hrs

What is the upper right end of the 95% confidence interval for women? Pick the closest number.

- a. .8 hrs b. 10.2 hrs c. 11.2 hrs d. 11.8 hrs e. 16 hrs
- 5. Do these two 95% confidence intervals overlap?
- a. Yes b. No
- 6. In estimating the average number of hours worked per week, what is the estimated difference between college men and women? Pick the closest number.
- a. 0.2 hours b. 0.8 hours c. 2 hours d. 3.2 hours e. 4 hours
- 7. Is this difference in average hours worked per week statistically significant with 95% confidence?
- a. Yes b. No
- 8. Assuming the same-size sample for each group, what is the minimum-size sample needed so these confidence intervals would not overlap? E.g., make the allowable margin of error no more than half the distance between the two sample averages. Pick the closest number.
- a. Smaller than actual number (confidence intervals already separated)
- b. 36 c. 39 d. 64 e. 100

New Problem. The average time worked per week is 13 hours for 100 randomly-sampled men (10 hours for 100 randomly-sampled women). The standard deviation is 6 hours per week for each randomly-selected group.

- 9. Is this difference in average hours worked per week statistically significant with 95% confidence?
- a. Yes b. No
- 10. Assuming the same-size sample for each group, what is the minimum-size sample needed so these confidence intervals (see the previous question) would not overlap? E.g., make the allowable margin of error no more than half the distance between the two sample averages. Pick the closest number.
- a. Smaller than actual number (confidence intervals already separated)
- b. 144 c. 225 d. 360 e. 400

Appendix D: Causal Content in Odyssey Challenges

Odyssey is an online forum. Everyone is anonymous; everyone grades everyone. Students give reasoned answers to various challenges. The program is described here in Schield (2014). Odyssey: A Journey to Lifelong Statistical Literacy. Copy at www.statlit.org/pdf/2014-Schield-ICOTS.pdf

Challenge #1: Bigger Tableware Helps Widen Waistlines

Read the article at www.StatLit.org/CP/2006-Bigger-Tableware-Helps-Widen-Waistlines.pdf

- 1) What kind of study is this? Experiment vs. observational study? Longitudinal vs. cross-sectional?
- 2) Are there any plausible confounders that didn't take into account? If so, indicate how they would confound the association.
- 3) Are there any opportunities for bias in this study? If so, what are they?
- 4) Evaluate the quality of the argument. How strongly do these statistics support the point of the story?

Challenge #2: Spanking Lowers IQ

Article at www.StatLit.org/CP/2009-Children-who-get-Spanked-have-lower-IQ.pdf

- (1) Is this an experiment or an observational study? Is this a longitudinal or cross-sectional study?
- (2) What idea seems most easily influenced by assembly? Give your reasons.
- (3) Identify a plausible confounder that might influence the results. Indicate how this confounder could influence the outcome and how it could be connected with the predictor.
- (4) If there is bias, what types of bias might influence this association?

Challenge #3: Pot Arrests More Likely for Blacks

Copy at www.StatLit.org/CP/2013-Pot-Arrests-More-Likely-For-Blacks.pdf

- 1. Critique this comparison: Marijuana arrest rates for black people were 3.73 times greater than those for white people nationally in 2010.
- 2. One explanation for this disparity in arrest rates is racial discrimination. What are two alternate explanations mentioned in the story? What is another explanation that is not mentioned in the story?
- 3. Of all the states in the US, Iowa has the highest ratio of Black vs white arrest rates for marijuana possession (Minnesota is 2nd). Give at least one plausible explanation.

Challenge#4: College students: Later classes, lower grades

Story at www.StatLit.org/CP/2011-College-Students-Sleep-Longer-But-Drink-More.pdf

- 1. Context: What is a plausible confounder for the association between class-start time and grades? Indicate how confounder relates to outcome and predictor. If none, give a reason why.
- 2. Assembly: What two categories or measures are most susceptible to assembly?
- 3. Error/bias: What kinds of bias are most likely or plausible in this study?
- 4. How strong is the argument that eliminating early-morning classes would improve students' grades?

Challenge #5: Study puts Sponge Bob in Hot Water

Story at www.StatLit.org/CP/2011-Study-puts-Sponge-Bob-in-Hot-Water.pdf

- 1. What kind of study is this?
- 2. What is the causal claim? Was this explicitly stated, implied or never stated?
- 3. Identify two plausible confounders -- or say why this can't be done in this case.
- 5. How strong are these statistics as evidence in supporting the related causal claims?

Appendix E: Students Comments on Confounding

Students taking Schield's course this spring were asked the following question:

QUESTION: How familiar were you with association, causation, confounding and mechanism before taking this class? If you were, where did you encounter or use it/them?

- #1: I was familiar with association and causation which I understand as something we use to explain if two variables have any relationship with each other. However for confounding and mechanism I have never heard or knew about it.
- #5: I had almost no idea what any of those words meant until I took this course
- #6: Before I started taking MIS264, I had never tried to understand or learned about association, causation, or confounders/confounding. I knew the words "association" and "causation" but I did not understand them in relation to analyzing data or understanding graphs, or experiments. I had known of the word "mechanism" but I was not understanding it in relation to understanding and analyzing data. I knew that a mechanism was a way of getting from step-A to step-B but I did not think of it in regards to association and causation.
- #8: I am familiar and know the definition of association, causation and mechanism. I encounter and use association, causation, and mechanism before and use them for previous class work. However I was not familiar with confounding until taking this class.
- #9: Before taking this class I wasn't very informed with confounding and mechanism before. I personally learned association and causation in psychology before this class but not in a statistical way. We learned that you are just comparing two variables for association. Causation in a sense where it can affect the outcome. It's the cause of something. I wasn't familiar with confounding or mechanism. I just never really thought about them before.
- #11: Out of 4 concepts, I was only familiar with association and causation and understood the basic difference between them: things that are associated doesn't mean that they cause one another to happen (I learned this in my Economics classes when we analyzed the law of demand and what influences the demand level). I did not understand the confounding and mechanism concepts before this class.
- #12: I was somewhat familiar with the term association. I had only really heard it before when people would say "association does not equal causation" usually when losing an argument where statistics are brought in (by "people" it's usually my brother). I was somewhat familiar with the concept and heard it used in the typical example of an increase in drowning, and an increase in ice cream sales within the same time period does not mean ice cream causes drowning. I was not really familiar with context before this class. I only know a vague version of context in the sense of what we were comparing a statistic to. I usually would use context in comparing death rates in time. The famous statistic of people dying in 19th century Europe had a life expectancy of around 25 for males, including infant deaths of course. I was really fascinated by the idea of a statistic being useless when not compared against another equal statistic. I was not familiar with confounding or mechanism before this course.
- #13: I really wasn't too familiar with any of any those concepts. I suppose I could say I mentally related things to causation and association but that is about it.

Appendix E: Students Comments on Confounding

#14: Before starting this class I knew the basic meaning of association and causation but didn't really know how they would be used in the statistical parts of the world. I knew that things were associated with each other through connection and that causes can give reason for why things happen. I had never heard of confounders before and never used the word mechanism when relating to stats

#15: Before taking this class, I had no idea what association, causation, confounding and mechanism were. I knew what they meant, but not in a statistical mind set. I knew association was something is known to something else. I thought that mechanism meant to fix something.

#18: I was only familiar with the association concept. Moreover, I don't think it was the same as we learn it now. Whenever I think of a song, or hear a song, it is associated with a certain moment in my life. With other concepts I was not familiar at all.

QUESTION: How valuable/useful do you think these concepts [association, causation, confounding and mechanism] will be in your future?

#1: I think it is important to understand the difference between association and causation, along with confounding. It will help us determine and analyze the data that we may be collecting in the business world. Therefore, knowing these terms will help us to analyze and interpret the data to be successful in our job. For Mechanisms, I don't understand it as much therefore I do not know the significance of it.

#5: They will be very helpful in the business world to be able to manipulate graphs and use them to my advantage

#6: I think that the concepts we are learning in this class are extremely helpful and important in the business world. Some of the things are a bit hard to wrap my head around, but I think, overall, I am understanding what we are learning. I think it is very important to understand association vs. causation, because in our society today we jump to conclusions so quickly, believe almost everything we read, and make silly decisions based off of very little factual information/evidence. I think that everyone should be looking deeper into the information they are given, to make better decisions in the long run.

#8: I think these concept will be useful in the future as working in the corporation when looking at stats on sale or understanding why sales are the way they are during a specific time of the year. In addition, these concept will be useful to understanding why the world is the way they are due to the stats and observation in the world.

#9: I think that all four of these concepts are very important to know and understand. We are business majors and having this course is going to help understand the core of statistics. We need to recognize what is behind the data and information we see day to day. This can help us and prepare us for our future. It's a interesting approach to the class and I like that its broken down in part and not overwhelming all at once.

#11: I think these concepts will definitely help me in terms of analyzing data, especially in the business field. From what I have seen, the business world is a bunch of confusing elements that are related in a way and what we have to do is to find the right ones. Besides that, I also think that these will help me in my daily life and the way I think about everything (for examples, association is definitely not causation; this will prevent me from making unnecessary mistakes).

Appendix E: Students Comments on Confounding

#12: I use these tools more than I thought, to be honest. I was intimidated about this course, and thought I knew really well how to decipher statistics, and I was wrong in this assumption. I'm realizing it's not enough simply to question these sources, but how the information is presented from these sources. I can see this in the odyssey series as we see many examples of studies that are not done very "truthfully", it feels very satisfying to look at a news report and have true critical thinking skills. This course, thus far has given me more confidence in my ability to interpret information, I currently use the mindset of a statistic being a polished, crafted gem, rather than a rock we find randomly. I think these concepts will be very useful in my future for whatever path I follow, as it enables me to assess data in much more lucid and in depth manner, than previous to this course.

#13: I think they are very useful in the way I will continue to interpret statistics and studies. They provide a unique way to look at results and show that there are many different factors that play a part in studies than we can see.

#14: I think that these four words and reasoning's could be very important in the future if I am in the business world doing stats projects. People use causation and association every day and I will continue to use these every day of my life. The other two are just deeper thoughts that I don't think will be used much as I get older unless I specifically need to try to find and label them. I think that people can be fine without using these words and thinking's because it is just a deeper level of thinking that involves more reasoning.

#15: They will be useful in a business stand point. Being able to explain a problem, or just a description of a situations I can use these words.

#18: These concepts will help me succeed in my business decision making. I will have to take CARE whenever an information is presented to me. C for context, A for assembly, R for Randomness, and E for Error. These concepts trigger us to think critically and make sense out of everything. I get very excited and challenged whenever we have to take CARE and break down the problem into details and discuss, I think this will be extremely beneficial in my future careers.

Appendix F: Bibliography of Schield's Causality Papers and Slides

- Relevant papers: General
- Schield, Milo (2004a). Statistical Literacy and Liberal Education at Augsburg College. *Peer Review*, Sept. 2004, 7-14. AAC&U. See www.StatLit.org/pdf/2004SchieldAACU.pdf
- Schield, Milo (2004b). Statistical Literacy Curriculum Design. IASE *Curricular Development in Statistics Education* Roundtable, pp. 54-74. Sweden. See www.statLit.org/pdf/2004SchieldIASE.pdf
- Schield, Milo (2010b). Assessing Statistical Literacy: TAKE CARE in *Assessment Methods in Statistical Education*. Edited by Bidgood, Hunt and Joliffe. Wiley Publishers, Ch. 11, p. 133-152. Excerpts at www.statlit.org/pdf/2010SchieldExcerptsAssessingStatisticalLiteracy.pdf
- Schield, Milo (2014). Two Big Ideas for Teaching Big Data: Coincidence and Confounding. ECOTS invited webinar. Copy at www.StatLit.org/pdf/2014-Schield-ECOTS.pdf
- Relevant papers: Linguistics
- Schield, M. and R. Raymond (2009). Distinguishing Association from Causation in Media Headlines. *ASA Proceedings*. [CD-ROM] P. 371-4385. See www.StatLit.org/pdf/2009SchieldRaymondASA.pdf
- Relevant papers: Epidemiology and Cornfield's Condition
- Schield, M. (1999b). Simpson's Paradox and Cornfield's Conditions, 1999 ASA Proceedings of Section on Statistical Education, pp. 106-111. See www.StatLit.org/pdf/1999SchieldASA.pdf.
- Schield, M. (2009). Confound Those Speculative Statistics. *2009 ASA Proceedings of Section on Statistical Education*. [CD-ROM]. P. 4255-4266. www.StatLit.org/pdf/2009SchieldASA.pdf
- Schield, M. (2011). Epidemiological Models and Spotty Statistics. The International Statistical Institute (ISI) Conference. Dublin. See www.StatLit.org/pdf/2011SchieldISI.pdf
- Relevant papers: Regression using an OLS Model with a binary predictor and binary confounder
- Schield, M. (2006). Understanding Confounding from Lurking Variables using Graphs. *ASA STATS Magazine*, fall 2006. pp. 14-18. See www.StatLit.org/pdf/2006SchieldSTATS.pdf.
- Schield, M, and T. Burnham (2002). Algebraic Relations between Relative Risk, Phi and Measures of Necessity and Sufficiency in 2x2 Tables. ASA Proceedings of Section on Statistical Education. 3089 3094. www.StatLit.org/pdf/2002SchieldBurnhamASA.pdf
- Schield, M. and T. Burnham (2003). Confounder-induced Spuriosity and Reversal: Algebraic Conditions for Binary Data Using a Non-Interactive Model. *ASA Proceedings of Section on Statistical Education*. {P. 3690-3697. See www.StatLit.org/pdf/2003SchieldBurnhamASA.pdf
- Schield, M. and T. Burnham (2004). Confounder Resistance and Confounder Intervals for a Binary Confounder. *2004 ASA Proceedings of the Section on Statistical Education*. [CD-ROM], 2781 2788. See www.statlit.org/pdf/2004SchieldBurnhamASA.pdf.
- **Brochures and Slides on Confounding**
- Schield, M. (2001). Statistical Literacy brochure: Critical thinking about statistics as evidence in arguments. See at www.statlit.org/pdf/2002-Augsburg-StatLit-Brochure.pdf
- Schield, M. (2008). Binary Confounders as Mathematical Objects –European Conference on Methodology at Oviedo, Spain. Slides www.statlit.org/pdf/2008SchieldBurnhamECOM6up.pdf

Appendix G: Bibliography of Causality Papers by Others

- McKenzie, John, Jr. (2004). Conveying the Core Concepts. ASA Section on Statistical Education, pp. Copy at www.statlit.org/pdf/2004McKenzieASA.pdf
- Millar, Anne (2010). Assessing Students' Attitudes: The Good, the Bad, and the Ugly. ASA Proceedings of the Section on Statistical Education, pp 1133-1143. Copy at www.statlit.org/pdf/2010MillarSchauASA.pdf
- Schau, Candice (2003). Students' Attitudes: the 'Other' Important Outcome in Statistics Education. ASA Proceedings of the Section on Statistical Education, pp 3673-3683. Copy at www.statlit.org/pdf/2003SchauASA.pdf
- Tintle, Nathan L., Beth Chance, George Cobb, Allan Rossman, Soma Roy, Todd Swanson and Jill VanderStoep (2013). Challenging the state of the art in post-introductory statistics. *Proceedings 59th ISI World Statistics Congress*, 25-30 August 2013, Hong Kong (Session IPS032). Copy at www.statistics.gov.hk/wsc/IPS032-P1-S.pdf
- Wainer, Howard (2002). The BK-Plot: Making Simpsons' Paradox Clear to the Masses. *Chance* 2002 15(3).
- Wakeford and McElvenny (2007). From epidemiological association to causation. *Occupational Medicine*. See www.StatLit.org/pdf/2007-Wakeford-McElvenny-Occupational-Medicine.pdf