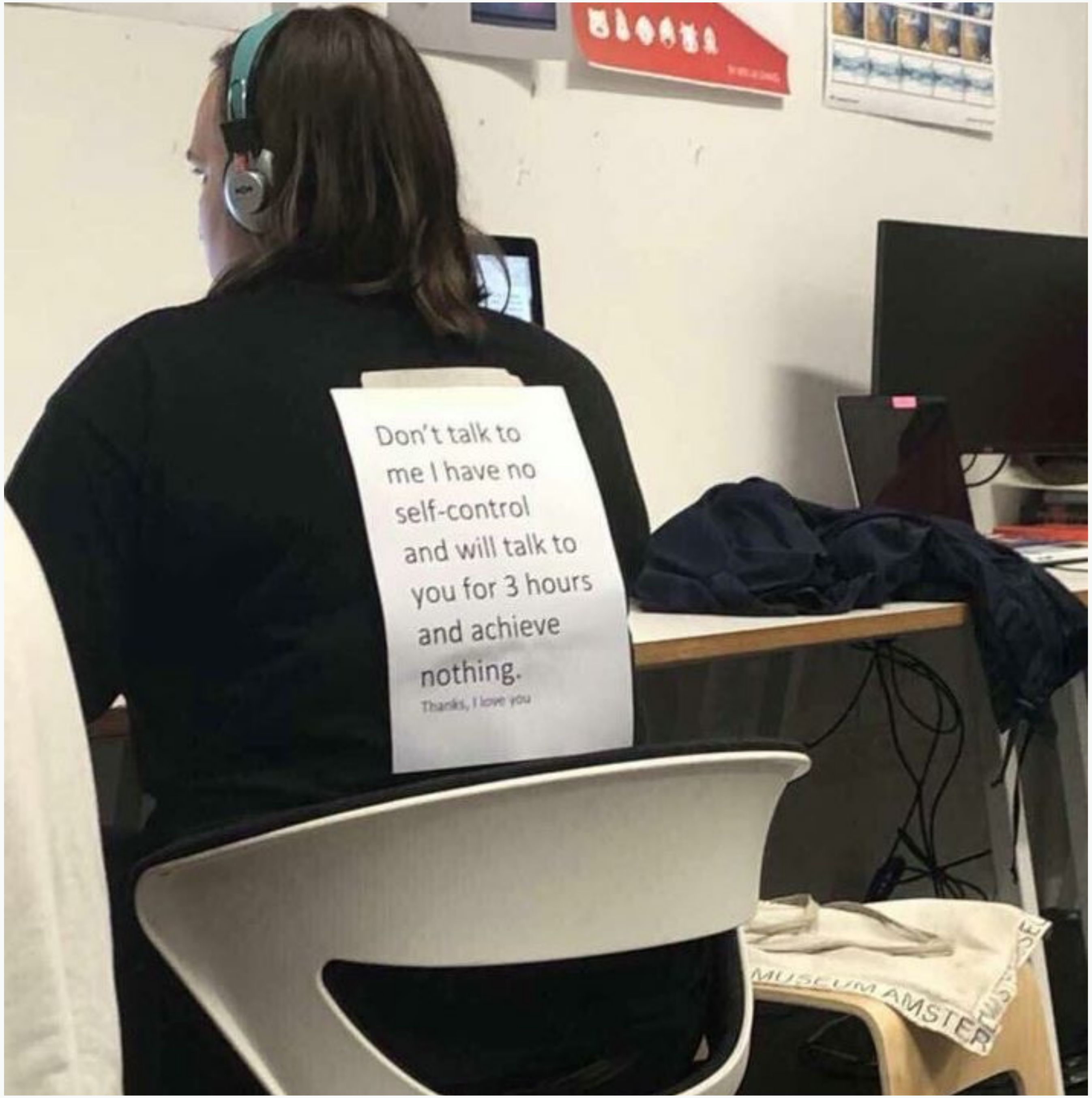
“Thanks. I love you.”



EDUC 7610

Chapter 6

Statistical vs. Experimental Control or CAUSALITY

Fall 2018

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What is real?

https://www.ted.com/talks/alan_smith_why_we_re_so_bad_at_statistics

To better understand the world, we need to control for other explanations of an observation

Experimental Control
manipulation and random assignment

Statistical Control
using information from covariates

Another TED Talk (mind-blowing): https://www.ted.com/talks/anil_seth_how_your_brain_hallucinates_your_conscious_reality

Experimental Control

Experimental control is reliant on
random assignment

Random assignment generally implies:

1. Experimental manipulation
2. Random assignment of one participant to a single group
3. Independent assignment
4. Random sampling (not always necessary)

Experimental Control

Experimental control is reliant on
random assignment

Strengths

1. **All covariates are validly controlled (even without being measured)**
2. Can more easily establish **causality** (directly or indirectly)
3. Avoids the problems of statistical control (e.g., selection, under- or over-control)

Weaknesses

1. The **mechanism** of causality is often unknown
2. Problems of **differential attrition**, learning, and other biases cannot be controlled
3. Difficulty in studying **side effects** of an experiment (there are more variables)
4. Ethical or other limitations to random assignment

Statistical Control

Sometimes we have to rely on
statistical control

Strengths

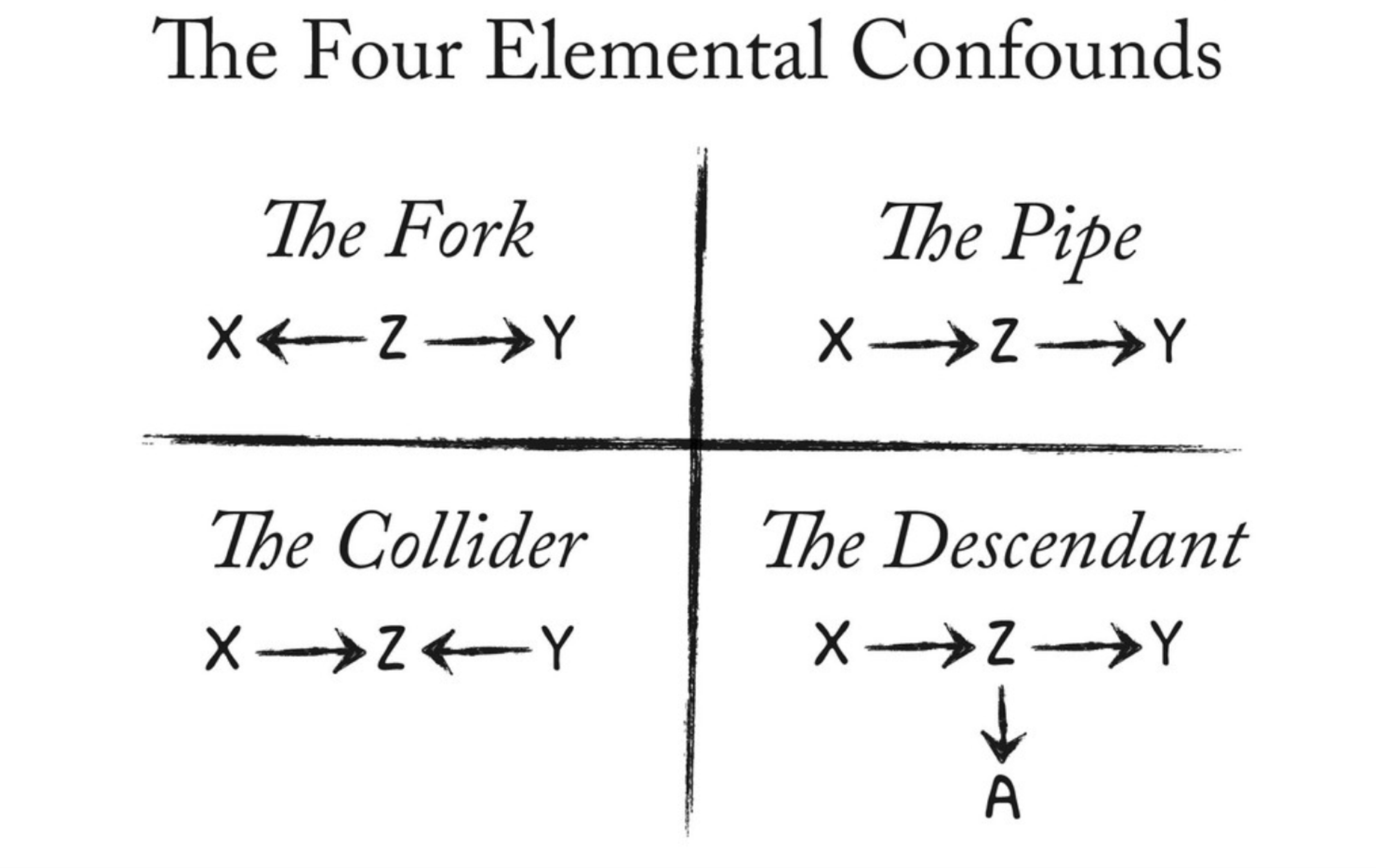
1. **Flexible to many different types of research designs**
2. Can help demonstrate causality in carefully selected models
3. Avoids the ethical and logistical problems of experiments

Weaknesses

1. Need all important covariates to be measured accurately
2. Problems of **differential attrition**, learning, and other biases cannot be controlled
3. Difficulty in demonstrating directionality of the cause/effect relationship
4. No way to know if we included everything we should have

Statistical Control

https://speakerdeck.com/rmcelreath/l06-statistical-rethinking-winter-2019?slide=10



The Four Elemental Confounds

The Fork

$$X \leftarrow Z \rightarrow Y$$

The Pipe

$$X \rightarrow Z \rightarrow Y$$

The Collider

$$X \rightarrow Z \leftarrow Y$$

The Descendant

$$\begin{tikzcd} X \arrow[r] & Z \arrow[r] \arrow[d] & Y \\ & A & \end{tikzcd}$$

The Fork

$$X \leftarrow Z \rightarrow Y$$

Open unless you condition on Z

The Pipe

$$X \rightarrow Z \rightarrow Y$$

Open unless you condition on Z

The Collider

$$X \rightarrow Z \leftarrow Y$$

Closed until you condition on Z

The Descendant

$$\begin{tikzcd} X \arrow[r] & Z \arrow[r] \arrow[d] & Y \\ & A & \end{tikzcd}$$

Conditioning on A is like conditioning on Z

Experimental + Statistical Control

The two are not mutually exclusive

We can supplement random assignment/experimental control with statistical control

Increases precision and power

Invulnerability to chance differences between groups

Quantifying and assessing indirect effects (mediation)

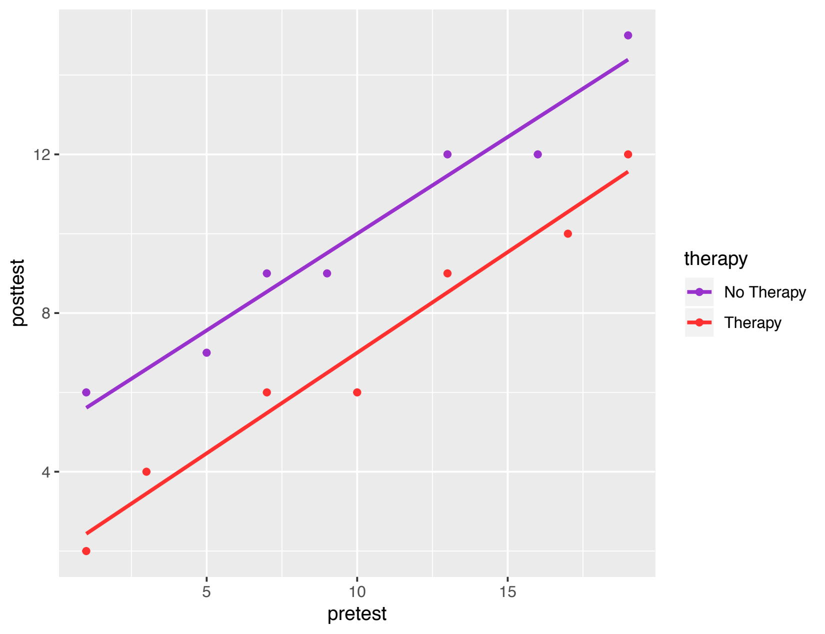
Increases Precision and Power

Consider this example from the book

Our data on PTSD

	id	posttest	pretest	therapy	gain
	<int>	<dbl>	<dbl>	<dbl>	<dbl>
1	1	2	1	1	1
2	2	4	3	1	1
3	3	6	7	1	-1
4	4	6	10	1	-4
5	5	9	13	1	-4
6	6	10	17	1	-7
7	7	12	19	1	-7
8	8	6	1	0	5
9	9	7	5	0	2
10	10	9	7	0	2
11	11	9	9	0	0
12	12	12	13	0	-1
13	13	12	16	0	-4
14	14	15	19	0	-4

Relationships among the variables



We want to know if there was a difference between the therapies

Increases Precision and Power

Three main ways of analyzing this data using the gain scores

T-test

Simple Regression

Multiple Regression

```
df %>%
  t.test(gain ~ therapy,
         data = .,
         var.equal = TRUE)

##         Two Sample t-test
##
## data:  gain by therapy
## t = 1.6672, df = 12, p-value = 0.1213
## 95 percent confidence interval:
##    -0.9207101  6.9207101
## sample estimates:
## mean in group 0 mean in group 1
##               0              -3
```

Increases Precision and Power

Three main ways of analyzing this data using the gain scores

T-test

```
df %>%
  t.test(gain ~ therapy,
         data = .,
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##        Two Sample t-test
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## 95 percent confidence interval:
##    -0.9207101  6.9207101
## sample estimates:
## mean in group 0 mean in group 1
##               0              -3
```

same

Simple Regression

```
df %>%
  lm(gain ~ therapy,
     data = .) %>%
  summary()

## Coefficients:
##                Estimate Std. Error t value Pr(>|t|)
## (Intercept) -7.121e-16      1.272   0.000    1.000
## therapy         -3.000      1.799  -1.667    0.121
```

Multiple Regression

Increases Precision and Power

Three main ways of analyzing this data using the gain scores

T-test

```
df %>%
  t.test(gain ~ therapy,
         data = .,
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Simple Regression

```
## Coefficients:
##                 Estimate Std. Error t value Pr(>|t|)
## (Intercept) -7.121e-16      1.272   0.000    1.000
## therapy         -3.000      1.799  -1.667    0.121
```

Multiple Regression

```
df %>%
  lm(gain ~ therapy + pretest,
     data = .) %>%
  summary()

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  5.01923    0.39024  12.862 5.68e-08 ***
therapy     -3.00000    0.36031  -8.326 4.46e-06 ***
pretest     -0.50192    0.02956 -16.980 3.07e-09 ***
```

Increases Precision and Power

Three main ways of analyzing this data using the gain scores

T-test

```
df %>%
  t.test(gain ~ therapy,
         data = .,
         var.equal = TRUE)

##         Two Sample t-test
##
## data:  gain by therapy
## t = 1.6672, df = 12, p-value = 0.1213
## 95 percent confidence interval:
##    -0.9207101  6.9207101
## sample estimates:
## mean in group 0 mean in group 1
##               0              -3
```

Simple Regression

```
## Coefficients:
##                Estimate Std. Error t value Pr(>|t|)
## (Intercept) -7.121e-16      1.272   0.000    1.000
## therapy         -3.000      1.799  -1.667    0.121
```

Same estimate
Different p-value

Multiple Regression

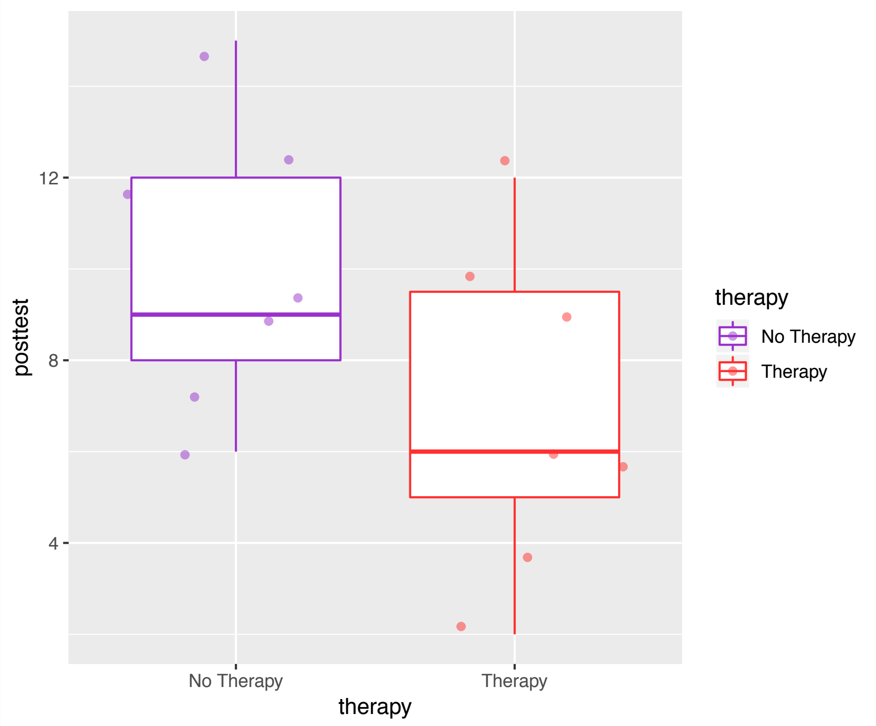
```
df %>%
  lm(gain ~ therapy + pretest,
     data = .) %>%
  summary()

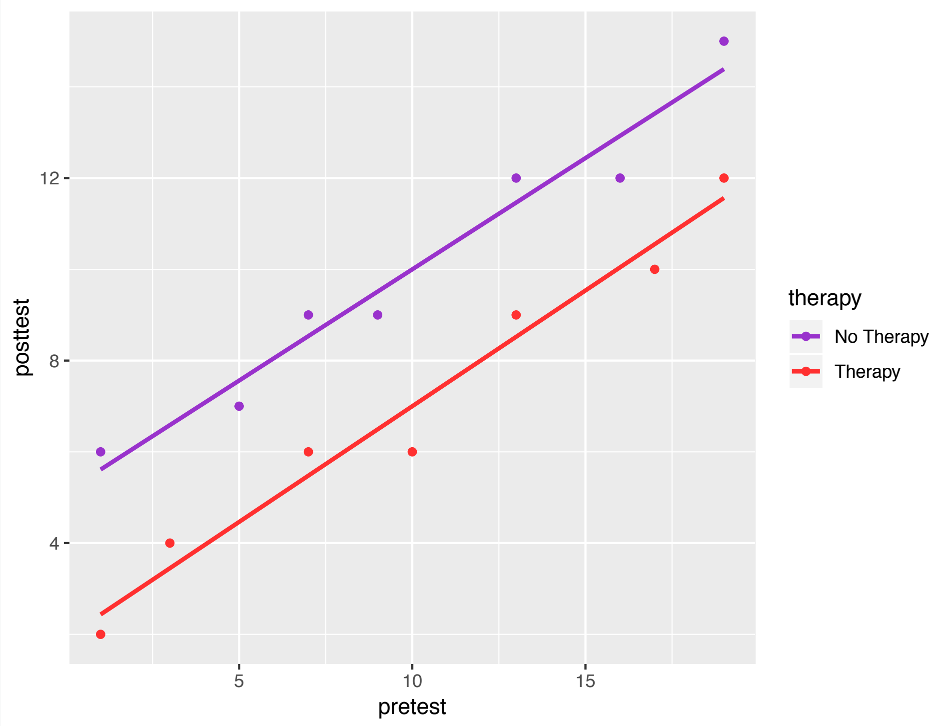
Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  5.01923    0.39024  12.862 5.68e-08 ***
therapy     -3.00000    0.36031  -8.326 4.46e-06 ***
pretest     -0.50192    0.02956 -16.980 3.07e-09 ***
```

Increases Precision and Power

Three main ways of analyzing this data using the gain scores

T-test | Simple Regression | Multiple Regression





Invulnerability to chance differences between groups

Anything using chance can have low chance things happen

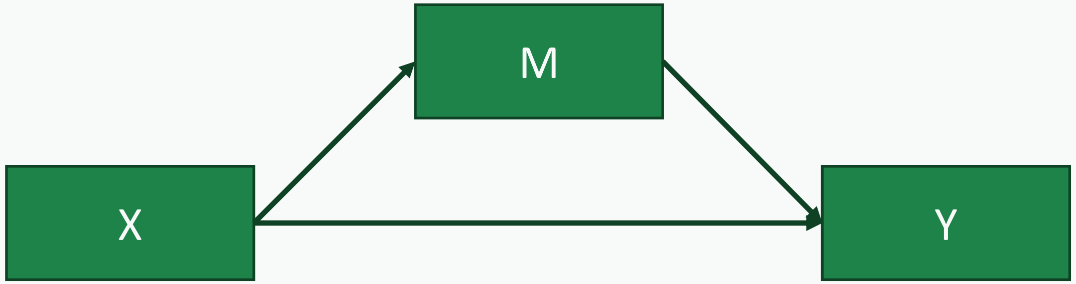
- ***There could be differences among the group even with random assignment just due to chance***

Statistical control can help in the situations *if* we have measured the covariate where the difference is

Quantifying and assessing indirect effects (mediation)

Often, an effect from one variable to another ”travels” through one or more other variables before affecting the outcome

- ***Tested via mediation analysis (we’ll discuss later on)***



Some final thoughts

Takeaways:

1. *Even in experiments, measure covariates so we can use statistical control with it*
2. *Experiments are not the only way to demonstrate causality*
3. *Use linear models to assess both experimental and non-experimental data for more precision*