

When Standard Methods Succeed

Lucy D'Agostino McGowan
Wake Forest University

when correlation *is* causation

When you have no confounders and there is a linear relationship between the exposure and the outcome, that *correlation is a causal relationship*



When you have no confounders and there is a linear relationship between the *exposure* and the outcome, that correlation is a causal relationship



When you have no confounders and there is a linear relationship between the exposure and the *outcome*, that correlation is a causal relationship



When you have no *confounders* and there is a linear relationship between the exposure and the outcome, that correlation is a causal relationship



randomized controlled trials

A/B testing

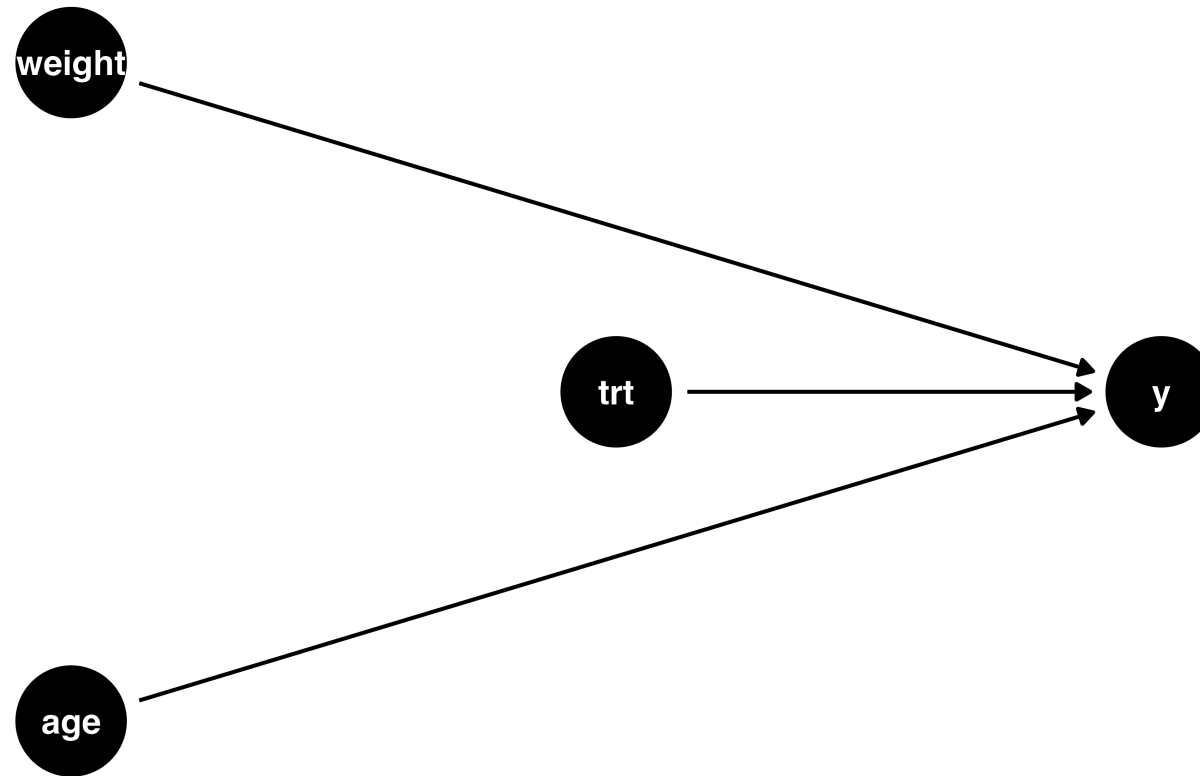
**Even in these cases, using the methods
you will learn here can help!**

- 1 Adjusting for baseline covariates can make an estimate *more efficient*
- 2 Propensity score weighting is *more efficient* than direct adjustment
- 3 Sometimes we are *more comfortable with the functional form of the propensity score* (predicting exposure) than the outcome model

Example

- simulated data (100 observations)
- Treatment is randomly assigned
- There are two baseline covariates: age and weight

Example



- True average treatment effect: 1

Unadjusted model

```
1 lm(y ~ treatment, data = data)
```

Characteristic	Beta	SE ¹	95% CI ¹	p-value
treatment	0.93	0.803	-0.66, 2.5	0.2

¹ SE = Standard Error, CI = Confidence Interval

Adjusted model

```
1 lm(y ~ treatment + weight + age, data)
```

Characteristic	Beta	SE ¹	95% CI ¹	p-value
treatment	1.0	0.204	0.59, 1.4	<0.001
weight	0.34	0.106	0.13, 0.55	0.002
age	0.20	0.005	0.19, 0.22	<0.001

¹ SE = Standard Error, CI = Confidence Interval

Propensity score adjusted model

Characteristic	Beta	SE	95% CI	p-value
treatment	1	0.202	0.6, 1.4	<0.00

Example

- simulated data (10,000 observations)
- Treatment is randomly assigned
- There are two baseline covariates: age and weight

Unadjusted model

```
1 lm(y ~ treatment, data = data)
```

Characteristic	Beta	SE ¹	95% CI ¹	p-value
treatment	0.96	0.083	0.80, 1.1	<0.001

¹ SE = Standard Error, CI = Confidence Interval

Adjusted model

```
1 lm(y ~ treatment + weight + age, data)
```

Characteristic	Beta	SE ¹	95% CI ¹	p-value
treatment	1.0	0.020	0.98, 1.1	<0.001
weight	0.20	0.010	0.18, 0.22	<0.001
age	0.20	0.000	0.20, 0.20	<0.001

¹ SE = Standard Error, CI = Confidence Interval

Propensity score adjusted model

Characteristic	Beta	SE	95% CI	p-value
treatment	1	0.02	1, 1.1	<0.001

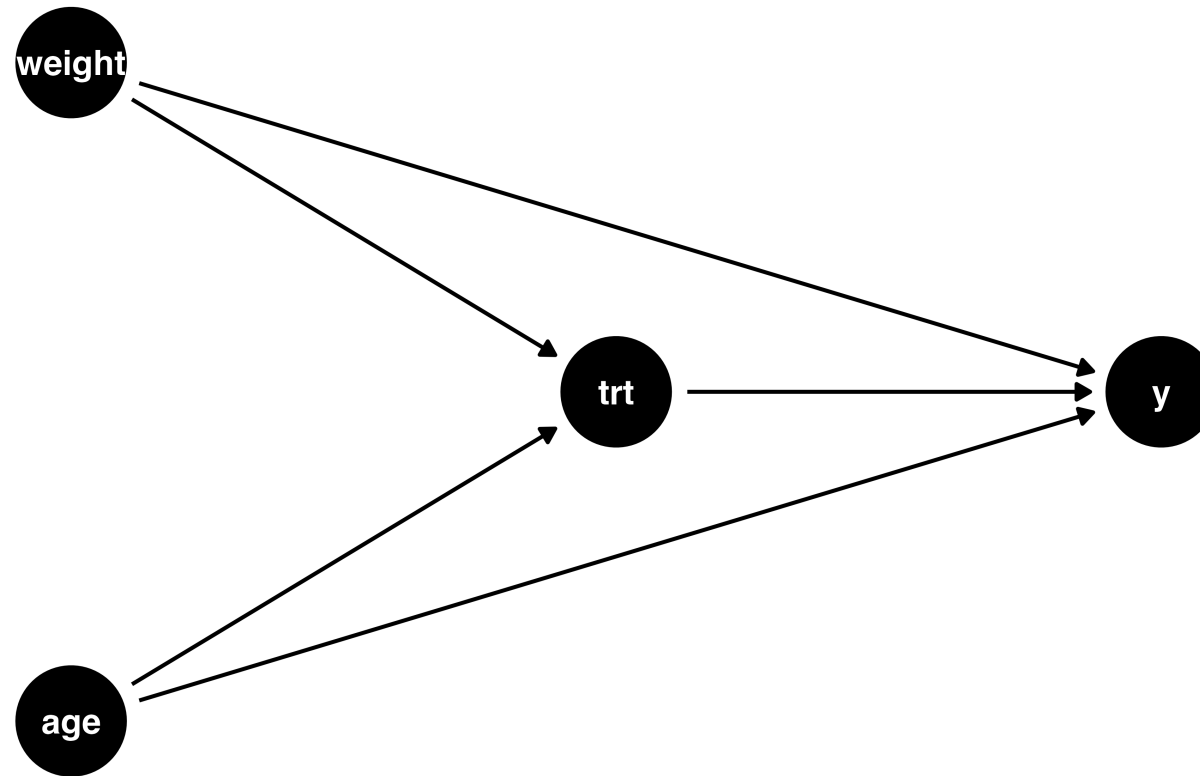
***time-varying* confounding**

Example

Example

- simulated data (10,000 observations)
- Treatment is **not** randomly assigned
- There are **two baseline confounders**: age and weight
- The treatment effect is **homogeneous**

Example



- True average treatment effect: 1

Unadjusted model

```
1 lm(y ~ treatment, data = data)
```

Characteristic	Beta	SE ¹	95% CI ¹	p-value
treatment	1.8	0.085	1.7, 2.0	<0.001

¹ SE = Standard Error, CI = Confidence Interval

Adjusted model

```
1 lm(y ~ treatment + weight + age, data)
```

Characteristic	Beta	SE ¹	95% CI ¹	p-value
treatment	0.98	0.021	0.94, 1.0	<0.001
weight	0.20	0.010	0.18, 0.22	<0.001
age	0.20	0.000	0.20, 0.20	<0.001

¹ SE = Standard Error, CI = Confidence Interval

Propensity score adjusted model

Characteristic	Beta	SE	95% CI	p-value
----------------	------	----	--------	---------

treatment	1	0.022	0.9, 1	<0.001
-----------	---	-------	--------	--------

