# When Standard Methods Succeed

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# 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**

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# 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 that 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)

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Treatment is **randomly** assigned

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There are **two baseline covariates**: age **and** weight

# Unadjusted model

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

| Characteristic | Beta | SE[1] | 95% CI[1] | p-value |
|---|---|---|---|---|
| treatment | 1.6 | 0.803 | -0.04, 3.1 | 0.056 |

[1] SE = Standard Error, CI = Confidence Interval

# Adjusted model

```
lm(y ~ treatment + weight + age,
```

| Characteristic | Beta | SE[1] | 95% CI[1] | p-value |
|---|---|---|---|---|
| treatment | 1.5 | 0.204 | 1.1, 1.9 | <0.001 |
| weight | 0.18 | 0.103 | -0.03, 0.38 | 0.087 |
| age | 0.20 | 0.005 | 0.19, 0.21 | <0.001 |

[1] SE = Standard Error, CI = Confidence Interval

# Propensity score adjusted model

| Characteristic | Beta | SE | 95% CI | p-value |
|---|---|---|---|---|
| treatment | 1.5 | 0.197 | 1.1, 1.9 | <0.001 |

# Example

**simulated** data (10,000 observations)

Treatment is **randomly** assigned

There are **two baseline covariates**: age **and** weight

# Unadjusted model

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

| Characteristic | Beta | SE[1] | 95% CI[1] | p-value |
|---|---|---|---|---|
| treatment | 0.89 | 0.082 | 0.73, 1.1 | <0.001 |

[1] SE = Standard Error, CI = Confidence Interval

# Adjusted model

```
lm(y ~ treatment + weight + age,
```

| Characteristic | Beta | SE[1] | 95% CI[1] | p-value |
|---|---|---|---|---|
| treatment | 1.0 | 0.020 | 0.97, 1.0 | <0.001 |
| weight | 0.19 | 0.010 | 0.17, 0.21 | <0.001 |
| age | 0.20 | 0.001 | 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 | <0.001 |

# time-varying confounding