

Instrumental Variables

EC 421, Set 11

Edward Rubin

Prologue

Schedule

Last Time

Causality

Today

- Review: Causality
- New: Instrumental variables

Upcoming

Stay tuned on Canvas

Causality

Review

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or we observe i in the control group, *i.e.*,

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but never both at the same time.

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If we want to know τ_i (or at least $\bar{\tau}$), what can we do?

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Idea: Estimate the **average treatment effect** as the difference between the average outcomes in the treatment group and the control group, *i.e.*,

$$Avg(y_i \mid D_i = 1) - Avg(y_i \mid D_i = 0)$$

where $D_i = 1$ if i received treatment, and $D_i = 0$ if i is in the control group.

Causality

Review

Result: We showed that even when the treatment effect is constant (meaning $\tau_i = \tau$ for all i),

$$\begin{aligned} & Avg(y_i \mid D_i = 1) - Avg(y_i \mid D_i = 0) \\ &= \tau + \underbrace{Avg(y_{0,i} \mid D_i = 1) - Avg(y_{0,i} \mid D_i = 0)}_{\text{Selection bias}} \end{aligned}$$

which says that the difference in the groups' means will give us a **biased estimate** for the causal effect of treatment **if we have selection bias**.

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A: (Formal) The *average untreated* outcome for a member of our **treatment group** (which we cannot observe) differs from the *average untreated* outcome for a member of our **control group**, i.e.,

$$Avg(y_{0,i} \mid D_i = 1) - Avg(y_{0,i} \mid D_i = 0)$$

Causality

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Practical problem: Selection bias is also difficult to observe

$$\underbrace{Avg(y_{0,i} \mid D_i = 1)}_{\text{Unobservable}} - Avg(y_{0,i} \mid D_i = 0)$$

(back to the *fundamental problem of causal inference*)

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Bigger problem: If selection bias is present, our estimate for τ is biased, preventing us from understanding the causal effect of treatment.

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Sounds a bit like omitted-variable bias, right? Our **treatment** variable is correlated with something that makes the two groups different.

Causality

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Example: Imagine we have two people—Al and Bri—and a single binary treatment, college. We are interested in the effect of college on earnings.

$$\text{Earn}_{1,\text{Al}} = \$60\text{K}$$

$$\text{Earn}_{0,\text{Al}} = \$30\text{K}$$

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but any real-world estimate would have serious selection issues since

$$\text{Earn}_{0,\text{Al}} \neq \text{Earn}_{0,\text{Bri}}.$$

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If Bri attended college ($D_{\text{Bri}}=1$) and Al did not ($D_{\text{Al}}=0$):

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- **Option 1: Distribute treatment** in a way such that the treatment and control groups are essentially identical (experiments).
- **Option 2: Build a control** group that *matches* the treatment group (life with observational data).

Instrumental variables

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Intro

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Recall: **Selection bias** means our **treatment** and **control** groups differ on some unobserved/omitted dimension. (**Endogeneity**)

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Instrumental variables (IV) is one route econometricians often take toward estimating the causal effect of a treatment/program.

Recall: **Selection bias** means our **treatment** and **control** groups differ on some unobserved/omitted dimension. (**Endogeneity**)

Instrumental variables attempts to separate out

- the **exogenous** part of x , which gives us unbiased estimates
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Instrumental variables attempts to separate out

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If we use only the exogenous (*good*) variation in x , then we can avoid selection bias/omitted-variable bias.

Instrumental variables

Introductory example

Example: If we want to estimate the effect of veteran status on earnings,

$$\text{Earnings}_i = \beta_0 + \beta_1 \text{Veteran}_i + u_i \quad (1)$$

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And OLS will likely be biased for (1) due to selection/omitted-variable bias.

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A₁: Choices to enlist in the military that are essentially random—or at least uncorrelated with omitted variables and the disturbance.

A₂: **No selection bias:**

$$Avg(\text{Earnings}_{0i} \mid \text{Veteran}_i = 1) - Avg(\text{Earnings}_{0i} \mid \text{Veteran}_i = 0) = 0$$

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Instruments

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A: An **instrument** is a variable that is

1. **correlated** with the **explanatory variable** of interest (**relevant**),
2. **uncorrelated** with the **disturbance** (**exogenous**).

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So if we want an instrument z_i for endogenous veteran status in

$$\text{Earnings}_i = \beta_0 + \beta_1 \text{Veteran}_i + u_i$$

1. **Relevant:** $\text{Cov}(\text{Veteran}_i, z_i) \neq 0$
2. **Exogenous:** $\text{Cov}(z_i, u_i) = 0$

Instrumental variables

Instruments: Relevance

Relevance: We need the instrument to cause a change in (correlate with) our endogenous explanatory variable.

We can actually test this requirement using regression and a t test.

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being draw led to service

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Instrumental review

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- Our instrument must be **uncorrelated with any other variable that affects the outcome**.

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- Our instrument must be **uncorrelated with any other variable that affects the outcome**.

In other words:

The instrument only affects our outcome through the endogenous variable.

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Not relevant

Exogenous

2. Physical fitness

Probably relevant

Not exogenous

3. Vietnam War draft

Relevant

Exogenous

Thus, only the Vietnam War's draft lottery appears to be a **valid instrument**.

If we have a *valid* instrument (*e.g.*, the draft lottery), how do we use it?

Instrumental variables

Estimation

Recall: We want to estimate the effect of veteran status on earnings.

$$\text{Earnings}_i = \beta_0 + \beta_1 \text{Veteran}_i + u_i$$

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1. The effect of the **instrument** on the **endogenous variable**, e.g.,

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$$\text{Earnings}_i = \beta_0 + \beta_1 \text{Veteran}_i + u_i$$

and we know that the draft affected veteran status.

$$\text{Draft} \rightarrow \text{Veteran status} \rightarrow \text{Earnings}$$

Using our assumptions on independence and exogeneity:

$$\begin{aligned} &(\text{Effect of the draft on earnings}) = \\ &(\text{Effect of the draft on veteran status}) \times \\ &(\text{Effect of veteran status on earnings}) \end{aligned}$$

Instrumental variables

Estimation

We just wrote out an expression for the effect of **the draft** on **earnings**, i.e.,

$$\begin{aligned} &(\text{Effect of } \textbf{the draft} \text{ on } \textbf{earnings}) = \\ &\quad (\text{Effect of } \textbf{the draft} \text{ on } \textbf{veteran status}) \times \\ &\quad (\text{Effect of } \textbf{veteran status} \text{ on } \textbf{earnings}) \end{aligned}$$

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but we want to know the effect of **veteran status** on **earnings**.

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$$\begin{aligned} (\text{Effect of } \text{veteran status} \text{ on } \text{earnings}) = \\ \frac{(\text{Effect of } \text{the draft} \text{ on } \text{earnings})}{(\text{Effect of } \text{the draft} \text{ on } \text{veteran status})} \end{aligned}$$

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Our **instrument** consistently estimates both parts of this fraction!

Instrumental variables

Estimation: Bring it all together

By estimating two regressions involving our **instrument**,

1. The effect of the **instrument** on the **endogenous variable**, e.g.,

$$\text{Veteran}_i = \gamma_0 + \gamma_1 \text{Draft}_i + v_i$$

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we can estimate our desired effect:

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we can estimate our desired effect:

$$(\text{Effect of } \text{veteran status} \text{ on } \text{earnings}) = \frac{\pi_1}{\gamma_1}$$

Instrumental variables

Estimation: Bring it all together

So with instrumental variables, we estimate β_1 using

$$\hat{\beta}_1^{\text{IV}} = \frac{\hat{\pi}_1}{\hat{\gamma}_1}$$

where $\hat{\pi}_1$ and $\hat{\gamma}_1$ come from the two equations we just discussed.

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$$\text{plim}\left(\hat{\beta}_1^{\text{IV}}\right) = \beta_1 + \frac{\text{Cov}(\text{Instrument}, u)}{\text{Cov}(\text{Instrument}, \text{Endog. variable})}$$

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which equals β_1 as long as our instrument is **exogenous** (numerator) and **relevant** (denominator).

Figure 1

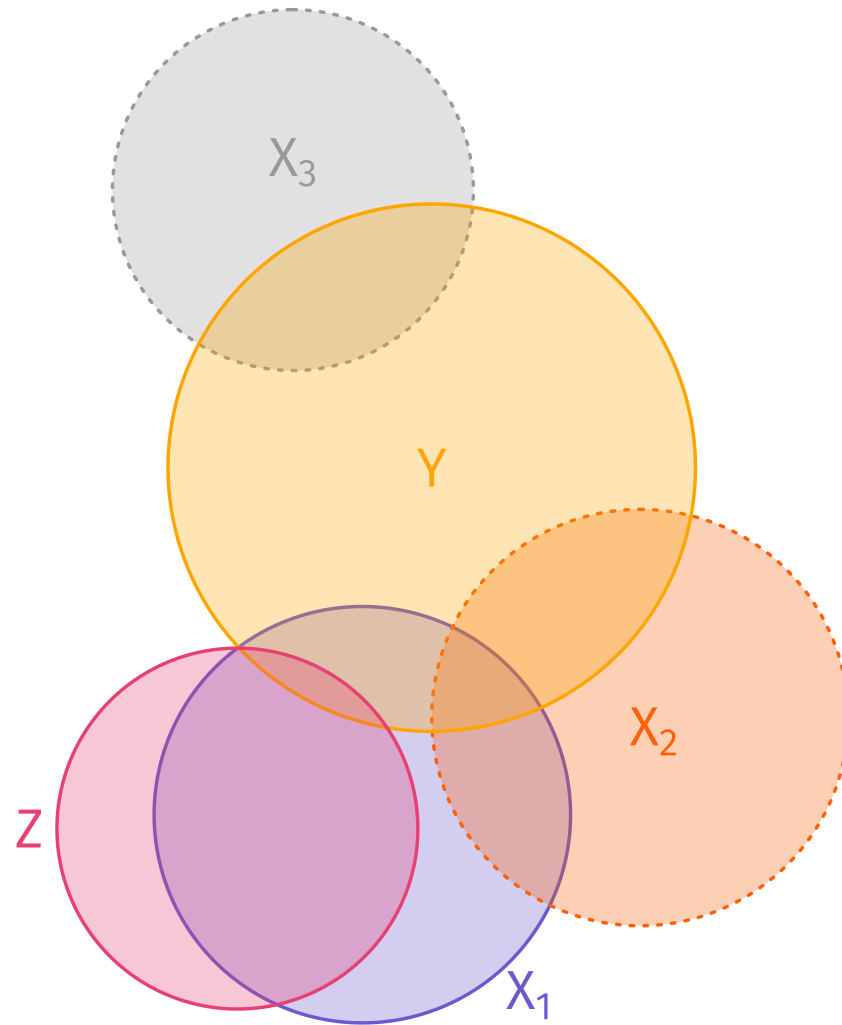


Figure 2

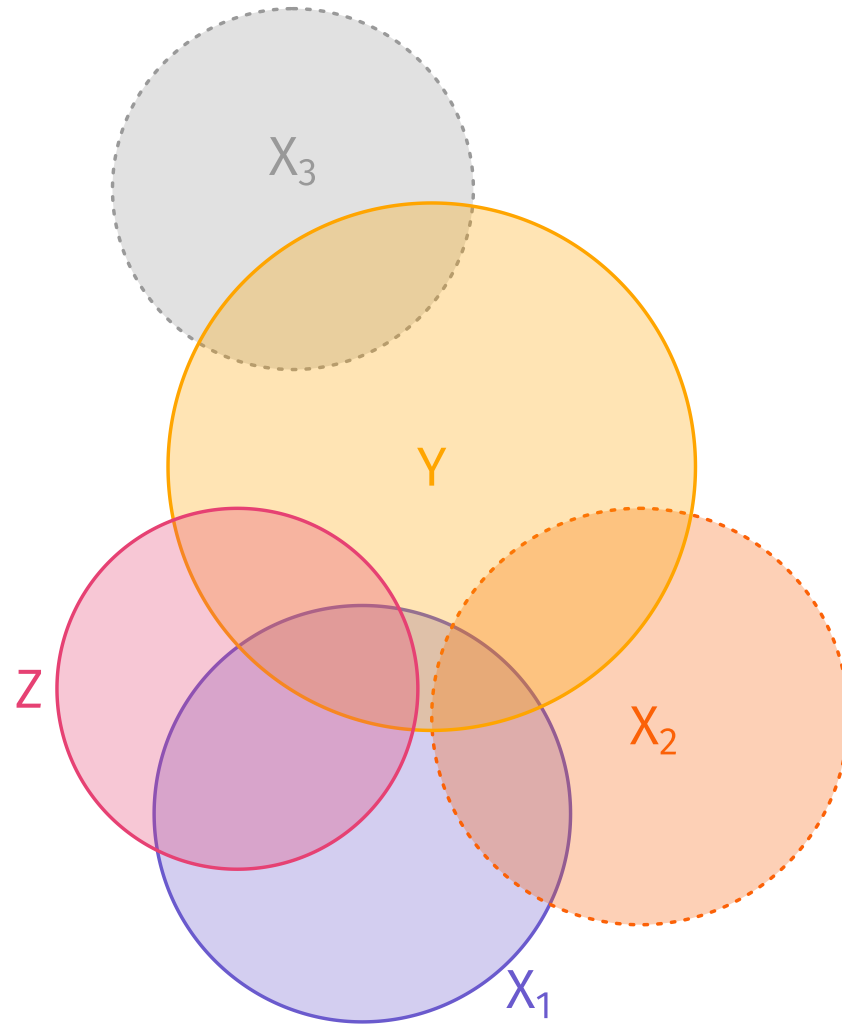


Figure 3

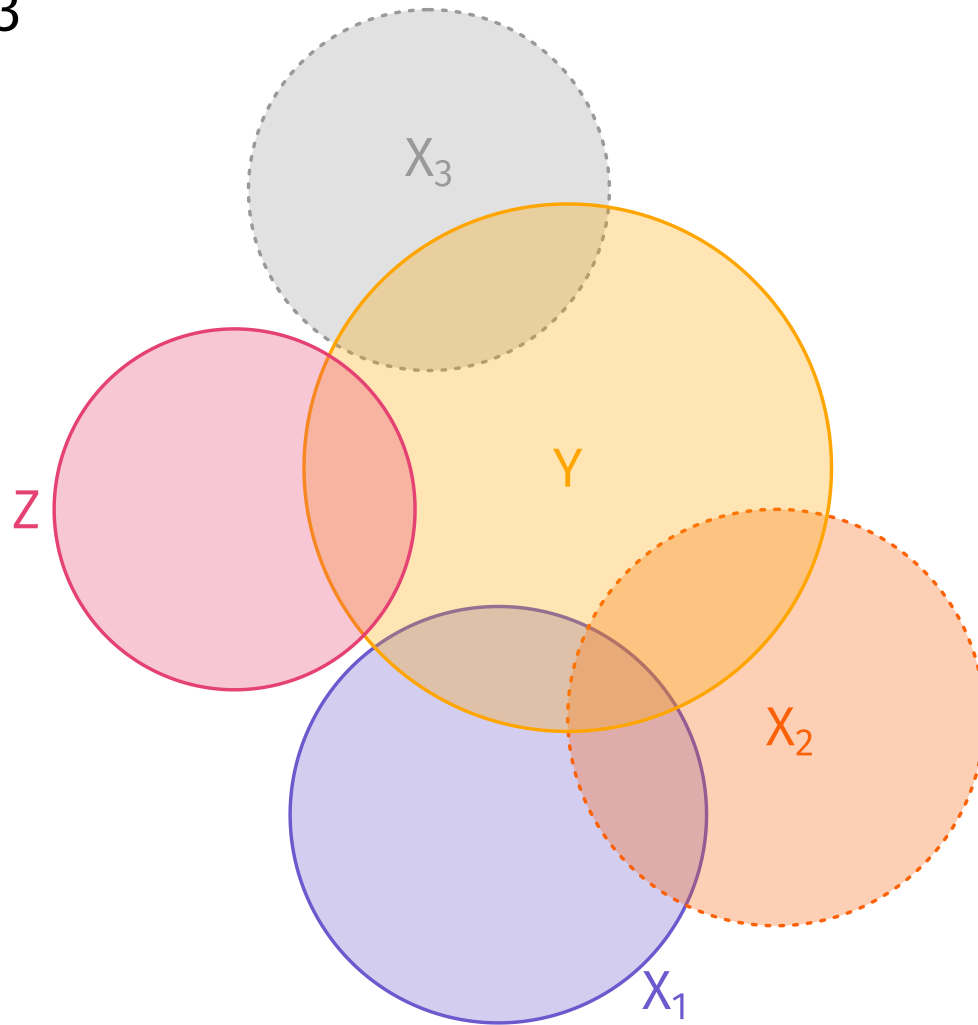
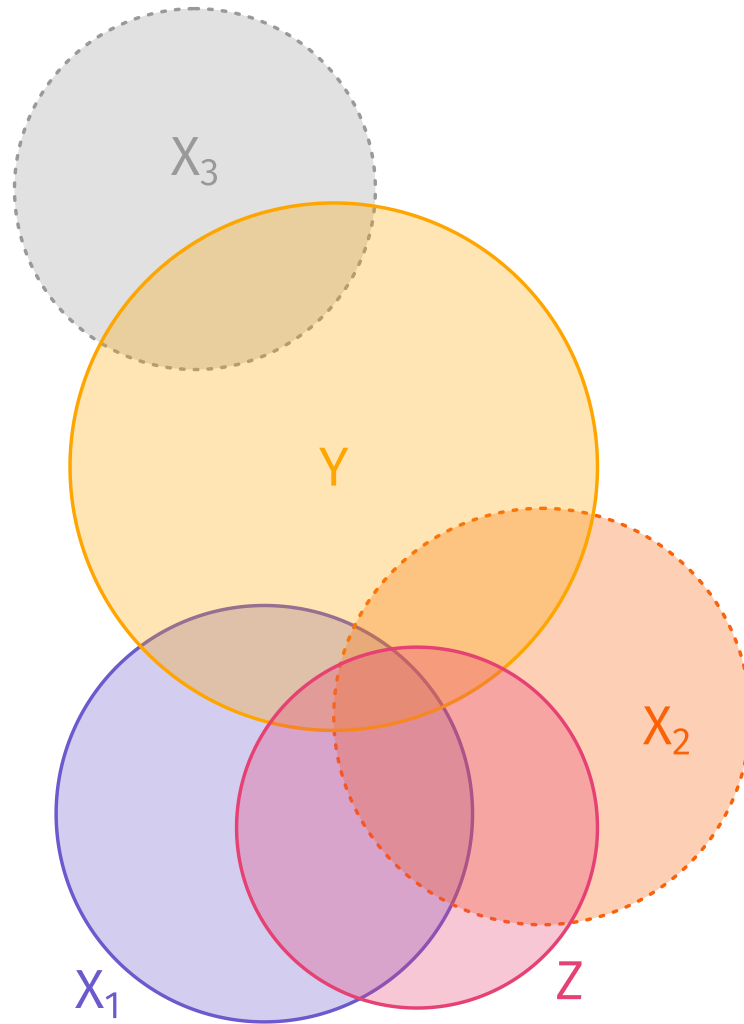


Figure 4



Venn diagram explanation

In these figures (Venn diagrams)

- Each circle illustrates a variable.
- Overlap gives the share of correlation between two variables.
- Dotted borders denote *omitted* variables.

Take-aways

- Figure 1: **Valid instrument** (relevant; exogenous)
- Figure 2: **Invalid instrument** (relevant; not exogenous)
- Figure 3: **Invalid instrument** (not relevant; not exogenous)
- Figure 4: **Invalid instrument** (relevant; not exogenous)

Let's work an example in \mathbb{R} .

Instrumental variables

Example in R

Back to our age-old battle to estimate the returns to education.

```
#> # A tibble: 722 × 4
#>   wage education education_dad education_mom
#>   <int>      <int>      <int>      <int>
#> 1   769         12         8         8
#> 2   808         18        14        14
#> 3   825         14        14        14
#> 4   650         12        12        12
#> 5   562         11        11         6
#> 6   600         10         8         8
#> 7 1154         15         5        14
#> 8 1000         12        11        12
#> 9   930         18        14        13
#> 10  900         15        12        12
#> # ... with 712 more rows
```

Instrumental variables

Example in \mathbb{R}

OLS for the returns to education with will likely (definitely) be biased...

$$\text{Wage}_i = \beta_0 + \beta_1 \text{Education}_i + u_i$$

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(Likely biased) OLS results:

Term	Est.	S.E.	t stat.	p-Value
Intercept	176.504	89.152	1.98	0.0481
Education	58.594	6.439	9.10	

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but what if mother's education provides a valid instrument?

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We can check/test the *relevance* of **mother's education** for **education**.

Instrumental variables

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This regression is known as the ***first stage***:

The effect of the **instrument** on our **endogenous explanatory variable**.

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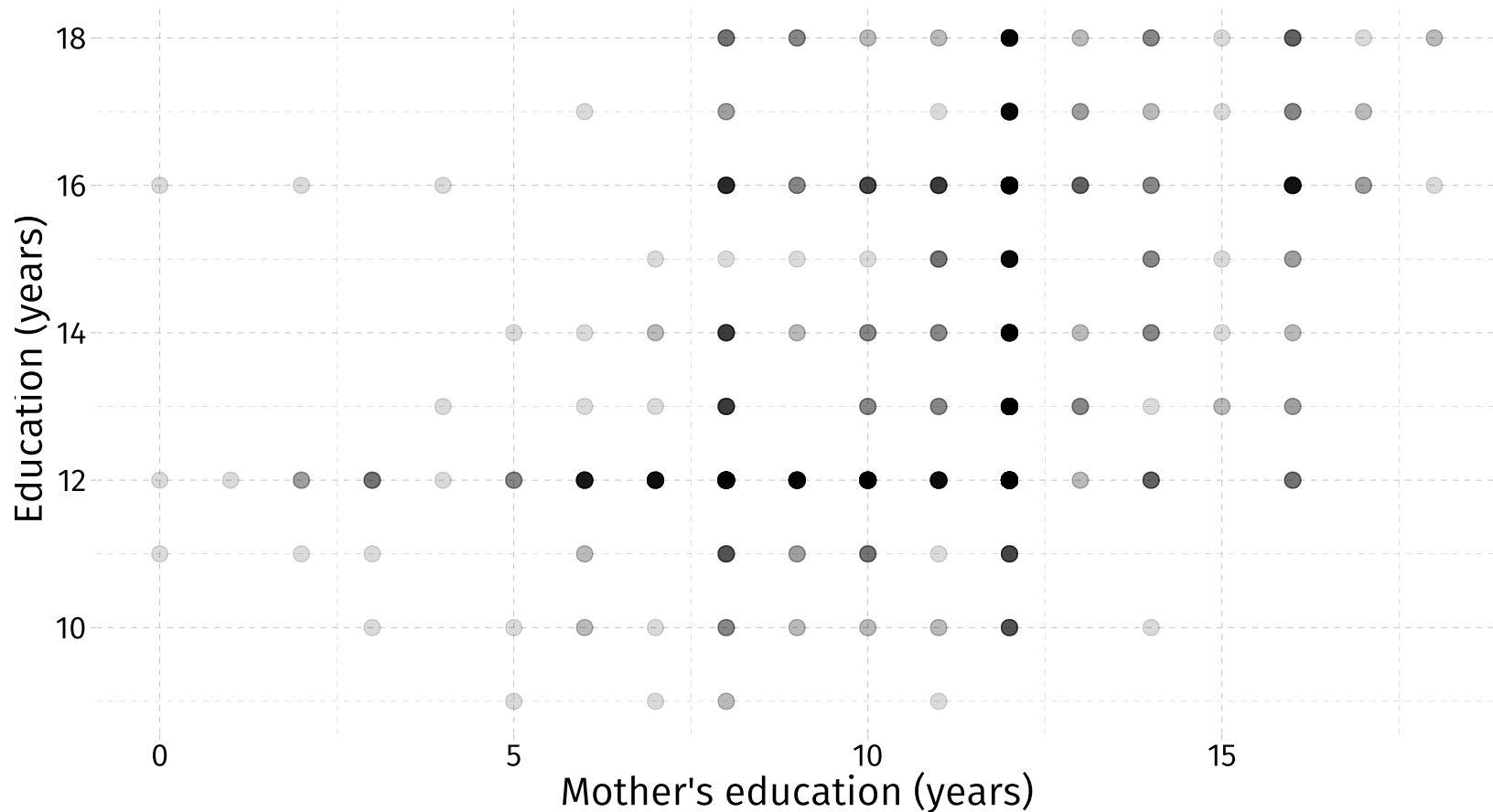
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The *p*-value suggests a very strong relationship (very *relevant*).

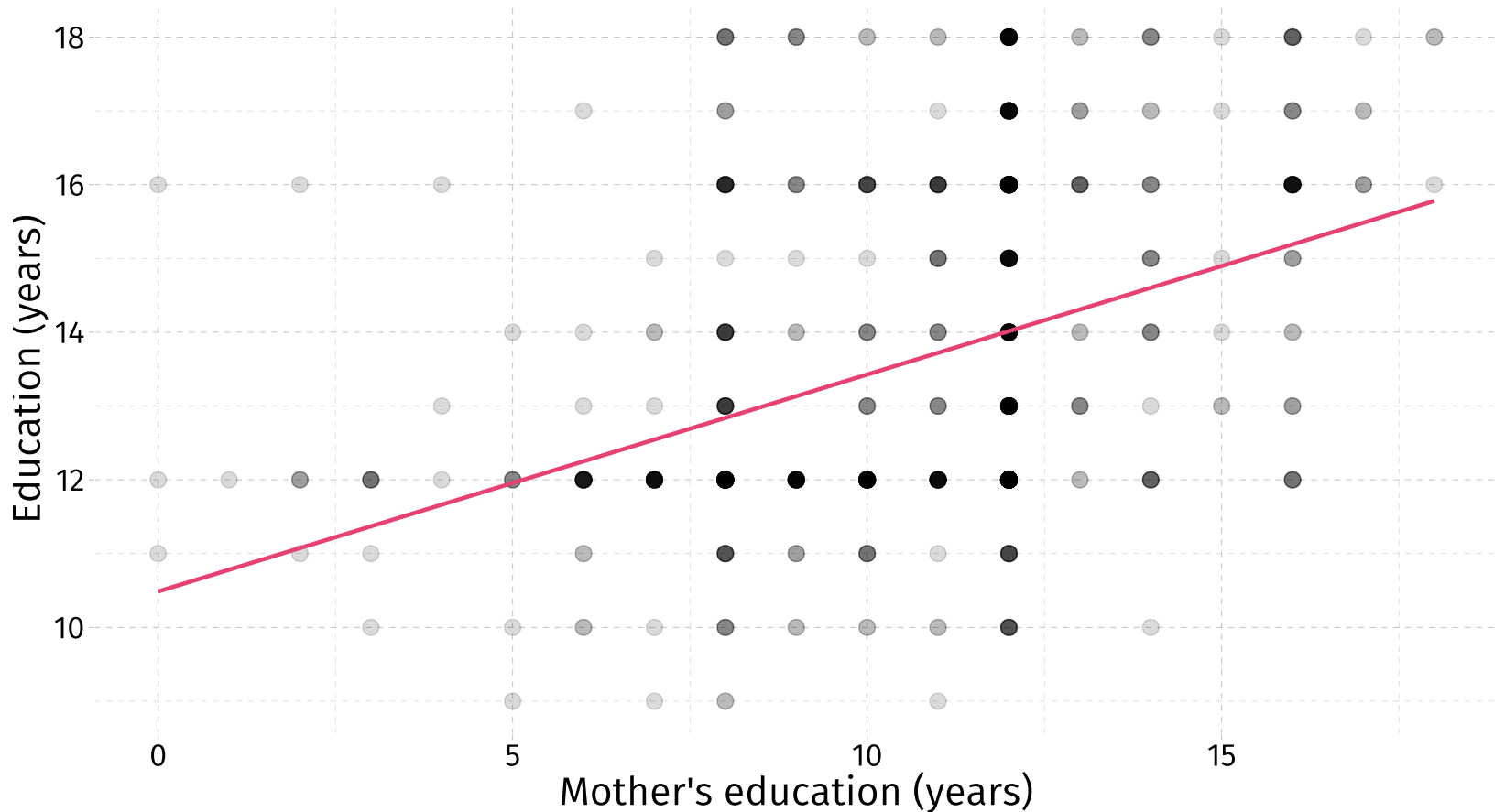
Instrumental variables

Visualizing the first stage



Instrumental variables

Visualizing the first stage



Instrumental variables

Exogeneity

Q: What does **exogeneity** mean in this case?

Instrumental variables

Exogeneity

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A: We need two things

1. **Mother's education (our instrument)** must only affect earnings through education (our endogenous explanatory variable).
2. **Mother's education** must be uncorrelated with other factors that affect wages (our outcome variable).

Instrumental variables

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We want to be able to compare two people (A and B) whose mothers have different levels of education and say that the only differences between the two people (A and B) are due to their mothers' educational levels.

Instrumental variables

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We want to be able to compare two people (*A* and *B*) whose mothers have different levels of education and say that the only differences between the two people (*A* and *B*) are due to their mothers' educational levels.

Q: Does *mother's education* seem likely to satisfy exogeneity?

Instrumental variables

Example in \mathbb{R}

Now, let's estimate the *reduced form*:

The effect of the instrument on our outcome variable.

$$\text{Wage}_i = \pi_0 + \pi_1(\text{Mother's Education})_i + w_i$$

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Reduced-form results:

Term	Est.	S.E.	t stat.	p-Value
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Q₁: How do we interpret this estimated coefficient ($\hat{\pi}_1$)?

Q₂: If our instrument is *valid*, can we interpret these estimates as **causal**?

Instrumental variables

Example in \mathbb{R}

So what is our IV-based estimate for the returns to education?

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1. In the **reduced-form equation**, we estimated $\hat{\pi}_1 \approx 31.81$.
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1. In the **reduced-form equation**, we estimated $\hat{\pi}_1 \approx 31.81$.
2. In the **first-stage equation**, we estimated $\hat{\gamma}_1 \approx 0.294$.

$$\implies \hat{\beta}_1^{\text{IV}} = \frac{\hat{\pi}_1}{\hat{\gamma}_1} = \frac{31.81}{0.294} \approx 108.2$$

Instrumental variables

Example in R

Alternative: Use the function `iv_robust()` from the `estimatr` package.

This new function `iv_robust` works very similar to our good friend `lm`:

```
iv_robust(y ~ x | z, data = dataset)
```

- `formula` Specify the regression followed by `|` and your instrument (`z`).
- `data` You still need a dataset.

Note: As you might guess by its name, `iv_robust` calculates heteroskedasticity-robust standard errors by default.

Instrumental variables

Example in R

In practice...

```
# Estimate our IV regression  
iv_est ← iv_robust(wage ~ education | education_mom, data = wage_df)
```

Term	Est.	S.E.	t stat.	p-Value
Intercept	-501.474	226.476	-2.21	0.0271
Education	108.214	16.810	6.44	

Instrumental variables

More

So now we know how to "do" instrumental variables

Instrumental variables

More

So now we know how to "do" instrumental variables *when we have one endogenous variable and one exogenous variable.*

Instrumental variables

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1. Estimate the reduced form (regress **outcome var.** on **instrument**).
2. Estimate the first stage (regress **expl. var.** on **instrument**).
3. Calculate the IV estimate using the estimates from (1) and (2).

Our magical **instrument** isolates the exogenous variation in our **endogenous variable**.

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A: Too bad.

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Q: What if we want more? (E.g., more instruments or endog. variables)

A: ~~Too bad.~~ Extend IV to **two-stage least squares (2SLS)**.

Two-stage least squares

Two-stage least squares

Intro

The intuition and insights of IV carry over into two-stage least squares.

Two-stage least squares

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Plus: The *first stage* that we've been discussing is actually the *first* of the *two stages* in two-stage least squares.

Two-stage least squares

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The intuition and insights of IV carry over into two-stage least squares.

Plus: The *first stage* that we've been discussing is actually the *first* of the *two stages* in two-stage least squares.

Endogenous model $\text{Outcome}_i = \beta_0 + \beta_1(\text{Endog. var.})_i + u_i$

First stage $(\text{Endog. var.})_i = \pi_0 + \pi_1 \text{Instrument}_i + v_i$

Second stage $\text{Outcome}_i = \delta_0 + \delta_1 \widehat{(\text{Endog. var.})}_i + \varepsilon_i$

Reduced form $\text{Outcome}_i = \pi_0 + \pi_1 \text{Instrument}_i + w_i$

where $\widehat{(\text{Endog. var.})}_i$ denotes the predicted values (*fitted values*) from the first-stage regression.

Two-stage least squares

Intro

Two-stage least squares is very flexible—we include other controls, additional endogenous variables, *and* have multiple instruments.

But don't get too distracted by this fancy flexibility.

We still need **valid** instruments.

Two-stage least squares

In R

Back to our *returns to education* example.

$$\text{Wage}_i = \beta_0 + \beta_1 \text{Education}_i + u_i$$

Imagine that mother's *and* father's education are both valid instruments.

Then our **first-stage regression** is

$$\text{Education}_i = \gamma_0 + \gamma_1 (\text{Mother's education})_i + \gamma_2 (\text{Father's education})_i + v_i$$

which we can estimate via OLS.

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Q: Why?

Two-stage least squares

In R

$$\text{Education}_i = \gamma_0 + \gamma_1(\text{Mother's education})_i + \gamma_2(\text{Father's education})_i + v_i$$

```
stage1 <- lm(education ~ education_mom + education_dad, wage_df)
```

First-stage results:

Term	Est.	S.E.	t stat.	p-Value
Intercept	9.845	0.305	32.31	
Mother's Education	0.149	0.032	4.62	
Father's Education	0.216	0.028	7.84	

Two-stage least squares

In R

$$\text{Education}_i = \gamma_0 + \gamma_1(\text{Mother's education})_i + \gamma_2(\text{Father's education})_i + v_i$$

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First-stage results:

Term	Est.	S.E.	t stat.	p-Value
Intercept	9.845	0.305	32.31	
Mother's Education	0.149	0.032	4.62	
Father's Education	0.216	0.028	7.84	

Our instruments each appear to be *relevant*.

Two-stage least squares

In R

$$\text{Education}_i = \gamma_0 + \gamma_1 (\text{Mother's education})_i + \gamma_2 (\text{Father's education})_i + v_i$$

```
stage1 <- lm(education ~ education_mom + education_dad, wage_df)
```

First-stage results:

Term	Est.	S.E.	t stat.	p-Value
Intercept	9.845	0.305	32.31	
Mother's Education	0.149	0.032	4.62	
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Our instruments each appear to be *relevant*.

Formally, we should jointly test them (e.g., F test).

Two-stage least squares

In R

Using our estimated first stage, we grab the *fitted* endogenous variable

$$\widehat{\text{Education}}_i = \hat{\gamma}_0 + \hat{\gamma}_1 (\text{Mother's education})_i + \hat{\gamma}_2 (\text{Father's education})_i$$

Two-stage least squares

In R

Using our estimated first stage, we grab the *fitted* endogenous variable

$$\widehat{\text{Education}}_i = \hat{\gamma}_0 + \hat{\gamma}_1 (\text{Mother's education})_i + \hat{\gamma}_2 (\text{Father's education})_i$$

```
# Add fitted values from first stage  
wage_df$education_hat ← stage1$fitted.values
```


Two-stage least squares

In R

Using our estimated first stage, we grab the *fitted* endogenous variable

$$\widehat{\text{Education}}_i = \hat{\gamma}_0 + \hat{\gamma}_1(\text{Mother's education})_i + \hat{\gamma}_2(\text{Father's education})_i$$

```
# Add fitted values from first stage  
wage_df$education_hat ← stage1$fitted.values
```

Now we use OLS (again) to estimate the **second-stage regression**

$$\text{Wage}_i = \delta_0 + \delta_1 \widehat{\text{Education}}_i + \varepsilon_i$$

Two-stage least squares

In R

$$\text{Wage}_i = \delta_0 + \delta_1 \widehat{\text{Education}}_i + \varepsilon_i$$

```
stage2 <- lm(wage ~ education_hat, wage_df)
```

Second-stage results:

Term	Est.	S.E.	t stat.	p-Value
Intercept	-454.683	198.149	-2.29	0.022
Fitted Education	104.789	14.462	7.25	

Ordinary least squares

Term	Est.	S.E.	t stat.	p-Value
Intercept	176.504	89.152	1.98	0.0481
Education	58.594	6.439	9.10	

Instrumental variables

Term	Est.	S.E.	t stat.	p-Value
Intercept	-501.474	226.476	-2.21	0.0271
Education	108.214	16.810	6.44	

Two-stage least squares w/ two instruments

Term	Est.	S.E.	t stat.	p-Value
Intercept	-454.683	198.149	-2.29	0.022
Education	104.789	14.462	7.25	

Two-stage least squares

In R

As you probably guessed, R will do both of the stages for you.

Two-stage least squares

In R

As you probably guessed, R will do both of the stages for you.

```
iv_robust(y ~ x1 + x2 + ... | z1 + z2 + ..., data)
```

Two-stage least squares

In R

As you probably guessed, R will do both of the stages for you.

```
iv_robust(y ~ x1 + x2 + ... | z1 + z2 + ..., data)
```

In our case, we have

- one explanatory variable (x) (**education**)
- two instruments (z) (**parents' educations**)

```
iv_robust(wage ~ education | education_mom + education_dad, data = wage_df)
```

Term	Est.	S.E.	t stat.	p-Value
Intercept	-454.683	199.946	-2.27	0.0233
Education, fitted	104.789	14.852	7.06	

Two-stage least squares

There's more!

Because 2SLS **isolates exogenous variation in an endogenous variable**, we apply it in other settings that are biased from *endogenous* relationships.

Two-stage least squares

There's more!

Because 2SLS **isolates exogenous variation in an endogenous variable**, we apply it in other settings that are biased from *endogenous* relationships.

Common applications

- **General causal inference** for observational data (as we've seen).
- **Experiments:** Randomize a treatment that affects an endog. variable.
- **Measurement error:** Regress noisy x_1 on noisy x_2 to capture signal.
- **Simultaneous relationships** (e.g., p and q from supply and demand).

However, in any 2SLS/IV setting, you need to mind the requirements for **valid instruments**—**exogeneity** and **relevance**.

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