Pooled OLS and Cluster-Robust Standard Errors

When 240 Observations Are Really Just 8

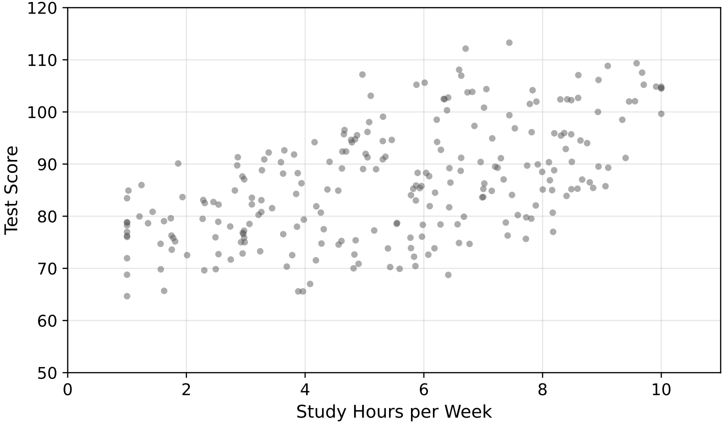
Jake Anderson

May 16, 2026

Outline

The Data

A school district tracks **study hours** vs. **test scores** for 240 students.



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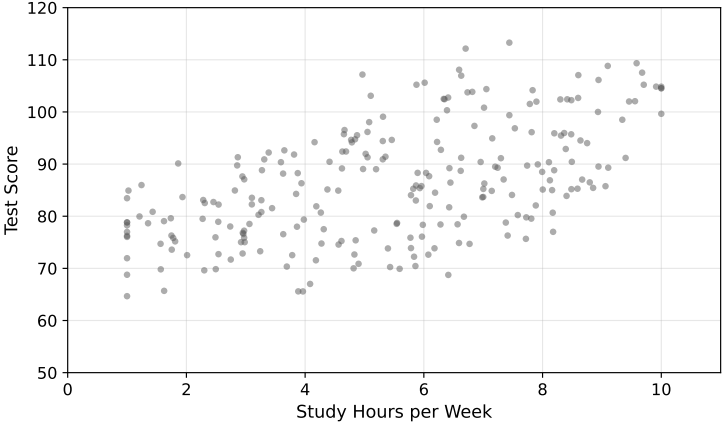

There appears to be a positive relationship. The true slope is $\beta_1 = 2.5$ points per hour. Can OLS recover it?

Setup: The Pooled OLS Model

We ignore any group structure and run a single regression:

$$\text{Score}_i = \beta_0 + \beta_1 \,\text{Hours}_i + \varepsilon_i$$

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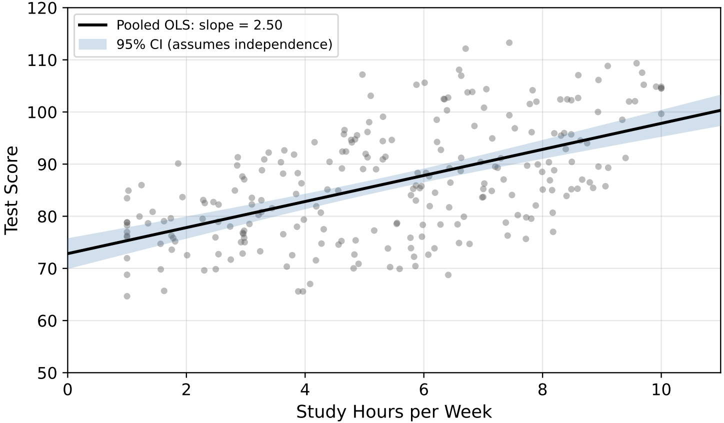
This treats all 240 students as **independent observations**.

- One intercept, one slope, one error term
- No distinction between "within classroom" and "between classroom" variation
- Standard OLS assumptions: ε_i independent, $\text{Var}(\varepsilon_i) = \sigma^2$

Pooled OLS Result



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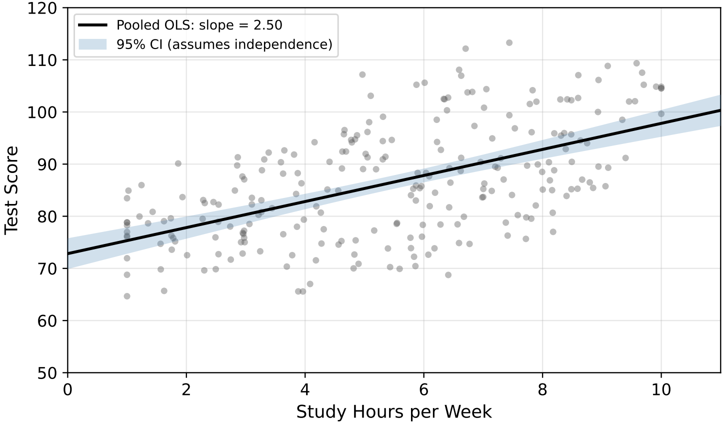

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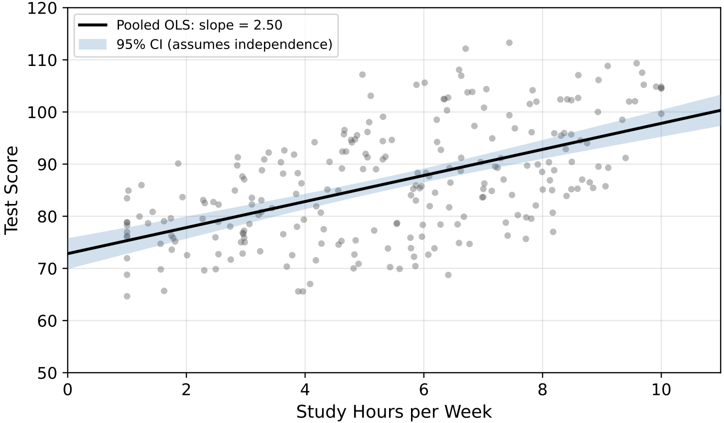

Result: $\hat{\beta}_1 = 2.50$, SE $= 0.239$. The 95% CI is [2.03, 2.97]. Tight, precise, and contains the true slope of 2.5. Looks great!

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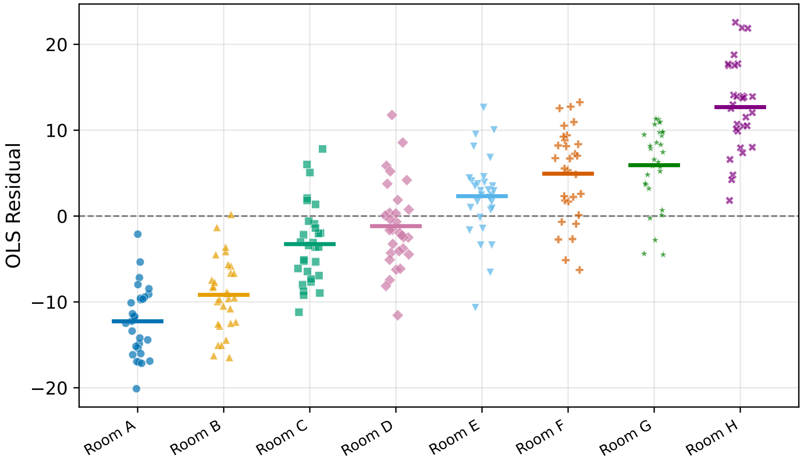
$\Longrightarrow$ Let's look at the OLS residuals to see if the independence assumption holds.

Residuals by Classroom



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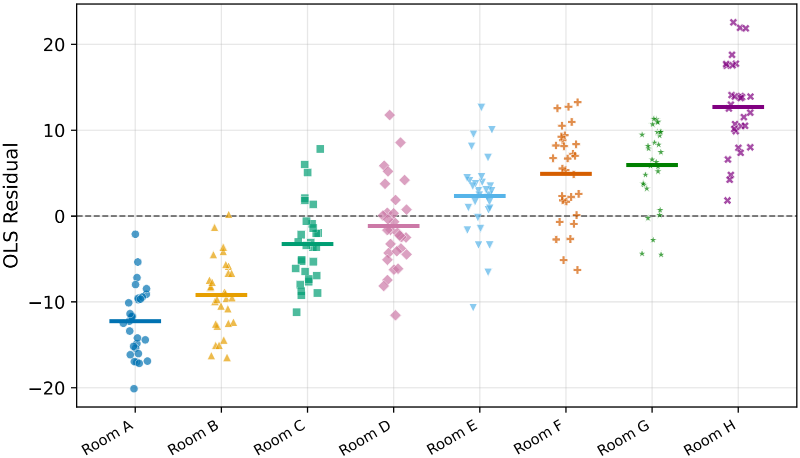
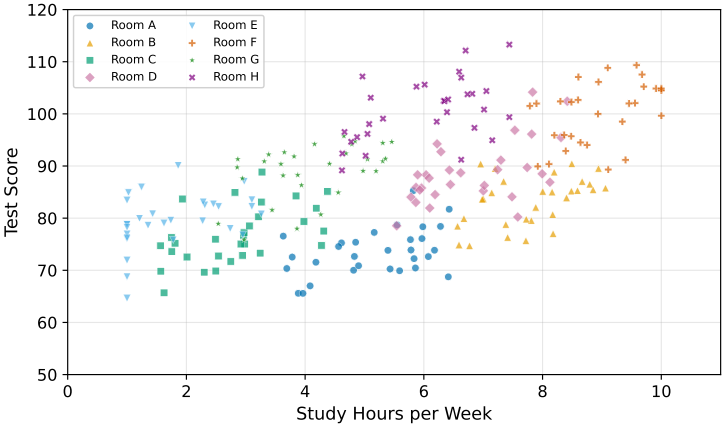


Room A residuals are **all negative** (mean $= -12.3$). Room H residuals are **all positive** (mean $= +12.7$). Within each classroom, residuals move together.

Reveal: Eight Classrooms

The 240 students come from **8 different classrooms**.



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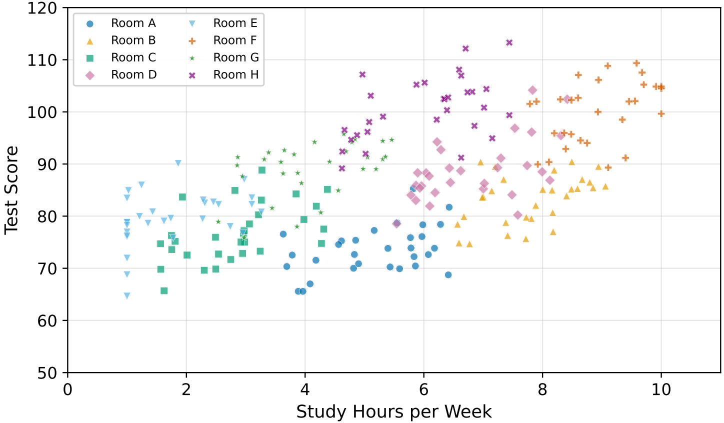

Students in the same classroom share a teacher, curriculum, and grading standard.

Why Residuals Are Correlated: The Composite Error

We now use double subscripts: student i within classroom j.

The true model has a **classroom-level component** that pooled OLS ignores:

$$\text{Score}_{ij} = \beta_0 + \beta_1 \, \text{Hours}_{ij} + \underbrace{u_j + e_{ij}}_{v_{ij}}$$

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Two students i and k in the **same classroom** j share the same u_j.

$\implies$ Their composite errors v_{ij} and v_{kj} are correlated, even if e_{ij} and e_{kj} are independent.

Consequence: Standard Errors Are Too Small

Recall the OLS variance formula for the slope:

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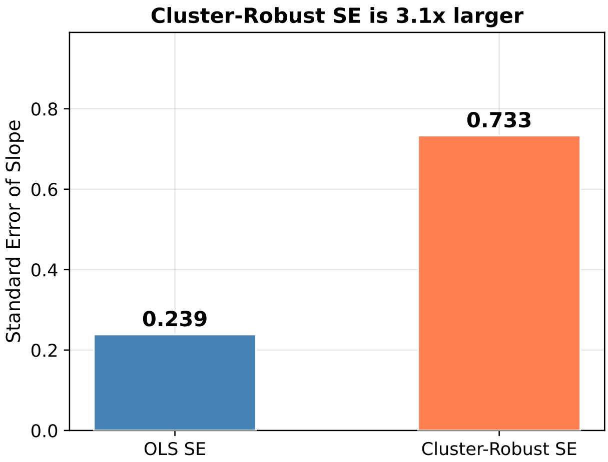
$\implies$ OLS standard errors are **too small**, confidence intervals are **too narrow**, and p-values are **too small**.

How Wrong: SE Comparison



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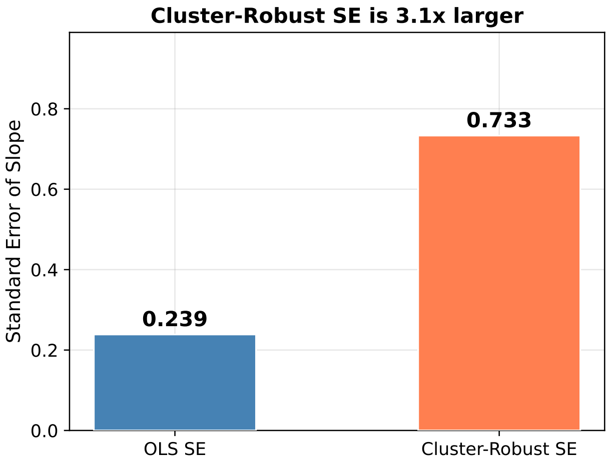
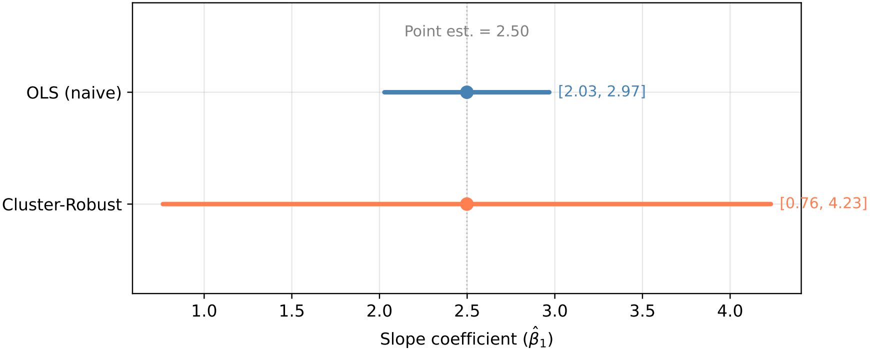


In this dataset, the cluster-robust SE is **3.1x larger** than the naive OLS SE.

Different SEs, Different Conclusions



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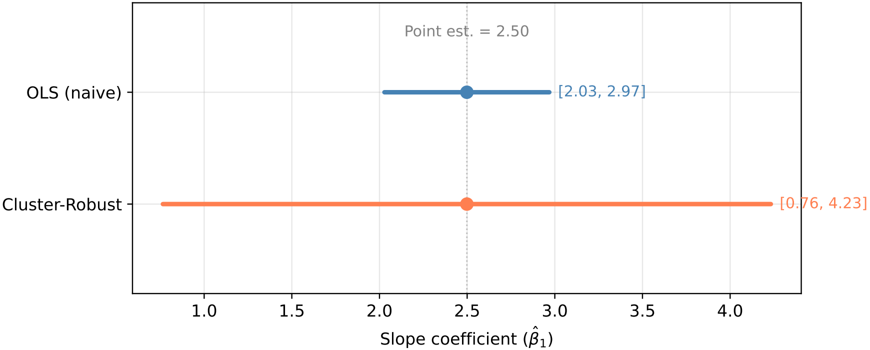

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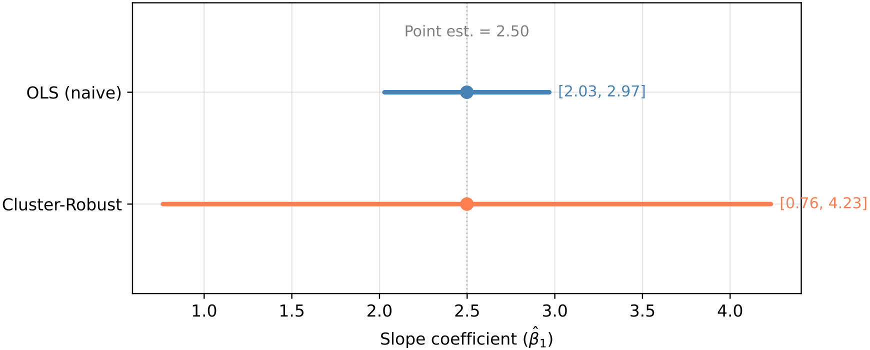

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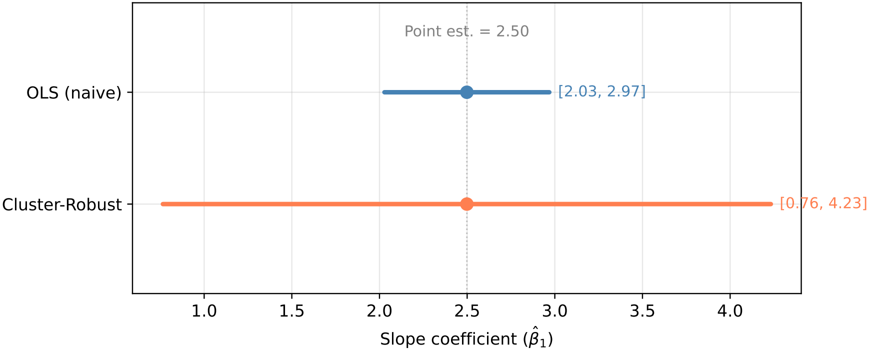

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The narrow OLS interval gives a false sense of precision.

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This is why Room A's residuals were all negative and Room H's were all positive: the classroom effect u_j dominates.

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What does it actually have?

- 240 observations clustered in 8 groups
- About 75% of the residual variance is shared (between-cluster), so 30 students per classroom contribute far less than 30 independent data points
- Effective sample size: $n_{\text{eff}} = \frac{n}{1+(m-1)\hat{\rho}} = \frac{240}{1+29\times 0.75} \approx 11$

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In Python (`statsmodels`):

```
OLS(y, X).fit(cov_type='cluster', cov_kwds={'groups': classroom})
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$\Longrightarrow$ Cluster-robust SEs recognize that 240 people from 8 families carry less information than 240 independent people.

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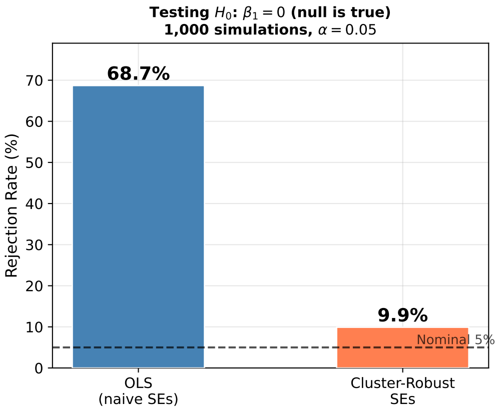
In this dataset, all three factors are present: $\hat{\rho} \approx 0.75$, hours vary by classroom, and each classroom has 30 students.

Simulation: How Often Does OLS Wrongly Reject?



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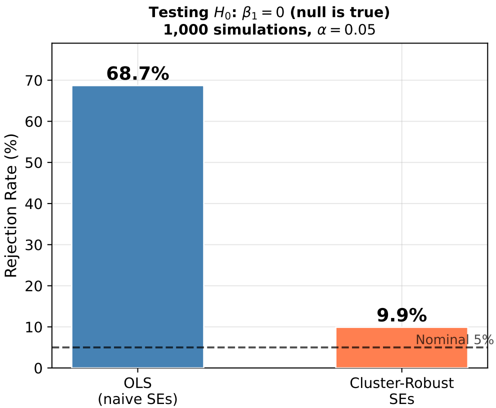

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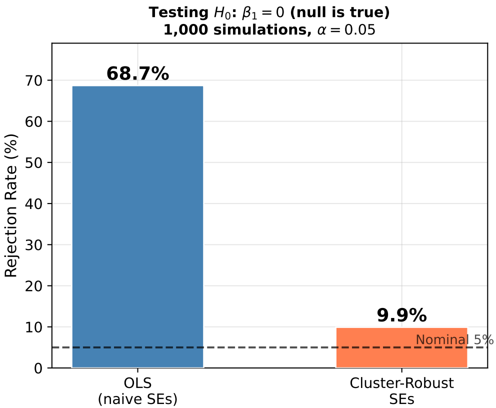

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OLS rejects at **68.7%** (should be 5%). Cluster-robust rejects at **9.9%**: still above 5% because with only 8 clusters the CR variance estimate is imprecise; the wider $t(7)$ critical value partially compensates but does not fully correct.

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$\implies$ Clustering corrects *inference* (SEs, CIs, p-values). It does not correct *estimation* (the slope itself). For that, you need **fixed effects**.

Comparison: Pooled OLS vs. Pooled+CR vs. FE

	Pooled OLS	**Pooled + CR SE**	**Fixed Effects**
Slope consistent?	Yes*	Yes*	Yes
SEs correct?	No	Yes	Yes**
Handles OVB?	No	No	Yes
Removes u_j?	No	No	Yes
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$\Longrightarrow$ Cluster-robust SEs and fixed effects solve **different problems**. You often need both: FE to remove bias, plus clustering on the FE residuals to get correct inference.

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- **Repeated observations:** the same individual observed over multiple time periods (panel data)

When to Cluster

Cluster your standard errors whenever observations share unobserved common shocks:

- **Shared environment:** students in the same classroom, workers in the same firm, patients in the same hospital
- **Group-level treatment:** a policy that affects everyone in a state, a school-wide intervention
- **Repeated observations:** the same individual observed over multiple time periods (panel data)

Rule of thumb: if you can point to a grouping variable that might create shared unobservables, cluster on it. The cost of clustering when it's unnecessary is small (slight efficiency loss). The cost of *not* clustering when you should is large (invalid inference).

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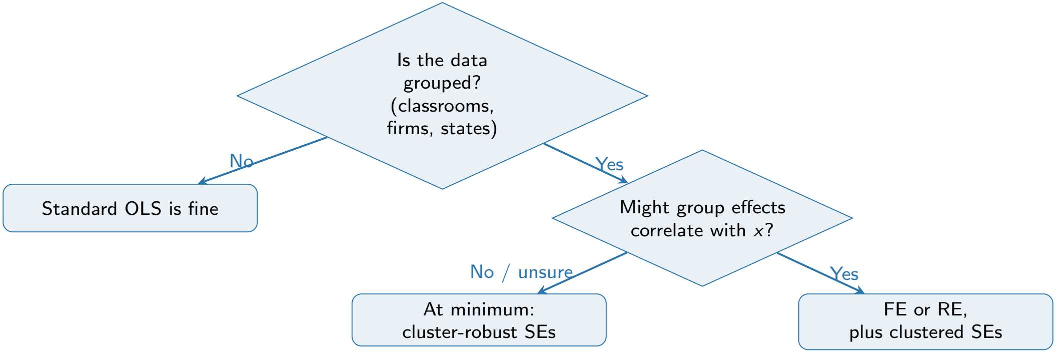
How many clusters are enough?

- With too few clusters (< 30), cluster-robust SEs can be unreliable
- In this dataset, we had only 8 clusters $\implies$ the CR test over-rejected slightly (9.9% instead of 5%)
- With few clusters, consider the wild cluster bootstrap (an advanced technique beyond our scope) or small-sample corrections

Decision Flowchart



Outline

Summary

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5. Clustering fixes *inference*, not *estimation*. If group effects are correlated with the regressor (OVB), you also need **fixed effects**.

Thank you!

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