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W 's are variables that are unobservable or excluded from the model

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Can we use selection on observables to tell us amount of selection on unobservables?

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- Combine $\text{Corr}(d, X\beta)$ with assumption about $\text{Corr}(d, \varepsilon)$ to properly “shade” $\hat{\alpha}$

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3. Observe how $\hat{\alpha}$ and R^2 change across steps 1 and 2
4. Make an assumption on λ such that $\text{Corr}(d, \varepsilon) = \lambda \text{Corr}(d, X\beta)$
5. Use all of the above information to get an interval on plausible $\hat{\alpha}$ TE