Instrumental Variables

Estimating effects in the presence of unmeasured confounding

ERHS 732

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- This type of variable offers an alternative approach that can give us an estimate of the effect of X on Y (or *an* effect of X on Y) under the alternative assumptions above

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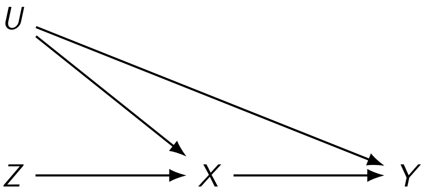

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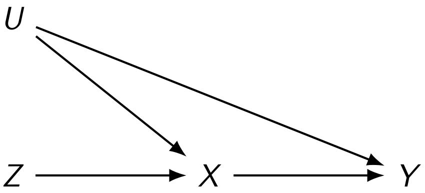
- Regardless of compliance however, Z acts as an instrument for the actual treatment X



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- We can also estimate the effect of exposure assignment Z on actual exposure X based on $E[X|Z=1]-E[X|Z=0]$
- We can redefine the exposure effect of interest as

$$E[Y^{x=1}-Y^{x=0}]=\frac{E[Y|Z=1]-E[Y|Z=0]}{E[X|Z=1]-E[X|Z=0]}$$

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  - The stronger the instrument the better

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- Some obvious applications have been popular in recent literature, but probably remain underutilized
- Natural and quasi-experimental desings offer frameworks where IV's can be of use
- However, the approach should always be used in light of its own limitations