lecture2&3

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Causality

Selection Bias in ATT with Observational Data

$E[Y_i^1|D_1 = 1] - E[Y_i^0|D_1 = 1] + E[Y_i^0|D_1 = 1] - E[Y_i^0|D_1 = 0]$
ATT:$E[Y_i^1|D_1 = 1] - E[Y_i^0|D_1 = 1]$
Selection Bias: $E[Y_i^0|D_1 = 1] - E[Y_i^0|D_1 = 0]$

Selection Bias in ATE with Observational Data

$E[Y_i^1] - E[Y_i^0] + Pr(D_i = 1)(E[Y_i^0|D_1 = 1] - E[Y_i^0|D_1 = 0]) + Pr(D_i = 0)(E[Y_i^1|D_1 = 1] - E[Y_i^1|D_1 = 0])$
ATT: $E[Y_i^1] - E[Y_i^0]$
Selection Bias: $Pr(D_i = 1)(E[Y_i^0|D_1 = 1] - E[Y_i^0|D_1 = 0]) + Pr(D_i = 0)(E[Y_i^1|D_1 = 1] - E[Y_i^1|D_1 = 0])$

Regression with a Single Regressor: Hypothesis Tests and Confidence Intervals

The Least Squares Assumptions:
1. $E(u|X = x) = 0$ (or we can say that there is no correlation between the focus and other factors, i.e. causality are 0) 2. $(X_i, Y_i), i = 1, ..., n$, are i.i.d. 3. Large outliers are rare $E(X4) < \inf, E(Y4) < \inf$.

$\hat{\beta} \sim N(\beta_1, \frac{\sigma_v^2}{n\sigma_X^4})$, where $v_i = (X_i \check{} \mu_X)u_i$ In other word, the model is normally distributed

$Test\hat{S}core = \beta_0 + \beta_1 STR$
β_1 is the slope of population regression line or the change in test score for a unit change in STR

t-testing
$\beta_{1,0} = 0$
$\frac{\hat{\beta_1} - \beta_{1,0}}{SE(\hat{\beta_1})}$

confidence interval
$\beta_1 = \{\hat{\beta_1} \pm C \times SE(\hat{\beta_1})\}$
C is the critical value

The G-M theorem says that among all possible choices of $\{w_i\}$, the OLS weights yield the smallest $var(\hat{\beta_1})$