

# Linear regression with multiple regressors.

JW ch. 6 :

$$(1) Y_i = \beta_0 + \beta_1 X_{1i} + u_i$$

$u_i$  contains all omitted factors - observed and unobserved.

Example:

$Y_i = \log \text{ income}$

$X_{1i} = \text{years of schooling}$

Then  $u_i$  contains effect of e.g.

- parents' level of schooling
- $i$ 's years of experience
- type of occupation

Is  $u_i$  uncorrelated with  $X_{1i}$ ?

Assume ~~the~~ ~~the~~ true model is

$$(2) Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \tilde{u}_i, \text{ where}$$

$X_{2i} \equiv \text{years of experience}$ ,  $\tilde{u}_i$  error term

such that  $E(\tilde{u}_i | X_{1i}, X_{2i}) = 0$

$$\Rightarrow (3) u_i = \beta_2 X_{2i} + \tilde{u}_i$$

Then  $\text{Cov}(X_{1i}, u_i)$  in ① becomes

$$\begin{aligned} \text{Cov}(X_{1i}, \beta_2 X_{2i} + \tilde{u}_i) &= \beta_2 \text{Cov}(X_{1i}, X_{2i}) \\ &+ \underbrace{\text{Cov}(X_{1i}, \tilde{u}_i)}_{\substack{= 0 \text{ if } (2) \text{ is true model}}} = \beta_2 \text{Cov}(X_{1i}, X_{2i}) \neq 0 \end{aligned}$$

Recall

$$\begin{aligned} \hat{\beta}_1 &= \beta_1 + \frac{\sum (X_{1i} - \bar{X}_1) u_i}{\sum (X_{1i} - \bar{X}_1)^2} \xrightarrow{p} \beta_1 + \frac{\text{Cov}(X_{1i}, u_i)}{\text{Var}(X_{1i})} \\ &\neq \beta_1 \end{aligned}$$

$\hat{\beta}_1$  is therefore inconsistent

Sign of the (asymptotic) bias depends on sign of the covariance between regressor and the ~~independent~~ error term

Example 2

Model is:

$$(1) \text{ Output}_i = \beta_0 + \beta_1 \cdot \text{manhours}_i + u_i$$

where  $i$  denotes firm  $i$ But true model is:

$$(2) \text{ Output}_i = \beta_0 + \beta_1 \text{manhours}_i + \beta_2 \text{capital}_i + \tilde{u}_i$$

where  $\tilde{u}_i$  is (correctly specified) errorterm, i.e.  $E(\tilde{u}_i | \text{manhours}_i, \text{capital}_i) = 0$ Bias of  $\hat{\beta}_1$  in equation (1) is

$$\frac{\text{Cov}(u_i, \text{manhours}_i)}{\text{Var}(\text{manhours}_i)} = \frac{\text{Cov}(\beta_2 \text{capital}_i + \tilde{u}_i, \text{manhours}_i)}{\text{Var}(\text{manhours}_i)}$$

$$= \beta_2 \frac{\text{Cov}(\text{capital}_i, \text{manhours}_i)}{\text{Var}(\text{manhours}_i)} + \underbrace{\frac{\text{Cov}(\tilde{u}_i, \text{manhours}_i)}{\text{Var}(\text{manhours}_i)}}_{= 0}$$

$$= \beta_2 \frac{\text{Cov}(\text{capital}_i, \text{manhours}_i)}{\text{Var}(\text{manhours}_i)}$$

$$\underbrace{\text{Cov}}_{70} \underbrace{\text{Var}(\text{manhours}_i)}_{70}$$

Example 3 : Model says that :

$$\begin{aligned} \text{grad}_i &= \beta_0 + \beta_1 \frac{\# \text{ teachers}}{\# \text{ students}} + u_i \\ &\equiv \beta_0 + \beta_1 (T/S)_i + u_i \end{aligned}$$

True model is :

$$\text{grad}_i = \beta_0 + \beta_1 (T/S)_i + \beta_2 \text{Minority}_i + \tilde{u}_i$$

where  $E(\tilde{u}_i | (T/S)_i, \text{Minority}_i) = 0$

and  $\text{Minority}_i = \begin{cases} 1 & \text{if has minority background} \\ 0 & \text{else} \end{cases}$

$$\text{Bias} = \frac{\text{Cov}((T/S)_i, \beta_2 \text{Minority}_i + \tilde{u}_i)}{\text{Var}((T/S)_i)}$$

$$= \frac{\beta_2 \text{Cov}((T/S)_i, \text{Minority}_i)}{\text{Var}((T/S)_i)}$$

In general : Important to include variables that are determinants of  $Y_i$  and correlated with the regressor of interest.

Multiple regression model

$$Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \dots + \beta_k X_{ki} + u_i$$

where

$$E(u_i | X_{1i}, \dots, X_{ki}) = 0 \Rightarrow$$

$$E(Y_i | X_{1i}, \dots, X_{ki}) = \beta_0 + \beta_1 X_{1i} + \dots + \beta_k X_{ki}$$

— i.e. the regression line

Partial or marginal effects :

$$\beta_k = \frac{\partial E(Y_i | X_{1i}, \dots, X_{ki})}{\partial X_{ki}}$$

i.e. holding all other variables constant

One cannot in general obtain  $\beta_k$  from single-regressor equation :

$$Y_i = \beta_0 + \beta_k X_{ki} + u_i$$

— because of omitted variable bias.

# Ordinary least squares (OLS)

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The OLS estimator of  $\beta_0, \beta_1, \dots, \beta_k$  is given by

$$\min_{\beta_0, \dots, \beta_k} \sum_{i=1}^n (Y_i - \beta_0 - \beta_1 X_{1i} - \dots - \beta_k X_{ki})^2$$

\* Predicted values:

$$\hat{Y}_i = \hat{\beta}_0 + \hat{\beta}_1 X_{1i} + \dots + \hat{\beta}_k X_{ki}$$

Residual:

$$\hat{u}_i = Y_i - \hat{Y}_i \Leftrightarrow Y_i = \hat{Y}_i + \hat{u}_i$$

The 1. order conditions give:

$$\begin{aligned} \frac{\partial}{\partial \beta_k} \sum_{i=1}^n (Y_i - \hat{\beta}_0 - \hat{\beta}_1 X_{1i} - \dots - \hat{\beta}_k X_{ki})^2 \\ = \sum_{i=1}^n (Y_i - \hat{\beta}_0 - \hat{\beta}_1 X_{1i} - \dots - \hat{\beta}_k X_{ki}) X_{ki} = 0 \end{aligned}$$

$$\Leftrightarrow \sum_{i=1}^n \hat{u}_i X_{li} = 0 \quad - \text{the residuals are uncorrelated with all the regressors!}$$

## The least squares assumptions: VII

$$A.1 \quad E(u_i | X_{1i}, \dots, X_{ki}) = 0$$

This implies that

$$\begin{aligned} \text{Cov}(u_i, X_{li}) &= E(u_i X_{li}) \\ &= E\left(E(u_i X_{li} | X_{1i}, \dots, X_{ki})\right) \quad [\text{double expectation}] \\ &= E\left(X_{li} E(u_i | X_{1i}, \dots, X_{ki})\right) \\ &= E\left(X_{li} \cdot 0\right) = 0 \end{aligned}$$

Thus the OLS estimator is a moment estimator:

$$\frac{1}{n} \sum_{i=1}^n u_i X_{li} = E(u_i X_{li}) = 0$$

which follows from 1. order conditions for OLS and A.1.

A.2 :

$$(X_{1i}, X_{2i}, \dots, X_{ki}, Y_i) \quad i = 1, \dots, n$$

are i.i.d

$$A.3 : \quad E(X_{1i}^4) < \infty, \dots, E(X_{ki}^4) < \infty,$$

$$E(Y_i^4) < \infty$$

— i.e. large outliers are unlikely

A.4. No perfect multicollinearity: no regressor should be a perfect linear function of other regressors.



More about multicollinearity:

Write  $Y_i = \beta_0 X_{0i} + \beta_1 X_{1i} + \dots + \beta_{k-1} X_{k-1,i} + u_i$

where  $X_{0i} \equiv 1$  for all  $i$

Multicollinearity means that one of the regressors can be written as a linear function of the other ones:

E.g.  $X_{k-1,i} = \sum_{j=0}^{k-1} a_j X_{j,i} = a_0 X_{0i} + \dots + a_{k-1} X_{k-1,i}$

for all  $i$  and some constants  $a_0, \dots, a_{k-1}$

Example:

$$Y_i = \beta_0 + \beta_1 \text{Man}_i + \beta_2 \text{Woman}_i + u_i$$

$$\text{Man}_i = \begin{cases} 1 & \text{if } i \text{ is man} \\ 0 & \text{else} \end{cases}, \quad \text{Woman}_i = \begin{cases} 1 & \text{if } i \text{ woman} \\ 0 & \text{else} \end{cases}$$

$$\Rightarrow \text{Man}_i + \text{Woman}_i = 1 \quad (\Leftrightarrow) \quad \text{Man}_i = 1 - \text{Woman}_i$$

$$\begin{aligned} \Rightarrow Y_i &= \beta_0 + \beta_1 (1 - \text{Woman}_i) + \beta_2 \text{Woman}_i + u_i \\ &= \beta_0 + \beta_1 + (\beta_2 - \beta_1) \text{Woman}_i + u_i \end{aligned}$$