Introductory Econometrics

Lecture 12: Properties of OLS in the multiple regression model

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Multiple regression and OLS

- Consider the multiple regression model with k regressors: $Y_i = \beta_0 + \beta_1 X_{1,i} + \beta_2 X_{2,i} + \ldots + \beta_k X_{k,i} + U_i$.
- Let $\hat{\beta}_0, \hat{\beta}_1, \ldots, \hat{\beta}_k$ be the OLS estimators: if

$$\hat{U}_i = Y_i - \hat{\beta}_0 - \hat{\beta}_1 X_{1,i} - \hat{\beta}_2 X_{2,i} - \ldots - \hat{\beta}_k X_{k,i},$$

then

$$\sum_{i=1}^{n} \hat{U}_i = \sum_{i=1}^{n} X_{1,i} \hat{U}_i = \ldots = \sum_{i=1}^{n} X_{k,i} \hat{U}_i = 0.$$

- As in Lecture 10, we can write $\hat{\beta}_1$ as

$$\hat{\beta}_1 = \frac{\sum_{i=1}^n \tilde{X}_{1,i} Y_i}{\sum_{i=1}^n \tilde{X}_{1,i}^2}, \text{ where}$$

  - $\tilde{X}_{1,i}$ are the fitted OLS residuals: $\tilde{X}_{1,i} = X_{1,i} - \hat{\gamma}_0 - \hat{\gamma}_2 X_{2,i} - \ldots - \hat{\gamma}_k X_{k,i}$.
  - $\hat{\gamma}_0, \hat{\gamma}_2, \ldots, \hat{\gamma}_k$ are the OLS coefficients: $\sum_{i=1}^n \tilde{X}_{1,i} = \sum_{i=1}^n \tilde{X}_{1,i} X_{2,i} = \ldots = \sum_{i=1}^n \tilde{X}_{1,i} X_{k,i} = 0$.
- Similarly, we can write $\hat{\beta}_2$ as

$$\hat{\beta}_2 = \frac{\sum_{i=1}^n \tilde{X}_{2,i} Y_i}{\sum_{i=1}^n \tilde{X}_{2,i}^2}, \text{ where}$$

  - $\tilde{X}_{2,i}$ are the fitted OLS residuals: $\tilde{X}_{2,i} = X_{2,i} - \hat{\delta}_0 - \hat{\delta}_1 X_{1,i} - \hat{\delta}_3 X_{3,i} - \ldots - \hat{\delta}_k X_{k,i}$.
  - $\hat{\delta}_0, \hat{\delta}_1, \hat{\delta}_3, \ldots, \hat{\delta}_k$ are the OLS coefficients: $\sum_{i=1}^n \tilde{X}_{2,i} = \sum_{i=1}^n \tilde{X}_{2,i} X_{1,i} = \sum_{i=1}^n \tilde{X}_{2,i} X_{3,i} = \ldots = \sum_{i=1}^n \tilde{X}_{2,i} X_{k,i} = 0$.

The OLS estimators are linear

- Consider $\hat{\beta}_1$:

$$\hat{\beta}_1 = \frac{\sum_{i=1}^n \tilde{X}_{1,i} Y_i}{\sum_{i=1}^n \tilde{X}_{1,i}^2} = \sum_{i=1}^n \frac{\tilde{X}_{1,i}}{\sum_{l=1}^n \tilde{X}_{1,l}^2} Y_i = \sum_{i=1}^n w_{1,i} Y_i,$$

  where

$$w_{1,i} = \frac{\tilde{X}_{1,i}}{\sum_{l=1}^n \tilde{X}_{1,l}^2}.$$

- Recall that $\tilde{X}_1$ are the residuals from a regression of X_1 against $X_2, \ldots, X_k$ and a constant, and therefore $w_{1,i}$ depends only on X's.

Unbiasedness

- Suppose that
  1. $Y_i = \beta_0 + \beta_1 X_{1,i} + \beta_2 X_{2,i} + \ldots + \beta_k X_{k,i} + U_i$.
  2. Conditional on X's, $\mathrm{E}[U_i] = 0$ for all i's.
     - Conditioning on X's means that we condition on $X_{1,1}, \ldots, X_{1,n}, X_{2,1}, \ldots, X_{2,n}, \ldots, X_{k,1}, \ldots, X_{k,n}$:

$$\mathrm{E}[U_i \mid X_{1,1}, \ldots, X_{1,n}, X_{2,1}, \ldots, X_{2,n}, \ldots, X_{k,1}, \ldots, X_{k,n}] = 0.$$

- Under the above assumptions:

$$\begin{aligned} \mathrm{E}\left[\hat{\beta}_0\right] &= \beta_0, \\ \mathrm{E}\left[\hat{\beta}_1\right] &= \beta_1, \\ \vdots \quad & \vdots \quad \vdots \\ \mathrm{E}\left[\hat{\beta}_k\right] &= \beta_k. \end{aligned}$$

Proof of unbiasedness

$$
\begin{aligned}
\hat{\beta}_1 = \frac{\sum_{i=1}^n \tilde{X}_{1,i} Y_i}{\sum_{i=1}^n \tilde{X}_{1,i}^2} &= \frac{\sum_{i=1}^n \tilde{X}_{1,i} \left(\beta_0 + \beta_1 X_{1,i} + \beta_2 X_{2,i} + \ldots + \beta_k X_{k,i} + U_i\right)}{\sum_{i=1}^n \tilde{X}_{1,i}^2} \\
&= \beta_0 \frac{\sum_{i=1}^n \tilde{X}_{1,i}}{\sum_{i=1}^n \tilde{X}_{1,i}^2} + \beta_1 \frac{\sum_{i=1}^n \tilde{X}_{1,i} X_{1,i}}{\sum_{i=1}^n \tilde{X}_{1,i}^2} + \beta_2 \frac{\sum_{i=1}^n \tilde{X}_{1,i} X_{2,i}}{\sum_{i=1}^n \tilde{X}_{1,i}^2} \\
&\quad + \cdots + \beta_k \frac{\sum_{i=1}^n \tilde{X}_{1,i} X_{k,i}}{\sum_{i=1}^n \tilde{X}_{1,i}^2} + \frac{\sum_{i=1}^n \tilde{X}_{1,i} U_i}{\sum_{i=1}^n \tilde{X}_{1,i}^2}
\end{aligned}
$$

Using the partitioned regression results from Lecture 10:

$$
\sum_{i=1}^n \tilde{X}_{1,i} = \sum_{i=1}^n \tilde{X}_{1,i} X_{2,i} = \ldots = \sum_{i=1}^n \tilde{X}_{1,i} X_{k,i} = 0, \sum_{i=1}^n \tilde{X}_{1,i} X_{1,i} = \sum_{i=1}^n \tilde{X}_{1,i}^2.
$$

Therefore,

$$
\hat{\beta}_1 = \beta_1 + \frac{\sum_{i=1}^n \tilde{X}_{1,i} U_i}{\sum_{i=1}^n \tilde{X}_{1,i}^2}.
$$

- We have that
$$\hat{\beta}_1 = \beta_1 + \frac{\sum_{i=1}^{n} \tilde{X}_{1,i} U_i}{\sum_{i=1}^{n} \tilde{X}_{1,i}^2}.$$
- Conditional on X's,
$$\mathrm{E}\left[U_i\right] = 0.$$
- Therefore, conditional on X's,

$$\begin{aligned}
\mathrm{E}\left[\hat{\beta}_1\right] &= \mathrm{E}\left[\beta_1 + \frac{\sum_{i=1}^{n} \tilde{X}_{1,i} U_i}{\sum_{i=1}^{n} \tilde{X}_{1,i}^2}\right] \\
&= \beta_1 + \mathrm{E}\left[\frac{\sum_{i=1}^{n} \tilde{X}_{1,i} U_i}{\sum_{i=1}^{n} \tilde{X}_{1,i}^2}\right] \\
&= \beta_1 + \frac{\sum_{i=1}^{n} \tilde{X}_{1,i} E\left(U_i\right)}{\sum_{i=1}^{n} \tilde{X}_{1,i}^2} \\
&= \beta_1.
\end{aligned}$$

Conditional variance of the OLS estimators

- Suppose that:
  1. $Y_i = \beta_0 + \beta_1 X_{1,i} + \beta_2 X_{2,i} + \ldots + \beta_k X_{k,i} + U_i$.
  2. Conditional on X's, $\mathrm{E}\left[U_i\right] = 0$ for all i's.
  3. Conditional on X's, $\mathrm{E}\left[U_i^2\right] = \sigma^2$ for all i's.
  4. Conditional on X's, $\mathrm{E}\left[U_i U_j\right] = 0$ for all $i \neq j$.
- The conditional variance of $\hat{\beta}_1$ given X's, is

$$\mathrm{Var}\left[\hat{\beta}_1\right] = \frac{\sigma^2}{\sum_{i=1}^{n} \tilde{X}_{1,i}^2}.$$

- Gauss-Markov Theorem: Under Assumptions 1-4, the OLS estimators are BLUE.

- We have $\hat{\beta}_1 = \beta_1 + \frac{\sum_{i=1}^n \tilde{X}_{1,i} U_i}{\sum_{i=1}^n \tilde{X}_{1,i}^2}$ and $\mathrm{E}\left[\hat{\beta}_1\right] = \beta_1$.
- Conditional on X's,

$$
\begin{aligned}
\mathrm{Var}\left[\hat{\beta}_1\right] &= \mathrm{E}\left[\left(\frac{\sum_{i=1}^n \tilde{X}_{1,i} U_i}{\sum_{i=1}^n \tilde{X}_{1,i}^2}\right)^2\right] \\
&= \left(\frac{1}{\sum_{i=1}^n \tilde{X}_{1,i}^2}\right)^2 \mathrm{E}\left[\left(\sum_{i=1}^n \tilde{X}_{1,i} U_i\right)^2\right] \\
&= \left(\frac{1}{\sum_{i=1}^n \tilde{X}_{1,i}^2}\right)^2 \mathrm{E}\left[\sum_{i=1}^n \tilde{X}_{1,i}^2 U_i^2 + \sum_{i=1}^n \sum_{j \neq i} \tilde{X}_{1,i} \tilde{X}_{1,j} U_i U_j\right] \\
&= \left(\frac{1}{\sum_{i=1}^n \tilde{X}_{1,i}^2}\right)^2 \left(\sum_{i=1}^n \tilde{X}_{1,i}^2 \sigma^2 + \sum_{i=1}^n \sum_{j \neq i} \tilde{X}_{1,i} \tilde{X}_{1,j} 0\right) \\
&= \left(\frac{1}{\sum_{i=1}^n \tilde{X}_{1,i}^2}\right)^2 \sigma^2 \sum_{i=1}^n \tilde{X}_{1,i}^2 = \frac{\sigma^2}{\sum_{i=1}^n \tilde{X}_{1,i}^2}.
\end{aligned}
$$

Conditional covariance of the OLS estimators

- Consider $\hat{\beta}_1$ and $\hat{\beta}_2$:

$$\begin{aligned}\hat{\beta}_1 &= \beta_1 + \frac{\sum_{i=1}^n \tilde{X}_{1,i} U_i}{\sum_{i=1}^n \tilde{X}_{1,i}^2},\\ \hat{\beta}_2 &= \beta_2 + \frac{\sum_{i=1}^n \tilde{X}_{2,i} U_i}{\sum_{i=1}^n \tilde{X}_{2,i}^2},\end{aligned}$$

  where
  - $\tilde{X}_1$ are the fitted residuals from the regression of X_1 against a constant and $X_2, X_{3,}, \ldots, X_k$.
  - $\tilde{X}_2$ are the fitted residuals from the regression of X_2 against a constant and $X_1, X_3, \ldots, X_k$.
- We will show that given Assumptions 1-4, conditional on X's:

$$\mathrm{Cov}\left[\hat{\beta}_1, \hat{\beta}_2\right] = \sigma^2 \frac{\sum_{i=1}^n \tilde{X}_{1,i}\tilde{X}_{2,i}}{\sum_{i=1}^n \tilde{X}_{1,i}^2 \sum_{i=1}^n \tilde{X}_{2,i}^2}$$

Conditional on X's,

$$\begin{aligned}
\mathrm{Cov}\left[\hat{\beta}_1, \hat{\beta}_2\right] &= \mathrm{E}\left[\left(\hat{\beta}_1 - \mathrm{E}\left[\hat{\beta}_1\right]\right)\left(\hat{\beta}_2 - \mathrm{E}\left[\hat{\beta}_2\right]\right)\right] \\
&= \mathrm{E}\left[\left(\frac{\sum_{i=1}^n \tilde{X}_{1,i} U_i}{\sum_{i=1}^n \tilde{X}_{1,i}^2}\right)\left(\frac{\sum_{i=1}^n \tilde{X}_{2,i} U_i}{\sum_{i=1}^n \tilde{X}_{2,i}^2}\right)\right] \\
&= \frac{1}{\sum_{i=1}^n \tilde{X}_{1,i}^2 \sum_{i=1}^n \tilde{X}_{2,i}^2} \mathrm{E}\left[\left(\sum_{i=1}^n \tilde{X}_{1,i} U_i\right)\left(\sum_{i=1}^n \tilde{X}_{2,i} U_i\right)\right] \\
&= \frac{1}{\sum_{i=1}^n \tilde{X}_{1,i}^2 \sum_{i=1}^n \tilde{X}_{2,i}^2} \mathrm{E}\left[\sum_{i=1}^n \tilde{X}_{1,i}\tilde{X}_{2,i} U_i^2 + \sum_{i=1}^n \sum_{j \neq i} \tilde{X}_{1,i}\tilde{X}_{2,j} U_i U_j\right] \\
&= \frac{1}{\sum_{i=1}^n \tilde{X}_{1,i}^2 \sum_{i=1}^n \tilde{X}_{2,i}^2} \sum_{i=1}^n \tilde{X}_{1,i}\tilde{X}_{2,i}\sigma^2.
\end{aligned}$$

Normality of the OLS estimators

- In addition to Assumptions 1-4, assume that conditional on X's, U_i's are jointly normally distributed.
- $\hat{\beta}_0, \hat{\beta}_1, \ldots, \hat{\beta}_k$ are linear estimators:

$$\hat{\beta}_j = \sum_{i=1}^{n} w_{j,i} Y_i = \beta_j + \sum_{i=1}^{n} w_{j,i} U_i,$$

where

$$w_{j,i} = \frac{\tilde{X}_{j,i}}{\sum_{l=1}^{n} \tilde{X}_{j,i}^2},$$

and $\tilde{X}_{j,i}$ are the residuals from the regression of $X_{j,i}$ against the rest of the regressors.
- It follows that $\hat{\beta}_0, \hat{\beta}_1, \ldots, \hat{\beta}_k$ are jointly normally distributed (conditional on X's).

Inclusion of irrelevant regressors

- Suppose that the true model is $Y_i = \beta_0 + \beta_1 X_{1,i} + U_i$.
- We could estimate β_1 by

$$\hat{\beta}_1 = \frac{\sum_{i=1}^{n} \left(X_{1,i} - \bar{X}_1\right) Y_i}{\sum_{i=1}^{n} \left(X_{1,i} - \bar{X}_1\right)^2}.$$

  Suppose that instead we regress Y against a constant, X_1 and additional $k-1$ regressors $X_2, \ldots, X_k$, i.e. we estimate β_1 by

$$\tilde{\beta}_1 = \frac{\sum_{i=1}^{n} \tilde{X}_{1,i} Y_i}{\sum_{i=1}^{n} \tilde{X}_{1,i}^2}.$$

- We have

$$\tilde{\beta}_1 = \frac{\sum_{i=1}^{n} \tilde{X}_{1,i} \left(\beta_0 + \beta_1 X_{1,i} + U_i\right)}{\sum_{i=1}^{n} \tilde{X}_{1,i}^2} = \beta_1 + \frac{\sum_{i=1}^{n} \tilde{X}_{1,i} U_i}{\sum_{i=1}^{n} \tilde{X}_{1,i}^2}.$$

- Since conditional on X's $\mathrm{E}\left[U_i\right] = 0$, $\tilde{\beta}_1$ is unbiased !

- When $Y_i = \beta_0 + \beta_1 X_{1,i} + U_i$,

$$\hat{\beta}_1 = \frac{\sum_{i=1}^{n} \left(X_{1,i} - \bar{X}_1\right) Y_i}{\sum_{i=1}^{n} \left(X_{1,i} - \bar{X}_1\right)^2} \text{ and } \tilde{\beta}_1 = \frac{\sum_{i=1}^{n} \tilde{X}_{1,i} Y_i}{\sum_{i=1}^{n} \tilde{X}_{1,i}^2} \text{ are both unbiased.}$$

- Conditional on X's,

$$\mathrm{Var}\left[\hat{\beta}_1\right] = \frac{\sigma^2}{\sum_{i=1}^{n} \left(X_{1,i} - \bar{X}_1\right)^2} \text{ and } \mathrm{Var}\left[\tilde{\beta}_1\right] = \frac{\sigma^2}{\sum_{i=1}^{n} \tilde{X}_{1,i}^2}.$$

- Since the true model has only X_1, by Gauss-Markov Theorem $\hat{\beta}_1$ is BLUE and

$$\mathrm{Var}\left[\hat{\beta}_1\right] \leq \mathrm{Var}\left[\tilde{\beta}_1\right].$$

- Without Gauss-Markov Theorem, one can show directly that $\sum_{i=1}^{n} \left(X_{1,i} - \bar{X}_1\right)^2 \geq \sum_{i=1}^{n} \tilde{X}_{1,i}^2$.

Proof of $\sum_{i=1}^{n}\left(X_{1,i}-\bar{X}_1\right)^2 \geq \sum_{i=1}^{n}\tilde{X}_{1,i}^2$

- $\tilde{X}_{1,i}$ are the fitted residuals from regressing $X_{1,i}$ against a constant, $X_{2,i},\ldots,X_{k,i}$:

$$X_{1,i}=\hat{\gamma}_0+\hat{\gamma}_2 X_{2,i}+\ldots+\hat{\gamma}_k X_{k,i}+\tilde{X}_{1,i}.$$

- Consider the sums-of-squares for this regression:

$$\begin{aligned} SST_1 &= \sum_{i=1}^{n}\left(X_{1,i}-\bar{X}_1\right)^2, \\ SSE_1 &= \sum_{i=1}^{n}\left(\hat{\gamma}_0+\hat{\gamma}_2 X_{2,i}+\ldots+\hat{\gamma}_k X_{k,i}-\bar{X}_1\right)^2, \\ SSR_1 &= \sum_{i=1}^{n}\tilde{X}_{1,i}^2. \end{aligned}$$

- Thus,

$$\sum_{i=1}^{n}\left(X_{1,i}-\bar{X}_1\right)^2-\sum_{i=1}^{n}\tilde{X}_{1,i}^2=SST_1-SSR_1=SSE_1\geq 0.$$

$\mathrm{Var}\left[\hat{\beta}_1\right]$ and the number of regressors k

- In $Y_i = \hat{\beta}_0 + \hat{\beta}_1 X_{1,i} + \hat{\beta}_2 X_{2,i} + \ldots + \hat{\beta}_k X_{k,i} + \hat{U}_i$, the variance of the OLS estimator $\hat{\beta}_1$ is

$$\mathrm{Var}\left[\hat{\beta}_1\right] = \frac{\sigma^2}{\sum_{i=1}^{n} \tilde{X}_{1,i}^2} = \frac{\sigma^2}{SSR_1},$$

  where SSR_1 is the residual sum-of-squares from the regression of X_1 against a constant and the rest of the regressors.
- Since SSR_1 can only decrease when we add more regressors, $\mathrm{Var}\left[\hat{\beta}_1\right]$ increases with k, if the added regressors are irrelevant but correlated with the included regressors.
- If the added regressors are uncorrelated with X_1, inclusion of such regressors will not affect SSR_1 (in large samples) or the variance of $\hat{\beta}_1$.
- If the added regressors are uncorrelated with X_1 and affect Y, their inclusion will reduce σ^2 without affecting SSR_1 and will reduce the variance of $\hat{\beta}_1$.

Estimation of variances and covariances

- In $Y_i = \hat{\beta}_0 + \hat{\beta}_1 X_{1,i} + \hat{\beta}_2 X_{2,i} + \ldots + \hat{\beta}_k X_{k,i} + \hat{U}_i$,

$$\mathrm{Var}\left[\hat{\beta}_1\right] = \frac{\sigma^2}{\sum_{i=1}^n \tilde{X}_{1,i}^2} \text{ and } \mathrm{Cov}\left[\hat{\beta}_1, \hat{\beta}_2\right] = \sigma^2 \frac{\sum_{i=1}^n \tilde{X}_{1,i}\tilde{X}_{2,i}}{\sum_{i=1}^n \tilde{X}_{1,i}^2 \sum_{i=1}^n \tilde{X}_{2,i}^2}.$$

- Variances and covariances can be estimated by replacing σ^2 with

$$s^2 = \frac{1}{n-k-1} \sum_{i=1}^n \hat{U}_i^2.$$

- Estimated variance and covariance:

$$\widehat{\mathrm{Var}}\left[\hat{\beta}_1\right] = \frac{s^2}{\sum_{i=1}^n \tilde{X}_{1,i}^2} \text{ and } \widehat{\mathrm{Cov}}\left[\hat{\beta}_1, \hat{\beta}_2\right] = s^2 \frac{\sum_{i=1}^n \tilde{X}_{1,i}\tilde{X}_{2,i}}{\sum_{i=1}^n \tilde{X}_{1,i}^2 \sum_{i=1}^n \tilde{X}_{2,i}^2}.$$