1 Algebra of Least Squares

Notation: y_i is a scalar, and x_i is a $K \times 1$ vector. Y is an $n \times 1$ vector, and X is an $n \times K$ matrix.

1.1 OLS estimator

As we have learned from the previous lecture, the parameter β in the linear projection model

$$\begin{aligned} y_i &= x_i'\beta + e_i \\ E[x_i e_i] &= 0 \end{aligned}$$

can be written as $\beta = \left(E\left[x_i x_i'\right]\right)^{-1} E\left[x_i y_i\right]$. In reality we possess a sample of n observations, not the population. We thus replace the population mean $E\left[\cdot\right]$ by the sample mean, and the resulting estimator is

$$\widehat{\beta} = \left(\frac{1}{n}\sum_{i=1}^{n} x_i x_i'\right)^{-1} \frac{1}{n}\sum_{i=1}^{n} x_i y_i = \left(X'X\right)^{-1} X'y.$$

This is one way to motivate the OLS estimator.

Alternatively, we can derive the OLS estimator from minimizing the sum of squared residuals $\sum_{i=1}^{n}\left(y_i - x_i'\beta\right)^2$. By a routine optimization, we obtain exactly the same $\widehat{\beta}$.

Definitions and properties

- Fitted value: $\widehat{Y} = X\widehat{\beta}$.
- Residual: $\widehat{e} = Y - \widehat{Y}$.
- Projector: $P_X = X\left(X'X\right)^{-1} X$; Annihilator: $M_X = I_n - P_X$.
- $P_X M_X = M_X P_X = 0$.
- Idempotent matrix: $P_X P_X = P_X$, $M_X M_X = M_X$.
- $\widehat{e} = Y - \widehat{Y} = Y - X\widehat{\beta} = M_X Y = M_X\left(X\beta + e\right) = M_X e$.
- $X'\widehat{e} = X M_X e = 0$.
- $\frac{1}{n}\sum_{i=1}^{n}\widehat{e}_i = 0$ if x_i contains a constant.

1.2 Goodness of Fit

The so-called R-square is the most popular measure of goodness-of-fit in the linear regression. R-square is well defined only when a constant is included in the regressors. Let $M_\iota = I_n - \frac{1}{n}\iota\iota'$, where ι is an $n \times 1$ vector of 1's. M_ι is the demeaner, that is, $M_\iota\left(z_1, \ldots, z_n\right)' = \left(z_1 - \overline{z}, \ldots, z_n - \overline{z}\right)'$, where $\bar{z} = \frac{1}{n}\sum_{i=1}^{n} z_i$. For any X, we can decompose $Y = P_X Y + M_X Y = \widehat{Y} + \widehat{e}$. The total variation is

$$Y'M_\iota Y = \left(\widehat{Y} + \widehat{e}\right)' M_\iota \left(\widehat{Y} + \widehat{e}\right) = \widehat{Y}'M_\iota\widehat{Y} + 2\widehat{Y}'M_\iota\widehat{e} + \widehat{e}'M_\iota\widehat{e} = \widehat{Y}'M_\iota\widehat{Y} + \widehat{e}'\widehat{e}$$

where the last equality follows by $M_\iota \widehat{e} = \widehat{e}$ as $\frac{1}{n}\sum_{i=1}^n \widehat{e}_i = 0$, and $\widehat{Y}'\widehat{e} = Y'P_X M_X e = 0$. R-square is $\widehat{Y}'M_\iota\widehat{Y}/Y'M_\iota Y$.

1.3 Frish-Waugh-Lovell Theorem

If $Y = X_1\beta_1 + X_2\beta_2 + e$, then $\widehat{\beta}_1 = \left(X_1'M_{X_2}X_1\right)^{-1} X_1'M_{X_2}Y$.

2 Statistical Properties of Least Squares

To talk about the statistical properties, we impose the following assumptions.

1. The data $(y_i, x_i)_{i=1}^n$ is a random sample from the same data generating process $y_i = x_i'\beta + e_i$.
2. e_i and x_i are independent.
3. $e_i \sim N\left(0, \sigma^2\right)$.

2.1 Normal Regression

Under the normality assumption, $y_i|x_i \sim N\left(x_i'\beta, \gamma\right)$, where $\gamma = \sigma^2$. The *conditional* likelihood of observing a sample $(y_i, x_i)_{i=1}^n$ is

$$\prod_{i=1}^n \frac{1}{\sqrt{2\pi\gamma}} \exp\left(-\frac{1}{2\gamma}\left(y_i - x_i'\beta\right)^2\right),$$

and the (conditional) log-likelihood function is

$$L(\beta, \gamma) = -\frac{n}{2}\log 2\pi - \frac{n}{2}\log\gamma - \frac{1}{2\gamma}\sum_{i=1}^n \left(y_i - x_i'\beta\right)^2.$$

Therefore, the maximum likelihood estimator (MLE) coincides with the OLS estimator, and $\widehat{\gamma}_{\mathrm{MLE}} = \widehat{e}'\widehat{e}/n$.

We can show the finite-sample exact distribution of $\widehat{\beta}$. Since

$$\widehat{\beta} = \left(X'X\right)^{-1} X'y = \left(X'X\right)^{-1} X'\left(X'\beta + e\right) = \beta + \left(X'X\right)^{-1} X'e,$$

we have the estimator $\widehat{\beta}|X \sim N\left(\beta, \sigma^2\left(X'X\right)^{-1}\right)$, and

$$\widehat{\beta}_k|X \sim N\left(\beta_k, \eta_k'\sigma^2\left(X'X\right)^{-1}\eta_k\right) \sim N\left(\beta_k, \sigma^2\left(X'X\right)_{kk}^{-1}\right),$$

where $\eta_k = \left(1\left\{l = k\right\}\right)_{l=1,\ldots,K}$ is the selector of the k-th element.

Consider the T-statistic

$$T_k = \frac{\widehat{\beta}_k - \beta_k}{\sqrt{s^2 \left(X'X\right)^{-1}_{kk}}} = \frac{\left(\widehat{\beta}_k - \beta_k\right) / \sqrt{\sigma^2 \left(X'X\right)^{-1}_{kk}}}{\sqrt{s^2/\sigma^2}}.$$

The numerator follows a standard normal, and the denominator follows $\chi^2(n-K)$. Therefore $T_k \sim t(n-K)$.

2.2 Gauss-Markov Theorem

Now we relax the normality assumption and statistical independence. Instead, we assume a random sample and

$$\begin{aligned} y_i &= x_i'\beta + e_i \\ E[e_i|x_i] &= 0 \qquad (1) \\ E\left[e_i^2|x_i\right] &= \sigma^2. \qquad (2) \end{aligned}$$

(1) is called the mean independence assumption, and (2) is the homoskedasticity assumption.

- Unbiasedness: $E\left[\widehat{\beta}|X\right] = E\left[\left(X'X\right)^{-1} XY|X\right] = E\left[\left(X'X\right)^{-1} X\left(X'\beta + e\right)|X\right] = \beta$. Unbiasedness does not rely on the homoskedasticity assumption.

- Variance:

$$\begin{aligned} \mathrm{var}\left(\widehat{\beta}|X\right) &= E\left[\left(\widehat{\beta} - E\widehat{\beta}\right)\left(\widehat{\beta} - E\widehat{\beta}\right)'|X\right] \\ &= E\left[\left(X'X\right)^{-1} X'ee'X\left(X'X\right)^{-1}|X\right] \\ &= \left(X'X\right)^{-1} X'E\left[ee'|X\right] X\left(X'X\right)^{-1} \\ &= \left(X'X\right)^{-1} X'\left(\sigma^2 I_n\right) X\left(X'X\right)^{-1} \\ &= \sigma^2\left(X'X\right)^{-1}. \end{aligned}$$

Gauss-Markov theorem justifies the OLS estimator as the efficient estimator among all linear unbiased ones. Efficient here means that it enjoys the smallest variance in a family of estimators.

There are numerous linearly unbiased estimators. For example, $\left(Z'X\right)^{-1} Z'y$ for $z_i = x_i^2$ is unbiased because $E\left[\left(Z'X\right)^{-1} Z'y\right] = E\left[\left(Z'X\right)^{-1} Z'\left(X\beta + e\right)\right] = \beta$.

Let $\tilde{\beta} = A'y$ be a generic linear estimator, where A is any $n \times K$ functions of X. As

$$E\left[A'y|X\right] = E\left[A'\left(X\beta + e\right)|X\right] = A'X\beta.$$

So the linearity and unbiasedness of $\tilde{\beta}$ implies $A'X = I_n$. Moreover, the variance

$$\mathrm{var}\left(A'y|X\right) = E\left[\left(A'y - \beta\right)\left(A'y - \beta\right)'|X\right] = E\left[A'ee'A|X\right] = \sigma^2 A'A.$$

Let $C = A - X\left(X'X\right)^{-1}$.

$$\begin{aligned} & A'A - \left(X'X\right)^{-1} \\ = & \left(C + X\left(X'X\right)^{-1}\right)'\left(C + X\left(X'X\right)^{-1}\right) - \left(X'X\right)^{-1} \\ = & C'C + \left(X'X\right)^{-1} X'C + C'X\left(X'X\right)^{-1} = C'C, \end{aligned}$$

where the last equality follows as

$$\left(X'X\right)^{-1} X'C = \left(X'X\right)^{-1} X'\left(A - X\left(X'X\right)^{-1}\right) = \left(X'X\right)^{-1} - \left(X'X\right)^{-1} = 0.$$

Therefore $A'A - \left(X'X\right)^{-1}$ is a positive semi-definite matrix. The variance of any $\tilde{\beta}$ is no smaller than the OLS estimator $\widehat{\beta}$.

Homoskedasticity is a restrictive assumption. Under homoskedasticity, $\mathrm{var}\left(\widehat{\beta}\right) = \sigma^2\left(X'X\right)^{-1}$. Popular estimator of σ^2 is the sample mean of the residuals $\widehat{\sigma}^2 = \frac{1}{n}\widehat{e}'\widehat{e}$ or the unbiased one $s^2 = \frac{1}{n-K}\widehat{e}'\widehat{e}$. Under heteroskedasticity, Gauss-Markov theorem does not apply.