

# 1 Linear Regression

## 1.1 Linear regression and Least Square Solution

$$Y = X\beta + \epsilon$$

Where Y is a  $n \times 1$  matrix, X is a  $n \times k$  matrix, beta is  $k \times 1$  vector and  $\epsilon$  is  $n \times 1$  vector with  $\epsilon_i$  begin iid with normal distribution.

### Assumptions

1. Linear
2. X matrix has full rank. In other words, no multicollinearity.
3. Homoscedasticity or equal variance of  $\epsilon$ . In other words, no autocorrelation between disturbances.  $cov(\epsilon_i, \epsilon_j) = 0$ .
6. Number of observations n must be greater than the number of parameters.

### Least Square Solution

The cost function is given by

$$f(\beta) = \|Y - X\beta\|^2 = (Y - X\beta)^T(Y - X\beta) = Y^TY - Y^TX\beta - \beta^TX^TY + \beta^TX^TX\beta$$

Since third term are scalar,

$$\beta^TX^TY = (\beta^TX^TY)^T = Y^TX\beta$$

$$f(\beta) = Y^TY - 2Y^TX\beta - \beta^TX^TX\beta = Y^TY - 2(X^TY)^T\beta + \beta^TX^TX\beta$$

The first term is a constant and its derivative is zero.

### The derivative of 2nd term

Consider the derivative of  $\alpha^T\beta$  with respect to  $\beta$ .

$$\begin{aligned}\alpha^T\beta &= \sum \alpha_i\beta_i \\ \frac{\partial \alpha^T\beta}{\partial \beta_i} &= \alpha_i\end{aligned}$$

Write the derivative in matrix form

$$\begin{pmatrix} \frac{\partial \alpha^T\beta}{\partial \beta_1} \\ \frac{\partial \alpha^T\beta}{\partial \beta_2} \\ \dots \\ \frac{\partial \alpha^T\beta}{\partial \beta_3} \end{pmatrix} = \begin{pmatrix} \alpha_1 \\ \alpha_2 \\ \dots \\ \alpha_p \end{pmatrix}$$

So if we let  $\alpha = X^TY$ , we have

$$\frac{\partial 2(X^TY)^T\beta}{\partial \beta} = 2X^TY$$

### The derivative of 3rd term

let  $A = X^TX$ ,

$$\beta^TX^TX\beta = \beta^T \begin{pmatrix} \sum_i A_{1k}\beta_k \\ \sum_i A_{2k}\beta_k \\ \dots \\ \sum_k A_{pk}\beta_k \end{pmatrix} = \sum_j \beta_j (\sum_k A_{jk}\beta_k)$$

To calculate the derivative of  $f(\beta)$ , we note there are only 3 cases that the derivative does not vanish

1)  $l = j = k$

$$\frac{f(\beta)}{\partial \beta_l} = 2A_{ll}\beta_l$$

2)  $l=j, j \neq k$

$$\frac{f(\beta)}{\partial \beta_l} = \sum_{k, k \neq l} A_{lk}\beta_k$$

3)  $l=k, j \neq k$

$$\frac{f(\beta)}{\partial \beta_l} = \sum_{j, j \neq l} A_{jl}\beta_j = \sum_{j, j \neq l} A_{lj}^T \beta_j$$

Therefore

$$\begin{aligned} \frac{f(\beta)}{\partial \beta_l} &= A_{ll}\beta_l + \sum_{k, k \neq l} A_{lk}\beta_k + A_{ll}\beta_l + \sum_{j, j \neq l} A_{lj}^T \beta_j \\ &= \sum_k A_{lk}\beta_k + \sum_j A_{lj}^T \beta_j \end{aligned}$$

The first term is the  $l$ th row of vector  $A\beta = X^T X\beta$ , and the 2nd term is the  $l$ th row of vector  $A^T \beta = X^T X\beta$ . So we put the whole derivative in matrix form

$$\frac{f(\beta)}{\partial \beta} = -2X^T Y + 2X^T X\beta$$

which is a  $p \times 1$  vector with each row corresponding to the derivative with respect to  $\beta_i$  letting the derivative equal to zero yields the **normal equation** and the estimation of  $\beta$

Normal equation

$$(X^T X)\hat{\beta} = X^T Y$$

Estimator of  $\beta$

$$\hat{\beta} = (X^T X)^{-1} X^T Y$$

Using the rule of matrix multiplication, we can rewrite  $X^T X$  as the f

$$\begin{aligned} X^T X &= \begin{pmatrix} \sum_{i=1}^N x_{1i}^T x_{i1} & \sum_{i=1}^N x_{1i}^T x_{i2} & \dots & \sum_{i=1}^N x_{1i}^T x_{ik} \\ \dots & \dots & \dots & \dots \\ \sum_{i=1}^N x_{ki}^T x_{i1} & \sum_{i=1}^N x_{ki}^T x_{i2} & \dots & \sum_{i=1}^N x_{ki}^T x_{ik} \end{pmatrix} \\ &= \sum_{i=1}^N \begin{pmatrix} x_{i1}x_{i1} & x_{i1}x_{i2} & \dots & x_{i1}x_{ik} \\ \dots & \dots & \dots & \dots \\ x_{ik}x_{i1} & x_{ik}x_{i2} & \dots & x_{ik}x_{ik} \end{pmatrix} \\ &= \sum_{i=1}^N \begin{pmatrix} x_{i1} \\ \dots \\ x_{ik} \end{pmatrix} \begin{pmatrix} x_{i1} & \dots & \dots & x_{ik} \end{pmatrix} \\ &= \sum_{i=1}^N X_i X_i^T \end{aligned}$$

where  $X_i$  is  $K \times 1$  vector, and  $X_i X_i^T$  is  $K \times K$  matrix. Similarly,

$$X^T Y = \sum_{i=1}^N X_i y_i$$

where  $X_i$  is  $K \times 1$  vector,  $y_i$  is a scalar, and  $X_i y_i$  is  $K \times 1$  vector. So the estimator of  $\beta$  is

$$\hat{\beta} = \left( \sum_{i=1}^N X_i X_i^T \right)^{-1} \left( \sum_{i=1}^N X_i y_i \right)$$

### Least Square Estimator for Simple Linear Regression

$$y = \beta_0 + \beta_1 X + \epsilon$$

$$\begin{aligned} & \begin{pmatrix} \beta_0 \\ \beta_1 \end{pmatrix} \\ &= (X^T X)^{-1} X^T Y \\ &= \left( \begin{pmatrix} 1 & 1 & \dots & 1 \\ x_1 & x_2 & \dots & x_n \end{pmatrix} \begin{pmatrix} 1 & x_1 \\ 1 & x_2 \\ \vdots & \vdots \\ 1 & x_n \end{pmatrix} \right)^{-1} \begin{pmatrix} 1 & 1 & \dots & 1 \\ x_1 & x_2 & \dots & x_n \end{pmatrix} \begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{pmatrix} \\ &= \frac{1}{n \sum x_i^2 - (\sum x_i)^2} \begin{pmatrix} \sum x_i^2 & -\sum x_i \\ -\sum x_i & n \end{pmatrix} \begin{pmatrix} \sum y_i \\ -\sum x_i y_i \end{pmatrix} \end{aligned}$$

So

$$\beta_0 = \frac{\sum x_i^2 \sum y_i - \sum x_i (\sum x_i y_i)}{n \sum x_i^2 - (\sum x_i)^2} \quad (1)$$

$$\beta_1 = \frac{n \sum x_i y_i - \sum x_i \sum y_i}{n \sum x_i^2 - (\sum x_i)^2} \quad (2)$$

$\beta_1$  can also be written using the covariance

$$\beta_1 = \frac{\sum_i^n (x_i - \bar{x})(y_i - \bar{y})}{\sum_i^n (x_i - \bar{x})(x_i - \bar{x})} \quad (3)$$

And it is easy to show

$$\begin{aligned}
\beta_2 &= \frac{\sum_i^n (x_i - \bar{x})(y_i - \bar{y})}{\sum_i^n (x_i - \bar{x})(x_i - \bar{x})} \\
&= \frac{\sum_i^n (x_i y_i - \bar{x} y_i - x_i \bar{y} + \bar{x} \bar{y})}{\sum_i^n (x_i^2 - 2\bar{x} x_i + (\bar{x})^2)} \\
&= \frac{\sum_i^n x_i y_i - \sum_i^n \bar{x} y_i - \sum_i^n x_i \bar{y} + \sum_i^n \bar{x} \bar{y}}{\sum_i^n x_i^2 - \sum_i^n 2\bar{x} x_i + \sum_i^n (\bar{x})^2} \\
&= \frac{\sum_i^n x_i y_i - (\frac{1}{n} \sum_j^n x_j)(\sum_i^n y_i) - (\sum_i^n x_i)(\frac{1}{n} \sum_j^n y_j) + \sum_i^n (\frac{1}{n} \sum_j^n x_i)(\frac{1}{n} \sum_k^n y_k)}{\sum_i^n x_i^2 - \sum_i^n 2(\frac{1}{n} \sum_j^n x_j)x_i + \sum_i^n (\frac{1}{n} \sum_j^n x_j)^2} \\
&= \frac{\sum_i^n x_i y_i - (\frac{1}{n} \sum_j^n x_j)(\sum_i^n y_i) - (\sum_i^n x_i)(\frac{1}{n} \sum_j^n y_j) + n(\frac{1}{n} \sum_j^n x_i)(\frac{1}{n} \sum_k^n y_k)}{\sum_i^n x_i^2 - \sum_i^n 2(\frac{1}{n} \sum_j^n x_j)x_i + n(\frac{1}{n} \sum_j^n x_j)^2} \\
&= \frac{\sum_i^n x_i y_i - \frac{1}{n}(\sum_i^n x_i)(\sum_j^n y_j) - \frac{1}{n}(\sum_i^n x_i)(\sum_j^n y_j) + \frac{1}{n}(\sum_j^n x_i)(\sum_k^n y_k)}{\sum_i^n x_i^2 - \frac{2}{n}(\sum_j^n x_j)(\sum_i^n x_i) + \frac{1}{n}(\sum_j^n x_j)^2} \\
&= \frac{\sum_i^n x_i y_i - \frac{1}{n}(\sum_i^n x_i)(\sum_j^n y_j)}{\sum_i^n x_i^2 - \frac{1}{n}(\sum_j^n x_j)(\sum_i^n x_i)} \\
&= \frac{n \sum_i^n x_i y_i - (\sum_i^n x_i)(\sum_j^n y_j)}{n \sum_i^n x_i^2 - (\sum_j^n x_j)(\sum_i^n x_i)} \\
&= \frac{n \sum x_i y_i - (\sum x_i)(\sum y_j)}{n \sum x_i^2 - (\sum x_i)^2}
\end{aligned}$$

which is the same as Eq.2. We can interpret  $\beta$  as ratio of the covariance of x and y to the variance of x.

## 1.2 Projection matrix

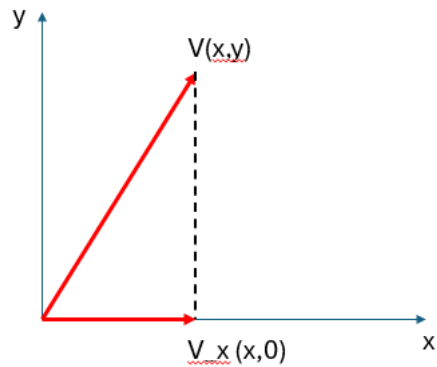
Given  $\hat{\beta} = (X^T X)^{-1} X^T Y$ , we have the predictor value of  $y = X\beta$

$$\hat{y} = X(X^T X)^{-1} X^T y$$

The matrix  $P = X(X^T X)^{-1} X^T$  is a projection matrix. It projects the vector of y into the column space of X.

### Understand the word projection

Let us understand this first through geometry point of view. Consider a vector on 2 dimensional space,  $V_1 = (x_1, y_1)^T$ , where  $x_1$  and  $y_1$  are the x and y component, respectively. If we project the vector V into x-line, then apparently we get  $V_x = (x_1, 0)^T$ , see graph below.



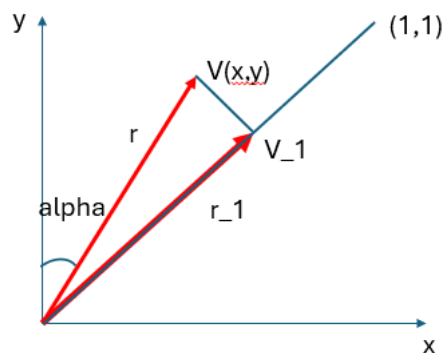
If we have a vector that is along the x axis

$$X = \begin{pmatrix} 1 \\ 0 \end{pmatrix}$$

The projection matrix of a vector into x line is

$$\begin{aligned} P_x &= x(x^T x)^{-1} x^T \\ &= \begin{pmatrix} 1 \\ 0 \end{pmatrix} \begin{pmatrix} 1 & 0 \end{pmatrix} \\ &= \begin{pmatrix} 1 & 0 \\ 0 & 0 \end{pmatrix} \end{aligned}$$

Applying this projection matrix to any 2 dimensional vector  $V$  gives  $(V_x, 0)^T$ . So it projects the vector into x line. Let us take another example. Imagine  $V_1$  is vector if we project  $V$  onto the line that has 45 degree angle with x axis. See below.



In order to calculate  $V_1$ , we see

$$r_1 = r \cos(\pi/4 - \alpha) = r \left( \frac{\sqrt{2}}{2} \frac{y}{r} + \frac{\sqrt{2}}{2} \frac{x}{r} \right) = \frac{\sqrt{2}}{2} y + \frac{\sqrt{2}}{2} x$$

$$V_{1x} = r_1 \cos(\pi/4) = \frac{x+y}{2}$$

$$V_{1y} = r_1 \sin(\pi/4) = \frac{x+y}{2}$$

After we understand this using geometry point of view, we can work out from algebra point of view. The vector we want to project onto is

$$i = \begin{pmatrix} 1 \\ 1 \end{pmatrix}$$

The projection matrix of a vector into x line is

$$\begin{aligned} P_x &= x(x^T x)^{-1} x^T \\ &= \begin{pmatrix} 1 \\ 1 \end{pmatrix} \left( \begin{pmatrix} 1 & 1 \end{pmatrix} \begin{pmatrix} 1 \\ 1 \end{pmatrix} \right)^{-1} \begin{pmatrix} 1 & 1 \end{pmatrix} \\ &= \frac{1}{2} \begin{pmatrix} 1 & 1 \\ 1 & 1 \end{pmatrix} \end{aligned}$$

Therefore we easily see

$$V_1 = \frac{1}{2} \begin{pmatrix} 1 & 1 \\ 1 & 1 \end{pmatrix} \begin{pmatrix} x \\ y \end{pmatrix} = \begin{pmatrix} \frac{1}{2}(x+y) \\ \frac{1}{2}(x+y) \end{pmatrix}$$

which is the same as what we get based on geometry. For n dimensional vector y, if our X matrix has rank of k, then the projection matrix P projects the vector y into k dimensional hyperplane. For example, if we define

$$i_N = \begin{pmatrix} 1 \\ 1 \\ \dots \\ 1 \end{pmatrix}$$

The projection matrix P is

$$P = i \frac{1}{N} i^T = \frac{1}{N} \begin{pmatrix} 1 & 1 & \dots & 1 \\ 1 & 1 & \dots & 1 \\ \dots & \dots & \dots & \dots \\ 1 & 1 & \dots & 1 \end{pmatrix}$$

### Projection matrix into null space

If  $P$  is a projection matrix, the matrix  $I - P$  is also a projection matrix. In linear regression model

$$y = X\beta + \epsilon$$

$$P = X(X^T X)^{-1} X^T$$

Define residual vector  $\hat{\epsilon}$

$$\hat{\epsilon} = (I - P)y = (I - X(X^T X)^{-1} X^T)y$$

And it is easy to show  $\hat{\epsilon}$  and  $X$  are orthogonal.

$$X^T \hat{\epsilon} = X^T (I - P)y = X^T (I - X(X^T X)^{-1} X^T)y = (X^T - X^T X(X^T X)^{-1} X^T)y = 0y = 0$$

For the above example, we define  $M = I - \frac{1}{N}ii^T$ , and  $My$  express the mean deviations of a vector.

#### Idempotent property of projection matrix

Consider the previous example that we project a vector  $V$  onto  $x$  axis, how about we do this projection twice, we would end up the same vector  $V_x$ . Using a little matrix algebra, it is easy to prove that for any project matrix  $P$ , we have  $PP = P$ .

### 1.3 Partitioned Regression and Regression

$$y = X\beta + \epsilon = X_1\beta_1 + X_2\beta_2 + \epsilon$$

The normal equation is

$$\begin{pmatrix} X_1^T X_1 & X_1^T X_2 \\ X_2^T X_1 & X_2^T X_2 \end{pmatrix} \begin{pmatrix} \hat{\beta}_1 \\ \hat{\beta}_2 \end{pmatrix} = \begin{pmatrix} X_1^T y \\ X_2^T y \end{pmatrix}$$

If  $X_1$  and  $X_2$  are orthogonal, namely,  $X_1^T X_2 = 0$ , then

$$\begin{aligned} \hat{\beta}_1 &= (X_1^T X_1)^{-1} X_1^T y \\ \hat{\beta}_2 &= (X_2^T X_2)^{-1} X_2^T y \end{aligned}$$

If  $X_1$  and  $X_2$  are not orthogonal, we can solve for  $\beta_2$  in the above normal equation set and get  $\beta_2$

$$\begin{aligned} \hat{\beta}_2 &= [X_2^T (I - X_1(X_1^T X_1)^{-1} X_1^T) X_2]^{-1} [X_2^T (I - X_1(X_1^T X_1)^{-1} X_1^T) y] \\ &= (X_2^T M_1 X_2)^{-1} (X_2^T M_1 y) \end{aligned}$$

Given the fact that  $M_1$  is symmetrical and idempotent, we can rewrite the above expression

$$\begin{aligned} \hat{\beta}_2 &= (X_2^T M_1 M_1 X_2)^{-1} (X_2^T M_1 M_1 y) \\ &= (X_2^T M_1^T M_1 X_2)^{-1} (X_2^T M_1^T M_1 y) \\ &= ((M_1 X_2)^T M_1 X_2)^{-1} ((M_1 X_2)^T M_1 y) \end{aligned} \tag{4}$$

The above uses the property that  $M_1^T = M_1$  and  $M_1 M_1 = M_1$

The  $\hat{\beta}_2$  is also the solution of

$$M_1 Y = M_1 X_2 \beta_2 + \epsilon$$

where  $M_1 y$  is the residual of  $y$  regressed on  $X_1$  and  $M_1 X_2$  is the residual of  $X_2$  regressed on  $X_1$ . For example, in simple linear regression

$$Y = \beta_0 + x\beta_1$$

Where  $X_1 = 1_N$ , so its projection matrix is  $i\frac{1}{N}i^T$ , and the corresponding M matrix is  $I - \frac{1}{N}ii^T$ . We try to calculate  $\beta$  using partition regression.

$$MY = (I - \frac{1}{N}ii^T)Y = Y - \bar{Y}MX = (I - \frac{1}{N}ii^T)Y = X - \bar{X}$$

Then

$$\beta_1 = ((MX)^T(MX))^{-1}((MX)^T(MY)) = \frac{\sum_i (x_i - \bar{x})(y_i - \bar{y})}{\sum_i (x_i - \bar{x})^2} \quad (5)$$

which is the same as Eq.3

#### 1.4 Variance componet identity

If we define our mean projection matrix P

$$P = i\frac{1}{N}i^T$$

and silimilarly we define mean deviation project matrix

$$M = I - P = i\frac{1}{N}i^T$$

We have

$$y = \hat{y} + \hat{\epsilon} = X\hat{\beta} + \hat{\epsilon}$$

Multiplying M matrix on the left, we have

$$My = MX\hat{\beta} + M\hat{\epsilon} = MX\hat{\beta} + \hat{\epsilon}$$

$$\begin{aligned} (My)^2 &= (MX\hat{\beta} + \hat{\epsilon})^T(MX\hat{\beta} + \hat{\epsilon}) \\ &= (\beta^T X^T M^T + \hat{\epsilon}^T)(MX\hat{\beta} + \hat{\epsilon}) \\ &= (MX\hat{\beta})^2 + \beta^T X^T M^T \hat{\epsilon} + (\beta^T X^T M^T \hat{\epsilon})^T + (\hat{\epsilon})^2 \end{aligned}$$

The 2nd and 3rd terms are zero because that 1)  $\hat{\epsilon}$  has zero mean, so  $M^T \hat{\epsilon} = M\hat{\epsilon} = \hat{\epsilon}$  and 2)  $X^T \hat{\epsilon} = 0$ , so

$$(My)^2 = (MX\hat{\beta})^2 + (\hat{\epsilon})^2$$

Rewriting the above equation using summation, we have

$$\sum_i (y_i - \bar{y})^2 = \sum_i (\bar{y}_i - \bar{\bar{y}})^2 + \sum_i (y_i - \hat{y})^2$$



Define

$$\begin{aligned} SST &= \sum_i (y_i - \bar{y})^2 \\ SSR &= \sum_i (\bar{y}_i - \bar{\bar{y}})^2 \\ SSE &= \sum_i (y_i - \hat{y})^2 \end{aligned}$$

Then we have

$$SST = SSR + SSE$$

### 1.5 Variance of $\hat{\beta}$ and $\sigma^2$ estimation

$$\begin{aligned} Var(\hat{\beta}) &= Var((X^T X)^{-1} X^T \epsilon) = (X^T X)^{-1} X^T Var(\epsilon) (X^T X)^{-1} X^T \\ &= \sigma^2 (X^T X)^{-1} X^T X (X^T X)^{-1} = \sigma^2 (X^T X)^{-1} \end{aligned}$$

The above derivation use the fact that  $\epsilon$  has a normal distribution with mean 0 and variance  $\sigma^2$ . For simple linear regression

$$Var(\hat{\beta}) = \frac{\sigma^2}{n \sum x_i^2 - (\sum x_i)^2} \begin{pmatrix} \sum x_i^2 & -\sum x_i \\ -\sum x_i & n \end{pmatrix}$$

$$Var(\hat{\beta}_0) = \frac{\sum x_i^2 \sigma^2}{n \sum x_i^2 - (\sum x_i)^2}$$

$$Var(\hat{\beta}_1) = \frac{n \sigma^2}{n \sum x_i^2 - (\sum x_i)^2}$$

Try

$$\begin{aligned} \Sigma(x_i - \bar{x})^2 &= \Sigma(x_i^2 - 2\bar{x}x_i + \bar{x}^2) = \Sigma_i(x_i^2 - 2(\Sigma_j \frac{x_j}{n})x_i + \frac{(\Sigma_j x_j)^2}{n^2}) \\ &= \Sigma_i x_i^2 - \frac{2}{n}(\Sigma_i x_i)^2 + \frac{(\Sigma_i x_i)^2}{n} = \Sigma_i x_i^2 - \frac{1}{n}(\Sigma x_i)^2 \end{aligned}$$

So

$$Var(\hat{\beta}_0) = \frac{\sum x_i^2 \sigma^2}{n \Sigma(x_i - \bar{x})^2}$$

$$Var(\hat{\beta}_1) = \frac{n \sigma^2}{n \Sigma(x_i - \bar{x})^2} = \frac{\sigma^2}{\Sigma(x_i - \bar{x})^2}$$

$$\begin{aligned}
SSE &= \sum_i (y - \hat{y}_i)^2 \\
&= (Y - X\beta)^T (Y - X\beta) \\
&= (Y - X(X^T X)^{-1} X^T Y)^T (Y - X(X^T X)^{-1} X^T Y) \\
&= (Y - PY)^T (Y - PY) \\
&= Y^T (1 - P)^T (1 - P) Y = Y^T (1 - P) Y \\
&= (X\beta + \epsilon)^T (1 - P) (X\beta + \epsilon) \\
&= \beta^T X^T (1 - P) X \beta + 2\beta^T X^T (1 - P) \epsilon + \epsilon^T (1 - P) \epsilon
\end{aligned}$$

$$E[SSE] = E[\epsilon^T (I - P) \epsilon] = E[\epsilon^T \epsilon] \text{trace}(I - P) = \sigma^2(n - k)$$

We obtain the unbiased estimator of  $\sigma^2$

$$\hat{\sigma}^2 = \frac{SSE}{n - k}$$

Therefore the estimator of variance of  $\beta$

$$\hat{Var}(\hat{\beta}_i) = \hat{\sigma}^2 (X^T X)^{-1}_{ii}$$

and the standard error of  $\beta_i$  is

$$SE(\hat{\beta}_i) = \sqrt{\hat{\sigma}^2 (X^T X)^{-1}_{ii}}$$

## 2 Properties of Least Square Estimators

When we have an estimator, we need to evaluate how good our estimator is? A few questions we can ask are 1) how far is the value of our estimator away from the true value, even in the ideal case when the sample size is infinite? 2) when 1) is true, with finite sample size, does the value of our estimator approach to the true value as the sample size increases? In other words, does the estimator converge to the true value as sample size goes to infinity? 3) when 1) and 2) are true, as the sample size increases, how fast does our estimator converge to the true value? 4) with 1), 2) and 3), what is the asymptotic distribution of the estimator? If the distribution is normal, it can be used to do interval estimation such as confidence interval. The 1st question defines unbiasedness, the 2nd one defines consistency, and the 3rd one defines efficiency.

## 2.1 Unbiasness

### Unbiased

$$\begin{aligned}\hat{\beta} &= (X^T X)^{-1} X^T Y \\ &= (X^T X)^{-1} X^T (X\beta + \epsilon) \\ &= (X^T X)^{-1} X^T X\beta + (X^T X)^{-1} X^T \epsilon \\ &= \beta + (X^T X)^{-1} X^T \epsilon\end{aligned}$$

Then the expectation of  $\hat{\beta}$  condition on  $X$  is

$$E[\hat{\beta}|X] = \beta + (X^T X)^{-1} X^T E(\epsilon|X)$$

$t$

The last term is zero by assumption of linear regression. So

$$E[\hat{\beta}] = \beta$$

The expectation of the estimator is the same as true value, this is called **unbiased**.

### Bias due to omission of relevant variables

Suppose we have a model

$$y = X_1\beta_1 + X_2\beta_2 + \epsilon$$

If we regression  $y$  on  $X_1$  only, our estimator is

$$\hat{\beta}_1 = (X_1^T X_1)^{-1} X_1^T y = \beta_1 + (X_1^T X_1)^{-1} X_1^T X_2 \beta_2 + (X_1^T X_1)^{-1} X_1^T \epsilon$$

On the second term, we see unless 1)  $X_1$  and  $X_2$  are orthogonal, or 2)  $\beta_2 = 0$ ,  $\beta_1$  is biased.

## 2.2 Consistency

The unbiasedness gives us a metric of measuring how good our estimator is, from population perspective. In reality, as our sample size is finite, we need ask ourselves does our estimator converges to true value when sample size is sufficiently large. We know

$$\hat{\beta} = \beta + (X^T X)^{-1} X^T \epsilon$$

$$\begin{aligned}\hat{\beta} &= \beta + (X^T X)^{-1} X^T \epsilon \\ &= \beta + (\sum_{i=1}^N X_i X_i^T)^{-1} X^T \epsilon \\ &= \beta + (\sum_{i=1}^N \frac{1}{N} X_i^T X_i)^{-1} (\frac{X^T \epsilon}{N})\end{aligned}$$

If  $X_i$ s are iid, then by law of large numbers

$$\frac{1}{n} \sum_{i=1}^n X_i^T X_i$$

converges to  $Q$  in probability.

$$\begin{aligned} & \frac{X^T \epsilon}{N} \\ &= \begin{pmatrix} \frac{1}{N} \sum_{i=1}^N x_{i1} \epsilon_i \\ \frac{1}{N} \sum_{i=1}^N x_{i2} \epsilon_i \\ \frac{1}{N} \sum_{i=1}^N x_{i3} \epsilon_i \\ \vdots \\ \frac{1}{N} \sum_{i=1}^N x_{ik} \epsilon_i \end{pmatrix} \\ &= \frac{1}{N} \sum_{i=1}^N X_i \epsilon_i = \bar{w} \end{aligned}$$

Where  $\bar{w}$  is a  $k \times 1$  vector. To see the asymptotical behavior of  $w$ , we consider its mean and asymptotical variance. The mean is

$$E[w_i] = E_X[E[w_i|x_i]] = E_X[X_i E[\epsilon|X_i]] = 0$$

$$Var[\bar{w}] = E[Var[\bar{w}|X]] + Var[E[\bar{w}|X]] = E[Var[\bar{w}|X]] + 0 = E[Var[\bar{w}|X]]$$

$$Var[\bar{w}|X] = E[\bar{w} \bar{w}^T | X] = \frac{1}{n} X^T E[\epsilon \epsilon^T] X \frac{1}{n} = \frac{\sigma^2}{n} \frac{X^T X}{n}$$

$$E[Var[\bar{w}|X]] = \frac{\sigma^2}{n} E\left(\frac{X^T X}{n}\right)$$

When  $\frac{X^T X}{n}$  converges to  $Q$ ,

$$E[Var[\bar{w}|X]] = 0$$

So  $\bar{w}$  converges to  $\mathbf{0}(k \times 1)$  vector. Then when  $N$  is sufficiently large,  $\hat{\beta}$  converges to  $\beta$ . This is the proof of consistency.

There are certain conditions in which the estimators become inconsistent.

1)  $X$  is not full rank, or  $X$  has multicollinearity 2)  $cov[X, \epsilon] \neq 0$

### 2.3 Efficiency

The least square estimator has the smallest variance, and this can be proved by Gauss-Markov theorem.

### 2.4 Multicollinearity

Suppose we have a regression model that contains two parameters

$$y = \beta_0 + X_1 \beta_1 + X_2 \beta_2$$

From above, we know variance of  $\hat{\beta}$  is

$$Var(\hat{\beta}) = \frac{\sigma^2}{(X^T X)^{-1}}$$

When X only contains 2 variables,  $X = (X_1, X_2)$

$$Var(\hat{\beta}_1) = \sigma^2 \frac{S_{22}}{S_{11}S_{22} - S_{12}^2} = \frac{1}{S_{11}(1 - \frac{S_{12}^2}{S_{11}S_{22}})} = \frac{1}{S_{11}(1 - r_{12}^2)}$$

$$Var(\hat{\beta}_2) = \sigma^2 \frac{S_{11}}{S_{11}S_{22} - S_{12}^2} = \frac{1}{S_{22}(1 - \frac{S_{12}^2}{S_{11}S_{22}})} = \frac{1}{S_{22}(1 - r_{12}^2)}$$

Where

$$S_{11} = \Sigma(x_{1i} - \hat{x}_1)^2$$

$$S_{22} = \Sigma(x_{2i} - \hat{x}_2)^2$$

$$S_{12} = \Sigma(x_{1i} - \hat{x}_1)(x_{2i} - \hat{x}_2)$$

$$r_{12} = \frac{S_{12}}{\sqrt{S_{11}S_{22}}}$$

$r_{12}$  is the correlation coefficient. In extreme case, when  $X_1$  and  $X_2$  are perfectly correlated, the variance becomes infinite.

### 3 Model Testing

#### Lagrange Multiplier(LM) test

Suppose we have two models, one is restricted, the other is unrestricted: Re-

stricted(R):  $y = X_1\beta_1 + \epsilon$

Unrestricted (U):  $y = X_1\beta_1 + X_2\beta_2 + \epsilon$

Given the unrestricted model, the likelihood function is

$$L(\beta_1, \beta_2, \sigma^2) = \frac{1}{(2\pi\sigma^2)^{n/2}} \exp\left(-\frac{1}{2\sigma^2}(y - X_1\beta_1 - X_2\beta_2)^T(y - X_1\beta_1 - X_2\beta_2)\right)$$

$$S_2 = \frac{\partial L}{\partial \beta_2} = \frac{1}{\sigma^2} X_2^T (y - X_1\beta_1 - X_2\beta_2)$$

When  $\beta_2 = 0$ , define

$$M_1 = I - X_1(X_1^T X_1)^{-1} X_1^T$$

and  $M_1 X_1 = 0$ .

$$S_2 = \frac{1}{\sigma^2} X_2^T (y - X_1\hat{\beta}_1) = \frac{1}{\sigma^2} X_2^T M_1 y = \frac{1}{\sigma^2} X_2^T M_1 (X_1\beta_1 + \epsilon) = \frac{1}{\sigma^2} X_2^T M_1 \epsilon$$

The last equal sign uses the fact  $M_1 X_1 = 0$ .

$$\begin{aligned} \text{Var}(X_2^T M_1 \epsilon) &= \text{Var}(X_2^T M_1 \epsilon) \\ &= X_2^T M_1 \text{Var}(\epsilon) (X_2^T M_1)^T \\ &= X_2^T M_1 M_1^T X_2 \text{Var}(\epsilon) \\ &= \sigma^2 X_2^T M_1 X_2 \end{aligned}$$

Define

$$V = X_2^T M_1 X_2$$

Then

$$\text{Var}(X_2^T M_1 \epsilon) = \sigma^2 V$$

So  $X_2^T M_1 \epsilon$  follows normal distribution with mean 0 and variance  $\sigma^2 X_2^T M_1 X_2$ .  
Define

$$Z = \frac{X_2^T M_1 \epsilon}{\sqrt{\sigma^2 X_2^T M_1 X_2}} = \frac{S_2}{\sqrt{\sigma^2 V}}$$

then  $Z$  follows standard normal distribution. The **Lagrange Multiplier (LM) test** is defined

$$LM = Z^2 = \frac{(X_2^T M_1 \epsilon)^2}{\sigma^2 X_2^T M_1 X_2} = \frac{S_2^2}{\sigma^2 V}$$

which follows  $\chi^2$  distribution with degree of freedom 1.

**F test**

We define

$$\begin{aligned} SSE_U &= \|y - X_1 \hat{\beta}_1 - X_2 \hat{\beta}_2\|^2 \\ SSE_R &= \|y - X_1 \hat{\beta}_1\|^2 \end{aligned}$$

F test is defined as

$$F = \frac{\frac{\text{Extra explained variation}}{\text{Degree of Freedom}}}{\frac{\text{Remaining unexplained variation}}{\text{Degree of Freedom}}} = \frac{SSE_R - SSE_U}{\frac{SSE_U}{n-1}}$$

Let  $X = (X_1, X_2)$ , and we define two projection matrices

$$\begin{aligned} P_U &= X(X^T X)^{-1} X^T \\ P_R &= X_1(X_1^T X_1)^{-1} X_1^T \end{aligned}$$

$$SSR_R - SSR_U = y^T P_R y - y^T P_U y = y^T (P_R - P_U) y$$

recall

$$\hat{\beta}_2 = (X_2^T M_1 X_2)^{-1} X_2^T M_1 y$$

The corresponding projection matrix is

$$M_1 X_2 (X_2^T M_1 X_2)^{-1} X_2^T M_1$$

The  $SSR_R - SSR_U$  is the additional variance explained by  $X_2$  after removing the linear space of  $X_1$  on  $X_2$ . This means the projection matrix corresponding to  $\beta_2$  is  $P_U - P_R$ . So we can get  $P_U - P_R$  using the interpretation of projection matrix instead solving for the projection matrix itself.

$$P_U - P_R = M_1 X_2 (X_2^T M_1 X_2)^{-1} X_2^T M_1$$

The extra explained sum of squares by the unrestricted model is

$$SSR_R - SSR_U = y^T (P_R - P_U) y = (X_2^T M_1 y)^T (X_2^T M_1 X_2)^{-1} X_2^T M_1 y$$

with 1 degree of freedom as  $X_2$  only contains 1 parameter.

$$F = \frac{SSR_R - SSR_U}{\frac{SSR_U}{n-k}} = \frac{(X_2 M_1 y)^T (X_2^T M_1 y)}{\hat{\sigma}^2 (X_2^T M_1 X_2)} = LM$$

We see that F test and LM test are equivalent.

#### **Wald Test**

Recall the estimator for  $\beta_2$  in Eq.4,

$$\hat{\beta}_2 = (X_2^T M_1 X_2)^{-1} (X_2^T M_1 y)$$

Substitue

$$y = X_1 \beta_1 + X_2 \beta_2 + \epsilon$$

we get

$$\hat{\beta}_2 = (X_2^T M_1 X_2)^{-1} (X_2^T M_1 \epsilon)$$

Since  $\epsilon \sim N(0, \sigma^2 I)$ , we obtain

$$\beta_2 \sim N(0, \sigma^2 (X_2^T M_1 X_2)^{-1})$$

Thus, scaling by  $1/\sigma^2$ , we arrive at

$$\frac{1}{\sigma^2} X_2^T M_1 \epsilon \sim N(0, X_2^T M_1 X_2)$$

Construct Wald test W

$$W = \frac{\hat{\beta}_2}{\sqrt{\hat{Var}(\hat{\beta}_2)}}$$

W follows t distribution. We now show W test is equivalent to LM test. Consider  $W^2$

$$\begin{aligned} W^2 &= \hat{\beta}^T (Var(\hat{\beta}))^{-1} \hat{\beta} = \frac{1}{\sigma^2} \hat{\beta}^T V \hat{\beta} = \frac{1}{\sigma^2} (V^{-1} S_2)^T V V^{-1} S_2 = \frac{1}{\sigma^2} S_2^T V^{-1} V V^{-1} S_2 \\ &= \frac{1}{\sigma^2} S_2^T V^{-1} S_2 \\ &= LM \end{aligned}$$

## 4 Panel Data Model

We can view panel data as a "two dimensional" data set in which the sample does not only come from different individuals, but also same individual across different time point. We can write the regression model as

$$y_{it} = \alpha_{it} + \sum_k x_{itk} \beta_{itk} + u_{it}$$

where  $1 < i < N$ ,  $1 < t < T$ , and  $1 < k < K$ . The equation has total sample size of  $NT$  with total number of parameter  $NT(K+1)$ , therefore it is not estimable. So we will make the following few assumptions

	$\alpha_{it} = \alpha_{is}$	$\alpha_{it} = \alpha_{jt}$	$\beta_{it} = \beta_{is}$	$\beta_{itk} = \beta_{jtk}$
Pooled	yes	yes	yes	yes
Fixed Effect	yes	no	yes	yes
Unrestricted	yes	no	yes	no

### 4.1 The unrestriced model

$$y_{it} = \alpha_i + \sum_k x_{itk} \beta_{ik} + u_{it}$$

The above equation can be written in matrix form:  
for  $i = 1$ ,

$$\begin{pmatrix} y_{11} \\ y_{12} \\ \dots \\ y_{1T} \end{pmatrix} = \begin{pmatrix} 1 & x_{111} & x_{112} & \dots & x_{11K} \\ 1 & x_{121} & x_{122} & \dots & x_{12K} \\ 1 & \dots & \dots & \dots & \dots \\ 1 & x_{1T1} & x_{1T2} & \dots & x_{1TK} \end{pmatrix} \begin{pmatrix} \alpha_1 \\ \beta_{11} \\ \beta_{12} \\ \dots \\ \beta_{1K} \end{pmatrix} + \begin{pmatrix} u_{11} \\ u_{12} \\ \dots \\ u_{1T} \end{pmatrix}$$

which we can also write as for  $i = 2$ ,

$$\begin{pmatrix} y_{21} \\ y_{22} \\ \dots \\ y_{2T} \end{pmatrix} = \begin{pmatrix} 1 & x_{211} & x_{212} & \dots & x_{21K} \\ 1 & x_{221} & x_{222} & \dots & x_{22K} \\ 1 & \dots & \dots & \dots & \dots \\ 1 & x_{2T1} & x_{2T2} & \dots & x_{2TK} \end{pmatrix} \begin{pmatrix} \alpha_2 \\ \beta_{21} \\ \beta_{22} \\ \dots \\ \beta_{2K} \end{pmatrix} + \begin{pmatrix} u_{21} \\ u_{22} \\ \dots \\ u_{2T} \end{pmatrix}$$

So for each  $i$ , we can write

$$Y_i = 1_T \alpha_i + X_i \beta_i + U_i$$

where  $Y_i = (y_{i1}, y_{i2}, \dots, y_{iT})^T$ ,  $1_T$  is a one vector of length  $T$ ,  $X_i$  is  $K \times T$  matrix,  $\beta_i = (\beta_{i1}, \beta_{i2}, \dots, \beta_{iK})^T$ , and  $U_i = (u_{i1}, u_{i2}, \dots, u_{iT})^T$ .

If we consolidate equation set for all the value of  $i$

$$\begin{pmatrix} Y_1 \\ Y_2 \\ \dots \\ Y_N \end{pmatrix} = \begin{pmatrix} 1_T & 0 & 0 & \dots & 0 \\ 0 & 1_T & 0 & \dots & 0 \\ 0 & 0 & 1_T & \dots & 0 \\ 0 & 0 & 0 & \dots & 1_{NT} \end{pmatrix} \begin{pmatrix} \alpha_1 \\ \alpha_2 \\ \dots \\ \alpha_N \end{pmatrix} + \begin{pmatrix} X_1 & 0 & 0 & \dots & 0 \\ 0 & X_2 & 0 & \dots & 0 \\ 0 & 0 & X_3 & \dots & 0 \\ 0 & 0 & 0 & \dots & X_N \end{pmatrix} \begin{pmatrix} \beta_1 \\ \beta_2 \\ \dots \\ \beta_N \end{pmatrix} + \begin{pmatrix} U_1 \\ U_2 \\ \dots \\ U_N \end{pmatrix}$$



To solve for  $\beta_i$ , we can use the strategy of partition regression.  $\beta_i$  is the solution of the the regression

$$MY_i = MX_i\beta + U$$

where

$$\begin{aligned} M &= I - \frac{1}{T}1_T1_T' \\ MY_i &= y_{it} - \bar{y}_i. \\ MX_i &= x_{it} - \bar{x}_i. \end{aligned}$$

Here to avoid duplicate notation, we denote the transposed matrix using  $'$ . The estimate of  $\beta$  is

$$\hat{\beta}_i = ((MX_i)^T(MX_i))^{-1}((MX_i)^T(MY_i)) = W_{xx,i}^{-1}W_{xy,i}$$

where

$$\begin{aligned} W_{xy,i} &= \sum_t^T (x_{it} - \bar{x}_i)(y_{it} - \bar{y}_i) \\ W_{xx,i} &= \sum_t^T (x_{it} - \bar{x}_i)(x_{it} - \bar{x}_i)^T \end{aligned}$$

## 4.2 The pooled model

$$y_{it} = \alpha + \sum_k x_{itk}\beta_k + u_{it}$$

The above equation can be written in matrix form:  
for  $i = 1$ ,

$$\begin{pmatrix} y_{11} \\ y_{12} \\ \dots \\ y_{1T} \\ y_{21} \\ y_{22} \\ \dots \\ y_{2T} \\ \dots \\ y_{NT} \end{pmatrix} = \begin{pmatrix} 1 & x_{111} & x_{112} & \dots & x_{11K} \\ 1 & x_{121} & x_{122} & \dots & x_{12K} \\ 1 & \dots & \dots & \dots & \dots \\ 1 & x_{1T1} & x_{1T2} & \dots & x_{1TK} \\ 1 & x_{211} & x_{212} & \dots & x_{21K} \\ 1 & x_{221} & x_{222} & \dots & x_{22K} \\ 1 & \dots & \dots & \dots & \dots \\ 1 & x_{2T1} & x_{2T2} & \dots & x_{2TK} \\ 1 & \dots & \dots & \dots & \dots \\ 1 & x_{NT1} & x_{NT2} & \dots & x_{NTK} \end{pmatrix} \begin{pmatrix} \alpha \\ \beta_1 \\ \beta_2 \\ \dots \\ \beta_K \end{pmatrix} + \begin{pmatrix} u_{11} \\ u_{12} \\ \dots \\ u_{1T} \\ u_{21} \\ u_{22} \\ \dots \\ u_{2T} \\ \dots \\ u_{NT} \end{pmatrix}$$

Similarly, using the solution of  $\beta$  from Eq.5, the estimated  $\beta$  can be written as

$$M = I - \frac{1}{NT}1_{NT}1_{NT}'$$

$$\begin{aligned}
\hat{\beta} &= ((MX)^T(MX))^{-1}((MX)^T(MY_i)) \\
&= \left( \sum_i^N \sum_t^T (x_{it} - \bar{x}_{..})(x_{it} - \bar{x}_{..})^T \right)^{-1} \sum_i^N \sum_t^T (x_{it} - \bar{x}_{..})(y_{it} - \bar{y}_{..}) \\
&= T_{xx}^{-1} T_{xy}
\end{aligned}$$

where

$$\begin{aligned}
T_{xy} &= \sum_i^N \sum_t^T (x_{it} - \bar{x}_{..})(y_{it} - \bar{y}_{..}) \\
T_{xx} &= \sum_i^N \sum_t^T (x_{it} - \bar{x}_{..})(x_{it} - \bar{x}_{..})^T
\end{aligned}$$

### 4.3 The fixed effect model

$$y_{it} = \alpha_i + \sum_k x_{itk} \beta_k + u_{it}$$

The above equation can be written in matrix form:

$$\begin{pmatrix} y_{11} \\ y_{12} \\ \dots \\ y_{1T} \\ y_{21} \\ y_{22} \\ \dots \\ y_{2T} \\ \dots \\ y_{NT} \end{pmatrix} = \begin{pmatrix} 1_T & 0 & 0 & \dots & 0 \\ 0 & 1_T & 0 & \dots & 0 \\ 0 & 0 & 1_T & \dots & 0 \\ 0 & 0 & 0 & \dots & 1_T \end{pmatrix} \begin{pmatrix} \alpha_1 \\ \alpha_2 \\ \dots \\ \alpha_N \end{pmatrix} + \begin{pmatrix} x_{111} & x_{112} & \dots & x_{11K} \\ x_{121} & x_{122} & \dots & x_{12K} \\ \dots & \dots & \dots & \dots \\ x_{1T1} & x_{1T2} & \dots & x_{1TK} \\ x_{211} & x_{212} & \dots & x_{21K} \\ x_{221} & x_{222} & \dots & x_{22K} \\ \dots & \dots & \dots & \dots \\ x_{2T1} & x_{2T2} & \dots & x_{2TK} \\ \dots & \dots & \dots & \dots \\ x_{NT1} & x_{NT2} & \dots & x_{NTK} \end{pmatrix} \begin{pmatrix} \beta_1 \\ \beta_2 \\ \dots \\ \beta_K \end{pmatrix} + \begin{pmatrix} u_{11} \\ u_{12} \\ \dots \\ u_{1T} \\ u_{21} \\ u_{22} \\ \dots \\ u_{2T} \\ \dots \\ u_{NT} \end{pmatrix}$$

Where  $1_T$  is a  $1 \times T$  vector. Similarly, using the solution of  $\beta$  from Eq.5, the M matrix is

$$M = I - \frac{1}{T} \begin{pmatrix} 1_{T \times T} & 0 & 0 & \dots & 0 \\ 0 & 1_{T \times T} & 0 & \dots & 0 \\ 0 & 0 & 1_{T \times T} & \dots & 0 \\ 0 & 0 & 0 & \dots & 1_{T \times T} \end{pmatrix}$$

the estimated  $\beta$  can be written as

$$\begin{aligned}\hat{\beta} &= ((MX)^T(MX))^{-1}((MX)^T(MY_i)) \\ &= \sum_i^N \sum_t^T [(x_{it} - \bar{x}_{i.})(x_{it} - \bar{x}_{i.})']^{-1} [\sum_i^N \sum_t^T (x_{it} - \bar{x}_{i.})(y_{it} - \bar{y}_{i.})] \\ &= W_{xx}^{-1} W_{xy}\end{aligned}$$

where

$$\begin{aligned}W_{xy} &= \sum_i^N \sum_t^T (x_{it} - \bar{x}_{i.})(y_{it} - \bar{y}_{i.}) \\ W_{xx} &= \sum_i^N \sum_t^T (x_{it} - \bar{x}_{i.})(x_{it} - \bar{x}_{i.})^T\end{aligned}$$

#### 4.4 The random effect model

In fixed effect model, we treat individual mean  $\alpha_i$  is a constant. In random effect model, we treat  $\alpha_i$  as a random variable. We write our random effect model as

$$y_{it} = \sum_k x_{itk} \beta_k + \alpha_i + u_{it}$$

Where  $\alpha_i \in Normal(0, \sigma_\alpha^2)$ ,  $u_{it} \in Normal(0, \sigma_u^2)$ ,  $E(\alpha_i u_{it}) = 0$ . Define

$$v_{it} = \alpha_i + u_{it}$$

The variance of  $v_{it}$  for fixed i is

$$E(v_{it} v_{is}) = E(\alpha_i + u_{it})(\alpha_i + u_{is}) = \sigma_\alpha^2 + \delta_{ts} \sigma_u^2$$

The last time is non-zero only when  $t = s$ . Thus, the covariance matrix for individual i is

$$V_i = \begin{pmatrix} \sigma_\alpha^2 + \sigma_u^2 & \sigma_\alpha^2 & \dots & \sigma_\alpha^2 \\ \sigma_\alpha^2 & \sigma_\alpha^2 + \sigma_u^2 & \dots & \sigma_\alpha^2 \\ \dots & \dots & \dots & \dots \\ \sigma_\alpha^2 & \sigma_\alpha^2 & \dots & \sigma_\alpha^2 + \sigma_u^2 \end{pmatrix}$$

where  $V_i$  is  $T \times T$  matrix. Stack together for all individuals, the whole covariance matrix is

$$V = \begin{pmatrix} V_1 & 0 & \dots & 0 \\ 0 & V_2 & \dots & 0 \\ \dots & \dots & \dots & \dots \\ 0 & 0 & \dots & V_N \end{pmatrix}$$

Based on the solution of GLS, we define

$$V_i^{-1/2} = \frac{1}{\sigma_u} [I - \frac{\theta}{T} 1_T 1_T']$$

where

$$\theta = 1 - \frac{\sigma_u}{\sqrt{\sigma_u^2 + T\sigma_\alpha^2}}$$

and the transformation of  $X_i$  and  $y_i$

$$\begin{aligned}\tilde{y}_i &= V_i^{-1/2} y_i = y_i - \theta \bar{y}_i \\ \tilde{X}_i &= V_i^{-1/2} X_i = X_i - \theta \bar{X}_i\end{aligned}$$

where  $y_i$  is  $T \times 1$  vector, and  $X_i$  is  $T \times K$  matrix. The estimator of  $\beta$  becomes

$$\hat{\beta}_{RE} = (\tilde{X}' V^{-1} \tilde{X})^{-1} (\tilde{X}' V^{-1} \tilde{Y})$$

With a little derivation, we can prove  $\beta_{RE}$  is a combination of estimator of pooled model and fixed effect model:

$$\hat{\beta}_{RE} = (1 - \omega) \hat{\beta}_{pooled} + \omega \hat{\beta}_{FE}$$

where

$$\omega = \frac{T\sigma_\alpha^2}{T\sigma_\alpha^2 + \sigma_u^2}$$

#### Connections to estimator of pooled model and fixed effect model

1) when  $\sigma_\alpha \gg \sigma_u$ , then  $\omega \rightarrow 1$ ,  $\theta \rightarrow 1$ , this leads to fixed-effect model. In fixed effect model

- a. Large  $\sigma_\alpha$  means large variation of  $\alpha$  for different  $i$ , in other words,  $\alpha_i$  is very different.
- b. Since  $Y_{it}$  for fixed  $i$  is center around  $\alpha_i$ , this means centers of  $Y_{it}$  given different  $i$  are far apart.
- c. The smaller  $\sigma_u$  compared to  $\sigma_\alpha$  means the variation of  $Y_{it}$  is small. Therefore, the probability density functions of  $Y_{it}$  for different  $i$  barely overlap, and their tails almost do not touch each other at all.

2) when  $\sigma_\alpha \ll \sigma_u$ , then  $\omega \rightarrow 0$ ,  $\theta \rightarrow 0$ , this leads to pooled model.

- a. Small  $\sigma_\alpha$  means  $\alpha_i$ s are almost identical.
- b. Since  $Y_{it}$  for fixed  $i$  is center around  $\alpha_i$ , this means centers of  $Y_{it}$  given different  $i$  are very close to each other.
- c. The larger  $\sigma_u$  compared to  $\sigma_\alpha$  means the variation of  $Y_{it}$  is large. Therefore, the probability density functions of  $Y_{it}$  for different  $i$  are completely overlapping. The difference between different individual  $i$  is hardly visible. So it is unnecessary to model the individual mean.