# Solutions of Homework 3 

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## 1 Question 1

### 1.1 Derive the restricted OLS $\tilde{\beta}$.

Under this restriction, we can rewrite the question as

$$
\begin{gathered}
\min _{\beta}(y-X \beta)^{\prime}(y-X \beta) \\
\text { s.t. } R \beta=r
\end{gathered}
$$

Applying the Lagrange multiplier, we can have

$$
L=(y-X \beta)^{\prime}(y-X \beta)-2 \lambda^{\prime}(R \beta-r)
$$

When the FOC equals to $0, \tilde{\lambda}$ and $\tilde{\beta}$ can be obtained to minimize the above equation.

$$
\begin{gathered}
\left\{\begin{array}{l}
\frac{\partial L}{\partial \tilde{\beta}}=-2 X^{\prime}(y-X \tilde{\beta})-2 R^{\prime} \tilde{\lambda}=0 \\
\frac{\partial L}{\partial \tilde{\lambda}}=-2(R \tilde{\beta}-r)=0
\end{array}\right. \\
\tilde{\beta}=\left(X^{\prime} X\right)^{-1} X^{\prime} y+\left(X^{\prime} X\right)^{-1} R^{\prime} \tilde{\lambda}=\hat{\beta}+\left(X^{\prime} X\right)^{-1} R^{\prime} \tilde{\lambda}
\end{gathered}
$$

Multiply R by both side, we have

$$
\begin{gather*}
R \tilde{\beta}=r=R \hat{\beta}+R\left(X^{\prime} X\right)^{-1} R^{\prime} \tilde{\lambda} \\
\tilde{\lambda}=\left(R\left(X^{\prime} X\right)^{-1} R^{\prime}\right)^{-1}(r-R \hat{\beta}) \\
\tilde{\beta}=\hat{\beta}+\left(X^{\prime} X\right)^{-1} R^{\prime}\left(R\left(X^{\prime} X\right)^{-1} R^{\prime}\right)^{-1}(r-R \hat{\beta}) \tag{1}
\end{gather*}
$$

### 1.2 Show the following: $\frac{\left(\tilde{u}^{\prime} \tilde{u}-\hat{u}^{\prime} \hat{u}\right) / G}{\hat{u}^{\prime} \hat{u} /(T-k)} \sim F(G, T-k)$.

In the previous section we have learned that:

$$
\frac{(R \hat{\beta}-r)^{\prime}\left(R\left(X^{\prime} X\right)^{-1} R^{\prime}\right)^{-1}(R \hat{\beta}-r) / G}{(y-X \hat{\beta})^{\prime}(y-X \hat{\beta}) /(T-k)} \sim F(G, T-k)
$$

where $G=\operatorname{rank}(R)$.
From equation (1), we can derive

$$
\hat{\beta}-\tilde{\beta}=\left(X^{\prime} X\right)^{-1} R^{\prime}\left(R\left(X^{\prime} X\right)^{-1} R^{\prime}\right)^{-1}(R \hat{\beta}-r)
$$

Multiply R by both sides, the following expression can be obtained:

$$
R(\hat{\beta}-\tilde{\beta})=R\left(X^{\prime} X\right)^{-1} R^{\prime}\left(R\left(X^{\prime} X\right)^{-1} R^{\prime}\right)^{-1}(R \hat{\beta}-r)=R \hat{\beta}-r
$$

Therefore, the numerator can be simplified as

$$
\begin{aligned}
(R \hat{\beta}-r)^{\prime}\left(R\left(X^{\prime} X\right)^{-1} R^{\prime}\right)^{-1}(R \hat{\beta}-r) & =(\hat{\beta}-\tilde{\beta})^{\prime} R^{\prime}\left(R\left(X^{\prime} X\right)^{-1} R^{\prime}\right)^{-1} R(\hat{\beta}-\tilde{\beta}) \\
& =(\hat{\beta}-\tilde{\beta})^{\prime}\left(X^{\prime} X\right)(\hat{\beta}-\tilde{\beta})
\end{aligned}
$$

Moreover, since

$$
\begin{aligned}
(y-X \tilde{\beta})^{\prime}(y-X \tilde{\beta}) & =(y-X \hat{\beta}+X \hat{\beta}-X \tilde{\beta})^{\prime}(y-X \hat{\beta}+X \hat{\beta}-X \tilde{\beta}) \\
& =(y-X \hat{\beta})^{\prime}(y-X \hat{\beta})+(\tilde{\beta}-\hat{\beta})^{\prime} X^{\prime} X(\tilde{\beta}-\hat{\beta}) \\
& -(y-X \hat{\beta})^{\prime} X(\tilde{\beta}-\hat{\beta})-(\tilde{\beta}-\hat{\beta})^{\prime} X^{\prime}(y-X \hat{\beta})
\end{aligned}
$$

and $X^{\prime}(y-X \hat{\beta})=X^{\prime} \hat{u}=0$,

$$
\begin{aligned}
&(y-X \tilde{\beta})^{\prime}(y-X \tilde{\beta})=\tilde{u}^{\prime} \tilde{u} \\
&=\hat{u}^{\prime} \hat{u}+(\tilde{\beta}-\hat{\beta})^{\prime} X^{\prime} X(\tilde{\beta}-\hat{\beta}) \\
&(R \hat{\beta}-r)^{\prime}\left(R\left(X^{\prime} X\right)^{-1} R^{\prime}\right)^{-1}(R \hat{\beta}-r)=(\hat{\beta}-\tilde{\beta})^{\prime}\left(X^{\prime} X\right)(\hat{\beta}-\tilde{\beta}) \\
&=\tilde{u}^{\prime} \tilde{u}-\hat{u}^{\prime} \hat{u}
\end{aligned}
$$

Summarizing, we can obtain

$$
\begin{equation*}
\frac{\left(\tilde{u}^{\prime} \tilde{u}-\hat{u}^{\prime} \hat{u}\right) / G}{\hat{u}^{\prime} \hat{u} /(T-k)} \sim F(G, T-k) \tag{2}
\end{equation*}
$$

1.3 Show the following: $\frac{\left(\hat{R}^{2}-\tilde{R}^{2}\right) / G}{\left(1-\hat{R}^{2}\right) /(n-k)} \sim F(G, T-k)$

Since the coefficients of determination of the restricted model and unrestricted model are

$$
\tilde{R}^{2}=1-\frac{\tilde{u}^{\prime} \tilde{u}}{y^{\prime} M y}, \quad \hat{R}^{2}=1-\frac{\hat{u}^{\prime} \hat{u}}{y^{\prime} M y}
$$

Hence,

$$
\tilde{u}^{\prime} \tilde{u}=\left(1-\tilde{R}^{2}\right) y^{\prime} M y, \quad \hat{u}^{\prime} \hat{u}=\left(1-\hat{R}^{2}\right) y^{\prime} M y
$$

Substitute for equation (2), we have

$$
\frac{\left(\left(1-\tilde{R}^{2}\right) y^{\prime} M y-\left(1-\hat{R}^{2}\right) y^{\prime} M y\right) / G}{\left(1-\hat{R}^{2}\right) y^{\prime} M y /(T-k)}=\frac{\left(\hat{R}^{2}-\tilde{R}^{2}\right) / G}{\left(1-\hat{R}^{2}\right) /(n-k)} \sim F(G, T-k)
$$

## 2 Question 2

### 2.1 Test $H_{0}: \alpha_{1}=\alpha_{2}=0$.

From the null hypothesis $H_{0}: \alpha_{1}=\alpha_{2}=0$, the alternative hypothesis can be derived as

$$
H_{1}: \alpha_{1} \neq 0 \text { or } \alpha_{2} \neq 0
$$

and restrictions are

$$
R_{1}=\left(\begin{array}{ccc}
0 & 1 & 0 \\
0 & 0 & 1
\end{array}\right), \quad r_{1}=\binom{0}{0}, \quad \alpha=\left(\begin{array}{c}
\alpha_{0} \\
\alpha_{1} \\
\alpha_{2}
\end{array}\right)
$$

where $R_{1} \alpha=r_{1}$. Besides, $k-1=3-1=2, T-k=(1997-1968)-3=26$
Therefore, we can easily derive F score from $R^{2}$

$$
F=\frac{R^{2} /(k-1)}{\left(1-R^{2}\right) /(T-k)}=\frac{0.986684 / 2}{(1-0.986684) / 26} \approx 963.2691
$$

which is much greater than the test statistic 5.526 under $1 \%$ significant level in $F \sim$ (2, 26).

Hence, we can reject the null hypothesis that $\alpha_{1}=\alpha_{2}=0$.

### 2.2 Test whether the production function is homogeneous.

If the production function is homogeneous, then we can hypothesize

$$
H_{0}: \alpha_{1}+\alpha_{2}=1, H_{1}: \alpha_{1}+\alpha_{2} \neq 1
$$

and the restrictions are

$$
R_{2}=\left(\begin{array}{lll}
0 & 1 & 1
\end{array}\right), \quad r_{2}=1
$$

where $R_{2} \alpha=r_{2}$.
Notice that the second model can be rewrite

$$
\begin{gathered}
\log \left(Y_{t} / L_{t}\right)=\beta_{0}+\beta_{1} \log \left(K_{t} / L_{t}\right)+u_{t} \\
\log Y_{t}-\log L_{t}=\beta_{0}+\beta_{1} \log K_{t}-\beta_{1} L_{t}+u_{t} \\
\log Y_{t}=\beta_{0}+\beta_{1} \log K_{t}+\left(1-\beta_{1}\right) \log L_{t}+u_{t}
\end{gathered}
$$

We can treat $\alpha_{1}$ as $\beta_{1}$ and $\alpha_{2}$ as $\left(1-\beta_{1}\right)$. Since $\beta_{1}+\left(1-\beta_{1}\right)=1$, the second model is the corresponding restricted model with $H_{0}$.

Under these conditions, the degree of freedoms are $G=\operatorname{rank}\left(R_{2}\right)=1, T-k=26$.
Then we can obtain the F score:

$$
F=\frac{\left(\hat{R}^{2}-\tilde{R}^{2}\right) / G}{\left(1-\hat{R}^{2}\right) /(T-k)}=\frac{0.986684-0.934448}{(1-0.986684) / 26} \approx 101.9928
$$

which is greater than the test statistic 7.721 under $1 \%$ significant level in $F \sim(1,26)$.
Thus, we should reject the hypothesis that the production function is homogeneous.

### 2.3 Test whether the structural change occurred after 1991.

Assume that there is no structural change after 1991, the hypotheses can be expressed as

$$
H_{0}: \gamma_{3}=\gamma_{4}=\gamma_{5}=0
$$

Similarly, we derive the restrictions as

$$
R_{3}=\left(\begin{array}{cccccc}
0 & 0 & 0 & 1 & 0 & 0 \\
0 & 0 & 0 & 0 & 1 & 0 \\
0 & 0 & 0 & 0 & 0 & 1
\end{array}\right), \quad r_{3}=\left(\begin{array}{l}
0 \\
0 \\
0
\end{array}\right), \quad \gamma=\left(\begin{array}{c}
\gamma_{0} \\
\gamma_{1} \\
\gamma_{2} \\
\gamma_{3} \\
\gamma_{4} \\
\gamma_{5}
\end{array}\right)
$$

where $R_{3} \gamma=r_{3}$.
Thus, we can find that the first model is the corresponding restricted model with the above hypotheses.

$$
\begin{gathered}
G=\operatorname{rank}\left(R_{3}\right)=3, T-k=29-6=23 \\
F=\frac{\left(\hat{R}^{2}-\tilde{R}^{2}\right) / G}{\left(1-\hat{R}^{2}\right) /(T-k)}=\frac{(0.987960-0.986684) / 3}{(1-0.987960) / 23} \approx 0.8125
\end{gathered}
$$

which is less than the test statistic 2.339 under $10 \%$ significant level in $F \sim(3,23)$.
Accordingly, we can not reject the hypothesis that no structural change occurred after 1991.

## 3 Question 3

### 3.1 Show that there exists $P$, such that $\Omega=P P^{\prime}$ when $\Omega$ is a positive definite matrix.

When $\Omega$ is positive definite, all its eigenvalues are positive. In general, $\Omega$ is symmetric and diagonalizable. Using the matrix of eigenvectors of $\Omega$ denoted by $A$ and the diagonal matrix $\Lambda$ where the elements are eigenvalues $\Lambda_{i}, \Omega$ can be decomposed as

$$
\Omega=A \Lambda A^{\prime}=A \sqrt{\Lambda} \sqrt{\Lambda} A^{\prime}=\left(A \Lambda^{\frac{1}{2}}\right)\left(A \Lambda^{\frac{1}{2}}\right)^{\prime}
$$

and we obtain $P=A \Lambda^{\frac{1}{2}}$.

### 3.2 What is the variance-covariance matrix, denoted by $\sigma^{2} \Omega$ ?

Since $\left\{u_{t}\right\}$ is mutually independent, $\operatorname{Cov}\left(u_{t}, u_{s}\right)=0$ for $t \neq s$. Then the variancecovariance matrix is denoted by

$$
\sigma^{2} \Omega=\sigma^{2}\left(\begin{array}{cccc}
z_{1}^{2} & 0 & \cdots & 0 \\
0 & z_{2}^{2} & \cdots & 0 \\
\vdots & \vdots & \ddots & \vdots \\
0 & 0 & \cdots & z_{T}^{2}
\end{array}\right)
$$

### 3.3 What is the variance-covariance matrix, denoted by $\sigma^{2} \Omega$ ?

Since $\left\{\epsilon_{t}\right\}$ is mutually independent with homogeneous variance $\sigma^{2}, \mathrm{~V}\left(u_{t}\right)=\rho^{2} \mathrm{~V}\left(u_{t-1}\right)+$ $\sigma^{2}$. In general, $|\rho|<1$, then

$$
\mathrm{V}\left(u_{t}\right)=\left(\rho^{2}\right)^{2} \mathrm{~V}\left(u_{t-2}\right)+\left(1+\rho^{2}\right) \sigma^{2}=\cdots=\left(1+\rho^{2}+\cdots+\rho^{T-1}\right) \sigma^{2}=\frac{1}{1-\rho^{2}} \sigma^{2}
$$

Similarly,

$$
\begin{gathered}
\operatorname{Cov}\left(u_{t}, u_{t-1}\right)=\operatorname{Cov}\left(\rho u_{t-1}+\epsilon_{t}, u_{t-1}\right)=\rho \mathrm{V}\left(u_{t-1}\right)+0=\rho \frac{\sigma^{2}}{1-\rho^{2}} \\
\operatorname{Cov}\left(u_{t}, u_{t-k}\right)=\rho^{k} \frac{\sigma^{2}}{1-\rho^{2}}, \quad k=0,1, \cdots, T-1
\end{gathered}
$$

Thus,

$$
\sigma^{2} \Omega=\frac{\sigma^{2}}{1-\rho^{2}}\left(\begin{array}{ccccc}
1 & \rho & \rho^{2} & \cdots & \rho^{T-1} \\
\rho & 1 & \rho & \cdots & \rho^{T-2} \\
\vdots & \vdots & \vdots & \ddots & \vdots \\
\rho^{T-1} & \rho^{T-2} & \rho^{T-3} & \cdots & 1
\end{array}\right)
$$

### 3.4 Derive b.

From 3.1, we know that there exists $P$ such that $\Omega=P P^{\prime}$. Multiply $P^{-1}$ on both sides of $y=X \beta+u$, we have

$$
y^{*}=X^{*} \beta+u^{*},
$$

where $y^{*}=P^{-1} y, X^{*}=P^{-1} X$, and $u^{*}=P^{-1} u$.
The variance of $u^{*}$ is

$$
\mathrm{V}\left(u^{*}\right)=\sigma^{2} P^{-1} \Omega P^{\prime-1}=\sigma^{2} I_{T} .
$$

Then the original regressio model can be rewritten as

$$
y^{*}=X^{*} \beta+u^{*}, u^{*} \sim N\left(0, \sigma^{2} I_{T}\right) .
$$

By application of OLS to the transformed regression model, we derive $b$ as

$$
b=\left(X^{* \prime} X^{*}\right)^{-1}\left(X^{* \prime} y^{*}\right)=\left(X^{\prime} \Omega^{-1} X\right)^{-1} X^{\prime} \Omega^{-1} y .
$$

### 3.5 Show that $\mathrm{V}(\boldsymbol{\beta})-\mathrm{V}(b)$ is a positive definite matrix by considering model in 3.3.

When we apply OLS directly to the regression model in 3.3 , the $\hat{\beta}$ is denoted as

$$
\hat{\beta}=\left(X^{\prime} X\right)^{-1} X^{\prime} y=\beta+\left(X^{\prime} X\right)^{-1} X^{\prime} u .
$$

The expectation and variance of $\hat{\beta}$ is given by

$$
\begin{gathered}
\mathrm{E}(\hat{\beta})=\beta \\
\mathrm{V}(\hat{\beta})=\sigma^{2}\left(X^{\prime} X\right)^{-1} X^{\prime} \Omega X\left(X^{\prime} X\right)^{-1}
\end{gathered}
$$

The GLS yields

$$
b=\beta+\left(X^{\prime} \Omega^{-1} X\right)^{-1} X^{\prime} \Omega^{-1} u
$$

of which the expectation and variance is

$$
\begin{gathered}
\mathrm{E}(b)=\beta \\
\mathrm{V}(b)=\sigma^{2}\left(X^{\prime} \Omega^{-1} X\right)^{-1}
\end{gathered}
$$

Compare OLS to GLS,

$$
\begin{aligned}
\mathrm{V}(\beta)-\mathrm{V}(b) & =\sigma^{2}\left(X^{\prime} X\right)^{-1} X^{\prime} \Omega X\left(X^{\prime} X\right)^{-1}-\sigma^{2}\left(X^{\prime} \Omega^{-1} X\right)^{-1} \\
& =\sigma^{2}\left(\left(X^{\prime} X\right)^{-1} X^{\prime}-\left(X^{\prime} \Omega^{-1} X\right)^{-1} X^{\prime} \Omega^{-1}\right) \Omega\left(\left(X^{\prime} X\right)^{-1} X^{\prime}-\left(X^{\prime} \Omega^{-1} X\right)^{-1} X^{\prime} \Omega^{-1}\right)^{\prime} \\
& =\sigma^{2} \underbrace{A}_{k \times T} \underbrace{\Omega}_{T \times T} A^{\prime} .
\end{aligned}
$$

Since $\Omega$ is a positive definite matrix, $A \Omega A^{\prime}$ is also positive definite matrix for any $x \in$ $\mathbb{R}^{k}, x \neq 0, x^{\prime}\left(A \Omega A^{\prime}\right) x>0$. Then $\mathrm{V}(\beta)-\mathrm{V}(b)$ is positive definite matrix, indicating that GLS estimator is more efficient than OLS estimator in this case.

