# Econometrics I: Solutions of Homework 7 

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## Contents

1 Solutions ..... 1
1.1 (1) ..... 1
1.2 (2) ..... 2
1.3 (3) ..... 3
1.4 (4) ..... 3
1.5 (5) ..... 4
1.6 (6) ..... 4
1.7 (7) ..... 4
1.8 (8) ..... 5
1.9 (9) ..... 6

## 1 Solutions

## 1.1 (1)

A transformation matrix $M$ is defined by

$$
M=I_{T}-\frac{1}{T} i i^{\prime}
$$

[^0]where $I_{T}$ is $T \times T$ identity matrix ${ }^{1}$. Then,
$$
M i=I_{T} i-\frac{1}{T} i\left(i^{\prime} i\right)=i-\frac{1}{T} i T=0
$$
and
$$
M e=I_{T} e-\frac{1}{T} i\left(i^{\prime} e\right)=e-\frac{1}{T} i \sum_{t=1}^{T} e_{t}=e .
$$

Note that third equality comes from the property of the OLS estimator, that is, $\sum_{t} e_{t} / T=\bar{e}=0$.

## $1.2 \quad$ (2)

First, I will show the first equality. By $M e=e$, premultiplying $e$ on $M$ yields

$$
\begin{aligned}
M e & =M y-M X \hat{\beta} \\
e & =M y-M X \hat{\beta} .
\end{aligned}
$$

Then, we obtain

$$
e^{\prime} e=y^{\prime} M^{\prime} M y-\hat{\beta}^{\prime} X^{\prime} M^{\prime} M X \hat{\beta}=y^{\prime} M y-\hat{\beta} X^{\prime} M X \hat{\beta}
$$

The second equality comes from the fact that $M$ is symmetric and idempotent. The $M$ is idempotent because

$$
\begin{aligned}
M^{2} & =\left(I_{T}-\frac{1}{T} i i^{\prime}\right)\left(I_{T}-\frac{1}{T} i i^{\prime}\right) \\
& =I_{T}-\frac{1}{T} i i^{\prime}-\frac{1}{T} i i^{\prime}+\frac{1}{T^{2}} i\left(i^{\prime} i\right) i^{\prime} \\
& =I_{T}-\frac{1}{T} i i^{\prime}-\frac{1}{T} i i^{\prime}+\frac{1}{T^{2}} i(T) i^{\prime} \\
& =I_{T}-\frac{1}{T} i i^{\prime}=M .
\end{aligned}
$$

Second, I will show the second equality. By $M e=e$ and $M i=0$, premultiplying $e=y-i \hat{\beta}_{1}-$ $X_{2} \hat{\beta}_{2}$ on $M$ gives

$$
\begin{aligned}
M e & =M y-M i \hat{\beta}_{1}-M X_{2} \hat{\beta}_{2} \\
e & =M y-M X_{2} \hat{\beta}_{2}
\end{aligned}
$$

[^1]Then, we obtain

$$
\begin{aligned}
e^{\prime} e & =\left(M y-M X_{2} \hat{\beta}_{2}\right)^{\prime}\left(M y-M X_{2} \hat{\beta}_{2}\right) \\
& =y^{\prime} M y-\hat{\beta}_{2}^{\prime} X_{2}^{\prime} M y-y^{\prime} M X_{2} \hat{\beta}_{2}+\hat{\beta}_{2}^{\prime} X_{2}^{\prime} M X_{2} \hat{\beta}_{2} \\
& =y^{\prime} M y-\hat{\beta}_{2}^{\prime} X_{2}^{\prime} M X_{2} \hat{\beta}_{2}-\hat{\beta}_{2}^{\prime} X_{2}^{\prime} M X_{2} \hat{\beta}_{2}+\hat{\beta}_{2}^{\prime} X_{2}^{\prime} M X_{2} \hat{\beta}_{2} \\
& =y^{\prime} M y-\hat{\beta}_{2}^{\prime} X_{2}^{\prime} M X_{2} \hat{\beta}_{2} .
\end{aligned}
$$

The third equality comes from $X_{2}^{\prime} M y=X_{2}^{\prime} M X_{2} \hat{\beta}_{2}$. This holds because

$$
\begin{aligned}
X_{2}^{\prime} e & =X_{2}^{\prime} M y-X_{2}^{\prime} M X_{2} \hat{\beta}_{2} \\
0 & =X_{2}^{\prime} M y-X_{2}^{\prime} M X_{2} \hat{\beta}_{2}
\end{aligned}
$$

Note that $X_{2}^{\prime} e=0$ holds since $X^{\prime} e=X^{\prime} y-X^{\prime} X \hat{\beta}=\left(X^{\prime} X\right) \hat{\beta}-X^{\prime} X \hat{\beta}=0$ by $\hat{\beta}=\left(X^{\prime} X\right)^{-1} X^{\prime} y$.

## 1.3 (3)

Since $y^{\prime} M y$ is a scalar,

$$
R^{2}=1-\frac{e^{\prime} e}{y^{\prime} M y}=\frac{y^{\prime} M y}{y^{\prime} M y}-\frac{e^{\prime} e}{y^{\prime} M y}=\frac{y^{\prime} M y-e^{\prime} e}{y^{\prime} M y}=\frac{\hat{\beta}_{2}^{\prime} X_{2}^{\prime} M X_{2} \hat{\beta}_{2}}{y^{\prime} M y}
$$

## 1.4 (4)

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

Since $u$ is normally distributed, $R b$ is also normally distributed. Expectation and variance of $R b$ are as follows:

$$
\begin{aligned}
& E(R \hat{\beta})=R \beta \\
& V(R \hat{\beta})=E\left[(R b-R \beta)(R b-R \beta)^{\prime}\right]=E\left[R\left(X^{\prime} X\right)^{-1} X^{\prime} u u^{\prime} X^{\prime}\left(X^{\prime} X\right)^{-1} R^{\prime}\right]=\sigma^{2} R\left(X^{\prime} X\right)^{-1} R^{\prime}
\end{aligned}
$$

Thus, the distribution of $R b$ is

$$
R \hat{\beta} \sim N\left(R \beta, \sigma^{2} R\left(X^{\prime} X\right)^{-1} R^{\prime}\right)
$$

## 1.5 (5)

By the question (4), we can replace $R \beta$ by $r$ if the null hypothesis is correct. Thus,

$$
R \hat{\beta} \sim N\left(r, \sigma^{2} R\left(X^{\prime} X\right)^{-1} R^{\prime}\right)
$$

or

$$
(R \hat{\beta}-r) \sim N\left(0, \sigma^{2} R\left(X^{\prime} X\right)^{-1} R^{\prime}\right)
$$

## 1.6 (6)

$$
R=\left(\begin{array}{ccccc}
0 & 1 & 0 & \cdots & 0 \\
0 & 0 & 1 & \cdots & 0 \\
\vdots & \vdots & \vdots & \vdots & \vdots \\
0 & 0 & 0 & \cdots & 1
\end{array}\right)=\left(0, I_{k-1}\right)
$$

where $R$ is $(k-1) \times k$ matrix. Thus, $G=k-1$ and $r=0$.

## $1.7 \quad$ (7)

We will show that, given $R$ and $r$,

$$
(R \hat{\beta}-r)^{\prime}\left(R\left(X^{\prime} X\right)^{-1} R^{\prime}\right)^{-1}(R \hat{\beta}-r)=\hat{\beta}_{2}^{\prime} X_{2}^{\prime} M X_{2} \hat{\beta}_{2} .
$$

By the solution to (6), define $R=\left(0, I_{k-1}\right)$ and $r=0$. Then, $R \hat{\beta}-r=\hat{\beta}_{2}$.
Next, given $R$ and $r$ as defined above, we will show $\left(R\left(X^{\prime} X\right)^{-1} R^{\prime}\right)^{-1}=X_{2}^{\prime} M X_{2}$. First, by $X=\left(i, X_{2}\right)$,

$$
\left(X^{\prime} X\right)^{-1}=\left(\binom{i^{\prime}}{X_{2}^{\prime}}\left(\begin{array}{ll}
i & X_{2}
\end{array}\right)\right)^{-1}=\left(\begin{array}{cc}
i^{\prime} i & i^{\prime} X_{2} \\
X_{2}^{\prime} i & X_{2}^{\prime} X_{2}
\end{array}\right)^{-1}=\left(\begin{array}{ll}
B_{11} & B_{12} \\
B_{21} & B_{22}
\end{array}\right)
$$

where $B_{i j}$ is unknown matrices. Then, we have

$$
R\left(X^{\prime} X\right)^{-1} R^{\prime}=\left(\begin{array}{ll}
0 & I_{k-1}
\end{array}\right)\left(\begin{array}{cc}
B_{11} & B_{12} \\
B_{21} & B_{22}
\end{array}\right)\binom{0}{I_{k-1}}=\left(\begin{array}{ll}
B_{21} & B_{22}
\end{array}\right)\binom{0}{I_{k-1}}=B_{22}
$$

Thus, we only need to calculate $B_{22}$. By the property of the inverse of a partitioned matrix,

$$
\begin{aligned}
B_{22} & =\left(X_{2}^{\prime} X_{2}-X_{2}^{\prime} i\left(i^{\prime} i\right)^{-1} i^{\prime} X_{2}\right)^{-1} \\
& =\left(X_{2}^{\prime} I_{T} X_{2}-X_{2}^{\prime}\left(\frac{1}{T} i i^{\prime}\right) X_{2}\right)^{-1} \\
& =\left(X_{2}^{\prime}\left(I_{T}-\frac{1}{T} i i^{\prime}\right) X_{2}\right)^{-1} \\
& =\left(X_{2}^{\prime} M X_{2}\right)^{-1}
\end{aligned}
$$

Hence, $\left(R\left(X^{\prime} X\right)^{-1} R^{\prime}\right)^{-1}=\left(\left(X_{2}^{\prime} M X_{2}\right)^{-1}\right)^{-1}=X_{2}^{\prime} M X_{2}$.
Finally, given $R=\left(0, I_{k-1}\right)$ and $r=0$, we obtain

$$
(R \hat{\beta}-r)^{\prime}\left(R\left(X^{\prime} X\right)^{-1} R^{\prime}\right)^{-1}(R \hat{\beta}-r)=\hat{\beta}_{2}^{\prime} X_{2}^{\prime} M X_{2} \hat{\beta}_{2} .
$$

## $1.8 \quad$ (8)

By solutions to (6) and (7), test statistic for $H_{0}: \beta_{2}=0$ is

$$
\frac{\hat{\beta}_{2}^{\prime} X_{2}^{\prime} M X_{2} \hat{\beta}_{2} /(k-1)}{e^{\prime} e /(T-k)} \sim F(k-1, T-k)
$$

We will show that

$$
\frac{R^{2} /(k-1)}{\left(1-R^{2}\right) /(T-k)}=\frac{\hat{\beta}_{2}^{\prime} X_{2}^{\prime} M X_{2} \hat{\beta}_{2} /(k-1)}{e^{\prime} e /(T-k)},
$$

where $R^{2}$ is the coefficient of determination.
By solutions to (3), we obtain

$$
\left(y^{\prime} M y\right) R^{2}=\hat{\beta}_{2}^{\prime} X_{2}^{\prime} M X_{2} \hat{\beta}_{2}
$$

and,

$$
\left(y^{\prime} M y\right)\left(1-R^{2}\right)=e^{\prime} e .
$$

Since $y^{\prime} M y$ is scalar, we can obtain

$$
\frac{\hat{\beta}_{2}^{\prime} X_{2}^{\prime} M X_{2} \hat{\beta}_{2} /(k-1)}{e^{\prime} e /(T-k)}=\frac{R^{2} /(k-1)}{\left(1-R^{2}\right) /(T-k)}
$$

## 1.9 (9)

First, we test $\beta=0$, using $t$-statistic. Recall that $t$-statistic is given by

$$
t=\frac{\hat{\beta}-\beta}{s / \sqrt{\sum_{t}\left(X_{t}-\bar{X}\right)^{2}}} \sim t(T-k)
$$

where $s^{2}$ is unbiased and consistent estimator of $\sigma^{2}$. Since $V(\hat{\beta})=\sigma^{2} / \sum_{t}\left(X_{t}-\bar{X}\right)^{2}$, we can calculate $t$-statistic as follows:

$$
t=\frac{\hat{\beta}-\beta}{S E(\hat{\beta})} .
$$

Thus,

$$
t=\frac{0.65-0}{0.240}=2.70833
$$

Under the degree of freedom is $4-2=2$, the test statistic at $1 \%, 5 \%$, and $10 \%$ significance level is $9.9248,4.3072$, and 2.9200 , respectively. Thus, we cannot reject the null hypothesis $\beta=0$.

Second, we test $\beta=0$, using $F$-statistic with $R^{2}$. By solutions to ( 8 ), a test statistic is given by

$$
\frac{R^{2} /(k-1)}{\left(1-R^{2}\right) /(T-k)}=\frac{0.786 /(2-1)}{(1-0.786) /(4-2)}=7.345794
$$

Under $F \sim F(1,2)$, the test statistic at $1 \%, 5 \%$, and $10 \%$ significance level is $98.50251,18.51282$, and 8.526316 , respectively. Thus, we cannot reject the null hypothesis $\beta=0$.
Overall, $F$-test obtains the same result as $t$-test. Note that the square of $t$-statistic is approximate to $F$-statistic, that is, $t^{2}=(2.70833)^{2}=7.335069 \approx 7.345794$.


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[^1]:    ${ }^{1}$ This matrix is different from the matrix $M$ that I used in solutions to HW5.

