## Exercise 4 -Answers

1. Given 50 observations split evenly into 2 periods, you decide to estimate $\mathrm{Y}_{i}=\mathrm{a}_{1}+\mathrm{b}_{1} \mathrm{X}_{i}+\mathrm{u}_{i 1} \quad$ in period 1
and
$\mathrm{Y}_{i}=\mathrm{a}_{2}+\mathrm{b}_{2} \mathrm{X}_{i}+\mathrm{u}_{i 2} \quad$ in period 2
Show how all four parameters could be obtained from a single OLS regression.
Suppose that RSS1 $=.6875$ and RSS2 $=2.4727$ and that the RSS from the pooled regression is 6.5565 .

Test the hypothesis of no structural change at the $5 \%$ and $1 \%$ level.
Proof
Above is the unrestricted form of the model (intercepts and the slopes vary in two periods)

In (partitioned) matrix form

$$
\mathrm{y}=\left[\begin{array}{l}
y_{1}  \tag{1}\\
\cdots \\
y_{2}
\end{array}\right]=\left[\begin{array}{cc}
X_{1} & 0 \\
0 & X_{2}
\end{array}\right]\left[\begin{array}{l}
a_{1} \\
b_{1} \\
a_{2} \\
b_{2}
\end{array}\right]+\left[\begin{array}{l}
u_{1} \\
u_{2}
\end{array}\right]=X \beta+u
$$

ie stack the data from the second period below that of the observations from the 1st period
in a way that allows the coefficients to differ between the periods
$\mathrm{y}=\left[\begin{array}{c}y_{1} \\ y_{2} \\ : \\ y_{N 1} \\ \cdots \\ y_{N 1+1} \\ y_{N 1+2} \\ : \\ y_{N 1+N 2}\end{array}\right]=\left[\begin{array}{cccc}1 & X_{1} & 0 & 0 \\ 1 & X_{2} & 0 & 0 \\ : & : & : & : \\ 1 & X_{N 1} & 0 & 0 \\ 0 & 0 & 1 & X_{N 1+1} \\ 0 & 0 & 1 & \\ : & : & : & \\ 0 & 0 & 1 & X_{N 1+N 2}\end{array}\right]\left[\begin{array}{l}a_{1} \\ b_{1} \\ a_{2} \\ b_{2}\end{array}\right]+\left[\begin{array}{l}u_{1} \\ u_{2}\end{array}\right]$

OLS on (1) gives $\hat{\beta}=\left[\begin{array}{c}\hat{a_{1}} \\ \hat{b_{1}} \\ \hat{a_{2}} \\ \hat{b_{2}}\end{array}\right]=\left(X^{\prime} X\right)^{-1} X^{\prime} y$

Using rules on inverse of partitioned matrices (the inverses of the elements on a diagonal partitioned matrix are just the inverses of the elements themselves)
$\hat{\beta}=\left[\begin{array}{cc}\left(X_{1}^{\prime} X_{1}\right)^{-1} & 0 \\ 0 & \left(X_{2}^{\prime} X_{2}\right)^{-1}\end{array}\right]\left[\begin{array}{l}X_{1}^{\prime} y \\ X_{2}^{\prime} y\end{array}\right]=\left[\begin{array}{l}\left(X_{1}^{\prime} X_{1}\right)^{-1} X_{1}^{\prime} y \\ \left(X_{2}^{\prime} X_{2}\right)^{-1} X_{2}^{\prime} y\end{array}\right]$
which is identical to those obtained by running OLS separately on the two
sub-samples
Compare this with estimates from the restricted model based on
$\mathrm{y}=\left[\begin{array}{l}y_{1} \\ y_{2}\end{array}\right]=\left[\begin{array}{ll}i_{1} & X_{1} \\ i_{2} & X_{2}\end{array}\right]\left[\begin{array}{l}a \\ b\end{array}\right]+\left[\begin{array}{l}u_{1} \\ u_{2}\end{array}\right]=X \beta+u$

(remember there are 4 parameters in the unrestricted model so $\mathrm{k}=4$ )
hence $F=24.72$
and from Tables $\mathrm{F}^{.05}[2,46]=3.2$
$F>F_{\text {critical }}$ so reject null (or no structural change)
2. Given data combined over 2 periods, consider the pooled regression of $y$ on a constant and a dummy variable to denote that the observation belongs to the second period

$$
\begin{equation*}
\mathrm{Y}_{t}=\mathrm{b}_{0}+\mathrm{b}_{1} \mathrm{D}_{t}+\mathrm{u}_{t} \tag{1}
\end{equation*}
$$

Show that the OLS estimates of $b_{0}$ and $b_{1}$ give, respectively, the mean value of $y$ in period 1 and the difference in mean values between period 2 and period 1.
(Hint: partition the data and use OLS matrix algebra).

Let period $1=1,2 \ldots$ N1 observations
period $2=\mathrm{N} 1+1 . \mathrm{N} 1+2, \ldots \mathrm{~N}=$ N2 observations

Let $i_{1}$ be an $N_{1} \times 1$ vector of ones and $i_{2}$ be an $N_{2} \times 1$ vector of ones

Then (1) can be written in partitioned matrix form as
$\left[\begin{array}{l}y_{1} \\ y_{2}\end{array}\right]=\left[\begin{array}{ll}i_{1} & 0 \\ i_{2} & i_{2}\end{array}\right]\left[\begin{array}{l}b_{0} \\ b_{1}\end{array}\right]+\left[\begin{array}{l}u_{1} \\ u_{2}\end{array}\right] \Leftrightarrow y=X \beta+u$
and so $\hat{\beta}=\left(X^{\prime} X\right)^{-1} X^{\prime} y$
where $X^{\prime} X=\left[\begin{array}{ll}i_{1}^{\prime} & i_{2}^{\prime} \\ 0 & i_{2}^{\prime}\end{array}\right]\left[\begin{array}{ll}i_{1} & 0 \\ i_{2} & i_{2}\end{array}\right]=\left[\begin{array}{cc}i_{1}^{\prime} i_{1}+i_{2}^{\prime} i_{2} i_{2}^{\prime} i_{2} \\ i_{2}^{\prime} i_{2} & i_{2}^{\prime} i_{2}\end{array}\right]$
Since $i_{j}$ is an $N_{j} \times 1$ vector then $i_{1}^{\prime} i_{1}=N_{1}$ and $i_{2}^{\prime} i_{2}=\left[\begin{array}{llll}1 & 1 & . & 1\end{array}\right]\left[\begin{array}{c}1 \\ 1 \\ \vdots \\ 1\end{array}\right]=N_{2}$
and so $X^{\prime} X=\left[\begin{array}{cc}N_{1}+N_{2} & N_{2} \\ N_{2} & N_{2}\end{array}\right]$

Similarly $X=\left[\begin{array}{cc}i_{1}^{\prime} & i_{2}^{\prime} \\ 0 & i_{2}^{\prime}\end{array}\right]\left[\begin{array}{l}y_{1} \\ y_{2}\end{array}\right]=\left[\begin{array}{c}i_{1}^{\prime} y_{1}+i_{2}^{\prime} y_{2} \\ i_{2}^{\prime} y_{2}\end{array}\right]$

Using the fact that $\bar{y}_{j}=\frac{\sum_{j} y_{j}}{N_{j}}$ and that $i_{j}^{\prime} y_{j}=\sum_{j} y_{j}$
then $X^{\prime} Y=\left[\begin{array}{c}N_{1} \overline{y_{1}}+N_{2} \overline{y_{2}} \\ N_{2} \overline{y_{2}}\end{array}\right]$

Hence $\hat{\beta}$

$$
\begin{gathered}
=\left[\begin{array}{cc}
N_{1}+N_{2} & N_{2} \\
N_{2} & N_{2}
\end{array}\right]^{-1}\left[\begin{array}{c}
N_{1} \overline{y_{1}}+N_{2} \overline{y_{2}} \\
N_{2} \overline{y_{2}}
\end{array}\right]=\frac{1}{N_{1} N_{2}}\left[\begin{array}{cc}
N_{2} & -N_{2} \\
-N_{2} & N
\end{array}\right]^{-1}\left[\begin{array}{c}
N_{1} \overline{y_{1}}+N_{2} \overline{y_{2}} \\
N_{2} \overline{\overline{y_{2}}}
\end{array}\right] \\
=\left[\begin{array}{c}
\frac{1}{N_{1}}\left(N_{1} \overline{y_{1}}+N_{2} \overline{y_{2}}\right)-\frac{1}{N_{1}}\left(N_{2} \overline{y_{2}}\right) \\
-\frac{1}{N_{1}}\left(N_{1} \overline{y_{1}}+N_{2} \overline{y_{2}}\right)+\frac{1}{N_{1}}\left(N \overline{y_{2}}\right)
\end{array}\right]=\left[\begin{array}{c}
\overline{y_{1}} \\
\overline{y_{2}}-\overline{y_{1}}
\end{array}\right]
\end{gathered}
$$

so the coefficient on the intercept in a model with no other covariates apart from the dummy variable gives the mean value of the dependent variable in period 1 and the coefficient on the dummy variable gives the difference in the mean value of the dependent variable between period 2 and period 1

Note that if additional covariates are added to the model so that
$\mathrm{y}=\mathrm{X}_{1} \beta_{1}+\mathrm{X}_{2} \beta_{2}+u$
where now the data are stacked such that $X_{1}=\left[\begin{array}{ll}i_{1} & 0 \\ i_{2} & i_{2}\end{array}\right]$ and $X_{2}=\left[\begin{array}{l}X_{2}^{1} \\ X_{2}^{2}\end{array}\right]$
then partitioned regression tells us that the OLS on (2) gives
$\left[\begin{array}{ll}X_{1}^{\prime} X_{1} & X_{1}^{\prime} X_{2} \\ X_{2}^{\prime} X_{1} & X_{2}^{\prime} X_{2}\end{array}\right]\left[\begin{array}{c}\hat{\beta}_{1} \\ \hat{\beta}_{2}\end{array}\right]=\left[\begin{array}{c}X_{1}^{\prime} y \\ X_{2}^{\prime} y\end{array}\right]$

The 1st row tells us that $\hat{\beta}_{1}=\left(X_{1}^{\prime} X_{1}\right)^{-1} X_{1}^{\prime} y-\left(X_{1}^{\prime} X_{1}\right)^{-1} X_{1}^{\prime} X_{2} \hat{\beta}_{2}$
(see lecture notes)
where $\hat{\beta}_{1}=\left[\begin{array}{l}\hat{b}_{0} \\ \hat{b}_{1}\end{array}\right]$
contains the coefficients on the intercept and on the time dummy
Now the term $\left(X_{1}^{\prime} X_{1}\right)^{-1} X_{1}^{\prime} X_{2}$ is a $\mathrm{k}_{1} x k_{2}$ matrix of OLS estimates from regressions of each of the
$\mathrm{k}_{2}$ variables in $\mathrm{X}_{2}$ on the set of $\mathrm{k}_{1}$ variables in $\mathrm{X}_{1}$

Eg if $X_{2}$ contains just 1 variable then

$$
\begin{aligned}
& \hat{\gamma}=\left(X_{1}^{\prime} X_{1}\right)^{-1} X_{1}^{\prime} X_{2} \Rightarrow\left[\begin{array}{l}
X_{2}^{1} \\
X_{2}^{2}
\end{array}\right]=\left[\begin{array}{ll}
i_{1} & 0 \\
i_{2} & i_{2}
\end{array}\right]\left[\begin{array}{l}
\hat{\gamma}_{1} \\
\hat{\gamma}_{2}
\end{array}\right] \\
& \Rightarrow \quad \hat{\gamma}_{1}=\bar{X}_{2}^{1} \quad \text { and } \hat{\gamma}_{2}=\bar{X}_{2}^{2}-\bar{X}_{2}^{1}
\end{aligned}
$$

so that (3) gives the adjusted OLS coefficients on the intercept and on the time dummy in a multiple regression as

$$
\left[\begin{array}{l}
\hat{b}_{0} \\
\hat{b}_{1}
\end{array}\right]=\left[\begin{array}{c}
\bar{y}_{1}-\hat{\beta}_{2} \overline{X_{2}^{1}} \\
\left(\overline{y_{2}}-\overline{y_{1}}\right)-\hat{\beta}_{2}\left(\overline{X_{2}^{2}}-\overline{X_{2}^{1}}\right)
\end{array}\right]
$$

ie this time the correction factor equals the mean (or the difference in the mean)
of the dependent variable minus the mean (or difference in mean) of the additional explanatory variables multiplied by its own OLS regression coefficient ie the coefficients are now net of the difference in the means of the other variables
3. Given
LnQ = -3.8766+1/.4106LnL+0.4162LnK

1929-67 $\quad \mathrm{R}^{2}=0.9937 \quad s=0.03755$
LnQ = -4.0576+1.6167LnL+0.2197LnK

1929-48

$$
\mathrm{R}^{2}=0.9759 \quad s=0.04573
$$

LnQ = -1.9564+0.8336LnL+0.6631LnK

1949-67

$$
\mathrm{R}^{2}=0.9904 \quad s=0.02185
$$

To test for equality of ceofficients across the two sub-periods use the chow test
$\mathrm{F}=\frac{\left(R S S_{\text {restriced }}-R S S_{\text {uressricted }} / q\right.}{\text { RSS }_{\text {urrestricted }} / N-k}$
where $\mathrm{RSS}_{\text {restricted }}=s_{\text {restricted }}^{2} *\left(N-k_{\text {resttict }}\right)=(0.03755)^{2} *(39-3)=0.0508$

$$
\begin{aligned}
\text { and } \mathrm{RSS}_{\text {unrestrict }} & =\text { RSS }_{29-48}+\text { RSS }_{49-67} \\
& =(0.04573)^{2} *(20-3)+(0.02185)^{2}(19-3) \\
& =0.0355+0.0076 \\
& =0.0431
\end{aligned}
$$

and so $\hat{F}=\frac{(0.0508-0.0431) / 3}{0.0431 / 39-(2 * 3)} \sim F[3,33]$

$$
=1.96
$$

From Tables the 5\% critical value for $\mathrm{F}[3,33]=2.89$
so $\hat{F}<\mathrm{F}_{\text {critical }}$
and hence accept the null hypothesis (that the coefficients are the same in both periods)
4. To test for differences between the two sub-samples again use the Chow test

This time can find unrestricted RSS using the fact that
$\hat{u}^{\prime} \hat{u}=y^{\prime} y-\hat{\beta}^{\prime} \quad X^{\prime} y=y^{\prime} y-y^{\prime} X\left(X^{\prime} X\right)^{-1} X^{\prime} y$
From information in the question

$$
\begin{aligned}
& \hat{u}_{1}^{\prime} \hat{u}_{1}=30-\left[\begin{array}{ll}
10 & 20
\end{array}\right]\left[\begin{array}{ll}
20 & 20 \\
20 & 25
\end{array}\right]^{-1}\left[\begin{array}{l}
10 \\
20
\end{array}\right] \\
& \quad=30-\left[\begin{array}{ll}
10 & 20
\end{array}\right]\left[\begin{array}{cc}
25 / 100 & -20 / 100 \\
-20 / 100 & 20 / 100
\end{array}\right]\left[\begin{array}{l}
10 \\
20
\end{array}\right] \\
& \quad=30-\left[\begin{array}{ll}
10 & 20
\end{array}\right]\left[\begin{array}{c}
-3 / 2 \\
2
\end{array}\right] \\
& \quad=5
\end{aligned}
$$

Similarly $\hat{u}_{2}^{\prime} \quad \hat{u}_{2}=24-\left[\begin{array}{ll}8 & 20\end{array}\right]\left[\begin{array}{ll}10 & 10 \\ 10 & 20\end{array}\right]^{-1}\left[\begin{array}{c}8 \\ 20\end{array}\right]$

$$
=3.2
$$

To find the restricted RSS need to find $X^{\prime} X$ for the combined (pooled) regression

Since $\quad X=\left[\begin{array}{c}X_{1} \\ . . \\ X_{2}\end{array}\right]$
ie a partitioned matrix with period 1 observations stacked above those from
period 2
then $\mathrm{X}^{\prime} \mathrm{X}=\left[\begin{array}{ll}X_{1}^{\prime} & X_{2}^{\prime}\end{array}\right]\left[\begin{array}{l}X_{1} \\ X_{2}\end{array}\right]=X_{1}^{\prime} X_{1}+X_{2}^{\prime} X_{2}$

$$
=\left[\begin{array}{ll}
20 & 20 \\
20 & 25
\end{array}\right]+\left[\begin{array}{ll}
10 & 10 \\
10 & 20
\end{array}\right]=\left[\begin{array}{ll}
30 & 30 \\
30 & 45
\end{array}\right]
$$

Similarly $X^{\prime} y=X_{1}^{\prime} y_{1}+X_{2}^{\prime} y_{2} \quad=\left[\begin{array}{c}10 \\ 20\end{array}\right]+\left[\begin{array}{c}8 \\ 20\end{array}\right]=\left[\begin{array}{l}18 \\ 40\end{array}\right]$
and $y^{\prime} \mathrm{y}=y_{1}^{\prime} y_{1}+y_{2}^{\prime} y_{2}=54$

So the restricted RSS $=54-\left[\begin{array}{ll}18 & 40\end{array}\right]\left[\begin{array}{ll}30 & 30 \\ 30 & 45\end{array}\right]^{-1}\left[\begin{array}{l}18 \\ 40\end{array}\right]=10.93$
and hence $F=\frac{\left(\text { RSS }_{\text {restriceed }}-\text { RSS }\right.}{\text { urressiciced }) / q}\left(\mathbb{R S S _ { \text { urressriceced } } / N - k}=\frac{[10.93-(5+3.2)] / 2}{(5+3.2) / 30-2(2)}=4.33\right.$

From tables the $5 \%$ critical value for $\mathrm{F}[2,26]=3.37$
so $\hat{F}>\mathrm{F}_{\text {critical }}$
and hence reject the null hypothesis (that the coefficients are the same in both periods)
5. You are asked to correct a simple consumption function equation for quarterly seasonal variation. Write down what the matrix of independent variables looks like for the corrected model. Now given

$$
\begin{array}{ccccl}
\mathrm{Ct}=6688+\underset{\text { 1322D }}{\text { 132 }} \text {-217D3 }+ \text { 183D4 }+.638^{*} \text { Income } & \mathrm{R} 2=.525 \\
(1711) & (683) & (602) & (654) & (.155)
\end{array} \mathrm{N}=100
$$

where the numbers in brackets are standard errors. On the basis of this regression you decide to test the hypothesis that only second quarter consumption differs from the rest, (why?). The result is that now

To seasonally adjust (quarterly) data inroduce a dummy variable for each quarter
$D_{1}=1$ if the observation appears in quarter i
$=0$ otherwise

To avoid the dummy variable trap include one less dummy variable than the total number of quarters
$X=$
$\left[\begin{array}{lllll}1 & 0 & 0 & 0 & X_{1} \\ 1 & 1 & 0 & 0 & X_{2} \\ : & 0 & 1 & 0 & \\ & 0 & 0 & 1 & \\ 1 & 0 & 0 & 0 & \\ 1 & 1 & 0 & 0 & \\ : & 0 & 1 & 0 & \\ 1 & : & : & : & \\ 1 & 0 & 0 & 1 & X_{N}\end{array}\right]=\left[\begin{array}{lllll}\text { const } & D_{2} & D_{3} & D_{4} & X\end{array}\right] \quad$ and $\quad \beta=\left[\begin{array}{c}\beta_{0} \\ \beta_{D 2} \\ \beta_{D 3} \\ \beta_{D 4} \\ \beta x\end{array}\right]$

From the regerssion output above can see that the 3rd and 4th quarter dummy variables are statistically insignificant

This suggests that a more restricted model which drops these variables may be acceptable.

H0: D3=D4=0
To test this formally use

(using $\mathrm{R}^{2}=1-($ RSS/TSS $) \quad$ )

$$
\text { Hence } \hat{F}=4.21
$$

From tables the $5 \%$ critical value for $F[2,95]=3.10$
so $\hat{F}>F_{\text {critical }}$
and hence reject the null hypothesis (that the 3rd and 4th quarter dummy variables have no explanatory value)
6. Given $\mathrm{y}=\mathrm{X}_{1} \beta_{1}+X_{2} \beta_{2}+v$
and $\mathrm{y}=\mathrm{X}_{1} \beta_{1}+u$
then the Frisch-Waugh theorem tells us that the OLS estimate of $\beta_{1}$ can be obtained from the alternative regression

$$
\begin{equation*}
\mathrm{M}_{X 2} y=M_{X 2} X_{1} \beta_{1}+\epsilon \tag{3}
\end{equation*}
$$

where $\mathrm{M}_{X 2}=I-X_{2}\left(X_{2}^{\prime} X_{2}\right)^{-1} X_{2} \quad$ is the idempotent "residual maker" matrix
and $M_{X 2} y$ are the residuals from a regression of $y$ on $X_{2}$ alone and $\mathrm{M}_{X_{2} X_{1}}$ are the residuals from a regression of $\mathrm{X}_{1}$ on $\mathrm{X}_{2}$ alone

OLS on (3) gives $\tilde{\beta}_{1}=\left(X_{1}^{\prime} M_{X 2}^{\prime} M_{X 2} X_{1}\right)^{-1} X_{1}^{\prime} M_{X 2}^{\prime} M_{X 2} y$

$$
=\left(X_{1}^{\prime} M_{X 2} X_{1}\right)^{-1} X_{1}^{\prime} M_{X 2} y
$$

sub. in true y from (2)

$$
\begin{aligned}
& =\left(X_{1}^{\prime} M_{X 2} X_{1}\right)^{-1} X_{1}^{\prime} M_{X 2}\left(X_{1} \beta_{1}+u\right) \\
\tilde{\beta}_{1} & =\beta_{1}+\left(X_{1}^{\prime} M_{X 2} X_{1}\right)^{-1} X_{1}^{\prime} M_{X 2} u
\end{aligned}
$$

Taking expectations $\mathrm{E}\left(\tilde{\beta}_{1}\right)=\mathrm{E}\left[\beta_{1}+\left(X_{1}^{\prime} M_{X 2} X_{1}\right)^{-1} X_{1}^{\prime} M_{X 2} u\right]$

$$
\begin{aligned}
& =\beta_{1}+E\left[\left(X_{1}^{\prime} M_{X 2} X_{1}\right)^{-1} X_{1}^{\prime} M_{X 2} u\right] \\
& =\beta_{1}
\end{aligned}
$$

So estimates on relevant variables from a model that includes irrelevant variables are unbiased

Now consider the estimates on the irrelevant variables.
Again the Frisch-Waugh theorem tells us that the OLS estimate of $\beta_{2}$ can be obtained from the alternative regression

$$
\begin{equation*}
\mathrm{M}_{X 1} y=M_{X 1} X_{2} \beta_{2}+\eta \tag{4}
\end{equation*}
$$

$$
\begin{aligned}
& \text { where now } \mathrm{M}_{X 1}=I-X_{1}\left(X_{1}^{\prime} X_{1}\right)^{-1} X_{1} \\
& \text { so } \tilde{\beta}_{2}=\left(X_{2}^{\prime} M_{X 1}^{\prime} M_{X 1} X_{2}\right)^{-1} X_{2}^{\prime} M_{X 1}^{\prime} M_{X 1} y \\
& \qquad=\left(X_{2}^{\prime} M_{X 1} X_{2}\right)^{-1} X_{2}^{\prime} M_{X 1} y
\end{aligned}
$$

sub. in for true $y$ from (2) $\tilde{\beta}_{2}=\left(X_{2}^{\prime} M_{X 1} X_{2}\right)^{-1} X_{2}^{\prime} M_{X 1}\left(X_{1} \beta_{1}+u\right)$

$$
=0+\left(X_{2}^{\prime} M_{X 1} X_{2}\right)^{-1} X_{2}^{\prime} M_{X 1} u
$$

(since $M_{X 1} X_{1}=0$ )
taking expectations $E\left[\tilde{\beta}_{2}\right]=E\left[\left(X_{2}^{\prime} M_{X 1} X_{2}\right)^{-1} X_{2}^{\prime} M_{X 1} u\right]=0$
so expected values of irrelevant variables (assuming model (2) is correct) are zero

## 7.

Given
True: $\quad \mathrm{y}=\mathrm{X}_{1} \beta_{1}+\mathrm{X}_{2} \beta_{2}+u$
Estimate: $\quad \mathrm{y}=\mathrm{X}_{1} \beta_{1}+v$
then OLS estimate of the residual variance based on (2) gives
$S^{2}=\frac{\hat{v}^{\prime} \hat{v}}{N-k_{1}}$
$\left(\mathrm{k}_{1}=\right.$
no. of parameters
where $\hat{v}=y-X_{1} \hat{\beta}_{1}=\left[I-X_{1}\left(X_{1}^{\prime} X_{1}\right)^{-1} X_{1}^{\prime}\right] y$

$$
=\mathrm{M}_{1} y
$$

and $\mathrm{M}_{1}$ is an idempotent matrix $\mathrm{M}_{1}^{\prime} M_{1}=M_{1}$
sub. in for true y from (1)
$\hat{v}=\mathrm{M}_{1}\left[X_{1} \beta_{1}+X_{2} \beta_{2}+u\right]=\mathrm{M}_{1} X_{2} \beta_{2}+M_{1} u \quad\left(\sin c e M_{1} X_{1}=0\right)$

$$
\begin{gathered}
\therefore \hat{v}^{\prime} \hat{v}=\left(M_{1} X_{2} \beta_{2}+M_{1} u\right)^{\prime}\left(M_{1} X_{2} \beta_{2}+M_{1} u\right)=\beta_{2}^{\prime} X_{2}^{\prime} M_{1} X_{2} \beta_{2}+u^{\prime} M_{1} X_{2} \beta_{2}+\beta_{2}^{\prime} X_{2}^{\prime} M_{1} u+u^{\prime} M \\
\quad \text { and } E\left(\hat{v}^{\prime} \hat{v} \hat{v}\right)=E\left[\beta_{2}^{\prime} X_{2}^{\prime} M_{1} X_{2} \beta_{2}+u^{\prime} M_{1} X_{2} \beta_{2}+\beta_{2}^{\prime} X_{2}^{\prime} M_{1} u+u^{\prime} M_{1} u\right] \\
\quad=E\left[\beta_{2}^{\prime} X_{2}^{\prime} M_{1} X_{2} \beta_{2}\right]+E\left[u^{\prime} M_{1} X_{2} \beta_{2}\right]+E\left[\beta_{2}^{\prime} X_{2}^{\prime} M_{1} u\right]+E\left[u^{\prime} M_{1} u\right]
\end{gathered}
$$

middle two terms are zero since $\mathrm{E}(\mathrm{u})=0$
$\therefore \mathrm{E}\left(\hat{v}^{\prime} \hat{v}\right)=\beta_{2}^{\prime} X_{2}^{\prime} M_{1} X_{2} \beta_{2}+E\left[u^{\prime} M_{1} u\right]$

Now $u^{\prime} \mathrm{M}_{1} u$ is a scalar
and can use the fact that $u^{\prime} u=\operatorname{tr}\left(u^{\prime} u\right)=\operatorname{tr}\left(u u^{\prime}\right)$ when u'u is a scalar
where the trace is the sum of the diagonal elements = sum of the characteristic
roots $=$ rank of idempotent matrix
$\left.\therefore \mathrm{E}\left(u^{\prime} M_{1} u\right)=E\left[\operatorname{tr}\left(u^{\prime} M_{1} u\right)\right]=E\left[\operatorname{tr} M_{1} \mathrm{u}^{\prime}\right)\right]$
(law of cyclic permutations; see eg Greene appendix A)

$$
\begin{aligned}
& =\operatorname{tr}\left[\mathrm{M}_{1} E\left(u \mathrm{u}^{\prime}\right)\right] \\
& \operatorname{tr}\left(\mathrm{M}_{1}\right) \sigma^{2} I_{N}
\end{aligned}
$$

$$
\text { Now } \begin{aligned}
\operatorname{tr}\left(\mathrm{M}_{1}\right) & =\operatorname{tr}\left[I_{N}-X_{1}\left(X_{1}^{\prime} X_{1}\right)^{-1} X_{1}^{\prime}\right]=\operatorname{tr}\left[I_{N}-X_{1}^{\prime} X_{1}\left(X_{1}^{\prime} X_{1}\right)^{-1}\right] \\
& =\operatorname{tr}\left[I_{N}-I_{k 1}\right] \\
& =\mathrm{N}-\mathrm{k}_{1}
\end{aligned}
$$

```
Hence \(E\left(\hat{v}^{\prime} \quad \hat{v}\right)=\beta_{2}^{\prime} X_{2}^{\prime} M_{1} X_{2} \beta_{2}+\sigma^{2}(N-k 1)\)
    \(>\sigma^{2}(N-k 1)\)
```

ie OLS estimate of residual variance no longer unbiased. It is biased upward by an amount equal to the increase in the RSS when $X_{2}$ is excluded from the model
8. Given the formula for omitted variable bias
$\hat{\beta}_{i}^{\text {omit }}=\hat{\beta}_{i}^{\text {true }}+\left(X_{1}^{\prime} X_{1}\right)^{-1} X_{1}^{\prime} X_{2} \hat{\beta}_{2}$
where $\mathrm{X}_{1}=$ age $\quad X_{2}=$ tenure

Hence bias in OLS estimate of age in omitted variable model A depends on
a) $\hat{\beta}_{2}=\hat{\beta}_{\text {tenure }}=\frac{\delta L n W}{\delta \text { Tenure }}=\frac{\% \Delta \text { HourlyWage }+100}{\text { UnitدTenure }}$
$\hat{\beta}_{\text {tenure }} *$ Unit $\Delta$ Tenure $* 100=\% \Delta$ HourlyWage
in this case $\hat{\beta}_{2}=0.017=$
A unit (1 year) increase in job tenure raises wages by $1.7 \%$
this would tend to raise the OLS estimate on age in the omitted variable model
A relative to that in the true model $B$
b) The covariance between $X_{1}$ and $X_{2} \equiv O L S$ coefficient from regression of $X_{2}$ on $\mathrm{X}_{1}$

This information is not given in the question, but can work out its effect since

which is just the coefficient from a regression of tenure $\left(\mathrm{X}_{2}\right)$ on $\mathrm{X}_{1}$ (age)
This is confirmed by the regression
reg tenure age

Source SS df MS
Number of obs =
6225
1520.11

Model $81512.3518 \quad 181512.3518$
$F(1,6223)=$
0.0000

Residual $333694.698 \quad 622353.6228022$
0.1963
0.1962

Total 415207.05622466 .7106443
Root MSE = 7.3228
tenure Coef. Std. Err. t P>t [95\% Conf. Interval]
age . 3093224 . 0079337 38.990 .000 . 2937697
. 3248751
$\begin{array}{llllll}\text { _cons } & -3.197329 & .3189538 & -10.02 & 0.000 & -3.822588\end{array}$
-2.572069
and because the correlation between age and job tenure is positive (older workers tend to stay in jobs longer)
the influence of this component on the bias is also upward

