

$$a. \quad x_1 = \begin{bmatrix} 1 & x_1 & x_2 & x_3 \end{bmatrix}$$

$$x_2 = \begin{bmatrix} x_4 & x_5 & x_6 \end{bmatrix}$$

$$H_1 = x_1 (x_1' x_1)^{-1} x_1'$$

$$\hat{\beta} = \begin{bmatrix} \hat{\beta}_1 \\ \hat{\beta}_2 \end{bmatrix}$$

Regress  $x_2$  on  $x_1$

$$(I - H_1) x_2 = \begin{bmatrix} (I - H_1) x_4 & (I - H_1) x_5 & (I - H_1) x_6 \end{bmatrix} = x_2^*$$

Regress  $Y$  on  $x_1$

$$(I - H_1) Y = Y^*$$

Regress  $Y^*$  on  $x_2^*$

$$\begin{aligned} \hat{\beta}_{2.1} &= (x_2^{*'} x_2^*)^{-1} x_2^{*'} Y^* = \left[ ((I - H_1) x_2)' ((I - H_1) x_2) \right]^{-1} ((I - H_1) x_2)' (I - H_1) Y \\ &= x_2' (I - H_1) (I - H_1) x_2 \end{aligned}$$

Regress  $Y$  on  $x_1$

$$\hat{\beta}_1 = (x_1' x_1)^{-1} x_1' Y$$

Regress  $Y$  on  $x_2$

$$\hat{\beta}_2 = (x_2' x_2)^{-1} x_2' Y$$

$$b. \quad W = \begin{bmatrix} X & Z \end{bmatrix} \quad W'W = \begin{bmatrix} X' & Z' \end{bmatrix} \begin{bmatrix} X & Z \end{bmatrix} = \begin{bmatrix} X'X & X'Z \\ Z'X & Z'Z \end{bmatrix} = \begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix}$$

If all inverses exist:

$$\begin{bmatrix} A_{11} & A_{12} \\ A_{21} & A_{22} \end{bmatrix}^{-1} = \begin{bmatrix} A_{11}^{-1} + B_{12} B_{22}^{-1} B_{21} & -B_{12} B_{22}^{-1} \\ -B_{22}^{-1} B_{21} & B_{22}^{-1} \end{bmatrix} \quad \begin{matrix} B_{22} = A_{22} - A_{21} A_{11}^{-1} A_{12} \\ B_{12} = A_{11}^{-1} A_{12} \\ B_{21} = A_{21} A_{11}^{-1} \end{matrix}$$

the last diagonal element of  $[W'W]^{-1}$

$$B_{22}^{-1} = [A_{22} - A_{21} A_{11}^{-1} A_{12}]^{-1}$$

Note:

$$H_1 = X(X'X)^{-1}X'$$

$$= [Z'Z - Z'X(X'X)^{-1}X'Z]^{-1} = [Z'Z - Z'H_1Z]^{-1}$$

$$Z^* = (I - H_1)Z$$

$$\frac{1}{Z^{*'}Z^*} = \frac{1}{Z'(I - H_1)(I - H_1)Z} = \frac{1}{Z'(I - H_1)Z} = \frac{1}{Z'Z - Z'H_1Z} =$$

$$[Z'Z - Z'H_1Z]^{-1} \rightarrow \text{therefore, the last diagonal element of } (W'W)^{-1} \text{ is equal to } \frac{1}{Z^{*'}Z^*}$$

this is a scalar

$$C. \quad H_{12} = X_1 X_2 (X_2' X_1' X_1 X_2)^{-1} X_2' X_1$$

$$\hat{\beta}_{2.1} = (X_2^{*'} X_2^*)^{-1} X_2^{*'} Y^*$$

$$(Y - X_2 \hat{\beta}_{2.1})' (I - H_1) (Y - X_2 \hat{\beta}_{2.1}) =$$

$$(Y' - \hat{\beta}_{2.1}' X_2') (I - H_1) (Y - X_2 \hat{\beta}_{2.1}) =$$

$$(Y' - Y^{*'} X_2^* (X_2^{*'} X_2^*)^{-1} X_2') (I - H_1) (Y - X_2 (X_2^{*'} X_2^*)^{-1} X_2^{*'} Y^*)$$

d. we know:

$$\hat{\beta}_{(0)} = (X_{(0)}^{*'} X_{(0)}^{*-1}) X_{(0)}^{*'} Y^*$$

$$\text{where } X_{(0)}^* = (I - \frac{1}{n} 11') X_{(0)}$$

$$Y^* = (I - \frac{1}{n} 11') Y$$

$$\text{var}(\hat{\beta}_{(0)}) = \text{var}((X_{(0)}^{*'} X_{(0)}^{*-1}) X_{(0)}^{*'} Y^*)$$

$$\text{let } A = (X_{(0)}^{*'} X_{(0)}^{*-1})^{-1} X_{(0)}^{*'}$$

$$= \text{var}(A Y^*)$$

$$= A \text{var}(Y^*) A'$$

$$= A B \text{var}(Y) B' A'$$

$$= A B \sigma^2 B' A'$$

$$\text{let } B = (I - \frac{1}{n} 11')$$

$$= \sigma^2 (X_{(0)}^{*'} X_{(0)}^{*-1})^{-1} X_{(0)}^{*'} (I - \frac{1}{n} 11') (I - \frac{1}{n} 11') [(X_{(0)}^{*'} X_{(0)}^{*-1})^{-1} X_{(0)}^{*'}]'$$

$$= \sigma^2 (X_{(0)}^{*'} X_{(0)}^{*-1})^{-1} X_{(0)}^{*'} (I - \frac{1}{n} 11') [(X_{(0)}^{*'} X_{(0)}^{*-1})^{-1} X_{(0)}^{*'}]'$$

$$= \sigma^2 (X_{(0)}^{*'} X_{(0)}^{*-1})^{-1} X_{(0)}^{*'} (I - \frac{1}{n} 11') X_{(0)}^{*'} (X_{(0)}^{*'} X_{(0)}^{*-1})^{-1}$$

$$= \sigma^2 (X_{(0)} (I - \frac{1}{n} 11') (I - \frac{1}{n} 11') X_{(0)})^{-1} X_{(0)} (I - \frac{1}{n} 11') (I - \frac{1}{n} 11') (I - \frac{1}{n} 11') X_{(0)} (X_{(0)}^{*'} X_{(0)}^{*-1})^{-1}$$

$$\sigma^2 (X_{(0)} (I - \frac{1}{n} 11') X_{(0)})^{-1} (X_{(0)} (I - \frac{1}{n} 11') X_{(0)}) (X_{(0)}^{*'} X_{(0)}^{*-1})^{-1}$$

$$= \sigma^2 I (X_{(0)}^{*'} X_{(0)}^{*-1})^{-1} = \sigma^2 (X_{(0)}^{*'} X_{(0)}^{*-1})^{-1}$$

we know:

$$\hat{\beta}_0 = (1'1)^{-1} 1'Y - (1'1)^{-1} 1' X_{(0)} \hat{\beta}_{(0)}$$

$$= \frac{A}{(1'1)^{-1} 1'Y - (1'1)^{-1} 1' X_{(0)} (X_{(0)}^{*'} X_{(0)}^{*-1}) X_{(0)}^{*'} (I - \frac{1}{n} 11') Y}$$

$$\text{var}(\hat{\beta}_0) = \text{var}(AY) - \text{var}(BY) + 2\text{cov}(AY, BY)$$

$$= A \text{var}(Y) A' - B \text{var}(Y) B' + 2A \text{var}(Y) B'$$

$$= A \sigma^2 I A' - B \sigma^2 I B' + 2A \sigma^2 I B'$$

$$= \sigma^2 A A' - \sigma^2 B B' + 2\sigma^2 A B'$$

$$= \sigma^2 (A A' - B B' + 2A B')$$

$$e. \quad (Y - \hat{Y}_c)' (Y - \hat{Y}_c) = (Y - \hat{Y})' (Y - \hat{Y}) + (\hat{Y} - \hat{Y}_c)' (\hat{Y} - \hat{Y}_c)$$

we know:  $Y - \hat{Y}_c = e_c$   
 $Y - \hat{Y} = e$

$$\rightarrow e_c' e_c = e' e + (\hat{Y} - \hat{Y}_c)'$$

From lecture we know:

$$e_c' e_c = e' e + (c\hat{\theta} - \gamma)' [c(X'X)^{-1}c']^{-1} (c\hat{\theta} - \gamma)$$

So we need to show:

$$(\hat{Y} - \hat{Y}_c)' (\hat{Y} - \hat{Y}_c) = (c\hat{\theta} - \gamma)' [c(X'X)^{-1}c']^{-1} (c\hat{\theta} - \gamma)$$

From lecture we also know:

$$\hat{Y}_c = X\hat{\theta}_c = X\hat{\theta} - X(X'X)^{-1}c'[c(X'X)^{-1}c']^{-1}(c\hat{\theta} - \gamma)$$

and  $\hat{Y} = X\hat{\theta}$

$$\begin{aligned} \hat{Y} - \hat{Y}_c &= X\hat{\theta} - [X\hat{\theta} - X(X'X)^{-1}c'[c(X'X)^{-1}c']^{-1}(c\hat{\theta} - \gamma)] \\ &= X(X'X)^{-1}c'[c(X'X)^{-1}c']^{-1}(c\hat{\theta} - \gamma) \end{aligned}$$

$$\begin{aligned} (\hat{Y} - \hat{Y}_c)' (\hat{Y} - \hat{Y}_c) &= [X(X'X)^{-1}c'[c(X'X)^{-1}c']^{-1}(c\hat{\theta} - \gamma)]' [X(X'X)^{-1}c'[c(X'X)^{-1}c']^{-1}(c\hat{\theta} - \gamma)] \\ &= [(c\hat{\theta} - \gamma)' [c(X'X)^{-1}c']^{-1} c \underbrace{(X'X)^{-1} X' X (X'X)^{-1} c'}_{I} [c(X'X)^{-1}c']^{-1} (c\hat{\theta} - \gamma)] \\ &= [(c\hat{\theta} - \gamma)' [c(X'X)^{-1}c']^{-1} \underbrace{c(X'X)^{-1}c' [c(X'X)^{-1}c']^{-1}}_I (c\hat{\theta} - \gamma)] \\ &= [(c\hat{\theta} - \gamma)' [c(X'X)^{-1}c']^{-1} (c\hat{\theta} - \gamma)] \end{aligned}$$

$$\therefore (Y - \hat{Y}_c)' (Y - \hat{Y}_c) = (Y - \hat{Y})' (Y - \hat{Y}) + (\hat{Y} - \hat{Y}_c)' (\hat{Y} - \hat{Y}_c)$$

F. From lecture we know:

$$R^2_{xz} = R^2_x + \frac{Z^{*'} Z^* \hat{c}^2}{SST}$$

$$SST = (Y - \bar{Y})' (Y - \bar{Y})$$

$$\text{show: } R^2_{xz} = R^2_x + (1 - R^2_x) r^2_{y|xz}$$

$$R^2_x = 1 - \frac{e'e}{SST}$$

$$\hat{c} = \frac{Z^{*'} e}{Z^{*'} Z^*}$$

$$r^2_{y|x_1, \dots, x_{k-1}} = \frac{(Y^{*'} X_k^*)^2}{(X_k^{*'} X_k^*)(Y^{*'} Y^*)}$$

$$\Rightarrow r^2_{y|X} = \frac{(Y^{*'} Z^*)^2}{(Z^{*'} Z^*)(Y^{*'} Y^*)}$$

$$\text{we need to show: } \frac{Z^{*'} Z^* \hat{c}^2}{SST} = (1 - R^2_x) r^2_{y|xz}$$

$$\hat{c} = \frac{Z^{*'} e}{Z^{*'} Z^*} \rightarrow \frac{Z^{*'} Z^* \hat{c}^2}{SST} = \frac{Z^{*'} Z^*}{SST} \frac{(Z^{*'} e)^2}{(Z^{*'} Z^*)^2} = \frac{(Z^{*'} e)^2}{SST (Z^{*'} Z^*)^2}$$

$$e = (I - H)Y = Y^*$$

$$\frac{(Z^{*'} Y^*)^2}{SST (Z^{*'} Z^*)^2} \quad \text{they are scalars: } = \frac{(Y^* Z^*)^2}{SST (Z^{*'} Z^*)}$$

$$(1 - R^2_x) r^2_{y|xz} = 1 - \left[ 1 - \frac{e'e}{SST} \right] \frac{(Y^{*'} Z^*)^2}{(Z^{*'} Z^*)(Y^{*'} Y^*)} = \frac{e'e}{SST} \frac{(Y^{*'} Z^*)^2}{(Z^{*'} Z^*)(Y^{*'} Y^*)}$$

$$= \frac{(Y^{*'} Y^*)(Y^{*'} Z^*)^2}{SST (Z^{*'} Z^*)(Y^{*'} Y^*)} = \frac{(Y^* Z^*)^2}{SST (Z^{*'} Z^*)}$$

g. from lecture we know:

$$(\hat{Y} - \bar{Y})'(\hat{Y} - \bar{Y})$$

$$(X\beta - \bar{Y})'(X\beta - \bar{Y})$$

$$(\beta'X' - \bar{Y})(X\beta - \bar{Y})$$

$$\beta'X'X\beta - \bar{Y}\beta'X' - \bar{Y}X\beta + \bar{Y}^2$$

Note:  $\hat{Y} = X\beta$

$$(X'X)^{-1}X'Y$$

$$Y'(X'X)^{-1}X$$

$$SSR = \hat{\beta}'X'X\hat{\beta} - n\bar{y}^2$$

$$E[SSR] = E[\hat{\beta}'X'X\hat{\beta} - n\bar{y}^2] = \underbrace{E[\hat{\beta}'X'X\hat{\beta}]}_{\text{scalar}} - nE[\bar{y}^2]$$

Note:  $E[\hat{\beta}\hat{\beta}'] = \text{var}(\hat{\beta}) + E(\beta)E(\beta)'$   
 $= \sigma^2(X'X)^{-1} + \beta\beta'$

Note:  $\text{tr}(\sigma^2 I) = n\sigma^2$

Note:  $E[\bar{y}^2] = \text{var}(\bar{y}) + E[\bar{y}]^2$   
 $= \frac{\sigma^2}{n} + E[\frac{1}{n}1'Y]^2$   
 $= \frac{\sigma^2}{n} + \left[\frac{1}{n}1'E(Y)\right]^2$   
 $= \frac{\sigma^2}{n} + \frac{1}{n^2} \underbrace{(1'X\beta)^2}_{\text{scalar}}$

$$\begin{aligned} &= E[\text{tr}(\hat{\beta}'X'X\hat{\beta})] - nE[\bar{y}^2] \\ &= E[\text{tr}(\hat{\beta}\hat{\beta}'X'X)] - nE[\bar{y}^2] \\ &= \text{tr}(E[\hat{\beta}\hat{\beta}'X'X]) - nE[\bar{y}^2] \\ &= \text{tr}(X'X E[\hat{\beta}\hat{\beta}']) - nE[\bar{y}^2] \\ &= \text{tr}(X'X(\sigma^2(X'X)^{-1} + \beta\beta')) - nE[\bar{y}^2] \\ &= \text{tr}(\sigma^2 I + X'X\beta\beta') - nE[\bar{y}^2] \\ &= \text{tr}(\sigma^2 I) + \text{tr}(X'X\beta\beta') - nE[\bar{y}^2] \\ &= n\sigma^2 + \text{tr}(X'X\beta\beta') - nE[\bar{y}^2] \\ &= n\sigma^2 + \underbrace{\text{tr}(\beta'X'X\beta)}_{\text{scalar}} - nE[\bar{y}^2] \\ &= n\sigma^2 + \beta'X'X\beta - nE[\bar{y}^2] \\ &= n\sigma^2 + \beta'X'X\beta - n\left[\frac{\sigma^2}{n} + \frac{1}{n^2}(1'X\beta)^2\right] \\ &= n\sigma^2 + \beta'X'X\beta - \sigma^2 + \frac{1}{n}(1'X\beta)^2 \end{aligned}$$

$$h. \quad Y = X\beta + \epsilon$$

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

$$\beta \sim N(\beta, \sigma^2 (X'X)^{-1})$$

$$Q = \begin{bmatrix} 1 & -2 & 3 & 1 \end{bmatrix} \begin{bmatrix} \hat{\beta}_0 \\ \hat{\beta}_1 \\ \hat{\beta}_2 \\ \hat{\beta}_3 \end{bmatrix}$$

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

$$\text{var}(Q) = \text{var}(C\hat{\beta}) = C \text{var}(\hat{\beta}) C' \\ = \sigma^2 C (X'X)^{-1} C'$$

$$Q \sim N(C\beta, \sigma^2 C (X'X)^{-1} C')$$

$$\text{when } C = \begin{bmatrix} 1 & -2 & 3 & 1 \end{bmatrix}$$

$$K=3$$

$$\sigma^2 \begin{bmatrix} 1 & -2 & 3 & 1 \end{bmatrix} \begin{matrix} C \\ (X'X)^{-1} \end{matrix} \begin{matrix} C' \\ \begin{bmatrix} 1 \\ -2 \\ 3 \\ 1 \end{bmatrix} \end{matrix} = \sigma^2 \begin{bmatrix} 1 & -2 & 3 & 1 \end{bmatrix} \begin{bmatrix} V_{00} - 2V_{01} + 3V_{02} + V_{03} \\ V_{10} - 2V_{11} + 3V_{12} + V_{13} \\ V_{20} - 2V_{21} + 3V_{22} + V_{23} \\ V_{30} - 2V_{31} + 3V_{32} + V_{33} \end{bmatrix}$$

$$= \sigma^2 \left[ (V_{00} - 2V_{01} + 3V_{02} + V_{03}) - 2(V_{10} - 2V_{11} + 3V_{12} + V_{13}) + 3(V_{20} - 2V_{21} + 3V_{22} + V_{23}) + (V_{30} - 2V_{31} + 3V_{32} + V_{33}) \right]$$

$$\begin{matrix} C \\ \begin{bmatrix} 1 & -2 & 3 & 1 \end{bmatrix} \end{matrix} \begin{bmatrix} \hat{\beta}_0 \\ \hat{\beta}_1 \\ \hat{\beta}_2 \\ \hat{\beta}_3 \end{bmatrix} =$$

$$Q \sim N(\hat{\beta}_0 - 2\hat{\beta}_1 + 3\hat{\beta}_2 + \hat{\beta}_3, \sigma^2 [(V_{00} - 2V_{01} + 3V_{02} + V_{03}) - 2(V_{10} - 2V_{11} + 3V_{12} + V_{13}) + 3(V_{20} - 2V_{21} + 3V_{22} + V_{23}) + (V_{30} - 2V_{31} + 3V_{32} + V_{33})])$$



Read in and create data

```
a <- read.table("http://www.stat.ucla.edu/~nchristo/statistics_c173_c273/jura.txt", header=TRUE)
y <- a$Pb

x1 <- a$Cd
x2 <- a$Co
x3 <- a$Cr
x4 <- a$Cu
x5 <- a$Ni
x6 <- a$Zn

ones <- rep(1, nrow(a))
X <- as.matrix(cbind(ones, x1, x2, x3, x4, x5, x6))
X1 <- as.matrix(cbind(ones, x1, x2, x3, x4))
X2 <- as.matrix(cbind(x5, x6))
```

## Question i

Part 1:

```
#H1 Matrix
H1 <- X1 %*% solve(t(X1) %*% X1) %*% t(X1)
#H matrix
H <- X %*% solve(t(X) %*% X) %*% t(X)

#H-H1 Matrix
mat <- round((H - H1) %*% (H - H1))

identical(round((H - H1)), mat)
```

```
## [1] TRUE
```

The matrix  $(H-H1)(H-H1)$  is the same as the matrix  $(H-H1)$  which means that  $(H-H1)$  must be idempotent.

Part 2:

```

#Beta hat using full regression
beta_hat <- solve(t(X) %*% X) %*% t(X) %*% y

H1 <- X1 %*% solve(t(X1) %*% X1) %*% t(X1)
X22 <- (diag(nrow(a)) - H1) %*% X2
y11 <- (diag(nrow(a)) - H1) %*% y

#Beta hat 1 from partial regression
beta_hat2 <- solve(t(X22) %*% X22) %*% t(X22) %*% y11

#Beta hat 2 from partial regression
beta_hat1 <- solve(t(X1) %*% X1) %*% t(X1) %*% y - solve(t(X1) %*% X1) %*% t(X1) %*% X2
%*% beta_hat2

beta_hat

```

```

##           [,1]
## ones 18.9100703
## x1   -1.5192122
## x2   -1.3608686
## x3   -0.1439250
## x4    0.9771788
## x5    0.4855964
## x6    0.3004051

```

```
beta_hat1
```

```

##           [,1]
## ones 18.9100703
## x1   -1.5192122
## x2   -1.3608686
## x3   -0.1439250
## x4    0.9771788

```

```
beta_hat2
```

```

##           [,1]
## x5 0.4855964
## x6 0.3004051

```

As you can see, the values of  $\hat{\beta}_0 \dots \hat{\beta}_5$  from full regression match the values of  $\hat{\beta}_0 \dots \hat{\beta}_3$  and  $\hat{\beta}_4, \hat{\beta}_5$  found using partial regression.

## Question j

Lagrange

```

ones <- rep(1, nrow(a))
X <- as.matrix(cbind(ones,x1, x2, x3, x4))
C <- as.matrix(rbind(c(1,2,-3,5,-1), c(2,-1,1,3,0)))
beta_hat <- solve(t(X) %*% X) %*% t(X) %*% y
gamma <- as.matrix(rbind(5,10))

#Beta hat using the constrained model
beta_hat_c <- beta_hat - solve(t(X) %*% X) %*% t(C) %*% solve(C %*% solve(t(X) %*% X) %
*% t(C)) %*% (C %*% beta_hat - gamma)
beta_hat_c

```

```

##           [,1]
## ones 4.1814535
## x1    0.1587391
## x2    0.2727253
## x3    0.5077022
## x4    1.2192669

```

## Canonical

```

C1 <- as.matrix(rbind(c(1,2), c(2,-1)))
C2 <- as.matrix(rbind(c(-3,5,-1), c(1,3,0)))
X1 <- as.matrix(cbind(ones,x1))
X2 <- as.matrix(cbind(x2, x3, x4))

Yr <- y - X1 %*% solve(C1) %*% gamma
X2r <- X2 - X1 %*% solve(C1) %*% C2

#Beta hat 1 and beta hat 2 using the constrained model
beta_hat_2c <- solve(t(X2r) %*% X2r) %*% t(X2r) %*% Yr
beta_hat_1c <- solve(C1) %*% (gamma - C2 %*% beta_hat_2c)

beta_hat_1c

```

```

##           [,1]
## [1,] 4.1814535
## [2,] 0.1587391

```

```
beta_hat_2c
```

```

##           [,1]
## x2 0.2727253
## x3 0.5077022
## x4 1.2192669

```

As you can see, the values of  $\hat{\beta}_{c0} \dots \hat{\beta}_{c4}$  obtained using Lagrange multipliers are the same as the values of  $\hat{\beta}_{c0}, \hat{\beta}_{c1}$  and  $\hat{\beta}_{c2} \dots \hat{\beta}_{c4}$  obtained using the canonical form of the model.