

1. (25 points) Consider the linear model

$$Y = X\beta + \epsilon, \quad (1)$$

where  $Y$  is  $n \times 1$ ,  $X$  is an  $n \times p$  matrix of fixed covariates with rank  $r < p$ ,  $\beta$  is  $p \times 1$ , and  $\epsilon \sim N_n(0, \Sigma)$ , where  $\Sigma$  is a known positive definite matrix.

- (a) Derive the distribution of

$$U = (Y - X\beta)' \Sigma^{-1} (Y - X\beta),$$

and derive the mean and variance of  $U$ .

Note: You are not allowed to simply state the result of a theorem to give your answer. You must *derive* the results.

- (b) Formally derive the set of all possible least squares solutions of  $\beta$ .

Note: You are not allowed to simply state a result or a formula for your answer. You must *derive* the result.

- (c) Show that  $\lambda'\beta$  is estimable if and only if

$$\lambda'(X'\Sigma^{-1}X)^-(X'\Sigma^{-1}X) = \lambda',$$

where a “-” denotes generalized inverse.

- (d) Assume  $X$  has rank  $p$ . Show that the BLUE of  $\beta$  is equal to  $(X'X)^{-1}X'Y$  if and only if there exists a non-singular  $p \times p$  matrix  $F$  such that  $\Sigma X = XF$ .
- (e) Assume  $X$  has rank  $p$ . Let  $s^2$  be defined as

$$s^2 = \frac{Y'(I - M)Y}{n - p}$$

where  $M$  denotes the orthogonal projection operator onto the column space of  $X$ . Show that

$$E(s^2) \leq \frac{1}{n - p} \sum_{i=1}^n \sigma_{ii},$$

where  $\sigma_{ii}$  denotes the  $i$ th diagonal element of  $\Sigma$ ,  $i = 1, \dots, n$ . Can the upper bound on  $E(s^2)$  be attained? Justify your answer.

Points: (a) 5; (b) 5; (c) 5; (d) 5; (e) 5.

5+

## 2) [2019 Qual Problem]

$$Y = X\beta + \varepsilon \quad ; \quad Y_{n \times 1}, \quad X_{n \times p}, \quad r(X) = r < p, \quad \beta_{p \times 1}, \quad \varepsilon \sim N_n(0, \Sigma)$$

$\Sigma$  known + DEF matrix

(a) Derive the distribution of  $U = (Y - X\beta)' \Sigma^{-1} (Y - X\beta)$

We know  $\Sigma$  is + DEF, so write  $\Sigma^{-1} = \Sigma^{-1/2} \Sigma^{-1/2}$  ← could also write  $\Sigma = QQ'$ , where  $Q$  nonsingular

$$\begin{aligned} \text{Then } U &= (Y - X\beta)' \Sigma^{-1/2} \Sigma^{-1/2} (Y - X\beta) \\ &= (\Sigma^{-1/2} (Y - X\beta))' (\Sigma^{-1/2} (Y - X\beta)) \end{aligned}$$

Since  $Y \sim N_n(X\beta, \Sigma)$ , then  $Y - X\beta \sim N_n(0, \Sigma)$  and  $\Sigma^{-1/2} (Y - X\beta) \sim N_n(0, I_n)$

The square of  $N_n(0, I_n)$  distribution is  $\chi^2_n$ , so  $U = (\Sigma^{-1/2} (Y - X\beta))' (\Sigma^{-1/2} (Y - X\beta)) \sim \chi^2_n$

PDF of  $\chi^2_n$ :  $f_U = \frac{1}{\Gamma(\frac{n}{2}) 2^{n/2}} U^{\frac{n}{2}-1} \exp(-u/2)$  for  $u > 0$ , or 0 otherwise.

→ Derive MGF to determine mean & var. of  $U$ .

$$\Psi_U(t) = E[e^{tu}] = \int_0^\infty e^{tu} \frac{1}{\Gamma(\frac{n}{2}) 2^{n/2}} u^{\frac{n}{2}-1} e^{-u/2} du = \int_0^\infty \frac{1}{\Gamma(\frac{n}{2}) 2^{n/2}} u^{\frac{n}{2}-1} e^{-u(\frac{1}{2}-t)} du$$

$$\text{Let } v = u(\frac{1}{2}-t) \rightarrow dv = (\frac{1}{2}-t) du \rightarrow \int_0^\infty \frac{1}{\Gamma(\frac{n}{2}) 2^{n/2}} \left(\frac{v}{\frac{1}{2}-t}\right)^{\frac{n}{2}-1} e^{-v} (\frac{1}{2}-t)^{-1} dv$$

$$\begin{aligned} &= \frac{1}{2^{n/2} (\frac{1}{2}-t)^{n/2}} \int_0^\infty \underbrace{\frac{1}{\Gamma(\frac{n}{2})} v^{\frac{n}{2}-1} e^{-v} dv}_{\text{pdf Gamma}(\frac{n}{2}, 1)} = 2^{-n/2} (\frac{1}{2}-t)^{-n/2} = (1-2t)^{-n/2} \end{aligned}$$

$$\text{So, } \Psi_U(t) = (1-2t)^{-n/2}$$

$$\rightarrow \text{1st Moment: } \Psi'_U(t) = -\frac{n}{2} (1-2t)^{-\frac{n}{2}-1} (-2) = n(1-2t)^{-\frac{n}{2}-1}, \text{ so } \Psi'_U(0) = n$$

$$\rightarrow \text{2nd Moment: } \Psi''_U(t) = n(-\frac{n}{2}-1)(1-2t)^{-\frac{n}{2}-2} (-2), \text{ so } \Psi''_U(0) = (-\frac{n^2}{2}-n)(-2) = n^2+2n$$

$$\text{Mean: } E(U) = n$$

$$\text{Var}(U) = E(U^2) - E(U)^2 = n^2 + 2n - n^2 = 2n$$

(b) Formally derive the set of all possible LS solutions of  $\beta$ .

Take the transformed model,  $Q^{-1}Y = Q^{-1}X\beta + Q^{-1}\varepsilon$ , where  $Z = QQ'$  since it is + DEF

Since  $Y \sim N_n(X\beta, \Sigma)$ , then  $Q^{-1}Y \sim N_n(X\beta, Q^{-1}\Sigma Q^{-1})$

and  $Q^{-1}\Sigma Q^{-1} = Q^{-1}(QQ')Q^{-1} = I_n$ . Thus  $Q^{-1}Y \sim N_n(X\beta, I_n)$

Call this model  $\tilde{Y} = \tilde{X}\beta + \tilde{\varepsilon}$ , where  $\tilde{Y} = Q^{-1}Y$ ,  $\tilde{X} = Q^{-1}X$ ,  $\tilde{\varepsilon} = Q^{-1}\varepsilon$ .

Let  $\tilde{M}$  be the OPO onto  $C(\tilde{X})$ :  $\tilde{M} = \tilde{X}(\tilde{X}'\tilde{X})^{-1}\tilde{X}'$

We know any LSE for  $\beta$  must satisfy:  $(\tilde{Y} - \tilde{X}\hat{\beta})'(\tilde{Y} - \tilde{X}\hat{\beta}) = \min_{\beta} (\tilde{Y} - \tilde{X}\beta)'(\tilde{Y} - \tilde{X}\beta)$

$$(\tilde{Y} - \tilde{X}\beta)'(\tilde{Y} - \tilde{X}\beta) = ((\tilde{Y} - \tilde{M}\tilde{Y}) + (\tilde{M}\tilde{Y} - \tilde{X}\beta))'((\tilde{Y} - \tilde{M}\tilde{Y}) + (\tilde{M}\tilde{Y} - \tilde{X}\beta))$$

$$= ((\tilde{Y} - \tilde{M}\tilde{Y}) - (\tilde{X}\beta - \tilde{M}\tilde{Y}))'((\tilde{Y} - \tilde{M}\tilde{Y}) - (\tilde{X}\beta - \tilde{M}\tilde{Y}))$$

$$= (\tilde{Y} - \tilde{M}\tilde{Y})'(\tilde{Y} - \tilde{M}\tilde{Y}) - \underbrace{(\tilde{Y} - \tilde{M}\tilde{Y})'(\tilde{X}\beta - \tilde{M}\tilde{Y})} - \underbrace{(\tilde{X}\beta - \tilde{M}\tilde{Y})'(\tilde{Y} - \tilde{M}\tilde{Y})} + (\tilde{X}\beta - \tilde{M}\tilde{Y})'(\tilde{X}\beta - \tilde{M}\tilde{Y})$$

$$\tilde{Y}'\tilde{X}\beta - \tilde{Y}'\tilde{M}\tilde{Y} - \tilde{Y}'\tilde{M}'\tilde{Y}\beta + \tilde{Y}'\tilde{M}'\tilde{M}\tilde{Y}$$

$$\cancel{Y'\tilde{X}\beta} - \cancel{\tilde{Y}'\tilde{M}\tilde{Y}} - \cancel{\tilde{Y}'\tilde{X}\beta} + \cancel{\tilde{Y}'\tilde{M}\tilde{Y}}$$

0

Similarly, this term is 0

$$= (\tilde{Y} - \tilde{M}\tilde{Y})'(\tilde{Y} - \tilde{M}\tilde{Y}) + (\tilde{X}\beta - \tilde{M}\tilde{Y})'(\tilde{X}\beta - \tilde{M}\tilde{Y})$$

This is clearly minimized when  $\tilde{X}\beta - \tilde{M}\tilde{Y} = 0 \Rightarrow \tilde{X}\beta = \tilde{M}\tilde{Y}$

So, to find LSE for  $\beta$ , we can solve  $\tilde{X}\beta = \tilde{M}\tilde{Y}$

Since  $X$  not full rank, we claim the solution to this is:  $\hat{\beta} = (\tilde{X}'\tilde{X})^{-1}\tilde{X}'\tilde{Y} - (I - \tilde{X}'(\tilde{X}'\tilde{X})^{-1}\tilde{X})Z$ ,  
where  $Z \in \mathbb{R}^p$ .

To prove this is the solution

First, we know  $\tilde{M}\tilde{Y} \in C(\tilde{X})$ , and  $\tilde{M}\tilde{Y} = \tilde{X}(\tilde{X}'\tilde{X})^{-1}\tilde{X}'\tilde{Y}$

Thus, for  $\tilde{X}\beta = \tilde{M}\tilde{Y} = \tilde{X}(\tilde{X}'\tilde{X})^{-1}\tilde{X}'\tilde{Y}$ , we can see that

$$\hat{\beta} = (\tilde{X}'\tilde{X})^{-1}\tilde{X}'\tilde{Y} \text{ is a solution}$$

→

Second, since  $X$  not full rank, we know any  $\hat{\beta}$  satisfying  $\tilde{X}\hat{\beta} = \tilde{M}\tilde{y}$  is LSE along with  $\hat{\beta} + m$  for  $m \in N(\tilde{X})$

Since  $N(\tilde{X}) = C(\tilde{X}')^\perp$ , then  $N(\tilde{X})$  has the same column space as  $C(\tilde{X}')^\perp$ ,

which is  $I - \tilde{M}_{\tilde{X}} = I - \tilde{X}'(\tilde{X}\tilde{X}')^{-1}\tilde{X}$

So, for  $m \in N(\tilde{X})$ , we know  $\forall z \in \mathbb{R}^p$ ,  $m = (I - \tilde{M}_{\tilde{X}})z$

$$\Rightarrow m = (I - \tilde{X}'(\tilde{X}\tilde{X}')^{-1}\tilde{X})z$$

So, putting this all together,

$$\hat{\beta} = (\tilde{X}'\tilde{X})^{-1}\tilde{X}'\tilde{y} + (I - \tilde{X}'(\tilde{X}\tilde{X}')^{-1}\tilde{X})z$$

(c) Show  $\lambda'\beta$  is estimable iff  $\lambda'(X'\Sigma^{-1}X)^{-1}(X'\Sigma^{-1}X) = \lambda'$

First, assume  $\lambda'\beta$  is estimable.

We know  $\lambda'\beta$  estimable in WLS model iff it is estimable in transformed model.

Again, since  $\Sigma = QQ'$ , let  $Q$  nonsingular

Then, we have transformed model  $Q^{-1}Y = Q^{-1}X\beta + Q^{-1}\varepsilon$ ;  $Q^{-1}Y \sim N_n(X\beta, I_n)$   
(as shown in (a) & (b))

So,  $\lambda'\beta$  estimable  $\Rightarrow \lambda'\beta \in C(Q^{-1}X) \Rightarrow \lambda = (Q^{-1}X)'b$  for some  $b \in \mathbb{R}^r$   
 $\Rightarrow \lambda' = b'(Q^{-1}X)$

$$\begin{aligned} \text{Then, } \lambda'(X'\Sigma^{-1}X)^{-1}(X'\Sigma^{-1}X) &= (b'(Q^{-1}X))(X'(QQ')^{-1}X)^{-1}(X'(Q^{-1}X)) \\ &= b'Q^{-1}X(X'Q^{-1}Q^{-1}X)^{-1}(X'Q^{-1}Q^{-1}X) \\ &= b'\underbrace{(Q^{-1}X)((Q^{-1}X)'(Q^{-1}X))^{-1}(Q^{-1}X)'}_{M_{Q^{-1}X}}(Q^{-1}X) \\ &= b'M_{Q^{-1}X}(Q^{-1}X) \\ &= b'(Q^{-1}X) = \underline{\underline{\lambda'}} \quad \checkmark \end{aligned}$$

Second, assume  $\lambda'(X'\Sigma^{-1}X)^{-1}(X'\Sigma^{-1}X) = \lambda'$

Transpose both sides:  $\lambda = (X'\Sigma^{-1}X)(X'\Sigma^{-1}X)^{-1}\lambda$

$$\begin{aligned} \text{Again, with } \Sigma = QQ' \rightarrow \lambda &= (X'(QQ')^{-1}X)(X'(QQ')^{-1}X)^{-1}\lambda \\ &= (Q^{-1}X)' \underbrace{(Q^{-1}X)((Q^{-1}X)'(Q^{-1}X))^{-1}}_{\text{call this } P} \lambda \\ &= (Q^{-1}X)'P \Rightarrow \lambda \in C((Q^{-1}X)') \end{aligned}$$

$\Rightarrow \lambda$  is estimable in the transformed model, and hence in the WLS model

(d)  $r(X) = p$ . Show the BLUE of  $\beta = (X'X)^{-1}X'Y$  iff  $\exists$  a non-singular  $p \times p$   $F$  s.t.  $\Sigma X = XF$

• First, assume the BLUE of  $\beta$  is  $\hat{\beta} = (X'X)^{-1}X'Y$

Now that  $X$  full rank, we know from (b) that any LSE for  $\beta$  must satisfy

$$\begin{aligned}\hat{\beta} &= (\tilde{X}'\tilde{X})^{-1}\tilde{X}'\tilde{Y} \\ &= ((Q^{-1}X)'(Q^{-1}X))^{-1}(Q^{-1}X)'Q^{-1}Y \\ &= (X'\Sigma^{-1}X)^{-1}X'\Sigma^{-1}Y\end{aligned}$$

Since  $X$  full rank,  $\beta$  is estimable, and by Gauss-Markov,  $\hat{\beta} = (X'\Sigma^{-1}X)^{-1}X'\Sigma^{-1}Y$  is BLUE of  $\beta$

Thus, with our assumption, we have:  $(X'X)^{-1}X'Y = (X'\Sigma^{-1}X)^{-1}X'\Sigma^{-1}Y$

$$\Leftrightarrow (X'X)^{-1}X' = (X'\Sigma^{-1}X)^{-1}X'\Sigma^{-1}$$

$$\text{Transposing} \Rightarrow X(X'X)^{-1} = \Sigma^{-1}X(X'\Sigma^{-1}X)^{-1}$$

$$\Leftrightarrow \Sigma X(X'X)^{-1} = X(X'\Sigma^{-1}X)^{-1}$$

$$\Leftrightarrow \Sigma X = X(X'\Sigma^{-1}X)^{-1}(X'X)$$

$$\Leftrightarrow \Sigma X = XF, \text{ where } F = (X'\Sigma^{-1}X)^{-1}(X'X),$$

which is non-singular,  $p \times p$  since  $(X'\Sigma^{-1}X)^{-1}$  and  $(X'X)$  are both bases for  $\mathbb{R}^p$  and  $p \times p$  invertible.

Thus,  $\Sigma X = XF$ ,  $F$  non-singular  $p \times p$ .

→

Now, assume  $\exists F$  non-singular  $p \times p$  st  $\Sigma X = XF$ .

Then,  $\Sigma X = XF$

$$\Leftrightarrow X = \Sigma^{-1} X F \Leftrightarrow X F^{-1} = \Sigma^{-1} X$$

So,  $\hat{\beta} = (X' \Sigma^{-1} X)^{-1} X' \Sigma^{-1} y$  (from results in (b))

$$= ((X F^{-1})' X)^{-1} (X F^{-1})' y$$

$$= (F^{-T} X' X)^{-1} (X F^{-1})' y$$

$$= (X' X)^{-1} F^T F^{-T} X' y$$

$$= (X' X)^{-1} X' y \quad \checkmark$$

(e)  $r(X) = p$ ,  $s^2 = \frac{Y'(I-M)Y}{n-p}$ ,  $M$  is ODO onto  $C(X)$

Show  $E(s^2) \leq \frac{1}{n-p} \sum_{i=1}^n \sigma_{ii}$ ;  $\sigma_{ii}$  is  $i$ th diagonal of  $\Sigma$

$$\begin{aligned} E(s^2) &= E\left(\frac{Y'(I-M)Y}{n-p}\right) = \frac{1}{n-p} E(Y'(I-M)Y) = \frac{1}{n-p} [E(Y)'(I-M)E(Y) + \text{tr}((I-M)\Sigma)] \\ &= \frac{1}{n-p} [(X\beta)'(I-M)(X\beta) + \text{tr}((I-M)\Sigma)] = \frac{1}{n-p} \text{tr}((I-M)\Sigma) = \frac{1}{n-p} [\text{tr}(\Sigma) - \text{tr}(M\Sigma)] \end{aligned}$$

$X\beta - MX\beta = X\beta - X\beta = 0$

$$= \frac{1}{n-p} \text{tr}(\Sigma) - \frac{1}{n-p} \text{tr}(M\Sigma)$$

Note that  $\text{tr}(\Sigma) = \sum_{i=1}^n \sigma_{ii}$ , so  $E(s^2) = \left(\frac{1}{n-p} \sum_{i=1}^n \sigma_{ii}\right) - \frac{1}{n-p} \text{tr}(M\Sigma)$

Thus, we must show  $\frac{1}{n-p} \text{tr}(M\Sigma) > 0$

$$\text{tr}(M\Sigma) = \text{tr}(M^2\Sigma) = \text{tr}(M'M\Sigma) = \text{tr}(M\Sigma M')$$

For the matrix  $M\Sigma M'$  and  $\forall z \in \mathbb{R}^n$ ,  $z'M\Sigma M'z = \underbrace{(M'z)'}_{\text{Scalar}} \Sigma \underbrace{(M'z)}_{\text{Scalar}} \geq 0$  since  $\Sigma$  is +DEF (by definition)

$\Rightarrow M\Sigma M'$  is +DEF  $\left\{ \begin{smallmatrix} \text{since} \\ z'M\Sigma M'z \geq 0 \end{smallmatrix} \right\}$ , so  $\lambda_i \geq 0$ , where  $\lambda_i$ 's are eigenvalues of  $M\Sigma M'$ .

$$\text{tr}(M\Sigma M') = \sum \lambda_i \geq 0, \text{ and clearly } \frac{1}{n-p} > 0$$

Putting this all together, 
$$\begin{aligned} E(s^2) &= \frac{1}{n-p} \sum_{i=1}^n \sigma_{ii} - \frac{1}{n-p} \text{tr}(M\Sigma M') \\ &= \frac{1}{n-p} \sum_{i=1}^n \sigma_{ii} - \frac{1}{n-p} \sum \lambda_i \\ &\leq \frac{1}{n-p} \sum_{i=1}^n \sigma_{ii} \quad \checkmark \end{aligned}$$

Can the upper bound of  $E(s^2)$  be obtained?

The only way this can be attained is if  $\frac{1}{n-p} \sum_{i=1}^n \lambda_i = 0 \Leftrightarrow \sum_{i=1}^n \lambda_i = 0$ , and since  $\lambda_i \geq 0$ , this would mean all  $\lambda_i = 0 \forall i$ .

Actually cannot achieve because  $\lambda_i > 0$  for all  $i$ , since  $M\Sigma M'$  is +DEF