

3.16

(a)

$$\begin{aligned}
 \mathbb{E}(\hat{\beta}^*|X) &= \mathbb{E}[(X'V^{-1}X)^{-1}X'V^{-1}(X\beta + \epsilon)] \\
 &= \mathbb{E}[\beta^0 + (X'V^{-1}X)^{-1}X'V^{-1}\mathbb{E}(\epsilon|X)] \\
 &= \beta^0
 \end{aligned} \tag{1}$$

Define $D^{*'} = D'C^{-1}$, let \hat{b} is another linear unbiased estimator

$$\hat{b} = D'Y = D'C^{-1}CY = D^{*'}Y^*$$

\hat{b} is unbiased

$$\begin{aligned}
 \Rightarrow \beta^0 &= \mathbb{E}(\hat{b}|X) = D^{*'}(X^*\beta^0) + D^{*'}\mathbb{E}(\epsilon^*|X) = D^{*'}X^*\beta^0 \Rightarrow D^{*'}X^* = I \\
 \Rightarrow \hat{b} &= D^{*'}Y^* = D^{*'}(X^*\beta + \epsilon^*) = \beta^0 + D^{*'}\epsilon^*
 \end{aligned}$$

$$\begin{aligned}
 Var(\hat{b}|X) - Var(\hat{\beta}^*|X) &= D^{*'}D^* - (X^{*'}X^{*'})^{-1} \\
 &= D^{*'}D^* - D^{*'}X^*(X^{*'}X^{*'})^{-1}X^{*'}D^* \\
 &= D^{*'}[I - X^*(X^{*'}X^{*'})^{-1}X^{*'}]D^* \\
 &= D^{*'}M^*D^* \\
 &= D^{*'}M^*M^{*'}D^* \\
 &= P.S.D
 \end{aligned} \tag{2}$$

where $M^* = I - X^*(X^{*'}X^{*'})^{-1}X^{*'}$

From (1) and (2), β^* is BLUE

(b)

$$\epsilon|X \sim N(0, V) \Rightarrow C'\epsilon C|X = \epsilon^*|X \sim N(0, C'VC) = N(0, I)$$

$$\begin{aligned}
 S^* &= \frac{e^{*'}e^*}{n-k} \\
 &= \frac{1}{n-k}\epsilon^*M^*\epsilon^* \\
 &= \frac{1}{n-k}\chi_{n-k}^2
 \end{aligned} \tag{3}$$

$$\begin{aligned}
Cov(\hat{\beta}^*, e^* | X) &= \mathbb{E}[(\hat{\beta}^* - \mathbb{E}\beta)(e^* - \mathbb{E}e^*)'] \\
&= \mathbb{E}[(\hat{\beta}^* - \mathbb{E}\beta)e^{*'}] \\
&= \mathbb{E}[(X^{*'}X^*)^{-1}X^*e^* | X] \\
&= \mathbb{E}[(X^{*'}X^*)^{-1}X^*M^*\epsilon^* | X] \\
&= (X^{*'}X^*)^{-1}X^*M^*\mathbb{E}[\epsilon^* | X] \\
&= 0
\end{aligned} \tag{4}$$

$$e^* = M^*\epsilon^* \sim N(0, M^*) \tag{5}$$

$$\begin{aligned}
\hat{\beta}^* - \beta^0 &= (X^{*'}X^*)^{-1}X^{*'}Y^* - \beta^0 \\
&= (X^{*'}X^*)^{-1}X^{*'}(X^*\beta^0 + \epsilon^*) - \beta^0 \\
&= (X^{*'}X^*)^{-1}X^{*'}X^*\epsilon^* \\
&\sim N(0, (X^{*'}X^*)^{-1})
\end{aligned} \tag{6}$$

$$\begin{aligned}
R\hat{\beta}^* - r &= R'(\hat{\beta}^* - \beta^0) \\
&\sim N(0, R'(X^{*'}X^*)^{-1}R)
\end{aligned} \tag{7}$$

For the normal distribution, co-variance=0 \Rightarrow independent \Rightarrow So the $\hat{\beta}^* - \beta^0$ is independent of $e^* \Rightarrow R\hat{\beta}^* - r$ is independent of S^*

From (6)

$$\Rightarrow \tilde{T}^* \frac{R\hat{\beta} - r}{\sqrt{R'(X^{*'}X^*)^{-1}R}} \sim N(0, 1) \text{ for } J = 1 \tag{8}$$

From (3)(8) and the independence,

$$\begin{aligned}
\frac{R\hat{\beta} - r}{\sqrt{S^{*2}R'(X^{*'}X^*)^{-1}R}} &= \frac{\frac{(\hat{\beta}-r)}{\sqrt{R'(X^{*'}X^*)^{-1}R}}}{\sqrt{S^{*2}}} \\
&\sim \frac{N(0, 1)}{\sqrt{\frac{1}{n-k}\chi_{n-k}^2}} \\
&\sim t_{n-k}
\end{aligned} \tag{9}$$

From (7),

$$\tilde{Q}^* = (R\hat{\beta} - r)'[R'(X^{*'}X^*)^{-1}R]^{-1}(R\hat{\beta} - r)' \sim \chi_J^2 \tag{10}$$

From (3) and (10), joint the independence, we can get

$$F^* = \frac{(R\hat{\beta} - r)'[R'(X^{*'}X^*)^{-1}R]^{-1}(R\hat{\beta} - r)' / J}{S^{*2}} = \frac{\frac{1}{J}\chi_J^2}{\frac{1}{n-k}\chi_{n-k}^2} \sim F(J, n - K) \quad (11)$$

(c) (8) and (10) is the answer.

(d) As the hint, the t-distribution has more heavier tail than $N(0,1)$ and so has a larger critical value at a given significance level. For the F distribution, when $n - k \rightarrow \infty$ the $F(J, n - k) \rightarrow \chi_J^2$. For the case of finite n-k, the $F(J, n - k)$ has more heavier tail than the χ_{n-k}^2 , so has a larger critical value at a given significance level. Those mean that (T^*, F^*) has less probability to reject H_0 when H_0 is not true. So the the $(\tilde{T}^*, \tilde{F}^*)$ are more powerful than (T^*, F^*)