

# MTH 442 Assignment 1

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1) Given,  $X_t = \beta_1 + \beta_2 t + W_t$   
 ~~$V_t = \frac{1}{(2q+1)} \sum_{j=-q}^q X_{t-j}$~~

The mean of moving average,

$$E[V_t] = \frac{1}{2q+1} \sum_{j=-q}^q E[X_{t+j}]$$
 ~~$= \frac{1}{2q+1} \sum_{j=-q}^q E[\beta_1 + \beta_2(t+j) + W_{t+j}]$~~

$$= \frac{1}{2q+1} \sum_{j=-q}^q [\beta_1 + \beta_2(t+j) + W_{t+j}]$$

$$= \frac{1}{2q+1} \sum_{j=-q}^q [\beta_1 + \beta_2(t-j)] \quad [ \because W_{t+j} \sim N(0, \sigma^2) ]$$

$$= \frac{1}{2q+1} \left[ \beta_1(2q+1) + \beta_2(2q+1) - \beta_2 \sum_{j=-q}^q j \right]$$

$$= \frac{1}{2q+1} [( \beta_1 + \beta_2 ) (2q+1) - 0 ]$$

$$= \beta_1 + \beta_2 t$$

Auto covariance Function,

$$\gamma_V(h) = \text{Cov}(V_t, V_{t+h})$$

We know,

$$V_t = \frac{1}{2q+1} \sum_{j=-q}^q X_{t-j}; \quad V_{t+h} = \frac{1}{2q+1} \sum_{k=-q}^q X_{t+h-k}$$

$$\therefore \text{Cov}(V_t, V_{t+h}) = \frac{1}{(2q+1)^2} \text{Cov}\left(\sum_{j=-q}^q X_{t-j}, \sum_{k=-q}^q X_{t+h-k}\right)$$

$$\begin{aligned}
 &= \frac{1}{(2q+1)^2} \sum_{j=-q}^q \sum_{k=-q}^q \text{Cov}(X_{t+j}, X_{t+h-k}) \\
 &= \frac{1}{(2q+1)^2} \sum_{j=-q}^q \sum_{k=-q}^q \text{Cov}(W_{t+j}, W_{t+h-k}) \\
 &= \frac{\sigma_w^2}{(2q+1)^2} \sum_{j=-q}^q \sum_{k=-q}^q I(j=k-h)
 \end{aligned}$$

Now, consider separate cases for  $h$ :

- When  $h=0$ ,  $j=k$ , so  $I(j-k=0)$  is 1 for every pair where  $j=k$ .  $\therefore$  There are  $2q+1$  such pairs.
- When  $h>0$ ,  $j=k-h$ , which implies  $k$  can range from  $-q+h$  to  $q$  (for  $-q \leq j \leq q$ ). The no. of such pairs is  $2q+1-h$ .
- When  $h<0$ , let  $h=-m$ , where  $m>0$ . Then  $k=j+h=j-m \Rightarrow k$  ranges from  $-q$  to  $q-m$   $\Rightarrow$  There are  $2q+1-|h|$  pairs.

$$\therefore \sum_{j=-q}^q \sum_{k=-q}^q I(j-k=h) = 2q+1-|h| \text{ for } |h| \leq 2q+1$$

$$\begin{aligned}
 \Rightarrow Y_V(h) &= \frac{\sigma_w^2}{(2q+1)^2} (2q+1-|h|) \\
 &= \frac{\sigma_w^2}{2q+1} \left[ 1 - \frac{|h|}{(2q+1)} \right]
 \end{aligned}$$

for  $|h| \leq 2q+1$

Given,

$$2) X_t = V_1 \sin(2\pi w_0 t) + V_2 \cos(2\pi w_0 t)$$

We say a time series is stationary weakly stationary if all of the following satisfy:

- Variance of the process is finite at each time point
- The mean value function  $\mu_t$  is constant and does not depend on  $t$ .
- The auto covariance function,  $r(s, t)$  depends on  $s$  and  $t$  only through their difference  $|s-t|$ .

Mean,

$$\begin{aligned} E[X_t] &= \sin(2\pi w_0 t) E[V_1] \\ &\quad + \cos(2\pi w_0 t) E[V_2] \\ &= 0 \quad [ \because E[V_1] = E[V_2] = 0 ] \end{aligned}$$

Further, it is given that  $E[V_1^2] = E[V_2^2] = \sigma^2$   
~~∴~~  $\text{Var}(X_t) = \text{Cov}(X_t, X_t)$

Auto Covariance Function,

$$\begin{aligned} r_V(h) &= \text{Cov}(X_t, X_{t+h}) \\ &= E[(X_t - E[X_t])(X_{t+h} - E[X_{t+h}])] \\ &= E[X_t X_{t+h}] \quad [ \because X_t, X_{t+h} \text{ have zero means} ] \end{aligned}$$

$$\begin{aligned} &= E[(V_1 \sin(2\pi w_0 t) + V_2 \cos(2\pi w_0 t))(V_1 \sin(2\pi w_0(t+h)) + V_2 \cos(2\pi w_0(t+h)))] \\ &= E[V_1^2 \sin(2\pi w_0 t) \sin(2\pi w_0(t+h)) \\ &\quad + V_1 V_2 \cos(2\pi w_0 t) \sin(2\pi w_0(t+h)) \\ &\quad + V_1 V_2 \sin(2\pi w_0 t) \cos(2\pi w_0(t+h)) \\ &\quad + V_2^2 \cos(2\pi w_0 t) \cos(2\pi w_0(t+h))] \end{aligned}$$

$$\begin{aligned} &= E[V_1^2] \sin(2\pi w_0 t) \sin(2\pi w_0(t+h)) \\ &\quad + E[V_2^2] \cos(2\pi w_0 t) \cos(2\pi w_0(t+h)) \end{aligned}$$

$$[ \because E[V_1 V_2] = E[V_1] E[V_2] = 0 \quad (\because V_1, V_2 \text{ are independent}) ]$$

$$\Rightarrow r_V(h) = \sigma^2 [\sin(2\pi w_0 t) \sin(2\pi w_0(t+h)) + \cos(2\pi w_0 t) \cos(2\pi w_0(t+h))]$$

$\left[ \because E[V_1^2] = E[V_2^2] = \sigma^2 \right]$

$$\Rightarrow r_V(h) = \sigma^2 \cos(2\pi w_0 h)$$

$\left[ \because \sin A \sin B + \cos A \cos B = \cos(A-B) \right]$

Also,  $\text{Var}(X_t) = r_V(0) = \sigma^2$

$\therefore \text{Var}(X_t)$  is finite for every  $t$ .

$\therefore$  the time series  $X_t$  is weakly stationary.

3) Given,  $X_t = W_t$

$$Y_t = W_t - \theta W_{t-1} + U_t$$

(a) Auto covariance Function,

$$\gamma_Y(h) = \text{Cov}(Y_t, Y_{t+h})$$

$$= E[Y_t Y_{t+h}]$$

$$= E[(W_t - \theta W_{t-1} + U_t)(W_{t+h} - \theta W_{t+h-1} + U_{t+h})]$$

$$= E[W_t W_{t+h} - \theta W_t W_{t+h-1} + U_{t+h} W_t - \theta W_{t-1} W_{t+h} + \theta^2 W_{t-1} W_{t+h-1} - \theta U_{t+h} W_{t-1} + U_t W_{t+h} - \theta U_t W_{t+h-1} + U_t U_{t+h}]$$

$$= E[W_t W_{t+h} - \theta W_t W_{t+h-1} - \theta W_{t-1} W_{t+h} + \theta^2 W_{t-1} W_{t+h-1} + U_t U_{t+h}]$$

$$\therefore E[U_i W_j] = E[U_i] E[W_j] = 0 \quad [ \text{as } U_i \text{ and } W_j \text{ are independent } \forall i, j ]$$

Now,  $E[W_t W_{t+h}] = \sigma_w^2$  for  $h=0$ ,  $0 \neq w$ .

$E[W_t W_{t+h-1}] = \sigma_w^2$  for  $h=1$ ,  $0 \neq w$ .

$E[W_{t-1} W_{t+h}] = \sigma_w^2$  for  $h=-1$ ,  $0 \neq w$ .

$E[W_{t-1} W_{t+h-1}] = \sigma_w^2$  for  $h=0$ ,  $0 \neq w$ .

$E[U_t U_{t+h}] = \sigma_u^2$  for  $h=0$ ,  $0 \neq w$ .

$\therefore ACF$ , For  $h=0$ :

$$\gamma_Y(0) = \sigma_w^2 + \theta^2 \sigma_w^2 + \sigma_u^2$$

For  $h=1$ ,

$$\gamma_Y(1) = -\theta \sigma_w^2$$

For  $h=-1$ :

$$\gamma_Y(-1) = -\theta \sigma_w^2$$

$|h| \geq 2:$

$$\gamma_Y(h) = 0$$

$$\therefore \gamma_y(h) = \begin{cases} \sigma_w^2 + \theta^2 \sigma_w^2 + \sigma_u^2 & , \text{ for } h=0 \\ -\theta \sigma_w^2 & , \text{ for } |h|=1 \\ 0 & , \text{ for } |h| \geq 2 \end{cases}$$

∴ Auto correlation function,

$$f_y(h) = \frac{\gamma_y(h)}{\gamma_y(0)} = \begin{cases} 1 & , h=0 \\ \frac{-\theta \sigma_w^2}{\sigma_w^2(1+\theta^2) + \sigma_u^2} & , |h|=1 \\ 0 & , |h| \geq 2 \end{cases}$$

where  $h \in \mathbb{Z}$

(b) For Cross - Correlation Function,  $\gamma_{x,y}(h)$ , we find the Cross-covariance function,

$$\begin{aligned} \gamma_{x,y}(h) &= \text{cov}(X_{t+h}, Y_t) \\ &= E[(X_{t+h} - E[X_{t+h}])(Y_t - E[Y_t])] \\ &= E[X_{t+h} Y_t] \\ &= E[W_{t+h} W_t - \theta W_{t+h} W_{t-1} + W_{t+h} U] \end{aligned}$$

$$E[W_{t+h} W_t] = \sigma_w^2 \quad \text{for } h=0 \quad ; \quad 0 \cdot 0 = 0$$

$$E[W_{t+h} W_{t-1}] = \sigma_w^2 \quad \text{for } h=-1 \quad ; \quad 0 \cdot 0 = 0$$

$$E[W_{t+h} U] = 0 \quad \text{for all } h$$

$$\begin{aligned} \therefore \gamma_{x,y}(h) &= E[W_{t+h} W_t] - \theta E[W_{t+h} W_{t-1}] \\ &= \begin{cases} \sigma_w^2 & \text{for } h=0 \\ -\theta \sigma_w^2 & \text{for } h=-1 \\ 0 & \text{for } h \in \mathbb{Z} \setminus \{0, -1\} \end{cases} \end{aligned}$$

$$\gamma_{x,y}(0) = \text{cov}(X_t, X_t) = \text{cov}(W_t, W_t) = \sigma_w^2$$

$$\gamma_{x,y}(-1) = \sigma_w^2 + \theta^2 \sigma_w^2 + \sigma_u^2 \quad [\text{From (a)}]$$

$$\begin{aligned}
 \text{CCF, } S_{X,Y}(h) &= \frac{\delta_{X,Y}(h)}{\sqrt{R_X(0) R_Y(0)}} \\
 &= \begin{cases} \sigma_w & \text{for } h = 0 \\ \frac{\sigma_w^2 (1 + \theta^2) + \sigma_u^2}{\sqrt{\sigma_w^2 (1 + \theta^2) + \sigma_u^2}} - \theta \sigma_w & \text{for } h = -1 \\ \frac{1}{\sqrt{1 + \theta^2 + \left(\frac{\sigma_u}{\sigma_w}\right)^2}} & \text{otherwise} \end{cases} \\
 &= \begin{cases} \frac{1}{\sqrt{1 + \theta^2 + \left(\frac{\sigma_u}{\sigma_w}\right)^2}} & \text{for } h = 0 \\ \frac{-\theta}{\sqrt{1 + \theta^2 + \left(\frac{\sigma_u}{\sigma_w}\right)^2}} & \text{for } h = -1 \\ 0 & \text{for } h \in \mathbb{Z} \setminus \{0, -1\} \end{cases}
 \end{aligned}$$

4) (a) Prove  $X_t$  is weakly stationary

Given,  $X_t = \sin(2\pi Vt)$  for  $t=1, 2, \dots$

- Mean,

$$E[X_t] = E[\sin(2\pi Ut)]$$

$$= \int_0^1 \sin(2\pi Ut) du$$

$\because U \sim U(0,1)$

$$= \frac{1}{2\pi t} [E[\cos(2\pi Ut)]]'$$

$$= \frac{1}{2\pi t} [-\cos(2\pi t) + \cos(0)]$$

$$= \frac{1 - \cos(2\pi t)}{2\pi t}$$

But,  $\cos(2\pi t) = 0 \forall t \in \mathbb{Z}$

$$\therefore E[X_t] = 0 \quad \forall t \in \mathbb{Z}$$

which satisfies the first condition for  
weak stationarity.

- Compute Variance

$$\text{Var}(X_t) = E[X_t^2] - (E[X_t])^2$$

Since  $E[X_t] = 0$ , we have,

$$\text{Var}(X_t) = E[X_t^2] = E[\sin^2(2\pi Ut)]$$

$$= \int_0^1 \sin^2(2\pi Ut) du$$

$$= \frac{1}{2} \int_0^1 [1 - \cos(4\pi Ut)] du$$

$$= \frac{1}{2} - \frac{1}{2} \int_0^1 \cos(4\pi Ut) du$$

$$= \frac{1}{2} - \frac{1}{8\pi t} [\sin(4\pi t)]_0^t$$

$$= \frac{1}{2} - \frac{1}{8\pi t} [\sin 4\pi t - 0]$$

$$= \frac{1}{2} \quad [\because \sin 4\pi t = 0 \quad \forall t \in \mathbb{Z}]$$

$\Rightarrow \text{Var}(X_t) = \frac{1}{2}$  is constant and does not

depend on  $t$ . This satisfies second condition for weak stationarity.

### • Compute Auto covariance Function $\gamma_X(h)$

$$\gamma_X(h) = E[(X_t - E[X_t])(X_{t+h} - E[X_{t+h}])]$$

$$= E[X_t X_{t+h}]$$

$$= E[\sin(2\pi Vt) \sin(2\pi V(t+h))]$$

$$= E[\frac{1}{2} \cos(2\pi Vh) - \cos(2\pi V(2t+h))]$$

$$= \frac{1}{2} \left[ \frac{1}{2\pi h} [\sin(2\pi Vh)]_0^t - [\sin(2\pi V(2t+h))]_0^t \right]$$

$$\gamma_X(h) = \cancel{\frac{1}{2}} \frac{\sin 2\pi h}{4\pi h} - \frac{\sin(2\pi(2t+h))}{4\pi(2t+h)}$$

$$\gamma_X(0) = \lim_{h \rightarrow 0} \frac{\sin 2\pi h}{4\pi h} - \frac{\sin 4\pi t}{8\pi t}$$

$$= \frac{1}{2} \lim_{h \rightarrow 0} \frac{\sin(2\pi h)}{(2\pi h)} - 0 \quad [\because \sin 4\pi t = 0 \quad \forall t \in \mathbb{Z}]$$

$$= \frac{1}{2}$$

$$\gamma_X(h) = 0 \quad \text{for } h \neq 0$$

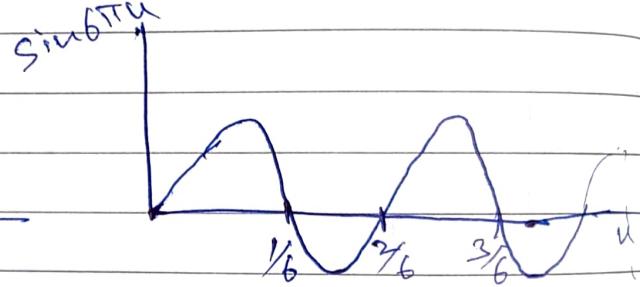
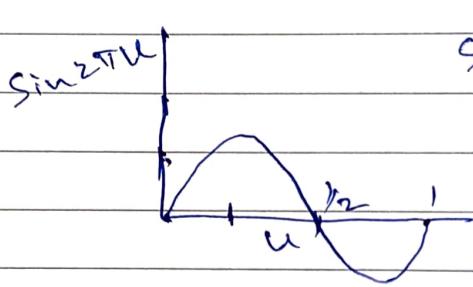
$$[\because \sin 2\pi h = \sin(2\pi(2t+h)) = 0 \quad \forall t, h \in \mathbb{Z}]$$

So, the ACF <sup>does not</sup> depend on  $t$ . This satisfies 3<sup>rd</sup> condition for weakly stationary series.

(b) A time series is strictly stationary if the joint distribution of any set of observations  $(X_{t_1}, X_{t_2}, \dots, X_{t_n})$  depends only on the time differences, and not on the specific times  $t_1, t_2, \dots, t_n$ .

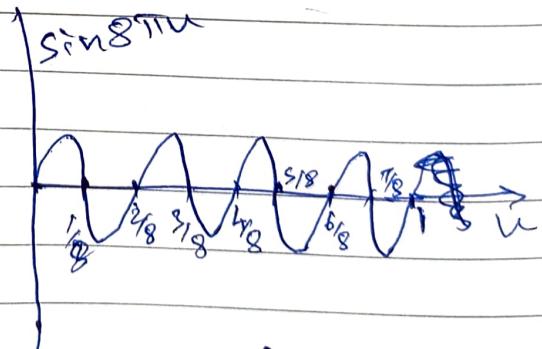
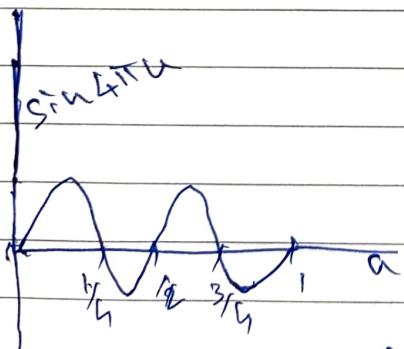
Consider the Example:

$$\begin{aligned} P(X_1 \leq 0, X_2 \leq 0) &= P(\sin(2\pi U) \leq 0, \sin(6\pi U) \leq 0) \\ &= P(U \in [1/2, 1] \cap [1/6, 1/3] \cup [5/6, 1]) \\ &= 0 + \frac{1}{6} + \frac{1}{6} = \frac{1}{3} \end{aligned}$$



But,  $P(X_2 \leq 0, X_4 \leq 0)$

~~$= P(U \in [1/2, 1] \cap [1/6, 1/3] \cup [5/6, 1])$~~ 
 $= P(\sin(4\pi U) \leq 0, \sin(8\pi U) \leq 0)$



$$= P(U \in [1/4, 1/2] \cap [1/8, 3/8] \cap [5/8, 7/8] \cap [9/8, 11/8])$$

$$= \frac{1}{4}$$

i. We can see that,  
 $P(X_1 \leq 0, X_3 \leq 0) \neq P(X_2 \leq 0, X_4 \leq 0)$

∴  $X_t$  is not strictly stationary.

5) (a) Consider the Auto covariance matrix,  
 $\Gamma = \{ \gamma(s-t); s, t = 1, \dots, n \}$

Now, to prove ACF is non-negative definite  
we need to prove.

$$\underline{\alpha}^T \underline{\Gamma} \underline{\alpha} \geq 0 \quad \forall \underline{\alpha} \in \mathbb{R}^n.$$

For any  $\underline{\alpha} \in \mathbb{R}^n$

$$\underline{\alpha}^T \underline{\Gamma} \underline{\alpha} = \sum_{s=1}^n \sum_{t=1}^n \alpha_s \gamma(s-t) \alpha_t$$

$$= \cancel{\text{Cov}} \sum_{s=1}^n \sum_{t=1}^n \alpha_s \text{Cov}(X_s, X_t) \alpha_t$$

$$= \text{Cov} \left\{ \sum_s \alpha_s X_s, \sum_t \alpha_t X_t \right\}$$

$$= \text{Var} \left\{ \sum_{s=1}^n \alpha_s X_s \right\}$$

$$\geq 0$$

[ $\because$  Variance is always non-negative]

$$\therefore \underline{\alpha}^T \underline{\Gamma} \underline{\alpha} \geq 0 \quad \forall \underline{\alpha} \in \mathbb{R}^n$$

(b) Consider the Sample Auto covariance,  
 $\hat{\gamma}(h) = \frac{1}{N} \sum_{t=1}^{N-h} (X_t - \bar{X})(X_{t+h} - \bar{X})$

$$\text{where } \bar{X} = \frac{1}{N} \sum_{t=1}^N X_t$$

To prove Sample ACF is non-negative definite, we need to prove,

$$\underline{\alpha}^T \hat{\Gamma}_n \underline{\alpha} \geq 0 \quad \forall \underline{\alpha} \in \mathbb{R}^n$$

where  $\hat{\Gamma}_n = \{ \hat{\gamma}(s-t) \}_{s,t=1}^n$

$$\text{Let } Y_t = X_t - \bar{X}$$

$$\therefore \hat{\gamma}(h) = \frac{1}{N} \sum_{t=1}^{N-h} Y_t Y_{t+h} \quad \text{for } h=0, 1, \dots, N-1$$

Construct the  $n \times 2n$  matrix

$$D = \begin{bmatrix} 0 & 0 & \dots & 0 & Y_1 & Y_2 & \dots & Y_N \\ 0 & \dots & 0 & Y_1 & Y_2 & \dots & Y_N & 0 \\ \vdots & & \ddots & \vdots & \vdots & \vdots & & \vdots \\ 0 & Y_1 & Y_2 & \dots & Y_N & 0 & \dots & 0 \end{bmatrix}$$

The matrix  $D$  is structured such that  $D D'$  captures the autocovariances at various lags for the mean-centered time series

$Y_t = X_t - \bar{X}$  normalizing by  $n$  gives us the sample ACF matrix  $\hat{\Gamma}_n$ , which consists of the sample autocorrelation  $\hat{\gamma}(s-t)$  for each pair  $s, t$ .

$$\therefore \hat{\Gamma}_n = \frac{1}{N} D D'$$

Then, for any  $a \in \mathbb{R}^n$ ,

$$\begin{aligned} a^T \hat{\Gamma}_n a &= \frac{1}{N} a^T D D' a = \frac{1}{N} c^T c \\ &= \frac{1}{N} \sum_{i=1}^N c_i^2 \geq 0 \end{aligned}$$

6) Given,

$$I(\underline{\theta}_1; \underline{\theta}_2) = T^{-1} E, \log \frac{f(y; \underline{\theta}_1)}{f(y; \underline{\theta}_2)}$$

~~$$Y \sim N(Z\beta, \sigma^2)$$~~

~~$$\text{or } Y = Z\beta + \varepsilon \quad Z \in \mathbb{R}^{T \times p}$$~~

~~$\beta \in \mathbb{R}^{p \times 1}$~~

where  $\varepsilon \sim N(0, \sigma^2)$

$$f_y(y; \underline{\theta}_1) = \frac{1}{(2\pi\sigma_1^2)^{T/2}} \exp \left[ -\frac{(y - Z\beta_1)^T (y - Z\beta_1)}{2\sigma_1^2} \right]$$

$$\log f_y(y; \underline{\theta}_1) = -\frac{T}{2} \log (2\pi\sigma_1^2)$$

$$-\frac{(y - Z\beta_1)^T (y - Z\beta_1)}{2\sigma_1^2}$$

$$\begin{aligned} \log \frac{f_y(y; \underline{\theta}_1)}{f_y(y; \underline{\theta}_2)} &= -\frac{T}{2} \log \left( \frac{\sigma_1^2}{\sigma_2^2} \right) - \frac{(y - Z\beta_1)^T (y - Z\beta_1)}{2\sigma_1^2} \\ &\quad + \frac{(y - Z\beta_2)^T (y - Z\beta_2)}{2\sigma_2^2} \end{aligned}$$

$$\begin{aligned} E, \left[ \log \frac{f(y; \underline{\theta}_1)}{f(y; \underline{\theta}_2)} \right] &= -\frac{T}{2} \log \frac{\sigma_1^2}{\sigma_2^2} - \frac{1}{2\sigma_1^2} E, [(y - Z\beta_1)^T (y - Z\beta_1)] \\ &\quad + \frac{1}{2\sigma_2^2} E, [(y - Z\beta_2)^T (y - Z\beta_2)] \end{aligned}$$

$$\begin{aligned} E, [(y - Z\beta_1)^T (y - Z\beta_1)] &= E, [\varepsilon_1^T \varepsilon_1] \\ &= T\sigma_1^2 \end{aligned}$$

$$E, [(y - Z\beta_2)^T (y - Z\beta_2)] = E, [(Z\beta_2 + \varepsilon_2 - Z\beta_2)^T (Z\beta_2 + \varepsilon_2 - Z\beta_2)]$$

$$= E[(Z(\underline{\beta}_1 - \underline{\beta}_2) + \underline{\varepsilon}_1)'(Z(\underline{\beta}_1 - \underline{\beta}_2) + \underline{\varepsilon}_1)]$$

$$= E[\underline{\varepsilon}_1' \underline{\varepsilon}_1] + \{Z(\underline{\beta}_1 - \underline{\beta}_2)\}'\{Z(\underline{\beta}_1 - \underline{\beta}_2)\}$$

$$= T \cancel{\sigma_1^2} + (\underline{\beta}_1 - \underline{\beta}_2)' Z' Z (\underline{\beta}_1 - \underline{\beta}_2)$$

$$\therefore I(\underline{\beta}_1; \underline{\beta}_2) = \frac{1}{T} \left[ \frac{-T}{2} \log \frac{\sigma_1^2}{\sigma_2^2} - \frac{1}{2\sigma_1^2} (T\sigma_1^2) \right]$$

$$+ \frac{1}{2\sigma_2^2} (T\sigma_1^2 + (\underline{\beta}_1 - \underline{\beta}_2)' Z' Z (\underline{\beta}_1 - \underline{\beta}_2))$$

$$= \cancel{T} - \frac{1}{2} \log \frac{\sigma_1^2}{\sigma_2^2} - \frac{1}{2} + \frac{\sigma_1^2}{2\sigma_2^2} + \frac{(\underline{\beta}_1 - \underline{\beta}_2)' Z' Z (\underline{\beta}_1 - \underline{\beta}_2)}{2T\sigma_2^2}$$

$$= \frac{1}{2} \left( \frac{\sigma_1^2}{\sigma_2^2} - \log \left( \frac{\sigma_1^2}{\sigma_2^2} \right) - 1 \right) + \frac{1}{2} \frac{(\underline{\beta}_1 - \underline{\beta}_2)' Z' Z (\underline{\beta}_1 - \underline{\beta}_2)}{T\sigma_2^2}$$