

$$\text{Let } R_t = \frac{P_t - P_{t-1}}{P_{t-1}} \approx \ln P_t - \ln P_{t-1}$$

P_t = Price of asset (RISKY) at time t

P_{t-1} = >> >>> >> >> >> $t-1$

R_t = Return of asset sold at time t
Bought at time $t-1$

Now the EXCESS Return of the asset
 Γ_t is given by

$$\Gamma_t = R_t - R_{t-1}^F \quad \text{Where}$$

R_{t-1}^F is the return of the RISK FREE
asset at time $t-1$.

NOTICE:

Interest rates and bond returns are quoted in an ANNUAL BASE e.g.

3% 6-month Bond means 3% in an annual Base.

Hence the risky asset return and the safe asset return must be at the same frequency. To transform the annual

return in the frequency we need we have to:

Example Let the interest rate (monthly) is 10% (annualised). To transform it in a monthly bond we have to

$$r = \sqrt[12]{1 + 0.1} - 1$$

$$= 0.00797 = 0.797\%$$

$$y_t = \underset{\substack{\wedge \\ x_{t1}=1}}{b_1} + x_{t2} b_2 + \dots + x_{tk} b_k + \boxed{\varepsilon_t}$$

$$E(\varepsilon_t) = 0, \quad V(\varepsilon_t) = \sigma^2$$

$$\forall t = 1, 2, \dots, \underline{n}$$

$$y_1 = \theta_1 + x_{12}\theta_2 + \dots + x_{1k}\theta_k + \varepsilon_1$$

$$y_2 = \theta_1 + x_{22}\theta_2 + \dots + x_{2k}\theta_k + \varepsilon_2$$

$$y_3 = \theta_1 + x_{32}\theta_2 + \dots + x_{3k}\theta_k + \varepsilon_3$$

$$\vdots$$

$$y_n = \theta_1 + x_{n2}\theta_2 + \dots + x_{nk}\theta_k + \varepsilon_n$$

$$\begin{pmatrix} y_1 \\ y_2 \\ y_3 \\ \vdots \\ y_n \end{pmatrix} = \begin{pmatrix} 1 \\ \vdots \\ 1 \end{pmatrix} \theta_1 + \begin{pmatrix} x_{12} \\ x_{22} \\ x_{32} \\ \vdots \\ x_{n2} \end{pmatrix} \theta_2 + \dots + \begin{pmatrix} x_{1k} \\ x_{2k} \\ \vdots \\ x_{nk} \end{pmatrix} \theta_k + \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{pmatrix}$$

$$\begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{pmatrix} = \begin{pmatrix} 1 & x_{11} & \dots & x_{1k} \\ 1 & x_{21} & \dots & x_{2k} \\ 1 & x_{31} & \dots & x_{3k} \\ \vdots & \vdots & \ddots & \vdots \\ 1 & x_{n1} & \dots & x_{nk} \end{pmatrix} \begin{pmatrix} \theta_1 \\ \theta_2 \\ \vdots \\ \theta_k \end{pmatrix} + \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{pmatrix}$$

$$\Rightarrow \underset{n \times 1}{Y} = \underset{n \times k}{X} \underset{k \times 1}{\theta} + \underset{n \times 1}{\varepsilon}$$

$$E(\varepsilon) = E \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{pmatrix} = \begin{pmatrix} E(\varepsilon_1) \\ E(\varepsilon_2) \\ \vdots \\ E(\varepsilon_n) \end{pmatrix} = \begin{pmatrix} 0 \\ 0 \\ \vdots \\ 0 \end{pmatrix}$$

$$V(\varepsilon) = E(\varepsilon \varepsilon') =$$

$$= E \left[\begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{pmatrix} (\varepsilon_1, \varepsilon_2, \dots, \varepsilon_n) \right] =$$

$$= E \begin{pmatrix} \varepsilon_1^2 & \varepsilon_1 \varepsilon_2 & \varepsilon_1 \varepsilon_3 & \dots & \varepsilon_1 \varepsilon_n \\ \varepsilon_2 \varepsilon_1 & \varepsilon_2^2 & \varepsilon_2 \varepsilon_3 & \dots & \varepsilon_2 \varepsilon_n \\ \varepsilon_3 \varepsilon_1 & \varepsilon_3 \varepsilon_2 & \varepsilon_3^2 & \dots & \varepsilon_3 \varepsilon_n \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \varepsilon_n \varepsilon_1 & \varepsilon_n \varepsilon_2 & \dots & \dots & \varepsilon_n^2 \end{pmatrix} = \begin{pmatrix} \sigma^2 & 0 & 0 & \dots & 0 \\ 0 & \sigma^2 & 0 & \dots & 0 \\ 0 & 0 & \sigma^2 & \dots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & \dots & \dots & 0 & \sigma^2 \end{pmatrix}$$

$$= \sigma^2 \begin{pmatrix} 1 & 0 & 0 & \dots & 0 \\ 0 & 1 & 0 & \dots & 0 \\ 0 & 0 & 1 & \dots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & \dots & 1 \end{pmatrix} = \sigma^2 I_n$$

$$V(\varepsilon_t) = \sigma^2 \Rightarrow V(\varepsilon_t) = E(\varepsilon_t - \underbrace{E(\varepsilon_t)}_0)^2 = E(\varepsilon_t^2) = \sigma^2 \quad \forall t = 1, 2, \dots, n$$

ΓΕΝΙΚΑ
Χ ΤΥΧΑΙΑ ΜΕΤΑΒΛΗΤΑ

$$V(x) = \int (x - E(x))^2 \quad \Rightarrow \quad V(x) = A(x^2)$$

A, $E(x) = 0$

$$\underbrace{Y}_{n \times 1} = \underbrace{X}_{n \times k} \underbrace{\beta}_{k \times 1} + \underbrace{\varepsilon}_{n \times 1}, \quad E(\varepsilon) = 0, \quad V(\varepsilon) = \sigma^2 I_n$$

$$\boxed{K+1} \leftarrow \text{ARGMIN}_{\beta} \sum_{t=1}^n \varepsilon_t^2$$

$$\min_{\beta} \sum_{t=1}^n \varepsilon_t^2 = \min_{\beta} \sum_t (y_t - \beta_1 - x_{t2}\beta_2 - \dots - x_{tk}\beta_k)^2$$

$$\min_{\beta} (\varepsilon_1 \ \varepsilon_2 \ \dots \ \varepsilon_n) \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{pmatrix} = \min_{\beta} \underbrace{\varepsilon' \varepsilon}_{1 \times n \quad n \times 1} =$$

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

$$S = (Y - X\beta)'(Y - X\beta)$$

$$\frac{\partial S}{\partial \beta} = 0 \Rightarrow 2(X'X)\hat{\beta} - 2X'Y = 0$$

$$\Rightarrow (X'X)\hat{\beta} - X'Y = 0 \Rightarrow \underbrace{(X'X)}_{\substack{k \times k \quad k \times 1}} \hat{\beta} = \underbrace{X'Y}_{\substack{k \times 1 \quad n \times 1 \\ k \times 1}}$$

$$\Rightarrow \hat{\beta} = (X'X)^{-1} X'Y$$

IFF $(X'X)^{-1}$ EXISTS $\Leftrightarrow$

NORMAL EQUAT.

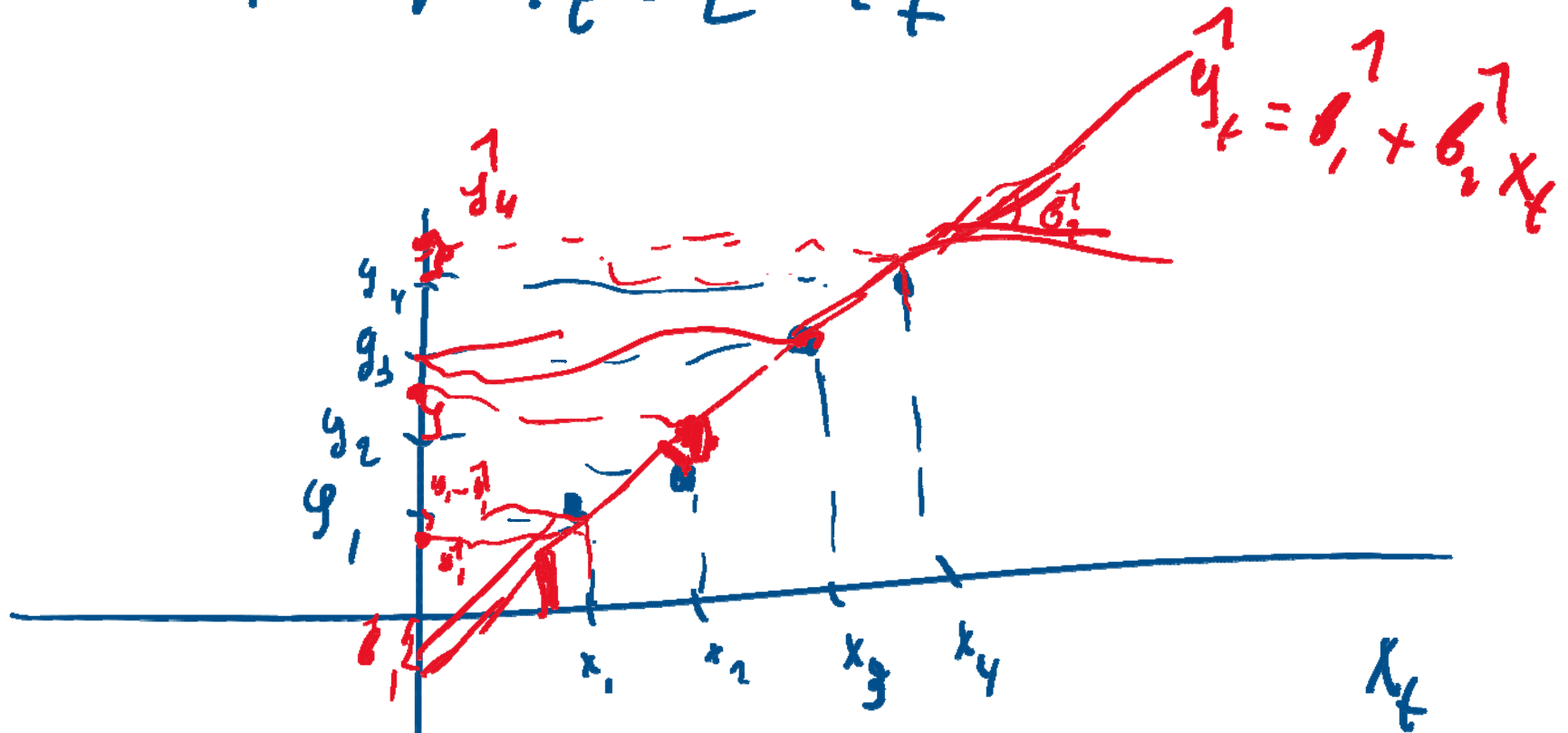
$$\Leftrightarrow \underbrace{|X'X|}_{K \times K} \neq 0 \quad \text{Για να είναι} \quad X'X \text{ MH-ΙΔΙΑΣΟΜΕΝΗ}$$

$$\Leftrightarrow r(X) = \quad \Leftrightarrow$$

$\uparrow$
 $RANK \text{ OF } X$

ΟΙ K ΕΞΕΛΓΕΝΕΙΣ ΜΕΤΑΒΛ. ΠΡΕΠΕΙ
 ΝΑ ΓΡΑΜΜΙΚΑ ΑΝΕΞΑΡΤΗΤΕΣ.
 ΑΛΛΑΔΗ ΝΑ ΜΗΝ ΕΧΩ ΠΟΛΥΣΓΡΑΜΜΙΚΟΤΗΤΑ
 (MULTICOLLINEARITY)

$$y_t = \theta_1 + x_t \theta_2 + \varepsilon_t$$



$$\hat{\varepsilon}_t = y_t - \hat{y}_t = y_t - \hat{\theta}_1 - \hat{\theta}_2 x_t$$

$$\hat{\beta} = (X'X)^{-1} X'y$$

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

↑
FITTED VALUES

$$\begin{aligned} y_1 &= \hat{\beta}_1 + x_{12} \hat{\beta}_2 + \dots + x_{1k} \hat{\beta}_k \\ \hat{y}_2 &= \hat{\beta}_1 + x_{22} \hat{\beta}_2 + \dots + x_{2k} \hat{\beta}_k \\ &\vdots \\ \hat{y}_n &= \hat{\beta}_1 + x_{n2} \hat{\beta}_2 + \dots + x_{nk} \hat{\beta}_k \end{aligned}$$

$$\varepsilon = y - \hat{y}$$

↑ ΚΑΤΑΛΟΙΠΑ (RESIDUALS)

$$\underset{n \times 1}{\hat{y}} = \underset{n \times 1}{X} \underset{1}{\hat{\beta}} = \underbrace{X (X'X)^{-1} X'}_{n \times n} \underset{n \times 1}{y} = P_X y$$

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

ΣΥΜΜΕΤΡΙΚΗ +
ΤΑΥΤΟΔΥΝΑΜΗ

$$P_X \text{ ΣΥΜΜΕΤΡΙΚΗ } \equiv P_X' = P_X$$

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

$$((AB\Gamma)' = \Gamma' B' A')$$

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

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

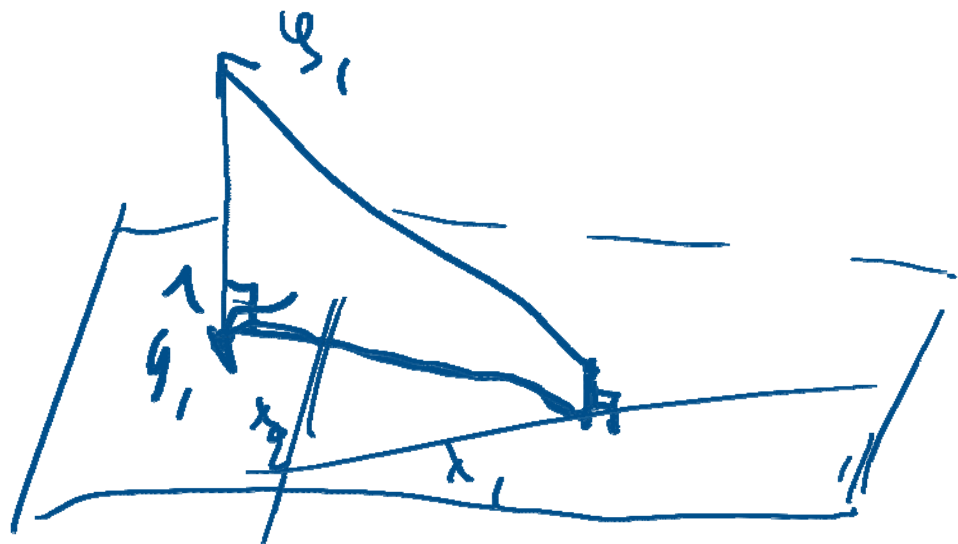
$$= X (X'X')^{-1} X' = X (X'X)^{-1} X' = P_x$$

ΟΛΩΣ P_x ΣΥΜΜΕΤΡΙΚΗ

$$P_X \text{ IDALUDYNAHA} \Leftrightarrow P_X^2 = P_X \cdot P_X = P_X$$

$$\begin{aligned} P_X^2 &= P_X \cdot P_X = (X(X'X)^{-1}X') (X(X'X)^{-1}X') \\ &= X(X'X)^{-1} \underbrace{X'X(X'X)^{-1}}_{= I_k} X' = \end{aligned}$$

$$= X(X'X)^{-1} I_k X' = X(X'X)^{-1} X' = P_X$$

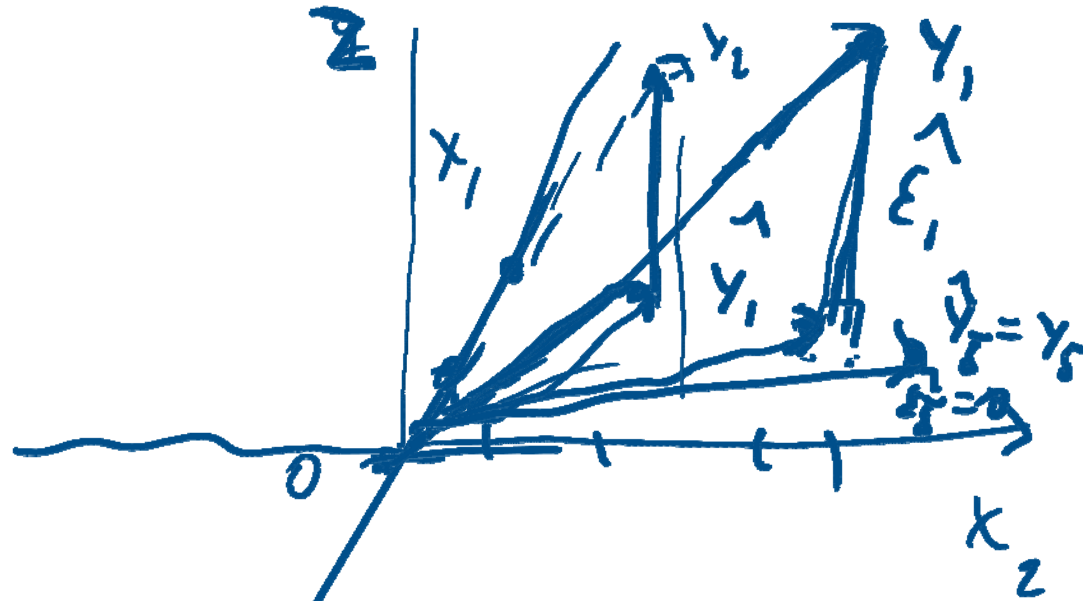


$$\hat{y} = (P_X) \underline{y}$$

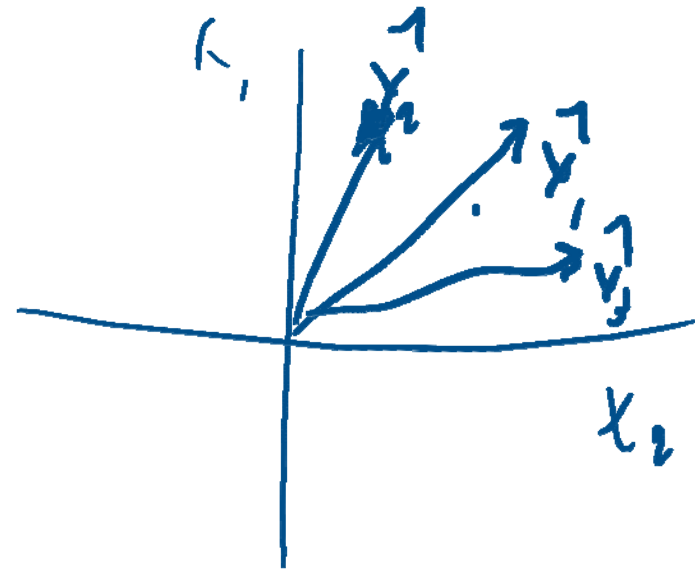
$$r(P_X) = r\left(X(X'X)^{-1}X'\right) \stackrel{P_X \text{ SYM} + \text{TA}Y}{=} \underline{\underline{\quad}}$$

$$= \text{tr}\left(X(X'X)^{-1}X'\right) = \text{tr}\left((X'X)^{-1}X'X\right) =$$

$$= \text{tr}(I_K) = K$$



$$\begin{aligned}\varepsilon_i^1 &= y_i - y_i^1 \\ \varepsilon_i^1 + y_i^1 &= y_i\end{aligned}$$



$$\frac{\text{ΓΕΝΙΚΑ}}{r(A) = \text{RANK}(A) \text{ ΒΑΘΜΟΣ ΤΗΣ } A}$$

= ΑΡΙΘΜΟΣ ΤΩΝ ΓΡΑΜΜΙΚΑ ΑΝΕΞΑΡΤΩΤΩΝ
ΓΡΑΜΜΩΝ Η" ΕΣΤΗΝ

$$r(A) \leq \min(n, k)$$

π.χ. $A_{10 \times 5}$ $r(A)$ ΤΟ ΠΟΛΥ ΘΑ ΕΙΝΑΙ 5

$A_{n \times n}$ (ΤΕ ΤΡΑΓΩ ΝΙΚΗ)

$$\begin{aligned} \text{ΤΟΤΕ } \operatorname{tr}(A) &= \operatorname{trace}(A) = \\ &= \chi_{\text{NOS}}(A) = \sum_{i=1}^n \alpha_{ii} = \alpha_{11} + \alpha_{22} + \dots + \alpha_{nn} \end{aligned}$$

= ΑΡΘΙΣΜΑ ΤΩΝ ΣΤΟΙΧΕΙΩΝ ΤΗΣ
ΚΥΡΙΑΣ ΔΙΑΓΩΝΙΟΥ.

$$A_{n \times n} \text{ SYMMETRIC} \quad \underline{A \sim A} \quad A' = A$$

$$A = \begin{pmatrix} 2 & 3 \\ 5 & 7 \end{pmatrix} \Rightarrow A' = \begin{pmatrix} 2 & 5 \\ 3 & 7 \end{pmatrix}$$

$$\text{tr}(AB) = \text{tr}(BA) = \text{tr}(rAB)$$

$$r(AA') = r(A'A) = r(A)$$

$$\underset{n \times 1}{\mathbf{Y}} = \underset{n \times k}{\mathbf{X}} \underset{k \times 1}{\boldsymbol{\beta}} + \underset{n \times 1}{\boldsymbol{\varepsilon}}$$

$$E(\boldsymbol{\varepsilon}) = \underset{=}{\mathbf{0}} \quad V(\boldsymbol{\varepsilon}) = \sigma^2 \mathbf{I}_n$$

$$\begin{aligned} \hat{\boldsymbol{\beta}} &= (\mathbf{X}'\mathbf{X})^{-1} \mathbf{X}'\mathbf{Y} = (\mathbf{X}'\mathbf{X})^{-1} \mathbf{X}'\mathbf{X} \boldsymbol{\beta} + (\mathbf{X}'\mathbf{X})^{-1} \mathbf{X}'\boldsymbol{\varepsilon} \\ &= \boldsymbol{\beta} + (\mathbf{X}'\mathbf{X})^{-1} \mathbf{X}'\boldsymbol{\varepsilon} \end{aligned}$$

$$E(\hat{\boldsymbol{\beta}}) = E[\boldsymbol{\beta} + (\mathbf{X}'\mathbf{X})^{-1} \mathbf{X}'\boldsymbol{\varepsilon}] =$$

$$= E(\boldsymbol{\beta}) + E[(\mathbf{X}'\mathbf{X})^{-1} \mathbf{X}'\boldsymbol{\varepsilon}] =$$

$$= \boldsymbol{\beta} + (\mathbf{X}'\mathbf{X})^{-1} \mathbf{X}' E(\boldsymbol{\varepsilon}) = \boldsymbol{\beta} \quad \hat{\boldsymbol{\beta}} \text{ UNBIASED ESTIMATE OF } \boldsymbol{\beta}.$$

0

$$\begin{aligned}
 V(\hat{\beta}) &= E \left\{ [\hat{\beta} - E(\hat{\beta})] [\hat{\beta} - E(\hat{\beta})]' \right\} \\
 &= E \left\{ (\hat{\beta} - \beta) (\hat{\beta} - \beta)' \right\} \\
 \hat{\beta} - \beta &= (X'X)^{-1} X' \varepsilon \quad \Rightarrow
 \end{aligned}$$

$$\begin{aligned}
 V(\hat{\beta}) &= E \left[(X'X)^{-1} X' \varepsilon \left[(X'X)^{-1} X' \varepsilon \right]' \right] \\
 &= E \left[(X'X)^{-1} X' \varepsilon \varepsilon' X (X'X)^{-1} \right] = \\
 &= (X'X)^{-1} X' E(\varepsilon \varepsilon') X (X'X)^{-1} =
 \end{aligned}$$

$$= (X'X)^{-1} X' \sigma^2 I_n X (X'X)^{-1} =$$

$$= \sigma^2 (X'X)^{-1} \cancel{X'X} (X'X)^{-1} =$$

$$= \sigma^2 (X'X)^{-1}$$

$$E(\hat{\beta}) = \beta, \quad V(\hat{\beta}) = \sigma^2 (X'X)^{-1}$$

$$Y = X\beta + \varepsilon$$

$n \times 1$ $n \times k$ $k \times 1$ $n \times 1$

1) $H \Sigma X E \Sigma H \quad \Sigma @ \Sigma T H$

2) $r(X) = k$ (NO MULTICOL.)

3) $E(\varepsilon) = 0, \quad V(\varepsilon) = \sigma^2 I_n$

$$V(\varepsilon) = E(\varepsilon \varepsilon') = E \left[\begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{pmatrix} (\varepsilon_1, \varepsilon_2, \dots, \varepsilon_n) \right]$$

$$= E \begin{pmatrix} \varepsilon_1^2 & \varepsilon_1 \varepsilon_2 & \varepsilon_1 \varepsilon_3 & \varepsilon_1 \varepsilon_4 & \dots & \varepsilon_1 \varepsilon_n \\ \varepsilon_2 \varepsilon_1 & \varepsilon_2^2 & \varepsilon_2 \varepsilon_3 & \varepsilon_2 \varepsilon_4 & \dots & \varepsilon_2 \varepsilon_n \\ \varepsilon_3 \varepsilon_1 & \varepsilon_3 \varepsilon_2 & \varepsilon_3^2 & \varepsilon_3 \varepsilon_4 & \dots & \varepsilon_3 \varepsilon_n \\ \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ \varepsilon_n \varepsilon_1 & \varepsilon_n \varepsilon_2 & \dots & \dots & \dots & \varepsilon_n^2 \end{pmatrix} =$$

$$= \begin{pmatrix} E\varepsilon_1^2 & E\varepsilon_1\varepsilon_2 & \dots & E\varepsilon_1\varepsilon_n \\ E\varepsilon_2\varepsilon_1 & E\varepsilon_2^2 & \dots & E\varepsilon_2\varepsilon_n \\ \vdots & \vdots & \ddots & \vdots \\ E\varepsilon_n\varepsilon_1 & \dots & \dots & E(\varepsilon_n^2) \end{pmatrix} =$$

$$= \begin{pmatrix} V(\varepsilon_1) & \text{Cov}(\varepsilon_1, \varepsilon_2) & \dots & \text{Cov}(\varepsilon_1, \varepsilon_n) \\ \text{Cov}(\varepsilon_2, \varepsilon_1) & V(\varepsilon_2) & \dots & \vdots \\ \vdots & \vdots & \ddots & \vdots \\ \text{Cov}(\varepsilon_n, \varepsilon_1) & \dots & \dots & V(\varepsilon_n) \end{pmatrix} =$$

$$= \begin{pmatrix} \sigma^2 & 0 & 0 & - & - & 0 \\ 0 & \sigma^2 & 0 & - & - & 0 \\ \vdots & & & & & \vdots \\ 0 & - & - & & \sigma & \sigma^2 \end{pmatrix} = \sigma^2 I_n$$

Theorem GAUSS-MARKOV ✓

↗
 $\hat{\beta}$ BEST LINEAR _{UNBIASED} ESTIMATOR of β .

$$\hat{\beta} = (X'X)^{-1} X'Y \quad (\text{LINEAR IN } Y)$$

$$\text{BEST} \equiv V(\hat{\beta}) \leq V(\tilde{\beta})$$

Όπου $\tilde{\beta}$ ΟΙ ΠΙΘΑΝΟΤΗΤΕΣ
ΓΡΑΜΜΙΚΟΣ ΑΜΕΡΟΛΗΠΤΟΣ ΕΚΤΙΜΗΤΗΣ
ΤΟΥ β .

ΕΣΤΙ $\tilde{\beta}$ ΑΛΗΘΕΣ LINEAR + UNBIASED
ESTIMATOR $\Rightarrow$

$$V(\hat{\beta}) \leq V(\tilde{\beta}) \Rightarrow$$

$V(\hat{\beta}) - V(\tilde{\beta})$ NEGATIVE DEFINITE
MATRIX.

$$V(\hat{\beta}) = \sigma^2 (X'X)^{-1}$$

$\begin{matrix} k \times 1 & 1 \times k \\ \hline k \times k \end{matrix}$

$$V(\hat{\beta}) = E \left[(\hat{\beta} - \beta) (\hat{\beta} - \beta)' \right]$$

$\begin{matrix} k \times 1 & 1 \times k \\ \hline k \times k \end{matrix}$

$$= \begin{pmatrix} V(\hat{\beta}_1) & \text{Cov}(\hat{\beta}_1, \hat{\beta}_2) & \dots & \text{Cov}(\hat{\beta}_1, \hat{\beta}_k) \\ \text{Cov}(\hat{\beta}_2, \hat{\beta}_1) & V(\hat{\beta}_2) & \dots & \text{Cov}(\hat{\beta}_2, \hat{\beta}_k) \\ \vdots & \vdots & \ddots & \vdots \\ \text{Cov}(\hat{\beta}_k, \hat{\beta}_1) & \dots & \dots & V(\hat{\beta}_k) \end{pmatrix}$$

$\begin{matrix} k \times 1 & 1 \times k \\ \hline k \times k \end{matrix}$

$$\sum_{t=1}^n \varepsilon_t^2 = \varepsilon' \varepsilon$$

$$\hat{\varepsilon} = Y - X\hat{\beta} = Y - X(X'X)^{-1}X'Y =$$

$$= \underbrace{[I_n - X(X'X)^{-1}X']}_{M} Y = MY$$

$$\begin{aligned} M' &= (I_n - X(X'X)^{-1}X')' = I_n' - (X(X'X)^{-1}X')' = \\ &= I_n - (X')'((X'X)^{-1})'X' = I_n - X(X'X)^{-1}X' = M \end{aligned}$$

M SYMMETRIC

$$M \cdot M = [I_n - X(X'X)^{-1}X'] [I_n - X(X'X)^{-1}X']$$

$$= I_n - X(X'X)^{-1}X' - X(X'X)^{-1}X' + \underbrace{X(X'X)^{-1}X'X(X'X)^{-1}X'}_I =$$

$$= I_n - X(X'X)^{-1}X' - \cancel{X(X'X)^{-1}X} + \cancel{X(X'X)^{-1}X}$$

$$= I_n - X(X'X)^{-1}X' = M \Rightarrow$$

✓ M ТАУТОДУННАМ.

$$M'X = MX = (I_n - X(X'X)^{-1}X')X =$$

$$= X - X \underbrace{(X'X)^{-1}X'}_{I_K} X = X - X = 0$$

M OPORTIONNEMENT THIS X ,

$$\varepsilon^1 = MY \Rightarrow \varepsilon^1 = M(X\beta + \varepsilon) \Rightarrow$$

$$\Rightarrow \varepsilon^1 = \underbrace{MX\beta}_{=0} + M\varepsilon \Rightarrow \boxed{\varepsilon^1 = M\varepsilon}$$

$$M = I_n - X(X'X)^{-1}X'$$

$$r(M) \stackrel{\text{SYM.}}{\stackrel{\text{TRYT.}}{=}} \text{tr}(M) = \text{tr}(I_n - X(X'X)^{-1}X')$$

$$= \text{tr}(I_n) - \text{tr}(X(X'X)^{-1}X') =$$

$$= n - \text{tr}((X'X)^{-1}X'X) = n - \text{tr}(I_k) =$$

$$= n - k < n \Rightarrow |M| \neq 0 \Rightarrow M^{-1} \text{ ΔΕΝ ΥΠΑΡΧΕΙ}$$