

Economics 670: Econometrics
 Department of Economics, Finance and Legal Studies
 University of Alabama
 Fall 2021

Midterm I - *Key*

The exam consists of three questions on three pages. Each question is of equal value.

1. Consider the model $y = X\beta + e$, where $E(e|X) = 0$ and $E(e^2|X) = \Omega$, where Ω is a known variance-covariance matrix. Our goal is to estimate β via minimizing the objective function $\tilde{e}'\Omega^{-1}\tilde{e}$, where $\tilde{e} = y - X\tilde{\beta}$. With this information

- (a) Derive the estimator $\tilde{\beta}$ of β .
- (b) Show that the estimator from part (a) is unbiased.
- (c) Derive the variance of the estimator from part (a).
- (d) Show that the variance from part (c) is smaller than that of the variance of the OLS estimator.

$$(a) (y - X\tilde{\beta})'\Sigma^{-1}(y - X\tilde{\beta})$$

$$\frac{\partial}{\partial \beta} = -2X'\Sigma^{-1}(y - X\tilde{\beta}) = 0$$

$$X\Sigma^{-1}y - X'\Sigma^{-1}X\tilde{\beta} = 0$$

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

$$(b) \tilde{\beta} = (X'\Sigma^{-1}X)^{-1}X'\Sigma^{-1}(X\beta + e)$$

$$= \beta + (X'\Sigma^{-1}X)^{-1}X'\Sigma^{-1}e$$

$$E(\tilde{\beta} - \beta | x) = (X'\Sigma^{-1}X)^{-1}X'\Sigma^{-1}E(e|x)$$

$$= 0$$

$$\begin{aligned}
 (c) \sqrt{(\tilde{\beta} - \beta | x)} &= \sqrt{[(x' \Sigma^{-1} x)^{-1} x' \Sigma^{-1} e]_x} \\
 &= (x' \Sigma^{-1} x)^{-1} x' \Sigma^{-1} V(e | x) x (x' \Sigma^{-1} x)^{-1} \\
 &= (x' \Sigma^{-1} x)^{-1} x' \Sigma^{-1} \Sigma \Sigma^{-1} x (x' \Sigma^{-1} x)^{-1} \\
 &= (x' \Sigma^{-1} x)^{-1} x' \Sigma^{-1} x (x' \Sigma^{-1} x)^{-1} \\
 &= (x' \Sigma^{-1} x)^{-1}
 \end{aligned}$$

$$\begin{aligned}
 (d) \hat{\beta}_{\text{OLS}} &= (x' x)^{-1} x' y \\
 \hat{\beta} - \beta &= (x' x)^{-1} x' e
 \end{aligned}$$

$$\begin{aligned}
 \sqrt{(\hat{\beta} - \beta | x)} &= \sqrt{[(x' x)^{-1} x' e]_x} \\
 &= (x' x)^{-1} x' V(e | x) x (x' x)^{-1} \\
 &= (x' x)^{-1} x' \Sigma x (x' x)^{-1}
 \end{aligned}$$

$$\sqrt{(\hat{\beta}_{\text{OLS}} - \beta | x)} - \sqrt{(\tilde{\beta} - \beta | x)} \geq 0 \quad ?$$

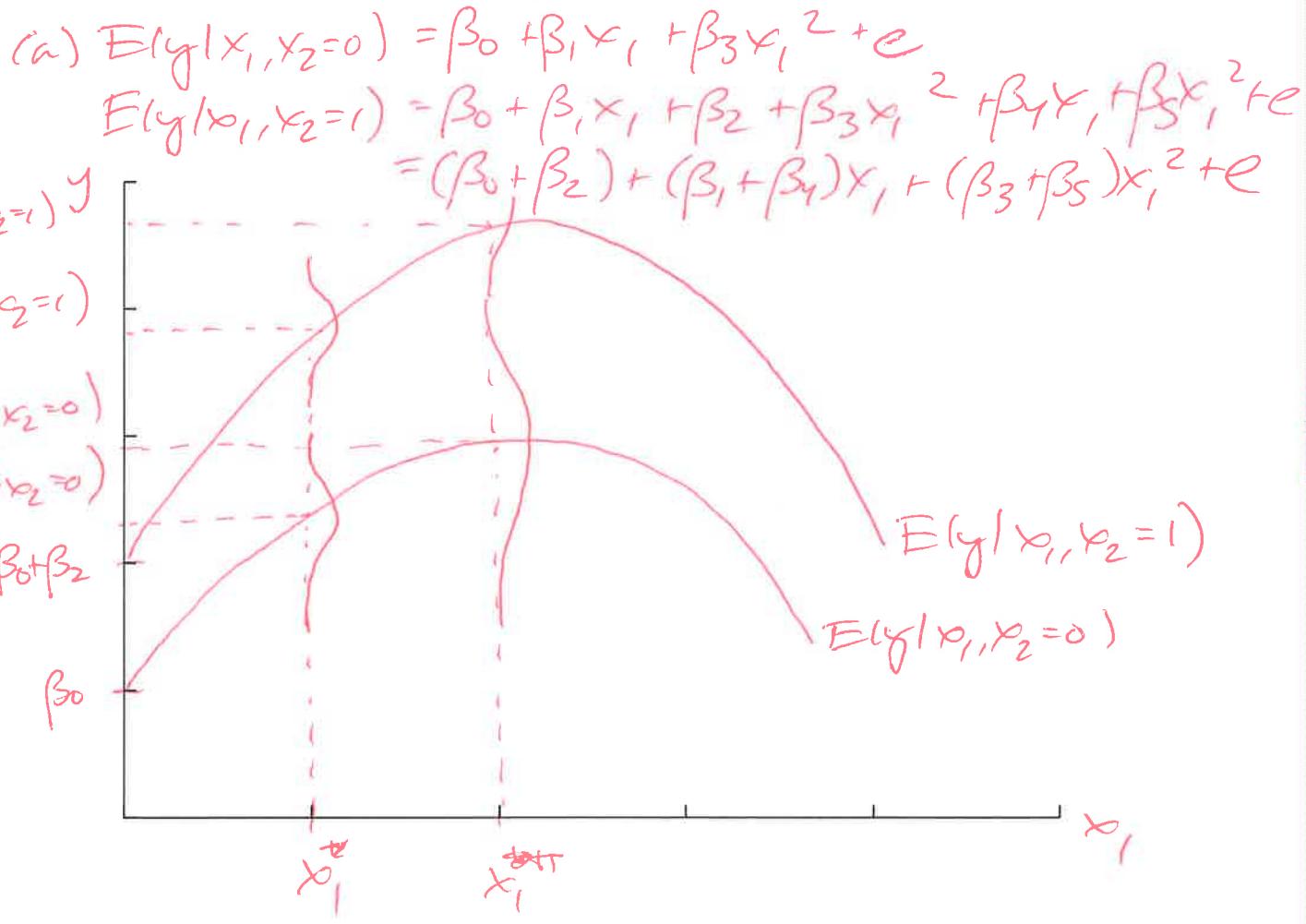
$$\begin{aligned}
 &(x' x)^{-1} x' \Sigma x (x' x)^{-1} - (x' \Sigma^{-1} x)^{-1} \\
 &= (x' x)^{-1} x' \Sigma x (x' x)^{-1} - (x' \Sigma^{-1} x)^{-1} \Sigma^{-1} \Sigma \Sigma^{-1} x (x' \Sigma^{-1} x)^{-1} \\
 &= [(x' x)^{-1} x' - (x' \Sigma^{-1} x)^{-1} x' \Sigma^{-1}] \Sigma [x (x' x)^{-1} - \Sigma^{-1} x (x' \Sigma^{-1} x)^{-1}] \\
 &= [(x' x)^{-1} x' - (x' \Sigma^{-1} x)^{-1} x' \Sigma^{-1}] \Sigma [(x' x)^{-1} x' - (x' \Sigma^{-1} x)^{-1} x' \Sigma^{-1}] \\
 &= A \Sigma A' \text{ which is pdl as } \Sigma \text{ is pdl}
 \end{aligned}$$

2. Consider a scenario whereby we have two explanatory variables: one continuous (x_1) and one binary (x_2). Suppose we wish to model the relationship between the outcome variable (y) and the explanatory variables (x_1, x_2) via

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_1^2 + \beta_4 x_1 x_2 + \beta_5 x_1^2 x_2 + e,$$

where $E(e|x_1, x_2) = 0$, $E(e^2|x_1, x_2) = \sigma^2(x_1, x_2) > 0$ where $\sigma^2(x_1, x_2)$ is a monotonically increasing function of x_1 . Further, $\beta_0, \beta_1, \beta_2, \beta_4 > 0$ and $\beta_3, \beta_5 < 0$. With this information

- (a) Write down the conditional expectation of y given x_1 and x_2 (for each value that x_2 can take).
- (b) In the figure below, draw the conditional expectations of y from part (a).
- (c) Pick any two values for x_1 , in the same figure, note the conditional expectation for each value (of x_1) you choose for each value x_2 can take. Plot and label a feasible distribution of the error (e) for each of the values for x_1 .



variance \uparrow w/ x_1 , $\sigma^2(x_1=x_1^*, x_2) > \sigma^2(x_1=x_1^{**}, x_2)$

3. Consider the R code below. Next to each line of code, briefly comment on what that line of code is doing (write formulas if necessary).

```

## R code for Question 3 - MT1      comment

rm(list=ls())    clear memory
set.seed(10122021) set random seed

n <- 1000 sample size = 1000
x <- runif(n, 0, 1) x ~ U[0, 1] from 0 to 1
e <- rnorm(n, 0, 1) e ~ N(0, 1)

y <- 1 + 0.5*x + x^2 + e       $y = \alpha + \beta_1 x + \beta_2 x^2 + \epsilon = 1 + 0.5x + x^2 + \epsilon$ 
ones <- matrix(1, nrow=n, ncol=1) column of ones
X <- cbind(ones, x, (x^2)) X = (1 x x^2) data matrix
b <- solve(t(X)%*%X)%*%(t(X)%*%y)  $\hat{\beta} = (X^\top X)^{-1} X^\top y$ 
yh <- X%*%b       $\hat{y} = X\hat{\beta}$ 
eh <- y - yh       $\hat{e} = y - \hat{y}$ 
d <- diag(eh^2) V(eh) = D = diag( $\hat{e}_1^2, \hat{e}_2^2, \dots, \hat{e}_n^2$ )
vb <- solve(t(X)%*%X)%*%t(X)%*%d%*%X%*%solve(t(X)%*%X)
V(beta) = (X%*%b)^\top D X%*%b

```