### Econometrics I - TA section

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### 2.4

Suppose that the random variables Y and X only take the values 0 and 1, and have the following joint probability distribution

	x = 0	x = 1
y = 0	.1	.2
y = 1	.4	.3

Find E(y|x),  $E(y^2|x)$  and var(y|x) for x = 0 and x = 1

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$$Pr(y = 0|x = 0) = \frac{Pr(y = 0, x = 0)}{P(x = 0)} = \frac{.1}{.1 + .4} = .2$$
  
•  $Pr(y = 1|x = 0) = \frac{.1}{.1 + .4} = .8$   
•  $Pr(y = 0|x = 1) = \frac{.2}{.2 + .3} = .4$   
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- E(y|x=1) = .6
- $var(y^2|x=0) = E(y^2|x=0) (E(y|x=0))^2 = .8 .8^2 = .16$
- $var(y^2|x=1) = E(y^2|x=1) (E(y|x=1))^2 = .24$

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Minimize 
$$E((e^2 - h(x))^2)$$



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$$E((e^{2} - h(x))^{2}) =$$

$$E((e^{2} - \sigma^{2}(x) + \sigma^{2}(x) - h(x))^{2}) =$$

$$E((e^{2} - \sigma^{2}(x))^{2}) + E((\sigma^{2}(x) - h(x))^{2}) + 2E((\sigma^{2}(x) - h(x))(e^{2} - \sigma^{2}(x)))$$

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$$E((\sigma^2(x) - h(x))(e^2 - \sigma^2(x)))$$

• Note  $\sigma^2(x) = E(e^2|x)$  so using LIE

$$= E(E((\sigma^{2}(x) - h(x))(e^{2} - \sigma^{2}(x))|x)) = 0$$



- **2.5** Show that  $\sigma^2(x)$  is the best predictor of  $e^2$  given x.
  - Thus

$$E((e^{2} - g(x))^{2}) = E((e^{2} - \sigma^{2}(x))^{2}) + E((\sigma^{2}(x) - h(x))^{2})$$

$$\geq E((e^{2} - \sigma^{2}(x))^{2})$$

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$$E(e|x) = 0$$
$$E(e^{2}|x) = \sigma^{2}$$
$$E(e^{3}|x) = x^{3}$$

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- What about  $P_1$  and  $P_2$ . Both are  $n \times n$

$$P = \begin{bmatrix} X_1 & X_2 \end{bmatrix} \begin{bmatrix} X_1' X_1 & X_1' X_2 \\ X_2' X_1 & X_2' X_2 \end{bmatrix}^{-1} \begin{bmatrix} X_1 & X_2 \end{bmatrix}' =$$

$$\begin{bmatrix} X_1 & X_2 \end{bmatrix} \begin{bmatrix} (X_1' X_1)^{-1} & 0 \\ 0 & (X_2' X_2)^{-1} \end{bmatrix}^{-1} \begin{bmatrix} X_1 & X_2 \end{bmatrix}' =$$

$$X_1 (X_1' X_1)^{-1} X_1' + X_2 (X_2' X_2)^{-1} X_2' =$$

$$P_1 + P_2$$

#### 3.22

You estimate a least-squares regression

$$y_i = x'_{1i}\tilde{\beta}_1 + \tilde{u}_i$$

and then regress the residuals on another set of regressors

$$\tilde{u}_i = x'_{2i}\tilde{\beta}_2 + \tilde{e}_i$$

Does this second regression give you the same estimated coefficients as from estimation of a least-squares regression on both set of regressors?

$$y_i = x'_{1i}\hat{\beta}_1 + x'_{2i}\hat{\beta}_2 + \hat{e}_i$$

Explain your reasoning. In other words, is it true that  $\tilde{eta}_2=\hat{eta}_2$ 



#### 3.22

- $\tilde{U} = Y X_1(X_1'X_1)^{-1}X_1'Y$
- $\bullet \ \ \tilde{\beta} = (X_2'X_2)^{-1}X_2'\tilde{U}$

#### Meanwhile

$$\hat{\beta} = \begin{bmatrix} X_1' X_1 & X_1' X_2 \\ X_2' X_1 & X_2' X_2 \end{bmatrix}^{-1} \begin{bmatrix} X_1 & X_2 \end{bmatrix}' Y$$

- Can use the partition inverse formula to show they are different
- $A^{-1} = \begin{bmatrix} (A_{11} A_{12}A_{22}^{-1}A_{21})^{-1} & -A_{11}^{-1}A_{12}(A_{22} A_{21}A_{11}^{-1}A_{12})^{-1} \\ -A_{22}^{-1}A_{21}(A_{11} A_{12}A_{22}^{-1}A_{21})^{-1} & (A_{22} A_{12}A_{11}^{-1}A_{12})^{-1} \end{bmatrix}$

So, no these are different.

# Computer questions

- Question 3.22
- Homework Question 1
- Homework Question 2