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ind for bo: $ \frac{\hat{\beta}^{OLS}}{\hat{z}_{i}} = \frac{\sum_{i} (X_{i} - \overline{X})(Y_{i} - \overline{Y})_{i}}{\sum_{i} (X_{i} - \overline{X})^{2}}  \text{var}(X_{i}) $ and for bo: $ \hat{\beta}^{OLS} = \overline{I} - \hat{\beta}^{OLS} \overline{X}_{i} $ From $(a)$ we've shown that $ \hat{\beta}^{OLS} = \frac{\sum_{i} (X_{i} - \overline{X})^{2}}{\sum_{i} (X_{i} - \overline{X})^{2}} $ $ = \frac{\sum_{i} (X_{i} - \overline{X})^{2}}{\sum_{i} (X_{i} - \overline{X})^{2}} $ $ = \frac{\sum_{i} (X_{i} - \overline{X})^{2}}{\sum_{i} (X_{i} - \overline{X})^{2}} $ $ = \frac{\sum_{i} (X_{i} - \overline{X})^{2}}{\sum_{i} (X_{i} - \overline{X})^{2}} $ $ = \frac{\sum_{i} (X_{i} - \overline{X})^{2}}{\sum_{i} (X_{i} - \overline{X})^{2}} $ $ = \frac{\sum_{i} (X_{i} - \overline{X})^{2}}{\sum_{i} (X_{i} - \overline{X})^{2}} $ $ = \frac{\sum_{i} (X_{i} - \overline{X})^{2}}{\sum_{i} (X_{i} - \overline{X})^{2}} $ $ = \frac{\sum_{i} (X_{i} - \overline{X})^{2}}{\sum_{i} (X_{i} - \overline{X})^{2}} $ $ = \frac{\sum_{i} (X_{i} - \overline{X})^{2}}{\sum_{i} (X_{i} - \overline{X})^{2}} $ $ = \frac{\sum_{i} (X_{i} - \overline{X})^{2}}{\sum_{i} (X_{i} - \overline{X})^{2}} $				Date	
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The can rearrange and solve for by which gives the OLS estimator by: $ \frac{1}{2} = \frac{1}{2} (X_i - \overline{X})(Y_i - \overline{Y})_{P} \cos(Y_i X_i) $ and for bo: $ \frac{1}{2} \cos x = \overline{Y} - \frac{1}{2} \cos x $ The cov( $X_i$ , $X_i$ )  From (a) we've shown that $ \frac{1}{2} \cos x = \overline{Y} + \frac{1}{2} \cos(X_i - \overline{X}) $ $ \frac{1}{2} \cos x = \overline{Y} + \frac{1}{2} \cos(X_i - \overline{X}) $ $ \frac{1}{2} \cos x = \overline{Y} + \frac{1}{2} \cos(X_i - \overline{X}) $ $ \frac{1}{2} \cos x = \overline{Y} + \frac{1}{2} \cos(X_i - \overline{X}) $ $ \frac{1}{2} \cos x = \overline{Y} + \frac{1}{2} \cos(X_i - \overline{X}) $ $ \frac{1}{2} \cos x = \overline{X} + \frac{1}{2} \cos(X_i - \overline{X}) $ $ \frac{1}{2} \cos(X_i - \overline{X}) \cos(X_i - \overline{X}) $ $ \frac{1}{2} \cos(X_i - \overline{X}) \cos(X_i - \overline{X}) $ $ \frac{1}{2} \cos(X_i - \overline{X}) \cos(X_i - \overline{X}) $ $ \frac{1}{2} \cos(X_i - \overline{X}) \cos(X_i - \overline{X}) $ $ \frac{1}{2} \cos(X_i - \overline{X}) \cos(X_i - \overline{X}) \cos(X_i - \overline{X}) $ $ \frac{1}{2} \cos(X_i - \overline{X}) \cos(X_i - \overline{X}) $ $ \frac{1}{2} \cos(X_i - \overline{X}) \cos(X_i - \overline{X}) \cos(X_i - \overline{X}) $ $ \frac{1}{2} \cos(X_i - \overline{X}) \cos(X_i - \overline{X}) \cos(X_i - \overline{X}) $ $ \frac{1}{2} \cos(X_i - \overline{X}) \cos(X_i - \overline{X}) \cos(X_i - \overline{X}) $ $ \frac{1}{2} \cos(X_i - \overline{X}) \cos(X_i - \overline{X}) \cos(X_i - \overline{X}) $ $ \frac{1}{2} \cos(X_i - \overline{X}) \cos(X_i - \overline{X}) \cos(X_i - \overline{X}) $ $ \frac{1}{2} \cos(X_i - \overline{X}) \cos(X_i - \overline{X}) \cos(X_i - \overline{X}) $ $ \frac{1}{2} \cos(X_i - \overline{X}) \cos(X_i - \overline{X}) \cos(X_i - \overline{X}) $ $ \frac{1}{2} \cos(X_i - \overline{X}) \cos(X_i - \overline{X}) \cos(X_i - \overline{X}) $ $ \frac{1}{2} \cos(X_i - \overline{X}) \cos(X_i - \overline{X}) \cos(X_i - \overline{X}) $ $ \frac{1}{2} \cos(X_i - \overline{X}) \cos(X_i - \overline{X}) \cos(X_i - \overline{X}) $ $ \frac{1}{2} \cos(X_i - \overline{X}) \cos(X_i - \overline{X}) \cos(X_i - \overline{X}) $ $ \frac{1}{2} \cos(X_i - \overline{X}) \cos(X_i - \overline{X}) \cos(X_i - \overline{X}) $ $ \frac{1}{2} \cos(X_i - \overline{X}) \cos(X_i - \overline{X}) \cos(X_i - \overline{X}) $ $ \frac{1}{2} \cos(X_i - \overline{X}) \cos(X_i - \overline{X}) \cos(X_i - \overline{X}) $ $ \frac{1}{2} \cos(X_i - \overline{X}) \cos(X_i - \overline{X}) $ $ \frac{1}{2} \cos(X_i - \overline{X}) \cos(X_i - \overline{X}) $ $ \frac{1}{2} \cos(X_i - \overline{X}) \cos(X_i - \overline{X}) $ $ \frac{1}{2} \cos(X_i - \overline{X}) \cos(X_i - \overline{X}) $ $ \frac{1}{2} \cos(X_i - \overline{X}) \cos(X_i - \overline{X}) $ $ \frac{1}{2} \cos(X_i - \overline{X}) \cos(X_i - \overline{X}) $ $ \frac{1}{2} \cos(X_i - \overline{X}) \cos(X_i - \overline{X}) $ $ \frac{1}{2} \cos(X_i - \overline{X}) \cos(X_i - \overline{X}) $ $ \frac{1}{2} \cos(X_i - \overline{X}) \cos(X_i - \overline{X}) $ $ \frac{1}{2} \cos(X_i - \overline{X}) \cos(X_i - \overline{X}) $ $ \frac{1}{2} \cos(X_i - \overline{X}) \cos(X_i - \overline{X}) $ $ \frac{1}{2} \cos(X_i - \overline{X}) \cos(X_i - \overline{X}) $ $ \frac{1}{2} \cos(X_i - \overline{X}) \cos(X_i - \overline{X}) $					
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$= \sum_{i} (X_i - X_i) \cdot \beta_i (X_i - X_i) + (X_i - X_i) (M_i - M_i)$		21(X) - X)	+ 1/2- B. + B. X+ 1/	12 30 t j.	ों हो हो
$= \sum_{i} (X_i - X_i) \cdot \beta_i (X_i - X_i) + (X_i - X_i) (M_i - M_i)$		ZilXz XI (for fixe	-X)2	we mak Ex	Proof. Assi
$= \frac{1}{2i} \left( \chi_{i} - \overline{\chi}_{j} \right)^{\nu}$	Marie Company	Z1 (Xi-X) B1 (Xi-	$\overline{x}$ )+ $(x_{\hat{i}}-\overline{x})(u_{\hat{i}}-\overline{x})$	-ū)]	
	Ass		=\bar{\chi}^\rangle \bar{\chi}^\rangle \bar{\chi}		
$\sum_{i} (X_i - X) (M_i - N) e = \frac{Cov(X_i, M_i)}{2}$		Zi(Xi-X)(Mi-	- u) e _ ov(>	(i, Mi)	Him
= ()+ = () () () () () () ()	=	PI+ Zi(Xi-X)	= 17 (sit var	(Xi)	
		( ) ( ) ( ) ( ) ( ) ( ) ( ) ( ) ( ) ( )			

(c) If E[uiXi] >0 and Eui=0, is the Bis consistent? Claim: Bis is consistent. Proof. Since cov(ui, Xi) = E(uiXi)-EuiEXi =0-0=0, Herefore by previous proof, we have Bias P BI+ Cov(Ui, Xi) = BI. cal) If EluiXi) >0, but Eui \$0, is the Box consistent? Claim: Bas is NOT consistant. Proof. Obvious without the zero assumption, the error term will have a systematic component that mean would bias the OLS estimates (e) If E[ui Xi] =0, is the Bis consistent? Claim: Bis is consistent Proof. Since E(ui)=E[E(w | Xi)]=0 tatt would to: and Then by the conclusion of (c), we finish the proof. 2. Let 12 = Bo+ BIXj+ WE but Euito, reparametrize the model sit. Ti= Bo+ Bixi tei S.t. Eei=0 Proof. Assume that Eni = u = 0, let Bo = Bx-u, Tie. Tt = Bo + BiXz + (mi-n) = Bx+ PiXi+ ei with (X) Eei=E(w-u) =0

3.	For a	a	model	without	the	intercep	it:	
					7	i= BIXi	+ 4	i

Derive \( \hat{\beta}\_{1}^{ous} \) for \( \hat{\beta}\_{1} \). Solution. We have:

SSE = 
$$\overline{z_i}(\overline{z_i} - b_i x_i)$$

$$= \overline{z_i}(\overline{z_i} - 2b_i z_i)(\overline{z_i} + b_i z_i)(\overline{z_i} + b_i z_i)$$

Bous = Zim Tixi we have: 12 210 tool

Bious = Zim Tixi

Zim Xi

4. (a) EX4.7. Show that 
$$\hat{\beta}_0$$
 is unbiased for  $\hat{\beta}_0$ .

Proof. We've shown that in simple regression model,  $\hat{\beta}_0 = \bar{\gamma} - \hat{\beta}_1 \bar{\chi}$ 

Therefore

$$E\hat{\beta}_0 = E\overline{Y} - E(\hat{\beta}_1 \overline{X})$$

$$= E(\beta_0 + \beta_1 \overline{X} + \overline{u}) - E(\hat{\beta}_1 \overline{X}).$$

(b) EX 4.9.

cr, 
$$\hat{\beta}_1 = 0 \Rightarrow \hat{R}^2 = 0$$
  
cr)  $\hat{R}^2 = 0 \Rightarrow \hat{\beta}_1 = 0$ 

cis Proof. If pizo, then

Ti= Bo + BiXi = Bo

The sum of squared error (residual) is:

SSR=ZA(Ti-Ti) = Zin (12-Bo)

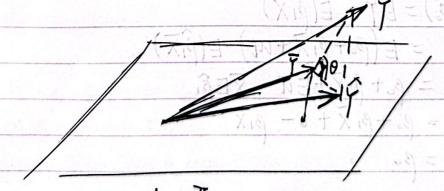
Under the assumption of strict exogeivity,  $\hat{\beta}_i$  is an unbiased estimates for p, Herefore

Therefore the best OLS prediction of any Xi is  $\hat{p}_{o}^{ols} = \overline{\gamma}$ , i.e.

Therefore

$$R^2 = 1 - \frac{SSR}{SST} = 0$$

cir, Proof. Claim: R' doesn't mean Biso. It may occur that the variability explained by the model is counteracted by the variability introduced due to the model 8 errors



R2 = cos20, 0 can be \$ ire. R2=0

(c) EX 4.10, b
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Sol. By the previous bemma, we have

$$\frac{1}{\sqrt{s}} = \frac{1}{n} \frac{var[(X_i - ux)u_i]}{[varX_i]^{\frac{1}{n}}}$$

$$= \frac{1}{n} \cdot \frac{var[(X_i u_i) - var(uxu_i)}{(varX_i)^{\frac{1}{n}}} - \frac{1}{n} \cdot \frac{E[(X_i u_i)^2] - E[(X_i u_i)^2] - uxvaru_i}{(varX_i)^2}$$

$$= \frac{1}{n} \cdot \frac{E[(u_i^2 | X_i^2)] - 0.2 \times 16}{0.16 \times 10}$$

$$= \frac{1}{n} \cdot \frac{4 - 0.3 \times 16}{0.16 \times 10} = \frac{1}{4 \times 10}$$

$$= \frac{1}{n} \cdot \frac{4 - 0.3v}{0.16v} = \frac{575}{4h}$$