Economics 471: Introductory Econometrics

Department of Economics, Finance and Legal Studies
University of Alabama

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Midterm II - Key

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

1. Consider a regression model through the origin: $y_i = \beta x_i + u_i$, i = 1, 2, ..., n, and the corresponding slope parameter estimator

 $\tilde{\beta} = \frac{\sum_{i=1}^n y_i x_i}{\sum_{i=1}^n x_i^2},$

but where the true data generating process (i.e., the truth) is $y_i = \beta x_i + \delta w_i + e_i$. We assume that e_i is mean zero, has a constant variance (σ^2) and is uncorrelated with both x_i and w_i . Given this information, answer the following:

- (a) What is the expected value of $\tilde{\beta}$?
- (b) Under what conditions is the estimator in part (a) unbiased?
- (c) Suppose we were to correctly specify the model $(y_i = \beta x_i + \delta w_i + u_i)$; what would the estimator of β be? What would the estimator of δ be? Call these estimators $\widehat{\beta}$ and $\widehat{\delta}$, respectively.
- (d) Consider the estimators in part (c); what is the variance of $\widehat{\beta}$? What is the variance of $\widehat{\delta}$?
- (e) Without using formal proofs, is $\widehat{\beta}$ a consistent estimator of β ? Is $\widehat{\delta}$ a consistent estimator of δ ? How do you know?

(a) $\hat{\beta} = \frac{\mathcal{E}(\beta_{2i} + \beta_{wi} + e_{i}) \mathcal{E}_{i}}{\mathcal{E}(\beta_{2i} + \beta_{wi} + e_{i}) \mathcal{E}_{i}} \mathcal{E}_{i}^{2}$ $= \beta + \frac{\partial \mathcal{E}(\beta_{wi})}{\partial \mathcal{E}(\beta_{i})} \mathcal{E}_{i}^{2} + \frac{\partial \mathcal{E}(\beta_{2i})}{\partial \mathcal{E}(\beta_{2i})} \mathcal{E}_{i}^{2}$ $= \beta + \frac{\partial \mathcal{E}(\beta_{wi})}{\partial \mathcal{E}(\beta_{wi})} \mathcal{E}_{i}^{2} \mathcal{E}_{i}^{2} \mathcal{E}_{i}^{2}$ $= \beta + \frac{\partial \mathcal{E}(\beta_{wi})}{\partial \mathcal{E}(\beta_{wi})} \mathcal{E}_{i}^{2} \mathcal{E}_{i}^{2} \mathcal{E}_{i}^{2}$ $= \beta + \frac{\partial \mathcal{E}(\beta_{wi})}{\partial \mathcal{E}(\beta_{wi})} \mathcal{E}_{i}^{2} \mathcal{E}_{i}^{2} \mathcal{E}_{i}^{2}$ $= \beta + \frac{\partial \mathcal{E}(\beta_{wi})}{\partial \mathcal{E}(\beta_{wi})} \mathcal{E}_{i}^{2} \mathcal{E}_{i}^{2} \mathcal{E}_{i}^{2}$ $= \beta + \frac{\partial \mathcal{E}(\beta_{wi})}{\partial \mathcal{E}(\beta_{wi})} \mathcal{E}_{i}^{2} \mathcal{E}_{i}^{2} \mathcal{E}_{i}^{2}$ $= \beta + \frac{\partial \mathcal{E}(\beta_{wi})}{\partial \mathcal{E}(\beta_{wi})} \mathcal{E}_{i}^{2} \mathcal{E}_{i}^{2} \mathcal{E}_{i}^{2}$ $= \beta + \frac{\partial \mathcal{E}(\beta_{wi})}{\partial \mathcal{E}(\beta_{wi})} \mathcal{E}_{i}^{2} \mathcal{E}_{i}^{2} \mathcal{E}_{i}^{2}$ $= \beta + \frac{\partial \mathcal{E}(\beta_{wi})}{\partial \mathcal{E}(\beta_{wi})} \mathcal{E}_{i}^{2} \mathcal{E}_{i}^{2} \mathcal{E}_{i}^{2}$ $= \beta + \frac{\partial \mathcal{E}(\beta_{wi})}{\partial \mathcal{E}(\beta_{wi})} \mathcal{E}_{i}^{2} \mathcal{E}_{i}^{2} \mathcal{E}_{i}^{2}$ $= \beta + \frac{\partial \mathcal{E}(\beta_{wi})}{\partial \mathcal{E}(\beta_{wi})} \mathcal{E}_{i}^{2} \mathcal{E}_{i}^{2} \mathcal{E}_{i}^{2}$ $= \beta + \frac{\partial \mathcal{E}(\beta_{wi})}{\partial \mathcal{E}(\beta_{wi})} \mathcal{E}_{i}^{2} \mathcal{E}_{i}^{2} \mathcal{E}_{i}^{2}$ $= \beta + \frac{\partial \mathcal{E}(\beta_{wi})}{\partial \mathcal{E}(\beta_{wi})} \mathcal{E}_{i}^{2} \mathcal{E}_{i}^{2} \mathcal{E}_{i}^{2}$ $= \beta + \frac{\partial \mathcal{E}(\beta_{wi})}{\partial \mathcal{E}(\beta_{wi})} \mathcal{E}_{i}^{2} \mathcal{E}_{i}^{2} \mathcal{E}_{i}^{2}$ $= \beta + \frac{\partial \mathcal{E}(\beta_{wi})}{\partial \mathcal{E}(\beta_{wi})} \mathcal{E}_{i}^{2} \mathcal{E}_{i}^{2} \mathcal{E}_{i}^{2}$ $= \beta + \frac{\partial \mathcal{E}(\beta_{wi})}{\partial \mathcal{E}(\beta_{wi})} \mathcal{E}_{i}^{2} \mathcal{E}_{i}^{2} \mathcal{E}_{i}^{2}$ $= \beta + \frac{\partial \mathcal{E}(\beta_{wi})}{\partial \mathcal{E}(\beta_{wi})} \mathcal{E}_{i}^{2} \mathcal{E}_{i}^{2} \mathcal{E}_{i}^{2} \mathcal{E}_{i}^{2}$ $= \beta + \frac{\partial \mathcal{E}(\beta_{wi})}{\partial \mathcal{E}(\beta_{wi})} \mathcal{E}_{i}^{2} \mathcal{E$

(d)
$$V(\hat{\beta}) = \frac{+2}{\sum (\log_i - \log_i)^2 (1 - R_i^2)}$$

$$R_i^2 \text{ is } R^2 \text{ from } \text{ reg.} \Rightarrow$$

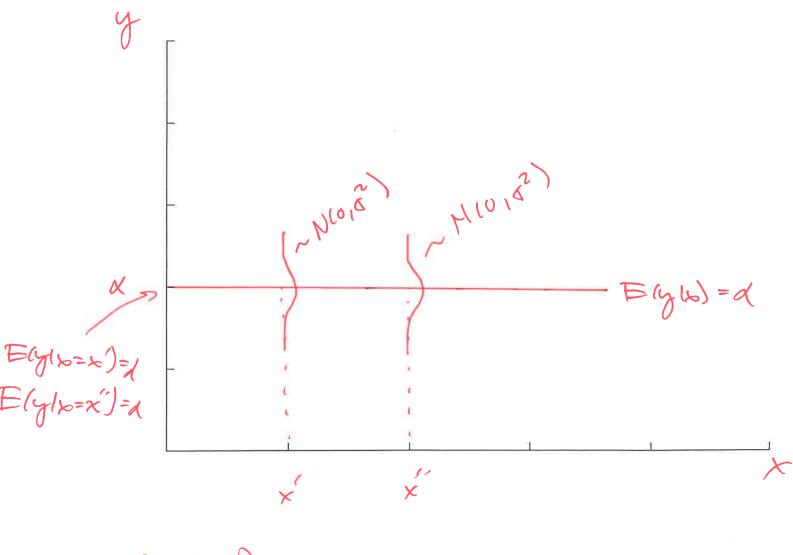
$$V(\hat{\delta}) = \frac{-2}{\sum (\omega_i - \omega_i)^2 (1 - R_i^2)}$$

$$R_i^2 \text{ is } R^2 \text{ from } \text{ reg.} \Rightarrow \Rightarrow$$

(e)
$$E(\hat{\beta}) = \beta \neq V(\hat{\beta}) \rightarrow 0 \text{ as } n \rightarrow \infty$$

 $E(\hat{\delta}) = \beta \neq V(\hat{\delta}) \rightarrow 0 \text{ as } n \rightarrow \infty$

- 2. Consider the population regression function $y = \alpha + u$. Assuming $\alpha > 0$, in the figure below, perform the following:
 - (a) Label the axes
 - (b) Plot and label the population regression curve.
 - (c) Pick two values for x, plot their conditional expectations (i.e., E(y|x)).
 - (d) For those two values of x in part (c), what is the marginal effect on E(y|x) for each (i.e., $\partial E(y|x)/\partial x$)?
 - (e) Assuming normally distributed, homoskedastic errors, plot and label the distribution of the error (u) for each of the points you listed in part (b).



3. Consider the relationship between average monthly rent paid on rental units (rent) versus average city income (avginc), total city population (pop) and the percentage of students in the population (pctstu). Two gretl output files are below which correspond to two separate models. The univariate model is

Model 1: OLS, using observations 1–128

Dependent variable: lnrent

	C	oefficient	Std	. Error	t-ratio	p-value	
	const –	2.48821	0.435659		-5.711	0.0000	
	Inavginc	0.841260	0.04	144821	18.91	0.000	00
	Mean dependent var	5.746	195	S.D. de	ependent v	аг	0.332707
	Sum squared resid	3.662	3.662210		regression	1 =	0.170485
R^2 $F(1, 126)$ Log-likelihood		0.739	0.739495		ed \mathbb{R}^2		0.737428
		357.6	357.6765		e(F)		1.29e-38
		45.82	45.82953		Akaike criterion		-87.65907
	Schwarz criterion	-81.95	501	Hanna	n–Quinn		85.34148

and the multivariate model is

Model 2: OLS, using observations 1–128

Dependent variable: lnrent

Coeffici		cient	Std. Error		t-ratio	p-val	p-value	
	const	-3.36831		0.46	33944	-7.260	0.0000	
	lnavginc	0.87	0.877139		113247	21.23	0.0000	
	lnpop 0.0313456		0.0270786		1.158	0.2493		
	pctstu 0.658487		0.12	20268	5.475	0.0000		
Mean dependent var			5.746195		S.D. dependent va		ar	0.332707
Sum squared resid			2.852256		S.E. of regression			0.151664
R^2			0.797110		Adjuste	$ed R^2$		0.792201
F(3,124) Log-likelihood			162.3895		P-value	e(F)		8.98e-43
			61.82675		Akaike	criterion	-	-115.6535
Schwarz criterion		n -	-104.2454		Hannar	n–Quinn	_	-111.0183

- (a) Interpret the coefficient on ln(avginc) in both Model 1 and Model 2.
- (b) Interpret the coefficients on ln(pop) and pctstu in Model 2.
- (c) Test the null hypothesis that ln(avginc) is irrelevant in both Model 1 and Model 2.
- (d) Test the null hypothesis that ln(pop) and pctstu are jointly irrelevant.
- (e) Using (at least three of) the model selection criteria we discussed in class, what model has better predictive power?

(a) 1: if augine 1 by 1%, predicted rent \$ 0.84% 2: holdig Inpup & petsu constant a l'est avgine => predicted 1 rent by 0.877% a 1% 1 in pap => predicted rent thy 0.03% holdy augine & papenstant (6) holdig argine of poten mostret, a 1% Time a proportion of the 0.65% (note: petstu is in do terms already) (c) 1: Ho: B=0 us. H: B =0 t = 0.841-0 = 18.91 >2 => repeat to $t = \frac{0.877 - 0}{0.041} = 21.23 > 2 \Rightarrow \text{ reject } H$ 2: Ho: B1=0 vs. 14: B1 =0 (d) to: Bz=Bz=0 th: Ho is not tre F= (SSPR-SSPn)/9 = (Pn-PR)/9 (1-Pn)/(n-6-1) $= \frac{(3.66 - 2.85)/2}{2.85/(128-4)} = \frac{(0.797 - 0.739)/2}{(1-0.797)/(128-4)}$ TLF > Fz, ry, as =) reject Ho model 1 model 2, allsmalter for molel 2