Solutions Manual for Econometrics

Second Edition

Badi H. Baltagi

Solutions Manual for Econometrics

Second Edition

Springer

Contents

completing the square

$$M_x(t) = \frac{1}{\sigma\sqrt{2\pi}}\int_{-\infty}^{+\infty} e^{-\frac{1}{2\sigma^2}\left\{\left[x-\left(\mu+t\sigma^2\right)\right]^2-\left(\mu+t\sigma^2\right)^2+\mu^2\right\}}dx$$
$$= e^{-\frac{1}{2\sigma^2}[\mu^2-\mu^2-2\mu t\sigma^2-t^2\sigma^4]}$$

The remaining integral integrates to 1 using the fact that the Normal density is proper and integrates to one. Hence $M_x(t) = e^{\mu t+\frac{1}{2}\sigma^2 t^2}$ after some cancellations.

c. For the *Poisson Distribution*,

$$M_x(t) = E(e^{Xt}) = \sum_{X=0}^{\infty} e^{Xt}\frac{e^{-\lambda}\lambda^X}{X!} = \sum_{X=0}^{\infty}\frac{e^{-\lambda}(\lambda e^t)^X}{X!}$$
$$= e^{-\lambda}\sum_{X=0}^{\infty}\frac{(\lambda e^t)^X}{X!} = e^{\lambda}e^t - \lambda = e^{\lambda(e^t-1)}$$

where the fifth equality follows from the fact that $\sum\limits_{X=0}^{\infty}\frac{a^X}{X!} = e^a$ and in this case $a = \lambda e^t$. This is the fundamental relationship underlying the Poisson distribution and what makes it a proper probability function.

d. For the *Geometric Distribution*,

$$M_X(t) = E(e^{Xt}) = \sum_{X=1}^{\infty}\theta(1-\theta)^{X-1}e^{Xt} = \theta\sum_{X=1}^{\infty}(1-\theta)^{X-1}e^{(X-1)t}e^t$$
$$= \theta e^t\sum_{X=1}^{\infty}\left[(1-\theta)\,e^t\right]^{X-1} = \frac{\theta e^t}{1-(1-\theta)e^t}$$

where the last equality uses the fact that $\sum\limits_{X=1}^{\infty}a^{X-1} = \frac{1}{1-a}$ and in this case $a = (1-\theta)e^t$. This is the fundamental relationship underlying the Geometric distribution and what makes it a proper probability function.

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for HO: Parameter=0	Prob > |T|
INTERCEP	1	3.316057	0.48101294	6.894	0.0001
LNRGDP	1	1.037499	0.04481721	23.150	0.0001

Linear Specificiation

Dependent Variable: EN1

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob > F
Model	1	6.7345506E14	6.7345506E14	386.28	0.0001
Error	18	3.1381407E13	1.7434115E12	6	
C Total	19	7.0483646E14			

Root MSE	1320383.09457	R-square	0.9555
Dep Mean	4607256.0000	Adj R-sq	0.9530
C.V.	28.65877		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for HO: Parameter=0	Prob > |T|
INTERCEP	1	-190151	383081.08995	-0.496	0.6256
RGDP	1	46.759427	2.37911166	19.654	0.0001

Linear Specification before the multiplication by 60

Dependent Variable: EN

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob > F
Model	1	187070848717	187070848717	386.286	0.0001
Error	18	8717057582.2	484280976.79		
C Total	19	195787906299			

Root MSE	22006.38491	R-square	0.9555
Dep Mean	76787.60000	Adj R-sq	0.9530
C.V.	28.6587		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob>|T|
INTERCEP	1	2.217240	0.92729847	2.391	0.0211
Z3 (LNY^.5)	1	-0.957085	0.42433823	-2.255	0.0291

MODEL: Z4=LNY^1

Dependent Variable: ABS_E

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	1	0.04284	0.04284	5.016	0.0302
Error	44	0.37581	0.00854		
C Total	45	0.41865			

Root MSE	0.09242	R-square	0.1023
Dep Mean	0.12597	Adj R-sq	0.0819
C.V.	73.36798		

Parameter Estimates

Variable	DF	Parameter Estimate	Standard Error	T for H0: Parameter=0	Prob>|T|
INTERCEP	1	1.161694	0.46266689	2.511	0.0158
Z4 (LNY^1)	1	-0.216886	0.09684233	-2.240	0.0302

c. Regression for Goldfeld and Quandt Test (1965) with first 17 obervations

Dependent Variable: LNC

Analysis of Variance

Source	DF	Sum of Squares	Mean Square	F Value	Prob>F
Model	2	0.22975	0.11488	2.354	0.1315
Error	14	0.68330	0.04881		
C Total	16	0.91305			

Root MSE	0.22092	R-square	0.2516
Dep Mean	4.85806	Adj R-sq	0.1447
C.V.	4.54756		

CHAPTER 12

Pooling Time-Series of Cross-Section Data

12.1 **a.** Premultiplying (12.11) by Q one gets

$$Qy = \alpha Q\iota_{NT} + QX\beta + QZ_{\mu}\mu + Q\nu$$

But $PZ_{\mu} = Z_{\mu}$ and $QZ_{\mu} = 0$. Also, $P\iota_{NT} = \iota_{NT}$ and $Q\iota_{NT} = 0$. Hence, this transformed equation reduces to (12.12)

$$Qy = QX\beta + Q\nu$$

Now $E(Q\nu) = QE(\nu) = 0$ and $\text{var}(Q\nu) = Q\,\text{var}(\nu)Q' = \sigma_{\nu}^2 Q$, since

$$\text{var}(\nu) = \sigma_{\nu}^2 I_{NT}$$

and Q is symmetric and idempotent.

b. For the general linear model $y = X\beta + u$ with $E(uu') = \Omega$, a necessary and sufficient condition for OLS to be equivalent to GLS is given by $X'\Omega^{-1}\bar{P}_X$ where $\bar{P}_X = I - P_X$ and $P_X = X(X'X)^{-1}X'$, see equation (9.7) of Chapter 9. For equation (12.12), this condition can be written as

$$(X'Q)(Q/\sigma_{\nu}^2)\bar{P}_{QX} = 0$$

using the fact that Q is idempotent, the left hand side can be written as

$$(X'Q)\bar{P}_{QX}/\sigma_{\nu}^2$$

which is clearly 0, since $\bar{P}_{QX}$ is the orthogonal projection of QX.

One can also use Zyskind's condition $P_X\Omega = \Omega P_X$ given in equation (9.8) of Chapter 9. For equation (12.12), this condition can be written as

$$P_{QX}(\sigma_{\nu}^2 Q) = (\sigma_{\nu}^2 Q)P_{QX}$$

But, $P_{QX} = QX(X'QX)^{-1}X'Q$. Hence, $P_{QX}Q = P_{QX}$ and $QP_{QX} = P_{QX}$ and the condition is met. Alternatively, we can verify that OLS and GLS yield