

ES1004 Econometrics by Example

Lecture 8: Dynamic Regression Models

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Gujarati textbook, second edition [chapter 7]

6th August 2016



CLRM Assumptions

A₁: model is linear in parameters

A₂: regressors are fixed non-stochastic

A₃: the expected value of the error term is zero $E(u_i|X) = 0$

A₄: homoscedastic or constant variance of errors $var(u_i|X) = \sigma^2$

A₅: no autocorrelation, $cov(u_i, u_j) = 0, i \neq j$

A₆: no multicollinearity; no perfect linear relationships among the X s

A₇: no specification bias

Basic Idea I

- CLRM assumes the model is 'correctly' specified
 - there is no such thing as a perfect model
- an econometric model tries to capture the main features of an economic phenomenon
 - taking into account the underlying economic theory, prior empirical work, intuition, and research skills
- no model can take into account every single factor that affects a particular object of research

Basic Idea II

- a 'correctly' specified model ...
 - 1 does not exclude any "core" variables
 - 2 does not include superfluous variables
 - 3 has the suitable functional form
 - 4 has no measurement errors

Basic Idea III

- a 'correctly' specified model ...
 - 5 takes into account outliers in the data
 - 6 the probability distribution of the error term is well specified
 - 7 includes non-stochastic regressors
 - 8 no simultaneity bias

Equilibrium in Theory

- economic theory is often stated in **static** or **equilibrium** form
 - e.g. the equilibrium price of a commodity (or service) is determined by the intersection of the relevant demand and supply curves
- however, equilibrium is not determined instantaneously
 - i.e., a process of trial and error which takes time
- neglecting the dynamic [time] aspect may lead to a specification error

Permanent Income Hypothesis

- Milton Friedman
 - current consumption is a function of permanent income
 - weighted average of quarterly income going back 16 quarters

$$Y_t = A + B_0X_t + B_1X_{t-1} + B_2X_{t-2} + \cdots + B_{16}X_{t-16} + u_t \quad (1)$$

- X_t income in the current period, X_{t-1} income lagged one quarter
- β weights attached to the income in the various quarters

Distributed Lag Model I

- current value of Y is affected by current and lagged values of X
- β_0
 - the short-run or impact multiplier
 - gives the change in the mean value of Y following a unit change in X in the same time period
- if the change in X is kept at the same level thereafter, $(\beta_0 + \beta_1)$ gives the change in mean Y in the next period
- the partial sums are called interim or intermediate multipliers

Distributed Lag Model II

- after k periods, we obtain

$$\sum_0^k \beta_k = \beta_0 + \beta_1 + \cdots + \beta_k \quad (2)$$

- known as the long run or total multiplier
- gives the ultimate change in mean consumption expenditure following a (sustained) unit increase in the income

Distributed Lag Model: An Example

$$Y_t = \text{constant} + 0.4X_t + 0.2X_{t-1} + 0.15X_{t-2} + 0.1X_{t-3}$$

- the impact multiplier 0.4, the interim multiplier 0.75, total or long-run multiplier 0.85
- if income increases by \$1000 in year t and assuming this increase is maintained, consumption will increase
 - \$400 in the first year
 - another \$200 in the second year
 - another \$150 in the third year
 - final total increase \$750
 - presumably, the consumer will save \$250

OLS Estimation

- we can estimate Eq. 1 by the usual OLS method
- however, this is **not practical**
 - 1 how do we decide how many lagged terms we use
 - 2 using several lagged terms leads to fewer degrees of freedom to do meaningful statistical analysis especially if the sample size is small
 - 3 successive values of the lagged term are likely to be correlated causing multicollinearity and imprecise estimation of the regression coefficients

Koyck Distributed Lag Model I

- we can express Eq. 1 in a general form as

$$Y_t = A + B_0X_t + B_1X_{t-1} + B_2X_{t-2} + \dots + u_t \quad (3)$$

- **infinite DLM** as we have not defined the length of the lag [how far back in time we want to travel]
- note that Eq. 1 represents a **finite DLM** with 16 lagged terms

Koyck Distributed Lag Model II

- Koyck uses the geometric probability distribution to estimate the parameters of Eq. 3
- assuming that all the β coefficients in Eq. 3 have the same sign, Koyck assumed that they decline geometrically as follows

$$B_k = \beta_0 \lambda^k, \quad k = 0, 1, \dots; \quad 0 < \lambda < 1 \quad (4)$$

- λ the rate of decline of decay
- $(1 - \lambda)$ the speed of adjustment [i.e., how fast consumption expenditure adjusts to the new income level]

Koyck Distributed Lag Model III

- the value of β_k in Eq. 4 depends on β_0 and λ
- a value of λ close to 1
 - β_k declines slowly [i.e., X values in distant past will have some impact on the current value of Y]
- a value of λ close to zero
 - the impact of X in the distant past will have little impact on the current Y
- assuming $0 < \lambda < 1$ means that
 - each successive β coefficient is numerically smaller than each preceding β
 - as we go back into the distant past, the effect of that lag on Y becomes progressively smaller

Koyck DLM Estimation

$$Y_t = A + B_0X_t + B_0\lambda X_{t-1} + B_0\lambda^2 X_{t-2} + B_0\lambda^3 X_{t-3} + \cdots + u_t \quad (5)$$

- not easy to estimate an infinite number of coefficients and the adjustment coefficient λ enters highly nonlinearly
- **Koyck transformation**

$$Y_t = A(1 - \lambda) + \beta_0 X_t + \lambda Y_{t-1} + v_t \quad (6)$$

- where $v_t = u_t - \lambda u_{t-1}$

Koyck transformation

$$Y_t = A(1 - \lambda) + \beta_0 X_t + \lambda Y_{t-1} + v_t$$

- not that the lagged value of the dependent variable appears as a regressor [autoregressive model]
- instead of estimating an infinite number of parameters in Eq.3, we estimate only three parameters in model 6

Autoregressive Model

$$Y_t = A(1 - \lambda) + \beta_0 X_t + \lambda Y_{t-1} + v_t$$

- the impact of a unit change in X on the mean value of Y
 - the short-run impact \rightarrow the coefficient of X , β_0
 - the long-run impact $\rightarrow \beta_0/(1 - \lambda)$
 - since λ lies between 0 and 1, the long-run impact will be greater than the short-run impact [it takes time to adjust to the changed income]

Autoregressive Model: Estimation I

$$Y_t = A(1 - \lambda) + \beta_0 X_t + \lambda Y_{t-1} + v_t$$

- estimating Eq. 6 poses formidable challenges
 - 1 even if u_t satisfies the classical assumptions, the composite error term v_t may not [will be serially correlated]
 - 2 since Y_t is stochastic, Y_{t-1} will be stochastic too
 - OLS assumes regressors to be either non-stochastic, or if stochastic, they must be distributed independently of the error term
 - Y_{t-1} and v_t are correlated \rightarrow OLS estimators are not even consistent
 - 3 we cannot use Durbin-Watson to test for serial correlation

Autoregressive Model: Estimation II

$$Y_t = A(1 - \lambda) + \beta_0 X_t + \lambda Y_{t-1} + v_t$$

- the Koyck model, although elegant, poses formidable estimation problems
- the error term v_t is autocorrelated but we can use HAC standard errors discussed in lecture 6
- the more serious problem is correlation between the lagged Y_t and the error term v_t
 - find a proxy for Y_{t-1} which is highly correlated with Y_{t-1} and yet uncorrelated with v_t [an instrumental variable IV]



Personal Consumption Expenditure: OLS Estimation

Dependent Variable: PCE

Method: Least Squares

Sample (adjusted): 1961 2009

Included Observations: 49 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-485.8849	197.5245	-2.459872	0.0177
DPI	0.432575	0.081641	5.298529	0.0000
PCE(-1)	0.559023	0.084317	6.630052	0.0000

R-squared	0.998251	Mean dependent var	19602.16
Adjusted R-squared	0.998175	S.D. dependent var	6299.838
S.E. of regression	269.1558	Akaike info criterion	14.08773
Sum squared resid	3332462	Schwarz criterion	14.20355
Log likelihood	-342.1493	Hannan-Quinn criter.	14.13167
F-statistic	13125.09	Durbin-Watson stat	0.708175
Prob(F-statistic)	0.000000		

Personal Consumption Expenditure: HAC

Dependent Variable: PCE

Method: Least Squares

Sample (adjusted): 1961 2009

Included Observations: 49 after adjustments

HAC standard errors & covariance (Bartlett kernel, Newey–West fixed bandwidth = 4.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-485.8849	267.7614	-1.814619	0.0761
DPI	0.432575	0.098339	4.398823	0.0001
PCE(-1)	0.559023	0.102057	5.477587	0.0000

R-squared	0.998251	Mean dependent var	19602.16
Adjusted R-squared	0.998175	S.D. dependent var	6299.838
S.E. of regression	269.1558	Akaike info criterion	14.08773
Sum squared resid	3332462	Schwarz criterion	14.20355
Log likelihood	-342.1493	Hannan–Quinn criter.	14.13167
F-statistic	13125.09	Durbin–Watson stat	0.708175
Prob(F-statistic)	0.000000		

Personal Consumption Expenditure: Proxy

Dependent Variable: PCE

Method: Least Squares

Sample (adjusted): 1961 2009

Included Observations: 49 after adjustments

HAC standard errors & covariance (Bartlett kernel, Newey–West fixed bandwidth = 4.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-1425.511	372.3686	-3.828224	0.0004
DPI	0.934361	0.175986	5.309287	0.0000
DPI(-1)	0.038213	0.177358	0.215455	0.8304

R-squared	0.996583	Mean dependent var	19602.16
Adjusted R-squared	0.996434	S.D. dependent var	6299.838
S.E. of regression	376.1941	Akaike info criterion	14.75736
Sum squared resid	6510013	Schwarz criterion	14.87318
Log likelihood	-358.5553	Hannan–Quinn criter.	14.80130
F-statistic	6707.481	Durbin–Watson stat	0.351356
Prob(F-statistic)	0.000000		

ARDL Model I

$$Y_t = A_0 + A_1 Y_{t-1} + A_2 Y_{t-2} + \cdots + A_p Y_{t-p} \\ + \beta_0 X_t + \beta_1 X_{t-1} + \beta_2 X_{t-2} + \cdots + \beta_q X_{t-q} + u_t$$

- the lagged Y s constitute the autoregressive part
- the lagged X s constitute the distributed part
- p autoregressive terms and q distributed lag terms

ARDL Model II

- advantages of an ARDL model
 - captures the dynamic effects of the lagged Y s and also those of the lagged X s
 - can eliminate autocorrelation in the error term if sufficient number of lags of both variables included
 - are often used for forecasting and estimating the multiplier effects of the regressors in the model

ARDL: Consumption Function

$$Y_t = A_0 + A_1 Y_{t-1} + \beta_0 X_t + \beta_1 X_{t-1} + u_t, \quad A_1 < 1 \quad (7)$$

- $Y_t = PCE$ and $X = DPI$
- ARDL (1,1) model [Eq. 7] enables us to find the dynamic effects of a change in DPI on current value and future values of PCE
- the immediate effect [impact multiplier] of a unit change in DPI given by β_0
- if the unit change in DPI is sustained, the long-run multiplier is given by $\frac{\beta_0 + \beta_1}{1 - A_1}$

ARDL: Assumptions

- we have to make certain assumptions
 - 1 the variables X and Y are stationary
 - 2 the expected mean value of the error term u_t is zero
 - 3 the error term is serially uncorrelated
 - 4 the X variables are exogenous - at least weakly so [uncorrelated with the error term]

ARDL: OLS estimation

Dependent Variable: PCE

Method: Least Squares

Sample (adjusted): 1961 2009

Included Observations: 49 after adjustments

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-281.2019	161.0712	-1.745823	0.0877
DPI	0.824591	0.097977	8.416208	0.0000
PCE(-1)	0.805356	0.081229	9.914632	0.0000
DPI(-1)	-0.632942	0.118864	-5.324935	0.0000

R-squared	0.998927	Mean dependent var	19602.16
Adjusted R-squared	0.998855	S.D. dependent var	6299.838
S.E. of regression	213.1415	Akaike info criterion	13.63990
Sum squared resid	2044318.	Schwarz criterion	13.79433
Log likelihood	-330.1775	Hannan-Quinn criter.	13.69849
F-statistic	13962.93	Durbin-Watson stat	1.841939
Prob(F-statistic)	0.000000		

ARDL: HAC

Dependent Variable: PCE

Method: Least Squares

Sample (adjusted): 1961 2009

Included Observations: 49 after adjustments

HAC standard errors & covariance (Bartlett kernel, Newey–West fixed bandwidth = 4.0000)

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-281.2019	117.3088	-2.397107	0.0207
PCE(-1)	0.805356	0.071968	11.19044	0.0000
DPI	0.824591	0.114989	7.171026	0.0000
DPI(-1)	-0.632942	0.119717	-5.286977	0.0000

R-squared	0.998927	Mean dependent var	19602.16
Adjusted R-squared	0.998855	S.D. dependent var	6299.838
S.E. of regression	213.1415	Akaike info criterion	13.63990
Sum squared resid	2044318.	Schwarz criterion	13.79433
Log likelihood	-330.1775	Hannan–Quinn criter.	13.69849
F-statistic	13962.93	Durbin–Watson stat	1.841939
Prob(F-statistic)	0.000000		

