VAR / co-integration / ARDL / ECM

1) step 1:- Check stationarity for individual
View -> unit root test -> OK.
~~Null~~ Ho:- It has unit root (non-stationary)
if Prob > 0.05 => accept Ho.

If non-stationary ~~sta~~ level 1. ((1st difference)
=> Stationary I(1)

2) If all series are stationary at different levels check for cointegration -> Bounce test

Sub-step

1) for finding out optimal lag, we will make ~~at~~ data open as a group.

2) Quick -estimate VAR -> standard VAR
-> endogenous variables (all variables)
-> lag Intervals (1 4 ~~to~~ for quarterly data)
-> OK.

3) Go down -> check AIC and SC (which is minimum) -> View -> Lag structure -> Lag length criteria -> check for '*'
AIC ~~gives~~ or SC (which is minimum)
This will give you the lag length.

3) Bounce Test

Before Bounce Test do ARDL test for that

Quick -> estimate equation -> (dependent & Independent)
equation -> Choose ARDL model -> OK.
Another ~~dogonal~~ dilogue box. -> choose the optimal lag as max lag

Trend specification → constant → ok.

View → coefficient Diagonsties → Long run form

bounds test → ok

go to F statistic

Check F statistic value compare with I (0) and I (1)

~~if value is great~~

~~if F statistic value is~~ > than I (1) or less than ~~I(0)~~

if F statistic value is < I (0) → ~~reject~~ cannot reject null hypothesis (there is no cointegration) so it means no long term relationship b/w variables, so we are using ARDL model for estimation.

if F statistic value is > I (1) → ~~Accept~~ reject null hypothesis (co-integration is present) so we will use ECM model

Do it for all data keeping one by one as dependent variable. if ~~all~~ in all cases co-integration is present do VECM model.

Estimating ARDL.

Select the data for ARDL model

Quick → estimate VAR ~~equation~~ → ~~dep c delp → ARDL~~

Eg:-

Dependent Variable	F-statistic	Cointegration	What next?
X	F "	NO	estimate ARDL (short-run model)
Y		Yes	Estimate ECM (Error correction model)
Z		NO	Estimate ARDL.

- for every model we will find optimal lags for that we will do VAR for each model.

Quick - estimate VAR - standard VAR → Endogenous variable (dependent variable) → lag → Exogenous variable (C and all independent variable) → OK.

After that same as substep ~~(2)~~ → (3)

do it for all models.

Estimate ARDL
Quick → estimate equation → ?.

Since ARDL we will take difference of all variables

d (dependent variable) c d (independent variable (-optimal lags))

d(dep Variable) (-optimal lags)

~~eg: d(x) c d(y(-1)) d(z(-1))~~ d(x(-1))

~~for lag 2~~ ~~d(x(-1)) d(x~~ ~~d(x(-1)(-2))~~

~~d(x) c d(y(-1)(-2)) d(z(-1)(-2))~~

→ OK

eg:- for lag 1

d(x) c d(x(-1)) d(y(-1)) d(z(-1))

for lag 2

d(x) c d(x(-1)) d(x(-2)) d(y(-1)) d(y(-2))

d(z(-1)) d(z(-2))

check for prob (variable significant)

If prob < 0.05 → significant

Check for R2 value, Durbin-watson Stat.

~~proc → make residual series → ordinary → ecm~~

* View → Residual diagnostics → serial correlation LM test

→ optimal lag → check F statistic

if prob. F > 0.05 → no correlation

View → Stability diagnostics → Recursive estimates →

CUSUM test → OK.

If the line is inside the significance model is

stable.

Estimate ECM

There will be 2 equation

1st will be long run model which will give us error correction term 2nd will be Error correction model = Shortterm + Error correction term

Quick → estimate equation →

eg:- depen variable c, dep variable (-Lag) Indep variable (-Lag) eg:- x c x(-1) y(-1) z(-1) → ok.

Proc → make residual series → Name for series (ECM)

→ ok.

~~Quick~~

~~Spl Estimating~~

~~Proc → e~~

Quick → Estimate equation →

d(dependent variable) c d (dependent variable (-lag)
d(Independent variable (-lag)
ecm(-lag)

eg:-
d(x) c d(x(-1)) d(y(-1)) d(z(-1))
ecm(-1) → ok.

check for significance of ECM

coefficient of ecm and probability of ecm

-ve (error correction will happen) < 0.05 significant

① view → Residual diagnostics → serial correlation → optimal lag → check F statis → if prob F > 0.05 → no-correction

② view → stability diagnostic → Recursive estimates →

CUSUM test → OK.

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Volatility.

Large changes in stock returns seem to be followed by further large changes → volatility clustering

Homoskedasticity → constant variance.

ARCH MODEL

→ Variance of the residuals at time t depends on the squared error terms from past periods.

→ It is better to model simultaneously the mean and the variance of a series when it is suspected that the conditional variance is not constant.

→ variance of the residuals (σ^2) depends on history or to have heteroskedasticity because the variance will change over time.

→ to allow this is to have the variance depend on one lagged period of the squared error. → ARCH(1)

$$Y_t = a + \beta' X_t + U_t \rightarrow \text{Mean equation}$$

$$U_t \mid \Omega_t \sim iid(0, h_t)$$

$$h_t = \gamma_0 + \gamma_1 U_{t-1}^2 \rightarrow \text{variance equation}$$

ARCH Model ~~for~~ By Eviews → Financial data.

① Test for stationarity

View → unit root test → Level → OK.

② Test for Heteroscedasticity

→ Lagrange Multiplier (LM) test for ARCH is used

eg:- Quick → estimate equation (to find ARCH 1 is present)

r_ftse c r_ftse(-1)

click ok.

View → Residuals Diagnostics → Heteroskedasticity test → ARCH → No of lags (1) → OK.

Check the probability value of obs* R squared if it is less than 0.05 then reject null hypothesis of homoskedasticity

So conclude ARCH(1) is present.

③ Estimate ARCH Model

~~Qui~~ Estimate equation → ARCH → select

ARCH (1) GARCH (0) → OK.

ARCH M - NONE

Threshold order - 0

~~equation~~

To get equation → View → representation

To view conditional variance and conditional standard deviation.

View → Garch Graphs → conditional SD graph.
" " → conditional variance.

To obtain variance series

Procs → Make garch variance series.

GARCH Model

ARCH model looks like moving average than autoregression. So they introduce GARCH model

$$Y_t = a + \beta' X_t + u_t$$

$$u_t | \Omega_t \sim iid\ N(0, h_t)$$

$$h_t = \gamma_0 + \sum_{i=1}^{p} \delta_i h_{t-i} + \sum_{j=1}^{q} \gamma_j u_{t-j}^2$$

h_t → depends both on past values of the stocks which are captured by the lagged squared residual terms, and on past values itself which are captured by lagged h_t terms.

GARCH(1,1)

$$h_t = \gamma_0 + \delta_1 h_{t-1} + \gamma_1 u_{t-1}^2$$

Estimation

Same as ARCH (1)

only difference GARCH (1) in estimate equation

After finding out this effect again check

ARCH LM-test.

View ⇒ Residual diagnostics → ARCH LM test

Check probability of obs* R2 square

< 0.05 Accept null

> 0.05 Accept Alternate hypothesis that

test statistics do not support for any additional ARCH effect remaining in the residuals of the models which implies that the variance equation is well specified for the market.

GARCH-M Model

⇒ It allow the conditional mean to depend on its own conditional variance.

⇒ To get the premium GARCH-M Model is used.

⇒ To capture risk.

⇒ Same as GARCH put in ARCH-M Model either variance or std. dev.

TGARCH Model

→ ARCH and GARCH Model are asymmetric. i.e matters is only the absolute value of innovation and not its sign

→ But in the stock markets there is (-ve and +ve) impact. -ve ~~impact~~ shocks in the market have a larger impact on volatility than do postive shocks of the same magnitude.

→ This model help us to capture asymmetrics in terms of negative and positive shocks.

→ To do this, simply add into the variance equation a multiplicative dummy variable to check whether there is a statistically significant difference when shocks are -ve.

- Model same as GARCH put threshold value 1

~~(Resid < 0) ⇒ * ARCH(1)~~ →

(Resid (-1) ^2 * (RESID (-1) < 0) is +ve and ~~a~~ statistically signifacant then the data there are asymmetrics in the news.

Specifically bad news has larger effects on the volatility of the series than good news.

EGARCH Model

⇒ This model makes the leverage effect exponential rather than quadratic and therefore the estimates of the conditional variance are guaranteed to be non-negative.

⇒ This is used for testing asymmetric

$\varepsilon_1 = \varepsilon_2 = 0$ → Model is symmetric

$\varepsilon_j < 0$ +ve shock generate less volatility than -ve shock.

~~So~~ same as TGARCH Instead of GARCH / TGARCH put EGARCH

If any -ve value is there in coefficients then ~~there~~ the bad news has larger effects on volatility of the series than good news.