Lecture Note of Bus 41202, Spring 2014: Analysis of Multiple Financial Time Series with Applications

Reference: Chapters 8 and 10 of the textbook.
We shall focus on two series (i.e., the bivariate case)

Time series:

\[ \mathbf{X}_t = \begin{bmatrix} x_{1t} \\ x_{2t} \end{bmatrix} . \]

Data: \( x_1, x_2, \ldots, x_T \).

Some examples: (a) U.S. quarterly GDP and unemployment rate series; (b) The daily closing prices of oil related ETFs, e.g. oil services holdings (OIH) and energy select section SPDR (XLE); quarterly GDP grow rates of Canada, United Kingdom, and United States.

**Why consider two series jointly?**
(a) Obtain the relationship between the series and (b) improve the accuracy of forecasts (use more information). See Figure 1 for the log prices of the two energy funds. The prices seem to move in unison.

Some background:

**Weak stationarity:** Both

\[ E(\mathbf{X}_t) = \begin{bmatrix} E(x_{1t}) \\ E(x_{2t}) \end{bmatrix} = \mathbf{\mu}, \quad \text{and} \]

\[ \text{Cov}(\mathbf{X}_t, \mathbf{X}_{t-j}) = \begin{bmatrix} \text{Cov}(x_{1t}, x_{1,t-\ell}) & \text{Cov}(x_{1t}, x_{2,t-\ell}) \\ \text{Cov}(x_{2t}, x_{1,t-\ell}) & \text{Cov}(x_{2t}, x_{2,t-\ell}) \end{bmatrix} = \mathbf{\Gamma}_j \]

are time invariant

**Auto-covariance matrix:** Lag-\( \ell \)

\[ \mathbf{\Gamma}_\ell = E[(\mathbf{X}_t - \mathbf{\mu})(\mathbf{X}_{t-\ell} - \mathbf{\mu})'] \]
\[
\begin{bmatrix}
E(x_{1t} - \mu_1)(x_{1,t-\ell} - \mu_1) & E(x_{1t} - \mu_1)(x_{2,t-\ell} - \mu_2) \\
E(x_{2t} - \mu_2)(x_{1,t-\ell} - \mu_1) & E(x_{2t} - \mu_2)(x_{2,t-\ell} - \mu_2)
\end{bmatrix}
= \begin{bmatrix}
\Gamma_{11}(\ell) & \Gamma_{12}(\ell) \\
\Gamma_{21}(\ell) & \Gamma_{22}(\ell)
\end{bmatrix}.
\]

**Not symmetric** if \(\ell \neq 0\). Consider \(\Gamma_1\):

- \(\Gamma_{12}(1) = \text{Cov}(x_{1t}, x_{2,t-1})\) (\(x_{1t}\) depends on past \(x_{2t}\))
- \(\Gamma_{21}(1) = \text{Cov}(x_{2t}, x_{1,t-1})\) (\(x_{2t}\) depends on past \(x_{1t}\))

Let the diagonal matrix \(D\) be

\[
D = \begin{bmatrix}
\text{std}(x_{1t}) & 0 \\
0 & \text{std}(x_{2t})
\end{bmatrix} = \begin{bmatrix}
\sqrt{\Gamma_{11}(0)} & 0 \\
0 & \sqrt{\Gamma_{22}(0)}
\end{bmatrix}.
\]

**Cross-Correlation matrix:**

\[
\rho_{\ell} = D^{-1}\Gamma_{\ell}D^{-1}
\]

Thus, \(\rho_{ij}(\ell)\) is the cross-correlation between \(x_{it}\) and \(x_{j,t-\ell}\).

From stationarity:

\[
\Gamma_{\ell} = \Gamma'_{-\ell}, \quad \rho_{\ell} = \rho'_{-\ell}.
\]

For instance, \(\text{cor}(x_{1t}, x_{2,t-1}) = \text{cor}(x_{2t}, x_{1,t+1})\).

**Testing for serial dependence**

Multivariate version of Ljung-Box \(Q(m)\) statistics available.

\(H_o : \rho_1 = \cdots = \rho_m = 0\) vs. \(H_a : \rho_i \neq 0\) for some \(i\). The test statistic is

\[
Q_2(m) = T^2 \sum_{\ell=1}^{m} \frac{1}{T-\ell} tr(\hat{\Gamma}_{\ell}\hat{\Gamma}_{0}^{-1}\hat{\Gamma}_{\ell}\hat{\Gamma}_{0}^{-1})
\]

which is \(\chi^2_{k^2_m}\). Note \(tr\) is the sum of diagonal elements.
Remark: Analysis of multiple financial time series can be carried out in R via the package MTS.

Demonstration: Consider the quarterly series of U.S. GDP and unemployment data

```r
> require(MTS)
> x=read.table("q-gdpun.txt",header=T)
> dim(x)
[1] 228 5
> x[1,]
   year mon day gdp unemp
1 1948 1 1 7.3878 3.7333
> z=x[,4:5]
> mq(z,10)
[1] "m, Q(m) and p-value:"
 [1] 1.0000 434.0739 0.0000
 [1] 2.0000 827.5327 0.0000
 [1] 3.0000 1176.616 0.0000
 [1] 4.0000 1486.840 0.0000
 [1] 5.0000 1767.619 0.0000
 [1] 6.0000 2026.774 0.0000
 [1] 7.0000 2268.947 0.0000
 [1] 8.0000 2496.995 0.0000
 [1] 9.0000 2713.950 0.0000
 [1] 10.0000 2921.077 0.0000
```
> dz=diffM(z) ### Take difference of individual series
> mq(dz,10)

[1] "m, Q(m) and p-value:"
[1] 1.0000 105.3880 0.0000
[1] 2.0000 153.2457 0.0000
[1] 3.0000 176.7565 0.0000
[1] 4.0000 196.1902 0.0000
[1] 5.0000 207.9687 0.0000
[1] 6.0000 212.5574 0.0000
[1] 7.0000 215.8745 0.0000
[1] 8.0000 221.8316 0.0000
[1] 9.0000 225.8715 0.0000
[1] 10.0000 228.1209 0.0000

The results show that the bivariate series is strongly serially corre-
lated.

**Vector Autoregressive Models (VAR)**

VAR(1) model for two return series:

\[
\begin{bmatrix}
    r_{1t} \\
    r_{2t}
\end{bmatrix} =
\begin{bmatrix}
    \phi_{10} \\
    \phi_{20}
\end{bmatrix} +
\begin{bmatrix}
    \phi_{11} & \phi_{12} \\
    \phi_{21} & \phi_{22}
\end{bmatrix}
\begin{bmatrix}
    r_{1,t-1} \\
    r_{2,t-1}
\end{bmatrix} +
\begin{bmatrix}
    a_{1,t} \\
    a_{2,t}
\end{bmatrix},
\]

where \( a_t = (a_{1t}, a_{2t})' \) is a sequence of iid bivariate normal random vectors with mean zero and covariance matrix

\[
\text{Cov}(a_t) = \Sigma =
\begin{bmatrix}
    \sigma_{11} & \sigma_{12} \\
    \sigma_{21} & \sigma_{22}
\end{bmatrix}
\]

where \( \sigma_{12} = \sigma_{21} \).

Rewrite the model as

\[
\begin{align*}
    r_{1t} &= \phi_{10} + \phi_{11}r_{1,t-1} + \phi_{12}r_{2,t-1} + a_{1t} \\
    r_{2t} &= \phi_{20} + \phi_{21}r_{1,t-1} + \phi_{22}r_{2,t-1} + a_{1t}
\end{align*}
\]

Thus, \( \phi_{11} \) and \( \phi_{12} \) denotes the dependence of \( r_{1t} \) on the past returns \( r_{1,t-1} \) and \( r_{2,t-1} \), respectively.
Unidirectional dependence

For the VAR(1) model, if $\phi_{12} = 0$, but $\phi_{21} \neq 0$, then

- $r_{1t}$ does not depend on $r_{2,t-1}$, but
- $r_{2t}$ depends on $r_{1,t-1}$,

implying that knowing $r_{1,t-1}$ is helpful in predicting $r_{2t}$, but $r_{2,t-1}$ is not helpful in forecasting $r_{1t}$.

Here $\{r_{1t}\}$ is an input, $\{r_{2t}\}$ is the output variable. This is an example of Granger causality relation.

If $\sigma_{12} = 0$, then $r_{1t}$ and $r_{2t}$ are not concurrently correlated.

**Stationarity condition:** Generalization of 1-dimensional case

Write the VAR(1) model as

$$r_t = \phi_0 + \Phi r_{t-1} + a_t.$$

$\{r_t\}$ is stationary if zeros of the polynomial $|I - \Phi x|$ are greater than 1 in modulus. Equivalently, if solutions of $|I - \Phi x| = 0$ are all greater than 1 in modulus.

Mean of $r_t$ satisfies

$$(I - \Phi)\mu = \phi_0, \quad \text{or}$$

$$\mu = (I - \Phi)^{-1}\phi_0$$

if the inverse exists.

Covariance matrices of VAR(1) models:

$$\text{Cov}(r_t) = \sum_{i=0}^{\infty} \Phi^i \Sigma (\Phi^i)'$$

so that

$$\Gamma_{\ell} = \Phi \Gamma_{\ell-1}$$
for $\ell > 0$.

Can be generalized to higher order models.

Building VAR models

- Order selection: use AIC or BIC or a stepwise $\chi^2$ test Eq. (8.18). See Section 8.2.4, pp 405-406.

  For instance, test VAR(1) vs VAR(2).

- Estimation: use ordinary least-squares method

- Model checking: similar to the univariate case

- Forecasting: similar to the univariate case

Simple AR models are sufficient to model asset returns.

**Program note:** Commands for VAR modeling

- VARorder: compute various information criteria for a vector time series

- VAR: estimate a VAR model

- refVAR: refine an estimated VAR model by fixing insignificant estimates to zero

- MTSdiag: model checking

- VARpred: predict a fitted VAR model.

**Co-integration**

Basic ideas

- $x_{1t}$ and $x_{2t}$ are unit-root nonstationary
• a linear combination of $x_{1t}$ and $x_{2t}$ is unit-root stationary

That is, $x_{1t}$ and $x_{2t}$ share a single unit root!

Why is it of interest?
Stationary series is *mean reverting*.
Long term forecasts of the “linear” combination converge to a mean value, implying that the long-term forecasts of $x_{1t}$ and $x_{2t}$ must be linearly related.
This mean-reverting property has many applications. For instance, pairs trading in finance.

**Example.** Consider the exchange-traded funds (ETF) of U.S. Real Estate. We focus on the iShares Dow Jones (IYR) and Vanguard REIT fund (VNQ) from October 2004 to May 2007. The daily adjusted prices of the two funds are shown in Figure 2. What can be said about the two prices? Is there any arbitrage opportunity between the two funds? The two series all have a unit root (based on ADF test). Are they co-integrated?

**Co-integration test**
 Several tests available, e.g. Johansen’s test (Johansen, 1988).

**Basic idea**
Consider a univariate AR(2) model

$$x_t = \phi_1 x_{t-1} + \phi_2 x_{t-2} + a_t.$$ 

Let $\Delta x_t = x_t - x_{t-1}$.
Subtract $x_{t-1}$ from both sides and rearrange terms to obtain

$$\Delta x_t = \gamma x_{t-1} + \phi_1^* \Delta x_{t-1} + a_t,$$
where \( \phi_1^* = -\phi_2 \) and \( \gamma = \phi_2 + \phi_1 - 1 \).
(Derivation involves simple algebra.)
\( x_t \) is unit-root nonstationary if and only if \( \gamma = 0 \).
Testing that \( x_t \) has a unit root is equivalent to testing that \( \gamma = 0 \) in
the above model.
The idea applies to general AR(\( p \)) models.

Turn to the VAR(\( p \)) case. The original model is
\[
X_t = \Phi_1 X_{t-1} + \cdots + \Phi_p X_{t-p} + a_t.
\]
Let \( Y_t = X_t - X_{t-1} \).
Subtracting \( X_{t-1} \) from both sides and re-grouping of the coefficient
matrices, we can rewrite the model as
\[
Y_t = \Pi X_{t-1} + \sum_{i=1}^{p-1} \Phi_i^* Y_{t-i} + a_t, \tag{1}
\]
where
\[
\Phi_{p-1}^* = -\Phi_p
\]
\[
\Phi_{p-2}^* = -\Phi_{p-1} - \Phi_p
\]
\[
\vdots = \vdots
\]
\[
\Phi_1^* = -\Phi_2 - \cdots - \Phi_p
\]
\[
\Pi = \Phi_p + \cdots + \Phi_1 - I.
\]

This is the Error-Correction Model (ECM).

**Important message:** The matrix \( \Pi \) is a zero matrix if there is no co-integration.

The **Key** concept related to pairs trading is that \( Y_t \) is related to \( \Pi X_{t-1} \).

To test for co-integration:

- Fit the model in Eq. (1),
- Test for the rank of \( \Pi \).

If \( X_t \) is \( k \) dimensional, and rank of \( \Pi \) is \( m \), then we have \( k - m \) unit roots in \( X_t \).

There are \( m \) linear combinations of \( X_t \) that are unit-root stationary.

If \( \Pi \) has rank \( m \), then

\[
\Pi = \alpha \beta
\]

where \( \alpha \) is a \( k \times m \) and \( \beta \) is a \( m \times k \) full-rank matrix.

\( Z_t = \beta X_t \) is unit-root stationary.

\( \beta \) is the co-integrating vector.

**Discussion**

- ECM formulation is useful
- Co-integration tests have some weaknesses, e.g. robustness
• Co-integration overlooks the effect of scale of the series

**Package**: The package **urca** of **R** can be used to perform co-integration test.

**Pairs trading**


**Motivation**: General idea of trading is to sell overvalued securities and buy undervalued ones. But the *true* value of the security is hard to determine in practice. Pairs trading attempts to resolve this difficulty by using *relative pricing*. Basically, if two securities have similar characteristics, then the prices of both securities must be more or less the same. Here the true price is not important.

**Statistical term**: The prices behave like random-walk processes, but a linear combination of them is stationary, hence, the linear combination is mean-reverting. Deviations from the mean lead to trading opportunities.

**Theory in Finance**: *Arbitrage Pricing Theory* (APT): If two securities have exactly the same risk factor exposures, then the expected returns of the two securities for a given time period are the same. [The key here is that the returns must be the same for all times.]

**More details**: Consider two stocks: Stock 1 and Stock 2. Let $p_{it}$ be the log price of Stock $i$ at time $t$. It is reasonable to assume that the time series $\{p_{1t}\}$ and $\{p_{2t}\}$ contain a unit root when they are analyzed individually.
Assume that the two log-price series are co-integrated, that is, there exists a linear combination $c_1p_{1t} - c_2p_{2t}$ that is stationary. Dividing the linear combination by $c_1$, we have

$$w_t = p_{1t} - \gamma p_{2t},$$

which is stationary. The stationarity implies that $w_t$ is mean-reverting. Now, form the portfolio $Z$ by buying 1 share of Stock 1 and selling short on $\gamma$ shares of Stock 2. The return of the portfolio for a given period $h$ is

$$r(h) = (p_{1,t+h} - p_{1,t}) - \gamma(p_{2,t+h} - p_{2,t})$$

$$= p_{1,t+h} - \gamma p_{2,t+h} - (p_{1,t} - \gamma p_{2,t})$$

$$= w_{t+h} - w_t$$

which is the increment of the stationary series $\{w_t\}$ from $t$ to $t + h$. Since $w_t$ is stationary, we have obtained a direct link of the portfolio to a stationary time series whose forecasts we can predict. Assume that $E(w_t) = \mu$. Select a threshold $\delta$.

**A trading strategy:**

- Buy Stock 1 and short $\gamma$ shares of Stock 2 when $w_t = \mu - \delta$.
- Unwind the position, i.e. sell Stock 1 and buy $\gamma$ shares of Stock 2, when $w_{t+h} = \mu + \delta$.

Profit: $r(h) = w_{t+h} - w_t = 2\delta$.

**Some practical considerations:**

- The threshold $\delta$ is chosen so that the profit out-weights the costs of two trades. In high frequency, $\delta$ must be greater than trading slippage, which is the same linear combination of bid-ask spreads
of the two stock, i.e. bid-ask spread of Stock 1 + \( \gamma \times \) (bid-ask spread) of Stock 2.

- Speed of mean-reverting of \( w_t \) plays an important role as \( h \) is directly related to the speed of mean-reverting.
- There are many ways available to search for co-integrating pairs of stocks. For example, via fundamentals, risk factors, etc.
- For unit-root and co-integration tests, see the textbook and references therein.

**Example:** Consider the daily adjusted closing stock prices of BHP Billiton Limited of Australia and Vale S.A. of Brazil. These are two natural resources companies. Both stocks are also listed in the New York Stock Exchange with tick symbols BHP and Vale, respectively. The sample period is from July 1, 2002 to March 31, 2006.

- How to estimate \( \gamma \)?
- Speed of mean reverting? (zero-crossing concept)

```r
> library(urca)
> help(ca.jo)  # Johansen's co-integration test

> da=read.table("d-bhp0206.txt",header=T)
> da1=read.table("d-vale0206.txt",header=T)
> head(da)
   Mon day year open high low close volume adjclose
1 7 1 2002 11.80 11.92 11.55 11.60 156700 8.39
6 7 9 2002 12.25 12.65 12.25 12.60 142000 9.12
> head(da1)
   Mon day year open high low close volume adjclose
1 7 1 2002 27.60 27.60 27.10 27.16 2307600 1.89
```
Figure 3: Daily log prices of BHP and VALE from July 1, 2002 to March 31, 2006.

> tail(da)
  Mon day year open high low close volume adjclose
941 3 24 2006 37.35 37.75 37.12 37.42 2251200 36.17

> dim(da)
[1] 946 9

bhp=log(da[,9])
> vale=log(da1[,9])
> plot(bhp,type='l')
> plot(vale,type='l')
> m1=lm(bhp~vale)
> summary(m1)

Call: lm(formula = bhp ~ vale)

Residuals:
    Min     1Q Median      3Q     Max
-0.151818 -0.028265  0.003121  0.029803  0.147105
Coefficients:

|        | Estimate | Std. Error | t value | Pr(>|t|) |
|--------|----------|------------|---------|----------|
| (Intercept) | 1.822648 | 0.003662 | 497.7   | <2e-16 *** |
| vale    | 0.716664 | 0.002354 | 304.4   | <2e-16 *** |

---

Residual standard error: 0.04421 on 944 degrees of freedom
Multiple R-squared: 0.9899,  Adjusted R-squared: 0.9899
F-statistic: 9.266e+04 on 1 and 944 DF,  p-value: < 2.2e-16

```r
> bhp1=ts(bhp,frequency=252,start=c(2002,127))
> vale1=ts(vale,frequency=252,start=c(2002,127))
> plot(bhp1,type='l')
> plot(vale1,type='l')
> x=cbind(bhp,vale)
> m1=ar(x)
> m1$order
[1] 2
> m2=ca.jo(x,K=2)
> summary(m2)
```

Johansen Procedure

Test type: maximal eigenvalue statistic (lambda max), with linear trend

Eigenvalues (lambda):

|   | 0.0406019854 | 0.0000101517 |

Values of test statistic and critical values of test:

```
test 10pct 5pct 1pct
r <= 1 | 0.01 6.50 8.18 11.65
r = 0 | 39.13 12.91 14.90 19.19
```

Eigenvectors, normalised to first column:
(These are the cointegration relations)

```
   bhp.l2 vale.l2
bhp.l2  1.000000  1.000000
vale.l2 -0.717784  2.668019
```

Weights W:
(This is the loading matrix)

```
   bhp.l2 vale.l2
bhp.d -0.06272119 -2.179372e-05
```
```r
> m3=ca.jo(x,K=2,type=c("trace"))
> summary(m3)

# Johansen-Procedure#

Test type: trace statistic , with linear trend

Eigenvalues (lambda):
[1] 0.0406019854 0.0000101517

Values of test statistic and critical values of test:

<table>
<thead>
<tr>
<th>test</th>
<th>10pct</th>
<th>5pct</th>
<th>1pct</th>
</tr>
</thead>
<tbody>
<tr>
<td>r &lt;= 1</td>
<td>0.01</td>
<td>6.50</td>
<td>8.18</td>
</tr>
<tr>
<td>r = 0</td>
<td>39.14</td>
<td>15.66</td>
<td>17.95</td>
</tr>
</tbody>
</table>

Eigenvectors, normalised to first column:
(These are the cointegration relations)

```

<table>
<thead>
<tr>
<th>bhp.l2</th>
<th>vale.l2</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.000000</td>
<td>1.000000</td>
</tr>
<tr>
<td>vale.l2</td>
<td>-0.717784</td>
</tr>
</tbody>
</table>

Weights W:
(This is the loading matrix)

```

<table>
<thead>
<tr>
<th>bhp.l2</th>
<th>vale.l2</th>
</tr>
</thead>
<tbody>
<tr>
<td>bhp.d</td>
<td>-0.06272119</td>
</tr>
<tr>
<td>vale.d</td>
<td>0.03303036</td>
</tr>
</tbody>
</table>

```
sigma^2 estimated as 0.000333: log likelihood = 2444.26, aic = -4880.52
> tsdiag(m4)
> plot(wt,type='l')

Multivariate Volatility Models

How do the correlations between asset returns change over time?

Focus on two series (Bivariate)
Two asset return series:

\[ \mathbf{r}_t = \begin{bmatrix} r_{1t} \\ r_{2t} \end{bmatrix}. \]

Data: \( \mathbf{r}_1, \mathbf{r}_2, \ldots, \mathbf{r}_T. \)

Basic concept
Let \( F_{t-1} \) denote the information available at time \( t - 1. \)
Partition the return as

\[ \mathbf{r}_t = \mu_t + \mathbf{a}_t, \quad \mathbf{a}_t = \Sigma_t^{1/2} \mathbf{\epsilon}_t \]

where \( \mu_t = E(\mathbf{r}_t|F_{t-1}) \) is the predictable component, and

\[ \text{Cov}(\mathbf{a}_t|F_{t-1}) = \Sigma_t = \begin{bmatrix} \sigma_{11,t} & \sigma_{12,t} \\ \sigma_{21,t} & \sigma_{22,t} \end{bmatrix}, \]

\( \{\mathbf{\epsilon}_t\} \) are iid 2-dimensional random vectors with mean zero and identity covariance matrix.

Multivariate volatility modeling
See Chapter 10 of the textbook
Study time evolution of \( \{\Sigma_t\}. \)

\( \Sigma_t \) is symmetric, i.e. \( \sigma_{12,t} = \sigma_{21,t} \)
There are 3 variables in $\Sigma_t$.
For $k$ asset returns, $\Sigma_t$ has $k(k + 1)/2$ variables.

**Requirement**

$\Sigma_t$ must be positive definite for all $t$,

$$\sigma_{11,t} > 0, \quad \sigma_{22,t} > 0, \quad \sigma_{11,t}\sigma_{22,t} - \sigma_{12,t}^2 > 0.$$  

The time-varying correlation between $r_{1t}$ and $r_{2t}$ is

$$\rho_{12,t} = \frac{\sigma_{12,t}}{\sqrt{\sigma_{11,t}\sigma_{22,t}}}.$$  

**Some complications**

- Positiveness requirement is not easy to meet
- Too many series to consider

**Some simple models available**

- Exponentially weighted covariance
- Use univariate approach, e.g. $\text{Cov}(X, Y) = \frac{\text{Var}(X+Y) - \text{Var}(X-Y)}{4}$.
- BEKK model
- Dynamic conditional correlation (DCC) models

**Exponentially weighted model**

$$\Sigma_t = (1 - \lambda) a_{t-1}a'_{t-1} + \lambda \Sigma_{t-1},$$  

where $0 < \lambda < 1$. That is,

$$\Sigma_t = (1 - \lambda) \sum_{i=1}^{\infty} \lambda^{i-1} a_{t-i}a'_{t-i}.$$
R command \texttt{EWMAvol} of the \texttt{MTS} package can be used.

**BEKK model** of Engle and Kroner (1995)

Simple BEKK(1,1) model

\[ \Sigma_t = A_0A_0' + A_1(a_{t-1}a_{t-1}')A_1' + B_1\Sigma_{t-1}B_1' \]

where \(A_0\) is a lower triangular matrix, \(A_1\) and \(B_1\) are square matrices without restrictions.

Pros: positive definite

Cons: Many parameters, dynamic relations require further study

Estimation: \texttt{BEKK11} command in \texttt{MTS} package can be used for \(k = 2\) and \(3\) only.

**DCC models:** A two-step process

- Marginal models: Use univariate volatility model for individual return series

- Use DCC model for the time-evolution of conditional correlation

Specifically, the volatility matrix can be written as

\[ \Sigma_t = V_tR_tV_t, \]

where \(V_t\) is a diagonal matrix of volatilities for individual return series and \(R_t\) is the conditional correlation matrix. That is,

\[ V_t = \text{diag}\{v_{1t}, v_{2t}, \ldots, v_{kt}\} \quad R_t = [\rho_{ij,t}] \]

where \(\rho_{ij,t}\) is the correlation between \(i\)th and \(j\)th return series.

Two types of DCC are available in the literature

1. Engle (2002):

\[ Q_t = (1 - \theta_1 - \theta_2)R_0 + \theta_1 Q_{t-1} + \theta_2 a_{t-1}a_{t-1}'. \]
$R_t = q_t^{-1}Q_t q_t^{-1}$,

where $0 \leq \theta_i$ and $\theta_1 + \theta_2 < 1$, $q_t = \text{diag}\{\sqrt{Q_{11,t}}, \sqrt{Q_{22,t}}, \ldots, \sqrt{Q_{kk,t}}\}$ and $R_0$ is the sample correlation matrix.

2. Tse and Tsui (2002):

$$R_t = (1 - \theta_1 - \theta_2)R_0 + \theta_1 R_{t-1} + \theta_2 \psi_{t-1},$$

where $0 \leq \theta_i$ and $\theta_1 + \theta_2 < 1$, and $\psi_{t-1}$ is the sample correlation matrix of $\{a_{t-1}, a_{t-2}, \ldots, a_{t-m}\}$ for a pre-specified positive integer $m$, e.g. $m = 3$.

**Discussion**

1. DCC model is extremely simple with two parameters

2. On the other hand, model checking tends to reject the DCC models.

**R** commands of the MTS package for DCC modeling:

1. dccPre: fit individual GARCH models (standardized return series is included in the output)

2. dccFit: estimate a DCC model for the standardized return series

3. MCHdiag: model checking of multivariate volatility models.

If time permits, demonstration will be given in class.