Advanced Risk Management

Computer Exercise Week 4

In this exercise, we apply the constant conditional correlation (CCC) and dynamic conditional correlation (DCC) models to the daily returns on a set of 4 international stock market indices: S&P 500, FTSE 100, DAX 30, and Nikkei 225. Because the arch package in Python does not support multivariate models yet, we use Stata. The data are given in `StockIndex.dta`; the business dates can be loaded from `index.stbcal`.

Most of the necessary Stata commands are already provided below; but you may wish to consult the following documentation:

- `https://www.stata.com/manuals13/tsmgarch.pdf`
- `https://www.stata.com/manuals13/tsmgarchdcc.pdf`

1. Load the data with the command

   ```
   use path/StockIndex.dta
   ```

   where `path` refers to the folder where you have stored the data set. Make sure to use business dates with the command

   ```
   bcal load path/index
   ```

   where the file `index.stbcal` should be downloaded from Canvas.
   Make a plot of each of the four returns, using the tsline command, e.g.,

   ```
   tsline Dax30, name(Dax)
   ```

   After you have created four of these graphs, you may combine them using

   ```
   graph combine Dax ...
   ```

   where on the dots you include the names that you gave to the other three plots.
   Do you see common patterns in volatility in the four indices? Can you say something about the correlation between them based on this information?

2. We start by fitting a CCC model for only two returns, `SP500` and `Dax30`. The syntax is

   ```
   mgarch ccc (SP500 Dax30), arch(1) garch(1)
   predict v_ccc*, variance
   predict r_ccc*, correlation
   estimates store CCC
   ```

   The first line implies that we estimate a GARCH(1,1) model for the two returns, and estimate the conditional correlation to be constant. The second and third line each create three time series (the time-varying variances and correlations) for later use, and the fourth line stores the estimated model under the name `CCC`, also for later use. Note that the `r_ccc` series are all constant over time by definition.

3. Next, we fit a DCC model for the same two returns, SP500 and Dax30. The syntax is a simple adaptation of the CCC code:

```
mgarch dcc (SP500 Dax30), arch(1) garch(1)
predict v_dcc*, variance
predict r_dcc*, correlation
estimates store DCC
```

   Obtain the estimates of the parameters α and β of the dynamic correlation equation (see Slide 9–10 of Week 4) from the output. Their sum should be less than one for there to be mean-reversion in the correlation; is that what you find?

4. Make a graph comparing the DCC and CCC correlations in one plot (using tsline). Do you find evidence of the suggestion that correlations go up in times of crisis?
   Also check if the DCC model is significantly better than the CCC model, using a likelihood ratio test:

```
lrtest CCC DCC
```

   What is the outcome of this test?

5. To see how important the time-variation in correlation is for risk management purposes, construct the time-varying standard deviation of a portfolio of the two indices, with weights $w_1 = w_2 = \frac{1}{2}$; first using the v_ccc* series, and then using the v_dcc* series. For this, use the well-known result

$$\mathrm{Var}(w_1 R_1 + w_2 R_2) = w_1^2 \,\mathrm{Var}(R_1) + w_2^2 \,\mathrm{Var}(R_2) + 2 w_1 w_2 \,\mathrm{Cov}(R_1, R_2).$$

   Make a graph comparing the CCC and DCC implied portfolio standard deviations, and discuss what you find.

6. To see how robust or sensitive the DCC model is, we end with fitting a DCC model to all four returns at the same time:

```
mgarch dcc (SP500 Dax30 FTSE100 Nikkei225), arch(1) garch(1)
```

   Again save the time-varying correlations using the

```
predict r_dcc4*, correlation
```

   and compare the correlation between SP500 and Dax30 from the two DCC models (the one from Question 3 and the one from this question).