Project Report **Part 2** - SF2943 Time Series Analysis

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1 (b) Peer Review

2) Analysis of an Article

3) Analysis of a Financial Time Series

The aim of this part was to model the *"risk"*, i.e. the cost, of holding one units worth of the OMXS30 stock index for a few days using a GARCH process in comparison to a naïve approach. Typically, evaluating risk for $k > 0$ days is to look at the quantiles in the left tail: $S_t – S_0$. S_t is the index value at closing time t and $t = 0$ is today.

(a1)

The quantiles were obtained from a set of 1 million simulations of the next day S_1. The values for S_0 for January 11th and February 9th 2018 were 1630.29 and 1500.18 respectively. The next corresponding values were calculate through iteration and are found below in Table 1 and 2. The historical values and log-returns of the OMXS30 were taken from the 11th January 2016, approximately 750 data points. The naive model was based on roughly 60 data points.

Table 1: GARCH(1, 1) OMXS30 Simulation Results for S_1 ($k = 1$).

Date	5% Quantile	X_1 (log-return)	σ_1
Jan. 11th, 2018	-7.483	-0.00460	0.00290
Feb. 9th, 2018	-8.333	-0.00557	0.00372

Table 2: **Naive** Model OMXS30 Simulation Results for S_5 ($k = 5$).

Date	5% Quantile	X_1 (log-return)	σ_1
Jan. 11th, 2018	-15.644	-0.00964	0.00292
Feb. 9th, 2018	-22.122	-0.0149	0.00634

As we can see, the GARCH(1, 1) model yielded a smaller change in the 5%-quantile than the Naive model and with a smaller resulting volatility in both simulations for S_1 and S_5. An comparison can be made to the values obtained from the historical OMXS30 data, shown below in Table 3.

Table 3: Comparison between Historical, GARCH(1,1) and Naive Results.

Forecasted S_1	Historical X_t	GARCH(1, 1) X_1	Naive X_1
Jan. 11th, 2018	-0.00161	-0.00460	-0.00964
Feb, 9th, 2018	-0.0130	-0.00557	-0.0149

The GARCH(1,1) forecast for S_1 after January 11th (S_0) was closer to the historical log-return than the Naive approach. However, for February 9th, the Naive approach was very close to the historical value and much closer compared to the GARCH(1,1) model.

(a2)

Again, the quantiles were obtained from a set of 1 million simulations for S_5. Once again, the values for S_0 for January 11th and February 9th 2018 remain unchanged.

Table 4: GARCH(1, 1) OMXS30 Simulation Results for S_5 ($k = 5$).

Date	5% Quantile	X_5 (log-return)	σ_5
Jan. 11th, 2018	-18.378	-0.0113	0.00501
Feb. 9th, 2018	-20.790	-0.00159	0.00483

Table 5: **Naive** Model OMXS30 Simulation Results for S_5 ($k = 5$).

Date	5% Quantile	X_5 (log-return)	σ_5
Jan. 11th, 2018	-34.838	-0.0216	0.00587
Feb. 9th, 2018	-49.117	-0.0333	0.00906

Once again, the naive approach yielded a larger volatility and a larger magnitude of the 5%-quantiles.

(b)

In this section, we compared the GARCH(1,1) fit to the historical log-returns. The graphs for two different time periods (in their corresponding descriptions) are shown below in Figure 1 and Figure 2. It can be seen that the GARCH(1,1) (in red) model stays close around the mean and is quite flat compared to the historical data. Some of the values are in line with the GARCH fit however most of them exhibit very dramatic changes not captured by the model. This is apparent in both Figure 1 and 2.

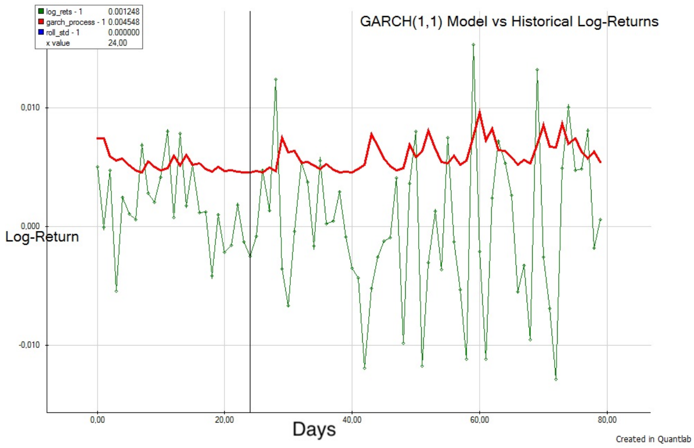

Figure 1: Historical Log-Returns vs. GARCH(1,1) (in red) Model from 1st October 2017 to 11th January 2018.

Figure 2: Historical Log-Returns vs. GARCH(1,1) (in red) Model from 9th November 2017 to 11th January 2018.