# MA 471 Project 2 report

Group 1

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In the first project, we have studied linear time series analysis. Now we look into the non-linear time series models

There are several non-linear time series models. In this project, we focus on the GARCH model which is a generalized ARCH model.

#### ARCH model

ARCH stands for Auto-Regressive Conditional Heteroskedasticity.

Heteroskedasticity is nothing but volatility.(deviation)

Conditional represents that the volatility of the series is dependent on the time where we are at currently.

Autoregressive here means that the volatility at a certain time point depends on the previous time points before it.

# ARCH(1) model

In this basic ARCH model, the volatility follows an AR(1) model

$$Var(a_t) = \sigma_t$$

$$\sigma_t = \alpha_0 + \alpha_1 \sigma_{t-1}$$

We model this using the formula

$$\varepsilon_{t} = W_{t}(\alpha_{0} + \alpha_{1} \varepsilon_{t-1}^{2})^{1/2}$$

Where w<sub>t</sub> is white noise.

## ARCH(p) model

This model includes the values of p previous times into account for the volatility of the present time.

$$\varepsilon_t = W_t(\alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \dots + \alpha_p \varepsilon_{t-p}^2)^{1/2} = W_t \sigma_t$$

#### **GARCH**

GARCH is a generalized ARCH model where the present volatility is not only determined on the previous values of the time series but also the volatilities at previous time points.

## **GARCH(1,1)**

This basic GARCH model is formulated using

$$\varepsilon_t = W_t(\alpha_0 + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1})^{1/2} = \varepsilon_t \sigma_t$$

Here volatility of present time is given a function of the value of time series at t-1 and also the volatility of the time series at time t-1.

### GARCH(p,q)

This model takes into account p previous values of the time series and the q previous volatilities to calculate the volatility of the current time.

The formula given for this is

$$\boldsymbol{\epsilon}_{t} = \boldsymbol{w}_{t} (\boldsymbol{\alpha}_{0} + \boldsymbol{\alpha}_{1} \boldsymbol{\epsilon}_{t-1}^{2} + \dots \dots + \boldsymbol{\alpha}_{p} \boldsymbol{\epsilon}_{t-p}^{2} + \boldsymbol{\beta}_{1} \boldsymbol{\sigma}_{t-1} + \dots \dots \boldsymbol{\beta}_{q} \boldsymbol{\sigma}_{t-q})^{1/2} = \boldsymbol{w}_{t} \boldsymbol{\sigma}_{t}$$

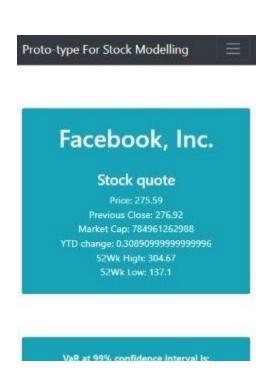
We have also added Value at Risk(VaR) and Expected Shortfall(Es) metric for the stocks.

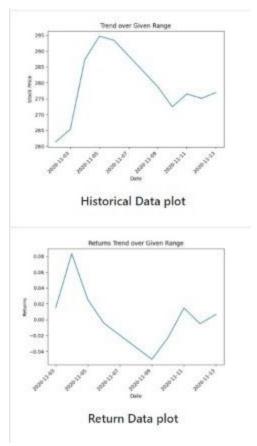
Value at Risk(VaR) Value at Risk (VaR) is a statistic that measures and quantifies the level of financial risk of a portfolio or position over a specific time frame. VaR modeling determines the potential for loss in the entity being assessed and the probability of occurrence for the defined loss. In other words, a 95% 1-day VaR of -0.05 implies we can be 95% certain that 1-day return of this portfolio/stock would be better than -0.05 or with 5% probability returns are worse than -0.05

**Expected Shortfall(ES)** Expected shortfall is also called Conditional Value at Risk(CVaR) which is an alternative to VaR to be used as a risk metric. The

expected shortfall at 95% confidence interval implies the expected return of the stock in the worst 5% cases, .i.e expectation of the tail end of the distribution.

The following results are generated for **Facebook**, **Inc.** from 1-11-2020 to 15-11-2020





The VaR is calculated at 95% and 99% confidence intervals.

VaR at 99% confidence interval is: -0.09263395067908509 VaR at 95% confidence interval is: -0.045009000783775344

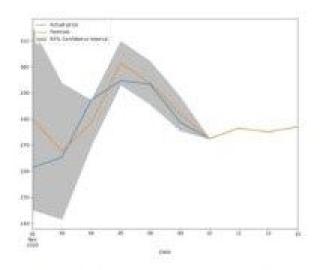
The expected shortfall is calculated at 95 and 99% confidence intervals.

Expected shortfall at 99% confidence interval is: -0.14252997678205148 Expected shortfall at 95% confidence interval is: -0.0717497001908978

Dep. Varia	ble:		ose No.	
Model: Date:		ARIMA(7, 0,	3) Log	
		Thu, 26 Nov 2		
Time:		20:41:38		
Sample:		11 02 2020		
		- 11-13-2	020	
Covariance	: Type:		opg	
	coef	std err		
const	279.9871	0.848	330.179	
ar.L1	1.2729	0.891	1.429	
ar.L2	0.5919	8.749	-0.791	
ar.L3	-0.7185	0.583	-1.233	
ar.L4	0.7137	0.580	1.231	
ar.L5	0.5918	0.757	0.782	
ar.l6	-1.2754	0.763	-1.671	
ar.17	0.9964	8.358	2.785	
ma.L1	0.8793	0.012	70.854	
ma.L2	-0.9574	8.008	-119.951	
ma.L3	-8.9286	8.011	85.590	
sigma2	0.0002	8.882	0.164	
Ljung-Box	(L1) (Q):		2.84	
Prob(Q):			0.15	
Heteroskedasticity (H):			0.82	
Prob(H) (t	0.01			

	u(11) (cm. s		9.01
		Warm	ings:
[1]	Covariance	matrix	calculated using the
[2]	Covariance	matrix	is singular or near-s

Dep. Varia	sble:	Close		R-50
Mean Model	l i	Constant Mean GARCH Normal		
Vol Model:				
Distributi	ion:			
Method:	Hax.	Maximum Likelihood		
				No.
Date:	ा	Thu, Nov 26 2020		Df F
Time:		20:41:38 D		Df P
		Me	an Mo	del
	coef	std err		t
mu	0.3082	1.156		9.267
		Volat	ility	Model
	coef	std err		t
onega	8.7765e-08	4.627	1.89	7e-08
alpha[1]	1.9288e-10	0.599	3.21	9c-10
beta[1]	0.8811	0.516		1.708



ARMA Model Forecast vs Actual Price over given Time Range

If we look at the summary of the GARCH model We have the parameters of the GARCH equation

```
Constant Mean - GARCH Model Results
Dep. Variable: Close R-squared:
Mean Model: Constant Mean Adj. R-squared:
Vol Model: GARCH Log-Likelihood:
Distribution: Normal AIC:
Method: Maximum Likelihood BIC:
                                                                               -0.013
-23.3233
                                                                                     54.6466
                                                                                     55.4355
No. Observations:
Date: Thu, Nov 26 2020 Df Residuals:
                                                                                              9
Time:
                                  22:50:56 Df Model:
                                                                                              4
                                         Mean Model
    _______
                      coef std err t P>|t| 95.0% Conf. Int.
    mu 0.3082 1.156 0.267 0.790 [ -1.957, 2.573]
Volatility Model
                                  Volatility Model
                      coef std err t P>|t| 95.0% Conf. Int.

    omega
    8.7765e-08
    4.627
    1.897e-08
    1.000 [ -9.068, 9.068]

    alpha[1]
    1.9288e-10
    0.599
    3.219e-10
    1.000 [ -1.174, 1.174]

    beta[1]
    0.8811
    0.516
    1.708
    8.754e-02 [ -0.130, 1.892]

                             Covariance estimator: robust
```

The equations for GARCH for the above implementation is as follows

$$r_t = \mu + \epsilon_t$$

$$e_t = \sigma_t e_t$$

$$\sigma^2_t = \omega + \alpha \epsilon^2_{t-1} + \beta \sigma^2_{t-1}$$

We have  $\alpha$ =1.9288e-10  $\beta$ =0.8811  $\omega$ =9.7765e-08  $\mu$ =0.3082

So the mathematical equation for the GARCH model is  $r_{\mbox{\tiny +}} = 0.3082 + \varepsilon_{\mbox{\tiny +}}$ 

$$\sigma_{t}^{2}=9.7765e-08+(1.9288e-10)\epsilon_{t-1}^{2}+0.8811\sigma_{t-1}^{2}$$

# **References**

Data retrieval API: <a href="https://github.com/ranaroussi/yfinance">https://github.com/ranaroussi/yfinance</a>
Stat models: <a href="https://www.statsmodels.org/stable/index.html">https://www.statsmodels.org/stable/index.html</a>

Arch model: <a href="https://arch.readthedocs.io/en/latest/#">https://arch.readthedocs.io/en/latest/#</a>

Analysis of Financial Time-series book bu Ruey S. Tsay