Risk Management — Assignment 3

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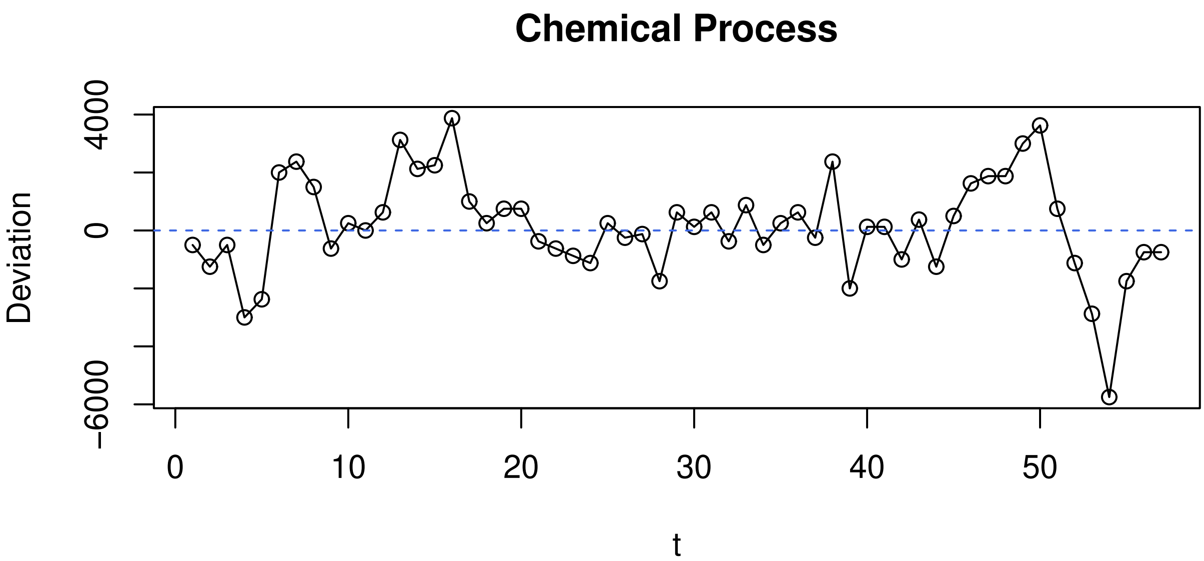
Autumn 2021

Question 1 – Chemical Process

```
(a) Stationarity of the series:
## load library
library(TSA)

## data
data(deere3)

## plot the time series
plot(deere3, xlab = "t", type="o", main="Chemical Process",
     ylab="Deviation")
abline(0, 0, col ="royalblue", lty=2)
```



The plotted time series does appear to have constant mean and variance over time, so at face-value it is worth exploring stationary models to fit the data.

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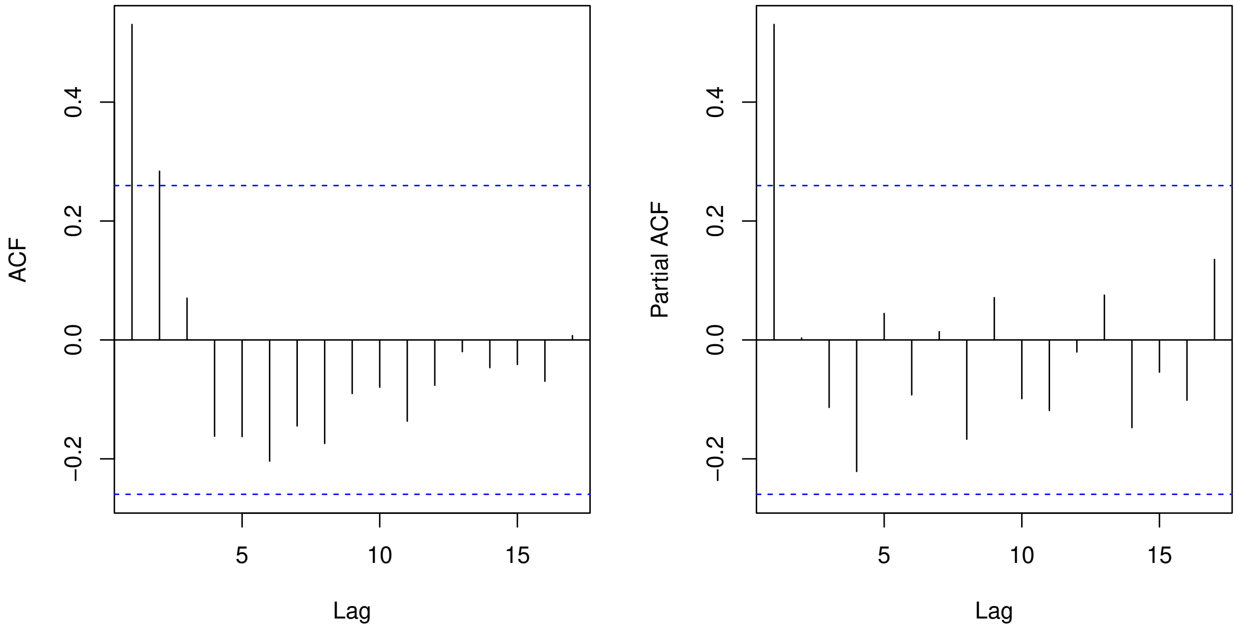
(b) ACF & PACF:

```
## parameters
par(mfrow=c(1,2), mar=c(6,5,2,1), oma=c(0,0,3,0))

## display ACF and PACF => AR(1)
acf(deere3, main="")
pacf(deere3, main="")
```



The **ACF** tails off and the **PACF** cuts off after lag 1.

Our tentative choice is therefore an AR(1) model.

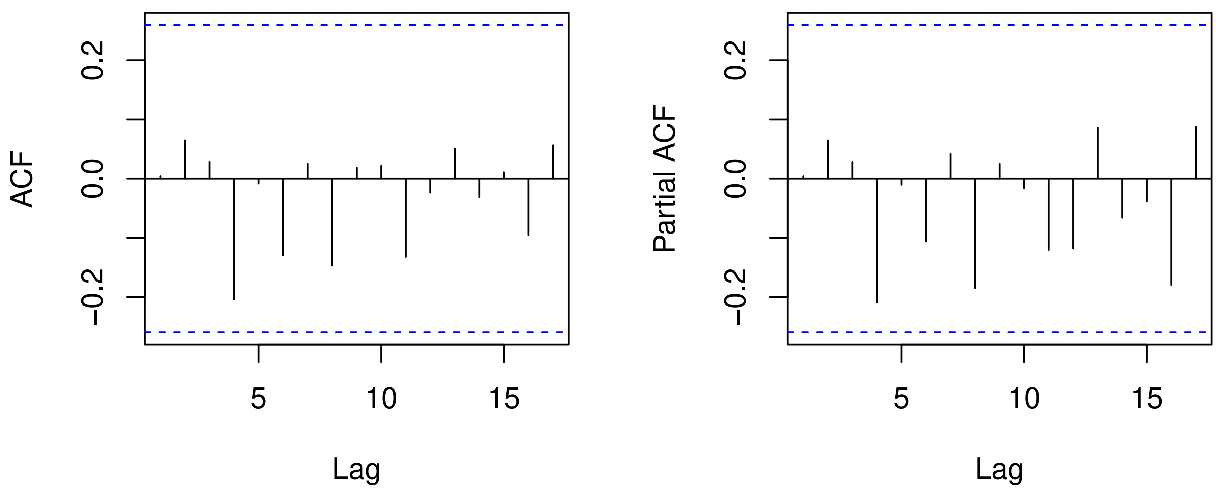
```
(c) Fitted AR(1) model:
## fit
ar.1 <- arima(deere3, order = c(1,0,0))
> ar.1$coef
        ar1   intercept
  0.5255466 124.3832183
```

Our model can be written as:

$$\begin{aligned} X_t &= \phi_1 \, X_{t-1} + \epsilon_t \\ &\approx 0.5 \, X_{t-1} + \epsilon_t \end{aligned}$$

Hence, the value of X_t is moderately positively correlated with the value at X_{t-1}.

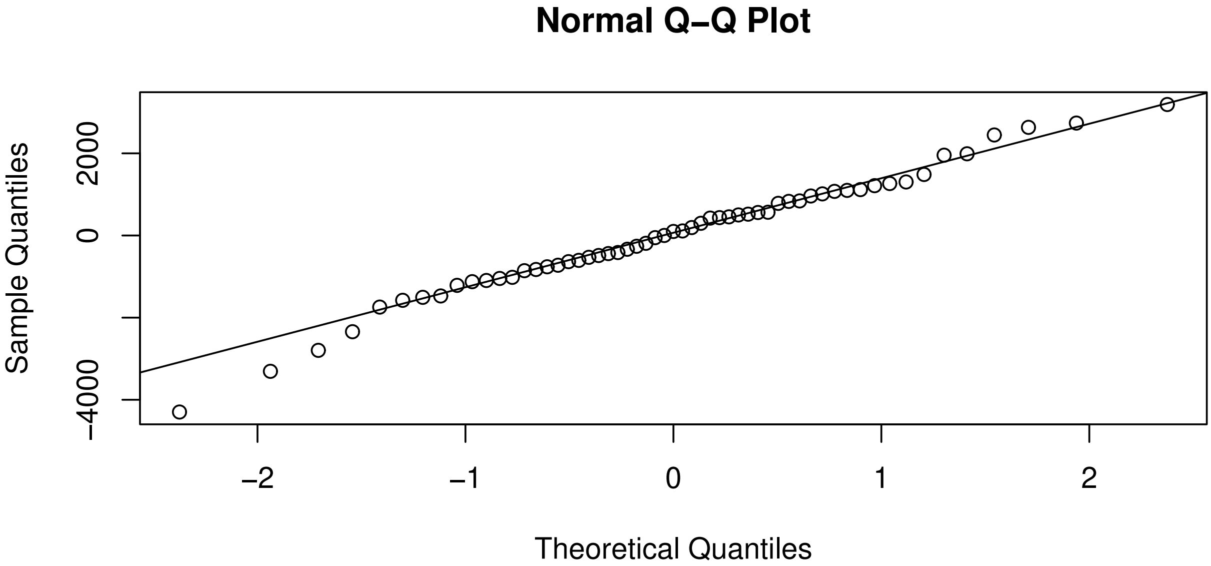
```
(d) Residual Diagnostics:
## plot
par(mfrow= c(1,2))
acf(residuals(ar.1), main="")
pacf(residuals(ar.1), main="")
```




```
## Box-Ljung test
> LB.test(ar.1)
data:  residuals from  ar.1
X-squared = 6.958, df = 11, p-value = 0.8025
```

The residuals appear to be white-noise.

```
(e) Q-Q Plot of Residuals:

## plot
par(mfrow= c(1,1))
qqnorm(residuals(ar.1)); qqline(residuals(ar.1))
```



The Q-Q Plot supports our claim in **(d)** and we conclude that the assumption of normality is reasonable.

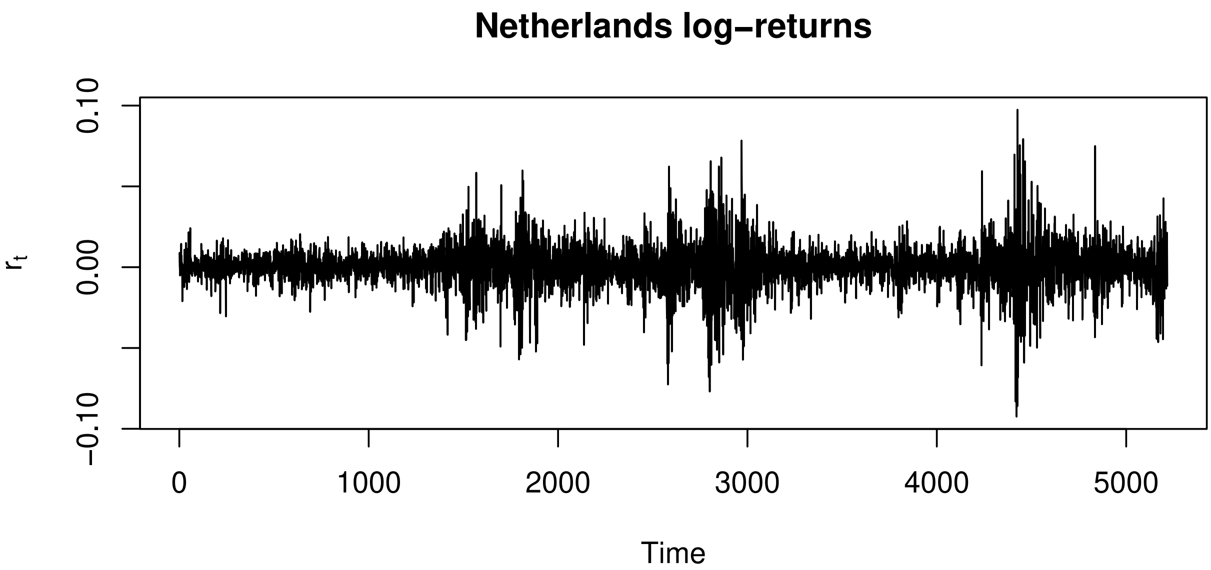
```
(f) Comparison with MA(1):

## fit
ma.1 <- arima(deere3, order = c(0,0,1))

> AIC(ar.1, ma.1)
     df       AIC
ar.1  3  997.0189
ma.1  3 1001.0523
```

We therefore prefer the AR(1) model according to AIC.

Question 2 – Dutch Equity Index

a) Plotting the log-returns:

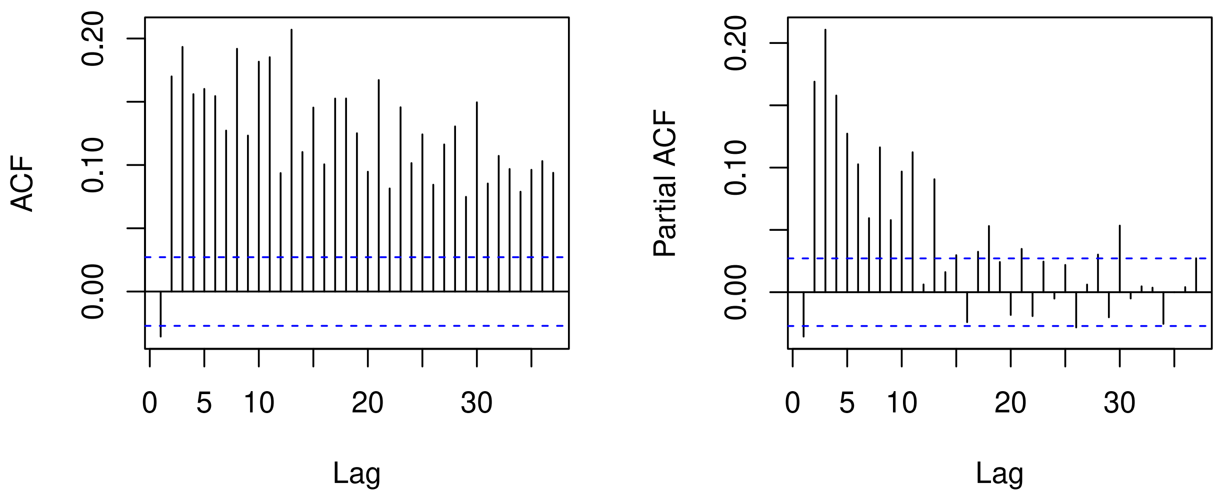
```
## read the data
Data <- read.table(file="RMIP Data Tutorial.txt", header=TRUE);
Data$Date <- as.Date(Data$Date, '%m/%d/%Y');

## log returns
netherlands.lr <- diff(log(Data$Netherlands))
greece.lr <- diff(log(Data$Greece))

## plot log returns
par(mfrow=c(1,1))
plot(netherlands.lr, xlab="Time", type="l",
     ylab=expression(r[t]), main="Netherlands log-returns")
```



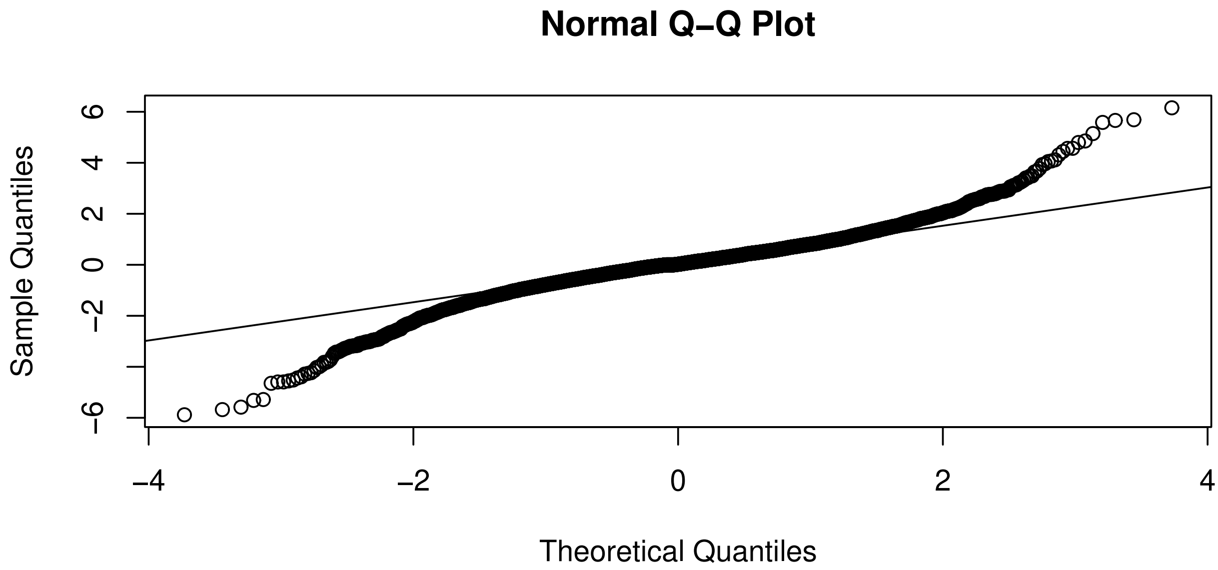
The plot appears to display constant mean, but there is certainly volatility clustering.

(b) Fitting an ARCH(1) Model:

```
library(tseries)
arch.1 <- garch(netherlands.lr, order = c(0,1), trace = FALSE)

> arch.1$coef
          a0           a1
0.0001096751 0.4286964426

## diagnostics
residuals.arch <- na.remove(residuals(arch.1))

## plotting residuals
par(mfrow=c(1,2))
acf(residuals.arch^2, main = "")
pacf(residuals.arch^2, main = "")
```



```
## Q-Q Plot
par(mfrow=c(1,1))
qqnorm(residuals.arch); qqline(residuals.arch)
```




```
## Box-Ljung Test
> LB.test(arch.1)
data:  residuals from  arch.1
X-squared = 32.122, df = 12, p-value = 0.001325
```

The diagnostics suggest that the assumption of normal innovations is unrealistic for our model.

```
(c) Predictive volatility:
pv <- arch.1$coef[1] + arch.1$coef[2] *
  (residuals.arch[length(residuals.arch)])^2

> pv
0.3662184

(d) Value-at-Risk:
alpha <- .95
sigma <- sqrt(pv)
value.at.risk <- sigma * qnorm(alpha)

> value.at.risk
0.9953994
```