Time series modeling of stock returns and the predictive ability of interest rate changes

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Outline

1. Introduction and Motivation
2. Data extraction and Pre-processing
3. ARMA Process
4. ARCH Process
5. GARCH Process
6. Breakpoints Identification
7. Homogenous Intervals by Breakpoints and Interest Rate Changes

Introduction and Motivation

Our motivation:

- The DAX varied much between the years 2001 and 2005.
- In the meantime, *the interest rates* were changed many times by the ECB.
- To describe the changes of stock returns and research the relationship between the stock returns and the interest rates, are our major goals in our report.

In order to implement our motivations:

- log returns, ARMA, ARCH, and GARCH models, breakpoints distinguish, predictive ability of returns to the interest rates are discussed in the following sections.

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Data Extraction and Pre-processing

1.data sources:

- data from European Central Bank(ecb,statistics)
- here is the link:*https://www.ecb.europa.eu*

2.pre-processing:

- mean
- difference
- log
- square

...

Data Extraction and Pre-processing

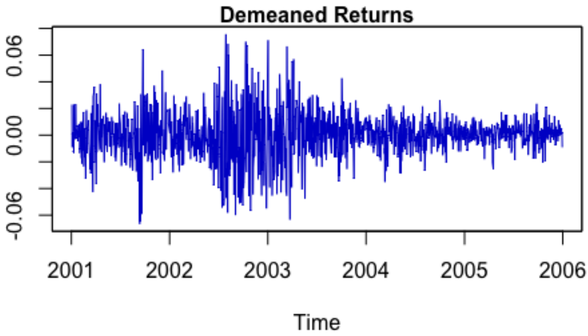

Figure 1: Plot of the returns over the years 2001 and 2005

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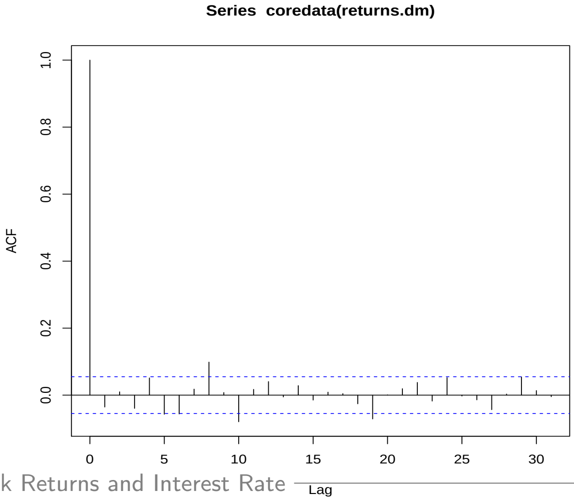
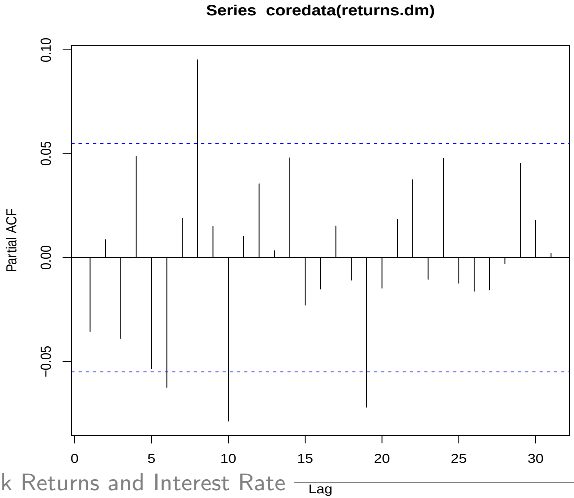
Autocorrelation Function



Partial Autocorrelation Function



ARMA Process

ARMA(p,q)model selection minimising AIC:

```
ltt.arima = 2
aic.arima.matrix = matrix(NA, ncol = ltt.arima + 1, nrow = ltt.arima + 1)
for (i in 0 : ltt.arima) {
  for (j in 0 : ltt.arima) {
    aic.arima.matrix[i + 1, j + 1] = AIC(arima(returns.dm, order = c(i, 0, j)))
  }
}
aic.arim.min = min(aic.arima.matrix)
which(aic.arima.matrix == aic.arim.min, arr.ind = T)
```

- ARMA(1,1) has the smallest AIC –> Best model for returns ARMA(1,1) ▸ Link for AIC

ARMA Process

ARMA(p,q)model selection minimising BIC: we also applied BIC to select appropriate model:

▸ Link for BIC

ARMA(p,q)model selection minimising HQIC: in order to make sure that we select the best-fitted model,we applied HQIC as well:

▸ Link for HQIC

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ARCH Process

Grid search to determine the best autoregressive conditional heteroskedasticity (ARCH) model.

```
ltt.arch = 10
aic.arch = NA
for(i in 1 : ltt.arch) {
  aic.arch[i] = AIC(garch(res.arima101, order = c(0,
      i)))
}
which(aic.arch == min(aic.arch), arr.ind = TRUE)
```

Result: ARCH(7) has the smallest values for all three information criteria (AIC, BIC, HQIC).

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GARCH Process

The same procedure for a generalized autoregressive conditional heteroscedasticity (GARCH) model.

- Result: GARCH(1,2) has the lowest AIC value, while GARCH(1,1) is the optimal GARCH model according to the BIC and HQIC.
- Compared to the best ARCH model, ARCH(7), both GARCH models above perform better.
- For a later comparison, we use a GARCH(1,1) model.

GARCH Process

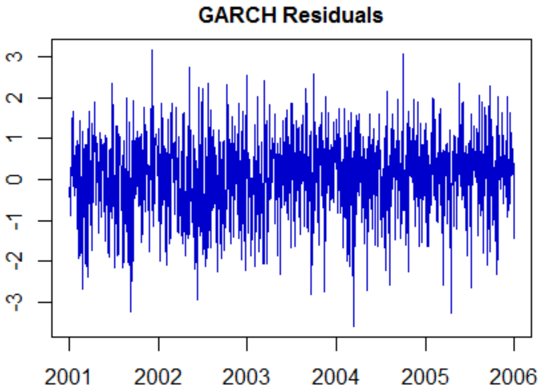

Figure 2: Residuals of the GARCH(1,1) model

GARCH Process

A very simple example of a function definition:

```
HQIC = function(n.like, k, n) {
  # Calculates and returns the Hannan-Quinn Information Criterion
  #
  # Args:
  #  n.like: negative log-likelihood, as for example produced by
  #          the 'garch' command from the 'tseries' package [scalar]
  #  k:      number of free parameters to be estimated [scalar]
  #  n:      number of data points [scalar]
  #
  # Returns:
  #  The Hannan-Quinn Information Criterion value in a numerical vector
  2 * n.like + 2 * k * log(log(n))
}
```

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Breakpoints Identification

In this section,we tried to identify the break points in

- Breakpoints
- Package "changepoint" and cpt.var function

```
cpt.var(returns, penalty = "MBIC", pen.value =
  0.05, know.mean = FALSE, method = "PELT")
```

- Changepoint Locations were 171 221 365 599 917 in dataset
- Corresponding dates were 2001.8.30, 2001.11.14, 2002.06.14, 2003.05.20, and 2004.05.20.

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Homogeneous Intervals

We standardize the intervals divided by the breakpoints to get homegeneous intervals. In the previous section, we concluded **five** breakpoints, *i.e.* six intervals.

Homogeneous Intervals

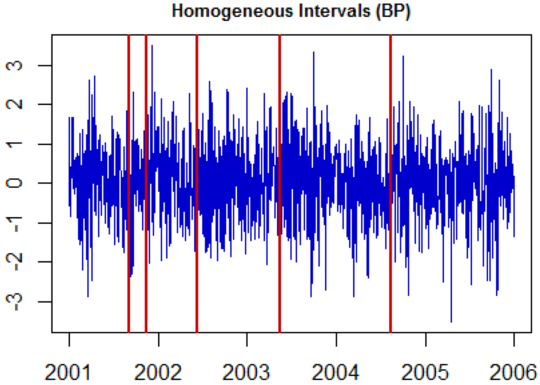

Figure 3: Combination of the six homogeneous intervals

Homogeneous Intervals

As the interest rates were changed **eight times** during these five years we regarded these time points as breakpoints. Then we also standardized these nine intervals to get a homogeneous series.

Homogeneous Intervals

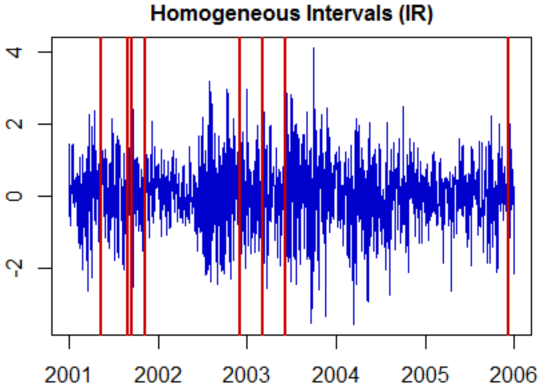

Figure 4: Combination of the six homogeneous intervals

Homogeneous Intervals

- Ljung-Box test on the standardized intervals still indicated heterogeneity
- GARCH model delivers far better results
- Some breakpoints are close to interest changes (i.e. 31.8.2001), indicating some effects on the volatility

▸ Link for Breakpoints determination and Homogeneous Intervals