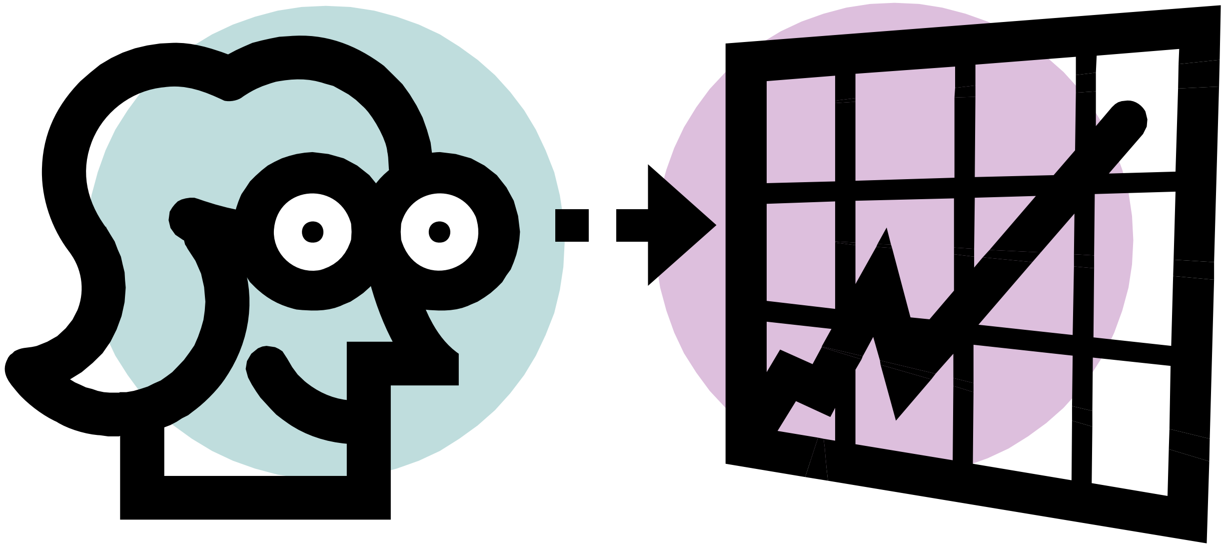
Bachelor Thesis

Option Pricing, the GARCH-M Approach



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Abstract

This thesis endeavours to examine if GARCH(1,1) or GARCH-M(1,1) is the better model in describing return series for option pricing. Both statistical and empirical experiments were performed. Both qualitative as well as quantitative tests have been done to check for correlation in the returns to see if GARCH modelling of the returns is suitable.

The performance of the models was tested using option prices. Black-Scholes option prices were calculated with a constant volatility, volatility using GARCH(1,1) and volatility using GARCH-M(1,1). These calculated prices were then in turn compared with the actual option prices.

The results are not conclusive on which GARCH model is better in performance, but GARCH(1,1) does seem to come out as the more preferred model. The constant volatility model, however, fits the actual prices better than both GARCH models.

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1 INTRODUCTION

1.1 Motivation

The financial market is a lot about numbers. Stock prices, option prices and various other prices rise and fall every moment of every day. Traders and analysts use many programs that are crunching numbers, trying to make sense in a world of chaos or seeming chaos. The assumption has to be seeming chaos or even unrecognized order; otherwise there is no sense in using models in the first place.

Although the financial market is not only influenced by numbers, e.g. news or human expectations, they do play a major part. Predicting future prices by finding patterns in a chaotic whirlwind of numbers is one of a trader's dream. Speculators resort to many methods in trying to predict the movement of stock prices. They rely on luck, astrology, fortune-telling or even intuitive feelings in their decision to choose which stock or option to invest in. Sometimes these methods seem to work and they tend to yield increased returns on certain occasions. Analysts on the other hand, study past data and use complicated models to try and capture trends, using these to forecast possible future prices. On certain occasions, models come out that truly work and achieve increased returns on investments, but even then they often don't last for very long.

The highly spiritual methodology a lot of speculators might use in consulting higher powers for advice on investments will not be discussed in this thesis. As for explanations for luck, it goes beyond our scope. One of the options left is the Analysts' methodology: the process of seeking and finding patterns in a series of prices.

But first let me go back and try to give an explanation for the positive results achieved by various methods mentioned above. Financial Theories based on the Efficient Market Hypothesis[1] don't exclude momentarily achieving extra returns; it only states that it is not possible to achieve systematically higher returns than the market. This is due to the assumption that if such an arbitrage position was found, many would take that position resulting in changes in demand and supply giving rise to new prices, whereby the market would reach a new equilibrium.

This thesis was born out of a notion that people want to be able to predict stock and option prices. They want to know where the economy is heading and want to be able to make the right investment decisions. The reason for this could be simply just to make more profit, but in the business world a more important reason underlies the search for predicting market prices and that is to reduce risk by implementing proper financial hedges. This could be achieved if asset prices or at least their expected movements could be accurately predicted.

There are scientific methods that are currently being used to forecast future asset prices or their movements. This can be done either through analysis of the fundamentals of the underlying asset or through the (technical) analysis of the past performance of the underlying asset. This thesis will use the latter as the basis for experimentation.

1.2 Background

This thesis will be taking a look at European stocks as the underlying asset to predict option prices hoping to give a trader support in the decision making process. Stock prices are discrete values and changes can be observed only when the exchange is open, but nevertheless the continuous-variable, continuous-time stochastic process proves to be a useful model for many purposes. There is, however, outcome of research saying, that the continuity assumption while working with discrete stock prices may not be completely sound[2]. But for this thesis the assumption will be that it is a continuous process.

[1] Van Aalst, P.C. et al. (1997). *Financiering en Belegging Deel 2,* 7de Druk, Rotterdam: Rhobeta, 105-139.
[2] Amilon, H. *GARCH Estimation and Discrete Stock Prices*, Lund University, Sweden

The stochastic process normally assumed for the return of a stock of a non-dividend-paying stock follows a generalized Wiener process. That means that it has a constant expected drift rate and a constant variance rate. A further extension to this process can be defined. This is known as an Itô process[3]. This is a generalized Wiener process in which both the expected drift rate and volatility rate are functions of the value of an underlying asset and time.

In the case of stock returns $\delta S/S$, the Itô process of a stock S is as follows:

$$\frac{\delta S}{S} = \mu(S,t)\,\delta t + \sigma(S,t)\,\eta\sqrt{\delta t} \tag{1.1}$$

where μ is the expected rate of return on the stock, expressed in decimal form, σ is the volatility of the stock price, η is a random draw from a standardized normal distribution and t is a unit of time, e.g. a year. A more abstract form of equation (1.1) can be given as

$$\begin{aligned} u_t &= \mu_t + \varepsilon_t \\ \varepsilon_t &= \sigma_t \eta_t \end{aligned} \tag{1.2}$$

where u is the return of a stock and ε is an unknown innovation consisting of the volatility of the stock price and a random draw from a standardized normal distribution. This model as can be seen involves two dynamic parameters: μ and σ. The parameter μ is the expected return earned by an investor per year. The parameter σ, the stock price volatility, can be interpreted as the standard deviation of the change in the stock price in one year.

In various researches it is observed that the volatility of returns or log-prices is high for certain periods and then low for others. E.g. the volatility of daily returns can be high one month and low the next. This property of time series of prices can be called "volatility clustering" and is usually approached by modelling the price process with an ARCH-type model.

[3] Mathematician Kiyosi Itô discovered this in 1951.

1.3 Problem

This brings me to the main focus of this research. As mentioned in the previous section 'volatility clustering' has been found when instead of using a constant volatility σ a function for volatility was used dependent on the price of the underlying asset and the time $\sigma(S,t)$. We have two parameters, so there are four options we can consider. First we have on one hand both μ and σ constant, which is the generalised Wiener process or simple Brownian motion. On the other extreme is the just mentioned Itô process with both parameters variable. In between we can as a third option keep μ constant and vary σ, which is done to detect volatility clustering. And finally there is the option of keeping σ constant and vary μ. As modelling volatility is widely done, This thesis will endeavour to find out whether changing the expected return from a constant μ to a function $\mu()$ will result in finding some kind of clustering indicating some sort of trend or expectation.

In the book of Hull (2003)[4] it is mentioned that due to the mean reverting nature of variances, the Generalized Autoregressive Conditional Heteroskedasticity (GARCH) model is more appealing for modelling volatility than the simple Exponentially Weighted Moving Average (EWMA) model. In a paper by David Rae[5] where he made a comparison of different methods for forecasting the volatility of New Zealand's interest rates and exchange rates, it is stated that the simple Ordinary Least Squares (OLS) regression is the preferred method for forecasting volatility, which in turn implies that a GARCH model (or one of its cousins) would be the best method for forecasting returns. As my premise is that past prices say something about today's price, there should be some autocorrelation present in the series of prices that will be used.

If autocorrelation is detected in the prices or returns, it will mean that a GARCH-model is suitable for modelling the time series. I've chosen to utilise a GARCH(p,q) model. The returns will be assumed to be dependent on the average expected return as well as the volatility rate, which in turn will be dependent on itself and noise or innovation from a previous period. The use of this model assumes that there is a certain degree of mean reversion as mentioned in Hull (2003). This characteristic has been proven to be good for

[4] Hull, J.C. (2003). *Options, Futures, and Other Derivatives*, fifth edition, Prentice Hall, 377-378.
[5] Rae, D. (1997). *Forecasting Volatility*, Economics Division, Financial Research Paper No. 9, The National Bank of New Zealand Limited.

modelling volatility. As mentioned earlier, this thesis will examine the effect of modelling the expected return as a non-constant function, next to modelling volatility.

In option pricing as well as risk management, where simulation methods are employed, it is required to be able to generate prices that approximately describe the return process in the past. The assumption made here is that historical prices say something about future prices. This challenges the basic assumption normally made about stock prices called the Markov property, which states that the present price of a stock impounds all the information contained in a record of past prices. This property is consistent with the weak form of the Efficient Market Hypothesis, which also claims that past information is contained in the current price.

We want to try and model the influence of past information. GARCH is often used to include this information. These models make volatility or variance dependent on the volatility or variance of a previous period, keeping the expected return constant. GARCH-M, however, models expected return as a function instead of a constant, in addition to modelling the volatility. Volatility is important in option price calculation. The goal of this study will be to test whether the GARCH-M model will be better compared to the GARCH model in option price calculation.

Options are priced in a way that their prices reflect the possible profits to be gained. Being able to describe the return process more accurately would entail a more accurate forecast or prediction of the gains of a certain option. This would result in a more accurate pricing of the option. The prices in this thesis will be generated by the widely used Black-Scholes formula developed by Fisher Black, Myron Scholes[6] and Robert Merton[7] in the early 70's. The formulae given in the next chapter require volatility as input. The volatility will be calculated in various ways. First we will calculate a single volatility for the whole period. Second we will be calculating the volatility using the two GARCH models. These three calculated option prices will be compared with the actual option prices.

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[6] Black, F. and Scholes, M. (1973). The Pricing of Options and Corporate Liabilities, *Journal of Political Economy, 81 (May/June 1973)*, 637-659.
[7] Merton, R.C. (1973). Theory of Rational Option Pricing, *Bell Journal of Economics and Management Science, 4 (Spring 1973)*, 141-183.

The main hypothesis of this thesis is that by varying the expected return a better option price can be calculated. Having a better idea of your risk position will give you an edge and advantage in the financial market, where derivatives are used to hedge the exposure to risk.

1.4 Structure

In the following chapters a report will be given on what methodology was used and why it was applied. In chapter 2, a more detailed description is given on the background of the hypothesis to be tested and the models to be used. Chapter 3 describes the data set and the methodology used to test the hypothesis that has been made. Chapter 4 will show the results gained through experimental simulation. And finally a conclusion will be drawn in chapter 5.

2 BACKGROUND

2.1 Introduction

In the previous chapter an introduction was given on the need to forecast option prices accurately in order to be able to better hedge risk. It was also mentioned that GARCH models will be used to model the expected return and the volatility instead of keeping them constant. In this chapter some notations, basic assumptions and theories of the models used will be first laid down before proceeding to describe the dataset and the methodology in the next chapter.

2.2 Notation

Although in the previous sections some symbols and formulas already have been used, in this section the notation will be put forth that is going to be used throughout this thesis:

c: Price of a European call option.

d_1, d_2: Parameters in option pricing formula. See for example the Black-Scholes formula.

f: Value of an option. f_T is the value of a derivative at time T and f_0 is the value of an option at time zero. f_i is used on occasion to denote the value of the ith option.

K: Strike price of an option.

N(x): Cumulative probability that a variable with a standardized normal distribution is less than x. A standardized normal distribution is a normal distribution has a mean of zero and a standard deviation of 1.0.

p: This is the value of a European put option.

r_f: Continuously compounded risk-free interest rate for an investment maturing in time *T*.

S: Price of asset underlying an option at a general time *t*. It could refer to the price of a stock and the price of a stock index.

S_T: Stock price at maturity.

S_0: Current stock price.

t: A future point in time.

T: Time to end of life of an option.

u_i: This denotes the return provided on an asset between observation *i* - 1 and observation *i*.

ε: Random sample from a standardized normal distribution.

μ: Expected return on an asset.

σ: Usually this is the volatility of an asset (i.e., $\sigma\sqrt{\delta t}$ is the standard deviation of the percentage change in the asset's price in time δt). It can also be used as the standard deviation.

φ(m,s): Normal distribution with mean *m* and standard deviation *s*.

2.3 Assumptions

Here a list of all the assumptions are given that were made for reasoning and modelling purposes. First the most basic assumptions for market participants are given, continued by describing premises made in modelling stock options and the factors involved. This section will also include the suppositions and formulae needed concerning the Black-Scholes option pricing model. Finally it will be concluded by a description of the GARCH models used within this thesis.

2.3.1 Market Participants

These are the basic assumptions that are held to be true and they will be held throughout this thesis. Here are four of them deemed to be true for market participants:

1. The market participants are subject to no transaction costs when they trade. In reality the cost for a transaction will discourage continuous trading, because the cost for changing your portfolio may be more than the gains from making such a change. In this thesis the simplification of no transaction costs will be maintained.
2. The market participants are subject to the same tax rate on all net trading profits.
3. The market participants can borrow money at the same risk-free rate of interest as they can lend money.
4. The market participants take advantage of arbitrage opportunities as they occur.

These assumptions I hold to be true for some market participants. Some, because these do not have to be true for all participants, but must be true or at least approximately true for key players in the market such as large investment banks. This assumption is not unreasonable, because the trading activities of these key market participants will determine for a great deal how a stock or option price is established.

The risk-free interest rate, r, is in theory the rate at which money is borrowed or lent without any risk, that means the money is certain to be repaid with no risk of default. Often it is thought of as the Treasury rate, which is the rate at which a national government borrows in its own currency. However, large financial institutions usually set it equal to the London Interbank Offer Rate (LIBOR). In this thesis the average yield over 2003 of the Dutch 10-year government bond will be used, which is 4,1252 %.

2.3.2 Stock Options

First we'll take a look at the factors affecting stock option prices, before looking at the assumptions made in deriving these prices. There are a number of relationships between European option prices and the underlying stock price. One of them and maybe the most important one is the put-call parity, which is a relationship between European call option prices and European put option prices.

There are six factors within the Black-Scholes Theory that we need to take into account that affect the price of a stock option:

1. The current stock price, S_0
2. The strike price, K
3. The time to expiration, T
4. The volatility of the stock price, σ
5. The risk-free interest rate, r
6. The dividends expected during the life of the option, D

Any change to anyone of these factors will result in a change in the price of an option. To keep things simple dividends are not taken into account in my experiments as they are already incorporated in the stock prices.

The assumptions here are similar to the assumptions for the market participants, which are no transaction costs, same tax rate on all net trading profits and borrowing and lending is possible at the risk-free interest rate. For the purposes of our analyses, it is also assumed that there are no arbitrage opportunities. The reason to assume this is, because market participants will be prepared to take advantage of such opportunities, which means that any available arbitrage would disappear very quickly in an efficient market.

2.3.3 The Black-Scholes Model

This model was developed in the early 1970s by Fischer Black, Myron Scholes, and Robert Merton. It was and still is considered a major breakthrough in the pricing of stock options until today. The model was first used for valuing European call and put options on a non-dividend-paying stock. There are also extensions to deal with dividend-paying stocks, European calls and puts and American calls.

The assumptions used for this model are as follows:

1. The stock price follows a wiener process with μ and σ constant.
2. The short selling of securities with full use of proceeds is permitted.
3. There are no transactions costs or taxes. All securities are perfectly divisible.
4. There are no dividends during the life of the derivative.
5. There are no riskless arbitrage opportunities.
6. Security trading is continuous.
7. The risk-free rate of interest, r, is constant and the same for all maturities.

Another point to take note of would be the requirement that the stock price distribution at maturity of the option is lognormal.

2.4 GARCH Model

Engle[8] introduced in 1982 the ARCH (Autoregressive Conditional Heteroskedasticity) process which differentiates between the unconditional and the conditional variance. The conditional variance changes over time as a function of past errors. In previous empirical applications a relatively long lag is called for. A fixed lag structure is often imposed to avoid problems with negative variance estimates, cf. Engle (1983)[9] and Engle and Kraft (1983)[10].

[8] Engle, R.F. (1982). Autoregressive conditional heteroskedasticity with estimates of the variance of U.K. inflation, *Econometrica 50*, 987-1008.
[9] Engle, R.F. (1983). Estimates of the variance of U.S. inflation based on the ARCH model, *Journal of Money Credit and Banking 15*, 286-301.

With regard to abovementioned problem the ARCH model was extended by Bollerslev[11] in 1986 to his GARCH (Generalized Autoregressive Conditional Heteroskedasticity) model to allow both a longer memory and a more flexible lag structure.

The GARCH(*p,q*) process is given by

$$\varepsilon_t \mid \psi_{t-1} \sim N(0, \sigma_t^2), \tag{2.1}$$

where Ψ_{t-1} denotes all available information at time *t-1* and ε_t are the innovations of the returns.

$$\sigma_t^2 = \alpha_0 + \sum_{i=1}^{p} \alpha_i \sigma_{t-i}^2 + \sum_{i=1}^{q} \beta_i \varepsilon_{t-i}^2 \tag{2.2}$$

where

$p \geq 0, \quad q \geq 0$

$\alpha_0 > 0, \quad \alpha_i \geq 0, \quad i = 1, \ldots, p,$

$\beta_i \geq 0, \quad i = 1, \ldots, q.$

For $p = 0$ the process is reduced to an ARCH(*q*) process, and for $p = q = 0$ ε_t will merely be white noise, uncorrelated random variables with zero mean and a given variance. In the GARCH(*p,q*) process the conditional variance is specified as a linear function of past sample variances and lagged conditional variances, whereas in the ARCH(*q*) process the conditional variance is specified as a linear function of only the past sample variances .

The abovementioned model is the general form of a GARCH model, but in this thesis only the GARCH(1,1) model will be used. Although for *p* and *q* any positive number can be chosen which has resulted in many GARCH models being developed in the past, the GARCH(1,1) model has often performed just as well as the others and is most popular[12]. I've

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[10] Engle, R.F. and Kraft, D. (1983). Multiperiod forecast error variances of inflation estimated from ARCH models, in: *A. ZeUner, ed., Applied time series analysis of economic data* (Bureau of the Census, Washington, DC) 293-302.
[11] Bollerslev, T. (1986). Generalized Autoregressive Conditional Heteroskedasticity. *Journal of Econometrics 31*, 307-327.
[12] Hull, J.C. (2003). *Options, Futures, and Other Derivatives*, fifth edition, Prentice Hall, 376.

chosen to use this model in my research because of its mean reverting property which makes it more appealing than a standard EWMA model as mentioned earlier. This property means that over time the variance tends to get pulled back to a long-run average. However, when the long-run average is equal to zero, it is reduced back to EWMA.

The equation for GARCH(1,1) is

$$\sigma_t^2 = \omega + \alpha\sigma_{t-1}^2 + \beta\varepsilon_{t-1}^2 \tag{2.3}$$

where

$$\omega = \gamma V_L \tag{2.4}$$

$$\gamma + \alpha + \beta = 1 \tag{2.5}$$

For the model to be stable, it is required that $\alpha + \beta < 1$. The "(1,1)" in GARCH(1,1) indicates that σ_n^2 is based on the most recent observation of ε^2 and the most recent estimate of the variance rate. The general GARCH(p,q) model calculates σ_n^2 from the most p observations on ε^2 and the most recent q estimates of the variance rate. Once ω, α and β have been estimated, γ can be calculated as $1 - \alpha - \beta$. The long-term variance V_L can the be calculated as ω/γ.

2.5 GARCH-IN-MEAN Models

In the previous section the conditional variance was shown to be modelled by GARCH. The GARCH-in-mean or GARCH-M model includes an added heteroskedastic term in the conditional mean equation (See equation 2.6). In equation (1.1) you can see that, generally, returns are dependent on a mean, a variance and a noise component.

The GARCH-M model models the mean by making it dependent on the variance. The variance will be modelled by GARCH(1,1) as described above.

$$\mu_t = \delta + \lambda\sigma_t^2 \tag{2.6}$$

In financial theory the relationship between risk and returns play an important role. CAPM, for example, implies a linear relationship between the expected returns of a market portfolio and the variance. If the risk (i.e. the variance) is not constant over time, then the conditional expectation of the market returns is a linear function of the conditional variance. The idea from Engle[13] was consequently used to estimate the conditional variances in GARCH and then the estimations are used in the conditional expectations' estimation. The term to be estimated could be interpreted as the risk premium.

Another reason in financial theory for using GARCH-M is because it explains to a certain degree, the presence of conditional left skewness observed in stock returns. This is in line with the volatility feedback effect[14], which amplifies the impact of bad news but dampens the impact of good news.

2.6 Maximum Likelihood

Historical observations will be used to estimate the parameters in these models. The approach used to estimate the parameters is the maximum likelihood method. It involves choosing values for the parameters that maximize the chance (or likelihood) of the data occurring. The first assumption made, is that the probability distribution of ε_i conditional on the variance is normal.

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[13] Engle, R.F., Lilien, D.M. and Robins, R. P. (1987), Estimating time varying risk premia in the term structure: The ARCH-M model, *Econometrica* 55, 391-407.

[14] Campbell, J.Y., and Hentschel, L. (1992). No news is good news: An asymmetric model of changing volatility in stock returns. *Journal of Financial Economics 31*, 281-318.

In Hull (2003)[15] the best parameters can be found by maximizing

$$\prod_{i=1}^{m}\left[\frac{1}{\sqrt{2\pi\sigma_i^2}}\exp\left(\frac{-\varepsilon_i^2}{2\sigma_i^2}\right)\right] \qquad (2.7)$$

where m is the number of observations.

Maximizing an expression is equivalent to maximizing the logarithm of the expression. Taking the logarithm of the expression in equation (2.7) and ignoring constant multiplicative factors, it can be seen that we wish to maximize

$$\sum_{i=1}^{m}\left(-\ln(\sigma_i^2 - \frac{\varepsilon_i^2}{\sigma_i^2}\right) \qquad (2.8)$$

An iterative search is used to find the parameters in the model that maximize the expression in equation (2.8).

2.7 Black-Scholes Formulae

The Black-Scholes formulae for the prices at time zero of a European call option on a non-dividend-paying stock and a European put option on a non-dividend-paying stock are

$$c = S_0 N(d_1) - Ke^{-rT} N(d_2) \qquad (2.9)$$

and

$$p = Ke^{-rT} N(-d_2) - S_0 N(-d_1) \qquad (2.10)$$

[15] Hull, J.C. (2003). *Options, Futures, and Other Derivatives*, fifth edition, Prentice Hall, 378-382.

where

$$d_1 = \frac{\ln(S_0 / K) + (r + \sigma^2 / 2)T}{\sigma\sqrt{T}} \quad (2.11)$$

$$d_2 = \frac{\ln(S_0 / K) + (r - \sigma^2 / 2)T}{\sigma\sqrt{T}} = d_1 - \sigma\sqrt{T} \quad (2.12)$$

The function $N(x)$ is the cumulative probability distribution function for a standardized normal distribution, $\varphi(0,1)$ will be less than x.

3 METHODOLOGY

3.1 Introduction

In this chapter a description is given of the dataset to be used for experimentation. Many charts and graphs will be included as that will give a better picture of the path the index and stock prices have taken or their returns. Pictures have been undervalued in science. Mandelbrot (2004)[16] says that this is partly due to the French mathematicians Lagrange and Laplace, who laboured to reduce all logical thought to precise formulae and carefully chosen words. Especially with computers in this time and age that can generate accurate charts and diagrams in a very short time, pictures have become a very useful tool for visual inspection before quantifying the data.

3.2 Dataset

Via DataStream, a database containing economic and financial data from IMF, OECD, national governments, the Deutsche Bundesbank, Stock exchanges and a number of yearly reports from major listed companies, I've requested the data from all the companies composing the Amsterdam Exchange (AEX) index in 2004 and the index itself.

The AEX is a weighted average of stock prices on the Amsterdam exchange and is therefore a good benchmark for this exchange. This index was started since 1983, then called EOE (European Options Exchange) Index, and is currently managed by the company Euronext. The index consists of the 24 most active securities in the Netherlands. The criteria for a company to be included in the AEX are the revenue and the tradability. The size of a

[16] Mandelbrot, B. B. and Hudson, R.L. (2004), *The (Mis)Behaviour of Markets, A Fractal View of Risk, Ruin and Reward*, Basic Books, 88-94.

company determines the weight of the company's stock price in the AEX. On 1 March every year the composition of the index is reviewed and adjusted.

The data used for this research consists of stock prices from 24 different companies (See Table 1) and the price of the index itself. The prices are corrected for stock splits and dividend. The daily closing prices were retrieved dated from 29 Dec 1989 to 31 Dec 2003. This means that the dataset consists of 3654 observations for each company and the index itself.

S/N	Company Name	Weight in AEX
1	ABN AMRO	10.95%
2	Aegon	5.75%
3	Ahold	3.60%
4	Akzo Nobel	3.44%
5	ASML	2.35%
6	Buhrmann	0.38%
7	DSM	1.68%
8	Elsevier	2.92%
9	Fortis	10.53%
10	Getronics	0.30%
11	Hagemeyer	0.29%
12	Heineken	2.43%
13	IHC Caland	0.59%
14	ING	11.12%
15	KPN	6.48%
16	Numico	1.81%
17	Philips	8.40%
18	Royal Dutch Oil	11.37%
19	TPG	2.73%
20	Unilever	8.54%
21	Van der Moolen	0.07%
22	Versatel	0.29%
23	VNU	2.30%
24	Wolters Kluwer	1.96%

Table 1: AEX Composition[17]

As I have selected the companies based on that they composed the AEX index in 2004, which was just an arbitrary choice to be able to choose companies from various sectors, there were companies which don't have price listings for the complete period. 6 of the 24 companies do not have prices for the whole period. To create a dataset of equal length for all the 24 companies the time series has to start at 23 Jul 1999, resulting in only 1159 observations, which is still quite a substantial amount covering about 2 and a half years.

[17] The composition with the weights were retrieved from Dutch Wikipedia webpage on the AEX (http://nl.wikipedia.org/wiki/AEX_Index)

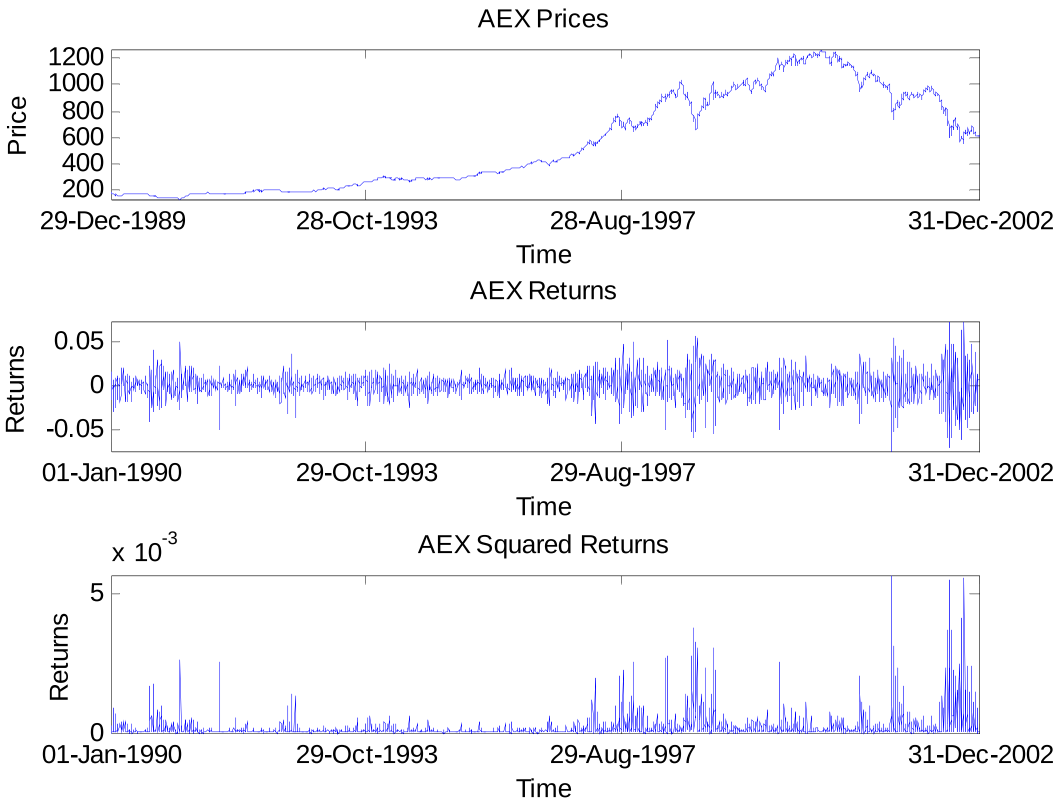

Figure 1: AEX Index prices, returns and squared returns.

As mentioned in the beginning of this section, the AEX can be used as a benchmark for the exchange of Amsterdam and the economy of the Netherlands in general. So in Figure 1 the prices, the returns and the squared returns, are shown giving an idea what has transpired in the economy of the Netherlands in the last 13 years. As you can see there are some major fluctuations both in the beginning of the 90s, around 1997 and before the end of 2002.

Option prices will be calculated by using the two GARCH models. Actual option prices of the AEX index and the 24 companies have also been retrieved for a period from 2 Jan 2003 to 30 Sep 2003 to compare the calculated option prices with. From these option prices both a call and put option were chosen of the AEX and every company in the AEX. To make the data of option prices more concise, an arbitrary choice was made to pick an option which was roughly on-the-money that means that the strike price was close to the spot price of the underlying asset, at the beginning of the dataset being used. All option data start on 2 Jan 2003. In Table 2 a list is given of the expiry date and strike price of the options that were used.

NAME	EXPDATE	EXERCISE
AEX	18-07-03	320
AAB	18-07-03	16
AGN	18-07-03	12
AH	18-07-03	12
AKZ	18-07-03	30
ASML	18-07-03	8
BUHR	18-07-03	4
DSM	18-07-03	42
FOR	18-07-03	16
GTN	18-07-03	1
HGM	18-07-03	6
HEI	18-07-03	36
IHC	18-07-03	50
ING	18-07-03	16
KPN	18-07-03	6
MOO	18-07-03	20
NUM	18-07-03	12
PHI	18-07-03	18
REN	18-07-03	11
RD	18-07-03	42
TPG	18-07-03	14
UN	18-07-03	58
VNU	18-07-03	24
VRSA	17-04-03	1
WKL	18-07-03	16

Table 2: Options used for comparison, identified by their expiry date and strike price.

Black-Scholes option price calculation with constant volatility will also be used as an extra benchmark for comparison next to the actual prices.

3.3 Experimental Setup

In this section a step by step description of the process of what was done and what was setup will be given. First it starts with some pre-processing of the stock prices and then tests on the dataset are performed to check it for GARCH presence, so as to be able to use GARCH models. Secondly, the models will be described. In the next chapter the results of the estimation process will be given and some post-processing will be done.

3.3.1 Pre-processing

In equation (1.1) can be seen that stock price changes or in other words stock price returns are being modelled. There are two ways to convert prices into returns, you can either convert to periodic compounded returns (See equation 3.1) or to continuously compounded returns (See equation 3.2).

$$u_t = \frac{S_t}{S_{t-1}} - 1 \tag{3.1}$$

$$u_t = \ln\left(\frac{S_t}{S_{t-1}}\right) \tag{3.2}$$

The reason why this is mentioned is because in modelling financial asset returns an implicit assumption is that the dependent variable is continuous. There is, however, a problem; the data used are discrete stock prices. This would mean that assuming continuity may not be appropriate in this case or any other financial case studies. The assumption of continuity will be kept, because of a paper by Henrik Amilon[18] where he mentions that the continuity assumption only fails when encountering tick size to price ratio similar to low-priced stocks and short price series. The effects of discreteness are therefore deemed negligible. So in this thesis equation (3.2) continuously compounded returns will be used as highly priced and highly active stocks with daily prices are being used. There is also a substantial price series.

As quoted from Mandelbrot in the beginning of the chapter, a picture says a thousand words, so look at Figure 2 where the returns of the AEX are plotted continuously as well as periodically. At first glance you don't see any difference, but when you look at the numbers, it will show a difference of roughly 0.00008[19]. This difference should be small enough to neglect the discreteness effect and assume continuity.

---

[18] Amilon, H., *GARCH Estimation and Discrete Stock Prices*, Department of Economics, Lund University, Sweden.

[19] The mean of the difference between continuously compounded returns and periodically compounded returns is 8.0808e-005 with a standard deviation of 0.0127.

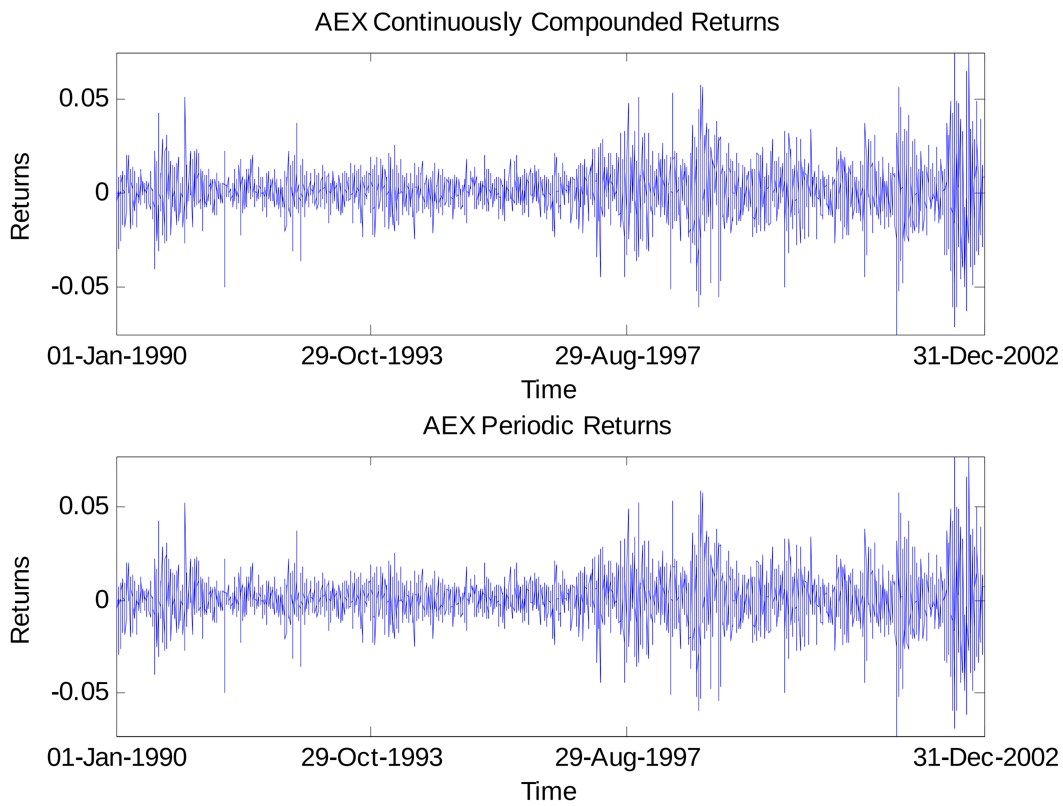

Figure 2: Continuously Compounded and Periodic Returns of the AEX

3.3.2 Presence of ARCH/GARCH

To justify modelling the returns by a GARCH model, the presence needs to be detected first. To detect the presence of a GARCH process, some qualitative and quantitative checks can be performed on the dataset. To check it qualitatively, plots will be made of the sample autocorrelation function (ACF) and the partial-autocorrelation function (PACF) on the returns, looking for signs of correlation. For quantitative checks, two tests will be employed, Ljung-Box-Pierce Q-Test and Engle's ARCH Test.

The Ljung-Box-Pierce Q-Test[20] (LBQ Test) can verify, at least approximately, if a significant correlation is present or not. It performs a lack-of-fit hypothesis test for model misspecification, which is based on the Q-statistic

[20] Description of the Ljung-Box-Pierce Q-Test is retrieved from the documentation of the software tool MATLAB GARCH toolbox under lbqtest.

$$Q = N(N+2)\sum_{k=1}^{L} \frac{r_k^2}{(N-k)} \tag{3.3}$$

where N = sample size, L = number of autocorrelation lags included in the statistic, and r_k^2 is the squared sample autocorrelation at lag k. Once you fit a univariate model to an observed time series, you can use the Q-statistic as a lack-of-fit test for a departure from randomness. Under the null hypothesis that the model fit is adequate, the test statistic is asymptotically chi-square distributed.

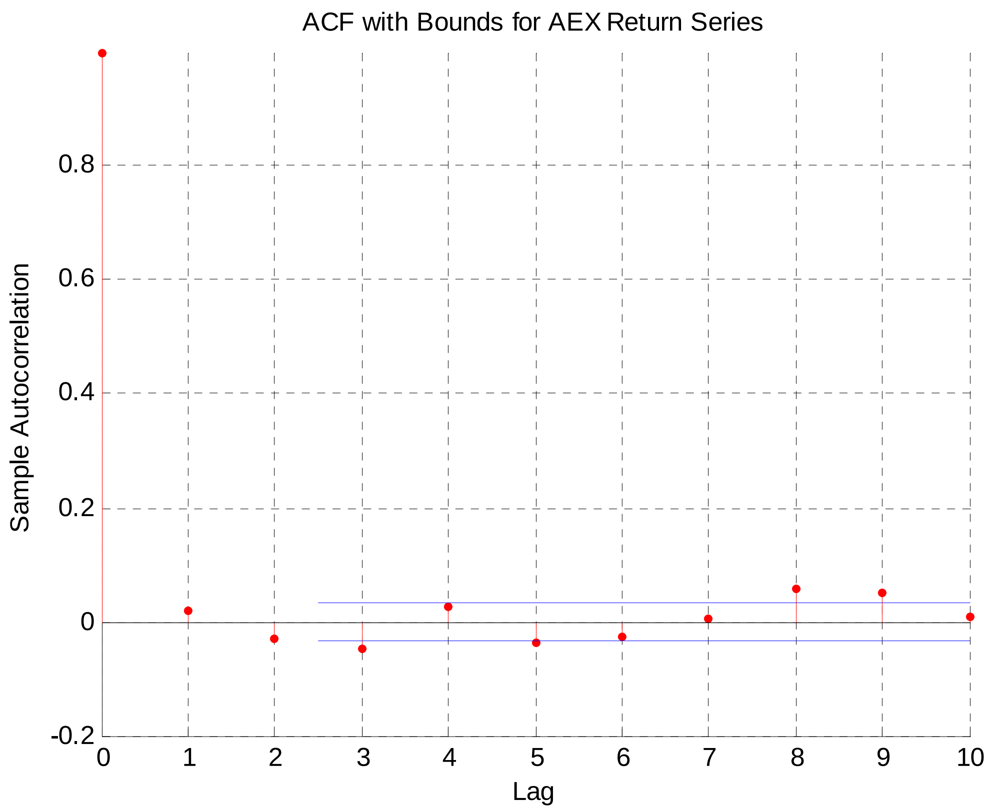

Figure 3: A plot of the sample autocorrelation function of the returns of the AEX.

As for Engle's ARCH Test[21], the ARCH test also tests the presence of significant evidence in support of GARCH effects (i.e. heteroskedasticity). It tests the null hypothesis that a time series of sample residuals consists of independent identically distributed (i.i.d.) Gaussian disturbances, i.e., that no ARCH effects exist. Given sample residuals obtained from a curve fit (e.g., a regression model), this test tests for the presence of M^{th} order ARCH effects by regressing the squared residuals on a constant and the lagged values of the previous M

[21] Description of Engle's ARCH Test is retrieved from the documentation of the software tool MATLAB GARCH toolbox under archtest.

squared residuals. Under the null hypothesis, the asymptotic test statistic, $T(R^2)$, where T is the number of squared residuals included in the regression and R^2 is the sample multiple correlation coefficient, is asymptotically chi-square distributed with M degrees of freedom. When testing for ARCH effects, a GARCH(P,Q) process is locally equivalent to an ARCH(P+Q) process.

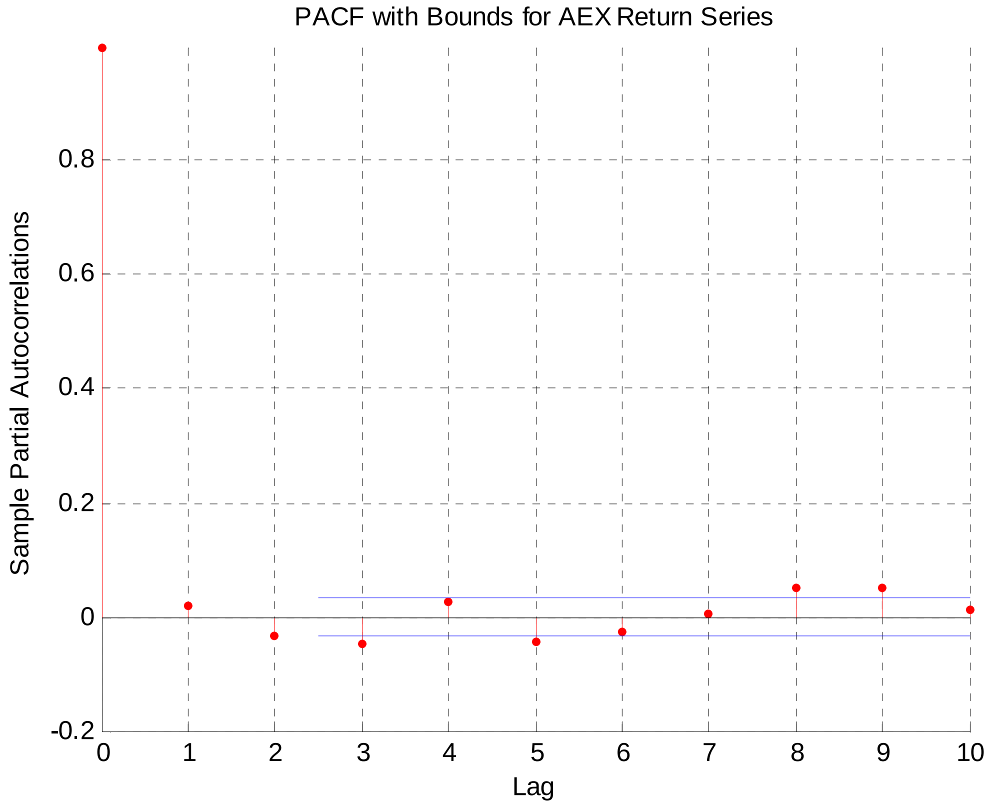

Figure 4: A plot of the Partial Autocorrelation Function of returns of the AEX.

First we take a look at the plots. In Figure 3 you can see an ACF-plot, which shows that the returns on the AEX do not contain autocorrelation. In Figure 4 a PACF-plot shows similar results. Both these plots are useful preliminary identification tools as they provide some indication of the broad correlation characteristics of the returns. So at first glance GARCH modelling isn't appropriate. In Appendix A the ACF-plots and in Appendix B the PACF-plots are given for the other 24 companies coming to the same conclusion that there is very little indication for using a correlation structure like GARCH.

Although the ACF of the raw returns exhibits little to no correlation, the ACF of the squared returns may still indicate significant correlation. In Figure 5 you will find a plot of the squared returns of the AEX. This shows that the variance process indeed shows correlation, justifying the use of autoregressive models.

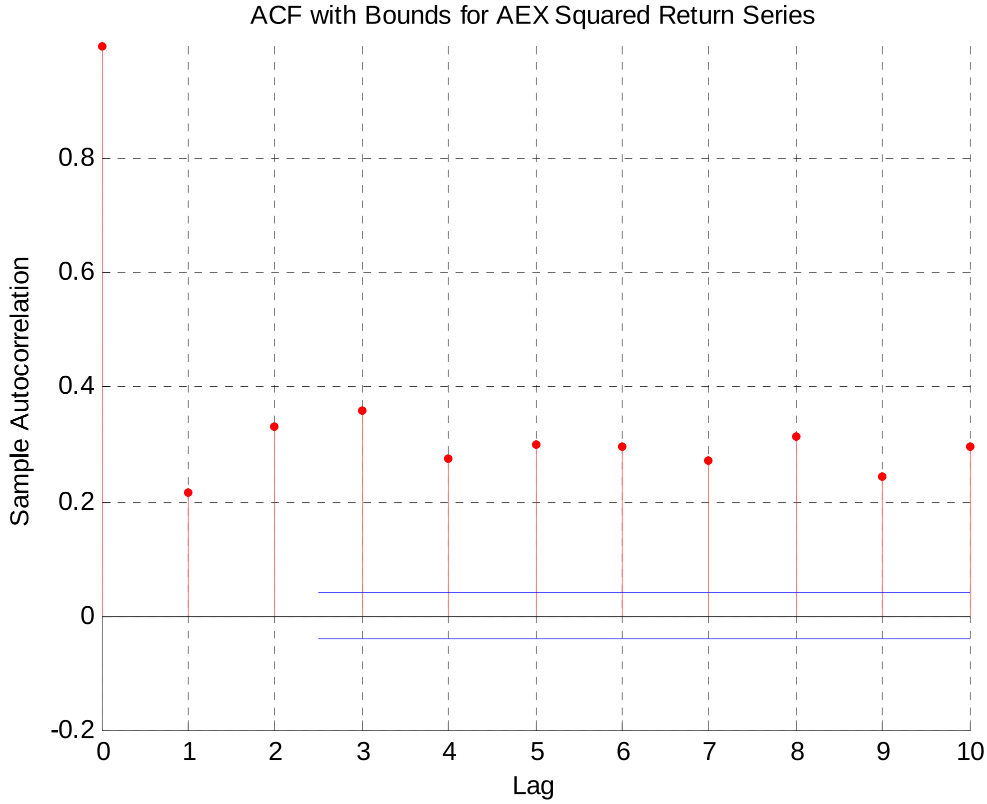

Figure 5: A plot of the Autocorrelation Function of the squared returns of the AEX.

In Appendix C ACF plots of the squared returns are made for the other companies. On visual inspection it can be noticed that not all companies show correlation even in their squared returns. In Table 2 you'll see a list of companies, whereby on the left are listed the companies with obvious correlation between the squared returns and on the right companies where there is none, at least not within a 95% confidence interval. In the middle a list of companies are given which show correlation only in the first few lags. The right column contains companies which should not do well with a GARCH model, but the middle column companies, seeing that GARCH(1,1) will be used, should generate models which will fit quite well.

Correlation	Correlation in first few lags	No Correlation
ABN AMRO	Heineken	Buhrmann
Aegon	IHC Caland	Getronics
Ahold	Van der Moolen	Numico
Akzo Nobel	Versatel	Unilever
ASML	VNU	Wolters Kluwer
DSM		
Elsevier		
Fortis		
Hagemeyer		
ING		
KPN		
Philips		
Royal Dutch Oil		
TPG		

Table 3: This table shows the companies divided into three groups on visual inspection of the ACF plots: containing correlation, containing little correlation and not containing any correlation with a 95% confidence interval.

To get a clearer picture, quantifying the preceding qualitative checks we'll use formal hypothesis tests, such as Ljung-Box-Pierce Q-test and Engle's ARCH test. The descriptions for both tests have already been given, so only the results and output of these tests will be described and shown.

The first test run on the dataset is the Ljung-Box-Pierce Q-test. This test will verify if there is significant correlation in the returns when tested for up to 5, 10, 15, 20 lags of the ACF at the 0.05 level of significance. The null hypothesis is that the model fit is adequate (no serial correlation at the corresponding element of lags). In Table 3 you can see the results. *H* is a boolean with 0 indicating acceptance of null hypothesis and 1 indicating rejection of the null hypothesis. *pValue* is the significance level at which this test rejects the null hypothesis of no serial correlation at a certain lag. *Stat* is the Q-statistic. *Critical value* is the value of the chi-square distribution for comparison with the corresponding element of the Q-statistic. As can be seen the null hypothesis of no serial correlation is rejected in the case of the AEX.

Lags	H	pValue	Stat	Critical Value
5	1	0,0014	19,6644	11,0705
10	1	0	42,9716	18,307
15	1	0	52,86	24,9958
20	1	0	66,811	31,4104

Table 4: Ljung-Box-Pierce Q-test results on AEX returns up to 5, 10, 15, 20 lags at a 0.05 level of significance.

In Appendix D you can see the results given by this test for the 24 companies in the AEX, run on the raw returns. The results for Buhrmann, DSM, Hagemeyer, Philips, TPG, Van der Moolen, Versatel and VNU show that with a significance level of 95% the null hypothesis cannot be rejected at least not for the first 5 lags, which means that the corresponding returns don't contain correlations.

Just like with the plots earlier, instead of running the test on the returns, the test was run on the squared returns as well. In Table 4 the results are given on AEX squared returns up to 5, 10, 15, 20 lags at a 0.05 level of significance. In this case, only Buhrmann and Getronics the null hypothesis is accepted. An anomaly to be noted is that Numico accepts the null after 5 lags. The results for the LBQ test on squared returns are shown in Appendix E.

Lags	H	pValue	Stat	Critical Value
5	1	0	1544,5	11,0705
10	1	0	2950	18,307
15	1	0	4124,5	24,9958
20	1	0	4925,4	31,4104

Table 5: Ljung-Box-Pierce Q-test results on AEX squared returns up to 5, 10, 15, 20 lags at a 0.05 level of significance.

The second test performed was Engle's ARCH test. This test shows if there is significant evidence in support of GARCH effects (i.e., heteroskedasticity). The test was performed including lags 5, 10, 15 and 20 of the squared sample residuals at a 5% significance level. In Table 4 the results for this test on the AEX is shown. *H* is a boolean with 0 indicating acceptance of null hypothesis that no ARCH effects exist; i.e., there is homoskedasticity and 1 indicating rejection of the null hypothesis. *pValue* is the significance level at which this test rejects the null hypothesis of no ARCH effects at a certain lag. *Stat* is the ARCH test statistic. *Critical value* is the value of the chi-square distribution for comparison with the corresponding element of the ARCH test statistic. The test on the AEX shows significant evidence in support of GARCH effects.

Lags	H	pValue	Stat	Critical Value
5	1	0	768,1356	11,0705
10	1	0	865,7376	18,307
15	1	0	902,3055	24,9958
20	1	0	906,73	31,4104

Table 6: Engle's ARCH test results on AEX returns including lags 5, 10, 15, 20 of the squared sample residuals at a 0.05 level of significance.

Again, the results for the other companies are shown in the Appendices, in Appendix F. The return series for Buhrmann and Getronics are once again unable to reject the null hypothesis of no GARCH effects. Numico only rejects the hypothesis after 5 lags. Although these companies do not appear to be suitable for GARCH modelling, the parameters for the models of these companies will be estimated and tested with the others.

3.3.3 Specification

As shown in the tests in the previous section, a GARCH process has been identified, which means there was correlation found in the series. Two companies, however, Buhrmann and Getronics did not show this property. In the following section a description will be given of the exact models used and an overview of the process will be given that was taken in doing this experiment.

But first an overview of what has to be done for this experiment will be given. The experiment consists of two parts. The first part is the estimation of parameters for the two chosen models and the second part is the calculation of option prices with these models.

There are a few steps that need to be taken in estimating the parameters of the models:

- Pre-estimation Analysis
- Parameter Estimation
- Post-estimation Analysis

Pre-estimation analysis was performed in section 3.3.2 indicating that the model to be used is appropriate.

As mentioned in the introduction GARCH(1,1) models will be implemented. In section 2.4 and 2.5 a description of the GARCH models were already given. Here a short recap of the two models will be given with the formulae that were used for parameter estimation.

In equation (1.1) you see the Itô process of a stock price. Two models will be compared, model I and II. Model I will be the widely used model for modelling volatility, GARCH. There are a number of extensions to the basic GARCH model. There are extensions or modifications towards allowing for long memory (Fractional GARCH), for seasonality (Seasonal or Periodic GARCH), and for the non-negativeness of the variances (Exponential GARCH)[22]. Model II will be such an extension, whereby expected returns are modelled next to the volatility. This model should allow the possibility that negative and positive returns follow different regimes or have a different impact on the returns series itself. The premise is that by varying expected returns or modelling expectancy the distribution of positive and negative returns will not be equal displaying excess skewness.

Consider series of returns u_t which follows a GARCH process as has been shown in section 3.3.2. The returns series u_t are dependent on expected returns μ and volatility σ with an unknown innovation.

$$\begin{aligned} u_t &= \mu_t + \varepsilon_t \\ \varepsilon_t &= \sigma_t \eta_t \end{aligned} \tag{3.4}$$

The conditional distribution of the innovations ε_t of the series u for time t is written

$$\varepsilon_t \mid \Psi_{t-1} \sim N(0, \sigma_t^2) \tag{3.5}$$

where Ψ_{t-1} denotes all available information at time $t-1$ and ε_t are the innovations of the returns.

The GARCH formulae have been mentioned in chapter 2. Model I assumes μ to be constant and σ to vary according to a GARCH process depending on previous σ and ε. Model I looks like

$$\sigma_t^2 = \omega + \alpha \sigma_{t-1}^2 + \beta \varepsilon_{t-1}^2 \tag{3.6}$$

[22] Frances, P.H. (1998). *Time series models for business and economic forecasting*, Cambridge University Press, 171-172.

with constraints

$$\alpha + \beta < 1$$
$$\omega > 0$$
$$\alpha \geq 0$$
$$\beta \geq 0$$

For regression purposes, the model can be rewritten as

$$\begin{aligned} u_t &= \gamma + \varepsilon_t \\ \varepsilon_t &= \sigma_t \eta_t \\ \sigma_t^2 &= \omega + \alpha \sigma_{t-1}^2 + \beta \varepsilon_{t-1}^2 \end{aligned} \tag{3.7}$$

where γ and ω are constants and $\eta_t \sim N(0,1)$.

Model II assumes both μ and σ to vary according to a GARCH process. The σ will be modelled according to equation (3.6). When the σ^2 is modelled in the μ the model is also called a GARCH-M[23] model. As for the μ, it will look like this

$$\mu_t = \delta + \lambda \sigma_t^2 \tag{3.8}$$

where δ is a constant and λ a parameter to be estimated.

The GARCH regression model for this model will be

$$\begin{aligned} u_t &= \delta + \lambda \sigma_t + \varepsilon_t \\ \varepsilon_t &= \sigma_t \eta_t \\ \sigma_t^2 &= \omega + \alpha \sigma_{t-1}^2 + \beta \varepsilon_{t-1}^2 \end{aligned} \tag{3.9}$$

adding an extra regressor that is the conditional standard deviation. This is, however, not just a juggling of formulae. In financial theory the relationship between risk and returns plays an important role. CAPM, for example, implies a linear relationship between the expected

[23] GARCH-in-mean.

returns of the market portfolio and the variance. If the risk (i.e. the variance) is not constant over time, then the conditional expectation of the market returns is a linear function of the conditional variance. The idea from Engle[24] was consequently used to estimate the conditional variances in GARCH and then the estimations will be used in the conditional expectations' estimation. This is the so called GARCH-in-Mean (GARCH-M) model. The $\lambda\sigma_t$ could be interpreted as the risk premium.

The parameters of these models will be estimated using the maximum likelihood method[25] to fit the return series as best as possible. This method uses a log-likelihood objective function (Equation 3.10) to find the most likely parameters that describe the series. It proceeds in three steps: first it infers process innovations (i.e. residuals) by inverse filtering given the observed data and parameter values. It's a whitening filter, transforming a possibly correlated process into an uncorrelated white noise process. Secondly, it infers conditional variances by using the inferred innovations. And finally, it uses the inferred innovations and conditional variances to evaluate the appropriate log-likelihood objective function.

$$LLF = -\frac{T}{2}\log(2\pi) - \frac{1}{2}\sum_{t=1}^{T}\log\sigma_t^2 - \frac{1}{2}\sum_{t=1}^{T}\frac{\varepsilon_t^2}{\sigma_t^2} \tag{3.10}$$

where T is the sample size, i.e., the number of rows in the series. The optimization repeats the three steps described above until suitable termination criteria are reached.

The criteria used for termination are the following: a maximum of iterations, a maximum of function evaluations and termination tolerance placed on constraint violations, log-likelihood functions and estimated parameter values. The default values for maximum iterations and maximum function evaluations are 400 and 100 times the number of parameters respectively. The values used for termination tolerance on constraint violations, log-likelihood functions and estimated parameter values are 10^{-7}, 10^{-6} and 10^{-6} respectively.

[24] Engle, R.F., Lilien, D.M. and Robins, R. P. (1987), Estimating time varying risk premia in the term structure: The ARCH-M model, *Econometrica* 55, 391-407.

[25] Description of Maximum Likelihood is retrieved from the documentation of the software tool MATLAB GARCH toolbox under maximum likelihood estimation.

3.3.4 Post-Estimation Analysis

After the estimation process, post-estimation analysis should be performed. This is similar to the testing done in section 3.3.2, but instead of looking for the GARCH process it is now necessary to see if the new models had any explanatory strength compared to the raw data of returns. Again qualitative and quantitative techniques will be employed.

There are three things that can be looked at. First, a plot to compare the Residuals, Conditional Standard Deviations and Returns. Then a plot to compare the Correlation of the Standardized Innovations. The innovations are the standardized by dividing the innovations by the volatilities. And finally the Correlation of the Standardized Innovations will be quantified by using a Q-test and the ARCH test. The results of this analysis will be given in the next chapter.

3.3.5 Model Selection

For model selection there are some tools and tests to employ, so before testing the models empirically three tests used for model selection will be performed first, Likelihood Ratio Test, Akaike (AIC) and Bayesian (BIC) information criteria. These test should give beforehand an idea how the models should perform. The option prices calculated later should then give a conclusive answer on the hypothesis made in this thesis.

Likelihood ratio hypothesis test[26] uses as input the optimized log-likelihood objective function (LLF) value associated with an unrestricted maximum likelihood parameter estimate, and the LLF values associated with restricted parameter estimates. The unrestricted LLF is the baseline case used to fit conditional mean and variance specifications to an observed univariate return series. The restricted models determine the null hypotheses of the test, and the number of restrictions they impose determines the degrees of freedom of the resulting chi-square distribution. In this case the restriction would be that the in-mean parameter λ would be equal to 0, so the degrees of freedom is 1.

[26] Description of Likelihood ratio hypothesis test is retrieved from the documentation of the software tool MATLAB GARCH toolbox under lratiotest.

The output given by this test are *H, pValue, Ratio* and *CriticalValue*. *H* is a Boolean decision. A 0 indicates acceptance of the restricted model under the null hypothesis. 1 indicates rejection of the restricted, null hypothesis model relative to the unrestricted alternative. *pValue* is the significance level at which this test rejects the null hypothesis of the restricted model. *Ratio* is the statistic calculated by multiplying the difference between the unrestricted LLF and restricted LLF by 2 (See equation 3.11). *CriticalValue* are the values of the chi-square distribution.

$$Ratio = 2(LLF_{unrestricted} - LLF_{restricted}) \tag{3.11}$$

Akaike (AIC) and Bayesian (BIC) information criteria[27] are used for model order selection. Both use the optimized LLF as input. They penalize models with additional parameters, parsimony is the basis of the AIC and BIC model order selection criteria. In equations (3.12) and (3.13) the definition of both the AIC and BIC statistic are given respectively.

$$AIC = (-2 * LLF) + (2 * NumParams) \tag{3.12}$$

$$BIC = (-2 * LLF) + (NumParams * \log(NumObs)) \tag{3.13}$$

where *NumParams* is the number of parameters and *NumObs* is the number of observations.

3.3.6 Option Price Simulation

Having estimated the models and done the post testing analysis and model selection tests, option prices will be calculated to compare it with the reality. All option prices will be calculated by the Black-Scholes option pricing formulae (equations 2.7 to 2.10). The formulae are described in chapter 2. Three prices will be generated, one with a constant volatility and two with volatility varying according to the estimations of either GARCH(1,1) or GARCH-M(1,1). These three option prices will then be compared to the actual option prices.

[27] Description of Akaike (AIC) and Bayesian (BIC) information criteria is retrieved from the documentation of the software tool MATLAB GARCH toolbox under aicbic.

Average percent mean-squared errors[28] will be used as the performance measure for this simulation. It is denoted as *AMSE(z)* and is given as

$$AMSE(z) = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{c_i - c_i(z)}{c_i}\right)^2 \qquad (3.14)$$

where, z denotes one of the three models which are used (volatility being constant, following GARCH(1,1) or GARCH-M(1,1)), c_i denotes the market price of the option, $c_i(z)$ denotes the option price estimated by model z and n denotes the total number of observations. This performance measure has the advantage that a €1 error on a €50 option carries less weight than a €1 error on a €5 option.

3.3.7 Analysis of Returns

The option prices are going to be modelled by Black-Scholes using either a constant volatility or a volatility according to GARCH(1,1) or GARCH-M(1,1). GARCH-M is different from the normal GARCH in its extra term in the returns function. As the option prices will primarily make use of the volatility function the difference between the two GARCH models will only be in the estimated parameters.

For this reason an extra test was deemed necessary to check the models. This check should involve the returns. The models formulae in equations (3.7) and (3.9) differ in the u_t function. As mentioned earlier, the expected returns is modelled as a function of the variance in GARCH-M instead of being constant in GARCH. The hypothesis will then be that the performance of the two models will depend on which expected return assumption, the parameter γ in the case of GARCH or $\gamma+\lambda\sigma^2$ in the case of GARCH-M, comes closer to the average returns. This could then be used as evidence for the use of either model.

[28] Harikumar, T. and De Boyrie, M.E. (2004). Evaluating of Black-Scholes and GARCH Models Using Currency Call Options Data, *Review of Quantitative Finance and Accounting, 23*, 299-312.

4 EXPERIMENTATION

4.1 Introduction

As mentioned in the previous chapter, the process has two parts. First, the parameters of the models have to be estimated. Second, with these models option prices are to be calculated. These will be compared with the actual option prices, using that as a benchmark. The simulation results will all be given in this chapter. To keep it concise I'll only show the AEX index results like in previous chapters, giving the results of the other 24 companies in appendices.

4.2 Parameter Estimation

In this section I'll show the results of the parameter estimations for the two models by displaying both the parameter estimates and their respective standard errors. But first the statistics (mean, volatility and variance) for the AEX index over the whole period of time will be given. The volatility here will be used as the constant volatility for Black-Scholes option pricing later. The statistics for the companies are given in Appendix G.

	Mean	Volatility	Variance
AEX	0,0004	0,2018	0,0407

Table 7: Mean, volatility and variance of AEX index returns.

4.2.1 Parameters of Model I

Parameter	Value	Standard Error	T Statistic
γ	0,000616	0,000154	4,001
ω	1,86E-06	2,01E-07	9,2723
α	0,89715	0,007361	121,8781
β	0,09014	0,006739	13,3751

Table 8: Parameters of Model I on the returns of the AEX.

In Table 7 the parameters are shown that were estimated on the AEX return series. Substituted into the model it will look something like this:

$$
\begin{aligned}
u_t &= 0{,}000616 + \varepsilon_t \\
\varepsilon_t &= \sigma_t e_t \\
\sigma_t^2 &= 1{,}86\text{E-}06 + 0{,}89715\sigma_{t-1}^2 + 0{,}09014\varepsilon_{t-1}^2
\end{aligned}
\tag{4.1}
$$

As can be seen in the equations (4.1), the constants are very low and have little effect. The hypothesis that γ or ω are not significantly different from 0 cannot be accepted. The majority of the effects, however, come from the variance and the innovations of the previous period, whereby the innovations seem to say relatively a lot less than the variance.

In Appendix H the results are given for the 24 companies, it should be noted that the hypothesis that γ is not significantly different from 0 is accepted for all companies except Buhrmann. This company also shows strange parameter estimates compared to the other companies. The ratio GARCH parameter (α) and ARCH parameter (β) are different compared to the other companies, whereby the β is a lot greater than the α, giving more emphasis on the previous innovation. The findings for this company may be explained by the findings in the pre-testing analysis, where this company did not show the presence of (G)ARCH effects. In the next section the parameters for model II will be estimated.

4.2.2 Parameters of Model II

Parameter	Value	Standard Error	T Statistic
δ	0,00045885	0,00021896	2,0956
λ	1,9012	1,8653	1,0193
ω	1,87E-06	2,02E-07	9,248
α	0,89644	0,0073763	121,529
β	0,090825	0,0067895	13,3773

Table 9: Parameters of Model II on the returns of the AEX.

Just like in the previous section, the results of the estimation procedure for Model II are shown in Table 8. Here you will see an extra value given, parameter λ, showing the effect of the variance in the mean model. It should be noted, however, that its value is not significantly different from 0. Substituted in to the model the equations will look like this:

$$\begin{aligned} u_t &= 0{,}00045885 + 1{,}9012\sigma_t + \varepsilon_t \\ \varepsilon_t &= \sigma_t e_t \\ \sigma_t^2 &= 1{,}87\text{E-}06 + 0{,}89644\sigma_{t-1}^2 + 0{,}090825\varepsilon_{t-1}^2 \end{aligned} \tag{4.2}$$

Similar to the previous model, the previous variance says a lot about the current variance, whereby the previous innovations say relatively a lot less about the current variance. Even though an extra parameter was added in the mean, the parameters for the variance and innovations are quite similar to those of model I. The estimated parameter for the variance-in-mean is however not significantly different from 0.

Even when looking at the results for the 24 companies, there is no parameter estimate which is significantly different from 0, except for probably Wolters Kluwer. Ahold, Hagemeyer and Numico give a negative value for the mean parameter. For all the results please refer to Appendix I.

In the next section post estimation analysis will be performed to see what effect the models had on the data and compare both models.

4.3 Post Estimation Analysis

In section 3.3.4 several tests were mentioned both qualitative as well as quantitative which was going to be performed after the estimation of the parameters for both models. In the next two sections the results to these tests for both models will be given. The qualitative checks will be a plot comparing the residuals, conditional standard deviations and returns, a plot of the standardized innovations and a plot of the ACF. As for the quantitative checks the Ljung-Box-Pierce Q-test and Engle's ARCH test will be run on the standardized innovations to check for correlation.

4.3.1 Model I

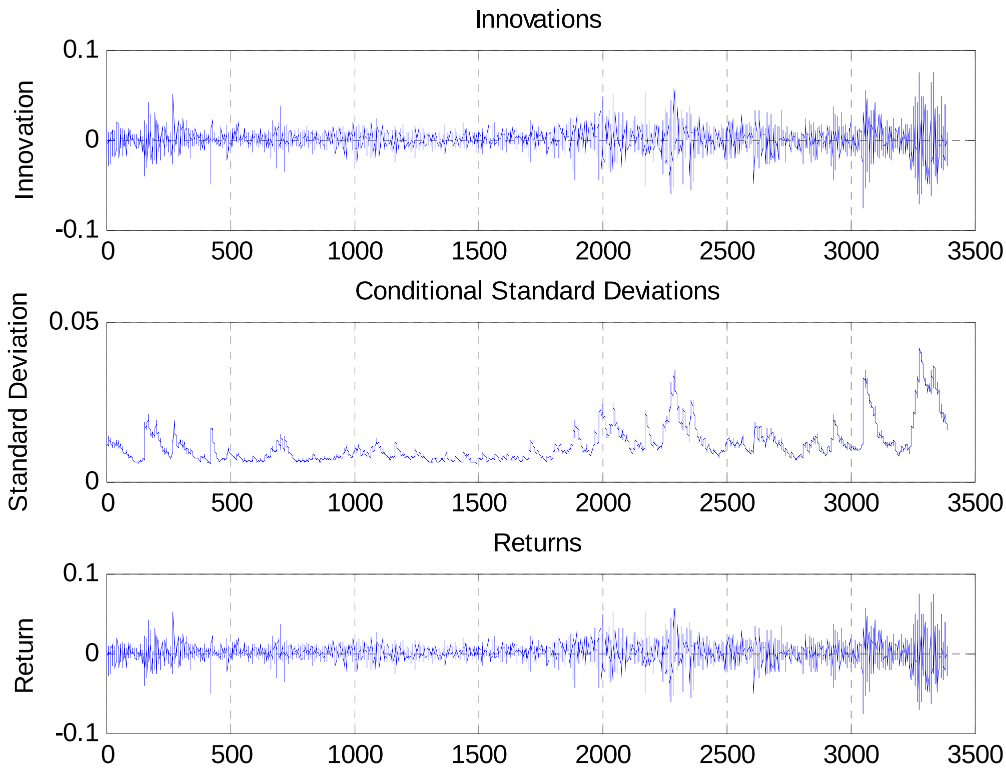

Figure 6: Plot of the residuals, conditional standard deviation and returns.

Here are the post estimation test results for model I. A plot of the residuals, conditional standard deviations, and returns is shown to inspect the relationship between them (See Figure 6). As can be seen in the plot of innovations and returns, they both exhibit volatility clustering

Second, a plot is made of the standardized innovations, which are the innovations divided by the standard deviation (See Figure 7). They appear generally stable with less clustering.

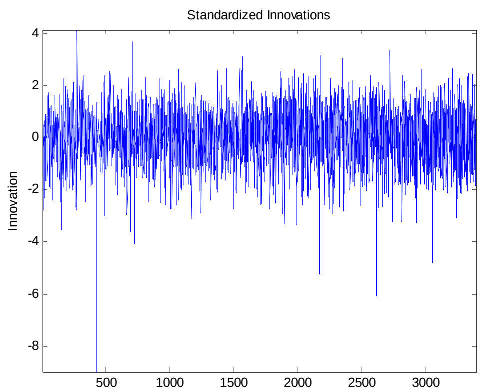

Figure 7: Plot of the standardized innovations.

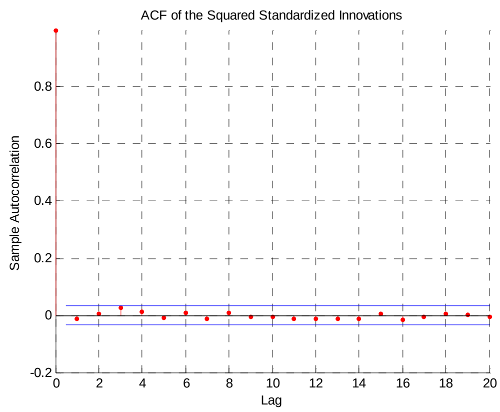

Figure 8: Plot of the ACF of the squared standardized innovations.

In Figure 8 the ACF of the squared standardized innovations can be seen, which show no more correlation. Comparing with Figure 5, it shows that this model sufficiently explains the heteroskedasticity in the raw returns.

	Ljung-Box-Pierce Q-Test				Engle's ARCH Test			
Lags	**H**	**pValue**	**Stat**	**Critical Value**	**H**	**pValue**	**Stat**	**Critical Value**
5	0	0,6378	3,4049	11,0705	0	0,627	3,476	11,0705
10	0	0,919	4,5524	18,307	0	0,9161	4,6019	18,307
15	0	0,9722	6,4011	24,9958	0	0,9704	6,4861	24,9958
20	0	0,9954	7,3431	31,4104	0	0,9962	7,1362	31,4104

Table 10: Ljung-Box-Pierce Q-test and Engle's ARCH test on standardized innovations of model I.

In Table 9 you will see the results of the two tests performed on the standardized innovations. Comparing these results of the Q-test and the ARCH test with the results of the same tests in the pre-estimation analysis (See Tables 3, 4 and 5), both the Q-test and the ARCH test indicate rejection (H = 1 with pValue = 0) of their respective null hypotheses, showing significant evidence in support of GARCH effects. In the post estimate analysis, using standardized innovations based on the estimated model, these same tests indicate acceptance (H = 0 with highly significant *pValues*) of their respective null hypotheses and confirm the explanatory power of this model.

In Appendix J the plot of residuals, standard deviations and returns, the ACF plot, LBQ test results and ARCH test results are shown. Looking at the ACF plot, LBQ test and ARCH test results you can notice that Buhrmann and ING jump out. The abovementioned model doesn't seem sufficient in explaining the heteroskedasticity for both companies. Even after modelling, correlation seems to exist in the innovations although only in later lags.

4.3.2 Model II

Similar to the previous section the plot of residuals, standard deviations and returns for inspection (See Figure 9) are shown. The plot looks similar to the one of model I in Figure 6 exhibiting volatility clustering.

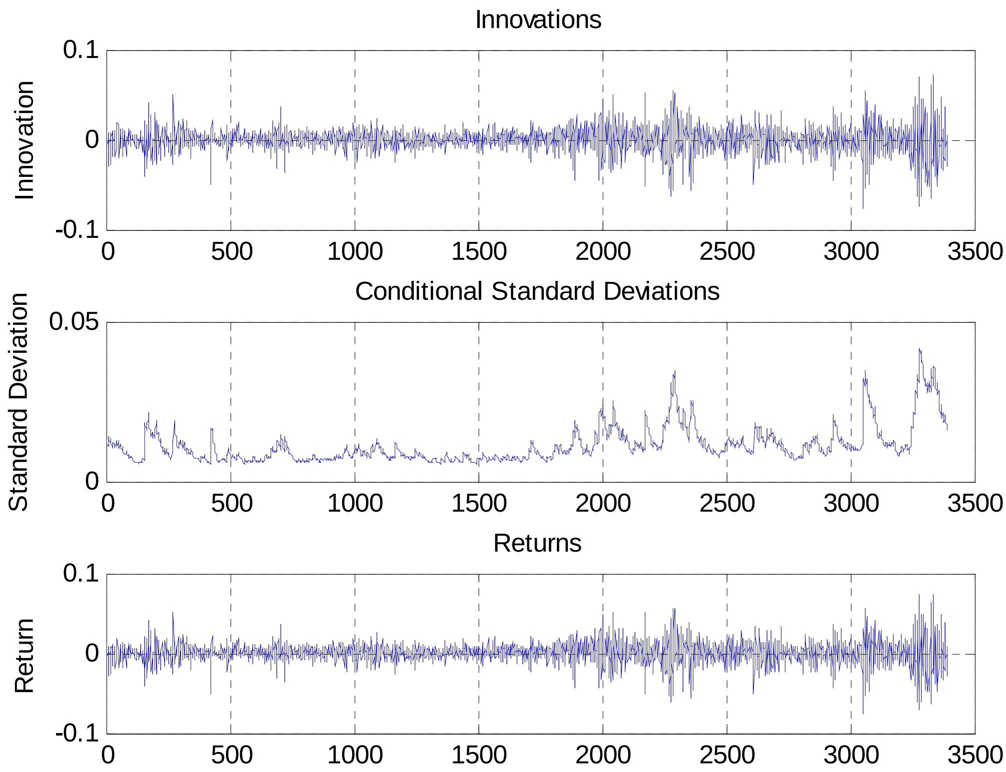

Figure 9: Plot of the residuals, conditional standard deviation and returns.

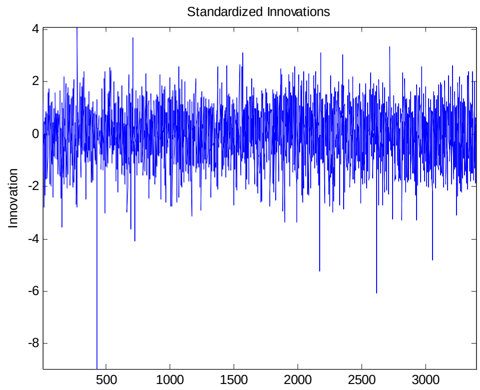

Figure 10: Plot of the standardized innovations

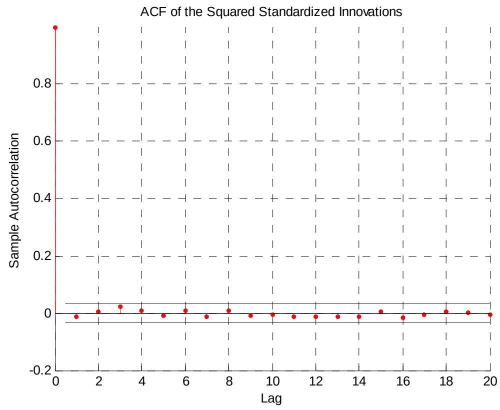

Figure 11: Plot of the ACF of the squared standardized innovations.

In Figure 10 and 11 you'll see the standardized innovations and the ACF plot of the squared standardized innovations respectively. Table 10 shows the results of the LBQ test and the ARCH test. If there is an improvement compared to model I, it is very minimal.

	Ljung-Box-Pierce Q-Test				Engle's ARCH Test			
Lags	**H**	**pValue**	**Stat**	**Critical Value**	**H**	**pValue**	**Stat**	**Critical Value**
5	0	0,6534	3,3028	11,0705	0	0,6431	3,3705	11,0705
10	0	0,924	4,4647	18,307	0	0,9213	4,5125	18,307
15	0	0,9732	6,3521	24,9958	0	0,9715	6,4337	24,9958
20	0	0,9954	7,3356	31,4104	0	0,9963	7,1144	31,4104

Table 11: Ljung-Box-Pierce Q-test and Engle's ARCH test on standardized innovations of model II.

Looking at Table 10, you can see once again that the null hypothesis is accepted, which confirms the explanatory power of the used model. The results for the 24 companies are shown in Appendix K. For Buhrmann and ING the model seems to be insufficient in explaining the all the heteroskedasticity.

4.4 Model Selection

Before calculating the option prices, model selection tests will be performed to examine the performance between the two models. In the previous section it was shown that the models had sufficient power to explain the heteroskedasticity in the series. In this section a comparison will be made between the two models. In section 3.3.5 three tests are described to be performed for model selection. The likelihood ratio test was performed and the results are shown in Table 11. The null hypothesis is accepted, so the GARCH(1,1) model seems to do better than the GARCH-M(1,1) model.

H	pValue	Stat	Critical Value
0	0,3144	1,0119	3,8415

Table 12: Likelihood Ratio Test Results on the two models of the AEX .

In Appendix L the results for this test are given for the 24 companies. For only one company model II seems to perform better: TPG. This company was not highlighted in previous testing as not being suitable for GARCH. Hopefully the next tests can shed some more light.

Two other tests were mentioned in section 3.3.5: AIC and BIC. The results for these tests are shown in Table 12. The results show that both AIC and BIC show preference for Model I. BIC imposes penalties for additional parameters, so BIC always provides a model with a number of parameters no greater than that chosen by AIC.

1,0e+004 *	**AIC**	**BIC**
Model I	-2,14471427134519	-2,14223294973447
Model II	-2,14461546367298	-2,14151381165958

Table 13: AIC and BIC Statistics for AEX.

In Appendix L again the results for both the AIC and BIC are shown for the 24 companies. AIC for Getronics, Heineken, IHC Caland, Philips, TPG and VNU show Model II as the preferred model. BIC on the other hand shows for all companies that Model I is to be preferred. The penalty given by BIC for the abovementioned companies for the extra parameter seems far greater than the preference the AIC shows for Model II, resulting in Model I being preferred. As mentioned throughout this thesis Getronics needs to be highlighted once again because it was deemed unfit for this type of modelling. Seeing that the BIC for the rest of the companies show preference for Model I, Model II doesn't seem significantly different or better than the standard GARCH(1,1)-model, at least not statistically.

4.5 Calculating Option Prices

After performing statistical tests, an empirical experiment will be done. As mentioned in section 3.3.6 option prices will be calculated using various methods for the volatility and compared with the actual prices. To do an initial assessment plots of the calculated option prices are made. Then to quantify the differences between the models a performance measure will be used. The performance measure used will be the Average percent mean-squared errors (See equation 3.14).

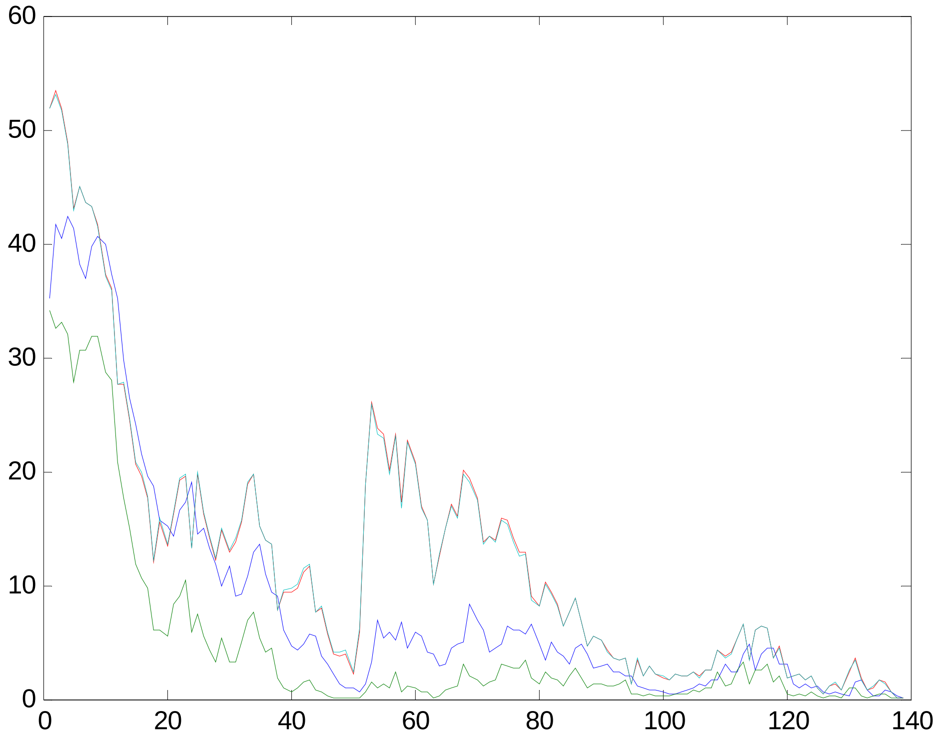

Figure 12: Plot of call option prices (blue line shows the actual prices, green line shows the Black-Scholes prices with constant volatility, red line shows the Black-Scholes prices with volatility varied by GARCH(1,1) and cyan line shows the Black-Scholes prices with volatility varied by GARCH-M(1,1).

In Figure 12 the plots are shown of the call option prices. The actual prices (blue line), Black-Scholes option prices with constant volatility (green line), GARCH(1,1) volatility (red line) and GARCH-M(1,1) volatility are plotted. On visual inspection the GARCH(1,1) and GARCH-M(1,1) prices are overlapping. This was expected seeing that the function used for volatility calculation is similar except for the estimated parameters. Another point to note is the undervaluing of the Black-Scholes option pricing model with constant volatility.

In Appendix M the call option prices both actually realised and calculated are plotted for the 24 companies. Three companies jump out: AEGON, Versatel and Wolkers Kluwer. Their plots are different from the other companies.

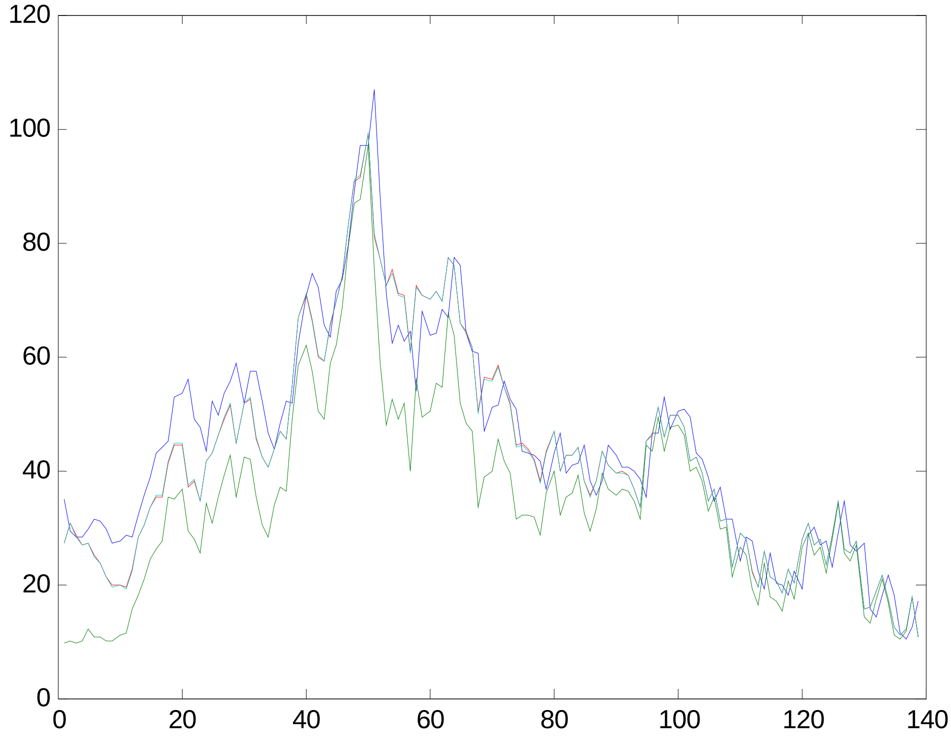

Figure 13: Plot of put option prices (blue line shows the actual prices, green line shows the Black-Scholes prices with constant volatility, red line shows the Black-Scholes prices with volatility varied by GARCH(1,1) and cyan line shows the Black-Scholes prices with volatility varied by GARCH-M(1,1).

In Figure 13 the put option prices are shown in a plot. The actual prices seem to be well described by the three models. In Appendix N the put option prices are plotted for the 24 companies. Now only AEGON and Wolkers Kluwer show a difference in their plots compared to the other companies.

To quantify the performance of the models the AMSE was calculated for the three models. In Table 14 the results are shown of the performance measure AMSE on the option prices calculated for the AEX. Using the Black-Scholes with constant volatility has the closest fit to the actual prices. As for the two GARCH models, GARCH(1,1) seems to outperform the GARCH-M(1,1) slightly.

	Constant	GARCH(1,1)	GARCH-M(1,1)
AEX	0,4216	4,2373	4,3273

Table 14: AMSE Results for AEX

In Appendix O the results are shown for the other 24 companies. Again is seen, how the constant volatility shows a closer fit to the actual prices. There are however exceptions. Aegon, ASML, KPN, Numico, Philips and Royal Dutch Oil show the GARCH models as performing better. If we would just compare the two GARCH models, GARCH(1,1) seems to perform better in more cases than GARCH-M(1,1).

4.6 Analysis of Returns

As mentioned in section 3.3.7 option pricing may not be a completely suitable test for determining if GARCH or GARCH-M is the better model. In the previous section it has shown that GARCH should be the preferred model of the two GARCH models, but seeing that only the volatility was used, it was only a difference in the estimated parameters. The extra mean parameter which was included was not taken into account in the previous section. So it seemed necessary to do an extra test with the returns.

The test will be to see which mean component of the two GARCH models is closer to the actual average expected returns. GARCH(1,1) has a constant term, whereas GARCH-M(1,1) has a constant component plus a variable component dependent on the variance. The assumption is that the volatility part of the model will have equal positive as well as negative values cancelling each other out, whereby the expected value of the returns will be the average of its returns. In Table 7 and Appendix G the mean of the returns were given for the AEX and the 24 companies. The expected value for returns using GARCH(1,1)-model will be equal to the γ parameter and the expected value for returns using GARCH-M(1,1) will be equal to $\gamma+\lambda\sigma_t^2$.

	Average Returns	GARCH(1,1)	GARCH-M(1,1)
AEX	0,00036467	0,00061620	0,00076266

Table 15: Expected Value of Returns for the AEX.

In Table 15 the results are shown for the returns of the AEX. It can be seen that the GARCH(1,1) expected return or mean value is closer to the actual average of the returns compared to the GARCH-M(1,1) result.

The results for the 24 companies are given in Appendix P. As shown in previous tests the GARCH(1,1) is the preferred model overall, but for Ahold, Buhrmann, Hagemeyer, Numico, Versatel and VNU the mean of the GARCH-M(1,1) seems closer to the actual average of returns than GARCH(1,1).

5 CONCLUSION

5.1 Introduction

In this chapter I'll recap on all that was done in this experiment and draw conclusions. I'll also give suggestions on how this experiment can and should be expanded in future research.

5.2 Recap

The endeavour to examine if GARCH(1,1) or GARCH-M(1,1) was the better model in describing return series for option pricing was done statistically and empirically.

The dataset was first tested by various statistical testing methods to see if GARCH modelling was suitable. Only for Buhrmann and Getronics the tests showed negative results. The other companies including the AEX index contained correlation in its returns or squared returns, which meant that a GARCH process was found and modelling with GARCH was appropriate.

After testing the dataset, the models were set up and run; the parameters were estimated. With these estimated parameters option prices were calculated by changing the volatility value in the Black-Scholes formulae.

Finally, seeing that the GARCH-M model didn't differ much in the volatility calculation from the GARCH model, the returns were examined more closely.

5.3 Findings

The dataset was shown to contain GARCH process or in other words correlation was found in either the returns or squared returns, which meant that GARCH modelling was suitable. After the models were applied it was shown that the models had explanatory strengths in describing the dataset as they reduced or removed the correlation.

When the models were used in option pricing, it showed that using a constant volatility calculated from past return series fit closer to the actual prices in many instances. There are however a few exceptions, whereby the GARCH models performed better or came closer to the actual prices.

As a final resort in examining the two models, the expected returns were calculated and compared with the actual average returns to see if GARCH or GARCH-M would have more explanatory power.

The conclusion is, that after all the testing and experiments GARCH(1,1) is only slightly better than GARCH-M(1,1). It should, however, be noted that although GARCH-M(1,1) has one more parameter, the model didn’t perform much better than GARCH(1,1). This could indicate overfitting by GARCH-M(1,1) model. Further testing should be done to be able to give a conclusive answer to the stated hypothesis in this thesis.

5.4 Further Research

Although GARCH(1,1) performed better in a few more instances than GARCH-M(1,1), it is by far not conclusive. This thesis was written with the Dutch economy in mind and looking at stock option prices. It may be that in other economies different results could be obtained. There are also other options which could be considered for comparing both models.

For this experiment the returns were used of the AEX and the companies that comprise the AEX. Another suggestion might be to look at excess returns instead of just the returns; that means looking at the returns above or below the returns of the market.

As stated in Campbell and Hentschel (1992) earlier, suggesting an asymmetric distribution of volatility, it would probably also give more insights in examining the distribution of returns, which was not explicitly done in this thesis.

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4. http://www.csc.fi/cschelp/sovellukset/stat/sas/sasdoc/sashtml/ets/chap8/sect22.htm
5. http://support.sas.com/rnd/app/examples/ets/garchex/index.htm#ets_garchex_garch
6. http://www1.elsevier.com/hes/books/02/04/049/0204049.htm

APPENDIX A: ACF-plots

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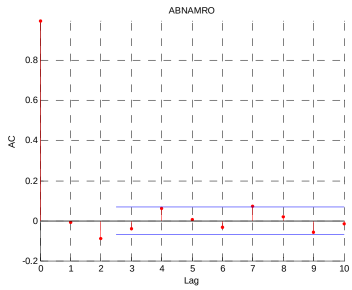

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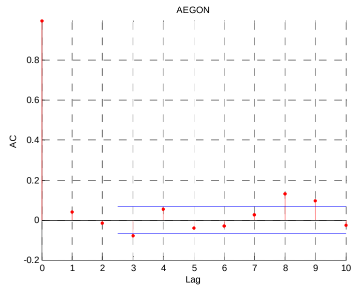

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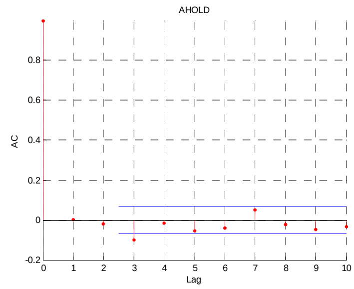

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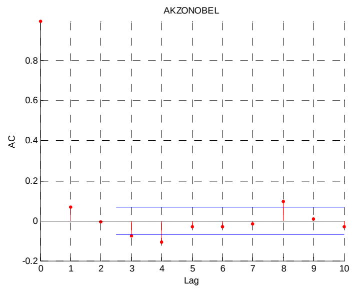

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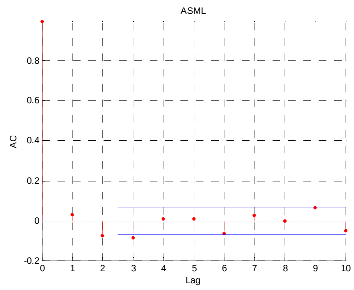

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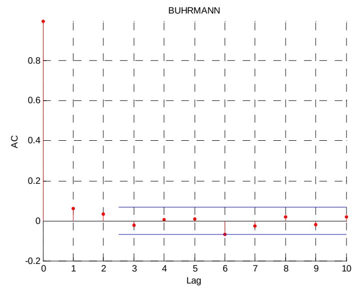

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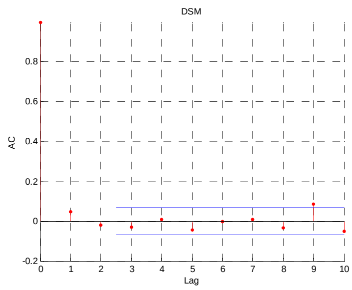

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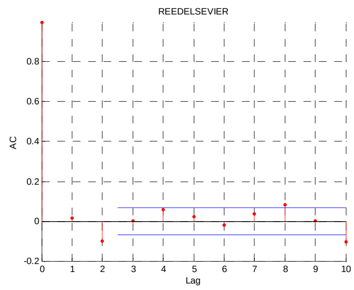

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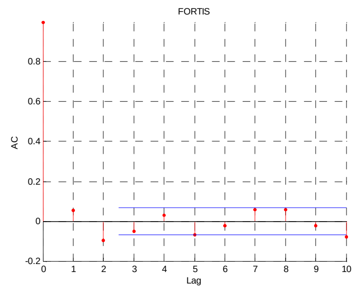

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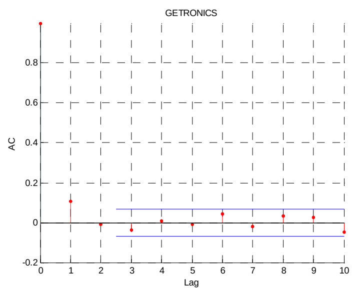

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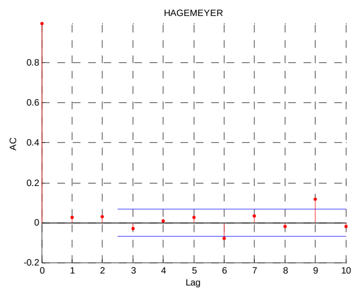

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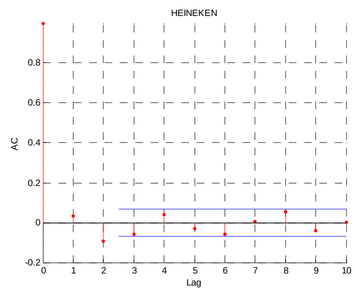

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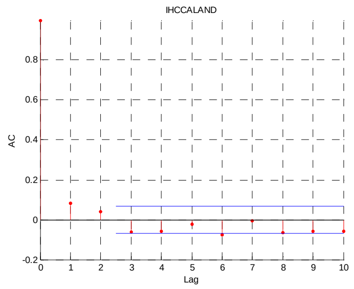

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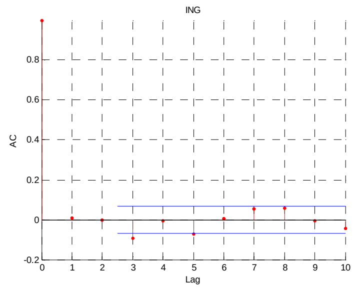

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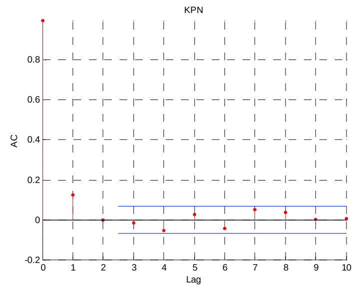

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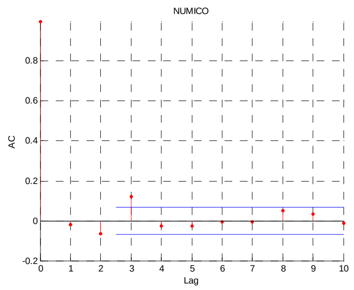

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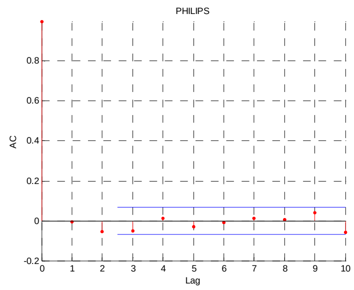

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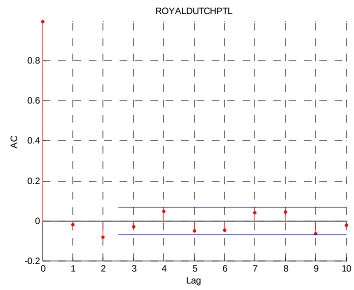

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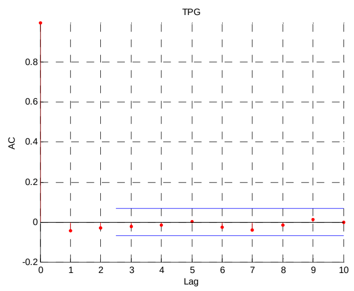

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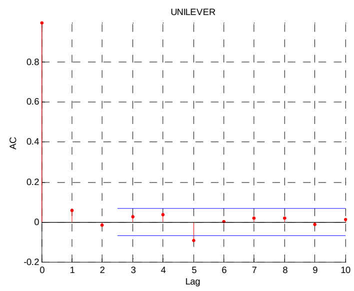

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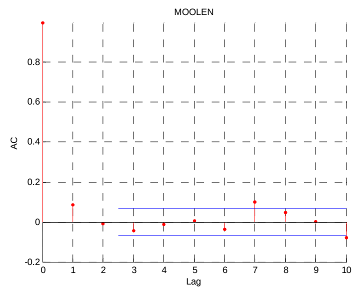

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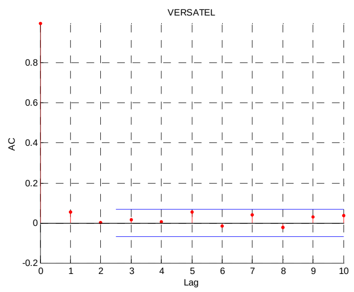

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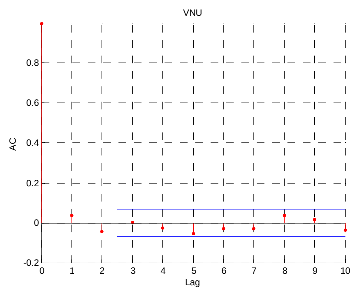
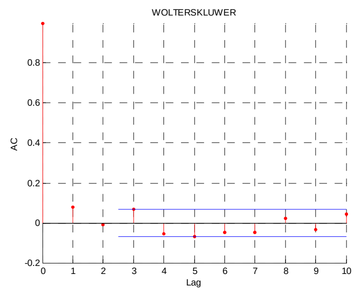
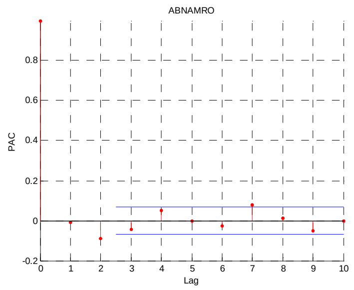


Wolters Kluwer



APPENDIX B: PACF-plots

ABNAMRO



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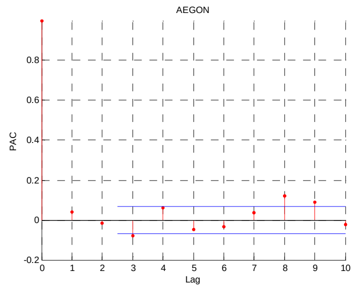

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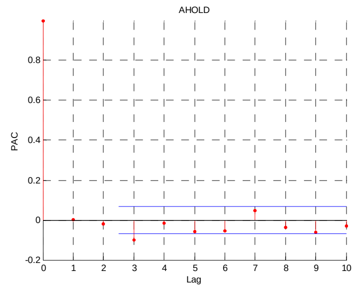
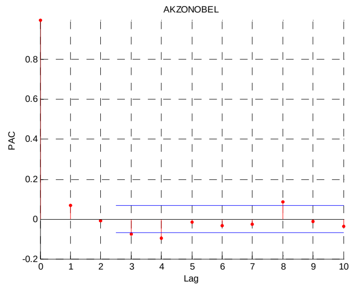
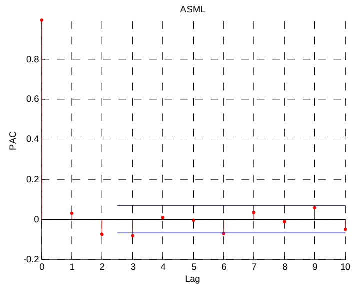


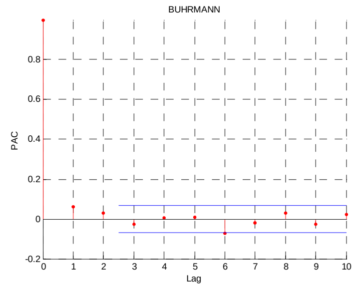
Akzo Nobel



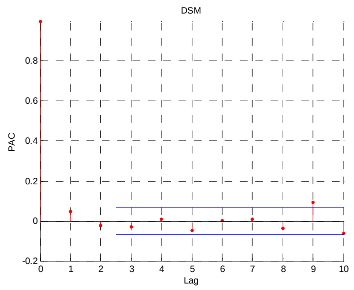
ASML



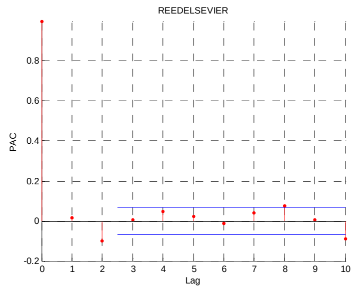
Buhrmann



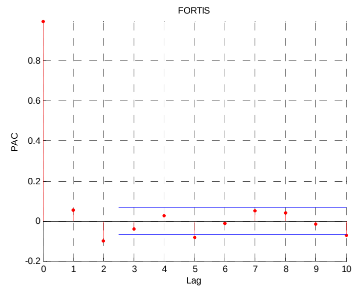
DSM



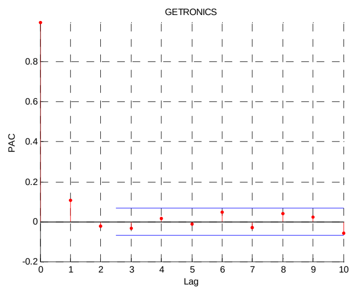
Elsevier



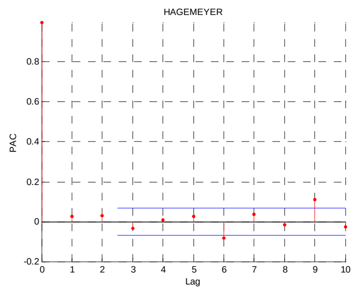
Fortis



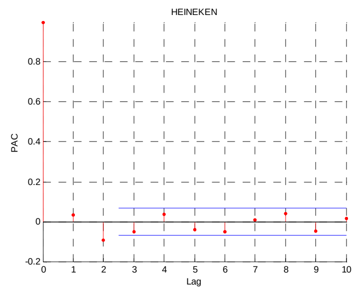
Getronics



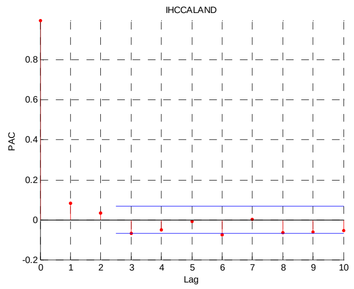
Hagemeyer



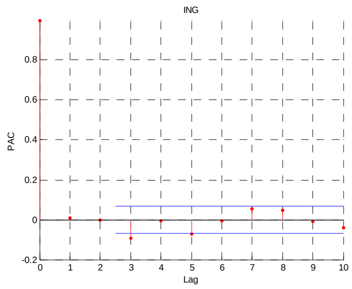
Heineken



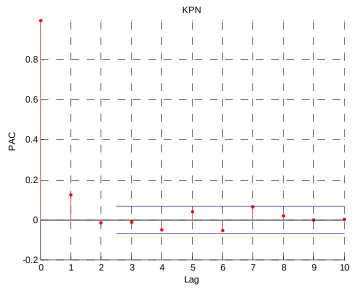
IHC Caland



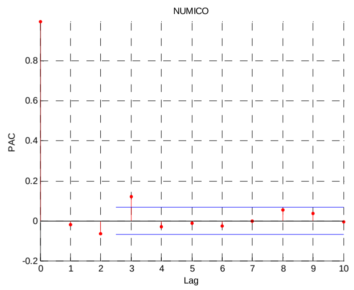
ING



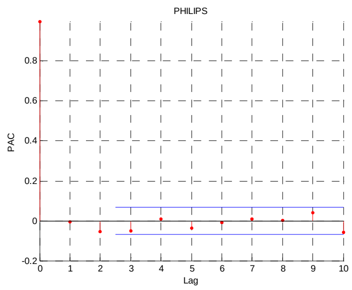
KPN



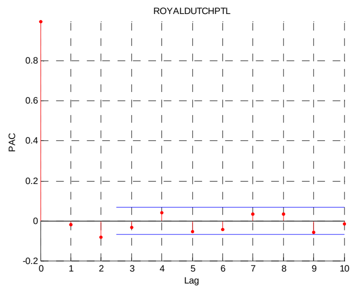
Numico



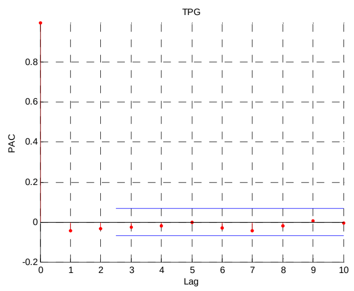
Philips



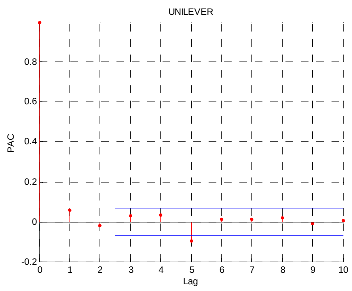
Royal Dutch Oil



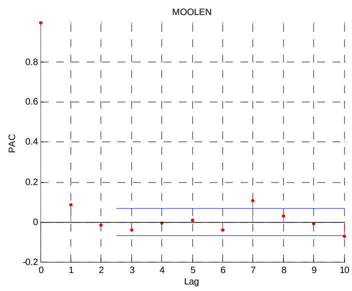
TPG



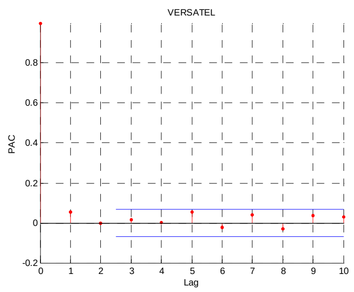
Unilever



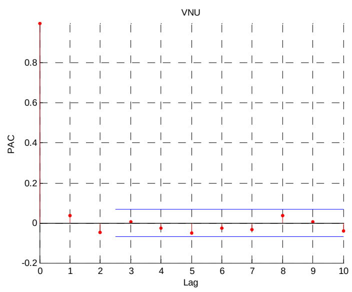
Van der Moolen



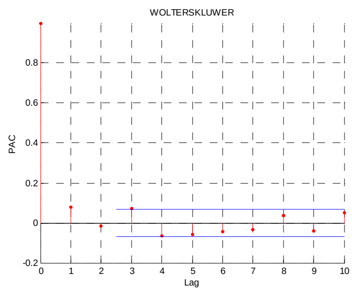
Versatel



VNU

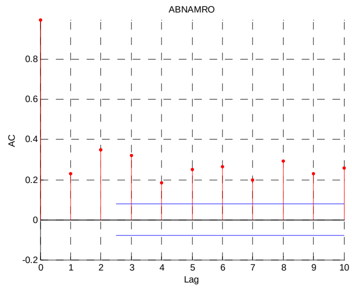


Wolters Kluwer

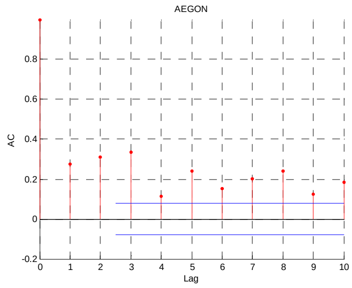


APPENDIX C: ACF-plots of u^2

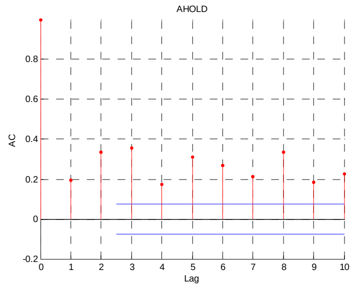
ABNAMRO



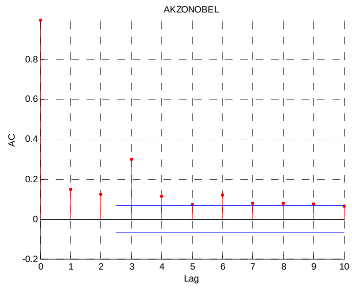
AEGON



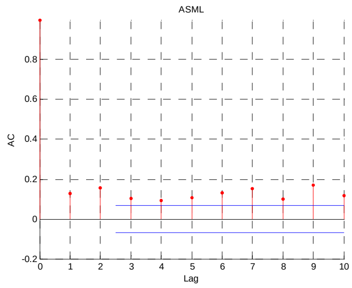
AHOLD



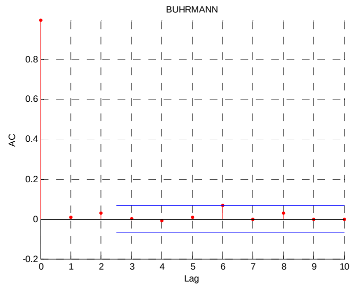
Akzo Nobel



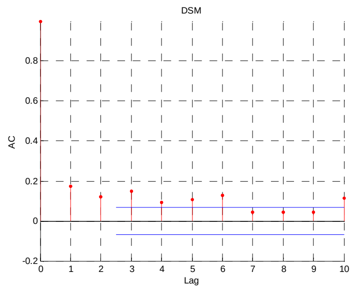
ASML



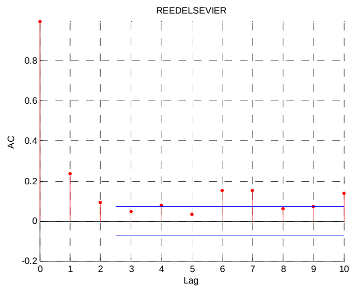
Buhrmann



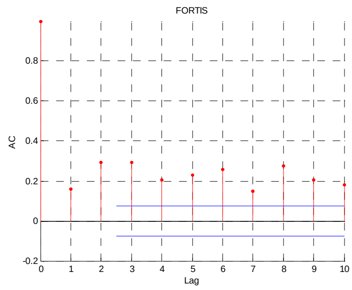
DSM



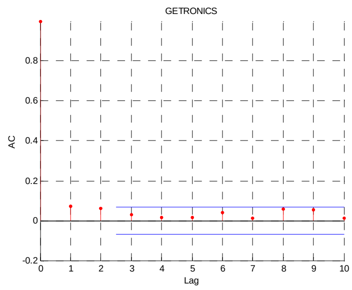
Elsevier



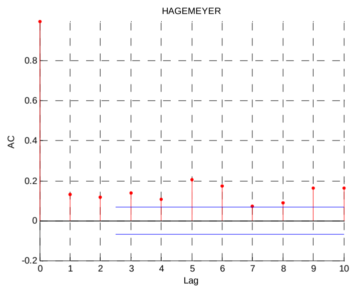
Fortis



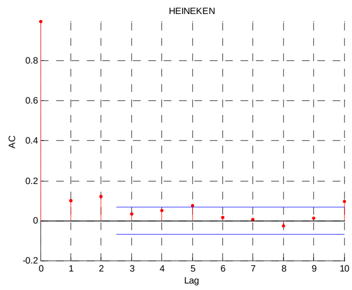
Getronics



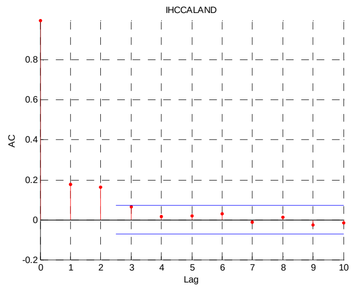
Hagemeyer



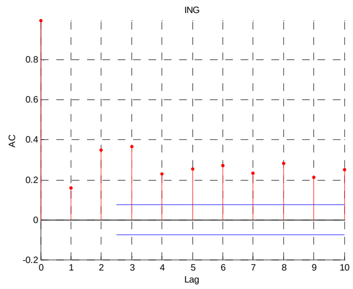
Heineken



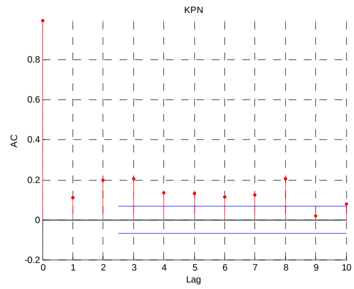
IHC Caland



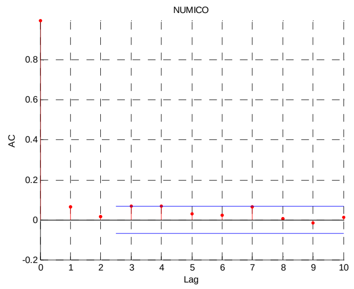
ING



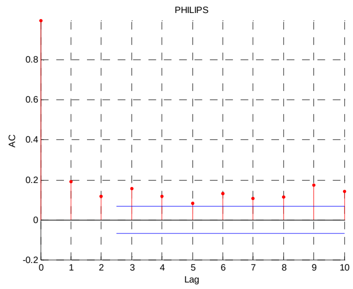
KPN



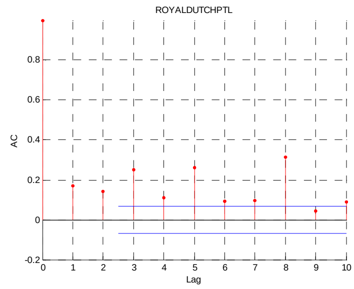
Numico



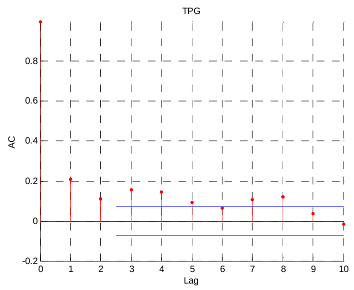
Philips



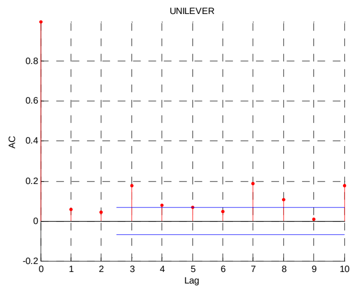
Royal Dutch Oil



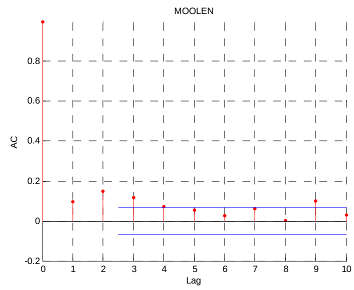
TPG



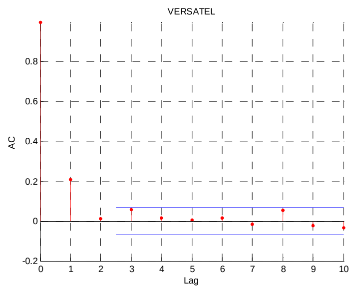
Unilever



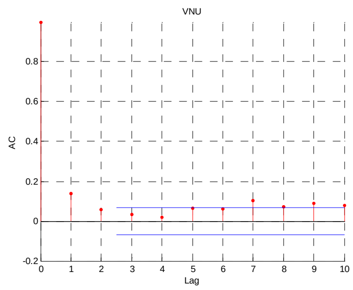
Van der Moolen



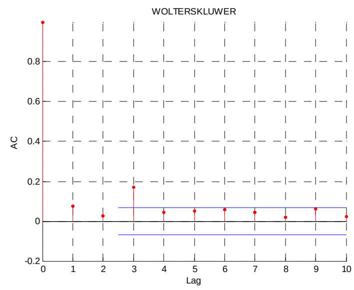
Versatel



VNU



Wolters Kluwer



APPENDIX D: LBQ Test on u

	ABNAMRO				AEGON				AHOLD			
Lags	H	pValue	Stat	Critical Value	H	pValue	Stat	Critical Value	H	pValue	Stat	Critical Value
5	1	0,0324	12,1832	11,0705	1	0,0493	11,1081	11,0705	1	0,0371	11,8363	11,0705
10	1	0,018	21,4756	18,307	1	0	37,5114	18,307	1	0,035	19,4398	18,307
15	1	0,0012	37,1871	24,9958	1	0	48,4111	24,9958	1	0,001	37,6865	24,9958
20	1	0	61,3296	31,4104	1	0	64,3299	31,4104	1	0	62,6615	31,4104

	Akzo Nobel				ASML				Buhrmann			
Lags	H	pValue	Stat	Critical Value	H	pValue	Stat	Critical Value	H	pValue	Stat	Critical Value
5	1	0,0012	20,1247	11,0705	1	0,0282	12,5283	11,0705	0	0,406	5,0815	11,0705
10	1	0,0008	30,105	18,307	1	0,0103	23,1342	18,307	0	0,3525	11,0651	18,307
15	1	0,0047	33,0188	24,9958	0	0,0592	24,3625	24,9958	0	0,599	13,0425	24,9958
20	1	0,001	45,2898	31,4104	1	0,0005	47,2483	31,4104	0	0,7805	14,9278	31,4104

	DSM				Elsevier				Fortis			
Lags	H	pValue	Stat	Critical Value	H	pValue	Stat	Critical Value	H	pValue	Stat	Critical Value
5	0	0,4002	5,1304	11,0705	1	0,0285	12,5014	11,0705	1	0,002	18,8954	11,0705
10	0	0,1234	15,2439	18,307	1	0,0009	29,9019	18,307	1	0,0004	32,086	18,307
15	0	0,1412	20,866	24,9958	1	0,0018	35,8988	24,9958	1	0,0019	35,7167	24,9958
20	0	0,1531	26,3981	31,4104	1	0,003	41,7095	31,4104	1	0,0007	46,5096	31,4104

	Getronics				Hagemeyer				Heineken			
Lags	H	pValue	Stat	Critical Value	H	pValue	Stat	Critical Value	H	pValue	Stat	Critical Value
5	1	0,0396	11,672	11,0705	0	0,6798	3,1311	11,0705	1	0,0157	13,9909	11,0705
10	0	0,0649	17,4521	18,307	1	0,0099	23,248	18,307	1	0,0203	21,1209	18,307
15	0	0,0684	23,8095	24,9958	1	0,0132	29,6656	24,9958	1	0,0026	34,8672	24,9958
20	0	0,1158	27,7374	31,4104	1	0,0024	42,4353	31,4104	1	0,0003	49,396	31,4104

	IHC Caland				ING				KPN			
Lags	H	pValue	Stat	Critical Value	H	pValue	Stat	Critical Value	H	pValue	Stat	Critical Value
5	1	0,0121	14,6209	11,0705	1	0,0267	12,6649	11,0705	1	0,0033	17,7113	11,0705
10	1	0,001	29,6114	18,307	1	0,0253	20,4512	18,307	1	0,0104	23,0912	18,307
15	1	0,0038	33,6502	24,9958	1	0,0101	30,5572	24,9958	1	0,0064	32,0243	24,9958
20	1	0,0045	40,3268	31,4104	1	0,0002	50,8034	31,4104	1	0,0191	35,1875	31,4104

	Numico				Philips				Royal Dutch Oil			
Lags	H	pValue	Stat	Critical Value	H	pValue	Stat	Critical Value	H	pValue	Stat	Critical Value
5	1	0,0021	18,823	11,0705	0	0,2917	6,1525	11,0705	1	0,0412	11,5684	11,0705
10	1	0,0137	22,2895	18,307	0	0,3603	10,9642	18,307	1	0,0192	21,2779	18,307
15	1	0,0401	25,808	24,9958	0	0,2979	17,3589	24,9958	0	0,0513	24,9027	24,9958
20	1	0,0083	38,21	31,4104	0	0,176	25,6982	31,4104	1	0,0335	33,0265	31,4104

	TPG				Unilever				Van der Moolen			
Lags	**H**	**pValue**	**Stat**	**Critical Value**	**H**	**pValue**	**Stat**	**Critical Value**	**H**	**pValue**	**Stat**	**Critical Value**
5	0	0,6302	3,4553	11,0705	1	0,0245	12,8809	11,0705	0	0,132	8,474	11,0705
10	0	0,829	5,8342	18,307	0	0,1829	13,7866	18,307	1	0,0036	26,1194	18,307
15	0	0,7178	11,4811	24,9958	1	0,0203	28,2104	24,9958	1	0,0162	28,969	24,9958
20	0	0,3545	21,7448	31,4104	1	0,0459	31,7597	31,4104	1	0,0306	33,3785	31,4104

	Versatel				VNU				Wolters Kluwer			
Lags	**H**	**pValue**	**Stat**	**Critical Value**	**H**	**pValue**	**Stat**	**Critical Value**	**H**	**pValue**	**Stat**	**Critical Value**
5	0	0,3424	5,6441	11,0705	0	0,2817	6,26	11,0705	1	0,005	16,7721	11,0705
10	0	0,4502	9,8896	18,307	0	0,3957	10,5248	18,307	1	0,0071	24,1985	18,307
15	0	0,201	19,2876	24,9958	0	0,4583	14,9047	24,9958	1	0,001	37,6162	24,9958
20	0	0,1653	26,0155	31,4104	0	0,2099	24,7821	31,4104	1	0,0017	43,6092	31,4104

APPENDIX E: LBQ Test on u^2

	ABNAMRO				AEGON				AHOLD			
Lags	H	pValue	Stat	Critical Value	H	pValue	Stat	Critical Value	H	pValue	Stat	Critical Value
5	1	0	338,1078	11,0705	1	0	318,1347	11,0705	1	0	358,2000	11,0705
10	1	0	622,1306	18,307	1	0	469,9267	18,307	1	0	639,4000	18,307
15	1	0	837,0658	24,9958	1	0	614,4195	24,9958	1	0	922,8000	24,9958
20	1	0	937,283	31,4104	1	0	702,7652	31,4104	1	0	1207,5000	31,4104

	Akzo Nobel				ASML				Buhrmann			
Lags	H	pValue	Stat	Critical Value	H	pValue	Stat	Critical Value	H	pValue	Stat	Critical Value
5	1	0	130,681	11,0705	1	0	64,8329	11,0705	0	0,9559	1,08	11,0705
10	1	0	163,6298	18,307	1	0	148,8345	18,307	0	0,7965	6,2196	18,307
15	1	0	168,2304	24,9958	1	0	180,9257	24,9958	0	0,9742	6,3013	24,9958
20	1	0	178,1208	31,4104	1	0	238,7446	31,4104	0	0,9981	6,4905	31,4104

	DSM				Elsevier				Fortis			
Lags	H	pValue	Stat	Critical Value	H	pValue	Stat	Critical Value	H	pValue	Stat	Critical Value
5	1	0	81,534	11,0705	1	0	66,3964	11,0705	1	0	261,1203	11,0705
10	1	0	114,1592	18,307	1	0	133,2729	18,307	1	0	474,028	18,307
15	1	0	141,2476	24,9958	1	0	238,9764	24,9958	1	0	616,7035	24,9958
20	1	0	159,2501	31,4104	1	0	255,7828	31,4104	1	0	704,1398	31,4104

	Getronics				Hagemeyer				Heineken			
Lags	H	pValue	Stat	Critical Value	H	pValue	Stat	Critical Value	H	pValue	Stat	Critical Value
5	0	0,0739	10,0481	11,0705	1	0	90,7089	11,0705	1	0	30,685	11,0705
10	0	0,0783	16,8277	18,307	1	0	174,0744	18,307	1	0	40,0923	18,307
15	0	0,1799	19,7968	24,9958	1	0	240,9943	24,9958	1	0	70,6315	24,9958
20	0	0,1813	25,5461	31,4104	1	0	257,7777	31,4104	1	0	77,5679	31,4104

	IHC Caland				ING				KPN			
Lags	H	pValue	Stat	Critical Value	H	pValue	Stat	Critical Value	H	pValue	Stat	Critical Value
5	1	0	57,6228	11,0705	1	0	360,2673	11,0705	1	0	116,121	11,0705
10	1	0	59,578	18,307	1	0	647,5247	18,307	1	0	185,825	18,307
15	1	0	77,0424	24,9958	1	0	786,3095	24,9958	1	0	193,7825	24,9958
20	1	0	89,6692	31,4104	1	0	919,9567	31,4104	1	0	204,2959	31,4104

	Numico				Philips				Royal Dutch Oil			
Lags	H	pValue	Stat	Critical Value	H	pValue	Stat	Critical Value	H	pValue	Stat	Critical Value
5	1	0,0194	13,4609	11,0705	1	0	84,9016	11,0705	1	0	174,7662	11,0705
10	0	0,0515	18,2089	18,307	1	0	168,9311	18,307	1	0	288,7013	18,307
15	0	0,0553	24,6211	24,9958	1	0	225,642	24,9958	1	0	334,6609	24,9958
20	1	0,0163	35,7843	31,4104	1	0	268,315	31,4104	1	0	380,802	31,4104

	TPG			
Lags	H	pValue	Stat	Critical Value
5	1	0	99,892	11,0705
10	1	0	127,9893	18,307
15	1	0	157,2736	24,9958
20	1	0	159,4898	31,4104

	Unilever			
Lags	H	pValue	Stat	Critical Value
5	1	0	43,4872	11,0705
10	1	0	116,6205	18,307
15	1	0	147,804	24,9958
20	1	0	162,9629	31,4104

	Van der Moolen			
Lags	H	pValue	Stat	Critical Value
5	1	0	48,3422	11,0705
10	1	0	62,0989	18,307
15	1	0	66,6551	24,9958
20	1	0	69,5217	31,4104

	Versatel			
Lags	H	pValue	Stat	Critical Value
5	1	0	44,0052	11,0705
10	1	0	47,9229	18,307
15	1	0	48,178	24,9958
20	1	0,0003	49,3838	31,4104

	VNU			
Lags	H	pValue	Stat	Critical Value
5	1	0,0001	25,8319	11,0705
10	1	0	57,0491	18,307
15	1	0	77,176	24,9958
20	1	0	91,05	31,4104

	Wolters Kluwer			
Lags	H	pValue	Stat	Critical Value
5	1	0	35,7111	11,0705
10	1	0	44,3537	18,307
15	1	0	66,2082	24,9958
20	1	0	73,4598	31,4104

APPENDIX F: ARCH Test

	ABNAMRO				AEGON				AHOLD			
Lags	**H**	**pValue**	**Stat**	**Critical Value**	**H**	**pValue**	**Stat**	**Critical Value**	**H**	**pValue**	**Stat**	**Critical Value**
5	1	0	174,8633	11,0705	1	0	175,859	11,0705	1	0	191,333	11,0705
10	1	0	207,5007	18,307	1	0	192,1491	18,307	1	0	218,4174	18,307
15	1	0	223,4433	24,9958	1	0	207,6608	24,9958	1	0	239,6748	24,9958
20	1	0	230,2287	31,4104	1	0	215,3135	31,4104	1	0	259,2456	31,4104

	Akzo Nobel				ASML				Buhrmann			
Lags	**H**	**pValue**	**Stat**	**Critical Value**	**H**	**pValue**	**Stat**	**Critical Value**	**H**	**pValue**	**Stat**	**Critical Value**
5	1	0	97,3448	11,0705	1	0	43,6392	11,0705	0	0,9558	1,0806	11,0705
10	1	0	100,6604	18,307	1	0	73,0157	18,307	0	0,8188	5,958	18,307
15	1	0	106,7066	24,9958	1	0	79,4602	24,9958	0	0,9784	6,0805	24,9958
20	1	0	111,969	31,4104	1	0	95,9901	31,4104	0	0,9987	6,162	31,4104

	DSM				Elsevier				Fortis			
Lags	**H**	**pValue**	**Stat**	**Critical Value**	**H**	**pValue**	**Stat**	**Critical Value**	**H**	**pValue**	**Stat**	**Critical Value**
5	1	0	53,3197	11,0705	1	0	54,5909	11,0705	1	0	145,9987	11,0705
10	1	0	65,629	18,307	1	0	98,8405	18,307	1	0	172,61	18,307
15	1	0	80,9516	24,9958	1	0	154,8009	24,9958	1	0	187,9873	24,9958
20	1	0	88,9471	31,4104	1	0	162,1303	31,4104	1	0	195,2936	31,4104

	Getronics				Hagemeyer				Heineken			
Lags	**H**	**pValue**	**Stat**	**Critical Value**	**H**	**pValue**	**Stat**	**Critical Value**	**H**	**pValue**	**Stat**	**Critical Value**
5	0	0,1247	8,631	11,0705	1	0	62,7577	11,0705	1	0,0002	24,6241	11,0705
10	0	0,2054	13,3383	18,307	1	0	87,4195	18,307	1	0,0002	34,0194	18,307
15	0	0,4741	14,688	24,9958	1	0	103,3713	24,9958	1	0	50,1508	24,9958
20	0	0,5156	19,0966	31,4104	1	0	107,6736	31,4104	1	0,0001	53,6678	31,4104

	IHC Caland				ING				KPN			
Lags	**H**	**pValue**	**Stat**	**Critical Value**	**H**	**pValue**	**Stat**	**Critical Value**	**H**	**pValue**	**Stat**	**Critical Value**
5	1	0	45,3359	11,0705	1	0	204,6654	11,0705	1	0	75,0918	11,0705
10	1	0	47,0004	18,307	1	0	224,5849	18,307	1	0	98,9525	18,307
15	1	0	56,5967	24,9958	1	0	241,5416	24,9958	1	0	101,4273	24,9958
20	1	0	64,622	31,4104	1	0	250,3545	31,4104	1	0	104,0559	31,4104

	Numico				Philips				Royal Dutch Oil			
Lags	**H**	**pValue**	**Stat**	**Critical Value**	**H**	**pValue**	**Stat**	**Critical Value**	**H**	**pValue**	**Stat**	**Critical Value**
5	1	0,0404	11,6197	11,0705	1	0	55,436	11,0705	1	0	117,2741	11,0705
10	0	0,1368	14,873	18,307	1	0	80,9606	18,307	1	0	159,1244	18,307
15	0	0,198	19,3578	24,9958	1	0	92,304	24,9958	1	0	160,067	24,9958
20	0	0,1758	25,7032	31,4104	1	0	94,1479	31,4104	1	0	165,0341	31,4104

	TPG				Unilever				Van der Moolen			
Lags	**H**	**pValue**	**Stat**	**Critical Value**	**H**	**pValue**	**Stat**	**Critical Value**	**H**	**pValue**	**Stat**	**Critical Value**
5	1	0	64,9561	11,0705	1	0	36,96	11,0705	1	0	35,0568	11,0705
10	1	0	74,3084	18,307	1	0	76,7894	18,307	1	0	42,4627	18,307
15	1	0	92,9353	24,9958	1	0	84,6341	24,9958	1	0,0001	44,2609	24,9958
20	1	0	100,419	31,4104	1	0	86,7326	31,4104	1	0,0007	46,5886	31,4104

	Versatel				VNU				Wolters Kluwer			
Lags	**H**	**pValue**	**Stat**	**Critical Value**	**H**	**pValue**	**Stat**	**Critical Value**	**H**	**pValue**	**Stat**	**Critical Value**
5	1	0	45,2578	11,0705	1	0,0004	22,4583	11,0705	1	0	32,1397	11,0705
10	1	0	50,827	18,307	1	0	38,4311	18,307	1	0,0001	34,6082	18,307
15	1	0	51,2643	24,9958	1	0	49,2395	24,9958	1	0	55,2958	24,9958
20	1	0,0001	52,3237	31,4104	1	0,0001	51,97	31,4104	1	0	56,8774	31,4104

APPENDIX G: Mean, Volatility, Variance

	Mean	Volatility	Variance
ABN AMRO	-0,0002	0,4050	0,1640
Aegon	-0,0011	0,4635	0,2148
Ahold	-0,0010	0,4094	0,1676
Akzo Nobel	-0,0003	0,3307	0,1094
ASML	-0,0009	0,7730	0,5975
Buhrmann	-0,0016	0,7141	0,5099
DSM	0,0004	0,3005	0,0903
Elsevier	0,0000	0,3781	0,1430
Fortis	-0,0006	0,3990	0,1592
Getronics	-0,0035	0,8068	0,6509
Hagemeyer	-0,0014	0,4699	0,2208
Heineken	-0,0001	0,2829	0,0800
IHC Caland	0,0002	0,3626	0,1315
ING	-0,0004	0,4344	0,1887
KPN	-0,0014	0,6992	0,4889
Numico	-0,0012	0,4416	0,1950
Philips	-0,0004	0,5897	0,3477
Royal Dutch Oil	-0,0002	0,3173	0,1007
TPG	-0,0004	0,3497	0,1223
Unilever	0,0000	0,2968	0,0881
Van der Moolen	0,0002	0,4351	0,1893
Versatel	-0,0042	1,0477	1,0977
VNU	-0,0003	0,4828	0,2331
Wolters Kluwer	-0,0008	0,4432	0,1964

APPENDIX H: Parameters of Model I

Parameter	ABNAMRO Value	ABNAMRO Std Error	ABNAMRO T Stat	AEGON Value	AEGON Std Error	AEGON T Stat	AHOLD Value	AHOLD Std Error	AHOLD T Stat	Akzo Nobel Value	Akzo Nobel Std Error	Akzo Nobel T Stat
γ	0,00047	0,000653	0,7196	-0,00026	0,000739	-0,3498	4,41E-05	0,000544	0,081	0,000186	0,000605	0,3079
ω	1,42E-05	2,85E-06	4,989	1,50E-05	4,15E-06	3,614	3,85E-06	1,91E-06	2,0111	2,68E-05	7,02E-06	3,8215
α	0,85447	0,013749	62,1461	0,8903	0,013508	65,9108	0,88798	0,016334	54,3655	0,78142	0,031375	24,9056
β	0,12203	0,012532	9,7374	0,090319	0,011203	8,0623	0,11199	0,017793	6,2941	0,16244	0,025972	6,2544

Parameter	ASML Value	ASML Std Error	ASML T Stat	Buhrmann Value	Buhrmann Std Error	Buhrmann T Stat	DSM Value	DSM Std Error	DSM T Stat	Elsevier Value	Elsevier Std Error	Elsevier T Stat
γ	0,00018	0,001484	0,1214	0,002886	0,001012	2,8516	0,000502	0,00057	0,8801	3,23E-05	0,000703	0,0459
ω	4,06E-05	1,67E-05	2,4352	0,000831	4,73E-05	17,5653	1,16E-05	3,21E-06	3,6113	1,38E-05	4,25E-06	3,2381
α	0,9159	0,017003	53,8666	0,034889	0,018946	1,8415	0,8737	0,019145	45,635	0,88869	0,016176	54,9382
β	0,068536	0,015423	4,4437	0,96511	0,049563	19,4724	0,095906	0,017241	5,5627	0,087922	0,01371	6,4129

Parameter	Fortis Value	Fortis Std Error	Fortis T Stat	Getronics Value	Getronics Std Error	Getronics T Stat	Hagemeyer Value	Hagemeyer Std Error	Hagemeyer T Stat	Heineken Value	Heineken Std Error	Heineken T Stat
γ	-0,00023	0,000611	-0,3753	-0,00343	0,001863	-1,8417	-0,00022	0,000795	-0,2814	-0,00013	0,000551	-0,2411
ω	1,60E-05	4,91E-06	3,2496	0,000156	3,06E-05	5,0854	3,28E-05	7,16E-06	4,5849	5,78E-06	2,23E-06	2,596
α	0,82474	0,022201	37,1486	0,87977	0,020598	42,7108	0,8465	0,021329	39,6878	0,94124	0,014713	63,9743
β	0,15381	0,016726	9,1959	0,063713	0,012204	5,2207	0,11537	0,017238	6,6927	0,041022	0,00974	4,2118

	IHC Caland			ING			KPN			Numico		
Parameter	Value	Std Error	T Stat	Value	Std Error	T Stat	Value	Std Error	T Stat	Value	Std Error	T Stat
γ	0,000707	0,000725	0,9746	0,000583	0,000611	0,9535	-0,00061	0,00139	-0,4383	-0,00094	0,000693	-1,3539
ω	0,000168	4,57E-05	3,6683	7,42E-06	2,29E-06	3,243	0,000119	3,34E-05	3,5569	4,20E-05	4,59E-06	9,1359
α	0,52221	0,10784	4,8424	0,88507	0,012161	72,7766	0,81803	0,02947	27,7586	0,82408	0,009273	88,8737
β	0,15201	0,031471	4,8301	0,10552	0,011991	8,7999	0,12372	0,019605	6,3107	0,13782	0,00826	16,6856

	Philips			Royal Dutch Oil			TPG			Unilever		
Parameter	Value	Std Error	T Stat	Value	Std Error	T Stat	Value	Std Error	T Stat	Value	Std Error	T Stat
γ	1,04E-05	0,001165	0,009	0,000145	0,00056	0,2581	-0,00032	0,000581	-0,5509	0,000193	0,000572	0,3369
ω	3,80E-05	1,82E-05	2,0943	8,43E-06	3,38E-06	2,4946	2,77E-05	6,70E-06	4,1299	5,35E-06	1,89E-06	2,8271
α	0,89736	0,027666	32,4357	0,88891	0,020865	42,6023	0,78714	0,027135	29,0083	0,93259	0,01006	92,7048
β	0,074955	0,018359	4,0828	0,089831	0,017006	5,2822	0,16398	0,023574	6,956	0,05348	0,008188	6,5313

	Van der Moolen			Versatel			VNU			Wolters Kluwer		
Parameter	Value	Std Error	T Stat	Value	Std Error	T Stat	Value	Std Error	T Stat	Value	Std Error	T Stat
γ	0,000173	0,000897	0,1924	-0,00549	0,001997	-2,7512	-0,00083	0,00091	-0,9086	-0,00035	0,000774	-0,4476
ω	0,000113	1,78E-05	6,3122	0,001136	0,000178	6,3815	1,51E-05	5,63E-06	2,6889	5,37E-05	7,39E-06	7,2621
α	0,73405	0,038568	19,0326	0,49347	0,049891	9,891	0,90784	0,017592	51,6042	0,77447	0,023518	32,9315
β	0,11615	0,019315	6,0136	0,26767	0,02548	10,5052	0,079476	0,018545	4,2855	0,1697	0,021032	8,0688

APPENDIX I: Parameters of Model II

	ABNAMRO			AEGON			AHOLD			Akzo Nobel		
Parameter	Value	Std Error	T Stat	Value	Std Error	T Stat	Value	Std Error	T Stat	Value	Std Error	T Stat
δ	7,19E-05	0,00092406	0,0778	-0,00080853	0,0011666	-0,6931	0,00025511	0,00073486	0,3472	-0,00082828	0,0012427	-0,6665
λ	1,1084	1,8495	0,5993	1,0921	1,7989	0,6071	-0,72715	1,664	-0,437	3,0477	3,2555	0,9362
ω	1,41E-05	2,86E-06	4,9497	1,50E-05	4,15E-06	3,6085	3,84E-06	1,92E-06	2,005	2,58E-05	6,75E-06	3,8226
α	0,85518	0,013803	61,9544	0,89056	0,01357	65,6286	0,88778	0,016285	54,5155	0,78785	0,029919	26,3328
β	0,12145	0,012694	9,5678	0,090055	0,011243	8,0099	0,11222	0,017745	6,324	0,15767	0,024896	6,3333

	ASML			Buhrmann			DSM			Elsevier		
Parameter	Value	Std Error	T Stat	Value	Std Error	T Stat	Value	Std Error	T Stat	Value	Std Error	T Stat
δ	-0,0020339	0,0033839	-0,6011	0,0032181	0,0012271	2,6224	-0,0007399	0,00121	-0,6115	-0,00082826	0,0013638	-0,6073
λ	1,1426	1,56	0,7324	-0,25289	0,52707	-0,4798	4,3821	3,8333	1,1432	2,0134	2,6425	0,7619
ω	4,11E-05	1,68E-05	2,4414	0,00084302	5,14E-05	16,4059	1,12E-05	3,17E-06	3,544	1,38E-05	4,28E-06	3,2176
α	0,91579	0,0171	53,5544	0,027578	0,021455	1,2854	0,87553	0,018886	46,3594	0,88799	0,016371	54,2432
β	0,06838	0,015451	4,4256	0,97242	0,051916	18,7307	0,094821	0,016952	5,5936	0,088711	0,013822	6,4183

	Fortis			Getronics			Hagemeyer			Heineken		
Parameter	**Value**	**Std Error**	**T Stat**	**Value**	**Std Error**	**T Stat**	**Value**	**Std Error**	**T Stat**	**Value**	**Std Error**	**T Stat**
δ	-0,00089657	0,00085457	-1,0492	-0,0090225	0,0041543	-2,1719	-0,00010537	0,0013639	-0,0773	-0,0029482	0,0017747	-1,6612
λ	1,9372	1,816	1,0667	2,5464	1,6428	1,5501	-0,19615	1,8476	-0,1062	10	6,0048	1,6653
ω	1,60E-05	4,95E-06	3,2214	0,0001696	3,36E-05	5,0413	3,28E-05	7,28E-06	4,5007	5,79E-06	2,23E-06	2,5903
α	0,8248	0,022277	37,024	0,86969	0,022404	38,8185	0,84662	0,021643	39,1168	0,94078	0,014425	65,22
β	0,15363	0,016619	9,2442	0,068616	0,013195	5,2002	0,1153	0,017298	6,6658	0,041477	0,0095627	4,3374

	IHC Caland			ING			KPN			Numico		
Parameter	**Value**	**Std Error**	**T Stat**	**Value**	**Std Error**	**T Stat**	**Value**	**Std Error**	**T Stat**	**Value**	**Std Error**	**T Stat**
δ	-0,003546	0,0025817	-1,3735	0,00025899	0,00078467	0,3301	-0,0020636	0,0029187	-0,707	1,90E-05	0,0015589	0,0122
λ	8,8273	5,2295	1,688	0,96433	1,4882	0,648	0,90954	1,6252	0,5596	-1,7128	2,4728	-0,6927
ω	0,00018647	4,62E-05	4,0351	7,45E-06	2,33E-06	3,1932	0,00012509	3,50E-05	3,577	4,24E-05	4,96E-06	8,5518
α	0,47833	0,10837	4,4137	0,88466	0,012292	71,9682	0,81191	0,030655	26,4851	0,82194	0,0099213	82,8457
β	0,1576	0,033416	4,7164	0,10597	0,011989	8,8394	0,12653	0,020081	6,3011	0,13935	0,0085832	16,2358

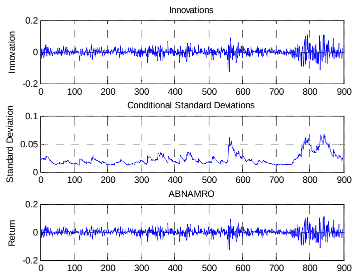
	Philips			Royal Dutch Oil			TPG			Unilever		
Parameter	**Value**	**Std Error**	**T Stat**	**Value**	**Std Error**	**T Stat**	**Value**	**Std Error**	**T Stat**	**Value**	**Std Error**	**T Stat**
δ	-0,0038952	0,0027483	-1,4173	-0,00040128	0,001113	-0,3605	-0,0024416	0,0012643	-1,9311	-0,00055799	0,001209	-0,4615
λ	3,3814	2,1472	1,5748	1,8796	3,2527	0,5779	5,9199	2,9992	1,9739	2,717	3,79	0,7169
ω	4,04E-05	1,91E-05	2,1179	8,46E-06	3,40E-06	2,4906	2,89E-05	6,79E-06	4,2528	5,48E-06	1,94E-06	2,8266
α	0,8925	0,028818	30,9701	0,88838	0,021103	42,0963	0,77992	0,026953	28,9366	0,93187	0,010285	90,608
β	0,078009	0,019142	4,0752	0,090306	0,017329	5,2113	0,16931	0,023357	7,249	0,053764	0,0083115	6,4687

	Van der Moolen			Versatel			VNU			Wolters Kluwer		
Parameter	**Value**	**Std Error**	**T Stat**	**Value**	**Std Error**	**T Stat**	**Value**	**Std Error**	**T Stat**	**Value**	**Std Error**	**T Stat**
δ	-0,00099605	0,002572	-0,3873	-0,0093956	0,0047084	-1,9955	-0,0031195	0,0019406	-1,6075	-0,001435	0,0008926	-1,6077
λ	1,7257	3,579	0,4822	1,0446	1,1903	0,8776	3,1994	2,3677	1,3513	1,905	0,92186	2,0664
ω	0,00011545	1,85E-05	6,2547	0,001188	0,00018508	6,4187	1,52E-05	5,54E-06	2,7464	0,00035478	2,73E-05	13,0014
α	0,7286	0,039651	18,3754	0,47987	0,051807	9,2625	0,90918	0,017403	52,2429	0,082485	0,046787	1,763
β	0,11761	0,019599	6,0007	0,26754	0,027318	9,7938	0,0778	0,018324	4,2458	0,59668	0,034845	17,1239

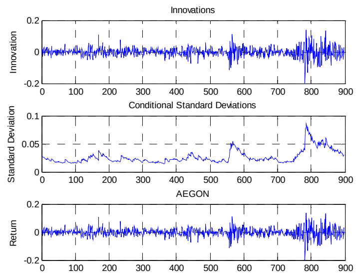
APPENDIX J: Model I Post Test Results

Residuals, conditional standard deviation and returns

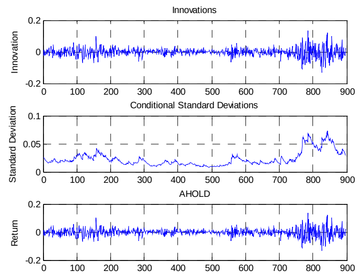
ABNAMRO



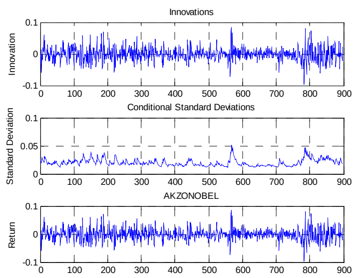
AEGON



AHOLD



Akzo Nobel



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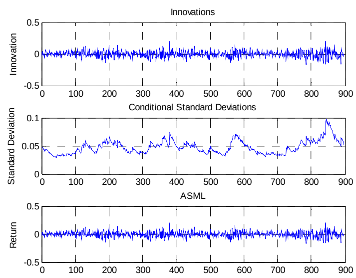
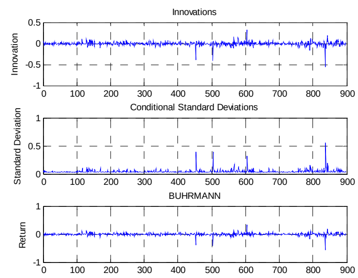
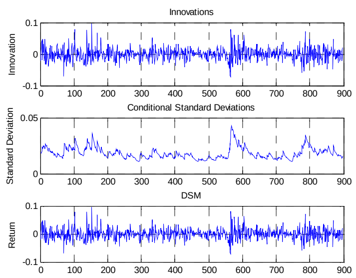


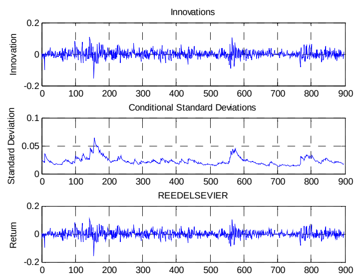
Buhrmann



DSM



Elsevier



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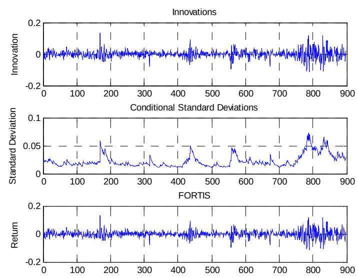

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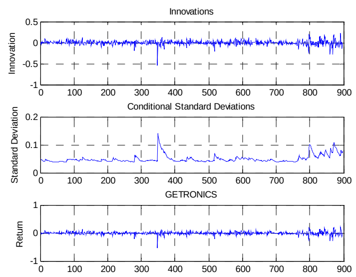
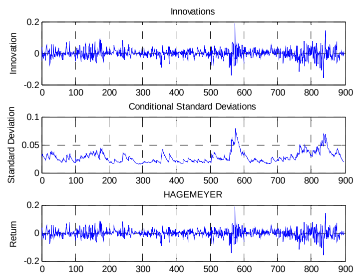


Hagemeyer



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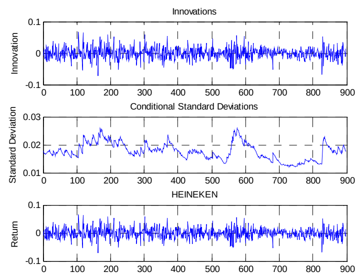

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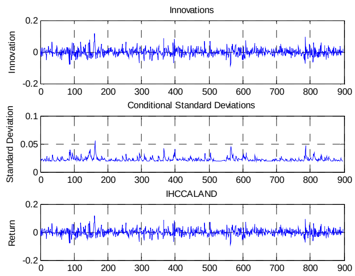
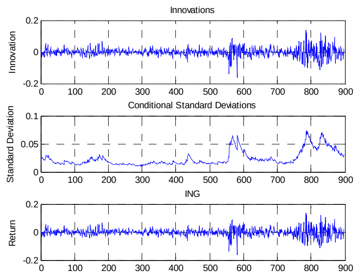
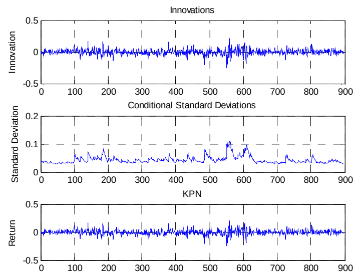


ING



KPN



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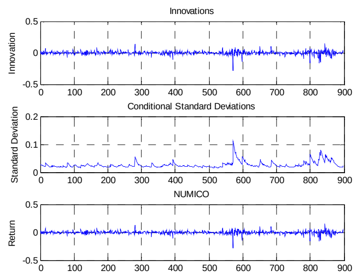
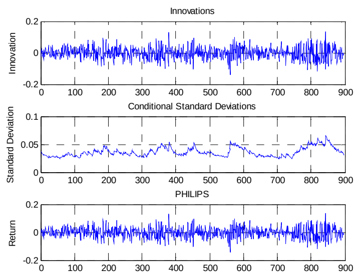
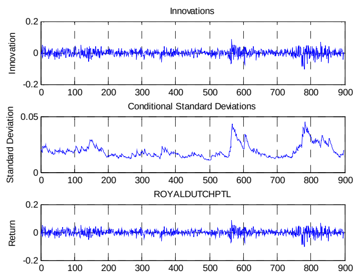


Philips



Royal Dutch Oil



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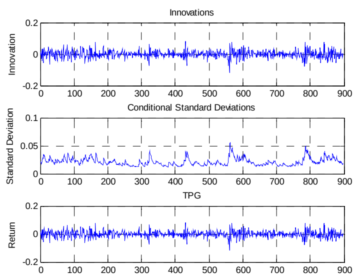
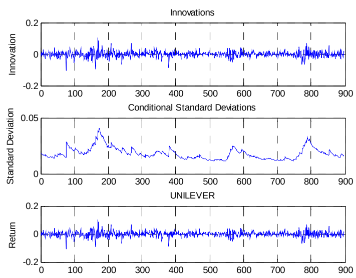
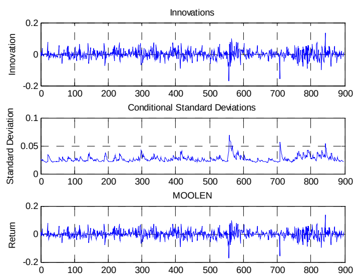


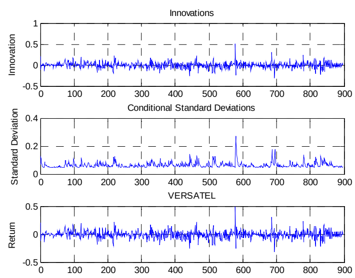
Unilever



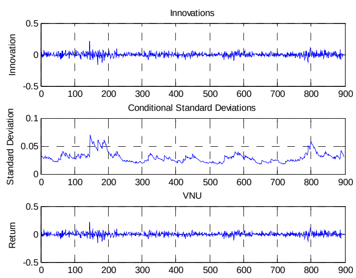
Van der Moolen



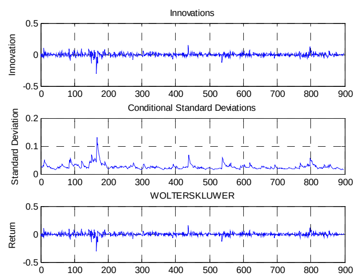
Versatel



VNU

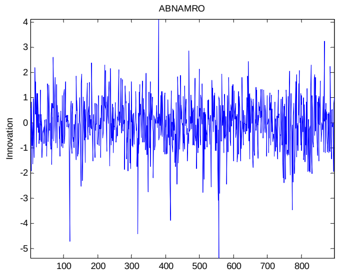


Wolters Kluwer

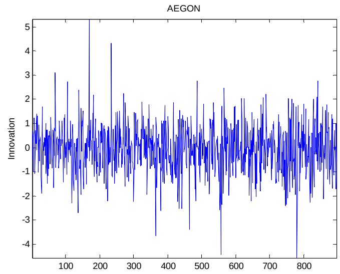


Standardized Innovations

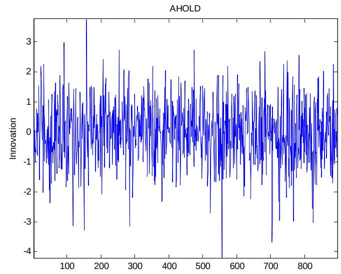
ABNAMRO



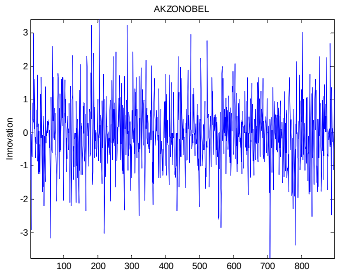
AEGON



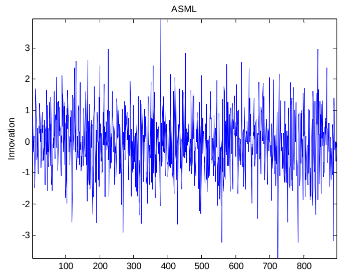
AHOLD



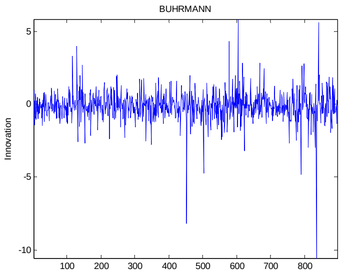
Akzo Nobel



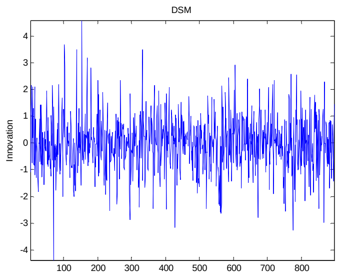
ASML



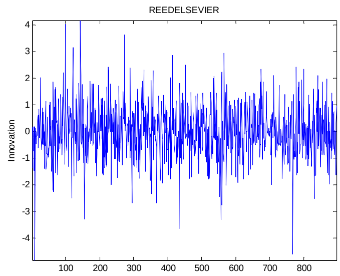
Buhrmann



DSM



Elsevier



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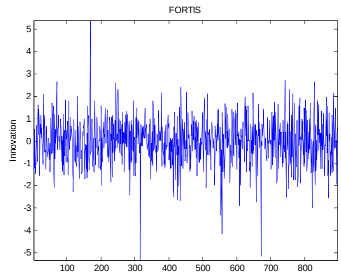
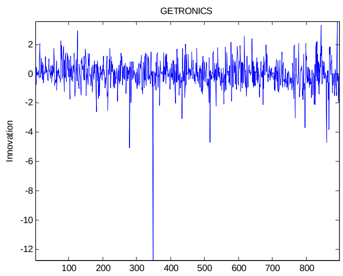
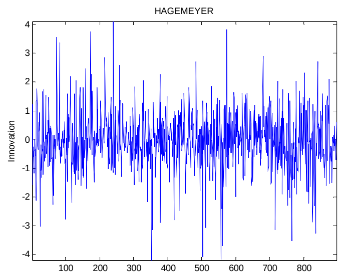


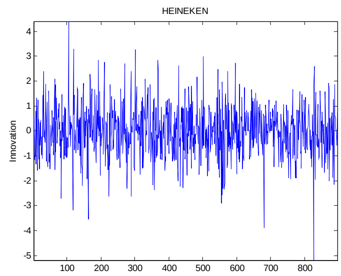
Getronics



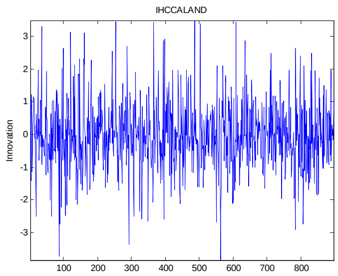
Hagemeyer



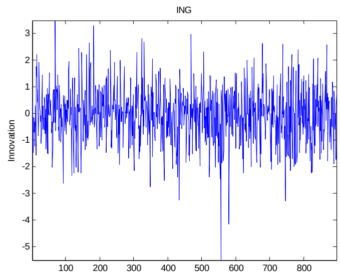
Heineken



IHC Caland



ING



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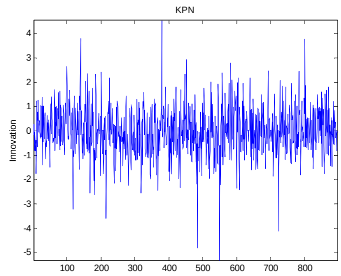

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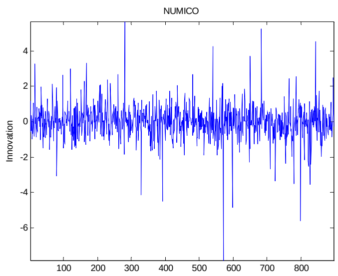
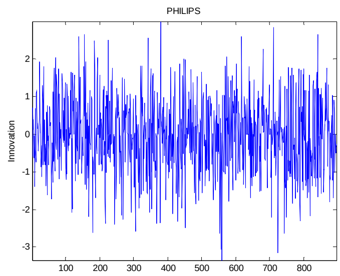
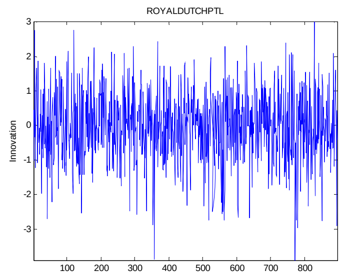


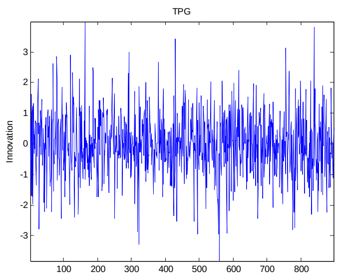
Philips



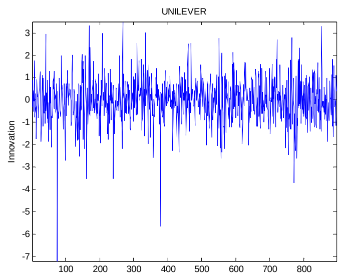
Royal Dutch Oil



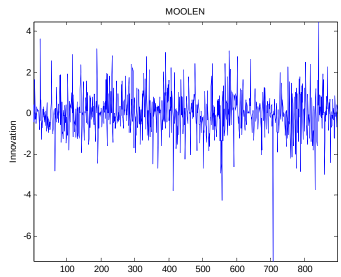
TPG



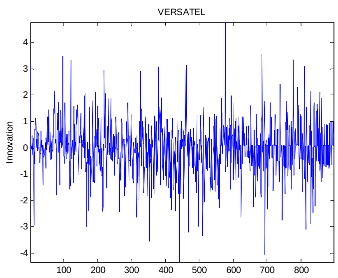
Unilever



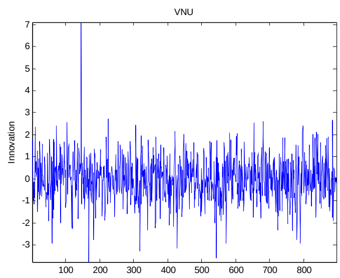
Van der Moolen



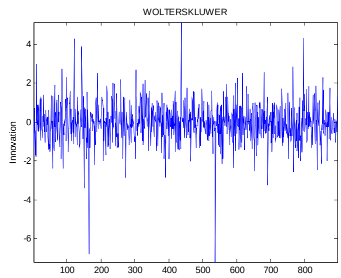
Versatel



VNU

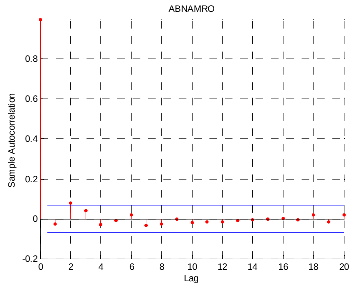


Wolters Kluwer

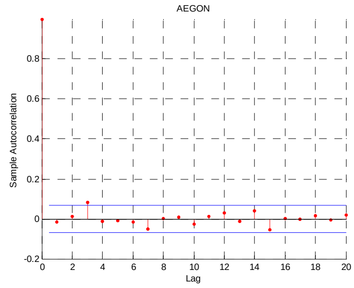


ACF of the Squared Standardized Innovations

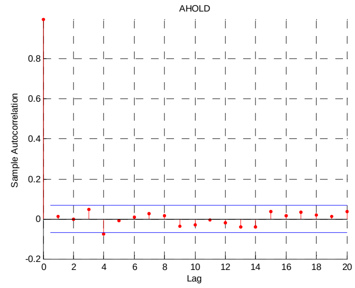
ABNAMRO



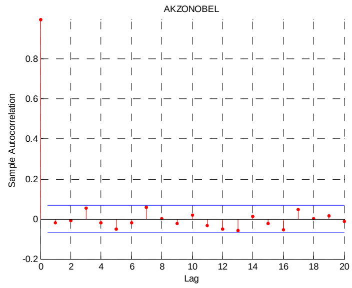
AEGON



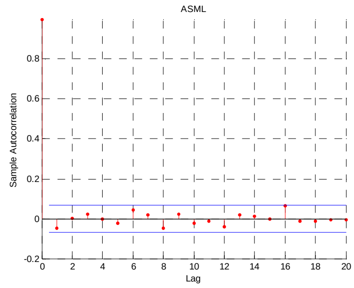
AHOLD



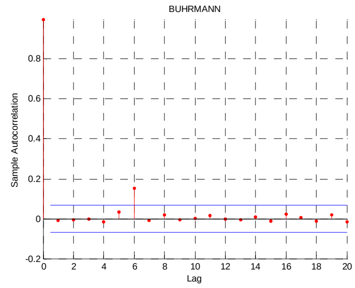
Akzo Nobel



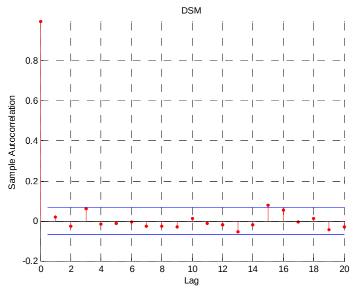
ASML



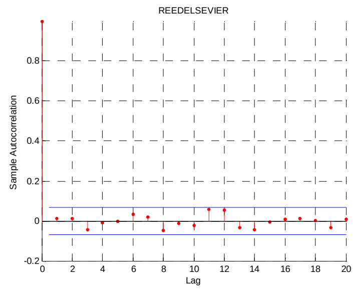
Buhrmann



DSM



Elsevier



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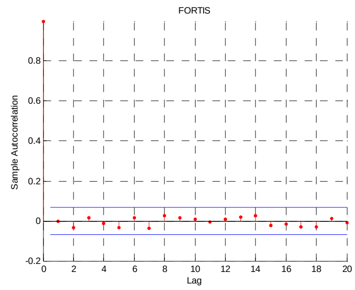
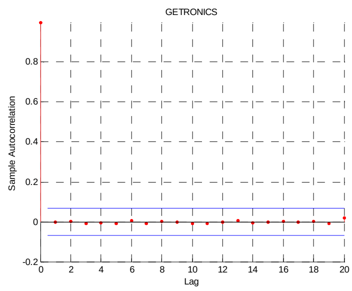
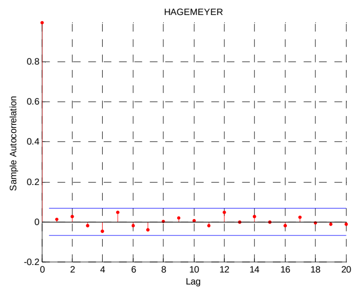


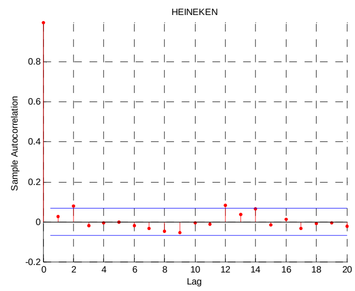
Getronics



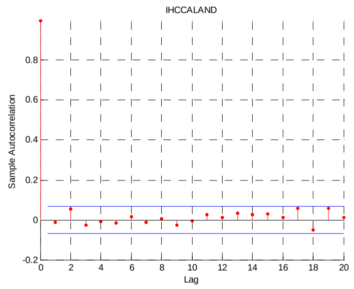
Hagemeyer



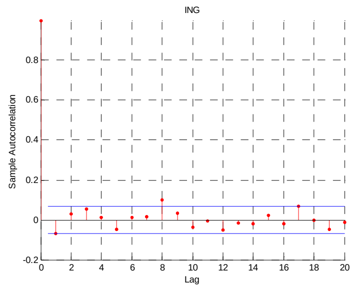
Heineken



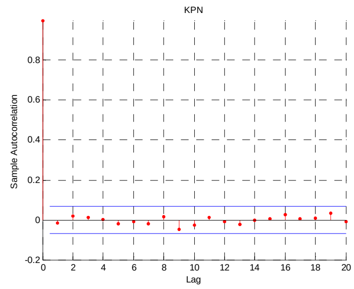
IHC Caland



ING



KPN



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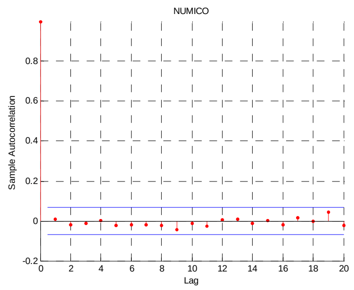
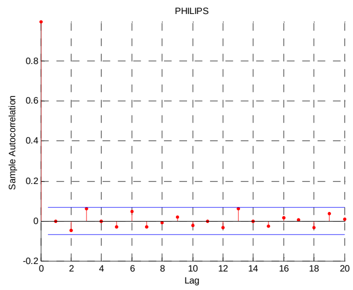
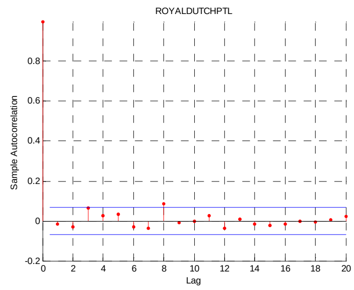


Philips



Royal Dutch Oil



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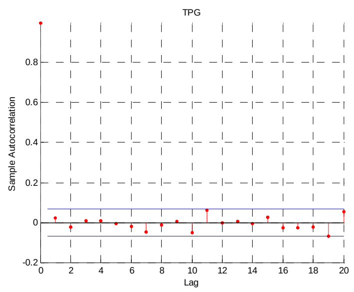
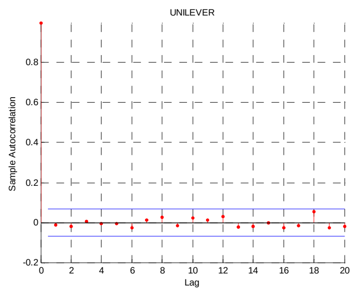
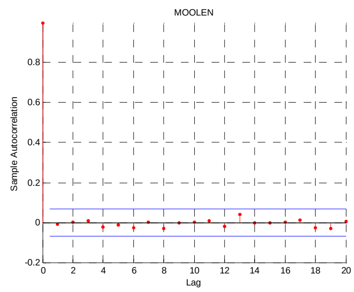


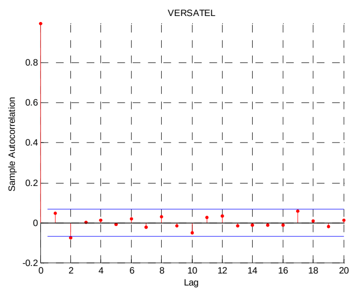
Unilever



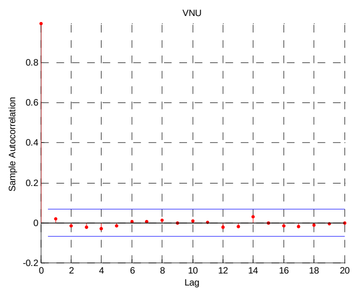
Van der Moolen



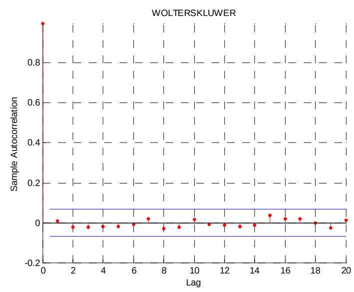
Versatel



VNU



Wolters Kluwer



Ljung-Box-Pierce Q-test

	ABNAMRO				AEGON				AHOLD			
Lags	H	pValue	Stat	Critical Value	H	pValue	Stat	Critical Value	H	pValue	Stat	Critical Value
5	0	0,1177	8,7916	11,0705	0	0,2569	6,5427	11,0705	0	0,1983	7,3145	11,0705
10	0	0,3569	11,008	18,307	0	0,4575	9,8075	18,307	0	0,4044	10,4209	18,307
15	0	0,7099	11,5884	24,9958	0	0,4434	15,1119	24,9958	0	0,4665	14,7914	24,9958
20	0	0,8976	12,5054	31,4104	0	0,7352	15,697	31,4104	0	0,6013	17,7891	31,4104

	Akzo Nobel				ASML				Buhrmann			
Lags	H	pValue	Stat	Critical Value	H	pValue	Stat	Critical Value	H	pValue	Stat	Critical Value
5	0	0,3305	5,7574	11,0705	0	0,6995	3,0034	11,0705	0	0,9381	1,269	11,0705
10	0	0,4492	9,9018	18,307	0	0,6034	8,2602	18,307	1	0,0104	23,0831	18,307
15	0	0,3046	17,2424	24,9958	0	0,8023	10,2721	24,9958	0	0,0733	23,5394	24,9958
20	0	0,3187	22,4089	31,4104	0	0,8052	14,4831	31,4104	0	0,2097	24,7865	31,4104

	DSM				Elsevier				Fortis			
Lags	H	pValue	Stat	Critical Value	H	pValue	Stat	Critical Value	H	pValue	Stat	Critical Value
5	0	0,4315	4,8737	11,0705	0	0,8161	2,2326	11,0705	0	0,8051	2,3078	11,0705
10	0	0,7094	7,1687	18,307	0	0,8028	6,1463	18,307	0	0,9101	4,7029	18,307
15	0	0,3406	16,6435	24,9958	0	0,4832	14,5643	24,9958	0	0,9761	6,206	24,9958
20	0	0,3486	21,8525	31,4104	0	0,7199	15,9472	31,4104	0	0,9907	8,1741	31,4104

	Getronics				Hagemeyer				Heineken			
Lags	H	pValue	Stat	Critical Value	H	pValue	Stat	Critical Value	H	pValue	Stat	Critical Value
5	0	0,9991	0,1971	11,0705	0	0,409	5,0567	11,0705	0	0,2351	6,8113	11,0705
10	0	1	0,3519	18,307	0	0,709	7,1736	18,307	0	0,2273	12,9356	18,307
15	0	1	0,506	24,9958	0	0,8051	10,2282	24,9958	0	0,0597	24,3305	24,9958
20	0	1	0,9477	31,4104	0	0,9367	11,3464	31,4104	0	0,1639	26,0572	31,4104

	IHC Caland				ING				KPN			
Lags	H	pValue	Stat	Critical Value	H	pValue	Stat	Critical Value	H	pValue	Stat	Critical Value
5	0	0,5824	3,774	11,0705	0	0,0834	9,7246	11,0705	0	0,9599	1,0324	11,0705
10	0	0,9039	4,8042	18,307	1	0,0174	21,5722	18,307	0	0,9354	4,2496	18,307
15	0	0,9135	8,248	24,9958	0	0,0508	24,9396	24,9958	0	0,9928	4,9231	24,9958
20	0	0,6466	17,0984	31,4104	1	0,0456	31,787	31,4104	0	0,9976	6,688	31,4104

	Numico				Philips				Royal Dutch Oil			
Lags	H	pValue	Stat	Critical Value	H	pValue	Stat	Critical Value	H	pValue	Stat	Critical Value
5	0	0,9656	0,9617	11,0705	0	0,2929	6,1396	11,0705	0	0,2766	6,3167	11,0705
10	0	0,9558	3,8025	18,307	0	0,4432	9,9689	18,307	0	0,1234	15,2441	18,307
15	0	0,9948	4,6347	24,9958	0	0,4519	14,9939	24,9958	0	0,2602	18,0463	24,9958
20	0	0,9946	7,5198	31,4104	0	0,6026	17,7687	31,4104	0	0,5405	18,7137	31,4104

		TPG				Unilever				Van der Moolen		
Lags	H	pValue	Stat	Critical Value	H	pValue	Stat	Critical Value	H	pValue	Stat	Critical Value
5	0	0,9603	1,0279	11,0705	0	0,9899	0,5565	11,0705	0	0,9818	0,7212	11,0705
10	0	0,8327	5,7882	18,307	0	0,988	2,6772	18,307	0	0,9947	2,1878	18,307
15	0	0,8312	9,8149	24,9958	0	0,9962	4,3832	24,9958	0	0,9973	4,1368	24,9958
20	0	0,537	18,7666	31,4104	0	0,9831	8,9855	31,4104	0	0,9992	5,7892	31,4104

		Versatel				VNU				Wolters Kluwer		
Lags	H	pValue	Stat	Critical Value	H	pValue	Stat	Critical Value	H	pValue	Stat	Critical Value
5	0	0,2072	7,1858	11,0705	0	0,8308	2,1308	11,0705	0	0,8845	1,7343	11,0705
10	0	0,3215	11,4775	18,307	0	0,9918	2,431	18,307	0	0,9604	3,686	18,307
15	0	0,5618	13,5254	24,9958	0	0,9972	4,1472	24,9958	0	0,9867	5,5212	24,9958
20	0	0,6458	17,1099	31,4104	0	0,9998	4,8848	31,4104	0	0,9971	6,8626	31,4104

Engle's ARCH test

		ABNAMRO				AEGON				AHOLD		
Lags	H	pValue	Stat	Critical Value	H	pValue	Stat	Critical Value	H	pValue	Stat	Critical Value
5	0	0,0902	9,5162	11,0705	0	0,2592	6,5161	11,0705	0	0,1951	7,3619	11,0705
10	0	0,319	11,5131	18,307	0	0,4776	9,5853	18,307	0	0,3766	10,7586	18,307
15	0	0,6805	11,9809	24,9958	0	0,4891	14,4851	24,9958	0	0,4037	15,6795	24,9958
20	0	0,9034	12,3539	31,4104	0	0,7518	15,4207	31,4104	0	0,5482	18,5958	31,4104

		Akzo Nobel				ASML				Buhrmann		
Lags	H	pValue	Stat	Critical Value	H	pValue	Stat	Critical Value	H	pValue	Stat	Critical Value
5	0	0,3859	5,2523	11,0705	0	0,6953	3,0305	11,0705	0	0,9411	1,2391	11,0705
10	0	0,4979	9,3646	18,307	0	0,6633	7,6463	18,307	1	0,0116	22,7873	18,307
15	0	0,4722	14,7145	24,9958	0	0,8172	10,0402	24,9958	0	0,0769	23,3566	24,9958
20	0	0,5097	19,1871	31,4104	0	0,8301	14,0079	31,4104	0	0,2349	24,1735	31,4104

		DSM				Elsevier				Fortis		
Lags	H	pValue	Stat	Critical Value	H	pValue	Stat	Critical Value	H	pValue	Stat	Critical Value
5	0	0,4137	5,0179	11,0705	0	0,8188	2,214	11,0705	0	0,8143	2,2451	11,0705
10	0	0,7254	7,0003	18,307	0	0,6323	7,9642	18,307	0	0,9105	4,6968	18,307
15	0	0,3503	16,4886	24,9958	0	0,301	17,3035	24,9958	0	0,9792	6,0326	24,9958
20	0	0,3288	22,2181	31,4104	0	0,4773	19,6928	31,4104	0	0,9912	8,095	31,4104

	Getronics				Hagemeyer				Heineken			
Lags	**H**	**pValue**	**Stat**	**Critical Value**	**H**	**pValue**	**Stat**	**Critical Value**	**H**	**pValue**	**Stat**	**Critical Value**
5	0	0,9992	0,1957	11,0705	0	0,3925	5,1954	11,0705	0	0,2344	6,8202	11,0705
10	0	1	0,3548	18,307	0	0,6539	7,743	18,307	0	0,3041	11,7222	18,307
15	0	1	0,5034	24,9958	0	0,7501	11,0346	24,9958	0	0,1415	20,8567	24,9958
20	0	1	0,9346	31,4104	0	0,9293	11,5948	31,4104	0	0,3356	22,0917	31,4104

	IHC Caland				ING				KPN			
Lags	**H**	**pValue**	**Stat**	**Critical Value**	**H**	**pValue**	**Stat**	**Critical Value**	**H**	**pValue**	**Stat**	**Critical Value**
5	0	0,5947	3,6909	11,0705	0	0,0737	10,0555	11,0705	0	0,9601	1,0298	11,0705
10	0	0,9167	4,593	18,307	1	0,0062	24,5826	18,307	0	0,9387	4,1837	18,307
15	0	0,9307	7,8222	24,9958	1	0,0184	28,5465	24,9958	0	0,9937	4,7995	24,9958
20	0	0,7199	15,9468	31,4104	1	0,0287	33,6368	31,4104	0	0,9987	6,1361	31,4104

	Numico				Philips				Royal Dutch Oil			
Lags	**H**	**pValue**	**Stat**	**Critical Value**	**H**	**pValue**	**Stat**	**Critical Value**	**H**	**pValue**	**Stat**	**Critical Value**
5	0	0,9651	0,968	11,0705	0	0,3254	5,8074	11,0705	0	0,2403	6,745	11,0705
10	0	0,9518	3,8989	18,307	0	0,536	8,9585	18,307	0	0,1302	15,0518	18,307
15	0	0,994	4,7546	24,9958	0	0,47	14,7445	24,9958	0	0,324	16,9153	24,9958
20	0	0,994	7,6333	31,4104	0	0,7061	16,1685	31,4104	0	0,5708	18,2522	31,4104

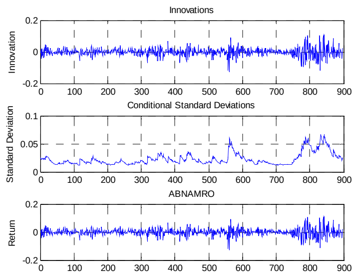
	TPG				Unilever				Van der Moolen			
Lags	**H**	**pValue**	**Stat**	**Critical Value**	**H**	**pValue**	**Stat**	**Critical Value**	**H**	**pValue**	**Stat**	**Critical Value**
5	0	0,9616	1,0119	11,0705	0	0,9895	0,5657	11,0705	0	0,9824	0,7111	11,0705
10	0	0,857	5,4791	18,307	0	0,9899	2,5665	18,307	0	0,9943	2,2249	18,307
15	0	0,8395	9,6771	24,9958	0	0,9972	4,146	24,9958	0	0,9972	4,1637	24,9958
20	0	0,5623	18,3809	31,4104	0	0,9877	8,5311	31,4104	0	0,9992	5,7665	31,4104

	Versatel				VNU				Wolters Kluwer			
Lags	**H**	**pValue**	**Stat**	**Critical Value**	**H**	**pValue**	**Stat**	**Critical Value**	**H**	**pValue**	**Stat**	**Critical Value**
5	0	0,1834	7,5408	11,0705	0	0,8402	2,0644	11,0705	0	0,8839	1,7395	11,0705
10	0	0,2734	12,1763	18,307	0	0,9939	2,2633	18,307	0	0,9588	3,7274	18,307
15	0	0,5649	13,4843	24,9958	0	0,9983	3,807	24,9958	0	0,9866	5,5275	24,9958
20	0	0,6593	16,9026	31,4104	0	0,9999	4,4827	31,4104	0	0,998	6,5237	31,4104

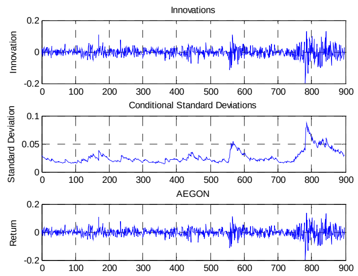
APPENDIX K: Model II Post Test Results

Residuals, conditional standard deviation and returns

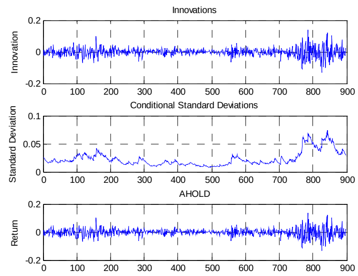
ABNAMRO



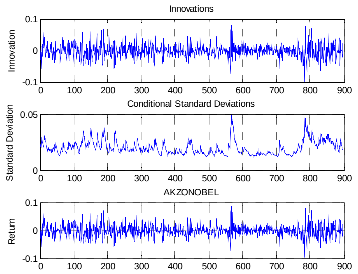
AEGON



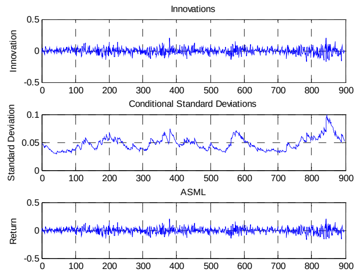
AHOLD



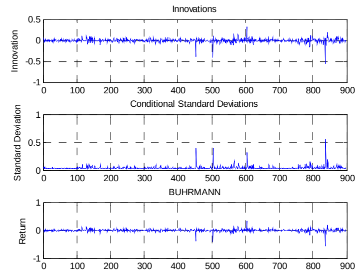
Akzo Nobel



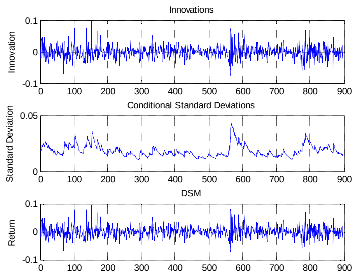
ASML



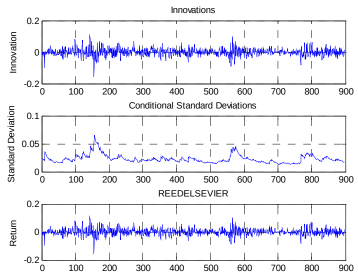
Buhrmann



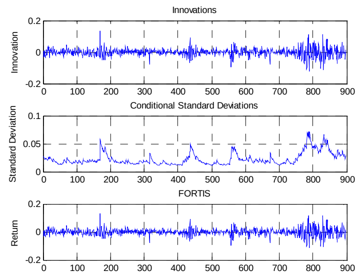
DSM



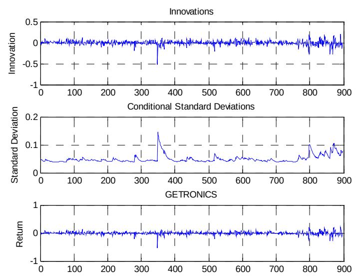
Elsevier



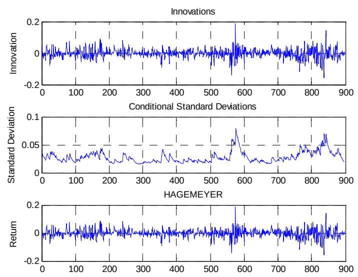
Fortis



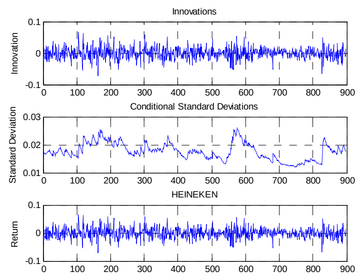
Getronics



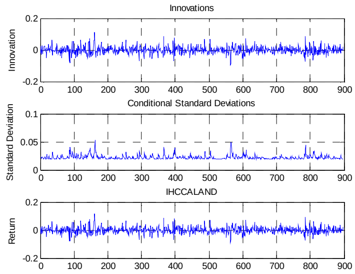
Hagemeyer



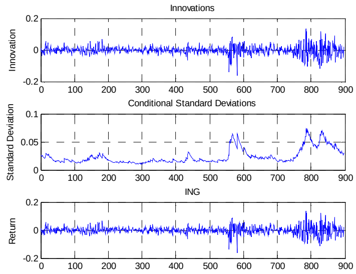
Heineken



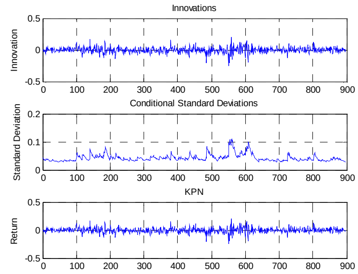
IHC Caland



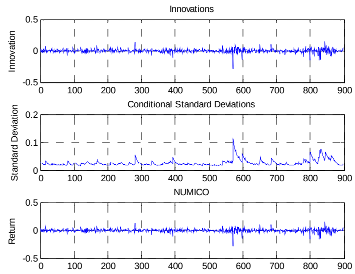
ING



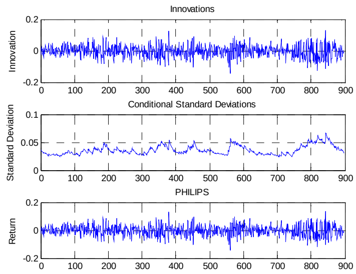
KPN



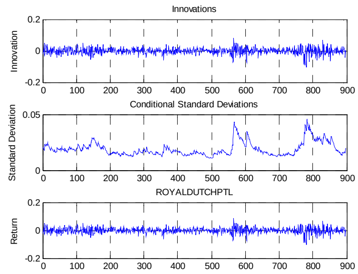
Numico



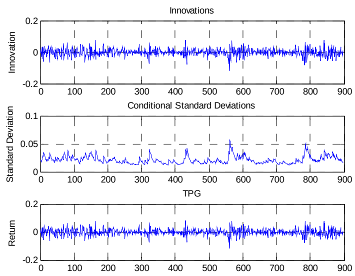
Philips



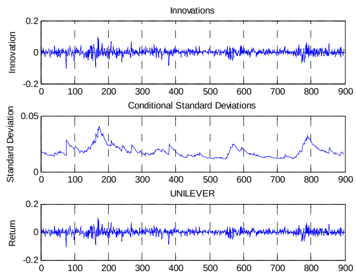
Royal Dutch Oil



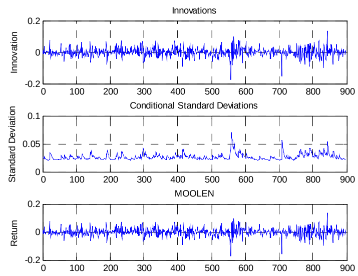
TPG



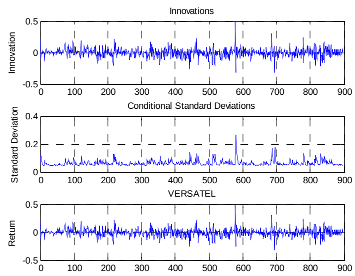
Unilever



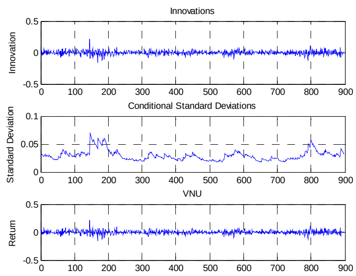
Van der Moolen



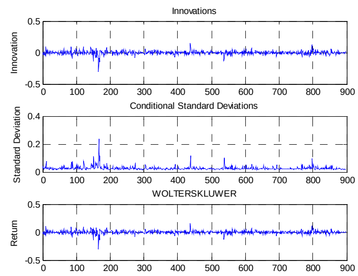
Versatel



VNU

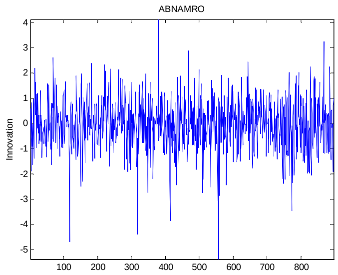


Wolters Kluwer

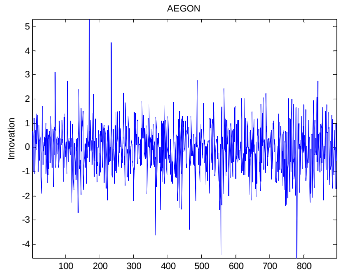


Standardized Innovations

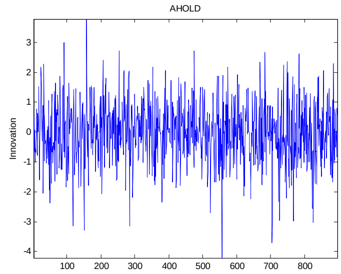
ABNAMRO



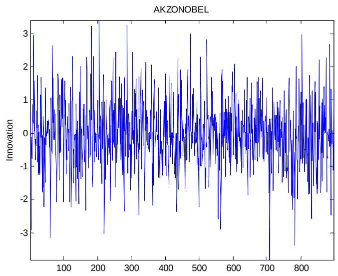
AEGON



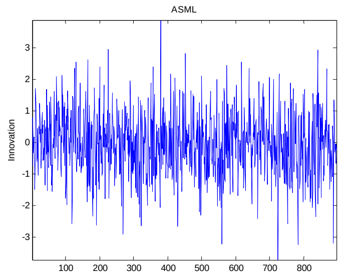
AHOLD



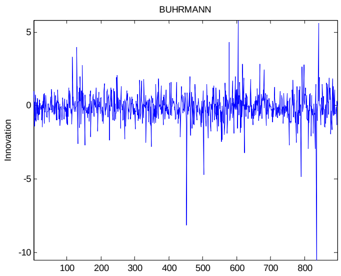
Akzo Nobel



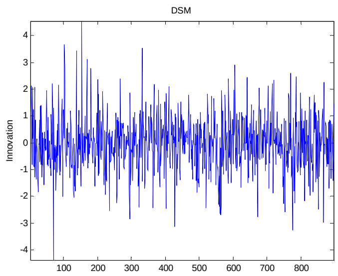
ASML



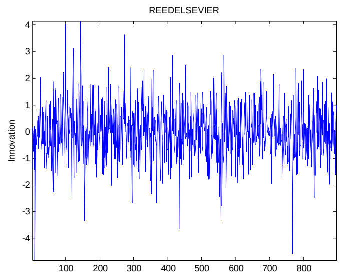
Buhrmann



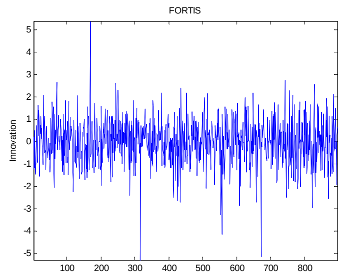
DSM



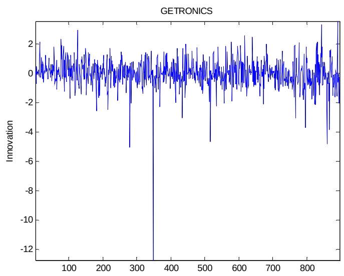
Elsevier



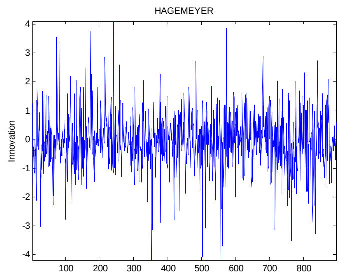
Fortis



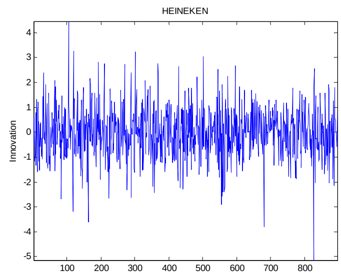
Getronics



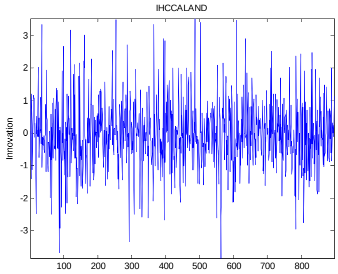
Hagemeyer



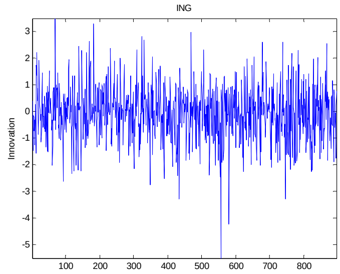
Heineken



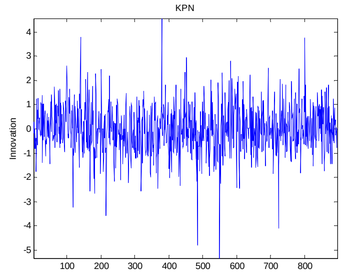
IHC Caland



ING



KPN



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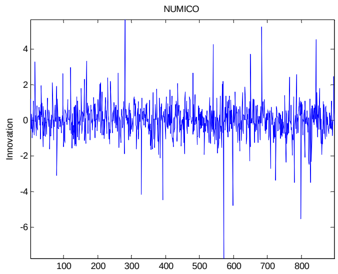
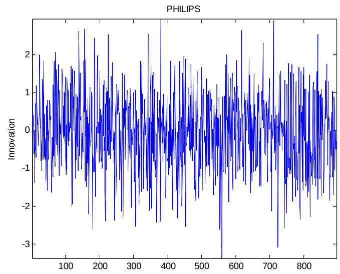
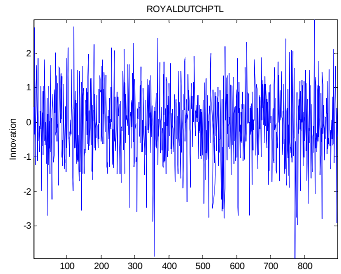


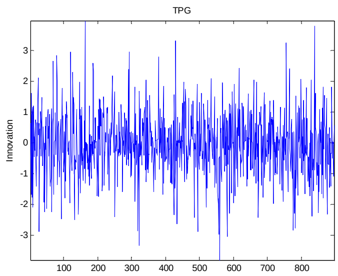
Philips



Royal Dutch Oil



TPG



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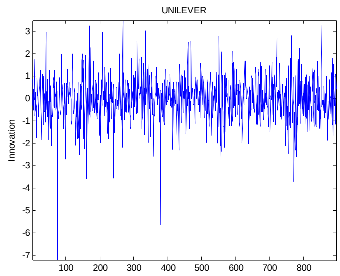
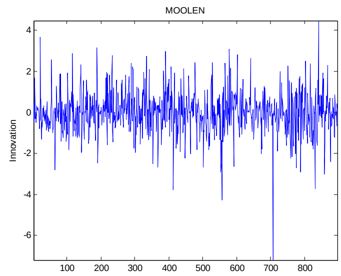
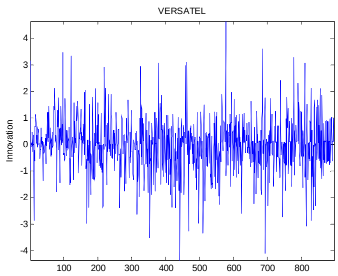


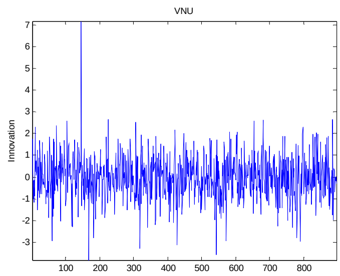
Van der Moolen



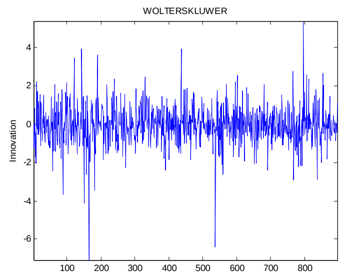
Versatel



VNU

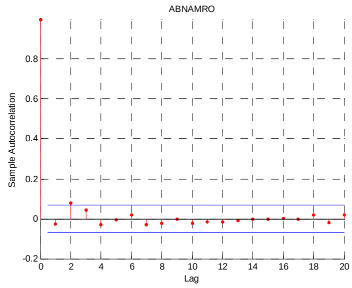


Wolters Kluwer

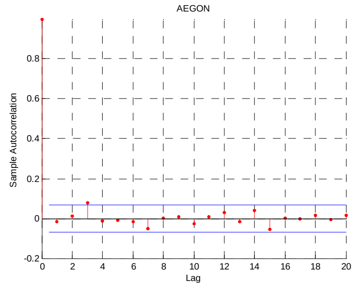


ACF of the Squared Standardized Innovations

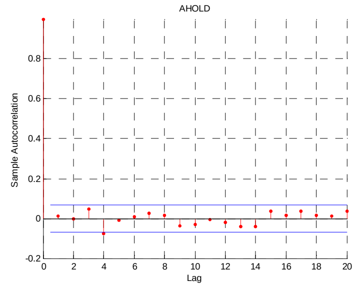
ABNAMRO



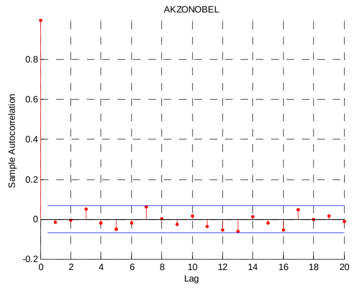
AEGON



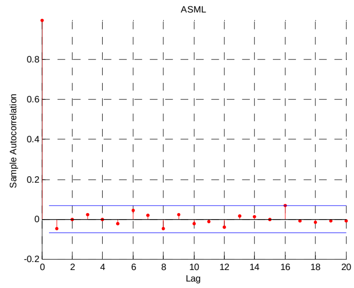
AHOLD



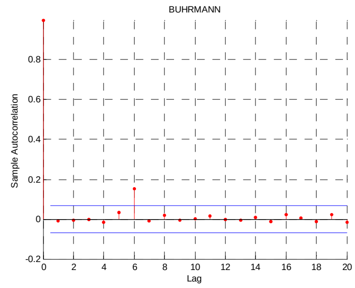
Akzo Nobel



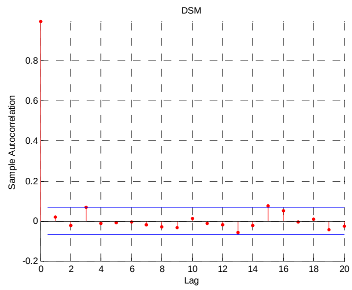
ASML



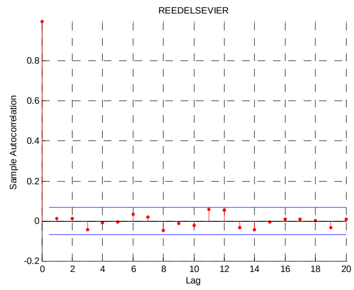
Buhrmann



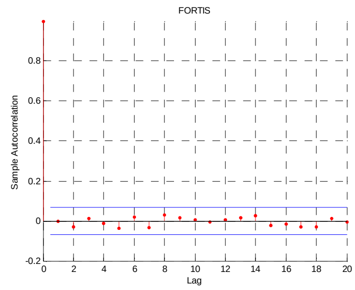
DSM



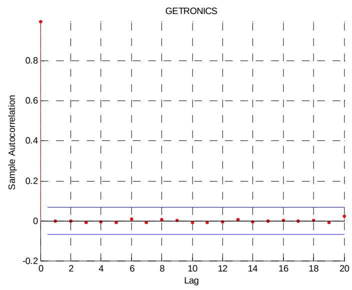
Elsevier



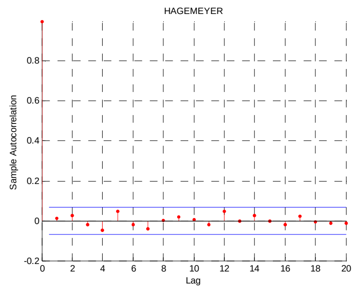
Fortis



Getronics



Hagemeyer



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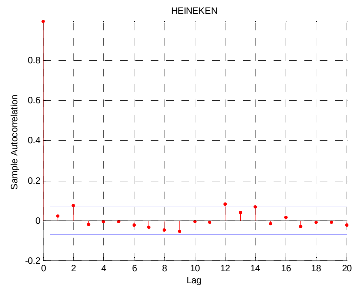
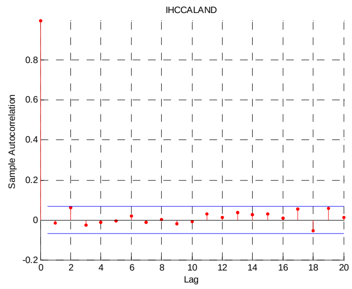


IHC Caland



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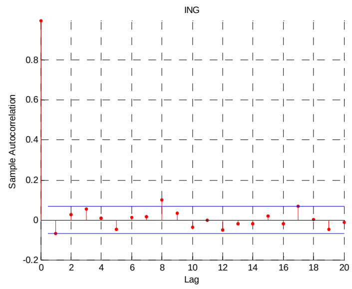
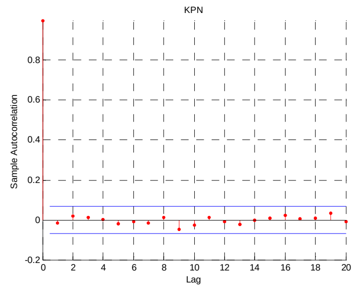


KPN



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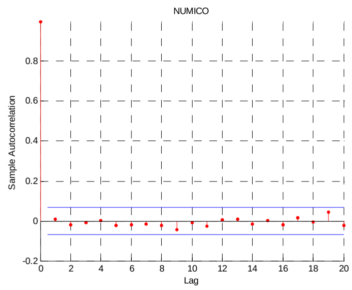

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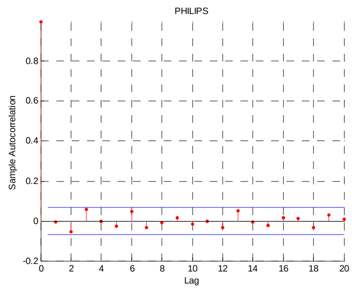
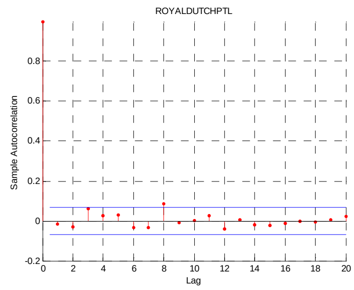
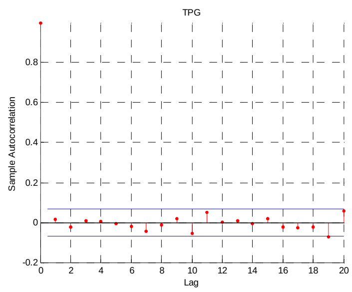


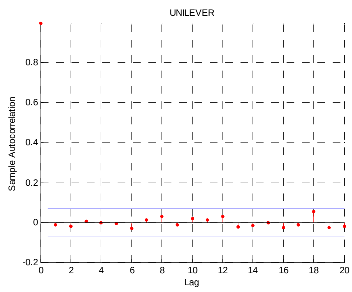
Royal Dutch Oil



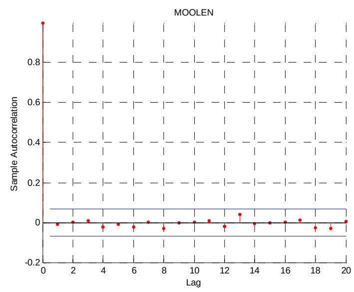
TPG



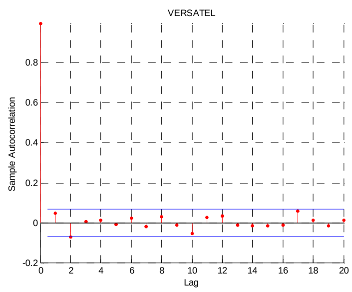
Unilever



Van der Moolen



Versatel



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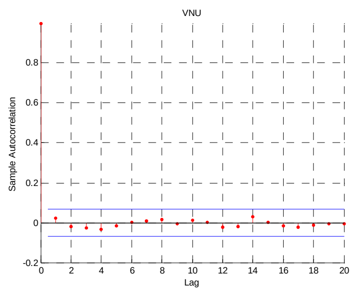
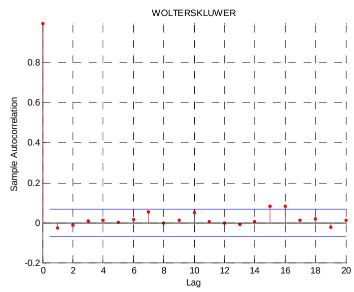


Wolters Kluwer



Ljung-Box-Pierce Q-test

	ABNAMRO				AEGON				AHOLD			
Lags	**H**	**pValue**	**Stat**	**Critical Value**	**H**	**pValue**	**Stat**	**Critical Value**	**H**	**pValue**	**Stat**	**Critical Value**
5	0	0,1221	8,6906	11,0705	0	0,279	6,2905	11,0705	0	0,2003	7,2842	11,0705
10	0	0,3703	10,8372	18,307	0	0,4919	9,4292	18,307	0	0,4112	10,3397	18,307
15	0	0,7206	11,4432	24,9958	0	0,4789	14,6229	24,9958	0	0,4685	14,764	24,9958
20	0	0,902	12,3911	31,4104	0	0,7649	15,1989	31,4104	0	0,6	17,8082	31,4104

	Akzo Nobel				ASML				Buhrmann			
Lags	**H**	**pValue**	**Stat**	**Critical Value**	**H**	**pValue**	**Stat**	**Critical Value**	**H**	**pValue**	**Stat**	**Critical Value**
5	0	0,3786	5,3159	11,0705	0	0,7165	2,8926	11,0705	0	0,9366	1,2834	11,0705
10	0	0,4614	9,764	18,307	0	0,6353	7,9338	18,307	1	0,0099	23,2248	18,307
15	0	0,282	17,6418	24,9958	0	0,8312	9,8151	24,9958	0	0,0706	23,6853	24,9958
20	0	0,3	22,7753	31,4104	0	0,8056	14,4745	31,4104	0	0,2023	24,9768	31,4104

	DSM				Elsevier				Fortis			
Lags	**H**	**pValue**	**Stat**	**Critical Value**	**H**	**pValue**	**Stat**	**Critical Value**	**H**	**pValue**	**Stat**	**Critical Value**
5	0	0,3966	5,1607	11,0705	0	0,8449	2,0308	11,0705	0	0,7982	2,3548	11,0705
10	0	0,6941	7,3285	18,307	0	0,8002	6,1765	18,307	0	0,9116	4,6777	18,307
15	0	0,3633	16,2863	24,9958	0	0,4776	14,6411	24,9958	0	0,9794	6,0216	24,9958
20	0	0,3919	21,09	31,4104	0	0,7225	15,9052	31,4104	0	0,992	7,9757	31,4104

	Getronics				Hagemeyer				Heineken			
Lags	**H**	**pValue**	**Stat**	**Critical Value**	**H**	**pValue**	**Stat**	**Critical Value**	**H**	**pValue**	**Stat**	**Critical Value**
5	0	0,9993	0,1773	11,0705	0	0,4101	5,0479	11,0705	0	0,2922	6,1464	11,0705
10	0	1	0,4162	18,307	0	0,7104	7,1585	18,307	0	0,2698	12,2319	18,307
15	0	1	0,5637	24,9958	0	0,8046	10,2368	24,9958	0	0,0571	24,4951	24,9958
20	0	1	1,0995	31,4104	0	0,9358	11,378	31,4104	0	0,16	26,1778	31,4104

	IHC Caland				ING				KPN			
Lags	**H**	**pValue**	**Stat**	**Critical Value**	**H**	**pValue**	**Stat**	**Critical Value**	**H**	**pValue**	**Stat**	**Critical Value**
5	0	0,5039	4,3234	11,0705	0	0,0841	9,7031	11,0705	0	0,9564	1,0735	11,0705
10	0	0,8755	5,2265	18,307	1	0,0172	21,6202	18,307	0	0,9423	4,1099	18,307
15	0	0,8831	8,8917	24,9958	0	0,0502	24,984	24,9958	0	0,9939	4,7639	24,9958
20	0	0,6222	17,4718	31,4104	1	0,045	31,8389	31,4104	0	0,9982	6,4341	31,4104

	Numico				Philips				Royal Dutch Oil			
Lags	**H**	**pValue**	**Stat**	**Critical Value**	**H**	**pValue**	**Stat**	**Critical Value**	**H**	**pValue**	**Stat**	**Critical Value**
5	0	0,9676	0,9349	11,0705	0	0,2848	6,2269	11,0705	0	0,3073	5,9891	11,0705
10	0	0,959	3,7224	18,307	0	0,451	9,8812	18,307	0	0,1417	14,7443	18,307
15	0	0,9947	4,6546	24,9958	0	0,5344	13,8831	24,9958	0	0,2862	17,5647	24,9958
20	0	0,9943	7,5764	31,4104	0	0,7109	16,0922	31,4104	0	0,5738	18,2062	31,4104

	TPG				Unilever				Van der Moolen			
Lags	H	pValue	Stat	Critical Value	H	pValue	Stat	Critical Value	H	pValue	Stat	Critical Value
5	0	0,9744	0,84	11,0705	0	0,9902	0,5494	11,0705	0	0,9798	0,755	11,0705
10	0	0,7944	6,2433	18,307	0	0,9859	2,7935	18,307	0	0,995	2,1588	18,307
15	0	0,8749	9,049	24,9958	0	0,9956	4,4915	24,9958	0	0,9972	4,1427	24,9958
20	0	0,5616	18,3922	31,4104	0	0,9827	9,0155	31,4104	0	0,9992	5,7555	31,4104

	Versatel				VNU				Wolters Kluwer			
Lags	H	pValue	Stat	Critical Value	H	pValue	Stat	Critical Value	H	pValue	Stat	Critical Value
5	0	0,2207	6,9989	11,0705	0	0,752	2,6613	11,0705	0	0,9639	0,9829	11,0705
10	0	0,3207	11,4886	18,307	0	0,9795	3,0804	18,307	0	0,7882	6,3143	18,307
15	0	0,5624	13,5174	24,9958	0	0,9939	4,7643	24,9958	0	0,6383	12,5328	24,9958
20	0	0,6411	17,1819	31,4104	0	0,9993	5,6662	31,4104	0	0,4551	20,0452	31,4104

Engle's ARCH test

	ABNAMRO				AEGON				AHOLD			
Lags	H	pValue	Stat	Critical Value	H	pValue	Stat	Critical Value	H	pValue	Stat	Critical Value
5	0	0,0948	9,3806	11,0705	0	0,2814	6,2641	11,0705	0	0,1979	7,3198	11,0705
10	0	0,3343	11,3042	18,307	0	0,5128	9,2049	18,307	0	0,3842	10,6656	18,307
15	0	0,6981	11,7467	24,9958	0	0,524	14,0207	24,9958	0	0,4047	15,6646	24,9958
20	0	0,9102	12,1667	31,4104	0	0,7811	14,9185	31,4104	0	0,5453	18,6398	31,4104

	Akzo Nobel				ASML				Buhrmann			
Lags	H	pValue	Stat	Critical Value	H	pValue	Stat	Critical Value	H	pValue	Stat	Critical Value
5	0	0,4291	4,8926	11,0705	0	0,7123	2,9201	11,0705	0	0,9396	1,2536	11,0705
10	0	0,4976	9,368	18,307	0	0,6946	7,3237	18,307	1	0,011	22,9264	18,307
15	0	0,4514	15,0005	24,9958	0	0,846	9,5688	24,9958	0	0,0738	23,5155	24,9958
20	0	0,4852	19,568	31,4104	0	0,8274	14,0602	31,4104	0	0,2265	24,3735	31,4104

	DSM				Elsevier				Fortis			
Lags	H	pValue	Stat	Critical Value	H	pValue	Stat	Critical Value	H	pValue	Stat	Critical Value
5	0	0,3784	5,3175	11,0705	0	0,8477	2,0106	11,0705	0	0,8077	2,2902	11,0705
10	0	0,712	7,142	18,307	0	0,623	8,0602	18,307	0	0,912	4,6725	18,307
15	0	0,3763	16,0866	24,9958	0	0,2819	17,6438	24,9958	0	0,9822	5,8492	24,9958
20	0	0,3615	21,6202	31,4104	0	0,458	19,9993	31,4104	0	0,9923	7,9352	31,4104

	Getronics				Hagemeyer				Heineken			
Lags	**H**	**pValue**	**Stat**	**Critical Value**	**H**	**pValue**	**Stat**	**Critical Value**	**H**	**pValue**	**Stat**	**Critical Value**
5	0	0,9993	0,1764	11,0705	0	0,3936	5,1858	11,0705	0	0,294	6,128	11,0705
10	0	1	0,416	18,307	0	0,6555	7,7272	18,307	0	0,3529	11,0599	18,307
15	0	1	0,5574	24,9958	0	0,7496	11,0421	24,9958	0	0,1381	20,9616	24,9958
20	0	1	1,0826	31,4104	0	0,9285	11,62	31,4104	0	0,3388	22,0321	31,4104

	IHC Caland				ING				KPN			
Lags	**H**	**pValue**	**Stat**	**Critical Value**	**H**	**pValue**	**Stat**	**Critical Value**	**H**	**pValue**	**Stat**	**Critical Value**
5	0	0,5085	4,2898	11,0705	0	0,075	10,0092	11,0705	0	0,9566	1,0711	11,0705
10	0	0,8822	5,1321	18,307	1	0,0059	24,7084	18,307	0	0,9449	4,0536	18,307
15	0	0,901	8,5259	24,9958	1	0,0185	28,5288	24,9958	0	0,9947	4,6518	24,9958
20	0	0,7069	16,1554	31,4104	1	0,0277	33,7758	31,4104	0	0,999	5,9232	31,4104

	Numico				Philips				Royal Dutch Oil			
Lags	**H**	**pValue**	**Stat**	**Critical Value**	**H**	**pValue**	**Stat**	**Critical Value**	**H**	**pValue**	**Stat**	**Critical Value**
5	0	0,9672	0,9408	11,0705	0	0,3153	5,9075	11,0705	0	0,2719	6,3699	11,0705
10	0	0,9558	3,8026	18,307	0	0,5377	8,9408	18,307	0	0,1491	14,5557	18,307
15	0	0,9939	4,7704	24,9958	0	0,5601	13,5474	24,9958	0	0,3493	16,5054	24,9958
20	0	0,9937	7,6952	31,4104	0	0,7944	14,68	31,4104	0	0,6015	17,7862	31,4104

	TPG				Unilever				Van der Moolen			
Lags	**H**	**pValue**	**Stat**	**Critical Value**	**H**	**pValue**	**Stat**	**Critical Value**	**H**	**pValue**	**Stat**	**Critical Value**
5	0	0,9759	0,8172	11,0705	0	0,9898	0,5581	11,0705	0	0,9806	0,7425	11,0705
10	0	0,8138	6,0169	18,307	0	0,988	2,6765	18,307	0	0,9946	2,1987	18,307
15	0	0,8783	8,985	24,9958	0	0,9969	4,2261	24,9958	0	0,9971	4,1792	24,9958
20	0	0,6076	17,6939	31,4104	0	0,9875	8,5593	31,4104	0	0,9992	5,7566	31,4104

	Versatel				VNU				Wolters Kluwer			
Lags	**H**	**pValue**	**Stat**	**Critical Value**	**H**	**pValue**	**Stat**	**Critical Value**	**H**	**pValue**	**Stat**	**Critical Value**
5	0	0,1971	7,3324	11,0705	0	0,7673	2,5608	11,0705	0	0,9635	0,9886	11,0705
10	0	0,2752	12,1492	18,307	0	0,9841	2,879	18,307	0	0,7828	6,3757	18,307
15	0	0,5644	13,4912	24,9958	0	0,9961	4,4076	24,9958	0	0,6646	12,1896	24,9958
20	0	0,6517	17,0189	31,4104	0	0,9996	5,2178	31,4104	0	0,4672	19,8516	31,4104

APPENDIX L: Model II Post Test Results

Likelihood Ratio Test

	Likelihood Ratio Test			
	H	pValue	Stat	Critical Value
ABN AMRO	0	0,573	0,3177	3,8415
Aegon	0	0,5431	0,3698	3,8415
Ahold	0	0,6346	0,2259	3,8415
Akzo Nobel	0	0,3053	1,051	3,8415
ASML	0	0,4558	0,5563	3,8415
Buhrmann	0	0,5552	0,348	3,8415
DSM	0	0,24	1,3808	3,8415
Elsevier	0	0,432	0,6174	3,8415
Fortis	0	0,2855	1,1407	3,8415
Getronics	0	0,0818	3,0278	3,8415
Hagemeyer	0	0,9235	0,0092	3,8415
Heineken	0	0,0608	3,516	3,8415
IHC Caland	0	0,0887	2,8975	3,8415
ING	0	0,54	0,3756	3,8415
KPN	0	0,5685	0,3252	3,8415
Numico	0	0,3746	0,7885	3,8415
Philips	0	0,1365	2,2169	3,8415
Royal Dutch Oil	0	0,5563	0,3461	3,8415
TPG	1	0,0319	4,605	3,8415
Unilever	0	0,4437	0,5867	3,8415
Van der Moolen	0	0,6277	0,2352	3,8415
Versatel	0	0,2826	1,1544	3,8415
VNU	0	0,1195	2,4238	3,8415
Wolters Kluwer	0	1	-12,8743	3,8415

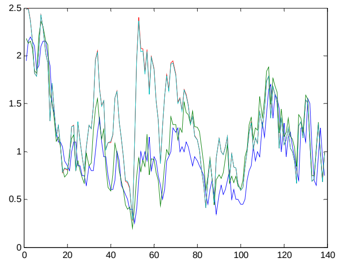
AIC and BIC

1,00E+03		AIC	BIC
ABN AMRO	**Model I**	-4,378892706	-4,358674907
	Model II	-4,377210441	-4,351938192
Aegon	**Model I**	-4,095465168	-4,075247369
	Model II	-4,093834973	-4,068562725
Ahold	**Model I**	-4,435693556	-4,415475758
	Model II	-4,433919483	-4,408647235

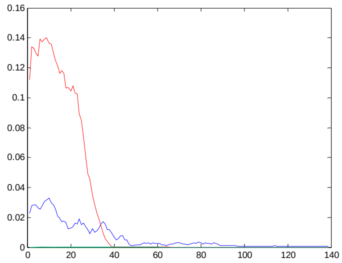
1,00E+03		AIC	BIC
Akzo Nobel	Model I	-4,513742478	-4,493524679
	Model II	-4,512793486	-4,487521238
ASML	Model I	-2,965150937	-2,944933139
	Model II	-2,963707206	-2,938434957
Buhrmann	Model I	-3,191119650	-3,170901851
	Model II	-3,189467694	-3,164195446
DSM	Model I	-4,670493933	-4,650276134
	Model II	-4,669874765	-4,644602516
Elsevier	Model I	-4,285171258	-4,264953460
	Model II	-4,283788621	-4,258516372
Fortis	Model I	-4,393862033	-4,373644235
	Model II	-4,393002722	-4,367730474
Getronics	Model I	-2,888645799	-2,868428000
	Model II	-2,889673586	-2,864401338
Hagemeyer	Model I	-3,960780825	-3,940563026
	Model II	-3,958790057	-3,933517808
Heineken	Model I	-4,716506542	-4,696288744
	Model II	-4,718022524	-4,692750276
IHC Caland	Model I	-4,282974845	-4,262757047
	Model II	-4,283872339	-4,258600091
ING	Model I	-4,360396309	-4,340178511
	Model II	-4,358771881	-4,333499632
KPN	Model I	-3,164311002	-3,144093203
	Model II	-3,162636182	-3,137363933
Numico	Model I	-4,033534005	-4,013316207
	Model II	-4,032322483	-4,007050235
Philips	Model I	-3,440833957	-3,420616159
	Model II	-3,441050873	-3,415778624
Royal Dutch Oil	Model I	-4,624940386	-4,604722587
	Model II	-4,623286506	-4,598014257
TPG	Model I	-4,415911470	-4,395693672
	Model II	-4,418516453	-4,393244205
Unilever	Model I	-4,697510135	-4,677292336
	Model II	-4,696096854	-4,670824606
Van der Moolen	Model I	-3,970974174	-3,950756376
	Model II	-3,969209388	-3,943937140
Versatel	Model I	-2,414000856	-2,393783058
	Model II	-2,413155302	-2,387883054
VNU	Model I	-3,822489878	-3,802272079
	Model II	-3,822913721	-3,797641472
Wolters Kluwer	Model I	-4,040051755	-4,019833956
	Model II	-4,025177497	-3,999905249

APPENDIX M: Call Option Prices

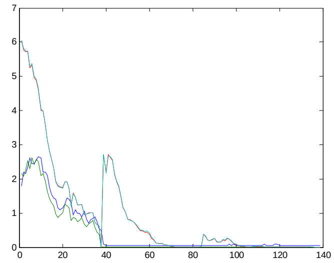
ABNAMRO



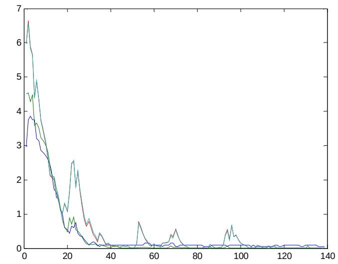
AEGON



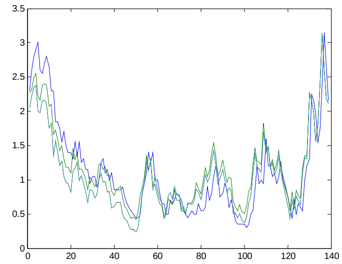
AHOLD



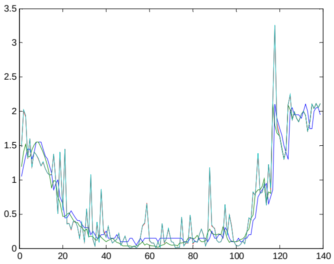
Akzo Nobel



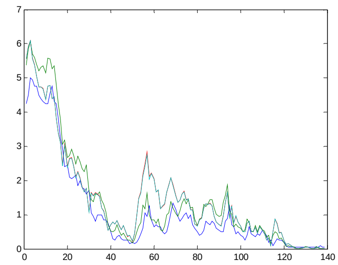
ASML



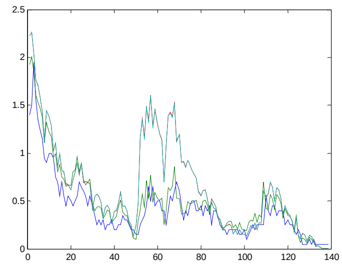
Buhrmann



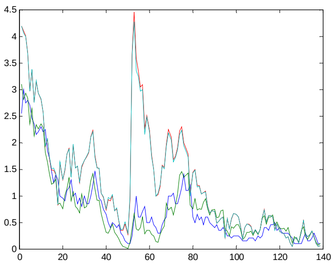
DSM



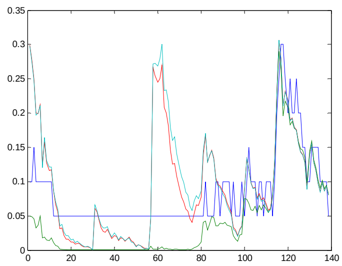
Elsevier



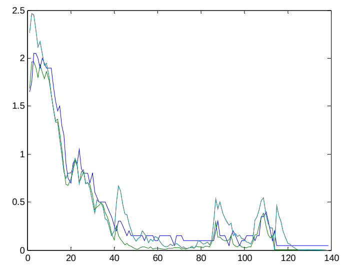
Fortis



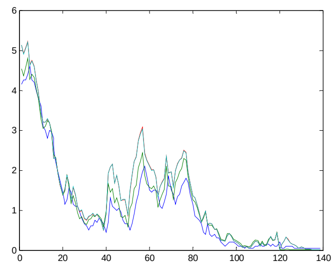
Getronics



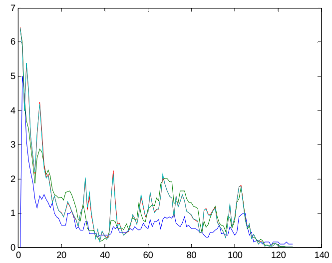
Hagemeyer



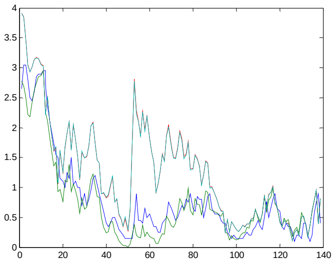
Heineken



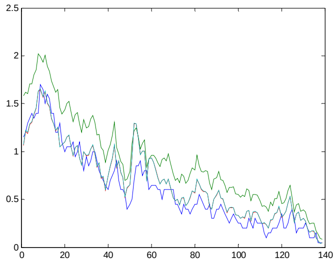
IHC Caland



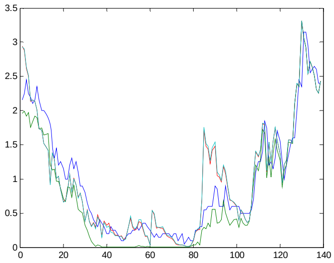
ING



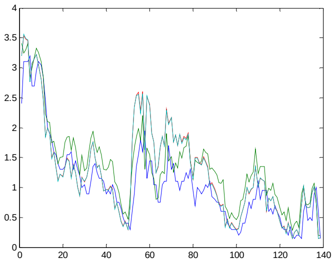
KPN



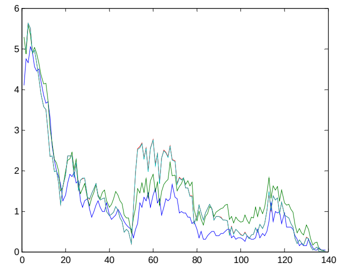
Numico



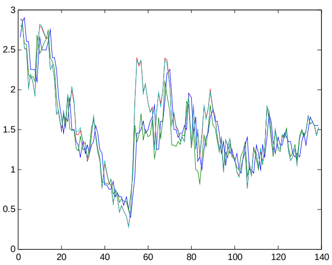
Philips



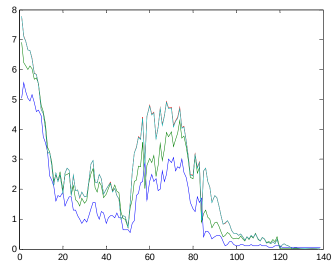
Royal Dutch Oil



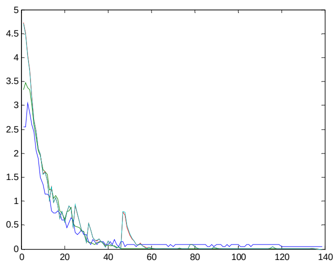
TPG



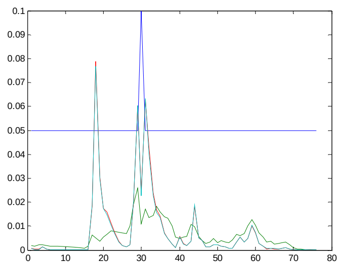
Unilever



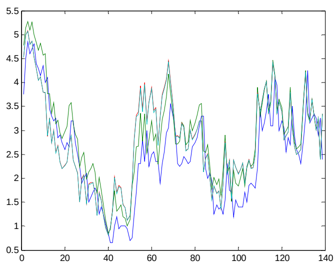
Van der Moolen



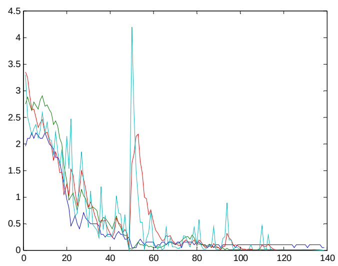
Versatel



VNU

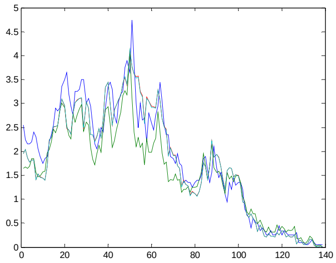


Wolters Kluwer

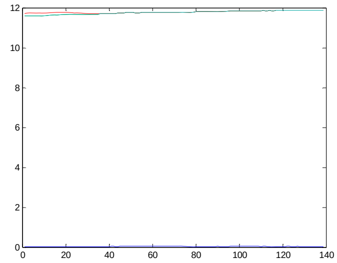


APPENDIX N: Put Option Prices

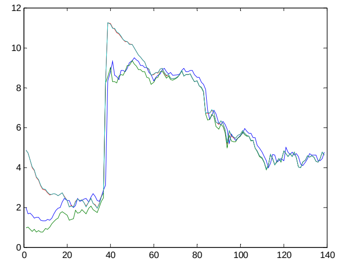
ABNAMRO



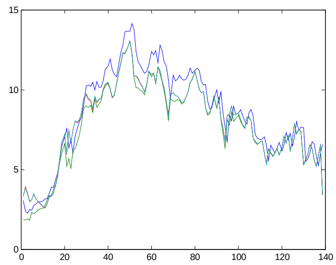
AEGON



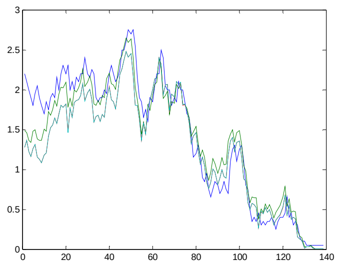
AHOLD



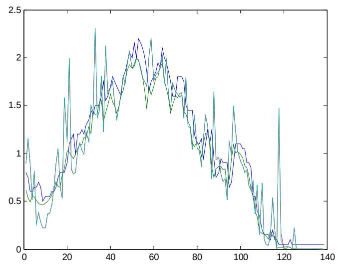
Akzo Nobel



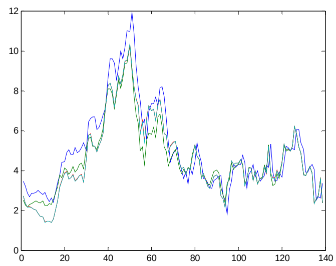
ASML



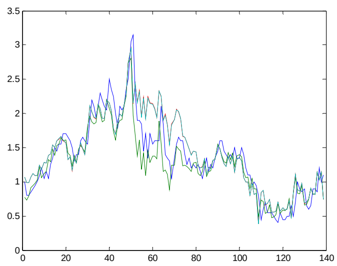
Buhrmann



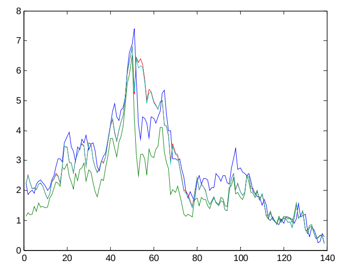
DSM



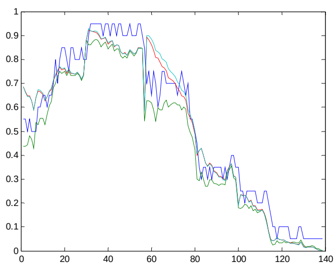
Elsevier



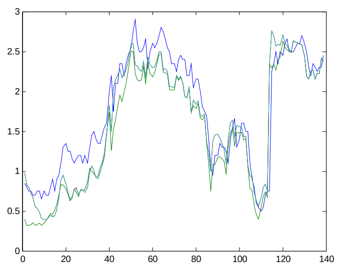
Fortis



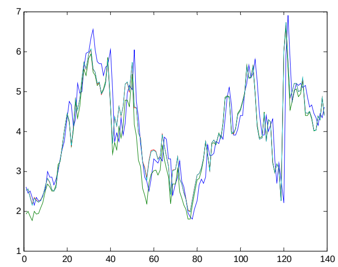
Getronics



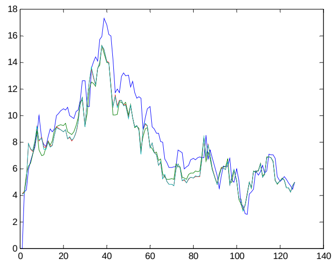
Hagemeyer



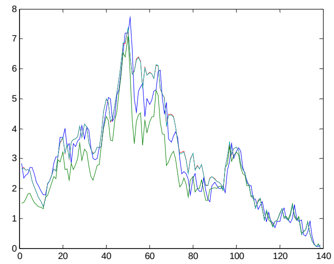
Heineken



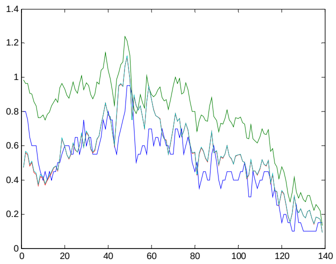
IHC Caland



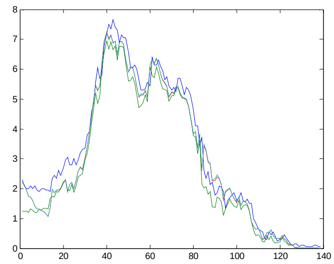
ING



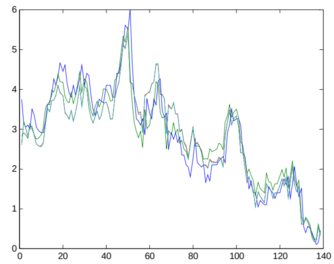
KPN



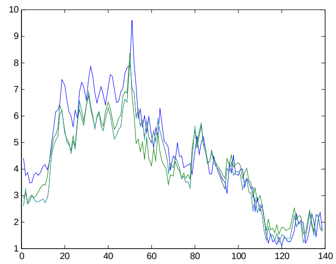
Numico



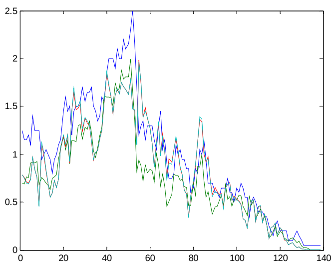
Philips



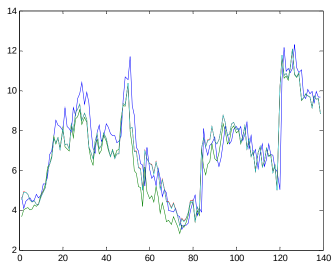
Royal Dutch Oil



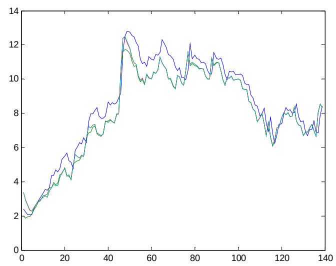
TPG



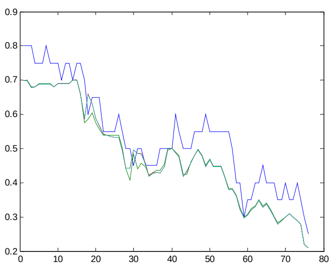
Unilever



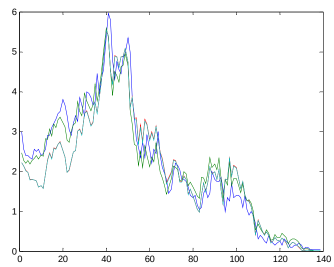
Van der Moolen



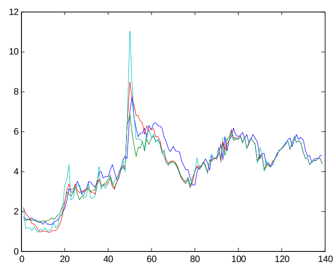
Versatel



VNU



Wolters Kluwer



APPENDIX O: AMSE

Average Percent Mean Squared Error

	Constant	GARCH(1,1)	GARCH-M(1,1)
ABN AMRO	0,1059	0,5308	0,5267
Aegon	1	5,2857	0,9999
Ahold	0,7435	131,0031	132,6739
Akzo Nobel	0,5574	4,6469	4,6331
ASML	0,1458	0,1096	0,1098
Buhrmann	0,1886	1,1471	1,1488
DSM	0,4244	1,1745	1,1594
Elsevier	0,2548	1,0277	1,0277
Fortis	0,2729	3,6779	3,6939
Getronics	0,5788	1,2874	1,6116
Hagemeyer	0,4491	1,706	1,7033
Heineken	0,5639	0,7053	0,7215
IHC Caland	0,6936	0,9223	0,9306
ING	0,3232	2,8114	2,8317
KPN	0,8102	0,1607	0,1643
Numico	0,389	0,2925	0,3067
Philips	0,5609	0,3527	0,3502
Royal Dutch Oil	1,0666	0,6083	0,6016
TPG	0,0284	0,052	0,0531
Unilever	1,6513	3,0967	3,0984
Van der Moolen	0,7067	2,2296	2,5217
Versatel	0,7949	0,8121	0,8133
VNU	0,1084	0,1521	0,1483
Wolters Kluwer	0,5735	32,7894	76,4345

APPENDIX P: Expected Value of Returns

	Average Returns	GARCH(1,1)	GARCH-M(1,1)
AEX	0,00036467	0,00061620	0,00076266
ABN AMRO	-0,00020000	0,00046959	0,00078547
Aegon	-0,00110000	-0,00025829	0,00010781
Ahold	-0,00100000	0,00004409	-0,00025303
Akzo Nobel	-0,00030000	0,00018642	0,00052706
ASML	-0,00090000	0,00018013	0,00071795
Buhrmann	-0,00160000	0,00288600	0,00250000
DSM	0,00040000	0,00050179	0,00085729
Elsevier	0,00000000	0,00003228	0,00033318
Fortis	-0,00060000	-0,00022925	0,00035579
Getronics	-0,00350000	-0,00343030	-0,00230000
Hagemeyer	-0,00140000	-0,00022372	-0,00027734
Heineken	-0,00010000	-0,00013292	0,00024611
IHC Caland	0,00020000	0,00070653	0,00099916
ING	-0,00040000	0,00058302	0,00098586
KPN	-0,00140000	-0,00060929	-0,00026485
Numico	-0,00120000	-0,00093760	-0,00140000
Philips	-0,00040000	0,00001044	0,00077566
Royal Dutch Oil	-0,00020000	0,00014457	0,00034990
TPG	-0,00040000	-0,00031983	0,00053055
Unilever	0,00000000	0,00019272	0,00041335
Van der Moolen	0,00020000	0,00017254	0,00030131
Versatel	-0,00420000	-0,00549460	-0,00460000
VNU	-0,00030000	-0,00082674	-0,00005232
Wolters Kluwer	-0,00080000	-0,00034648	0,00030321