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„ Asset Volatility Forecasting using News Sentiment Data: An Empirical Investigation“

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Abstract German

Ziel dieser Arbeit ist, die Frage zu beantworten, ob positive und negative exogene Nachrichtendaten von Unternehmen zur Schätzung der Volatilität ihrer Vermögenswerte beitragen. Diese Arbeit kommt zu drei Ergebnisse. Erstens haben negative und positive Finanznachrichten einen gegensätzlichen Einfluss auf die Vermögensrenditen von Unternehmen. Positive Nachrichten sind mit höheren Vermögensrenditen, während negative Nachrichten mit niedrigeren Renditen verbunden sind. Zweitens wirken sich positive und negative Nachrichten nicht symmetrisch auf die Volatilität der Renditen aus. Daher erzielt die Verwendung asymmetrischer Modelle zur Schätzung der Volatilität von Anlagerenditen bessere Ergebnisse. Drittens tragen exogene Unternehmensnachrichten bei der Vorhersage der extremen Ausreißer der Volatilität von Anlagerenditen bei.

Executive Summary

This thesis aims to answer the question whether positive and negative exogenous news data of companies contribute to the estimation of their asset volatility. This work finds three primary results. Firstly, negative and positive financial news have a contrary influence on the asset returns of firms. Consequently, positive news are associated with higher asset returns, while negative news are linked to lower returns. Secondly, positive and negative news do not have a symmetric effect on the volatility of asset returns. Thus, using asymmetric models for estimating the volatility of asset returns provides more accurate results. Thirdly, exogenous companies' news data helps to forecast the extreme outliers of volatility of asset returns.

Outline of my thesis

At the beginning of the thesis, I describe the importance of the research topic and provide a brief literature overview on the subject and the models. In the next part, the data used is introduced, followed by a more detailed description of the models. Next, I explain the part that deals with the results of the previously explained models. The last part discusses the empirical findings from prior research.

1 Introduction and literature review

Both risk management and asset pricing heavily rely on the relationship between news and market volatility. Indeed, it has been found that information about individual institutions' health conditions and the general macroeconomic situation can influence investors' decisions. There may exist a direct correlation between the news arrival and volatility or the so-called conditional variance (Fama, 1970). Moreover, Clark (1973) highlights the link between risk and information by pointing out that the rate at which information arrives at the market is serially correlated with the volatility of stock returns. Furthermore, a research carried out by Kalev et al. (2004) figured out that news arrivals appear to exhibit a strong correlation with the conditional variance of stock returns. They used high-frequency data from the Australian Stock Exchange and controlled for potential influence factors like trading volume and high opening volatility. They discovered that including a news variable in the conditional variance equation of the Generalized Autoregressive Conditional Heteroscedasticity (GARCH) model reduces the persistency of volatility when using intraday data. However, in contrast to the earlier findings Mitchell & Mulherin (1994) found that there was no significant correlation between news and market activity. Additionally, they discovered that patterns in the news announcements cannot explain the day-of-the-week seasonality in market activity.

The interest in predicting the volatility of asset returns, by using the information of news, arises from different areas. For practitioners, forecasting the volatility of asset returns is particularly important in the field of risk management, for instance, to hedge investors' decisions. For academics, on the other hand, predicting the volatility of asset returns has implications for stock market efficiency. Moreover, it can be used to demonstrate evidence about the mutual correlation between the real economy and the fluctuations within the financial markets (Zhang et al., 2018).

After discussing the importance of modelling or predicting the volatility of asset returns, different modelling and forecasting approaches have been proposed in the literature in the past years. Earlier, the most popular volatility prediction method was the Autoregressive Conditional Heteroscedasticity (ARCH) model that was initially proposed by Engle (1982). Bollerslev (1986) generalized the ARCH (q) model into the Generalized ARCH or GARCH (p,q) model, which is an infinite-order ARCH model. Within a GARCH(1,1) model the effect of the shock on the current asset returns declines geometrically over time. Baillie & Bollerslev (1989) and Engle & Ng (1993) explain that adding the previous lag of the conditional variance to the ARCH(1) model, represented by the GARCH(1,1) model to predict the conditional variance, is preferred most of the time. More recently, Hansen & Lunde (2005) discovered that it is hard to outperform the forecasting performance of a GARCH(1,1) model. However, both the ARCH or GARCH model fail to capture some key features when modelling the volatility of asset returns like the leverage or asymmetric effect of shocks. This phenomenon was first discovered by Black (1976). This effect occurs, when an unexpected decrease in price (bad news) is associated with a higher increase in the predicted volatility than for an unexpected increase in price (good news) or when big news have a stronger effect on volatility than small news. Caporin & Costola (2019) argue that the leverage and asymmetry effects, which are often used as synonyms, do not show identical outcomes. The authors proposed a new definition of the two effects and explained that most GARCH models allow for asymmetry but not for leverage effects. Nelson (1990) first introduced the Exponential GARCH, also called the EGARCH model, to capture such asymmetric effects. The main difference between the GARCH and the EGARCH model is the fact that, firstly, within the EGARCH model, good news and bad news can have a different impact on the volatility and, secondly, big news can have a greater influence on the volatility. Glosten, Jagannathan and Runkle (1993) introduced another type of GARCH model defined as the GJR-GARCH model to capture the asymmetric effect within time series data.

In order to better perceive the asymmetric effect of different types of GARCH models, Engle & Ng (1993) developed the news impact curve that gauges how news information is integrated into the volatility estimation. The findings imply that the EGARCH model may account for the majority of the asymmetry without requiring a separate model of the news impact. In specific, the news impact curve relates past return shocks (news) to the current volatility of returns.

1.1 Sentiment Analysis

Since it has been discovered that negative and positive return shocks within time series have often an asymmetric effect on the volatility of returns (Engle & Ng, 1993), there has been an increasing interest in the sentiment (e.g. good, bad or neutral) of news and their effects on the stock markets. Understanding whether price fluctuations in financial markets are influenced by economic or by political news, is the subject of an expanding number of empirical and theoretical investigations (Broadstock & Zhang, 2019;

Smales, 2014). Smales (2014) found that, during the time of the COVID-19 pandemic, people's sentiments had an asymmetric impact on the stock market. Furthermore, it has been found that social media news can have a significant influence on the stock market dynamics, particularly in times of economic or political uncertainty. In terms of data available, Cepoi (2020) marked that especially the COVID-19 pandemic led to a huge amount of published news, while the stock markets around the world experienced a very volatile time. It has been discovered that there is an asymmetric dependency between COVID-19-related news and stock market returns across the top six countries most affected by the pandemic. Normally, an increase in price is called a bullish sentiment and a downward trend in price is known as a bearish sentiment.

Previous studies have also investigated the Investor Sentiment Index (ISI), which represents a measure to gauge the overall sentiment prevailing in the market. The ISI is mainly used to understand price fluctuations (Da et al., 2015; Tetlock, 2007). The sentiment index proposed by Tetlock (2007) quantitively measures the interactions between media and stock markets. There is evidence provided that high media pessimism predicts a downward pressure on market prices and high market trading volumes (Sevilla et al., 2022). Sentiment analysis has also been used to predict future agricultural product price trends in order to draw some conclusions for farmers and consumers. Xu and Hsu (2022) explain that predicted agricultural product prices can influence the production value of the country. In addition, the authors investigate whether data can explain the impact on agricultural product prices. Moreover, Duong et al. (2013) and Kalev (2004) consider the amount of news published in their model used. By doing so, they highlight intraday volatility patterns of the S&P/ASX 200 Index by estimating an EGARCH model. They find that the rate of information appearance has a positive effect on the volatility. Ho et al. (2013) investigate the correlations between firm-level returns volatility and public news sentiment. Therefore, they related intraday firm-specific and macroeconomic news sentiment data to high-frequency return data and fitted different types of GARCH models. Their results include that firm-related news accounts for a bigger proportion of volatility persistency than macroeconomic news. Moreover, they agree together with Crouhy & Rockinger (1997) and Riordan et al. (2013) that negative news influences volatility to a greater extent than positive news. Furthermore, Ho et al. (2013) find that some GARCH models including sentiment data are especially important when working with high-volatility return data in comparison to a low-volatility regime. Furthermore, Sidorov et al. (2013) looked at trading volume as a proportional proxy for information arrivals to the market and the number of daily press releases on stocks (news intensity) as an alternative explanatory variable for the basic GARCH model. While Berry and Howe (1994) find only a positive relationship between public news and trading volume but an insignificant relationship with price volatility, Sidorov et al. (2014) argue that the GARCH(1,1) model augmented with news volume performs better than the simple GARCH model.

It has been possible to discover that the sentiment of news on volatility might be correlated. However, as news data are presented as qualitative data, but only quantitative data can be incorporated into various models, the sentiment news data needs to be transformed beforehand. In the past, some firms have developed linguistic analytics that processes the textual input of news and transforms it into quantitative score-based data. However, with the exponentially growing area of artificial intelligence (Roser, 2023; Sevilla et al., 2022), language and image recognition systems are improving rapidly (Roser, 2023). In particular, sentiment analysis of financial news that identifies the "mood" (e.g. positive, negative, or neutral), is becoming more readily available and inexpensive thanks to enhanced trained AI models (Haque et al., 2022).

Recent years have shown a volatile development in the financial markets (Smales, 2014) and research has shown that implementing sentiment data performs better when predicting volatility of asset returns for a high-volatility regime by using high-frequency data (Ho et al., 2013). Additionally, the opinions of previous research about the best models for volatility prediction including exogenous sentiment data are still severely divided and need to be further investigated.

2 Data

In this thesis, two panel datasets will be used: (1) market data including daily closing prices of seven assets, downloaded by Bloomberg, from the time period 02/01/2020 to 30/12/2022 and (2) sentiment data including financial news released per second for seven assets. The seven assets are chosen from the EUROSTOXX50 and should represent a diverse result due to the versification of sectors of the chosen assets. Additionally, the assets were chosen based on their cap size, in which a bigger cap size was preferred due to more sentiment data points available. While it is theoretically possible to conduct the estimation for the entire EUROSTOXX50 or any other index, however, it was technically unfeasible and falling beyond the scope of this master´s thesis. Due to the fact that the sentiment data is released per asset and, therefore, per firm, downloading it for a full index would result in an enormous dataset.

2.1 Market Data

The market data represents a panel dataset of seven assets and their daily closing prices downloaded by Bloomberg. Initially, it was planned to use intraday data (30-min ticks), but due to the limited availability of data, only daily closing prices were used within this master's thesis. The asset return data contains in total of 772 data points for each asset.

2.2 News Data

The sentiment data represents the financial news released on a particular trading day per asset and has been downloaded by RavenPack (Source). The dataset contains the following columns:

(1) Date: Date JJJJ-MM-TT of the news released.
(2) Timestamp: Timestamp JJJ-MM-TT MM:SS of news released.
(3) ID: Name of the particular asset.
(4) Relevance: Relevance of the news released reaching from a value of 0-100 only values equal to or bigger than 70 have been included.
(5) Event Sentiment Score: Indicating whether the news is assumed to be positive or negative. The value of the score reaches from -1 to +1, where only values between -1 and -0.5 (negative news) and between 1 and 0.5 (positive news) have been included. Therefore, the dataset only takes news with a strong sentiment score into consideration.
(6) Event Relevance: Indicating the relevance of the negative, positive or neutral event.
(7) Event Text: Provides parts of the news released.
(8) Event Type: Stating the type of news (e.g., Press-Release, Full-Article, Hot-News-Flash etc.)
(9) Source Name: Stating the source where the news has been published.

Columns (6) – (8) were included solely to provide a more detailed view of the data´s structure, and they are not directly utilized in the estimation process. In the next step, the data has been transformed, introducing three new columns and column (5) Event Sentiment Score has been adapted:

(1) Positive News Count: The total amount of positive news released on a particular trading day.
(2) Negative News Count: The total amount of negative news released on a particular trading day.
(3) Total News: The total amount of positive and negative news released on a day.
(4) Transformed Event Sentiment Score: The average sentiment score of a particular trading day, reaching from -1 to +1.

3 Models

There are different types of models that are used to explain serial correlation within an instrument, namely the Autoregressive (AR) model of order p, the Moving Average model of order q and the combination of those, called Autoregressive Moving Average (ARMA) model of order p, q. The AR, MA and ARMA models do not inherently account for conditional heteroskedasticity, and therefore they do not take volatility clustering into account. The residuals of an ARMA model are by definition white noise. Whereas autocorrelation within the residuals would indicate a miss specification of the model. Conditional heteroscedasticity means that the heteroskedasticity is conditional on periods of increased variance. For example, a shock like the COVID-19 pandemic might be a period of increased variance or a volatility cluster for certain assets, and the conditional variance within this period therefore might be serially correlated. In order to explain such periods of varying variance or volatility clusters, more sophisticated models like ARCH or GARCH are needed.

Therefore, to investigate whether negative and positive financial news have an influence on the volatility, different models are considered, which are all based on Autoregressive Conditional Heteroscedasticity (ARCH) modes, introduced by Engle (1982). The basic idea of such models is, that they utilize an autoregressive process for the variance itself. Therefore, those models account for changes in the variance by using past values of the variance. Thus, the variance does not need to be constant over time but rather can be time-varying. Such models are often used in the area of financial econometrics to predict the conditional variance of a time series, for example, to evaluate how risky an asset is. Therefore, predicting higher volatility would indicate a riskier asset. However, ARMA and ARCH models do not mutually exclude each other, because the ARCH model is simply a further development of an ARMA model and, therefore, they can also be combined into an ARMA-(G)ARCH model (Engle, 1982).

3.1 ARCH

Engle introduced (1982) a model allowing time-varying conditional variance, the Auto Regressive Conditional Heteroscedasticity (ARCH) model. Within the ARCH model, the variance is allowed to be dependent. The **Equation (1)** for asset returns is defined as follows:

$$\mathrm{Y_t} = \mu_\mathrm{t} + \sigma_\mathrm{t} u_t^*. \tag{1}$$

$\mathrm{Y_t}$ is defined as asset returns, meaning the differenced and logarithmic values of the daily closing price and μ_t as time-varying mean. As financial data often deals with non-stationary data, taking the first difference of the time series can reduce the series to stationary white noise. It is assumed that the mean

is constant over time and, therefore, $\mu_t = \mu$. The time-variant variance of the asset returns is represented by σ_t. u_t^* demonstrates a white noise error term, that is, i.i.d. (identically and independently distributed) with mean zero and variance one.
The volatility model for an ARCH(q) model can be seen in **Equation (2)**:

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i u_{t-i}^2, \tag{2}$$

where the conditional variance σ_t^2 is estimated by a constant term ω and one or more terms of lagged error terms $(Y_{t-1} - \mu_{t-1})^2$. Therefore, $\sigma_t = (Y_t - \mu_t)$ and the innovations u_t are defined as $u_t = \sigma_t u_t^*$, where $u_t^* \sim$ i.i.d. $\mathcal{N}(0,1)$. In order to assure that the conditional variance σ_t^2 stays positive, the assumptions $\omega > 0$ and $\alpha \geq 0$ need to hold.

3.2 GARCH Model

Sometimes a very high order of ARCH terms (q) is needed to capture the dynamic behavior of the conditional variance (Tsay, 2013). Therefore, GARCH(p,q) models are often a more efficient method to model the conditional variance. According to Bollerslev (1986), the GARCH (Generalized Autoregressive Conditional Heteroscedasticity) model has been marked as the most successful and commonly known models to predict volatility. GARCH models are able to capture volatility clustering, consider time-varying volatility phenomena over a long period and provide very good in-sample estimates. Where an "in-sample" estimate indicates building an accurate model for the real data without forecasting any values. The GARCH (p,q) **Equation (1)** is defined as follows:

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} \alpha_i u_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2, \tag{3}$$

where again the restrictions $\omega > 0$, $\alpha \geq 0$ and $\beta \geq 0$ need to hold, to assure that σ_t^2 stays positive. The innovations u_t of the process $Y_t = \mu_t + u_t$ follow a GARCH model if the conditional variance σ_t^2 is modelled as a function of past quadratic innovations u_{t-i}^2 and past conditional variances σ_{t-i}^2. If $\beta_j = 0$, thus p = 0, meaning the GARCH(p,q) process follows only an ARCH(q) process. The GARCH process includes the lagged conditional variance term in the process.

One of the most established and well performing model is the GARCH(1,1) (Hansen & Lunde, 2005), that is defined as follows:

$$\sigma_t^2 = \omega + \alpha u_{t-1}^2 + \beta \sigma_{t-1}^2. \tag{4}$$

It needs to be ensured that $\alpha + \beta < 1$, so that the predicted conditional variance σ_t^2 always returns to the long-run variance and stays stationary. The unconditional variance of a stationary GARCH(1,1) process for u_t equals the unconditional mean of the ARMA(1,1) process u_t^2.

$$V(u_t) = E(u_t^2) = \frac{\omega}{1 - (\alpha + \beta)}, \tag{5}$$

where the volatility persists for a long time if the persistence factor $\alpha + \beta$ is close to 1.

As already mentioned, often high orders of an ARCH process are needed to capture the dynamic behavior of the volatility and, therefore, the GARCH model is often considered as the more efficient model. It can also be shown that the GARCH(1,1) process has an ARCH(∞) representation for u_t^2. The GARCH(1,1) can be transformed as follows:

$$\sigma_t^2 = \omega + \alpha u_{t-1}^2 + \beta\sigma_{t-1}^2, \tag{6}$$

$$\sigma_t^2(1 - \beta L) = \omega + \alpha u_{t-1}^2, \tag{7}$$

where L denotes to the lag operator of σ_t^2. The equation can further be transformed to:

$$\sigma_t^2 = \frac{\omega}{1-\beta} + \alpha \sum_{j=1}^{\infty} \beta^{j-1} u_{t-j}^2, \tag{8}$$

$$\sigma_t^2 = \omega^* + \sum_{j=1}^{\infty} \phi_j u_{t-j}^2 = \omega^* + \phi_1 u_{t-1}^2 + \phi_2 u_{t-2}^2 + \ldots, \tag{9}$$

with the coefficients $\omega^* = \frac{\omega}{1-\beta}$, and $\phi_j = \alpha\beta^{j-1}$, where $j \geq 2$. The parameter β acts like a discount factor of past volatility shocks since $\beta < 1$. The higher β, the more information of the past is carried into the present.

To summarize, in a GARCH(1,1) process with $\beta \neq 0$, the conditional variance σ_t^2 at time t is influenced by the previous innovation shocks u_{t-1}^2 like in the ARCH process, but additionally influenced by the lagged conditional variance σ_{t-1}^2. As a result, the conditional variance at time t-1 differs from the unconditional variance. Nevertheless, the GARCH process is still unable to capture the leverage effect due to its symmetric distribution of positive and negative autocorrelated error terms. If the autocorrelation within the variance is non-linear and negative and positive shocks show an asymmetric behavior, models like the EGARCH (Nelson, 1991) or GJR-GARCH (Glosten et al., 1993) model might be more suitable.

3.3 EGARCH

The ARCH as well as the GARCH model are able to capture volatility clustering. However, Nelson (1991) argued that the GARCH model fails to capture the asymmetric relationship between asset returns and positive and negative changes in volatility. GARCH models essentially specify the behavior of the square of the sample data. In this case, a few outliers can dominate the sample. The EGARCH model accounts for asymmetric volatility behavior, by including an additional term in the model. As a result, within the EGARCH model good news and bad news, meaning negative and positive residuals, respond differently to the conditional variance (Engle & Ng, 1993). The EGARCH model was proposed to overcome the restriction of symmetry in the GARCH model, and in particular, to capture the leverage effect (Black, 1976). Taking the natural logarithm of the conditional variance σ_t^2 should guarantee a non-negative conditional variance, meaning that the positivity restrictions do not need to hold for the EGARCH model. The EGARCH (p,q) model is represented as follows:

$$ln(\sigma_t^2) = \omega + \sum_{i=1}^{q} \alpha_i g(u_{t-i}) + \sum_{j=1}^{p} \beta_j ln(\sigma_{t-j}^2), \tag{10}$$

where

$$g(u_{t-i}) = \phi u_{t-i} + \psi(|u_{t-i}| - E|u_{t-i}|), \tag{11}$$

The sequence $g(u_{t-i})$ is by construction a zero-mean i.i.d. normal random sequence.

The EGARCH(1,1) is specified as follows:

$$ln(\sigma_t^2) = \omega + \alpha[\phi u_{t-1} + \psi(|u_{t-1}| - E|u_{t-1}|)] + \beta ln(\sigma_{t-1}^2). \tag{12}$$

3.4 GJR-GARCH

An alternative way to model asymmetric volatility is the Glosten, Jagannathan and Runkle GARCH (GJR-GARCH) model, proposed by Glosten, Jagannathan, & Runkle (1993). It enables the conditional variance to react differently to past positive and negative shocks. This model has a second parameter to account for the leverage effect included. In practice, the GJR-GARCH model is easier to implement, since the variance is directly modelled instead of using the natural logarithm (Hayashi, 2000). The GJR-GARCH(1,1) is specified as:

$$\sigma_t^2 = \omega + \sum_{i=1}^{q} (\alpha_i + \gamma I_{t-i}) u_{t-i}^2 + \sum_{j=1}^{p} \beta_j \sigma_{t-j}^2, \tag{13}$$

where

$$I_{t-i} = \begin{cases} 1, & if\ u_{t-i} < 0 \\ 0, & if\ u_{t-i} \geq 0 \end{cases}.$$

Additionally, the positivity restrictions $\omega > 0$, $\alpha_i \geq 0$ (for i = 1, …., q), $\gamma \geq 0$ (for i = 1, …., q) and $\beta_j \geq 0$ (for j = 1, …., p) need to be imposed again. The binary variable I_{t-1} ensures that negative and positive shocks of innovations can have asymmetric impacts on the conditional variance. As the negative shock is associated with being multiplied with $(\alpha + \gamma)$ and the positive shock only with α, negative shocks will be weighted more than positive shocks. The unconditional variance is given by:

$$\mathbb{E}[\sigma_t^2] = \frac{\omega}{1 - \alpha - \kappa\gamma - \beta}, \tag{14}$$

where $\kappa = P(u_t < 0)$, such that $\kappa = ½\ if\ u_t$ is symmetrically distributed. Necessary conditions for stationarity are $\omega > 0$ and $0 < \alpha + \kappa\gamma + \beta < 1$

3.5 News Augmented GARCH Model

To evaluate the impact of financial news on volatility and its enhancement of the volatility estimation accuracy, three time-varying parameters for the external variables will be estimated via Maximum Likelihood Estimation:

$$PNews_{t,k} = \left|\overline{SentimentScore}_{t,k}\right| * TP_{News_{t,k}}, \tag{15}$$

$$NNews_{t,k} = \left|\overline{SentimentScore}_{t,k}\right| * TN_{News_{t,k}}, \tag{16}$$

$$LNews_{t,k} = (TP\_News + TN\_News)_{t-1,k}, \tag{17}$$

where the sentiment score is defined as $-1 \leq \overline{\left|SentimentScore_t\right|} \leq 1$ and is the average sentiment score of all news released within one time point t for a particular asset k. The more important the news at time t, the higher the sentiment score. Due to the fact that the sentiment score can take on negative and positive values, only the absolute value is multiplied with the following regressors. TP_News denotes the total amount of positive news at time t for an asset k and TN_News refers to the total amount of negative news published at time t for an asset k. LNews is the total amount of positive and negative news released at time t-1.

3.5.1 Model

With a mean specified as $\mu = \mathbb{E}(Y_t)$ and a variance defined as $V(Y_t) = \mathbb{E}((Y_t - \mu_t)^2)$ of a stationary time series Y_t, the time series at time t can be modelled as:

$$Y_t = \mu_t + \sigma_t u_t^*. \tag{18}$$

The conditional expectation $\mathbb{E}(Y_t|\, I_{t-1}) = \mu_t$, given all information I_{t-1} available at time t-1, is constant with mean μ, when the conditional expectation is independent of I_{t-1}. The conditional variance is modelled as $\mathrm{V}(\mathrm{Y_t}|I_{t-1}) = \mathbb{E}((\mathrm{Y_t} - \mu_t)^2|I_{t-1}) = V(u_t|I_{t-1}) = \sigma_t^2$.

The model can be rewritten as follows:

$$\Rightarrow \mathrm{u}_t^2 = (Y_t - \mu_t)^2 = \sigma_t^2 {u_t}^{2^*},$$

where u_t^* is a zero mean white noise process with variance one.

To examine the influence of positive, negative, and lagged news on asset returns and their conditional variance, two evaluation options are considered.

A. Modification of the mean equation

One performed method is to include the three exogenous variables into the mean equation, specified as follows:

$$Y_t = \mu + \delta_1 PNews_t + \delta_2 NNews_t + \delta_3 LNews_{t-1} + \mathrm{u}_t, \tag{19}$$

δ representing the estimated parameters for the three exogenous variables and $u_t = \sigma_t u_t^*$.

B. Modification of the variance equation

Another considered variant is the inclusion of the three exogenous variables into the variance equation. For a GARCH(1,1) model the conditional variance is defined as follows:

$$\sigma_t^2 = \omega + \alpha u_{t-1}^2 + \beta\sigma_{t-1}^2 + \delta_1 PNews_t + \delta_2 NNews_t + \delta_3 LNews_{t-1} \tag{20}$$

3.6 Distribution (Normal, Student's t, GED)

To ensure precise specification of the GARCH model, the distribution of the innovations u_t must be correctly specified. As previously stated u_t is expressed as:

$$u_t = \sigma_t u_t^*, \tag{21}$$

where u_t^* is identically and independently distributed with zero mean and variance one ($u_t^* \sim$ i.i.d N(0,1)). There are three distributions for u_t considered in this thesis: (1) the Gaussian (normal) distribution, the Student's t distribution, and the Generalized Error distribution (GED) (Nelson, 1991) which are recommended to test for in GARCH models (Chuang et al., 2007). If the assumption for u_t is Gaussian, the kurtosis can be calculated as:

$$\kappa = 3\frac{1-\alpha^2}{1-3\alpha^2}. \tag{22}$$

A value bigger than three indicates a thick-tailed distribution, meaning more outliers are generated. Therefore, the student's t distribution (Bollerslev, 1987) $T_\nu(0,(\nu-2))$, with ν degrees of freedom or the GED (Nelson, 1991) distribution are found to be more suitable for (G)ARCH models. The density of the student's t distribution is formally defined as:

$$f(u) = \frac{\Gamma\left(\frac{\nu+1}{2}\right)}{\sqrt{\nu\pi}\,\Gamma\left(\frac{\nu}{2}\right)}\left(1+\frac{u^2}{\nu}\right)^{-\left(\frac{\nu+1}{2}\right)}, \tag{23}$$

where $\nu > 0$ and Γ denotes the gamma function.

The density of the GED distribution, normalized to zero mean and variance equal to one is defined as:

$$f(u) = \frac{\nu\exp[-\frac{1}{2}|u/\lambda|^\nu]}{\lambda 2^{(-2/\nu)}\Gamma(1/\Gamma)}, \tag{24}$$

where $-\infty < u < \infty$ and $0 < \nu \leq \infty$ and Γ is the gamma function and

$$\lambda = [2^{(-2/\nu)}\Gamma(1/\nu)/\Gamma(3/\nu)]^{1/2}, \tag{25}$$

ν gives the thickness of the tails. If $\nu = 2$, normal distribution for u is assumed. For $\nu < 2$, the distribution of u has thicker tails and for $\nu > 2$, the distribution of u has thinner tails than the normal distribution. The lower, the degrees of freedom, the fatter the tails of the distribution (Nelson, 1991).

3.7 Maximum Likelihood Estimation

The GARCH family models (GARCH(1,1), EGARCH(1,1), GJR-GARCH(1,1)) are estimated using the Maximum Likelihood Estimation (MLE) under the assumption of a Gaussian distributed, student's t distributed and GED distributed innovation. For each distribution the parameter vector $\theta = (\mu, \omega, \alpha, \beta, (\gamma), (\phi), (\psi))$ will be estimated. The maximum likelihood function depends on the distribution of the innovations u_t.

For Gaussian distributed innovations u_t the fitted model is defined as:

$$Y_t | I_{t-1} \sim \mathcal{N}(\mu, \sigma_t^2(\theta)),$$

where

$$\sigma_t^2(\theta) = \omega + \sum_{\mathrm{i}=1}^{\mathrm{q}} \alpha_{\mathrm{i}} \mathrm{u}_{t-\mathrm{i}}^2 + \sum_{\mathrm{j}=1}^{\mathrm{p}} \beta_{\mathrm{j}} \sigma_{t-\mathrm{j}}^2, \tag{26}$$

and the maximum log likelihood function is defined as:

$$logp(y_{1,\dots,}y_T | \theta) = -\frac{1}{2}\left(\sum_{t=1}^{T} \frac{\mathrm{u}_{t-\mathrm{i}}^2}{\sigma_t^2(\theta)} + log\sigma_t^2(\theta)\right) + constant. \tag{27}$$

The MLE is consistent and asymptotically efficient and for large sample sizes also unbiased. The MLE will be performed for all GARCH family models under the assumption of gaussian, student's t and GED distributed innovations u_t.

3.8 Model Evaluation

The goodness-of-fit is evaluated by using the Bayesian Information Criterion (BIC), which closely related to the Akaike Information Criterion (AIC). The BIC punishes higher orders to account for over-fitting the parameters of the model (Schwarz, 1978). The BIC is formally given by:

$$BIC = -2logL(\theta) + klog(n), \tag{28}$$

where $logL(\theta)$ denotes the MLF, k represents the number of parameters, and n is the sample size. The lowest BIC is interpreted as the best model for representing the real data. It needs to be noted that an additional inclusion of a parameter will always lead to a bigger BIC. Therefore, it is important to check if the parameters are important for modelling the sample data.

3.9 Forecasting

The forecast for a GARCH(1,1) model with conditional variance:

$$\sigma_t^2 = \omega + \alpha \mathrm{u}_{t-1}^2 + \beta \sigma_{t-1}^2, \tag{29}$$

where $t = 1, \dots, T$ represents the in-sample period to the last day T, the 2021-12-30 and the unconditional variance can be calculated as:

$$\sigma^2 = \frac{\omega}{1 - (\alpha + \beta)}. \tag{30}$$

Therefore, the h-step ahead forecast $\mathbb{E}(\mathrm{u}_{t+\mathrm{h}}^2 | I_t)$ can be shown as:

$$\mathbb{E}(\mathrm{u}_{t+\mathrm{h}}^2 | I_t) = \mathbb{E}(\sigma_{t+h}^2) = \sigma^2 + (\alpha + \beta)^{h-1}[\sigma_{t+1}^2 - \sigma^2]. \tag{31}$$

When $\alpha + \beta < 1$, the process is stationary. The conditional variance is assumed to converge towards the unconditional one $\mathbb{E}_t[\sigma_{t+h}^2] \rightarrow \sigma^2$ when $\mathrm{h} \rightarrow \infty$.

It is assumed that at time t, all past values of u_t^2 and σ_t^2 are known. In the one-step-ahead forecast, the u_t^2 is observable as it is the last estimated residual in the GARCH(1,1) model. The volatility of the two-step-ahead period t+2 is based on the expectation of $\mathrm{u}_{\mathrm{t}+1}^2$. This process carries on until the last observation in the out-of-sample period, here until 2022-12-30. There are two common approaches when forecasting, either the (a) rolling or (b) recursive approach (Fama & MacBeth, 1973; S. P. Sidorov et al., 2014). The (a) rolling approach re-estimates the parameters by using a fixed window of data points and re-estimates the parameters for each step ahead in the future. In contrast, the recursive specification uses an expanding window in order to re-estimate the parameters, by only adding the new datapoint.

Here two versions are considered: (1) the estimation at time point T, here the 2021-12-30, for 1 year ahead by using the past information up to time point t and (2) a rolling forecast, using a rolling window of 257 time for forecasting the future. When doing a multi-step-ahead forecast, the conditional variance forecast should converge towards the unconditional variance. However, when estimating the conditional variance, the one-step-ahead forecast is more important, therefore, the rolling forecast will give more relevant information. The (2) rolling forecast should capture, whether the inclusion of exogenous variables (negative and positive news) helps to better forecast the one-step-ahead volatility.

3.10 Evaluation of the Forecast

In order to evaluate the different estimation results the Mean Squared Error (MSE) can be used (Patton, 2011). The MSE is computed by taking the difference between the predicted variance and the realized variance in the out-of-sample period. The MSE is defined as follows:

$$MSE = \frac{1}{n} \sum_{t=1}^{n} (\sigma_t^2 - \hat{\sigma}_t^2)^2, \tag{32}$$

where the σ_t^2 symbolizes the realized volatility, which should represent the real volatility, at time t and $\hat{\sigma}_t^2$ showing the predicted one-step-ahead forecast for the rolling window. The result is divided by 257, representing the rolling window. As the MSE only gives information about the average best fit but does not present how well the fitted models capture outliers and, if the models are over-/ or underestimated, plotting the realized volatility and the predicted values can give more information about the structure over time. Here the realized volatility σ_t^2 is approximated by using the daily squared asset returns. It needs to be noted that realized volatility should be interpreted carefully, as it aims to represent the "actual" conditional variance which is unobservable. Therefore, the method stated leads to a quite noisy result (Andersen & Bollerslev, 1998). According to Andersen and Bollerslev (1986) a better estimate of the realized daily volatility would be to use intra-day data to build the sum of 30 minutes squared returns. Hansen and Lunde (2005) pointed out, how the realized variance using intra-day data can be computed and used as comparison value. Moreover, Patton (2011) highlights the problem of the presence of noise in the volatility proxy of squared returns and provide insights that volatility proxies, such as the intra-daily range and differently calculated realized volatility, led to better results. Due to limitations of the availability of intra-day asset data, the daily squared asset returns of the out-of-sample period will be used as a proxy for the "real" volatility.

3.11 Tests

In order to test for (1) the stationarity, (2) the autocorrelation in the squared error terms and (3) the gaussian distribution of the error terms the following test are considered.

3.11.1 Stationarity and Augmented Dickey-Fuller Test

In order to test if the financial time series is stationary, the Augmented Dickey-Fuller (ADF) Test can be carried out. The ADF test relies on the idea of testing for the presence of a unite root in an autoregressive time series (Dickey & Fuller, 1979). The tested hypotheses are:

H_0: The process possesses a unit root and it is non-stationary.

H_1: The process possesses no unit root and is likely to be stationary.

If the null hypothesis is accepted, it would indicate that the process is a random walk. This would mean that the process has no memory of where it has been at each particular instance of time. However, if the null hypothesis can be rejected then the process is unlikely to be a random walk. The test will be carried out on the time series of the daily closing prices of all seven assets and differenced in case of non-stationarity.

3.11.2 ARCH Effect

An uncorrelated time series can have a serially dependent conditional variance, but also a time-dependent unconditional variance. In the second case, the process would be not stationary. If there is autocorrelation in the squared time series, it is said to have autoregressive conditional heteroscedastic (ARCH) effects. Engle's ARCH LM Test (Engle, 1982) is a Lagrange multiplier test to assess the significance of the ARCH effects:

H_0: There is most likely no autocorrelation in squared the error term.

H_1: There is autocorrelation in the squared error term.

In order to conduct Engle's LM ARCH test, a lag order needs to be specified. Additionally, the correlogram of the squared time series can be used to evaluate whether an ARCH model is needed.

3.11.3 Normality

In order to assess the distribution of the error term, the Shapiro-Wilk Normality Test by Samuel Sanford Shapiro and Martin Wilk (1965) is carried out.

H_0: The Shapiro-Wilk Test shows that the error term may be normally distributed.

H_1: The estimated error term are not normally distributed.

Additionally, the calculated kurtosis, the visualization of a QQ-plot and histogram of the error term can be used to judge the normality distribution and make assumptions about a distribution with fatter tails.

4 Results and data analysis

4.1 Time series and stationarity

Figure 1 in the appendix shows the raw time series for all seven assets, which are the daily asset return closing prices from 02/01/2022 to 30/12/2022.

There are two patterns visible among the seven assets, however, one asset is not comparable with the other assets' patterns and shows a very different behavior. The assets, including Siemens (Industrial Goods and Services), Deutsche Telecom (Telecommunications Services), BNP (Financial Services) and Allianz (Insurance), show a very similar pathway. At first, the closing prices sharply decrease in March 2020, which was followed by a slower increase approximately until August 2021. From then onwards there is a gentler, but very volatile decrease until around August 2022, followed by a sharper increase until December 2022. A second very similar history can be seen of the two assets ASML (Technology) and L'Oreal (Consumer Goods and Services). However, the sharp and intense decrease in March 2022 is missing. The asset SAP (Technology) shows a very different behavior. While the asset closing prices of SAP plump as well in March 2020, there is a very sharp increase until approximately July 2020 and an extremely harsh fall in October 2020. This development is followed by a slow, but volatile rise until December 2021. From then onwards the pathway of the asset SAP is comparable with the others.

In order to assess whether the time series is stationary, the Augmented Dickey-Fuller (ADF) test has been performed. The test was carried out on the raw time series, where the null hypothesis, stating that the time series is considered non-stationary due to an existing unit root, cannot be rejected at a one per cent level. The corresponding p-value of the ADF test statistic can be found in the 3th column **Table 1**: Results of the Augmented Dickey Fuller Test. However, when performing the ADF test on the differenced and logarithmic time series (returns), the null hypothesis can be rejected at a one per cent level. For both tests nine lags are considered. The mean of the differenced and logarithmic asset returns for the in-sample period can be found in the last column of **Table 1**: Results of the Augmented Dickey Fuller Test. The mean for all assets is close to or equal to zero.

Table 1: Results of the Augmented Dickey Fuller Test

Number	Assets	Augmented Dickey Fuller Test Lag order = 9 p-value	Mean
1	ASML	0.8814	0.08161435
2	L'Oreal	0.735	0.0304089
3	Siemens	0.7016	0.02424821
4	SAP	0.2798	-0.03099706
5	Deutsche Telekom	0.0123	0.03119447
6	Allianz	0.1123	-0.01263858
7	BNP	0.278	-0.0008054836

4.2 Differenced time series

In order to see potential volatility clustering during the time span, the differenced and logarithmic returns are plotted and can be found in the appendix at **Figure 2**. All assets show clustered volatility around March 2020 and different smaller volatility clusters between March 2020 and December 2022. However, there is a remarkable negative outlier for the asset SAP and a bit smaller but still extraordinary outlier for the asset BNP in October 2020 visible. In general, as clusters can be observed the variance of the time series is considered to be heteroskedastic. Therefore, it is expected that there is a variance present which is non-constant but rather time-varying over time.

4.3 ARCH effect

One possible way to draw assumptions about volatility clusters (the ARCH effect) is to check the autocorrelation of the squared time series. **Figure 3** and **Figure 4** show the presence of autocorrelation as well as partial autocorrelation of the squared time series for all assets. Autocorrelation or partial autocorrelation (ACF and PACF) within the non-squared time series and therefore within the log-returns of the assets provides information about the ARMA order. A combination of an ARMA and GARCH model is possible and has been considered in the first place. However, as including ARMA terms was not recommended for most of the fitted models and showed a very different order suggestion for the remaining ones, it has not been further investigated in this work.

4.4 GARCH(1,1) with an Gaussian Distribution

In the fourth row and second column of **Table 6** to **Table 12**, the results of a fitted GARCH(1,1) with the assumption of normal distribution for the innovation u_t for each asset can be found. All values within a row without a colored background are results for a GARCH(1,1), EGARCH(1,1) or GJR-GARCH(1,1) model excluding the exogenous financial news variables. Those models serve as benchmark models. By analyzing the GARCH(1,1) model with normal distribution, it can be seen that all α and all β are significant at a 1% significance level. The value α represents the volatility persisting factor and shows stronger persistence when closer to 1. Here the value lies in the range from 0.08 to 0.2 for all assets. As the parameter β is unequal to 0 and significant for all assets, a GARCH model is expected to be more efficient in capturing the volatility of the asset returns than a simple ARCH model. As the calculated mean of the asset returns is unequal to zero, presented in **Table 1**: Results of the Augmented Dickey Fuller Test, it has been first included in all the models, however, due to insignificance results for most of the assets, the mean has been excluded in all models. The fitted model for the conditional variance under Gaussian distribution for all seven assets corresponds to:

$$Y_t | I_{t-1}, \theta \sim \mathcal{N}\left(0, \sigma_{t-1}^2(\theta)\right).$$

Table 2: Results of the Shapiro-Wilk Normality Test and Kurtosis

Number	Assets	Shapiro-Wilk Normality Test P-value – GARCH (norm, without news variables)	Kurtosis P-value – GARCH (norm, without news variables)
1	ASML	4.896e-11	4.137985

2	L'Oreal	3.393e-12	4.155795
3	Siemens	2.2e-16	5.102966
4	SAP	2.2e-16	69.4926*
5	Deutsche Telekom	2.2e-16	6.370577
6	Allianz	2.2e-16	9.87968
7	BNP	7.549e-16	5.565738

*(huge outlier)

In order to evaluate, whether the innovations are indeed Gaussian distributed, the QQ-Plot and the histogram of the residuals have been plotted and presented in the appendix from **Figure 5** to **Figure 6** and furthermore, the Shapiro-Wilk Normality Test as well as the kurtosis has been calculated and displayed in **Table 2.** All visualizations and calculations are based on the estimated standardized residuals of a fitted GARCH(1,1) model.

In the QQ-Plots (**Figure 5**), and in the histograms (**Figure 6**), it can be seen that the estimated standardized residuals of the GARCH(1,1) process without the news variable do not follow a normal distribution. For some assets there are extreme outliers, however, more extreme on the negative side.

Furthermore, the results of the Shapiro-Wilk Normality Test, found in **Table 2**: Results of the Shapiro-Wilk Normality Test and Kurtosis in the 3rd column, confirm the findings of the QQ-Plot and the histogram. With the null hypothesis of the Shapiro-Wilk Normality Test stating that the estimated standardized residuals are normally distributed, the null hypothesis needs to be rejected at a 1% significance level for all assets. Additionally, the calculated Kurtosis, presented in **Table 2**: Results of the Shapiro-Wilk Normality Test and Kurtosis in the 4th column, agrees with the calculated normality test as well as the visualizations. A standard normal distribution has a kurtosis of three. The calculated kurtosis of all assets exceeds this value. Therefore, in total, a student's t or general error distribution (GED) might be a better fit for the conditional distribution.

4.5 Model fit

In the following section, we are going to analyze the results of the models fitted. On the one hand, the symmetric GARCH(1,1) models and on the other hand the asymmetric GARCH family models like the EGARCH(1,1) and the GJR-GARCH(1,1). For all three GARCH type models the following models are considered:

(1) the **benchmark models** including no exogenous variables,
(2) the **mean models** including exogenous variables in the mean equation and
(3) the **conditional variance models** including exogenous variables in the conditional variance equation.

The (1) benchmark model investigates whether there is an asymmetry within the residuals of the asset returns but without any exogenous news variables. Whereas the (2) mean model explores a potential effect of external financial news on the asset returns directly. Lastly, the (3) variance model aims to provide insights about the possible effect of external financial news on the volatility of asset returns.

All models are fitted with different assumptions about the distribution of the residuals, namely the Gaussian, the student's t and the GED distribution.

In the first place, the calculated BIC result of the fitted models, including GARCH(1,1), EGARCH(1,1) and GJR-GARCH(1,1), with (1) no additional news variables included, (2) news variables included in the mean equation and (2) news included the variance equation, are considered as model evaluation criteria. Therefore, the model presenting the lowest BIC per category, meaning per GARCH type model and equation model among different distributions, is rated as the best model.

However, in particular, this thesis aims to investigate the potential effect of negative and positive news variables on the conditional variance of asset returns, the significance level of the exogenous news parameters are again reviewed among the three models presenting the lowest BIC score. Therefore, if the model chosen by the lowest BIC presents highly insignificant exogenous news parameters, another model showing better results might be rated as the best model instead, referring a higher significance level of the included exogenous variables. This strategy has been chosen, as at this stage there was more clarification about the fact, that the exogenous variables included might show a lower significance level due to lack of availability to high-frequency asset return data. Therefore, choosing the best model not only according to the BIC, but adjusting it for the significance level of the exogenous variables, should provide insights about the most suitable model or distribution when including exogenous variables. The amount of best-rated models per category is shown in **Table 3** and the adjusted results are displayed in **Table 4**.

There is always one best model per category and per asset. The regression results of each asset and for all models with all distributions can be found in **Table 6** to **Table 12**. In each table and, consequently, for each asset, one column is highlighted in dark green to indicate the selected best model.

The results are presented in a way to address the two main goals, namely:

(1) to find if there is a dominant model or distribution that fits the sample data best, and
(2) if the model including exogenous news variables in the
    (a) mean equation and
    (b) conditional variance equation
  explain the volatility of the asset returns better.

Table 3: Best fitted models according to the BIC

	Best fitted model according to the BIC									
	Distribution	norm			std			GED		
	Models	GARCH	EGARCH	GJR-GARCH	GARCH	EGARCH	GJR-GARCH	GARCH	EGARCH	GJR-GARCH
Assets	Without news				3	2			1	1
	With news in the mean equation				4	3				
	With news in the				3	1	1		2	

	variance equation									
					10	6	1		3	1

Table 4: Best fitted models according to the BIC adjusted for significance of exogenous news parameters

	Best model according to the BIC adjusted for significance of exogenous news parameters									
	Distribution	norm			std			GED		
	Models	GARCH	EGARCH	GJR-GARCH	GARCH	EGARCH	GJR-GARCH	GARCH	EGARCH	GJR-GARCH
Assets	Without news				3	2			1	1
	With news in the mean equation				3	3		1		
	With news in the variance equation				1	1	1		4	
					7	6	1	1	5	1

When taking only the BIC in consideration shown in **Table 5**, the model under assumption of normal distribution is never rated as the best model. In contrast, the student's t distribution performs as a winner. Regarding the type of the GARCH(1,1) model, is the rating for the simple GARCH(1,1) and the EGARCH(1,1) model almost equally good. However, when considering only the BIC value, the simple GARCH(1,1) with student's t distribution is rated as the best model to model the conditional variance for the sample data.

There is no major change after adjusting the results for the significance level of the exogenous news parameters. The student's t distribution is still the best method to model the conditional variance for all models. However, the EGARCH(1,1) model demonstrates better results than the simple GARCH(1,1) model. Remarkable is that the EGARCH(1,1) model under GED distribution shows good results for the model including news in the conditional variance equation. Therefore, according to the results, the student's t distribution is suitable for models without exogenous variables or, when including exogenous variables only in the mean equation. However, when including exogenous variables in the variance equation, the GED distribution displays better results. Furthermore, when including the exogenous variables in the variance equation, choosing the EGARCH(1,1) over the GARCH(1,1) model is more suitable.

4.6 Mean model

The signs of the estimated parameter for the mean model show that positive news (Mxreg1) have on average a positive effect on the asset returns, ceteris paribus. Negative news (Mxreg2) and the amount of total news (Mxreg3) have on average a negative effect on the asset returns, ceteris paribus.

4.7 Variance model

The results show that positive news (Vxreg1) and negative news (Vxreg2) have on average a positive effect on the conditional variance, ceteris paribus, while the amount of total news (Vxreg3) have on average a negative effect on the conditional variance, ceteris paribus. Therefore, negative news, as well as positive news, would indicate higher volatility of asset returns, ceteris paribus.

The stationarity of all models has been checked. However, some fitted models for certain assets explode and show very big BIC results and are therefore excluded from the analysis.

4.8 Forecast

When generating the multi-step-ahead forecast, it can be seen that the conditional variance converges towards the unconditional variance. However, due to the fact, that the 1-step-ahead rolling forecast is more relevant, the plots displaying the converging have not been included.

In **Figure 7** the squared asset returns and the 1-step-ahead rolling forecast for each asset are plotted. The forecast is generated for one year, which is 256 time points. Even though all models have been forecasted, only the beforehand selected best models are presented. Three main questions have been used to analyze the performance of the forecast:

(1) How well are the outliers captured by the models?
(2) Which models have the tendency to under-/overestimate risk?
(3) How does the model chosen by the lowest MSE behave?

For the asset ASML, the outliers are best captured by the GJR-GARCH(1,1) model with GED distribution and without exogenous variables. In general, the model has the tendency to overestimate volatility. However, the biggest outlier is better captured by the GARCH(1,1) model with GED distribution including the exogenous variables in the variance equation. The model with the lowest MSE, which can be seen in **Table 13**, is the GARCH(1,1) model with GED distribution including exogenous variables in the variance model. However, this model needs to be treated carefully as it often underestimates volatility.

For the asset L'Oreal, the EGARCH(1,1) model with student's t distribution excluding and including exogenous variables rather overestimates the volatility. None of the models is able to capture the outliers. According to the lowest MSE, the EGARCH(1,1) model with student's t distribution including exogenous variables into the mean model is rated as the best model.

For the asset Siemens, the biggest outlier has been captured best by the GARCH(1,1) model with student's t distribution without exogenous variables. However, along the time frame, most of the other outliers are better represented by the EGARCH(1,1) model including exogenous variables into the variance equation. The former stated model has the tendency to overestimate volatility.

In the first half of the forecast, all models show very similar results for the asset SAP. However, the GARCH(1,1) model with student's t distribution and the GARCH(1,1) model with GED distribution including exogenous variables in the mean equation are better in capturing the more extreme outliers. The former model represents a lower MSE.

The outliers for the asset Deutsche Telekom have been best represented by the GARCH(1,1) model with student's t distribution without exogenous variable. The best model chosen by the MSE, represented by the GARCH(1,1) model with student's t distribution including exogenous variables into the variance equation, is a model with a tendency to underestimate volatility.

For the asset Allianz, the EGARCH(1,1) model with student's t distribution and without exogenous variables captures best the outliers. This model has also been chosen according to the lowest MSE.

The GJR-GARCH(1,1) model with student's t distribution including exogenous variables into the variance model captures best the extreme outliers for the asset BNP. This model also represents the lowest MSE. In contrast, for 2/3 of the forecast, the EGARCH(1,1) model with student's t distribution excluding any exogenous variables has the tendency to overestimate volatility.

After analyzing all the assets, two patterns are detected: (1) models excluding any exogenous variables have the tendency to overestimate low volatility and capture better volatility in comparison to models, where exogenous variables are included in the mean or in the variance equation and (2) models including exogenous variables into the variance equation capture better extreme outliers.

5 Discussion

Previous research suggested that including sentiment data in especially volatile time periods can lead to models with better data fit. As the time around the COVID-19 pandemic showed very volatile behavior in the financial markets (Cepoi, 2020), the time period considered has been chosen from the beginning of 2020 to the end of 2022. Those assumptions are reflected in the volatile behavior of all 7 asset returns during this time period.

According to the theory including sentiment data in the volatility model, bad news should lead to a higher volatility increase than good news (CROUHY & ROCKINGER, 1997; Riordan et al., 2013). However, asymmetric effects are only shown when including bad and good news in the mean equation, indicating that bad news have a negative effect on the asset returns, while positive news lead to higher asset returns. Conversely, when including the sentiment data in the volatility model, the outcome does not support the theory or show the same results. According to the results, positive and negative news indicate on average an increase in volatility. According to the theory, it would be conjectured that there is an asymmetric effect of negative and positive news, assuming that negative news has a bigger weight on the volatility than positive news (Black, 1976). Possible explanations for this controversial result could be that previous researchers, who detected significant results, worked with high-frequency news data and linked them to intraday asset data (Ho et al., 2013; Kalev et al., 2004). One possibility to take advantage of the negative news effect is to only include negative news but exclude the positive news variable.

With regard to the forecasting performance, it is important to pay attention to the comparison values for the forecasted values. While within this work only squared asset returns have been used as a realized volatility proxy, Patton (2011), as well as Hansen and Lunde (2005), suggested using intraday asset return data to receive a less noisy realized volatility proxy. However, when comparing the forecast models by using the MSE, excluding any sentiment data leads on average to an overestimation of volatility. This might be even preferred when favoring decision making based on a risk-averse behavior, especially when estimating volatility caused by negative news (Egging-Bratseth & Siddiqui, 2023). Nevertheless, including sentiment data shows on average better results for capturing extreme outliers of volatility. Due to the asymmetric behavior of positive and negative news, assuming that the weight for the latter is bigger, it might be beneficial to only include negative sentiment news into the model for seizing potential extreme outliers.

Therefore, according to the results, implementing a negative news sentiment variable into an asymmetric EGARCH(1,1) model under the assumption of GED distributed residuals is on average better at capturing extreme outliers of asset return volatility.

6 Conclusion

This work has been conducted to evaluate whether including exogenous news data fosters the estimation of volatility of asset returns. As the ARCH and GARCH model fails to capture most of the time present asymmetric behavior of time series data, the EGARCH(1,1) and GJR-GARCH(1,1) were used to account for this issue. Under the assumption that negative news have a stronger effect on the volatility than positive news, the EGARCH and GJR-GARCH seem to be a suitable model for the data. By comparing the GARCH(1,1), EGARCH(1,1) and GJR-GARCH(1,1) each with the normal, student's t and GED distribution, it is visible that the EGARCH(1,1) model with student's t or GED distribution captures best the data. The GED distribution is especially suitable when including exogenous news in the volatility estimation of asset returns. However, incorporating sentiment data shows on average a better result to capture extreme outliers but also often underestimates volatility. Negative news have clearly a negative effect on asset returns whereas positive news are oppositely influenced.

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8 List of Figures

9 List of Tables

10 Appendix

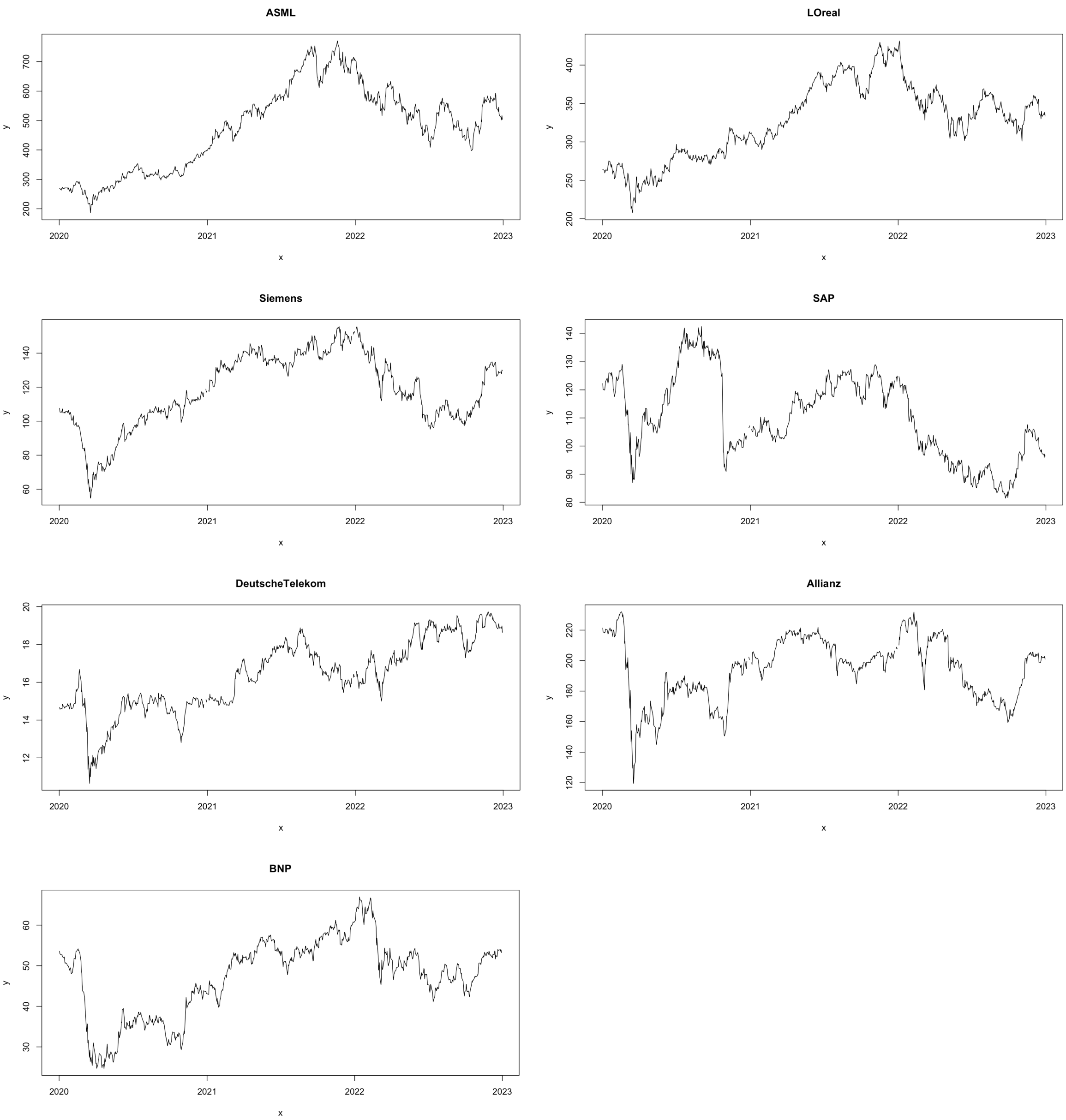

Figure 1: Time series of the asset prices

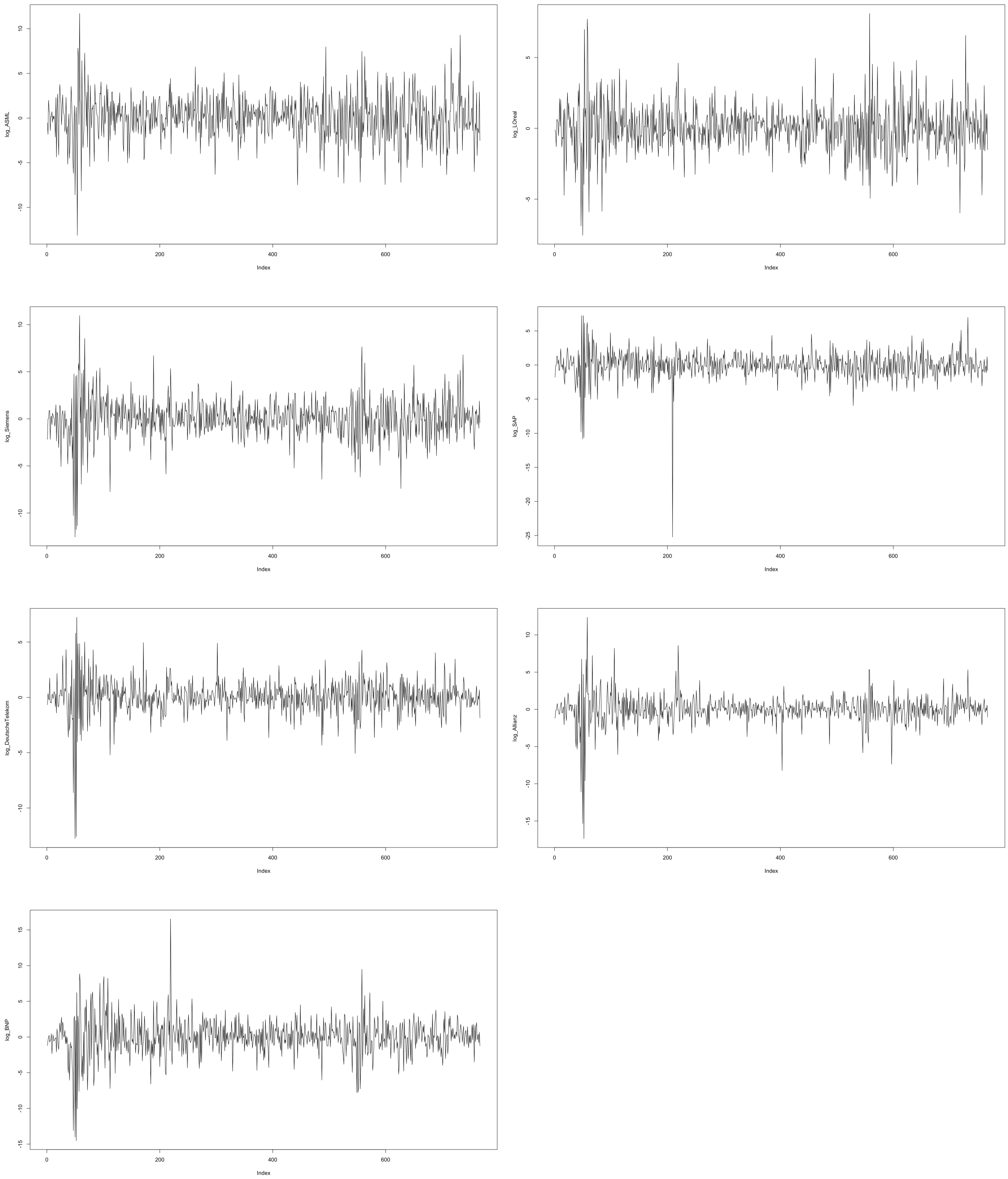

Figure 2: Differenced and logarithmic time series

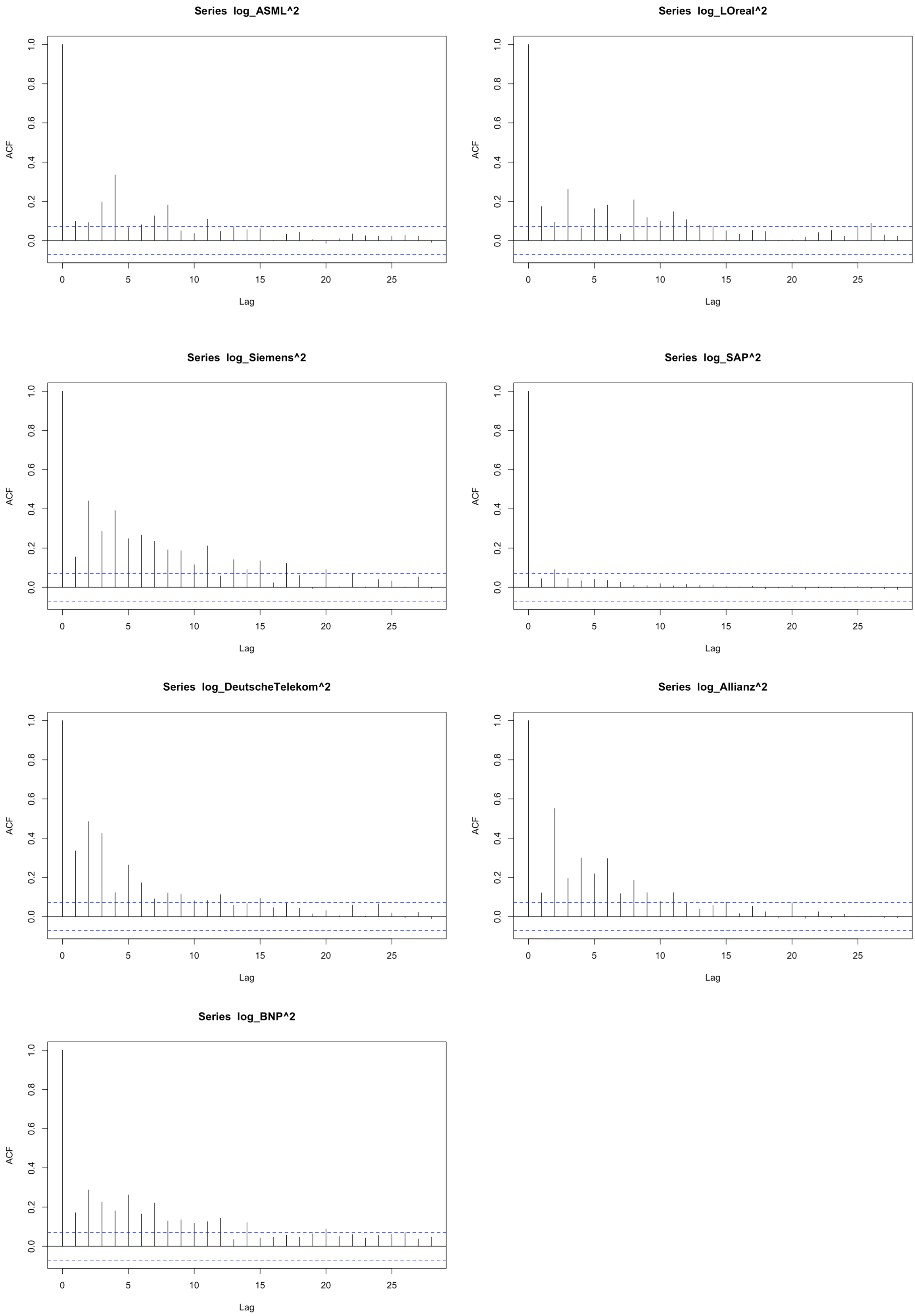

Figure 3: ACF of the quadratic time series (asset returns)

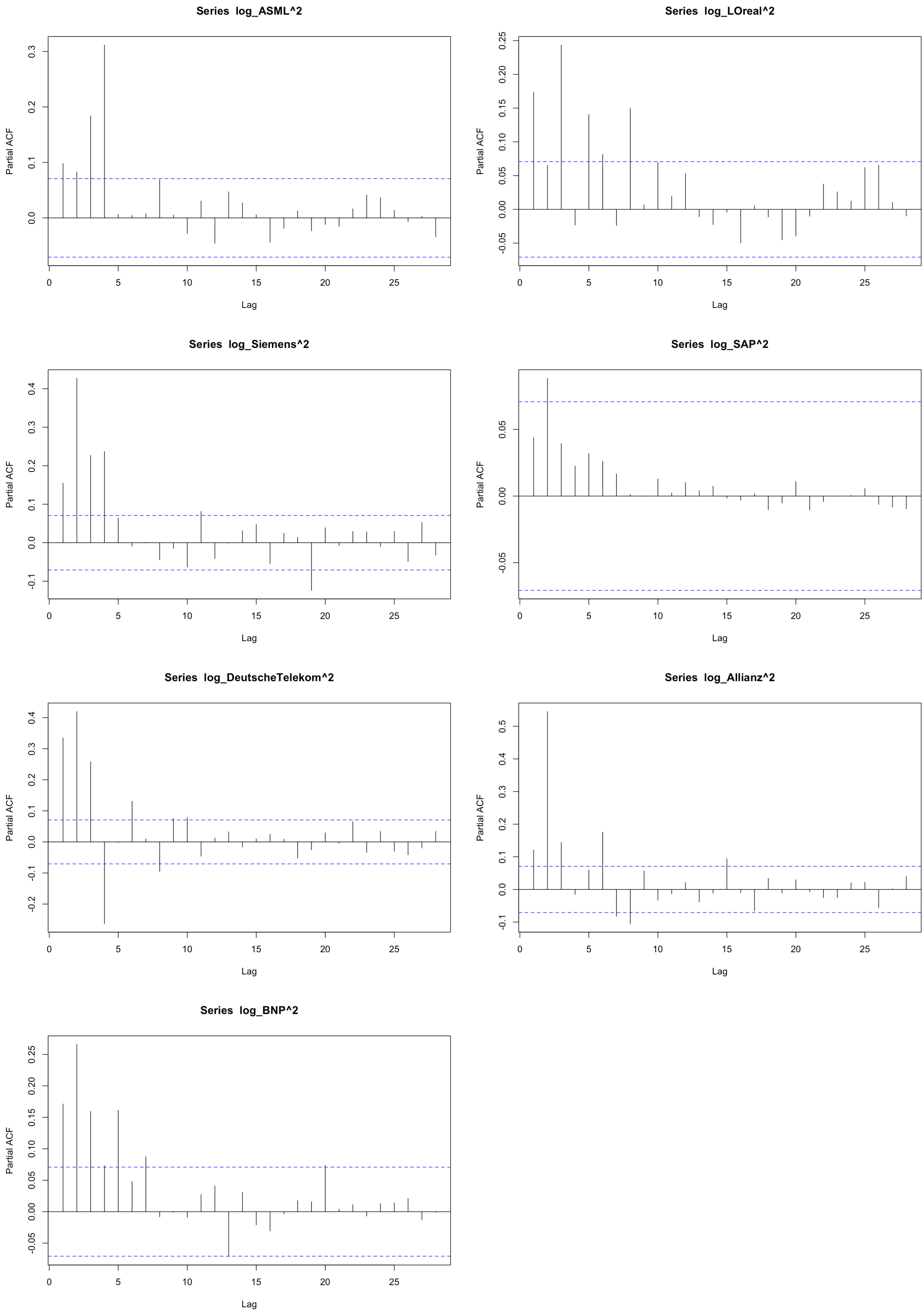

Figure 4: PACF of the quadratic time series (asset returns)

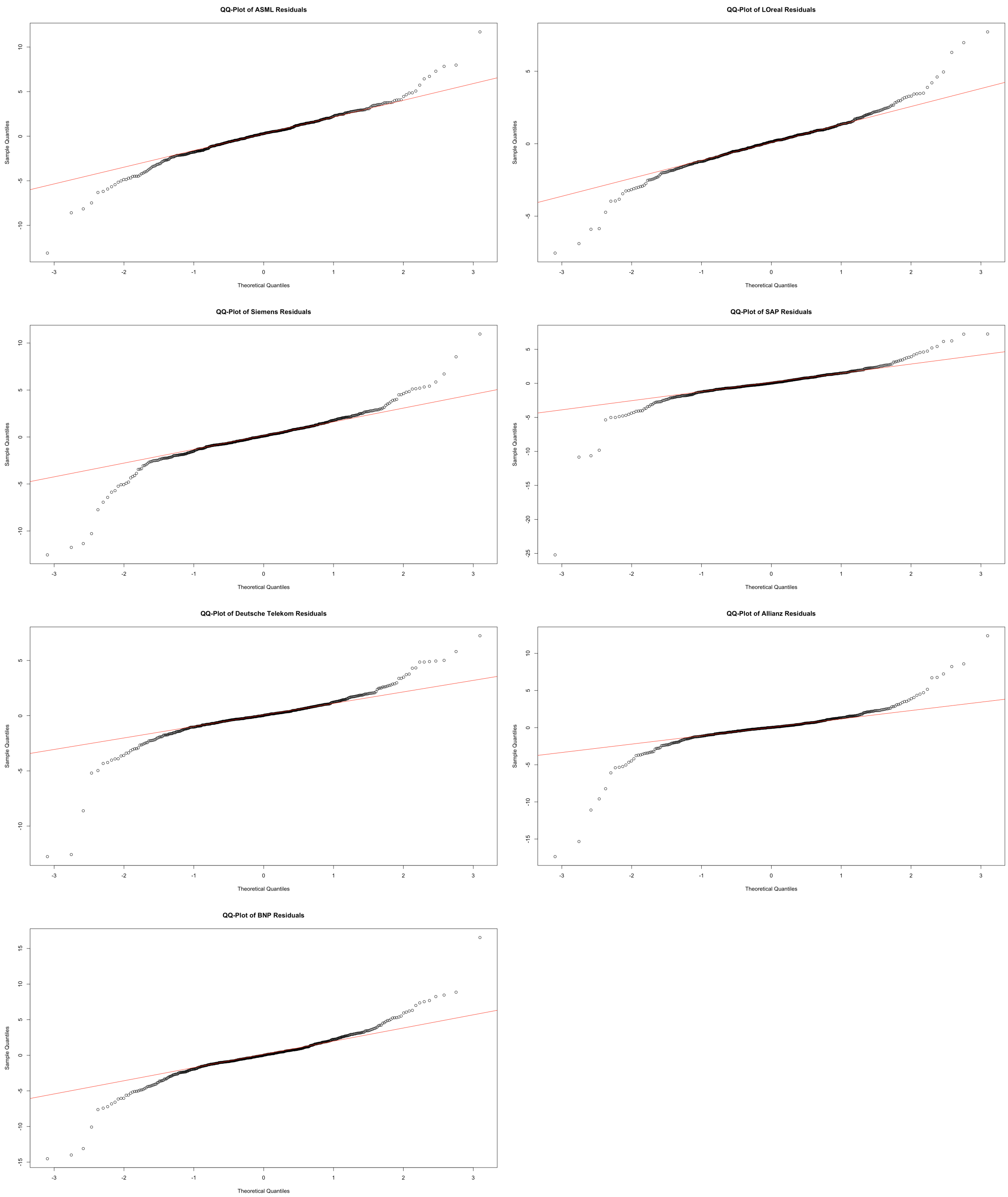

Figure 5: Normal Q-Q plots

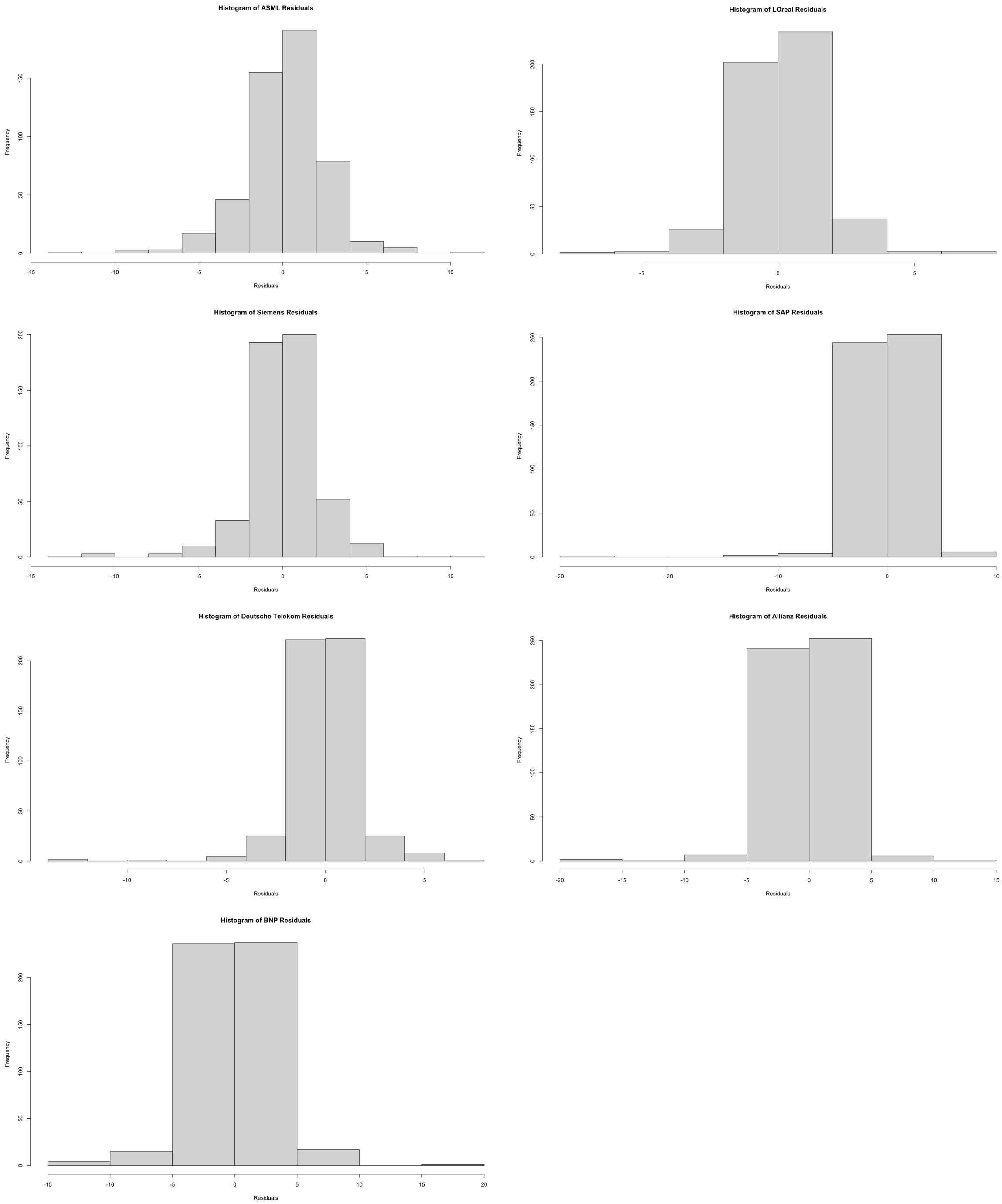

Figure 6: Histogram of the residuals distribution

Table 5: The BIC of all fitted models

	BIC									
	Parameters	norm			std			GED		
	Models	GARCH	EGARCH	GJR-GARCH	GARCH	EGARCH	GJR-GARCH	GARCH	EGARCH	GJR-GARCH
ASML	Without news	4.400763	4.406879	4.392766	4.390269	4.397047	4.388585	4.390567	4.396807	**4.387394**
	With news in the mean equation	4.423971	4.433273	4.419479	**4.410876**	4.421100	4.419479	4.411550	4.421402	4.419479
	With news in the variance equation	4.430854	7.424412	4.421138	4.418204	4.422330	4.415547	4.420524	**4.424847**	4.416180
Allianz	Without news	3.793004	3.794688	3.797331	3.589733	**3.587824**	3.590502	3.606755	3.609977	3.611187
	With news in the mean equation	3.716366	3.700697	3.701869	3.613196	**3.590235**	3.701869	3.620071	3.606045	3.701869
	With news in the variance equation	3.746946	27.782422	3.750738	**3.612852**	3.668036	3.613408	3.619417	3.618841	3.623488
BNP	Without news	4.578369	4.552967	4.556991	4.509070	**4.484666**	4.489273	4.513605	4.493023	4.497138
	With news in the mean equation	4.588500	4.570090	4.576622	4.524632	**4.511453**	4.576622	4.532340	5.880836	4.576622
	With news in the variance equation	4.614114	10.836637	4.593664	4.545743	4.591495	**4.525668**	4.550278	4.528404	4.533811
Deutsche Telecom	Without news	3.514887	3.531771	3.522073	**3.383412**	3.397466	3.387869	3.397176	3.412774	3.404335
	With news in the mean equation	3.468311	3.485202	3.477437	**3.380803**	3.396110	3.477437	3.388079	3.404634	3.477437
	With news in the variance equation	3.505948	5.054031	3.511529	**3.406462**	3.406802	3.407044	3.415143	10.631581	3.419415
L'Oreal	Without news	3.585565	3.555817	3.563638	explosion	explosion	explosion	3.563218	**3.543913**	3.549584
	With news in the mean equation	3.615081	**3.587225**	3.594072	3.594064	**3.574153**	3.594072	3.594599	3.577096	3.594072
	With news in the variance equation	3.619617	12.699763	3.593719	3.598245	**3.569759**	3.579331	3.598655	3.572310	3.583302
SAP	Without news	4.274826	4.158994	4.190739	**3.832687**	3.858454	3.842563	3.896973	3.908411	3.902037

	With news in the mean equation	4.106371	4.084391	4.073361	**3.865741**	3.889881	4.073361	3.925009	3.933674	4.073361
	With news in the variance equation	3.896851	20.020146	3.924313	3.843344	3.842647	3.854516	3.852469	**3.840339**	3.862841
Siemens	Without news	4.084577	4.089226	4.081755	**4.028484**	4.041360	4.033505	4.038276	4.047682	4.041721
	With news in the mean equation	4.096349	4.101732	4.095893	**4.036159**	4.049414	4.095893	4.047076	4.056321	4.095893
	With news in the variance equation	4.121250	32.177821	4.118428	**4.065157**	4.252250	4.070178	4.074949	4.071265	4.078394

Table 6: Estimated Parameters - ASML

Estimated Parameters - ASML									
Parameters	norm			std			GED		
Models	GARCH	EGARCH	GJR-GARCH	GARCH	EGARCH	GJR-GARCH	GARCH	EGARCH	GJR-GARCH
ω	0.4871330***	0.16303***	0.544385***	0.4917669*** Shape: 8.2363489	0.16303*** Shape: 7.87473	0.505598*** Shape: 8.929219	0.4828973*** Shape: 1.4862090	0.15624** Shape: 1.48575	0.516766*** Shape: 1.526769
ω $(mean)$	0.486376***	0.146870***	0.514899***	0.007897** Shape: 7.648753	0.149829*** Shape: 7.402002	0.486426** Shape: 8.188730	0.488381*** Shape: 1.452773	0.141667** Shape: 1.459355	0.496335** Shape: 1.497706
ω $(variance)$	0.442188**		0.515761	0.457645** Shape: 8.093730	0.146965** Shape: 7.576923	0.496901 Shape: 8.842612	0.445022** Shape: 1.490385	0.165975** Shape: 1.487335	0.505753 Shape: 1.536510
α	0.1716152***	-0.11628***	0.054988	0.1629370***	-0.12557***	0.049077	0.1656371***	-0.12323***	0.047724***
α $(mean)$	0.168181***	-0.103767***	0.056132	0.163654***	-0.108366***	0.053306	0.165284***	-0.106118**	0.052684
α $(variance)$	0.174438***		0.054041	0.168051***	-0.136440***	0.050890	0.170718***	-0.136247***	0.050575
β	0.7399052***	0.90460***	0.751687***	0.7474545***	0.90114 ***	0.769220***	0.7453471***	0.90445***	0.764361***
β $(mean)$	0.741354***	0.912602***	0.761650***	0.745730***	0.906657***	0.774712***	0.743277***	0.910585***	0.769454***
β $(variance)$	0.732643***		0.731657***	0.730790***	0.904879***	0.741125**	0.731866***	0.890826***	0.736847***
γ		0.23781***	0.190425***		0.23463**	0.185029**		0.23040**	0.189483**
γ $(mean)$		0.229580***	0.169070***		0.234596***	0.161156**		0.229074**	0.164204**
γ $(variance)$			0.207785*		0.208888**	0.204004		0.230456***	0.208176**
Mxreg1	0.017140*	0.014848	0.013915	0.019864**	0.017495	0.017003*	0.022184**	0.019322*	0.018198*
Mxreg2	-0.049462	-0.056600*	-0.053299	-0.035083	-0.039752	-0.038810	-0.030009	-0.037280	-0.035691
Mxreg3	0.006125	0.006849	0.004930	0.007897*	0.008636	0.007401	0.007700**	0.008315**	0.007184
Vxreg1	0.038224		0.035419	0.053559	0.010727*	0.049803		0.009135	0.043684
Vxreg2	0.000000		0.000000	0.000000	0.030033*	0.000000		0.029059	0.000000

Vxreg3	0.000000		0.007658	0.000000	-0.004500	0.002765		-0.003631	0.004077

Table 7: Estimated Parameters - Allianz

Estimated Parameters - Allianz									
Parameters	norm			std			GED		
Models	GARCH	EGARCH	GJR-GARCH	GARCH	EGARCH	GJR-GARCH	GARCH	EGARCH	GJR-GARCH
ω	0.22686***	0.076775***	0.18865***	0.26708** Shape: 3.28415	0.028655** Shape: 3.063473	0.21719** Shape: 3.33799	0.22142** Shape: 0.98998	0.032998 Shape: 0.998125	0.18244** Shape: 0.99567
$\omega\ (mean)$	0.160954***	0.041168***	0.107486***	0.186785* Shape: 3.521439	0.014103 Shape: 3.849876	0.099108* Shape: 4.044422	0.164401*** Shape: 1.083339	0.019313** Shape: 1.119481	0.101942** Shape: 1.125291
$\omega\ (variance)$	0.193280***		0.16340***	0.219502** Shape: 3.413114	0.881487*** Shape: 2.100000	0.168930 Shape: 3.442514	0.188502** Shape: 1.055712	0.014695	0.153236** Shape: 1.062400
α	0.19315***	-0.097484***	0.11170**	0.33094***	-0.136319***	0.14895*	0.26048***	-0.112179***	0.13098*
$\alpha\ (mean)$	0.218144***	-0.143177***	0.081828**	0.275641***	-0.165519***	0.058895	0.238273***	-0.153787***	0.068926
$\alpha\ (variance)$			0.19292***	0.391266***	-0.568640***	0.184444**	0.322997***	-0.140025***	0.178295**
β	0.74719***	0.945091***	0.77533***	0.66806***	0.972839***	0.71023***	0.69630***	0.958282***	0.73200***
$\beta\ (mean)$	0.739863***	0.968876***	0.788034***	0.723359***	0.983631***	0.805349***	0.726104***	0.975330***	0.789520***
$\beta\ (variance)$	0.291749***		0.65687***	0.612201***	0.718520***	0.659855***	0.621988***	0.977053***	0.653685***
γ		0.270874***		0.12825**	0.249449***	0.27963**		0.263817***	0.20868*
$\gamma\ (mean)$		0.240875***	0.228658***		0.186750***	0.269510***		0.213849***	0.262927***
$\gamma\ (variance)$	0.641112***		0.19136**		1.967454***	0.337355**		0.181594***	0.254153*
Mxreg1	0.032954***	0.024941***	0.030283***	0.016168*	0.016108**	0.018440*	0.025915***	0.016941***	0.023967***
Mxreg2	-0.169154***	-0.178060***	-0.174518***	-0.091090**	-0.139154***	-0.135970***	-0.112809***	-0.132943***	-0.132512***
Mxreg3	0.006982	0.006652*	0.006054	0.003851	0.005403	0.004341	0.001165***	0.002077**	0.001338**
Vxreg1	0.000000		0.00000	0.004799	-0.003165	0.009375	0.008835	0.047393***	0.011732
Vxreg2	0.144414***		0.14356***	0.168213	0.088988***	0.149870	0.144149*	0.029359*	0.136415*
Vxreg3	0.007454		0.00901	0.004744	-0.008387	0.002972	0.002797	-0.018982***	0.002405

Table 8: Estimated Parameters - BNP

Estimated Parameters - BNP									
Parameters	norm			std			GED		
Models	GARCH	EGARCH	GJR-GARCH	GARCH	EGARCH	GJR-GARCH	GARCH	EGARCH	GJR-GARCH
ω	0.23708***	0.038104	0.115783*	0.14192 Shape: 4.22750	0.011859 Shape: 4.404424		0.18368* Shape: 1.21351	0.014017 Shape: 1.239219	0.071819 Shape: 1.237976
$\omega\ (mean)$	0.227008***	0.043226***	0.136015	0.152429* Shape: 4.637348	0.006820 Shape: 4.699454	0.048088 Shape: 4.677379	0.182525* Shape: 1.249533		0.082736 Shape: 1.265872
$\omega\ (variance)$	0.220322**		0.115781	0.14198 Shape: 4.22696	0.374530*** Shape: 4.661030	0.044673 Shape: 4.338173	0.18370* Shape: 1.21351	0.007132 Shape: 1.252196	0.071817 Shape: 1.237980

α	0.13662***	-0.115136***	0.017014	0.10742***	-0.114813***		0.11815***	-0.116446***	0.005485
α (mean)	0.156293***	-0.113549***	0.036284	0.129617**	-0.112090***	0.006327	0.137082***		0.904204***
α (variance)	0.140029***		0.017015	0.10743**	-0.143317**	0.001224	0.11816***	-0.118722***	0.005485
β	0.83484***	0.982393***	0.896364***	0.88579***	0.992953***		0.85935***	0.991016***	0.920898***
β (mean)	0.819281***	0.977112***	0.870512	0.862239***	0.993521***	0.930228***	0.842703***		0.143244***
β (variance)	0.830305***		0.896364***	0.88579***	0.793262***	0.938679***	0.85935***	0.991477***	0.920899***
γ		0.159289***	0.155515***		0.088984***			0.097758***	0.138741***
γ (mean)		0.209574***	0.157703		0.109360***	0.124889***			
γ (variance)			0.155515***		0.453307***	0.127841***		0.098483***	0.138739***
Mxreg1	0.004037	0.002778**	0.004503	0.005896	0.002771	0.004059	0.003143		0.003794*
Mxreg2	-0.044430	-0.028446	-0.019183	0.026635	0.006610	0.025346	0.014584		0.028768
Mxreg3	0.024755***	0.022400***	0.021106***	0.022126***	0.016112**	0.016852**	0.020996***		0.018087***
Vxreg1	0.000000		0.000000	0.00000	-0.006173	0.000000	0.00000	-0.001697	0.000000
Vxreg2	0.000000		0.000000	0.00000	0.002275	0.000000	0.00000	-0.004997	0.000000
Vxreg3	0.006689		0.000000	0.00000	0.000810	0.000000	0.00000	0.002569	0.000000

Table 9: Estimated Parameters - Deutsche Telekom

Estimated Parameters – Deutsche Telekom									
Parameters	norm			std			GED		
Models	GARCH	EGARCH	GJR-GARCH	GARCH	EGARCH	GJR-GARCH	GARCH	EGARCH	GJR-GARCH
ω	0.17181***	0.071285***	0.214489***	0.17228** Shape: 3.44923	0.052419 Shape: 3.471931	0.21194** Shape: 3.46711	0.17228** Shape: 3.44923	0.045549* Shape: 1.091560	0.199557** Shape: 1.097157
ω (mean)	0.163521***	0.057855***	0.186137***	0.176840** Shape: 3.987102	0.041230** Shape: 4.032301	0.200667** Shape: 4.020546	0.162734*** Shape: 1.155525	0.036415* Shape: 1.162144	0.187134*** Shape: 1.154921
ω (variance)	0.085879**	0.469497***	0.101843*	0.116221 Shape: 3.819482	0.010060 Shape: 4.106871	0.142538 Shape: 3.859619	0.104723* Shape: 1.148440		0.131574 Shape: 1.152068
α	0.13142***	-0.030404	0.074647*	0.18994***	-0.075606	0.11221*	0.18994***	-0.052856	0.089147*
α (mean)	0.156056***	-0.030010	0.100624**	0.181968***	-0.069271*	0.096947	0.161712***	-0.049209	0.092455
α (variance)	0.120878***	-0.048705	0.062498	0.164705**	-0.082146**	0.074295	0.140763***		0.065632
β	0.79184***	0.925988***	0.775785***	0.77615***	0.936383***	0.74894***	0.77615***	0.929267***	0.757034***
β (mean)	0.767480***	0.930779***	0.763976***	0.758241***	0.935359***	0.747449***	0.761906***	0.932092***	0.754650***
β (variance)	0.806167***	0.848363***	0.089103	0.775939***	0.950701***	0.752259***			0.763284***
γ		0.267853***	0.098592		0.330807***	0.19022		0.292465***	0.131397
γ (mean)		0.292564***	0.082065		0.296807***	0.160178*		0.288205***	0.117788
γ (variance)		1.062088***			0.259987***	0.201380			0.147468
Mxreg1	0.045935***	0.047680***	0.046079***	0.038157***	0.039565***	0.037073***	0.035907***	0.039493***	0.034332***
Mxreg2	-0.001927	-0.008695	-0.009294	0.007078	0.001904	-0.000181	0.031961	0.025299	0.026273
Mxreg3	-0.009169**	-0.008151*	-0.009198**	-0.005499	-0.004854	-0.005551	-0.004416***	-0.004542***	-0.004303***

Vxreg1	0.038673**	0.088670***	0.041781**	0.036286	0.040905***	0.042980	0.034925*		0.040194*
Vxreg2	0.000000	-1.563713***	0.000000	0.000000	0.024450	0.000000	0.000000		0.000000
Vxreg3	0.000000	-0.038537***	0.000000	0.000000	-0.015994**	0.000000	0.000000		0.000000

Table 10: Estimated Parameters - L'Oreal

Estimated Parameters – L'Oreal									
Parameters	norm			std			GED		
Models	GARCH	EGARCH	GJR-GARCH	GARCH	EGARCH	GJR-GARCH	GARCH	EGARCH	GJR-GARCH
ω	0.063060*		0.034992**	0.073939 Shape: 6.133435		0.044135* Shape: 7.063671	0.065512 Shape: 1.404228		0.03799* Shape: 1.46970
$\omega\ (mean)$	0.061349*	0.015412***	0.033508**	0.074771 Shape: 6.280920	0.014478*** Shape: 7.288605	0.042704* Shape: 7.239734	0.065150 Shape: 1.413378	0.013179***	0.036260* Shape: 1.482884
$\omega\ (variance)$	0.067548			0.077634 Shape: 6.149308	0.009544 Shape: 7.357413		0.067000	0.026827 Shape: 1.472928	
α	0.085389***		0.000000	0.079132**		0.000000	0.081657**		0.03799
$\alpha\ (mean)$	0.081445***	-0.118349***	0.000000	0.079727**	-0.121270***	0.000000	0.080179**	-0.117474***	0.000000
$\alpha\ (variance)$	0.096692*			0.087981*	-0.137268***		0.089526*	0.000000	
β	0.887558***		0.932891***	0.890122***		0.926863***	0.889314***		0.93102***
$\beta\ (mean)$	0.891533***	0.986164***	0.933460***	0.888765***	0.985105***	0.926540***	0.890565***	0.986029***	0.931493***
$\beta\ (variance)$	0.868045***			0.874418***	0.979893***		0.875412***	0.927719***	
γ			0.110938***			0.117408***			0.11169***
$\gamma\ (mean)$		0.071571***	0.108439***		0.056379***	0.117674***		0.065074***	0.109690***
$\gamma\ (variance)$					0.030752***			0.113987***	
Mxreg1	0.024541	0.021995*	0.022708*	0.021166	0.017947	0.019392	0.024261	0.019935	0.021328
Mxreg2	-0.055619	-0.063101	-0.054143	-0.044337	-0.042139	-0.043201	-0.057099	-0.063601	-0.056374
Mxreg3	0.003064	-0.002817	-0.000311	0.000708	-0.002498	-0.001098	0.002114	-0.001382	0.000475
Vxreg1	0.011462			0.003378	0.011570*		0.008786	0.000021	
Vxreg2	0.000000			0.000002	0.043833**		0.000000	0.000000	
Vxreg3	0.000000			0.002713	-0.004445		0.000318	0.004782	

Table 11: Estimated Parameters - SAP

Estimated Parameters - SAP									
Parameters	norm			std			GED		
Models	GARCH	EGARCH	GJR-GARCH	GARCH	EGARCH	GJR-GARCH	GARCH	EGARCH	GJR-GARCH
ω	0.67515***	0.10349***	0.37934***	0.37206*** Shape: 4.23052	0.096449** Shape: 4.156882	0.37336*** Shape: 4.31584	0.41235*** Shape: 1.00726	0.094277*** Shape: 1.037229	0.393676*** Shape: 1.033131
$\omega\ (mean)$	0.478838***	0.137142***	0.426730***	0.353873*** Shape: 4.221296	0.090247** Shape: 4.181340	0.355743*** Shape: 4.316613	0.397670*** Shape: 1.002125	0.088883** Shape: 1.076790	0.347916*** Shape: 1.087562

$\omega\ (variance)$	0.579411***		0.490943***	0.472677 Shape: 5.260691	0.120566* Shape: 6.321493	0.447094 Shape: 5.316985	0.535350*** Shape: 1.306152	0.071227** Shape: 1.399567	0.515340*** Shape: 1.316649
α	0.18224***	-0.22085***	0.00000***	0.20599***	-0.044242	0.13878*	0.19953***	-0.098579**	0.075727
$\alpha\ (mean)$	0.147839***	-0.151109***	0.000001	0.199468***	-0.061358	0.121023*	0.193987***	-0.108494**	0.056331
$\alpha\ (variance)$	0.261397***		0.000000	0.263192**	-0.105492*	0.203274	0.263108***	-0.105244**	0.188732**
β	0.71124***	0.93249***	0.73769***	0.70357***	0.911490***	0.70707***	0.71004***	0.917657***	0.723494***
$\beta\ (mean)$		0.906541***	0.766820***	0.714222***	0.918123***	0.720262***	0.717251***	0.924320***	0.750784***
$\beta\ (variance)$	0.467863***		0.615109***	0.522455**	0.858324***	0.543980***	0.478587***	0.919741***	0.495711***
γ		0.13417***	0.52262***		0.260295***	0.12107		0.215193***	0.226188*
$\gamma\ (mean)$	0.731597***	0.229302***	0.267357***		0.251096***	0.140601		0.222221***	0.224162**
$\gamma\ (variance)$			0.324241***		0.420104***	0.099034		0.315973***	0.133486
Mxreg1	0.003082	0.002643	0.001510	0.000629	0.000195	0.000183	-0.001945***	-0.001216***	-0.000938***
Mxreg2	-0.140589***	-0.107892***	-0.127609***	-0.012167	-0.014601	-0.013146	-0.008873***	-0.044478***	-0.060286***
Mxreg3	0.000884	0.000132	0.000044	-0.001719	-0.002034	-0.001875	-0.001624***	-0.001697***	-0.001469***
Vxreg1	0.002384		0.000001	0.016265	0.015222***	0.016293	0.010445	0.017363***	0.011044
Vxreg2	0.535492***		0.399020***	0.320441	0.044641***	0.292694	0.445000**	0.038305***	0.421566**
Vxreg3	0.000000		0.000000	0.000000	-0.007761***	0.000000	0.000000	-0.009304***	0.000000

Table 12: Estimated Parameters - Siemens

Estimated Parameters - Siemens									
Parameters	norm			std			GED		
Models	GARCH	EGARCH	GJR-GARCH	GARCH	EGARCH	GJR-GARCH	GARCH	EGARCH	GJR-GARCH
ω	0.37108***	0.096551***	0.307511***	0.29897** Shape: 5.17771	0.059776 Shape: 5.139118	0.239338* Shape: 5.339740	0.33003** Shape: 1.29912	0.071649* Shape: 1.307916	0.278024** Shape: 1.320781
$\omega\ (mean)$	0.356289***	0.094628***	0.303402***	0.267557** Shape: 5.079044	0.055190 Shape: 4.997942	0.222674* Shape: 5.186203	0.304840** Shape: 1.283275	0.066806* Shape: 1.287087	0.265697** Shape: 1.298270
$\omega\ (variance)$	0.37109***		0.30751***	0.29898* Shape: 5.17835	1.858077 Shape: 2.100000	0.239307* Shape: 5.340329	0.33004* Shape: 1.29906	0.078231** Shape: 1.325715	0.27802** Shape: 1.32079
α	0.18380***	-0.085077**	0.047309	0.14947***	-0.075392**	0.049918	0.16127***	-0.080478*	0.050114
$\alpha\ (mean)$	0.179750***	-0.077582**	0.058155	0.141312***	-0.066670*	0.055699	0.154800***	-0.074356*	0.056231
$\alpha\ (variance)$	0.18380***		0.04731**	0.14946	0.589917***	0.049905	0.16123	-0.077785**	0.05012
β	0.72637***	0.933004***	0.790437***	0.77943***	0.953392***	0.831377***	0.75416***	0.941777***	0.805490***
$\beta\ (mean)$	0.731394***	0.932639***	0.782953***	0.793541***	0.954925***	0.833695***	0.764894***	0.943403***	0.804439***
$\beta\ (variance)$	0.72637***		0.79044***	0.77944***	0.460496**	0.831385***	0.75420***	0.949265***	0.80549***
γ		0.273910***	0.167882*		0.242913**	0.117718*		0.258197***	0.141547**
$\gamma\ (mean)$		0.282076***	0.156176**		0.246458***	0.104707*		0.260515***	0.131497*
$\gamma\ (variance)$			0.16788***		-0.061313	0.117726*		0.228169***	0.14154*
Mxreg1	0.008362***	0.007306***	0.007740***	0.008115***	0.007572***	0.007873***	0.007363***	0.007302***	0.007318***

Mxreg2	0.031018**	0.027267*	0.029131**	0.032450**	0.030825**	0.030202**	0.028149	0.025281	0.025583
Mxreg3	-0.001610	-0.001558	-0.001849	-0.001296	-0.001463***	-0.001398	-0.001461***	-0.001459***	-0.001460***
Vxreg1	0.00000		0.00000	0.00000	0.004373	0.000000	0.00000	0.006269	0.00000
Vxreg2	0.00000		0.00000	0.00000	0.021866	0.000000	0.00000	0.011115	0.00000
Vxreg3	0.00000		0.00000	0.00000	-0.003290	0.000000	0.00000	-0.005123**	0.00000

Table 13: MSE vs. squared returns

MSE (comparison with squared returns)							
Assets/ Best Models	ASML	Allianz	BNP	DeutscheTelekom	L'Oreal	SAP	Siemens
ASML_sigma_for_gjrgarch_ged	120.5011						
ASML_sigma_for_garch_std_mean	112.821						
ASML_sigma_for_garch_ged_var	111.8411						
Allianz_sigma_for_egarch_std		23.40737					
Allianz_sigma_for_egarch_std_mean		24.10321					
Allianz_sigma_for_egarch_ged_var		23.44457					
BNP_sigma_for_egarch_std			85.89409				
BNP_sigma_for_egarch_std_mean			80.62016				
BNP_sigma_for_gjrgarch_std_var			68.08795				
DeutscheTelekom_sigma_for_garch_std				6.760657			
DeutscheTelekom_sigma_for_garch_ged_mean				6.836766			
DeutscheTelekom_sigma_for_garch_std_var				6.808473			
Loreal_sigma_for_egarch_std					44.10105		
Loreal_sigma_for_egarch_std_mean					43.96893		
Loreal_sigma_for_egarch_ged_var					44.37424		
SAP_sigma_for_garch_std						17.87124	
SAP_sigma_for_garch_ged_mean						18.44203	
SAP_sigma_for_egarch_ged_var						21.17904	
Siemens_sigma_for_garch_std							47.73138
Siemens_sigma_for_garch_std_mean							48.59504
Siemens_sigma_for_egarch_ged_var							51.99378

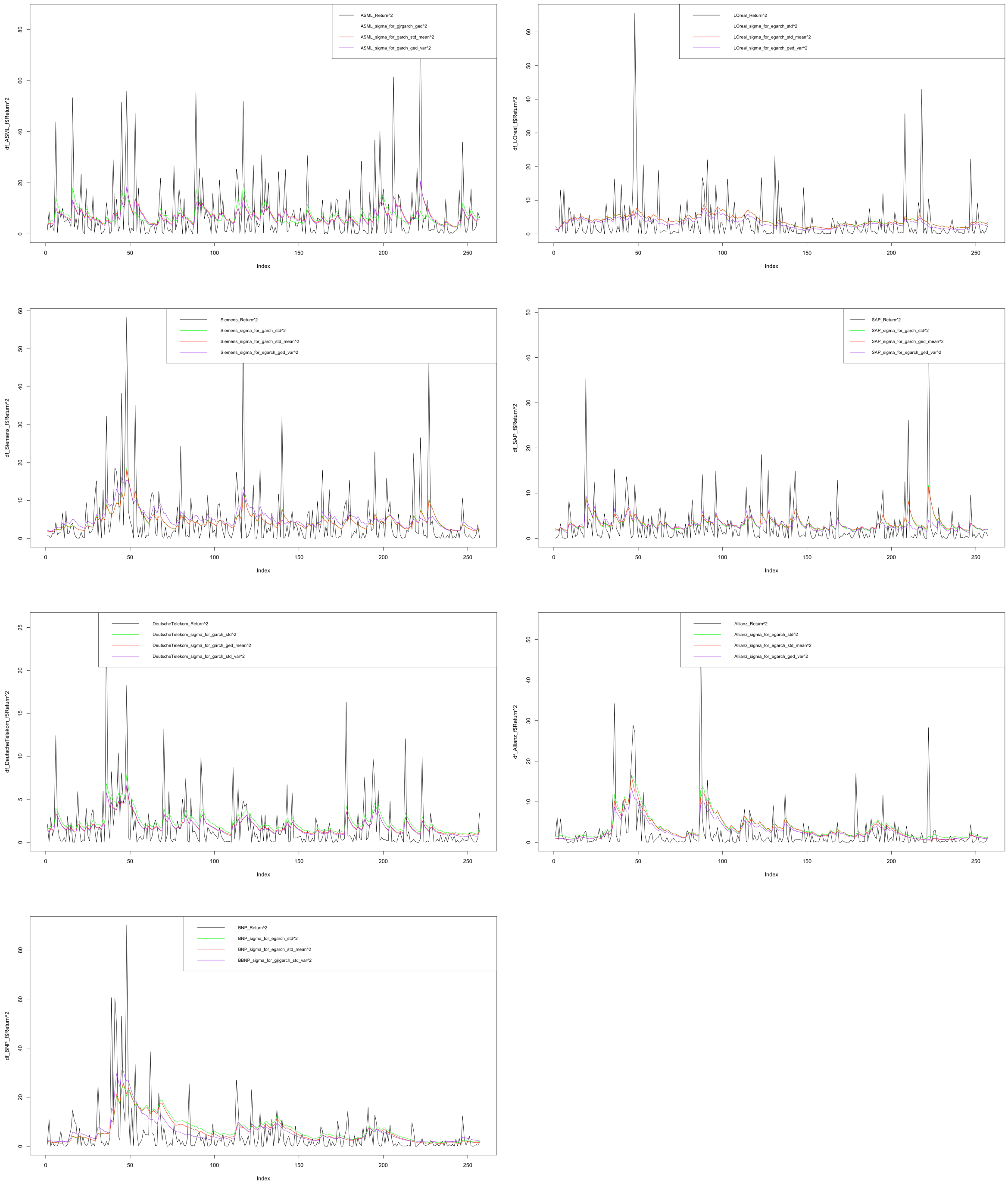

Figure 7: Squared returns vs. 1-step ahead forecast