Estimating Value at Risk (VaR) and Expected Shortfall (ES) of market returns using ARMA and GARCH models.

(A case study of Rwanda Forex Market.)

By

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DECLARATION

I declare that this dissertation entitled **Estimating Value at Risk (VaR) and Expected Shortfall (ES) of market returns using ARMA and GARCH models** is the result of my own work and has not been submitted for any other degree at the University of Rwanda or any other institution.

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APPROVAL SHEET

This dissertation entitled **Estimating Value at Risk (VaR) and Expected Shortfall (ES) of market returns using ARMA and GARCH models** written and submitted by ELYSEE NSENGIYUMVA in partial fulfilment of the requirements for the degree of Master of Science in Data Science majoring in Actuarial Science is hereby accepted and approved. The rate of plagiarism tested using Turnitin is 14% which is less than 20% accepted by the African Centre of Excellence in Data Science (ACE-DS).

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DEDICATION

I dedicate this thesis to God Almighty, to my beloved wife, parents and siblings, for their love and support.

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Abstract

There is tremendous turnover and liquidity that causes currency prices to fluctuate every second, so traders and investors are constantly looking for ways to protect themselves from these threats and unexpected fluctuations. This study consists of Estimating Value at Risk (VaR) and Expected Shortfall (ES) of market returns using ARMA and GARCH models in Rwanda forex market for each FX return time series for the sample size of 5 selected most traded currencies out of 62 present in Rwanda forex market with 2118 observations. The general objective of this study is to estimate the Value-at-Risk (VaR) and the Expected Shortfall (ES) of Rwanda forex market returns using ARMA and GARCH models. This study used unsupervised machine learning algorithms such as K-means clustering and hierarchical clustering methods. Using hierarchical clustering on this table 4.3, we observed that there are three groups which tend to have similar behavior such as group one: GBP and EUR, group two : USD and KES and group three : EGP. By using K-means clustering on this table 4.2, we observed that EGP is the riskiest currency. Fitting AR(1) + GARCH(1,1), we observed that the sum of alpha and beta are less than one, therefore we have stationary time series. Value at Risk (VaR) and Expected Shortfall (ES) are very important risk measures to consider when you invest in forex market in Rwanda. We observed that on this following table 4.10, USD, has small average loss (ES = 4626.5 FRW) compared to other currencies that traded in Rwanda market, thus we can invest in USD. We can invest in other currencies except EGP with high average loss 40725 FRW.

Keywords: Value at Risk (VaR), Expected Shortfall (ES), Forex market, Hierarchical Clustering.

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List of Symbols and Acronyms

GBP British Pound

EUR Euro

USD United States Dollar

KES Kenya Shilling

EGP Egyptian Pound

VaR Value at Risk

ES Expected Shortfall

ARMA Autoregressive Moving Average

GARCH Generalized AutoRegressive Conditional Heteroskedasticity

FRW Rwandan franc

ARCH AutoRegressive Conditional Heteroskedasticity

FX Foreign Exchange

ACF Auto-correlation function

ECN Electronic Communication Network

BIS Bank of International Settlement

1. General introduction

1.1 Research background

Forex or FX refers to the foreign exchange market in which brokerage firms and commercial banks communicate with each other on a timely basis to buy and sell currencies worldwide through electronic communication networks (ECNs). The forex market has the largest number of financial transactions between investors and financial interactions between investors. (Bagheri et al., 2014) and financial intermediaries that make it the largest and most lucrative financial market for future earnings worldwide. According to the international settlement fund, FX markets reached $\$6.6$ trillion a day in April 2019, up from $\$5.1$ trillion three years earlier, according to the bank of international settlement (BIS). The growth in FX derivatives trading, especially in FX swaps, outpaced that of spot trading. With 88% on one side of all trades, the US dollar held its dominant currency position. The share of trade in the euro, on the one hand, has risen somewhat to 32%. On the other hand, the proportion of trades involving the Japanese yen decreased by about 5 percentage points, although the yen remained the third most frequently traded currency (on the one hand, 17% of all trades). In fiscal year 2017/2018, the Rwandan Franc (FRW) depreciated by 3.6% against a depreciation of 6.0% in the previous fiscal year. The FRW depreciated by 5.5%, 4.4% and 4.7% over the same period, relative to the EURO, GBP and Japanese Yen respectively. The FRW depreciated by 4.9 percent against the USD by the end of December 2019 relative to December 2018, higher than 4.0 percent reported in 2018, mainly due to the high import bill for capital and intermediate products, in line with large infrastructure projects and the manufacturing sub-sector increase, respectively. The FRW depreciated 4.9 percent, 8.5 percent, 2.8 percent and 6.3 percent, respectively, relative to the USD, British Pound, Euro and Japanese Yen. The FRW depreciated 4.5 percent, 3.7 percent and 5.1 percent against the Kenyan, Tanzanian and Ugandan Shillings, respectively, compared to regional currencies, while it appreciated 0.2 percent against the Burundian franc. An desirable feature of the forex market is that, by keeping a low balance in order to access the forex market, any investor can open their forex brokerage company trading account. The forex market is, like stocks, bonds and other capital markets, considered to be a highly volatile market. An significant predictor of macroeconomic policies is exchange rate fluctuation, the derivative component of volatility. It is related to either the high/up or down/low direction of price movement. Factors influencing the foreign exchange market are impeded by economic indicators such as reporting GDP variance, interest rate, employment, unemployment, factory order survey, and so on. Natural catastrophes are also uncertain, such as floods, earthquakes, wars, political disturbances, etc., which could have a direct impact on the forex market trend.

Forex is a decentralized global network of trading partners, including banks, public and private institutions, retailers, speculators and central banks, that participate in the money buying and selling system. Trading between dealers is a major turnover and so forex has the highest liquidity of all financial, equity and commodity markets. The forex market is a spot market, which means that it trades at the existing market price, as determined by supply and demand within the marketplace Chadraba and D O'Keefe (2011). Value at risk (VaR) can be used as the primary measure of market risk generated in the early 1990s to quantify financial market risk. The world suffered from an unprecedented economic crisis at the time that led to significant bank losses and defaults. The conclusion of these disasters was that, in the absence of business risk supervision and control, enormous sums of money could be lost. This led to the introduction of a new risk system, VaR, by financial institutions and regulators. Maybe the most influential pioneer of business risk systems was the risk metrics approach, developed by JP Morgan in 1989. They used VaR, defined as the maximum probable loss over the next trading day, based on standard portfolio theory and estimates of standard deviations and correlations between different financial instruments. Over time, other models have been developed by the financial industry, not only based on parametric portfolio assumptions, but also based on historical time series and Monte Carlo simulations. Recommendations for the management of derivatives were established by the non-profit international financial organization 'G-30' in 1993, where VaR played a significant role as a risk indicator. In 1988, the Basel committee on banking supervision also introduced the well-known Basel rounds I, II and III in which the latter stressed the use of VaR as a measure of market risk while retaining the amount of regulatory capital that a financial institution must retain. To some extent, the recent financial crisis has demonstrated the inadequacy of conventional risk indicators, such as value at risk. Although the current and forthcoming regulatory frameworks for the regulation and risk management of the banking sector, Basel II and Basel III, respectively, still conform to this measure, appropriate risk measures for internal use are still needed by financial institutions and actors. In this thesis, we consider the Expected Shortfall risk measure and Value at Risk. Risk management is a systematic approach to the detection, assessment and monitoring of risks in their broadest sense, whatever they may be (Jorion, 2001). Value at risk is the most commonly used risk metric for asset or portfolio risk, which should also be used by banks and financial institutions under the Basel system (VaR) An additional drawback to VaR is that when VaR is surpassed, it does not inform us what the losses look like. The estimated Shortfall (ES), which is the average of the losses within a certain amount of the loss distribution, is an alternative risk indicator that addresses precisely this issue. In other words, ES not only tells us about the possibility of major losses occurring, but also tells us about the possible extent of these losses. ES not only has the sub-additivity property previously stated, but also fulfills the other requirements of a "coherent" risk measure as outlined in (Artzner, 1999). ES, however, also has several downsides that may clarify why it is less commonly used than VaR. (Yamai et al., 2002) showed that the ES calculation requires a much larger sample to achieve the same backtesting accuracy as VaR, which is not surprising given that ES first relies on the VaR estimate and then adds additional estimates. In comparison, VaR backtests have a much better theoretical base than ES backtests do. There are a few stylized financial return facts that must at least be taken into consideration when choosing a risk measure. We will pay special attention to three of these frequently found phenomena in this thesis. Clustering of volatility is the term used to explain the fact that big changes in asset prices appear to be accompanied by more major changes, and that minor changes are always followed by small changes (Dralle, 2011). In calculating the risk for the following days, a proper risk estimate should then take account of a sudden increase in volatility and not to regard the spike as a one-off incident. Another well-known fact is that financial data tends to be produced from fat tail distributions, meaning that the probability of significant losses or gains can be underestimated by using a normal distribution to model returns.Therefore, for a distribution or simulation technique that better models truth, the analytical simplicity of normal distribution can need to be sacrificed in order not to underestimate risks.

1.2 Statement of the Problem

Stability surges outside trade markets (Canova and Marrinan, 1993). Due to the impact they seem have on a country's financial viewpoint (Gali and Monacelli, 2005), Outside dealers are continually trying to find ways to guard themselves from these risks and undesirable changes. It is not a straightforward work to figure cash markets and thus returns.

This is because of the enormous turnover and liquidity that causes currency prices to oscillate every second. Moreover, when merchants and investors swap currencies, they sell the national currency of one country against another. Since currencies are exchanged in pairs, traders and investors have to examine several variables that impact not just one representative currency, but two. Therefore, a thorough knowledge of different micro and macroeconomic, monetary, political and fundamental variables is required in order for traders and investors to get a clearer picture of where currency prices could be going in the future. However, traders and investors can understand investment losses with the correct approach or gain a competitive advantage in forecasting currency prices and therefore returns.

1.3 General objective

The general objective of this study is to estimate the Value-at-Risk (VaR) and the Expected Shortfall (ES) of Rwanda forex market returns using ARMA and GARCH models.

1.3.1 Specific objectives

1. Determining the riskiest asset among the currencies analysis using clustering methods.
2. Fitting ARMA + GARCH models to forex returns in Rwanda market.
3. Estimate VaR and ES for each FX return time series.

1.4 Research questions

1. What is the riskiest currency analysis using clustering methods ?
2. Is fitting ARMA + GARCH models of currency return time series produce stationary time series ?
3. which currency with small value at risk (VaR) and expected shortfall (ES) ?

1.5 Justification of the Study

The Rwanda forex market is the youngest forex market in the region. An significant contribution to the growth of the financial sector and the economy of the country as a whole is the increase in foreign direct investment and portfolio investment due to the rising interest in Africa. An investigation into the key currency markets of sub-Saharan africa will therefore help to determine the viability of the region's markets in relation to the major global markets, increase investor faith and attract additional capital inflows. Furthermore, the effect of currency price correlations and uncertainty spillovers on asset pricing makes this research crucial to investors as it can help diversify international portfolios. Although there are a large number of studies on african forex market correlation.

1.6 The scope of the project

This study is within forex market area in Rwanda; and focused on estimating VaR and ES of market returns using ARMA and GARCH models. The data that used come from at national bank of Rwanda website (www.bnr.rw).

The study used the following currencies: GBP,EUR,USD,KES and EGP.

1.7 Interest of the project

This research is interested because the youngest forex market in the region is the Rwanda forex market, and here in Rwanda there are few research on currency market. The FX market is the world's most liquid market, meaning that at any given time there are a large number of buyers and sellers trying to make a deal. Individuals, corporations and banks convert more than $5 trillion dollars of currency every day and the vast majority of this activity is intended to make a profit. High forex liquidity means it is possible to complete transactions quickly and easily, so transaction costs or spreads are also very low. This provides opportunities for traders to speculate on only a few pips of price fluctuations. The reserves are used to preserve economic stability. It is important because the exchange rate, the price of one currency in terms of another, helps to determine a nation's economic health and thus the well-being of all the people living in it. A weak (solid) domestic currency tends to assist (hurt) exporters because they can sell more (less) internationally, whereas a strong currency hurts (helps) consumers because they would be more (less) expensive for imported goods. The exchange rate is also important because it can benefit or hurt particular interests within a country.

2. Literature review

2.1 Theoretical review

The 2007-08 financial crisis and its aftermath led to various reforms in the regulation of the financial system and banking supervision. The third basel accord (on Banking Supervision, 2010), where fresh focus is put, is a major shift. As basel III is globally implemented (implementation is supposed to be implemented), The efficient estimation and forecasting of market losses seems to play an important role in both developed and emerging financial markets. The increasing interest of international financial investors in investing in emerging financial markets highlights the importance of quantifying and forecasting accurate market risk. Lower liquidity, regular internal and external shocks as well as a higher degree of insider trading that causes the market to be more volatile (Miletic and Miletic, 2013) represent the fundamental characteristics of emerging markets. In comparison with developed countries, emerging markets are marked by a greater effect of internal trade and high uncertainty, illiquidity and market shallowness, so the assessment of VaR with conventional methods assuming normal distribution is much more difficult Žiković and Aktan (2009). The required estimation and forecasting of VaR was discussed in numerous papers: (Alexander and Leigh, 1997) and (Manganelli and Engle, 2001). Still, for risk measurement, there is no such thing as a universal model that is sufficient. The literature dealing with VaR calculation in developed financial markets, both the literature on and empirical research into VaR models in emerging financial market are not very extensive (these include (da Silva and de Melo Mendes, 2003), (Gencay and Selcuk, 2004). Bucevska (2013) claims that the short historical time-series data did not allow for the performing of reliable econometric analysis (most of the stock markets in these countries were established in the early 1990s).

The VaR calculation literature in established financial markets (including (da Silva and de Melo Mendes, 2003), (Gencay and Selcuk, 2004)) is not very detailed, both the literature on VaR models in emerging financial markets and the empirical research on them. By following the expected shortfall (ES), which is a risk assessment metric that quantifies the amount of tail risk an investment portfolio has. Andjelic and Djakovic (2012) has been investigated for the efficiency of the risk metrics system as well as the GARCH and Integrated GARCH (IGARCH) models in VaR forecasting of the forex exchange index in the Serbian financial market. They concluded that GARCH models combined with extreme value theory (the peaks-over-threshold method) minimize the mean value of VaR, and that these models are better than the risk metrics method and the IGARCH model. The findings obtained have important consequences for the estimation of VaR under uncertain conditions that need to be discussed by investors in emerging capital markets. In selected emerging central and eastern european capital markets (Croatia, Czech, Hungary and Serbia), Miletic and Miletic (2013)has implemented GARCH models, including time-varying volatility and strong tails to the empirical distribution of returns. They showed that in most analyzed cases, GARCH models with a t-distribution of residuals have a stronger VaR estimate than GARCH models with normal errors in the case of a confidence level of 99%, while in the case of a confidence level of 95%, the opposite is true. Compared to GARCH models with a normal distribution, historical simulations or risk metrics methods, the back testing results for the crisis era showed that GARCH models with a t-distribution of residuals have better VaR estimates.

The rapid development of African stock markets in the past decade has led to significant development of African capital markets (Piesse and Hearn, 2005). Before 1989, there were only five stock markets in Sub-Saharan Africa (SSA) and three stock markets in North Africa. There is a problem of low liquidity in the African securities market, which means that the local market is more difficult to support with its own trading system, market analysis, brokers, etc., because the business volume will only be too low.

According to (Piesse and Hearn, 2005), African securities markets have traditionally provided a limited and narrow range of products, and the main function of the financial sector is to provide domestic financing sources to make up for government budget deficits. Common factors that still hinder the development of the stock market include lack of legal protection for investors and creditors. Assuming that there are sufficiently close institutional links, regional market integration is still a viable method for establishing a well-functioning stock market. Need to support the benefits of integration, including a more competitive global market and increased liquidity levels, and the Association of African Stock Exchanges (ASEA). In most cases, the African market is still small and inactive. South Africa is an exception, it has a very successful financial market and a stock exchange connected to the capital markets of the world.

The dynamics of the integration of African securities markets have aroused interest in the literature; see, for example, (Yartey and Adjasi, 2007).

This is mainly concentrated in larger markets, many of which are seen as future integration centers, extending from regional centers to smaller peripheral markets. However, there is very little modeling work for smaller "micro" stock markets and those that focus on single market research, such as (Smith et al., 2002). Not only are these markets very small, they are also complicated by policy choices favored by governments and regulators, who must strike a balance between protecting emerging domestic markets and attracting much-needed foreign investment to promote economic growth. This article has two purposes. The first is to compare two common econometric models used by investors and regulators to model time series and stock prices. This is particularly interesting because it allows you to compare the performance of the model and capture the nuances in the time series, as these markets suffer from varying degrees of insufficient liquidity. The second is to review the level of volatility in these markets, which helps to reveal and compare the impact of these different levels of liquidity. All models are based on the total market return index to evaluate investment, because these indices, in addition to price changes, also explicitly consider the behavior of the company and dividends. Therefore, this work is valuable to the investment community interested in diversifying investment portfolios under the medium variance framework and to regulators who want to better understand the motivations behind their investment decisions in the market.

The markets included in the document are three frontier markets, Mozambique, Namibia and Swaziland, and an emerging market, South Africa. In the literature, there are two methods for modeling the time series of the total return index: the generalized autoregressive conditional heteroscedasticity model (GARCH) developed by Bollerslev (1986) and the standard capital asset valuation model (CAPM). There is a large body of literature that uses GARCH and GARCH in Mean (GARCH) models to capture time series effects on stock price series. In the larger African equity markets, recent work has focused on evaluating weak forms of price efficiency (Jefferis and Smith, 2005).

This article follows ZalewskaMitura et al. (1997) and Zalewska and Hall (1999) to generate the time-varying parameters of the GARCHM framework by applying the Kalman filter, which uses the mean equation as a simple development of the AR (1) model. If the efficiency hypothesis holds weakly, then the first-order coefficient of lagged returns should not be significantly different from zero. Jefferis and Smith (2005) found that although several markets became more fragile and efficient during the 1990s, South Africa was the only market with unpredictable returns during the entire sample period. There is a large body of theoretical and empirical literature using CAPM, which has recently been enhanced by adding the risk of covariance to other variables commonly used in equity valuations. For example, Fama and French (1993) and Liu (2006) incorporated the book value to market relationship and company size into the original CAPM framework, further increasing the liquidity premium. Liquidity itself is measured first using a prespecified structure, such as Amihud's (2002) structure, which classifies stocks in the sample group, and the premium itself generated by the difference between the returns of the highest stocks and lower. assets. Although the common liquidity structure in the literature works well for more liquid assets, Lesmond (2006) noted that these measures have not been conclusive for very low liquidity assets. Phylaktis and Ravazzolo (2004) discussed another common problem in valuing emerging equity markets: the risk of covariance of exchange rates or exchange premiums. It was found that the enhanced CAPM model with a currency premium was superior to the standard model, which is particularly relevant given the recent capital market liberalization in many emerging markets.

Finally, Collins and Abrahamson (2006) applied a CAPM-type model when calculating the cost of stocks in a set of sample markets in Africa, and pointed out that investors often use standard CAPM-type models to assess potential opportunities. Due to difficulties in liquidity measures in extremely low liquidity markets, and since the three countries in this study are members of a common currency area (except Mozambique), currency premiums are unnecessary and a simple single-factor CAPM model is appropriate of describes two methods for modeling total return series, GARCH and CAPM, and describes the application of medium variance portfolio optimization techniques. There is a large body of theoretical and empirical literature using CAPM, which has recently been enhanced by adding the risk of covariance to other variables commonly used in equity valuations. For example, (Fama et al., 1993) incorporated the book value to market relationship and company size into the original CAPM framework, further increasing the liquidity premium. Liquidity itself is measured first using a prespecified structure, such as Amihud's (2002) structure, which classifies stocks in the sample group, and the premium itself generated by the difference between the returns of the highest stocks and lower. assets. Although the common liquidity structure in the literature works well for more liquid assets, Lesmond (2006) noted that these measures have not been conclusive for very low liquidity assets. Phylaktis and Ravazzolo (2004) discussed another common problem in valuing emerging equity markets: the risk of covariance of exchange rates or exchange premiums. It was found that the enhanced CAPM model with a currency premium was superior to the standard model, which is particularly relevant given the recent capital market liberalization in many emerging markets. Finally, Collins and Abrahamson (2006) applied a CAPM-type model when calculating the cost of stocks in a set of sample markets in Africa, and pointed out that investors often use standard CAPM-type models to assess potential opportunities. Due to difficulties in liquidity measures in extremely low liquidity markets, and since the three countries in this study are members of a common currency area (except Mozambique), currency premiums are unnecessary and a simple single-factor CAPM model is appropriate of describes two methods for modeling total return series, GARCH and CAPM, and describes the application of medium variance portfolio optimization techniques.

2.2 Empirical review

GARCH model was then selected as the most fitting one for the remainder of the (Kambadza et al., 2012) analysis. Following an analysis of the volatility series within the VAR system, it was found that volatility interactions are restricted between African markets in the same way as return co-movements, apart from markets that are near trading partners and also large economies. In addition, domestic developments are more important than global innovations in describing current volatility. Volatility was found to be fundamentally persistent and asymmetric in most markets, while in Morocco and Nigeria it was found to be explosive. The evidence also indicates that volatility increased significantly in most markets during the 2008 financial crisis: (Kambadza et al., 2012). For its analysis of volatility linkages between return structures of Sub-Saharan African stock market indices, (Piesse and Hearn, 2005) has developed a robust dataset that scrutinizes the entire Sub-Saharan African region. They identified ten national exchanges that are collectively the most influential in the region. The following nations are: Botswana, Ghana, Kenya, Malawi,Mauritius, Namibia, Nigeria, South Africa, Zambia, Zimbabwe. The data sample for the period January 1993 to January 2000 consisted primarily of the weekly closing values of a detailed index set for all the markets under consideration. In order to capture the volatility asymmetry that is a common characteristic of the countries studied in such a way that bad news and good news have a different effect on future volatility, the EGARCH analysis was used (Piesseand Hearn, 2005: 42). Piesse and Hearn (2005) has argued that volatility spillovers are more likely to occur among countries with close links in terms of related systems of stock exchange trading, membership of the common currency area, or trade relations. The results of the study confirmed this theory, as evidence of spillovers of volatility was found from Botswana and Zimbabwe to South Africa. In fact, this was because of their trade and macroeconomic relations stemming from their integration into the SADC and their shared focus on exports to the European Union. While the dominance of the South African market should be sufficient to avoid any spillover of volatility from smaller markets, the strong interdependencies of localized trade between the three markets are likely to constitute the channel of transmission of bi-directional volatility ties between the three markets.

Piesse and Hearn (2005) was also noted for the presence of regional instability patterns in the west african markets (i.e. Ghana and Nigeria) and Kenya and the SADC countries. Finally, a bi-directional volatility relationship between Mauritius and Zimbabwe was created, while volatility was found to unidirectionally affect both the East African and Southern African markets in Mauritius, with the exception of South Africa Piesse and Hearn (2005). Finally, the (Agyei-Ampomah, 2011) study centered on the nature and scope of the interactions between the African share market and its relationships with other regional and global indices. Four IFC Global African nations, namely South Africa, Egypt, Nigeria and Morocco, and six countries identified as frontier economies, were the countries sampled (i.e. Botswana, Ghana, Ivory Coast, Kenya, Mauritius and Tunisia). By using the monthly returns of all market share indices for the period January 1998 to December 2007, the author attempted to overcome a number of microstructural biases present in these markets, such as stale pricing and non-synchronous trading of (Agyei-Ampomah, 2011). To evaluate the accuracy of VaR estimates on Thailand's stock exchange, Aad et al. (2015) utilizes a board of long-memory GARCH-class systems. They conclude that VaR estimates using the FIGARCH model with normal distribution are more reliable than those generated using the short-memory model of GARCH. In general, literature has covered information on advanced capital markets in support of LM, asymmetries and fat-tails. Despite the fact that in the last two decades, emerging markets have attracted foreign investors' attention as a means of higher returns, such as by diversifying international portfolio risk, only a few studies have addressed the issue of persistence of volatility and VaR-ES forecasts. In a more recent report, (Aloui and Mabrouk, 2010) addresses the extreme downside risk to major ,middle eastern oil producing countries and investigates the implications of the global financial crisis. It estimates VaR and ES under the GED distribution and shows that the spillover effect of the global crisis varied from country to country, but among the community of six countries, the Dubai financial market was the most badly affected market.

2.3 The gap

There are little research in Rwanda on estimating Value at Risk (VaR) and Expected Shortfall (ES) of market returns using ARMA and GARCH models. In this work, we shall mainly focus on the following points in line with the gap: Determining the riskiest asset among the currencies analysis using clustering methods, fitting ARMA + GARCH models to forex returns in Rwanda market and estimate VaR and ES for each FX return time series.

3. Research Methodology

In this chapter, estimating Value at Risk and Expected Shortfall of market returns using ARMA and GARCH models are discussed, so as to solve the problem of currency fluctuations. As suggested by the topic, this study shall utilize machine learning algorithms to arrive at its objectives. This section defines the analytical approaches to be taken to solve the problem.

3.1 Research Design

This is analytic research of time series data which consists of 5 selected currency returns in Rwanda forex market. This is intended to estimate Value at Risk (VaR) and Expected Shortfall (ES) of market returns using ARMA and GARCH models.

3.2 Sampling Method

Purposive sampling method has been used. We selected 5 most traded currencies out of 62 present in Rwanda forex market.These currencies includes, British Pound (GBP), Euro (EUR), United States Dollar (USD), Kenya Shilling (KES), and Egyptian Pound (EGP).

3.2.1 Sample Size

The sample size of this study is 2118 observations from 5 selected currencies. These are secondary data from national bank of Rwanda website (www.bnr.rw), from January 2012 up to July 2020. Spread, which is the absolute difference between the selling and buying prices. Currencies were used against FRW, in this analysis. Formally, the spread is defined as

$$Spread = |Sell - buy| \tag{3.2.1}$$

from (David Ruppert, 2015) Returns is computed as follows: For each exchange rate, relative to currency, C, where, C={GBP, EUR, USD, KES and EGP}

$$Return_t = ln(\frac{spread_t}{spread_{t-1}}) \tag{3.2.2}$$

In this study, R software was used to process data and implement the proposed algorithms relative to each model.

3.3 Stationary models

3.3.1 ARMA model

An ARMA (p,q) model combines terms from both AR and MA and is defined as follows.

$$(Y_t - \mu) = \phi_1(Y_{t-1} - \mu) + ... + \phi_p(Y_{t-p} - \mu) + \varepsilon_t + \theta_1\varepsilon_{t-1} + ... + \theta_q\varepsilon_{t-q} \tag{3.3.1}$$

Using a backward operator, equation (3.2.1) can be written as

$$(1 - \theta_1 B - ... - \phi_p B^p)(Y_t - \mu) = 1 + \theta_1 B + ...\theta_q B^q \varepsilon_t \tag{3.3.2}$$

The white noise method is ARMA (0,0) because if p=q=0, it decreases to $(Yt - \mu) = \varepsilon t)$ In practice the ARMA(1,1) model is commonly used. One can assume that $\mu = 0$ when computing the variance and Auto Correlation Function (ACF). Multiplying the model

$$Y_t = \phi Y_{t-1} + \theta\varepsilon_{t-1} + \varepsilon_t \tag{3.3.3}$$

by ε_t and taking expectations, one has

$$Cov(Y_t, \varepsilon_t) = E(Y_t\varepsilon_t) = \sigma_\varepsilon^2 \tag{3.3.4}$$

3.3.2 GARCH model

From (David Ruppert, 2015) page $[427]$

ARCH(p) process is defined formally as

$a_t = \sigma_t\varepsilon_t$ where

$$\sigma_t = \sqrt{\omega + \sum_{i=1}^{p} \alpha_i a_{t-i}^2} \tag{3.3.5}$$

GARCH(p,q) model is

$$a_t = \sigma_t\varepsilon_t \tag{3.3.6}$$

in which

$$\sigma_t = \sqrt{\omega + \sum_{i=1}^{p} \alpha_i a_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2} \tag{3.3.7}$$

where σ_t^2 is variance, a_t is an ARCH(p) process, ε_t is a gaussian white noise and ω, α, β are constants. In this work, an AR(1)+GARCH(1,1) will be used to fit individual currency returns versus FRW.

3.4 Value at Risk and Expected Shortfall

If the loss over the T holding time is L, then $VaR(\alpha)$ is the L upper quantile of αth. Similarly, if the revenue is $R = -L$, $VaR(\alpha)$ is less than αth of R. $VaR(\alpha)$ solves distributions of continuous losses for

$$P\{L > \ VaR(\alpha)\} = P\{L \geq \ VaR(\alpha) = \alpha \tag{3.4.1}$$

And for every distribution of losses, continuous or not,

$$Var(\alpha) = inf\{x : p(L > x) \leq \alpha\} \tag{3.4.2}$$

It is replaced by new risk measures, which are expected losses because the loss exceeds VaR, which is referred to as the expected shortfall.

$$ES(\alpha) = \frac{\int_0^{\alpha} VaR(u)du}{\alpha} \tag{3.4.3}$$

This is the VaR(u) average for all u that is less than or equal to α. If there is a continuous distribution of L

These above formulae of Value at Risk (VaR) and Expected Shortfall (ES) are defined in page $[554]$ at (David Ruppert, 2015).

4. Results and Discussion

In this chapter, we analyze the data and present the findings, all analysis were done using R software. This study used clustering machine learning algorithms to estimate VaR and ES of market returns using ARMA and GARCH models.

4.1 Data Descriptives

The study used time series data of forex market returns in Rwanda, consisting of 2118 observations with 6 variables.

4.1.1 Basic Statistics and Correlation Coefficients

a) Pearson correlation.

On figure 4.1 indicates the correlation, by observing, we see the following strongly correlated currencies KES, and USD = 0.78, GBP, and EUR = 0.67, While EGP is weakly correlated with other currencies as follows, EGP, and GBP = 0.13, EGP, and EUR = 0.17.

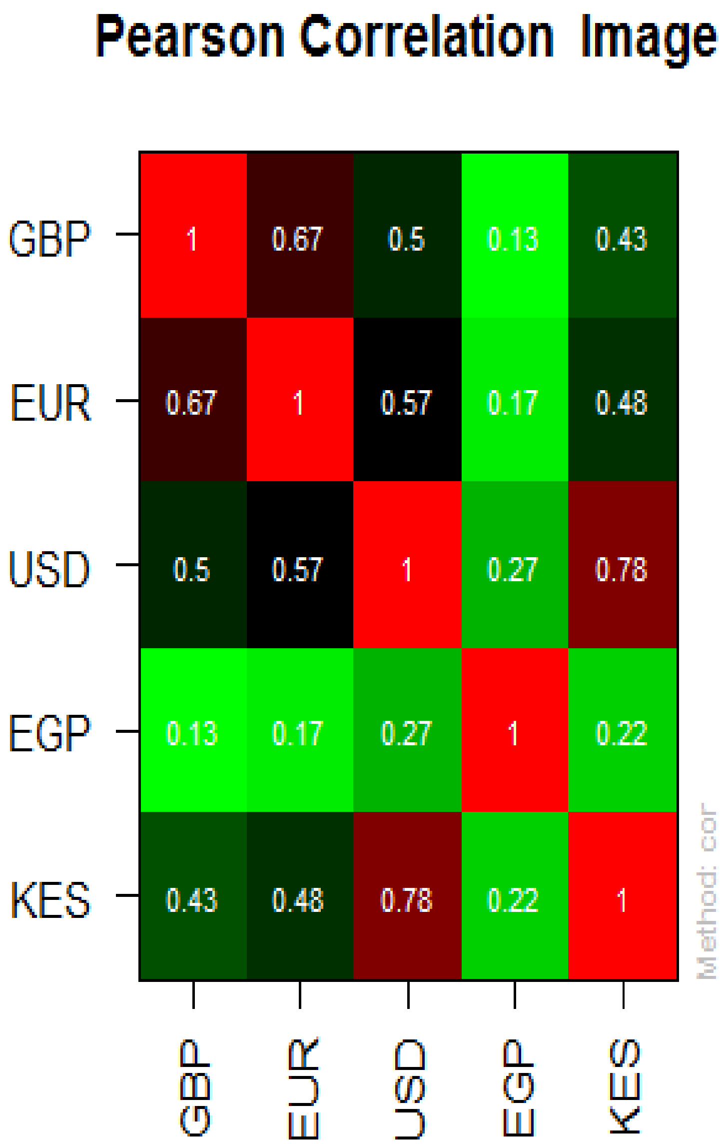

Figure 4.1: Correlation coefficients.

b) Descriptive Statistics.

1. On tables 4.1 , we observe that EGP, has variance 1.887937 it has the highest variance . It indicates that there is high variability of data from the mean.

2. From these table, 4.1, we observe that EGP has small skewness.

3. The following currencies: USD, EGP and KES have the highest kurtosis means that they have heavy tails, or outliers. While GBP has smallest kurtosis, it has light tail.

Table 4.1: Basic statistics.

Item	GBP	EUR	USD	EGP	KES
nobs	2118.0	2118.0	2118.0	2118.0	2118.0
Minimum	-5.202478	-2.501899	-4.374155	-53.951468	-4.571807
Maximum	16.802249	17.370965	17.202157	17.179351	17.235890
Mean	0.021182	0.024387	0.030896	-0.015140	0.019364
Variance	0.478086	0.426137	0.168784	1.887937	0.252242
Stdev	0.691438	0.652792	0.410833	1.374022	0.502237
Skewness	6.564135	9.073165	35.126775	-28.180600	18.942341
Kurtosis	168.509404	236.070576	1457.642425	1135.836482	657.322365

4.1.2 Forex return time series

On this graph 4.2, we observe that there is high fluctuation on the same date 2020-07-01, for the following currencies GBP, EUR, USD, and KES except for EGP, this is the impact of COVID-19. We observe that USD has less fluctuation, while EGP has high fluctuation. Figure 4.2 shows returns of 5 asset classes in the FX returns in Rwanda market. This returns calculated as in equation 3.2.2.

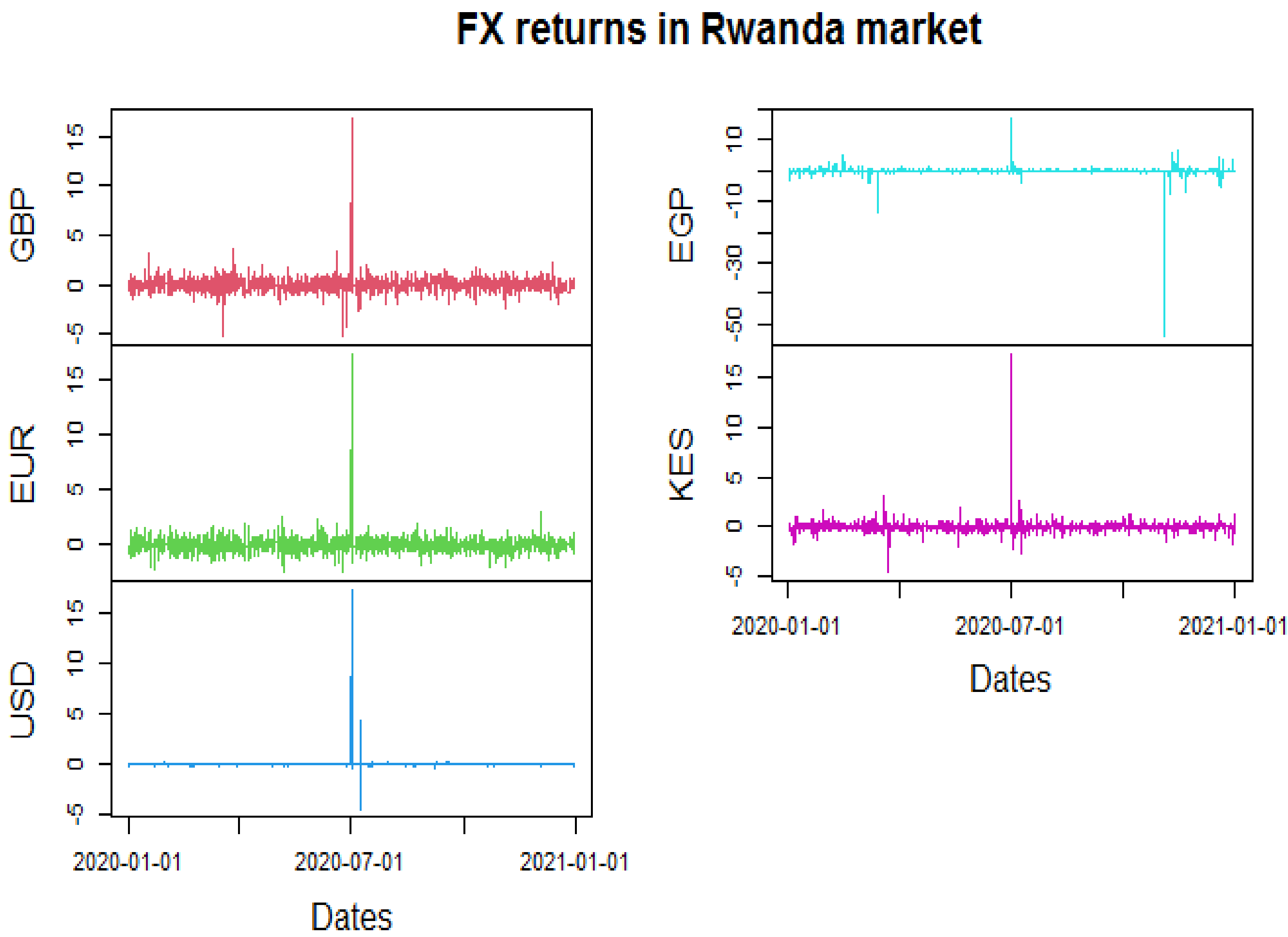

Figure 4.2: Forex Returns in Rwanda market.

4.2 Data Analysis

In this section, three points will be treated, clustering methods, fitting ARMA + GARCH models,and estimating VaR and ES for each currency return time series.

4.2.1 Clustering methods

This study used several clustering machine learning algorithms for identifying and grouping similar currency of 5 selected currency returns in Rwanda forex market.Two methods will be used, including hierarchical clustering and K-means clustering.

a) Hierarchical clustering

A hierarchical clustering is performed on asset returns, for the clustering of n objects. Each object is initially assigned to its own cluster and then the algorithm proceed iteratively, joining the two most similar clusters at each point, continuing until only one cluster is present. On the figure

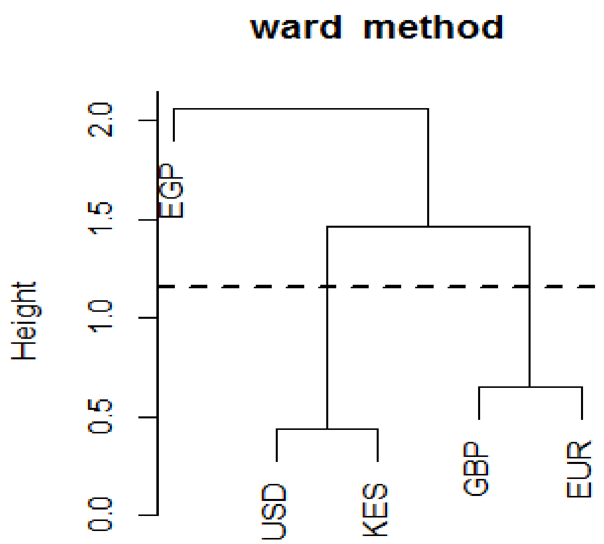

Figure 4.3: Hierarchical clustering.

4.3, we observe that, grouping similar and dissimilar asset returns, in Rwanda FX market,related clusters are identified by the full linkage process. It shows that we have three groups which tend to have similar behavior such as group one: GBP and EUR group two : USD and KES and group three : EGP

b) K-means clustering

The k-means algorithm calculates the number of centroids for the K-means algorithm and then assigns each data point to the closest cluster while keeping the centroids as small as possible. Using this algorithm, the asset is divided into two types, one with a lower risk and one with a high risk asset. See on table 4.2.

Table 4.2: k-means cluster.

GBP	EUR	USD	KES	EGP
1	1	1	1	2

The higher the number the more riskier the currency. Group one (lower risk) we find the assets GBP, EUR, USD, and KES. Group two (high risk) we find the asset EGP . Among the risk, is that it might be harder to make transactions with the Egyptian Pound in Rwanda currency market.

4.2.2 Fitting ARMA + GARCH model

In this subsection, equations 3.3.5 through 3.3.7 are used for each currency return time series.

a) Fitting AR(1) + GARCH(1,1) from GBP/FRW return

using standard distribution, one gets the following results

Table 4.3: GARCH Model of GBP/FRW.

Item	Estimate	Std.Error	t value	Pr($>|t|$)
mu	0.009741	0.009954	0.97860	0.327778
ar1	-0.005549	0.014533	-0.38183	0.702590
omega	0.002672	0.000797	3.35100	0.000805
alpha1	0.019187	0.002460	7.79874	0.0000
beta1	0.979567	0.000145	6765.54431	0.0000

Information criteria are akaike 1.5475 and bayes 1.5688. ar1, and μ are not statistically significant because their p value is greater than 0.05. Rewriting equation 3.3.5 and 3.3.7, one has

$$\sigma_t = \sqrt{0.002672 + 0.019187 a_{t-i}^2} \tag{4.2.1}$$

and

$$\sigma_t = \sqrt{0.002672 + 0.019187 a_{t-i}^2 + 0.979567 \sigma_{t-j}^2} \tag{4.2.2}$$

respectively. We observe that the sum of alpha and beta are less than one, therefore we have stationary time series, see on the following figures 4.4, 4.5 and 4.6

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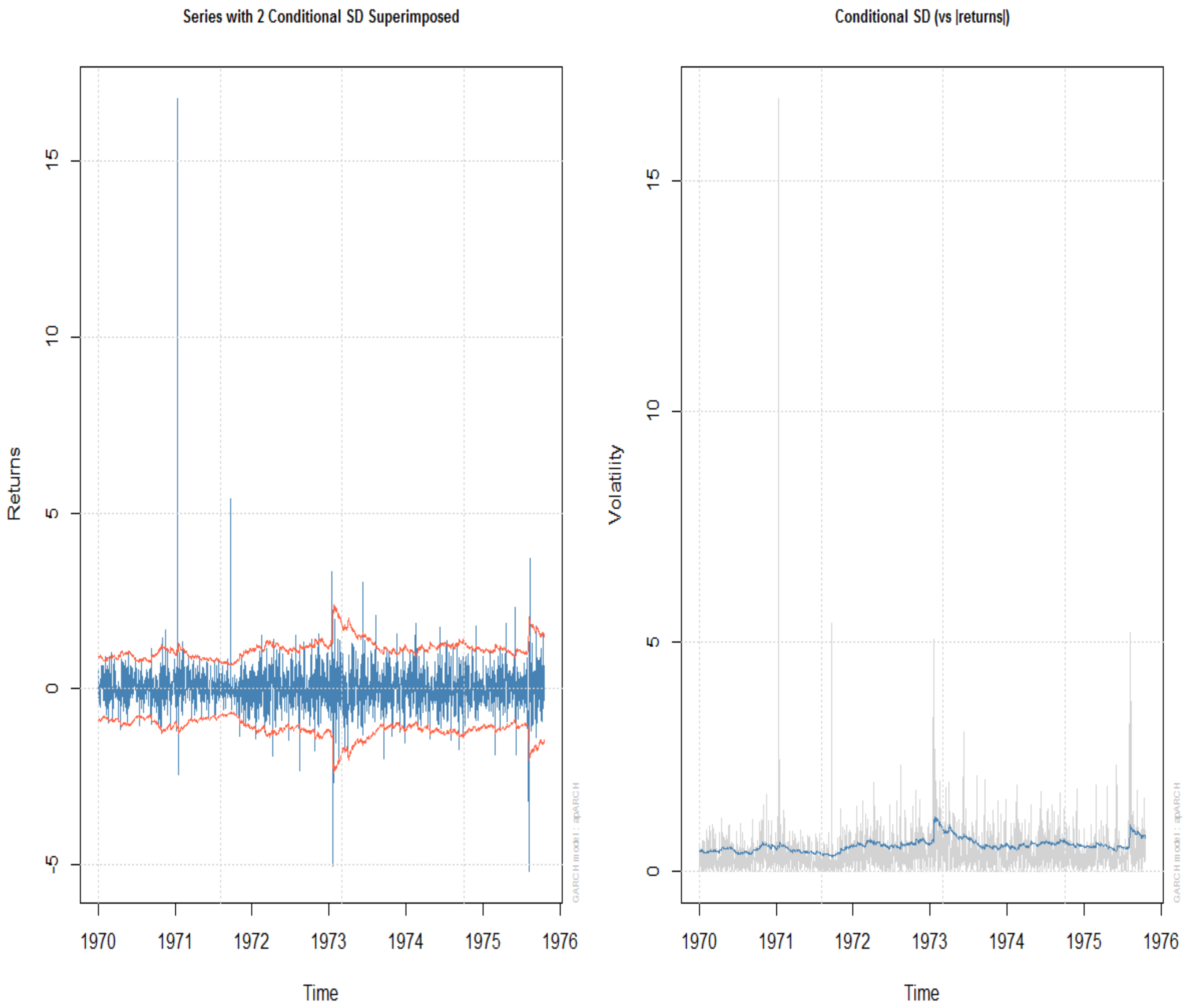

Figure 4.4: Series with 2 conditional SD superimposed for GBP.

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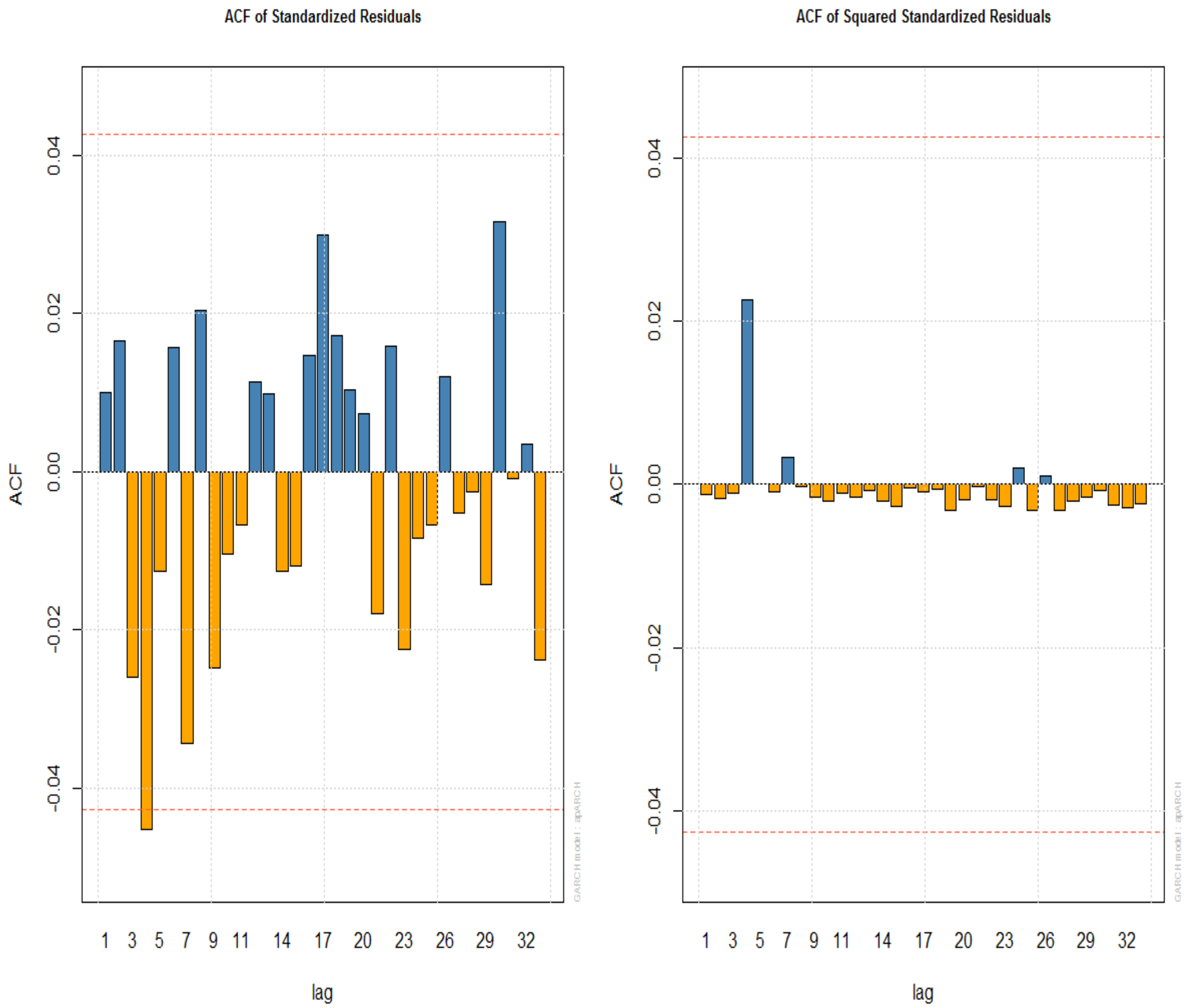

Figure 4.5: ACF of standardized Residuals of GBP.

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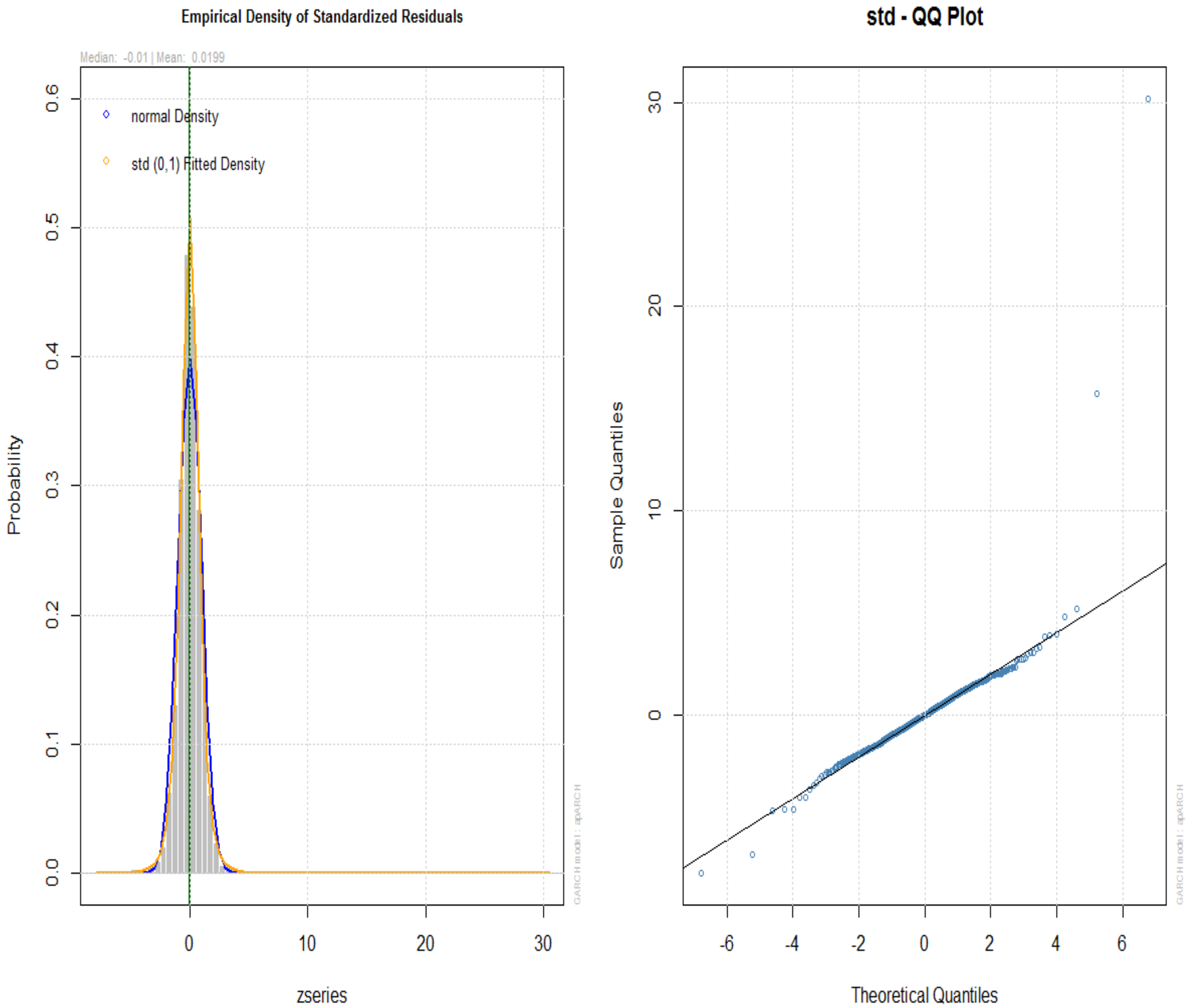

Figure 4.6: Empirical Density of Standardized Residuals of GBP.

b) Fitting AR(1) + GARCH(1,1) from EUR/FRW return

Using normal distribution, one gets the following results

Information criteria are akaike 1.9724 and bayes 1.9858 . All the estimates are statistically significant because their p value is less than 0.05. Rewriting equation 3.3.5 and 3.3.7, one has

$$\sigma_t = \sqrt{0.000476 + 0.065772 a_{t-i}^2} \tag{4.2.3}$$

and

Table 4.4: GARCH Model of EUR/FRW.

Item	Estimate	Std.Error	t value	Pr($>|t|$)
mu	-0.106883	0.000026	-4129.0	0
ar1	-0.019284	0.000005	-4128.7	0
omega	0.000476	0.000000	4128.7	0
alpha1	0.065772	0.000016	4117.8	0
beta1	0.908653	0.000221	4118.1	0

$$\sigma_t = \sqrt{0.000476 + 0.065772a_{t-i}^2 + 0.908653\sigma_{t-j}^2} \tag{4.2.4}$$

respectively. We observe that the sum of alpha and beta are less than one, therefore we have stationary time series, see on the following figures 4.7, 4.8 and 4.9

Table 4.5: Weighted Ljung-Box Test on Standardized Residuals of GBP/FRW.

	Statistic	P value
Lag[1]	0.3025	0.5823
Lag[2*(p+q)+(p+q)-1][2]	0.3059	0.9938
Lag[4*(p+q)+(p+q)-1][5]	1.6245	0.8152
d.o.f=1, H0 : No serial correlation		

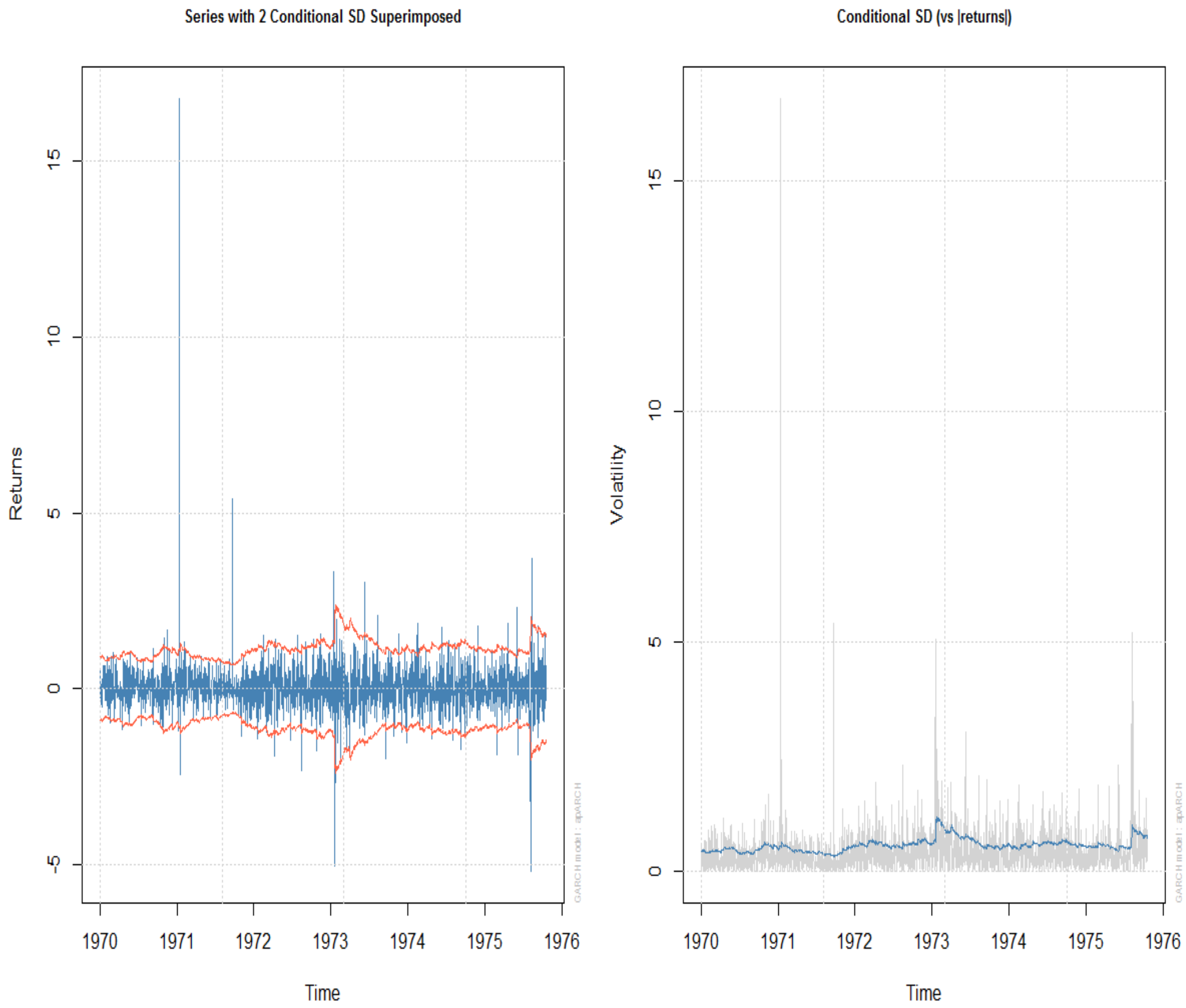

Figure 4.7: Series with 2 conditional SD superimposed for EUR.

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Table 4.6: Adjusted Pearson Goodness-of-Fit Test.

Item	group	statistic	p-value(g-1)
1	20	174.5	3.725e-27
2	30	174.2	1.204e-22
3	40	189.8	1.019e-21
4	50	216.3	6.778e-23

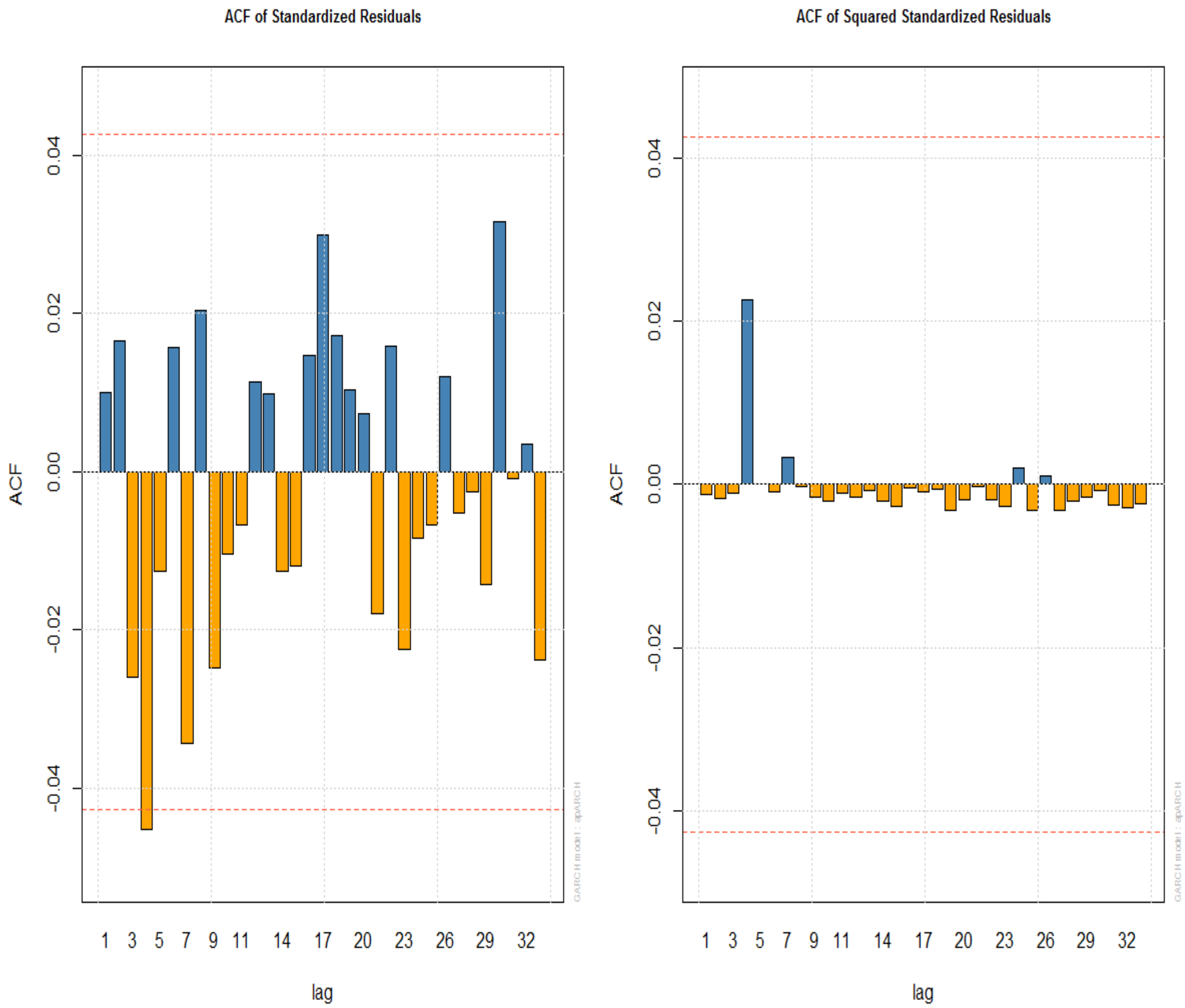

Figure 4.8: ACF of standardized Residuals of EUR.

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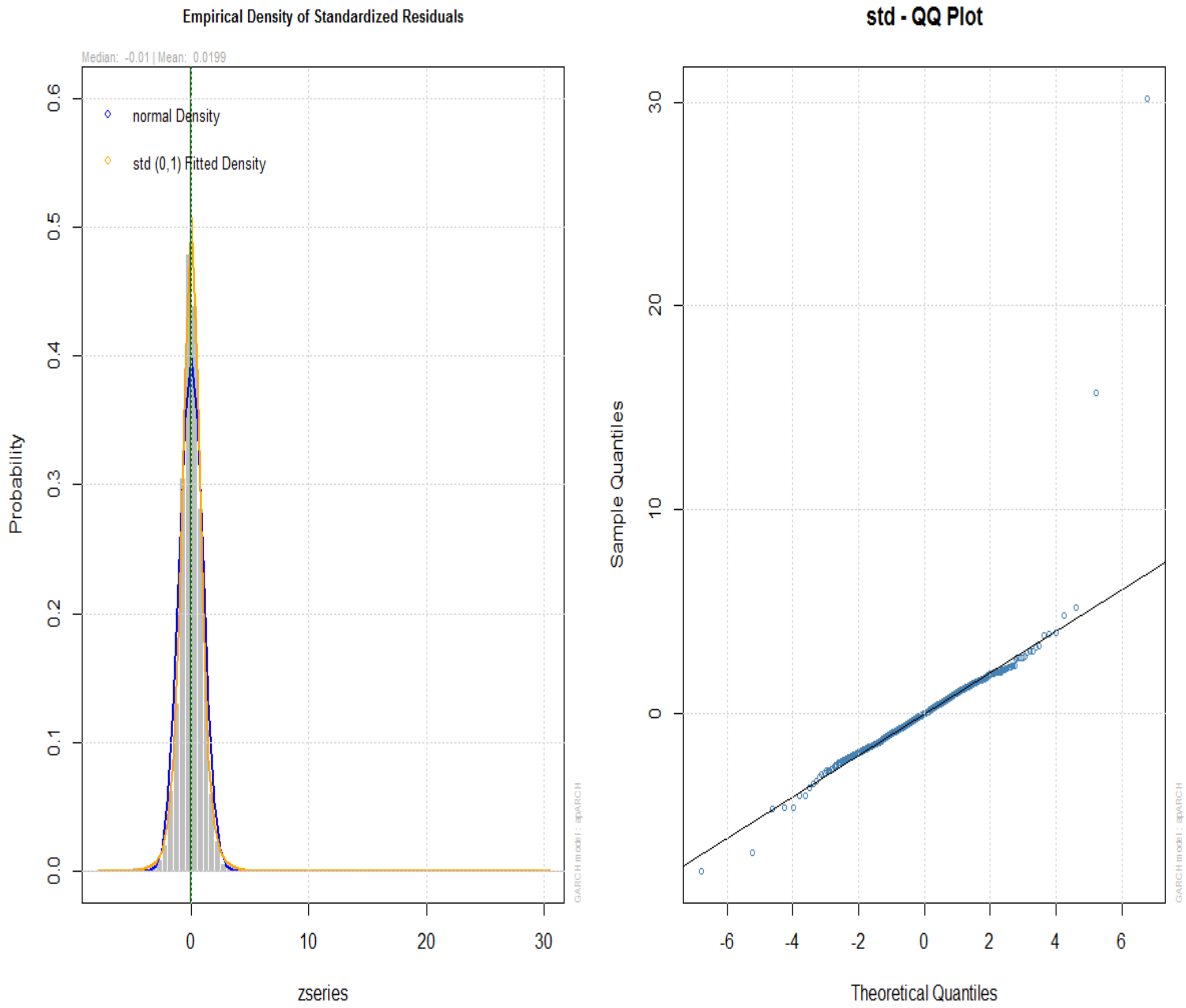

Figure 4.9: Empirical Density of Standardized Residuals of EUR.

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c) Fitting AR(1) + GARCH(1,1) from USD/FRW return

Using normal distribution, one gets the following results

Table 4.7: GARCH Model of USD/FRW .

Item	Estimate	Std.Error	t value	Pr($>|t|$)
mu	0.016651	0.000296	56.2526	0.000000
ar1	0.085352	0.027458	3.1084	0.001881
omega	0.000004	0.000001	3.2041	0.001355
alpha1	0.184938	0.008142	22.7148	0.000000
beta1	0.814062	0.003077	264.6039	0.000000

Information criteria are akaike -4.4984 and bayes -4.4850. All the estimates are statistically significant because their p value is less than 0.05. Rewriting equation 3.3.5 and 3.3.7, one has

$$\sigma_t = \sqrt{0.000004 + 0.184938 a_{t-i}^2} \tag{4.2.5}$$

and

$$\sigma_t = \sqrt{0.000004 + 0.184938 a_{t-i}^2 + 0.814062 \sigma_{t-j}^2} \tag{4.2.6}$$

respectively. We observe that the sum of alpha and beta are less than one, therefore we have stationary time series. We observe that the distribution is plotted on the horizontal axis on theoretical quantiles, the data are not dispersed. See on the following figures 4.10, 4.11 and 4.12.

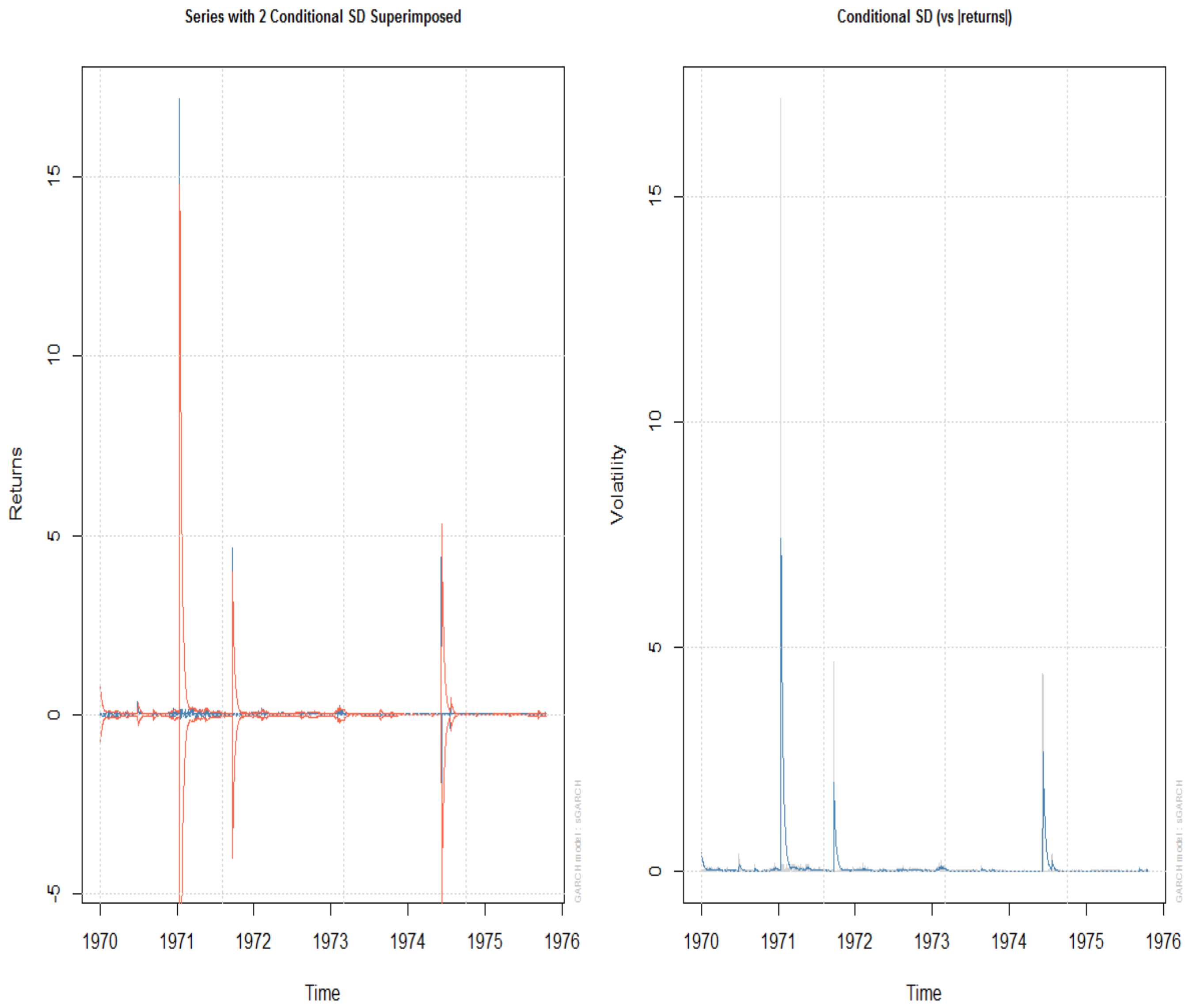

Figure 4.10: Series with 2 conditional SD superimposed for USD.

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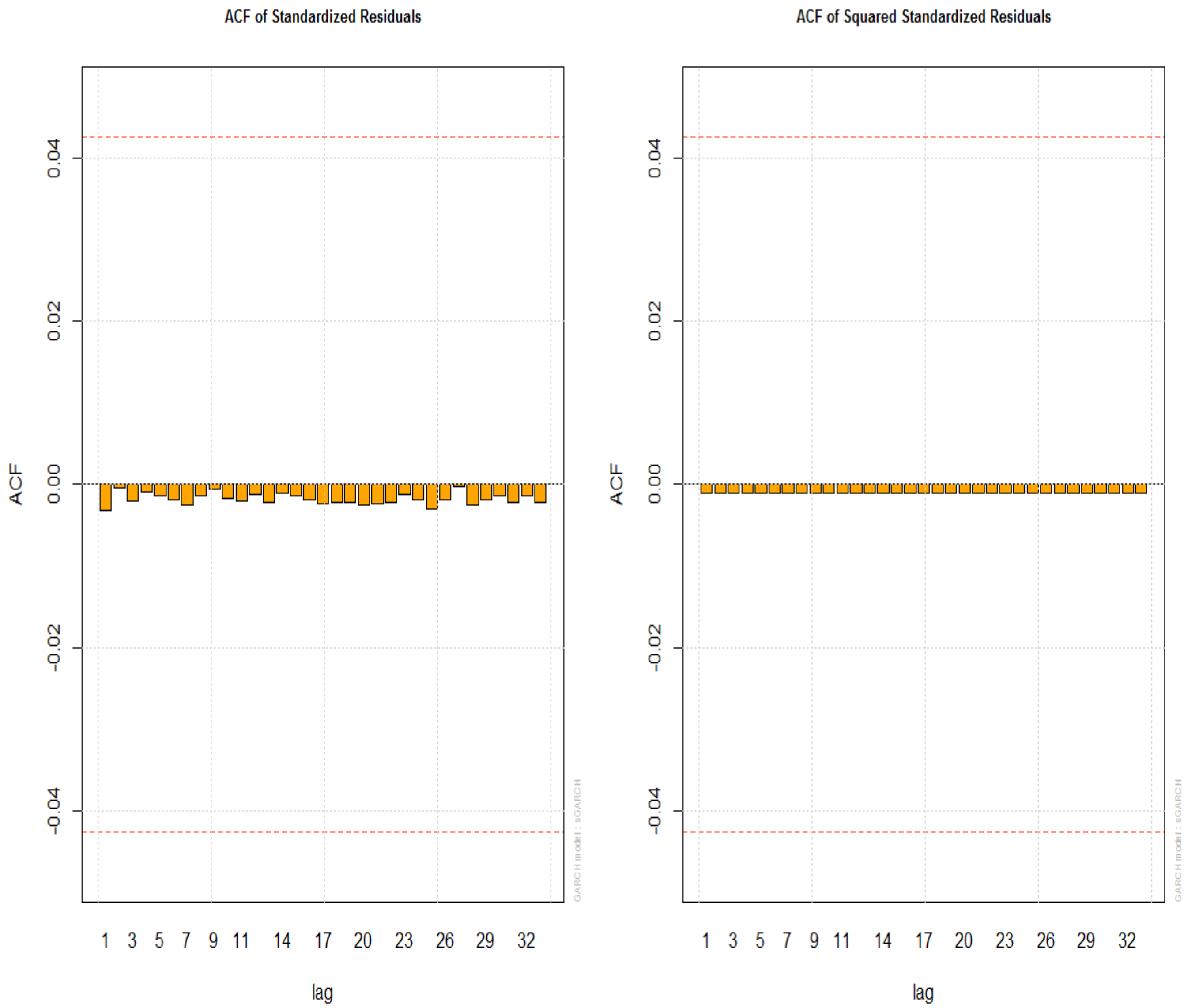

Figure 4.11: ACF of standardized Residuals of USD.

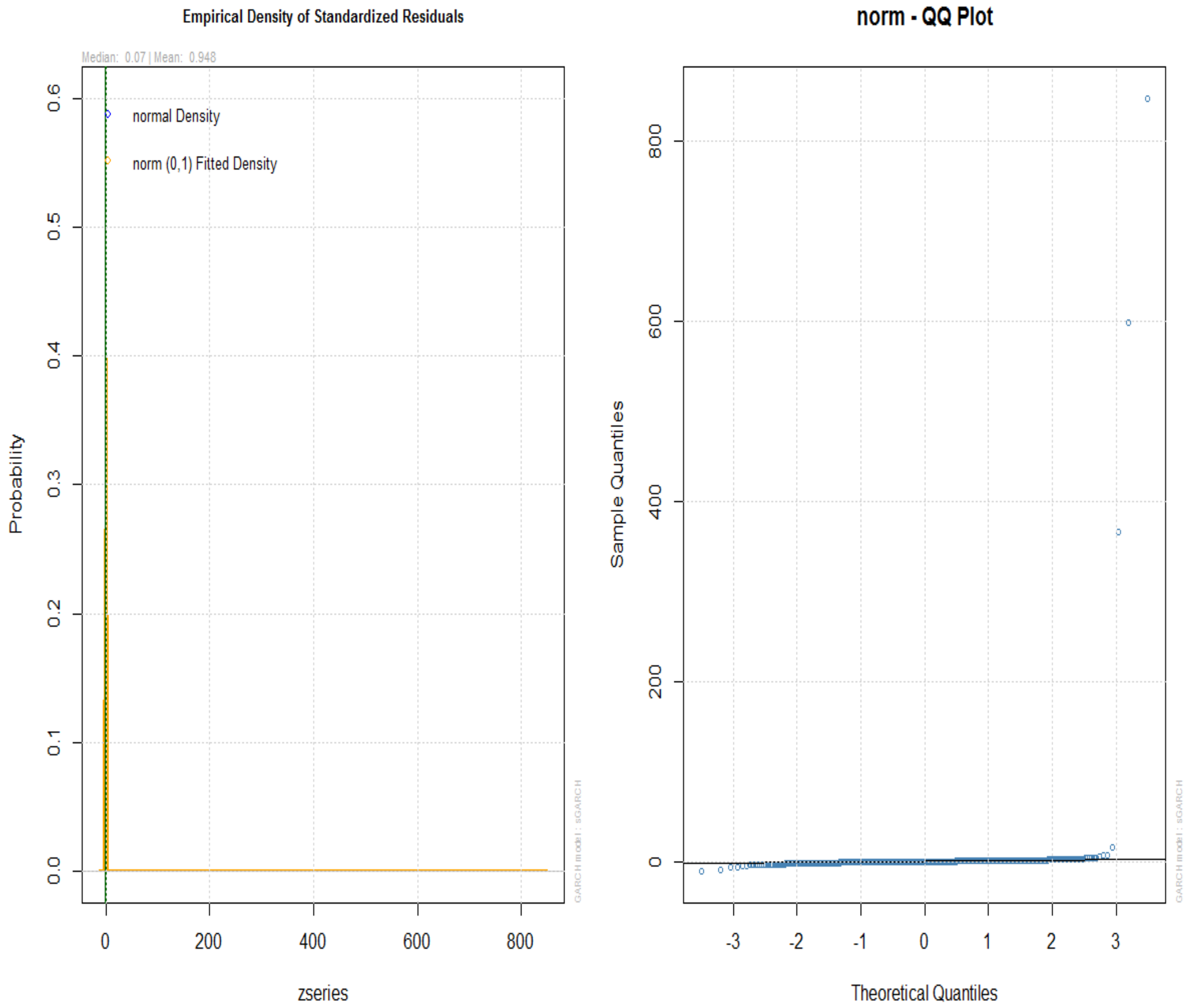

Figure 4.12: Empirical Density of Standardized Residuals of USD.

d) Fitting AR (1) + GARCH (1,1) from EGP/FRW return

Using the normal distribution, one gets the following results.

Table 4.8: GARCH Model of EGP/FRW.

Item	Estimate	Std.Error	t value	Pr($>|t|$)
mu	0.026972	0.004249	6.3482	0.00000
ar1	-0.118698	0.044664	-2.6576	0.00787
omega	0.025638	0.001351	18.9785	0.00000
alpha1	0.707418	0.058205	12.1540	0.00000
beta1	0.291582	0.025625	11.3790	0.00000

Information criteria are akaike 0.28279 and bayes 0.29615. All the estimates are statistically significant because their p value is less than 0.05. Rewriting equation 3.3.5 and 3.3.7, one has

$$\sigma_t = \sqrt{0.025638 + 0.707418a_{t-i}^2} \tag{4.2.7}$$

and

$$\sigma_t = \sqrt{0.025638 + 0.707418a_{t-i}^2 + 0.291582\sigma_{t-j}^2} \tag{4.2.8}$$

respectively.

We observe that the sum of alpha and beta are less than one, therefore we have stationary time series. We observe that the distribution is plotted on the horizontal axis on theoretical quantiles, the data are more dispersed. It is heavy tailed. See on the following figures 4.13, 4.14 and 4.15.

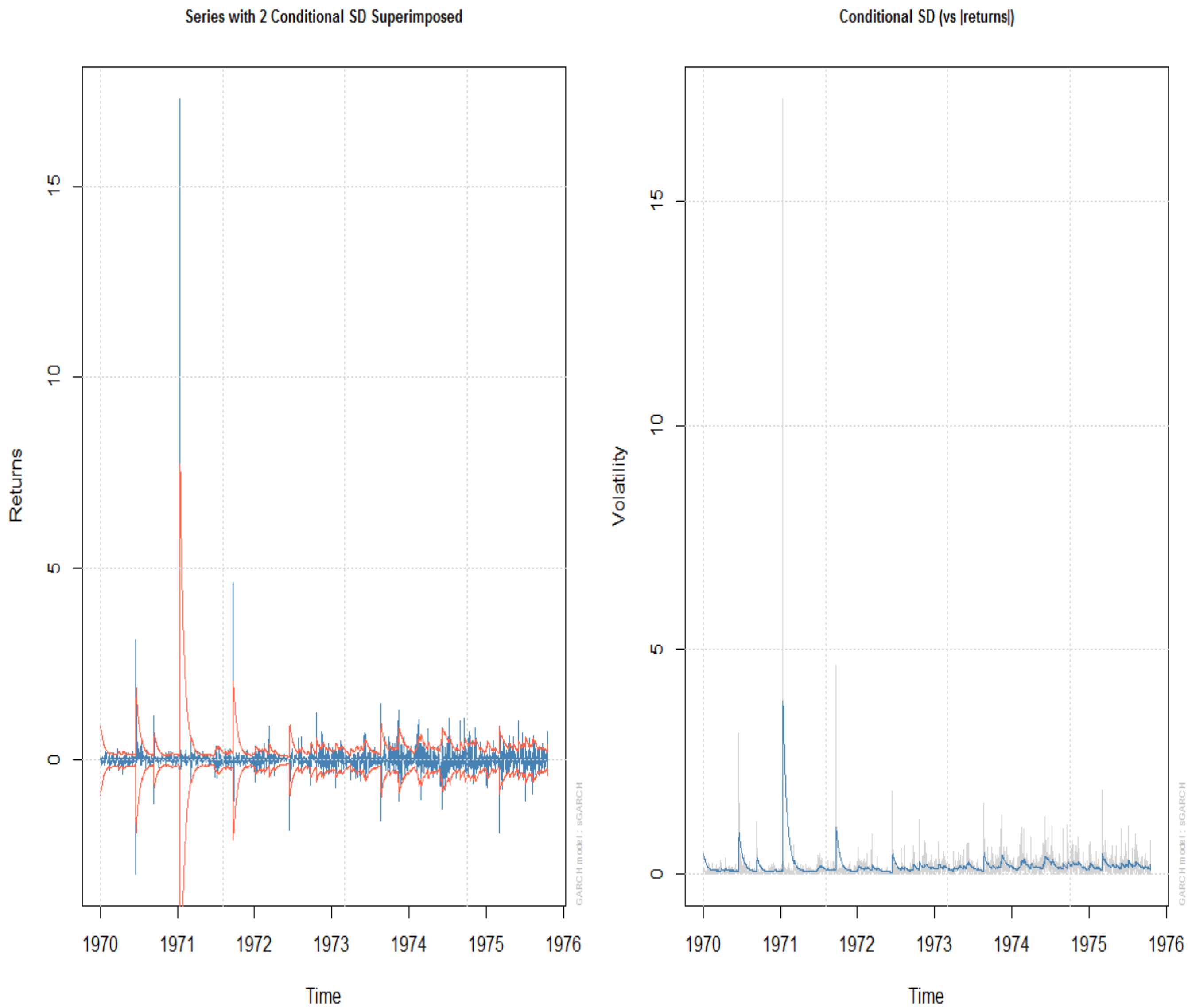

Figure 4.13: Series with 2 conditional SD superimposed for EGP.

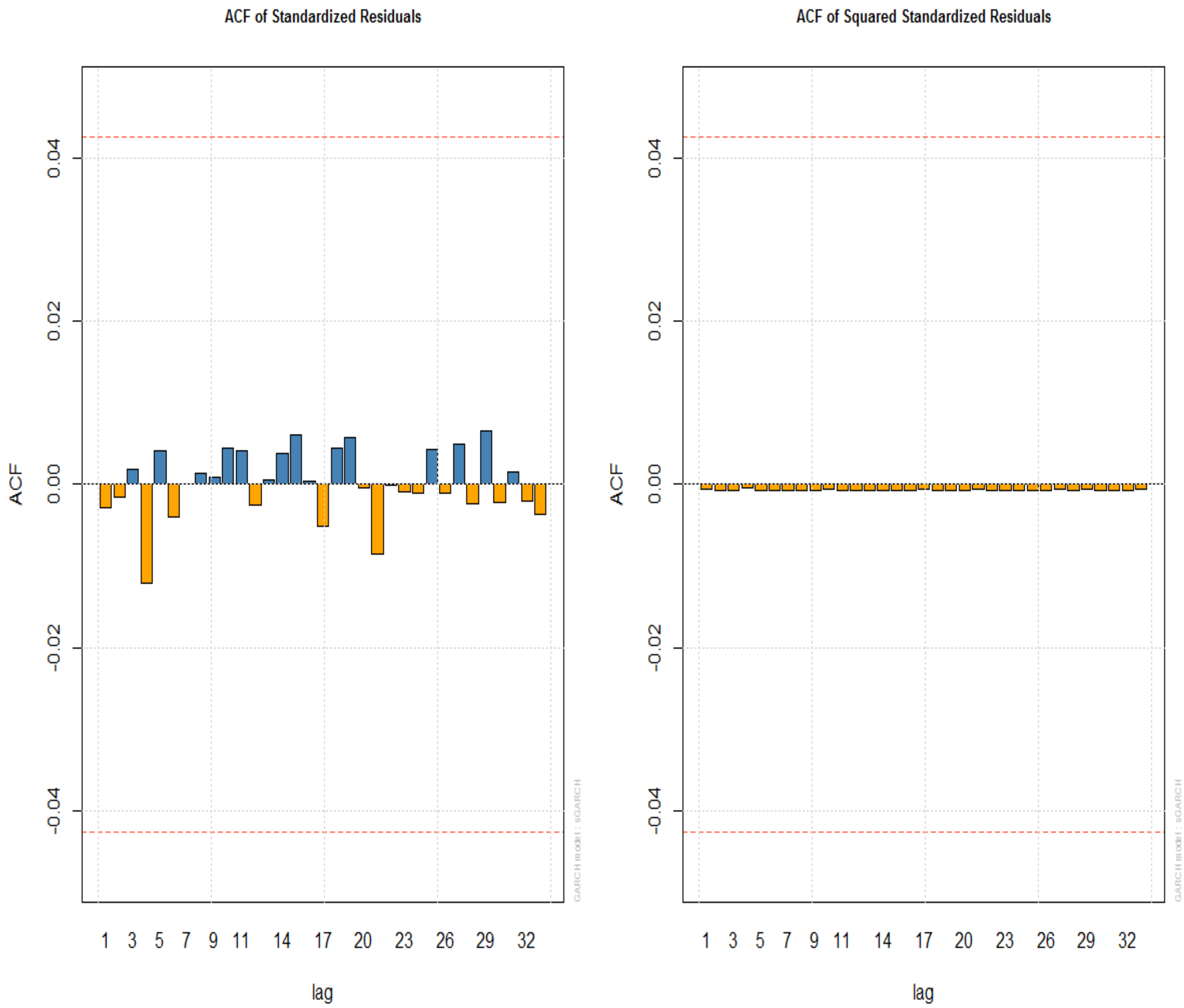

Figure 4.14: ACF of standardized Residuals of EGP.

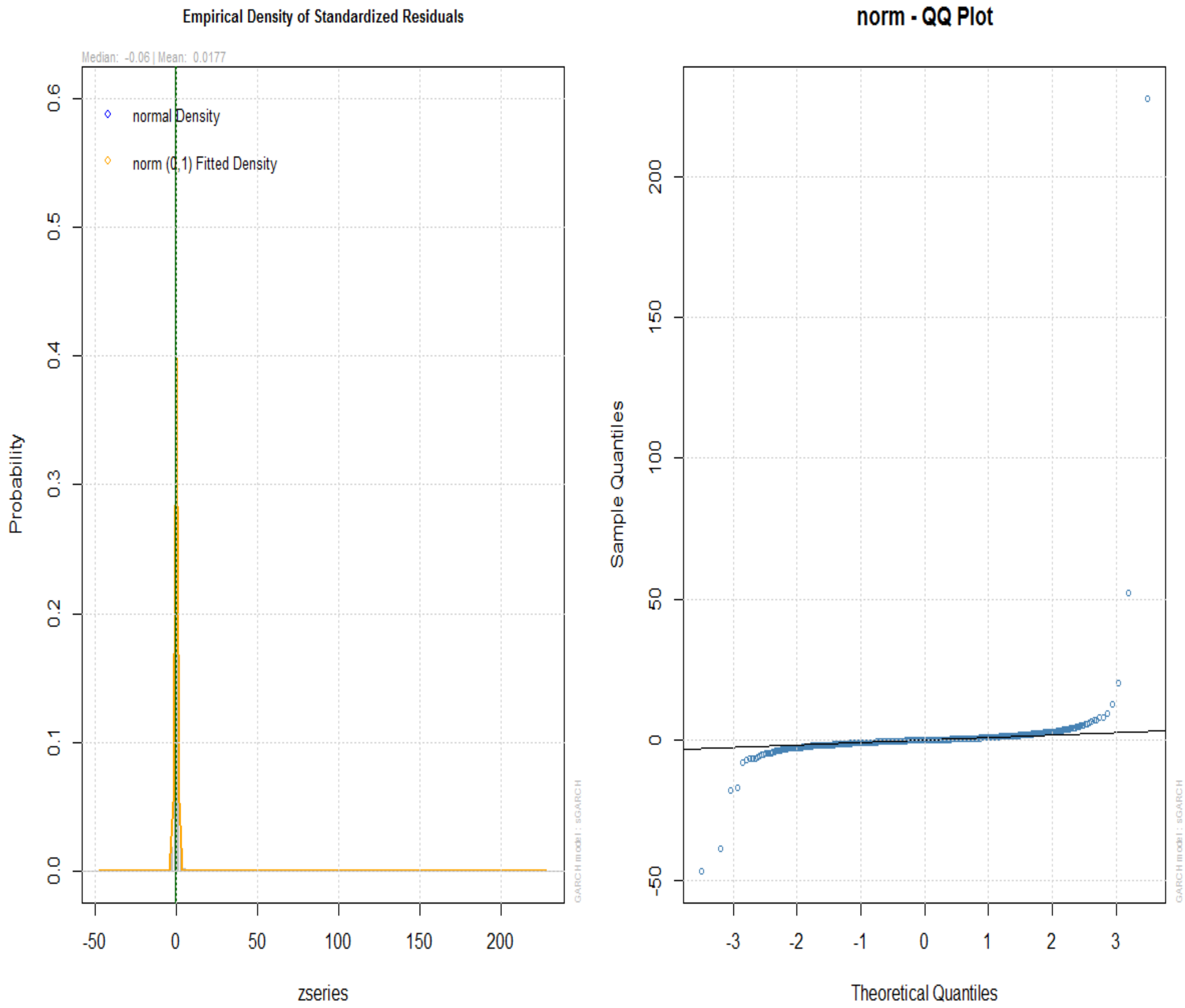

Figure 4.15: Empirical Density of Standardized Residuals of EGP

e) Fitting AR(1) + GARCH(1,1) from KES/FRW return

Using the normal distribution, one gets the following results.

Table 4.9: GARCH Model of KES/FRW.

Item	Estimate	Std.Error	t value	Pr($>|t|$)
mu	0.128535	0.045572	2.8205	0.004795
ar1	0.550951	0.035313	15.6021	0.000000
omega	0.000267	0.000126	2.1262	0.033487
alpha1	0.054797	0.001346	40.7175	0.000000
beta1	0.904631	0.003076	294.0832	0.000000

Information criteria are akaike 1.6154 and bayes 1.6288. All the estimates are statistically significant because their p value is less than 0.05. Rewriting equation 3.3.5 and 3.3.7, one has

$$\sigma_t = \sqrt{0.000267 + 0.054797 a_{t-i}^2} \tag{4.2.9}$$

and

$$\sigma_t = \sqrt{0.000267 + 0.054797 a_{t-i}^2 + 0.904631 \sigma_{t-j}^2} \tag{4.2.10}$$

respectively. We observe that the sum of alpha and beta are less than one, therefore we have stationary time series. We observe that the distribution is plotted on the horizontal axis on theoretical quantiles, the data are more dispersed. It is heavy tailed. See on the following figures 4.16, 4.17 and 4.18

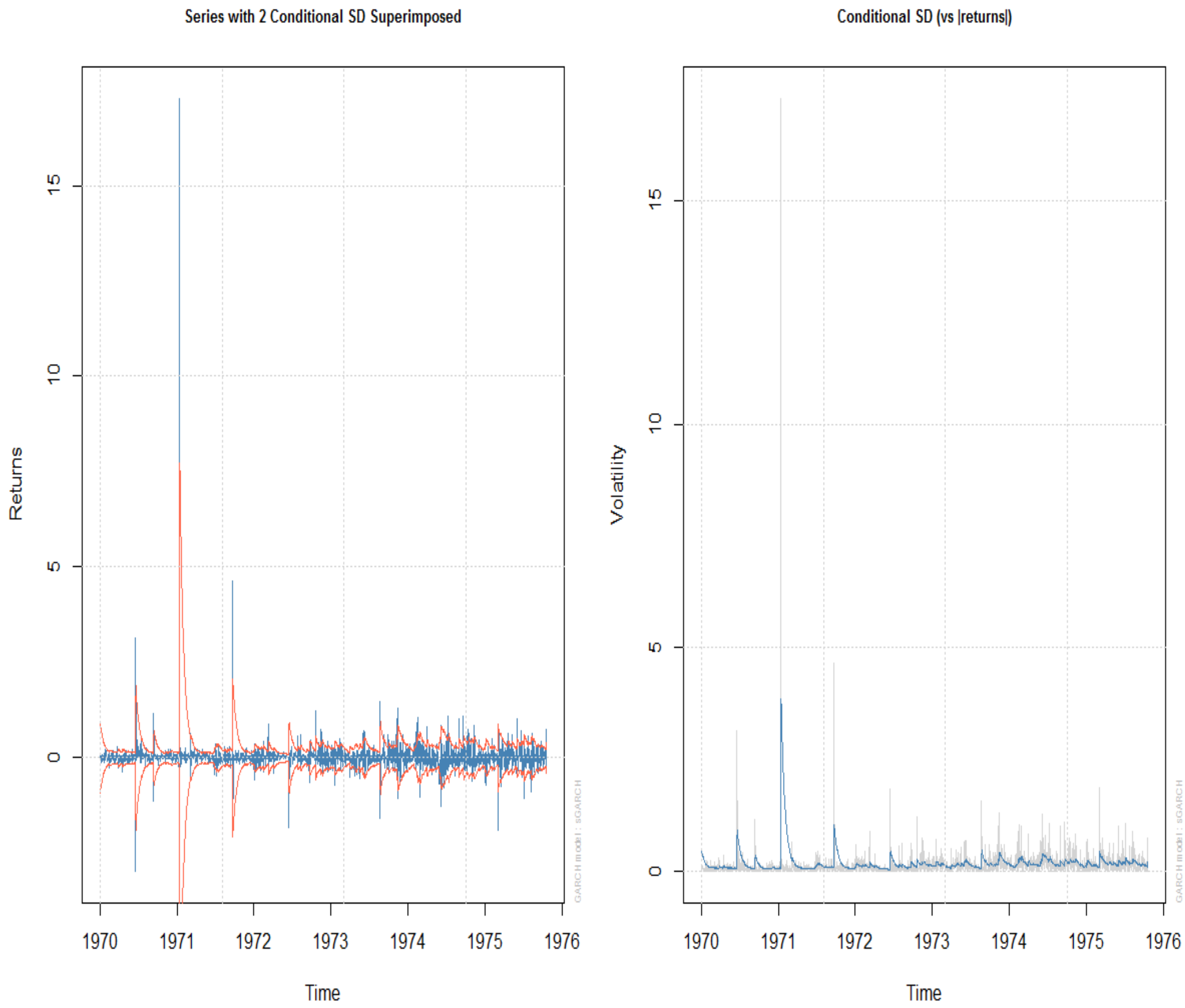

Figure 4.16: Series with 2 conditional SD superimposed for KES.

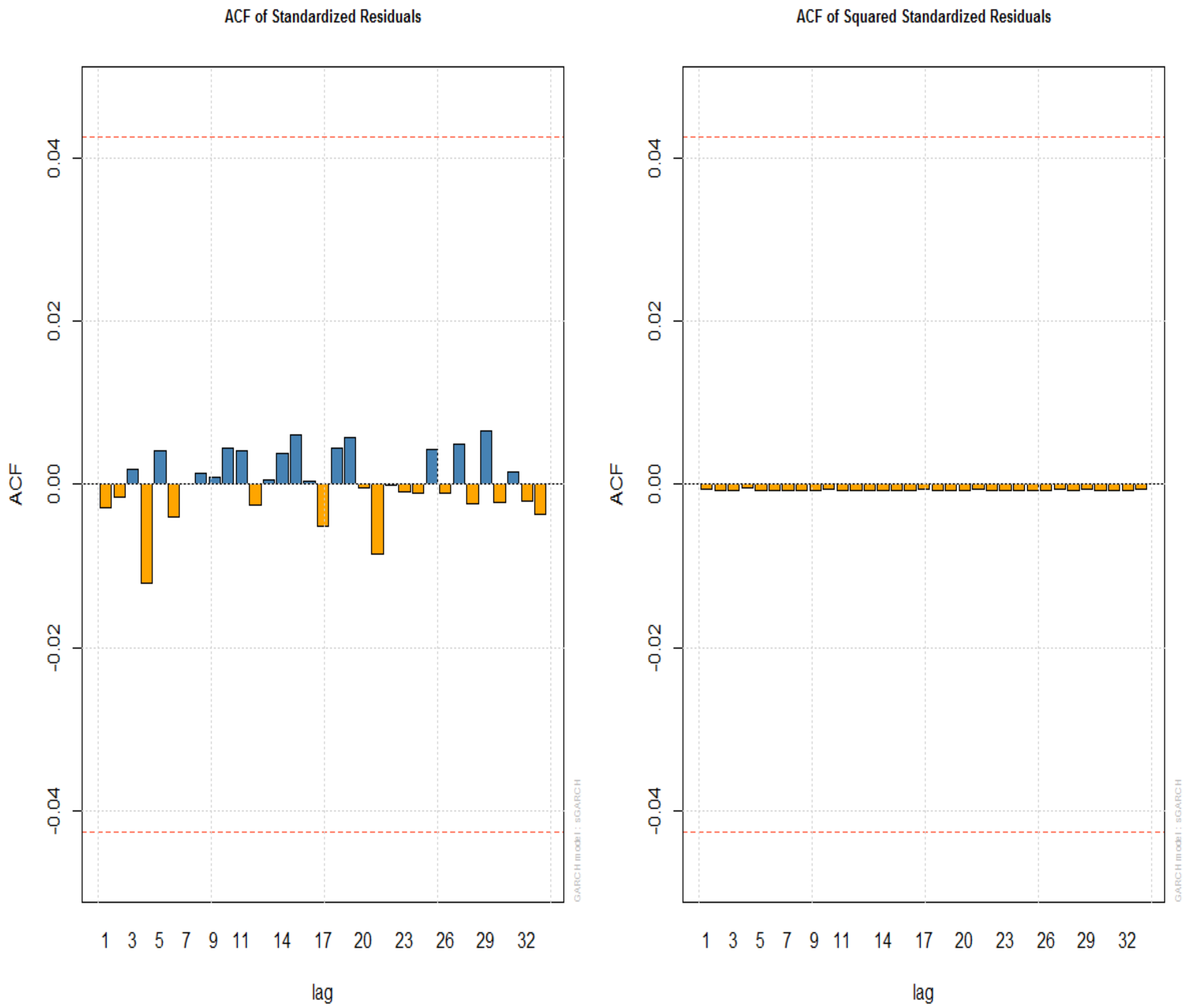

Figure 4.17: ACF of standardized Residuals of KES.

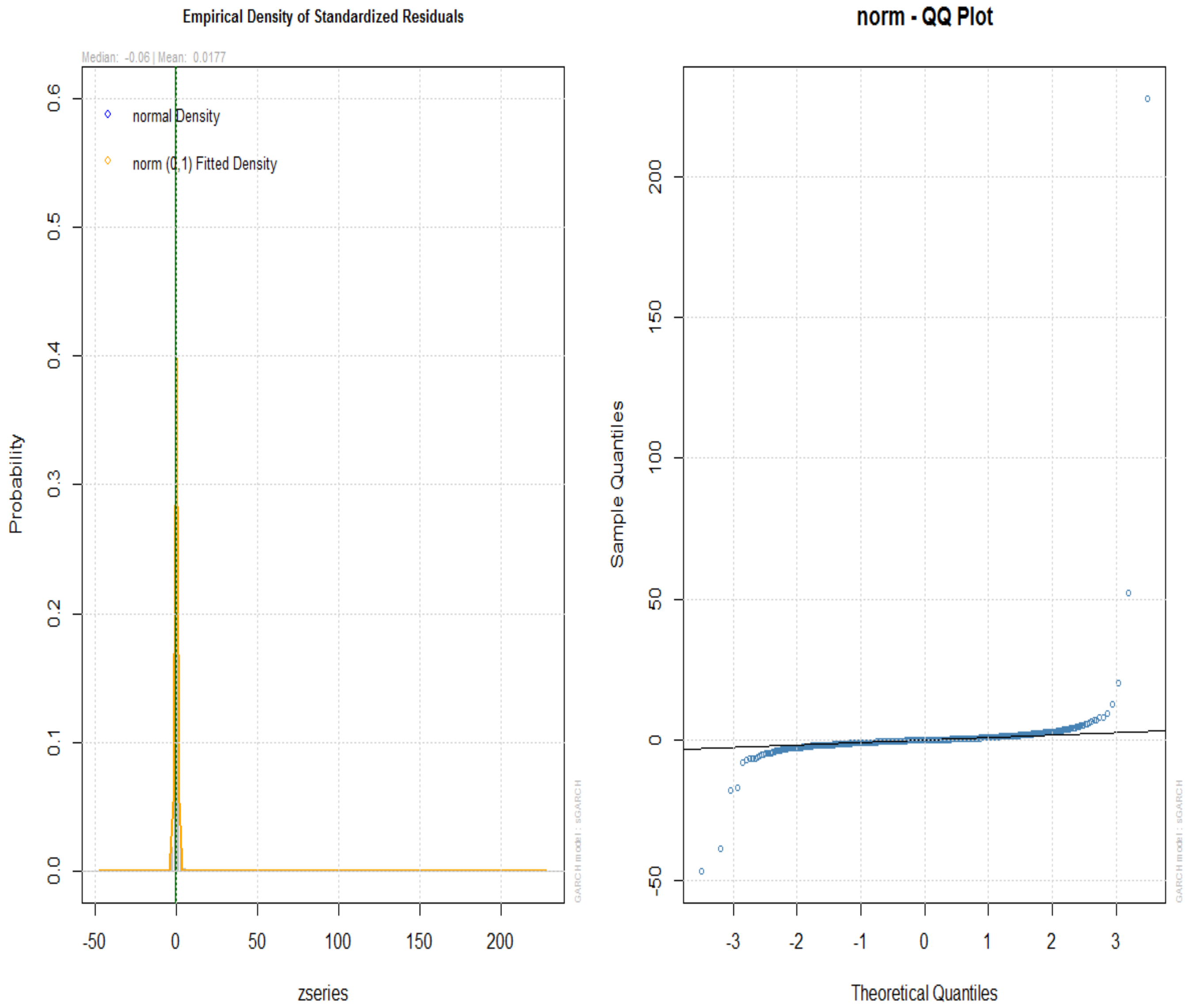

Figure 4.18: Empirical Density of Standardized Residuals of KES.

4.2.3 Estimated VaR and ES using AR(1)+GARCH(1,1)

In this section we are going to discuss the estimated VaR and ES by using AR(1)+ GARCH(1,1), where we have to know the currencies with high average loss and the one with small average loss.

For GBP, we estimate that within the next 1 day, on an investment of $\$20000$ which is equivalent to 19600000 FRW, there is a loss of 17326 FRW which is the VaR(0.05, 1 day) =17326 FRW and the average loss which is ES (0.05) = 26238 FRW. For EUR, we estimate that within the

Table 4.10: VaR and ES using AR(1)+GARCH(1,1)

Currency	VaR 95 % CI	ES 95 % CI
GBP	17326	26238
EUR	16390	24729
USD	477.15	4626.5
EGP	5971.1	40725
KES	7764.4	20397

next 1 day, on an investment of $\$20000$ which is equivalent to 19600000 FRW, there is a loss of 16390 FRW which is the VaR(0.05, 1 day) =16390 FRW and the average loss which is ES (0.05) = 24729 FRW. For USD, we estimate that within the next 1 day, on an investment of $\$20000$ which is equivalent to 19600000 FRW, there is a loss of 477.15 FRW which is the VaR(0.05, 1 day) = 477.15 FRW and the average loss which is ES (0.05) = 4626.5 FRW. On the following table 4.10, we observed that USD has small loss compared to other currencies as its VaR = 477.15 FRW and ES = 4626.5 FRW.

For EGP, we estimate that within the next 1 day, on an investment of $\$20000$ which is equivalent to 19600000 FRW, there is a loss of 5971.1 FRW which is the VaR(0.05, 1 day) =5971.1 FRW and the average loss which is ES (0.05) = 40725 FRW, On the following table 4.10, EGP has high loss compared to other currencies as its ES = 40725 FRW.

For KES, we estimate that within the next 1 day, on an investment of $\$20000$ which is equivalent to 19600000 FRW, there is a loss of 7764.4 FRW which is the VaR(0.05, 1 day) =7764.4 FRW and the average loss which is ES (0.05) = 20397 FRW.

4.3 Summary

The study have managed to determine the riskiest currency among other currencies by using clustering methods. By K-means clustering on table 4.2 we observed that EGP is riskiest currency. By fitting the returns using AR(1)+GARCH(1,1), it produces stationary time series because the sum of alpha and beta are less than one, as it is indicated on this table 4.7. The study determined the Value at Risk (VaR) and Expected Shortfall (ES) for each currency return time series, where USD On the following table 4.10, we observe that it has small loss compared to other currencies as its VaR = 477.15 FRW and ES = 4626.5 FRW, while EGP has high loss compared to other currencies as its VaR = 5971.1 FRW and ES = 40725 FRW.

5. Conclusion and Recommendation.

5.1 Conclusion

This study estimated Value at Risk (VaR) and Expected Shortfall (ES) of market returns in Rwanda using ARMA and GARCH models. A case study is Rwanda forex market, the data used were daily exchange rate series for the period from January 2012 to July 2020. After determining the riskiest asset among the currencies analysis using clustering methods, we observed that on this table 4.2, EGP is the riskiest currency that traded in Rwanda by using K-means clustering. Using hierarchical clustering, we observed that on this figure 4.3, we have three groups which tend to have similar behavior such as group one: GBP and EUR, group two : USD and KES and group three : EGP.

Fitting AR(1) + GARCH(1,1), we observed that the sum of alpha and beta are less than one for all currencies. Therefore, this model has been producing stationary time series, then we can use it to forecast Value at Risk (VaR) and Expected Shortfall (ES). Estimated VaR and ES for each FX return time series, we observed that on the following table 4.10, USD, has small average loss (ES= 4626.5 FRW), while EGP has high average loss ES= 40725 FRW, compared with other most traded currencies in Rwanda, thus we can invest in USD.

5.2 Recommendation

Based on the results of the study, we recommend to the investors, foreign traders and policy makers to adopt this proposed model solution for estimating Value at Risk and Expected Shortfall of market returns using ARMA and GARCH models. We recommend that for future research to include more currencies that traded in Rwanda market so as to get more insight about other currencies. Also could focus on nonparametric estimation of VaR and ES.

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